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

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Abstract

Theoretical predictions on how bilateral bargaining affects total welfare are ambiguous. Prices paid to hospitals by insurers are determined in yearly bilateral negotiations in all U.S. states except Maryland. This paper uses the unique all-payer health care regulation of Maryland to empirically analyze how removing bilateral bargaining from the health care market affects overall welfare. We estimate a structural model of hospital and insurer demand that captures consumer behavior, and a generalized linear model that explains Maryland's hospital pricing rule. The parameter estimates used in counterfactual analysis are obtained using hospital-, insurer-, and patient-level data from 2010. In the counterfactual world, we apply a Maryland-style pricing regime to New Jersey, and simulate the responses of hospitals, insurers, and patients. We find that removal of bargaining between hospitals and insurers is beneficial to total welfare, however benefits producers at the expense of consumers. Our results indicate that if New Jersey were to implement a hospital rate setting rule, producer surplus would go up by 1.6 billion dollars and consumer welfare would decrease by 720 million dollars a year. The increase in producer surplus is partially due to the fact that all insurers except Blue Cross Blue Shield (BCBS) switch to lower cost hospitals, decrease their premiums, and increase their enrollment. BCBS, who formerly covered more than half of the enrollees in the state, increases its premiums to maintain full coverage of hospitals in the market since it likely no longer benefits from discounts from hospitals. Increasing BCBS premiums also leads to an increase in producer surplus, and is the leading factor behind the decrease in consumer welfare. As BCBS is a dominant player in the market, we also investigate the impacts of keeping its markup constant as well as keeping its premium-network combination constant. We find that total surplus increases for both cases, however, only when BCBS is not allowed to change its premiums do we see an increase in consumer surplus and a fall in the number of uninsured.

1 Introduction

National health care expenditure in the U.S. has been on the rise since the 1960s. Total expenditure on health care has been increasing faster than the Gross Domestic Product (GDP) over this period: health care spending 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. The increase in prices charged by hospitals to insurers has prompted an empirical literature that focuses on investigating the effect of hospital mergers on negotiated prices taking the price discrimination through bilateral bargaining in the market as given. The goal of this paper is to empirically analyze the welfare effects of removing bargaining and thus price discrimination in the health care market.

Literature on the welfare effects of bilateral contracting provide evidence that many market features can shift hospitals (suppliers) and insurers (retailers) away from obtaining monopoly surplus. It has been shown to be the case 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.[2] While an argument can be made that each in turn apply to the health care market, the case of a monopoly supplier with unobservable contracts provides the most straightforward interpretation. Once contracts have been established, even if those contracts achieve monopoly profits or the vertically integrated profits, a hospital (supplier) and insurer (retailer) 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.[3] With a more competitive insurer market the reduction is more likely to be passed on to consumers. To empirically investigate the impact of the removal of bargaining on total welfare, we focus on an all-payer rate setting system where hospitals and insurers may no longer negotiate prices.

Today, Maryland is the only state in the United States that operates an all-payer system where the prices charged by individual hospitals to insurers are regulated.[4] While each hospital charges separate prices,

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

[2] Each is explored in greater detail in the following papers O'Brien and Shaffer (1992), Rey and Stiglitz (1988), Rey and Triole (1986).

[3] See Dobson and Waterson (1997), von Ungern-Sternberg (1997), Chen (2003).

[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.

the price a hospital charges to all insurers is the same. In this paper, we present a framework to analyze the effects of removing price discrimination by enforcing a single price between insurers and a hospital. In particular, we investigate the effects of implementing a Maryland style all-payer system in New Jersey.[5] 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. The measure of expected utility is used to account for the fact that insurers do not include access to every hospital in their market. With expected utility included as an insurer characteristic, we then estimate consumers' demand for insurance. Given demand estimates and hospital price estimates from a Maryland style pricing rule, we allow insurers to re-optimize their premiums and networks of hospitals. We find that insurers switch away from high-cost hospitals and premiums go down on average with a positive effect on total welfare in the market. Simulation results suggest that if New Jersey were to switch to a Maryland style all-payer system, it would experience a gain of more than 1.6 billion dollars in producer surplus. Moreover, the monetary value of the loss in consumer welfare would be about 288 dollars per consumer or up to a loss of 720 million dollars at the state level. As Blue Cross Blue Shield (BCBS) accounts for the majority of change in producer surplus, we also examine the effects of setting its premiums to a constant markup as well as not allowing BCBS to re-optimize at all. We still retain an overall surplus increase in both cases, however, only when we do not allow re-optimization by BCBS do we see that the increase in welfare comes from the consumer side. It is also the only case where the number of uninsured falls, suggesting that when prices are negotiated, BCBS uses its market power to obtain lower prices from hospitals, which, it then passes on to consumers.

This paper is related to several strands of literature. First is the work that investigates government regulation in the hospital industry.[6] 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.[7] The findings of Dranove and Cone (1985) indicate that states with hospital rate setting experienced 1.32 percent smaller increases in expenses per admission. They also find that not all rate setting programs were imposed in response to fast growing costs, therefore the negative average effect reported in the literature is unbiased. 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

[5]New Jersey was chosen due to data availability.

[6]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).

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

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 setting as a removal of price discrimination and measure its effects on consumer welfare and 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 found that consumer welfare would increase if health plans included all the hospitals in their networks keeping prices and premiums fixed. While her conclusion is highly intuitive, it does 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 (2016) looks at the role of adverse selection in insurer's decisions to include a single star hospital in their network and finds adverse selection provides 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 counter-factual change in the price regime.

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.[8] 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 markets surplus. Importantly, these papers find that merging allows hospitals to raise prices without any change in the efficiency of merging hospitals. While the existing papers take the market as is, our counter-factual abstracts from the bargaining process all together and is only concerned with the implications for overall welfare.

Since imposing a Maryland style price rule in the market will remove the price competition among hospitals, 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) found 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) supports this theory with empirical findings showing that when the National Health Service of the

[8]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), and Prager (2016).

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. While one might argue hospital rate setting will result in decreased quality in the light of these results, we refrain from such concerns as the rate setting agencies also regulate hospital quality. Furthermore, there is little evidence in the empirical literature that DRG-based payment systems such as rate setting and PPS reduce the quality of care.[9] Dor and Farley (1996) analyze the post-PPS era and find that hospital quality increases with the generosity of the third-party payer.[10] We assume that hospital quality remains unchanged among the privately insured patients and investigate the change of price structure alone.

Finally, we also connect to empirical literature that investigates wholesale 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. His model is quite thorough and benefits from granular price data whereas 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.

The rest of the paper is structured as follows. Section 2 briefly explains the history of health care in the United States and hospital rate setting in detail. 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.

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

[10] Dor and Farley (1996) use service intensity as a measure of hospital quality. In their analysis, private insurers are the most generous third-party payers.

2 Industry Background

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 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[11] 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)

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

suggest regulation to be used as a second-best choice, a necessary solution if not desirable. It is necessary as the market forces only have a marginal impact on the health care spending.

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 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 the costs.[12]

Competition, both in the hospital market and in the health plan market, is expected to drive hospital costs down. High concentration of hospitals in the market encourages hospitals to cut costs as they will be competing on price basis to be included in health plan networks.[13] Competition among health plans is also expected to restrain hospital costs and control the quantity of the services provided.[14] 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. While leaving all the work to the market forces to obtain these desirable outcomes seems appealing, the competitive approach encourages horizontal and vertical consolidation among providers. 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.[15] While regulation has proved to be effective in cutting hospital prices, it also has its flaws. The major concern with price regulation is cost shifting. If hospital prices are not regulated for all payers, then hospitals have an incentive to shift costs and charge the unregulated payers more. Also, if the prices are regulated only for inpatient care, one might expect the prices of outpatient care or home health services to go up. Incentives of hospitals to underprovide quality and overprovide services are also concerns that accompany the implementation of price regulation, however state governments regulate quality and quantity in most cases.

[12]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.

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

[14]See Hadley (1995).

[15]See Ho (2009) among others.

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

Altman and Rodwin (1988) summarize the strategies used to contain health care spending both by competition and by regulation. On the competition frontier, increasing consumer co-payments and deductibles to fight with moral hazard, HMO competition, and prudent purchaser programs such as large insurance plans receiving discounts from providers in return for greater volume of patients were used. Authors conclude that while competition may increase efficiency, it will 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 partial budget regulation (PPS). Among these, hospital rate setting and PPS proved to be effective in cutting costs.[16] The power of PPS to cut costs is also encouraging for our analysis as PPS and Maryland pricing rule are similar in that price per admission to a hospital for a specific DRG is fixed.

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.[17] 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 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.[18] These amendments also gave rise to utilization review to control the quantity and quality

[16] See Hadley (1995).

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

[18] 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.

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.[19] 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.[20] 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 drived 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.[21] During this period, growth in price of health care accounted 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[22] which makes

[19]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 icnreased from 13% in 1980 to 18% in 1981. See Mayes (2007) and Sloan (1983).

[20]See Schramm et al. (1986)

[21]Consumers were concerned about receiving constrained care under such plans. Employers also abondoned 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 levarage to hospitals.

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

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.[23] 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.

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.[24] 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.).[25] 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

accounted for 20% of the overall expenditure.

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

[24] The first state to adopt a mandatory hospital rate setting was New York State. In the following years, six more states also adopted this madatory regulatory approach and rate setting commisions 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 particulary 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.

[25] 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.

Opposition to rate setting was strong. Regulated hospitals feared that revenues would not meet expenses, so they would be forced to use their capital reserves to manage the shortfalls. However, the study by Schramm et al. (1986) shows that the 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 their accumulated capital.

In many states, mandatory rate setting programs were abondoned (except for Maryland and West Virginia) starting in the 1990s, mostly due to the pressure by hospital associations to encourage price competition. The success of managed care and Health Maintenance Organizations (HMOs) in driving provider prices down also contributed to abondoning of such regulations as critics believed the market can control costs better.[26] Today, in 49 U.S. states, hospital prices are determined at yearly negotiations between insurers and hospitals. As a result of this bargaining, there is distortion in the market: hospitals, especially the ones that have market power, can price discriminate among insurers and charge above the market price.

Maryland's hospital rate setting program is the only remaining all-payer 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[27] 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.

[26] For a detailed history review of hospital rate setting, see Murray and Berenson (2015).
[27] The goals of HSCRC can be found on their website: http://www.hscrc.state.md.us

HSCRC controls and oversees hospital costs in Maryland and prohibits price discrimination or discounts to private insurers. The cost control system has a hybrid nature where per-unit per-case constraints based on DRGs are applied to inpatient care and per-visit constraints are applied to outpatient care. The hybrid case-mix system is called the "guaranteed inpatient revenue system" as hospitals are allowed to incrementally increase their unit charges to meet the pre-targeted per-case revenues once they achieve to reduce their unit costs, length of stay for inpatient services, or ancillary use per day throughout the year. HSCRC also imposes volume controls to remove the incentives of hospitals to increase profits by increasing their service volumes. Other features of the Maryland regulation include a screening system that compares relative efficiency of hospitals in various peer groups, an uncompensated care pooling mechanism that equalizes magnitude of funding across hospitals, and incentive-based quality programs. A detailed explanation of the state legislation and its evolution throughout the years can be found in Murray and Berenson (2015).

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.[28] These early papers that regress change in hospital expenses on a regulation dummy are usually criticized in several aspects.[29] First, the dummy coefficient 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.

[28] 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).

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

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[30] 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 California during 1982-1986. Over this period, hospital competition in California was triggered by the changes of a state law.[31] 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.

[30] 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.

[31] 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).

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.

All in all, there are two major conclusions of this literature. First, mature mandatory rate-setting programs led to a reduction in hospital cost growth.[32] Second, state level mandatory rate setting have been more effective than other regulatory programs both in cost and non-cost aspects.[33] 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. In this paper, we show that this is indeed the case by using economic methods.

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)

[32]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).

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

and number of uninsured by state to supplement our dataset.

We use SID data from Maryland, New Jersey, Arizona, Kentucky, and Washington. These states cover 503 hospitals and 675,954 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 14 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 as 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)	14.1	21.909	0.036	311.902
Female	0.664	0.472	0	1
Age	28.108	21.846	0	64

Notes: N = 675,954 discharges.

Table 2 provides a summary of select variables from the hospital dataset.[34] We report information on 503 hospitals that operate in the five states mentioned above. We observe ownership type (government, 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

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

Table 2: Hospital Characteristics

	Mean	**SD**	**Min**	**Max**
Cancer Accreditation	0.320	0.211	0	1
Teaching Hospital	0.072	0.125	0	1
Blue Cross Contract	0.881	0.107	0	1
Hospital Beds	178.38	167.93	6	1,006
General Hospital	0.590	0.492	0	1
Neonatal Intensive Care	0.159	0.366	0	1
Birthing Room	0.410	0.492	0	1
Cardiac Surgery	0.179	0.384	0	1
Oncology Services	0.491	0.500	0	1
Palliative Care	0.292	0.455	0	1
CT Scanner	0.590	0.492	0	1
Ultrasound	0.583	0.494	0	1
Kidney Transplant	0.036	0.186	0	1
Women's Health Center	0.400	0.490	0	1
Admissions	7,843	9,021	39	68,717
Inpatient Days	44,880	48,175	347	283,272
Full-time Physicians	24.058	66.828	0	779
Full-time Nurses	225.245	274.481	1	2,124

Notes: N = 503 hospitals.

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 demand for hospitals by consumers and demand for insurance plans by consumers. Next, given the demand estimates, we calculate the producer surplus (for hospitals and plans) and consumer surplus in New Jersey under a Maryland style pricing rule and in its absence.

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 = 520 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.[35] 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:

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

where x_h is a vector of observed hospital characteristics, v_{il} is a vector of observed consumer characteristics such as location 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:

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

In particular, let the specification for the utility be:

$$u_{ihl} = \theta x_h + \lambda x_h v_{il} + \epsilon_{ihl} \quad (3)$$

[35]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:

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

where H_m is the set of hospitals in the market.

Since we observe the actual shares, we use maximum likelihood to obtain the parameter estimates $\hat{\lambda}$ and $\hat{\theta}$. Unlike the health plan demand model (presented next), this model does not account for unobserved characteristics or unobserved quality of hospitals.[36] We have very rich hospital characteristics data, therefore we assume that the 83 characteristics we use in the estimation capture the quality of hospitals. Identification in this model comes from the variation in patients' hospital choice sets across markets. In our model, patients' choice sets are defined by zip codes. In particular, we put a hospital in a patient's choice set if another patient who lives in the same zip code visited that hospital. Results of 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 q:

$$\hat{u_{qhl}} = \hat{\theta} x_h + \hat{\lambda} x_h v_{ql} + \epsilon_{qhl} \tag{5}$$

Then, we calculate expected utility for patient type q 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:

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

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

[36] 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). Given the large number of observations and covariates, our estimation ran into convergence issues on the first stage. Therefore, we collapsed the two-stage process into one estimating equation.

Expected Utility Aggregation:

As we only observe the hospital networks of insurers in New Jersey and Maryland we use an aggregate measure of expected utility in health plan demand. For New Jersey and Maryland we create a population weighted average

$$EU_{jm} = \sum_{q} \frac{n_q}{n_m} eu_{qj} \tag{7}$$

where n_q is the number of q type individuals and n_m is the number of individuals in the market.

For the states where we don't observe exact insurer networks, we use the number of hospitals insurers contract with and assign the average expected utility from a hospital network of that size using a representative agent of the most populated ZCTA.[37] For a single network of hospitals, the expected utility for insurer j is:

$$eu_j^{rep} = \sum_{l} p_l^{rep} log\left(\sum_{h \in H_j} exp(\hat{\theta} x_h + \hat{\lambda} x_h v_l^{rep}) \right) \tag{8}$$

In order to save computation time we draw a million possible hospital networks (hn) and average across them to get expected utility for plan j as:

$$EU_j^{rep} = \frac{1}{1000000} \sum_{hn} (eu_j^{rep}) \tag{9}$$

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 with and without expected utility and then move onto BLP estimation which is the model used for the calculation of welfare. In all health plan demand specifications, markets are defined by states. We have 50 markets in total and observe 520 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:

[37] The data for this calculation come from the Census and Nationwide Inpatient Sample(NIS). The census provides population information while NIS is used to calculate p_l^{rep}.

$$u_{ijr} = \sum_k x_{jkr}\beta_k + \xi_{jr} + \epsilon_{ijr} \tag{10}$$

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:

$$u_{ij} = \sum_k x_{jk}\beta_k + \xi_j + \epsilon_{ij} = \delta_j(x_j, \xi_j, \beta) + \epsilon_{ij} \tag{11}$$

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 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:

$$s_j = \frac{e^{\delta_j}}{1 + \sum\limits_{g=1}^{G} e^{\delta_g}} \tag{12}$$

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

$$s_o = \frac{1}{1 + \sum\limits_{g=1}^{G} e^{\delta_g}} \tag{13}$$

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

$$\frac{s_j}{s_o} = e^{\delta_j} \Longrightarrow ln(s_j) - ln(s_o) = \delta_j \tag{14}$$

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:

$$\delta_j = \sum_k x_{jk}\beta_k + \xi_j \tag{15}$$

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:

$$\xi_j = \delta_j - \sum_k x_{jk}\beta_k = ln(s_j) - ln(s_o) - \sum_k x_{jk}\beta_k \tag{16}$$

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:

$$\min_\beta \xi(\beta)'ZWZ'\xi(\beta) \quad where \quad W = (E[Z'\xi\xi'Z])^{-1} \tag{17}$$

The analytical solution to this problem is:

$$\beta = (X'ZWZ'X)^{-1}(X'ZWZ'\delta) \tag{18}$$

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:

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:

$$w_{ij} = \xi_j + z_j\lambda + \beta_1 EU_j + \beta_2 prem_j + \gamma_1\nu_i EU_j(H_j) + \gamma_2\frac{prem_j}{y_i} + \eta_{ij} = \delta_j + \mu(y_i,\nu_i) + \eta_{ij} \tag{19}$$

where ξ_j are unobserved plan characteristics, z_j are the observed plan characteristics, and $prem_j$ is plan j's premium, y_i and ν_i are random draws from a log-normal distribution, and η_{ij} are idiosyncratic shocks to consumer tastes that are assumed to be i.i.d. Type 1 Extreme Value. δ_j is the mean utility level that a patient gets from plan j. It is the presence of the interaction terms μ that allows us to capture the heterogeneity of preferences. In this setting, consumes 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. As in BLP (1995), we use simulation techniques to obtain the predicted shares:

$$\hat{s_{jm}}(\lambda,\gamma,\beta) = \frac{1}{ns}\sum_{i=1}^{ns}\frac{exp\left(\xi_{jm} + z_{jm}\lambda + \beta_1 EU_{jm} + \beta_2 prem_{jm} + \gamma_1\nu_i EU_{jm}(H_{jm}) + \gamma_2\frac{prem_{jm}}{y_i}\right)}{1 + \sum_{k\in P} exp\left(\xi_{km} + z_{km}\lambda + \beta_1 EU_{km} + \beta_2 prem_{km} + \gamma_1\nu_i EU_{km}(H_{km}) + \gamma_2\frac{prem_{km}}{y_i}\right)} \tag{20}$$

where ns is the number of random draws, and P is the set of plans in the market. Dropping the market subscript and simplifying notation, we get:

$$\hat{s_j}^{ns} = \frac{1}{ns} \sum_i \frac{exp(\delta_j + \mu(x_j, \nu_i, \sigma))}{1 + \sum_j exp(\delta_j + \mu(x_j, \nu_i, \sigma))} \tag{21}$$

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:

$$\delta^h = \delta^{h-1} + ln(s) - ln(\hat{s}) \tag{22}$$

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 $\xi_j = \delta_j - z_j\kappa$. 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 for Arizona, Kentucky, Maryland, New Jersey, and Washington and hospital characteristics come from AHA. We estimate a conditional logit model where the utility specification is given by:

$$u_{ihl} = \theta x_h + \lambda x_h \nu_{il} + \epsilon_{ihl} \tag{23}$$

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[38] 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 2%. Remaining covariates are interactions of services offered by the hospital with the relevant MDCs. The results are intuitive. A patient diagnosed

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

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:

$$u_{ij} = \sum_k x_{jk}\beta_k + \xi_j + \epsilon_{ij} = \delta_j(x_j, \xi_j, \beta) + \epsilon_{ij} \tag{24}$$

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 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 of the characteristics of the other plans ($x_n, n \neq j$) in the same market. These characteristics are premium, age, size (enrollment), Weiss rating, number of physicians, NCQA score, and NCQA's three measures for plan performance. These instruments satisfy the three traditional conditions of instrumental variables. They are relevant as they are correlated with premiums via competition and markups (as implied by the first order conditions in the supply side and the pricing equation), 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

Table 4: Hospital Demand Results

Variable	Marginal Effect	Variable	Marginal Effect
Distance (miles)	-0.018*** (0.0001)	Burn care*Burns	1.242*** (0.063)
Distance squared	0.00003*** (0.0000003)	Alcohol/drug abuse care* Alcohol/drug use	1.113*** (0.017)
Birthing room	0.061*** (0.004)	Psychiatric care* Mental diseases	1.059*** (0.020)
Blood Donor Center	0.198*** (0.003)	Birthing room* Pregnancy, childbirth	0.161*** (0.005)
Chemotherapy	0.145*** (0.004)	Mammograms* Skin, tissue, breast	0.034** (0.011)
Optical colonoscopy	0.036*** (0.002)	Optical colonoscopy* Digestive system	0.101*** (0.004)
HIV-AIDS services	0.119*** (0.002)	Cardiac surgery* Circulatory system	0.370*** (0.008)
Translation services	0.038*** (0.002)	Chemotherapy* Ear, nose, mouth, throat	0.228*** (0.027)
Intraoperative MRI	0.120*** (0.003)	Chemotherapy* Skin, tissue, breast	0.041** (0.016)
Tomography 64+ slice	0.097*** (0.002)	Chemotherapy* Male reproductive system	0.218*** (0.026)
Ultrasound	0.062*** (0.005)	Neurological services* Nervous system	0.325*** (0.015)
Tissue transplant	0.222*** (0.005)	Oncology services* Ear, nose, mouth, throat	0.086** (0.031)
Women's health center	0.068*** (0.003)	Oncology services* Female reproductive system	0.136*** (0.012)
Medical/surgical care* Circulatory system	0.176*** (0.020)	MRI*Nervous system	0.186*** (0.016)
Medical/surgical care* Hepatobiliary, pancreas	0.437*** (0.034)	Tomography 64+ slice* Nervous system	0.119*** (0.006)
Medical/surgical care* Skin, tissue, breast	0.210*** (0.027)	PET/CT*Nervous system	0.106*** (0.005)
Medical/surgical care* Male reproductive system	0.598*** (0.079)	Heart transplant* Circulatory system	0.176*** (0.005)
Medical/surgical care* Female reproductive system	0.843*** (0.046)	Kidney transplant* Kidney and urinary tract	0.218*** (0.007)
Medical/surgical care* Pregnancy, childbirth	0.467*** (0.028)	Liver transplant* Digestive system	0.053*** (0.006)
Obstetrics care* Pregnancy, childbirth	0.509*** (0.008)	Lung transplant* Respiratory system	0.214*** (0.008)
Obstetrics care* Newborns, other neonates	0.530*** (0.008)	Tissue transplant* Skin, tissue, breast	0.076*** (0.008)

Notes: Results from maximum likelihood estimation. Marginal effects (evaluated at the mean) are reported for each covariate. N = 675,954 discharges from 503 hospitals in five states. Delta-method standard errors in parantheses. *** statistically significant at 1% level, ** statistically significant at 5% level, * statistically significant at 10% level.

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 nonelderly uninsured by nonelderly population of that state.

The parameter estimates are reported in Table 5. The first three columns follow the conditional logit framework introduced by Berry (1994). Columns (1) and (2) use insurer data at the national level and show that inclusion of large plan fixed effects improves the fit of the model. According to column (2) results, a \$100 increase in monthly premiums decreases the probability of choice of that plan by 20.9%. On average, consumers prefer plans that have been on the market for a longer time, however the performance ratings reported by NCQA do not play a role in patients' decisions and are dropped in the final BLP specification. The coefficient on PPO/Indemnity dummy is positive and significant, implying patients prefer PPO/Indemnity plans to HMO/POS plans. Since PPO/Indemnity plans offer higher flexibility with regard to provider network, this is as expected.

The third column of Table 5 reports the parameter estimates from the same logit specification with an added explanatory variable. This new variable is the expected utility the average individual gets from the network of hospitals offered by that insurance plan. Hence, construction of the expected utility variable requires knowledge of hospital networks offered by each insurer in the market. We observe the hospital networks only in two markets: New Jersey and Maryland. Therefore, we use 21 health plans from these two markets to estimate the model.

The last column of Table 5 shows the final BLP estimates where expected utility and premiums are interacted with ν_i and y_i, respectively. The estimation results indicate that individuals care about the network of hospitals offered by their insurance plans. The coefficient in front of the expected utility variable is both positive and significant. The premium coefficient estimate has the correct sign and is statistically significant. Same is true for PPO plans. The quality rating of the plan as reported by the Weiss Guide affect the probability that an individual chooses a health plan in a positive way. These estimates from the last column are the figures used for simulation of the counterfactuals.

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

Table 5: Health Plan Demand Results

	(1)	(2)	(3)	(4)
Premium ($00)	-0.111***	-0.209***	-0.002	-0.408**
	(0.032)	(0.042)	(-0.067)	(0.197)
Age	0.019***	0.033***	0.006	0.029***
	(0.004)	(0.006)	(0.006)	(0.005)
Number of Physicians	-0.0002***	-0.0001***	-0.0008***	-0.013***
	(0.00005)	(0.00004)	(0.0001)	(0.001)
PPO/Indemnity	0.203	0.339**	0.251	0.178
	(0.195)	(0.165)	(0.222)	(0.184)
Weiss Rating	0.153***	0.137***	0.322***	0.111***
	(0.042)	(0.039)	(0.057)	(0.038)
Score	-0.183**	-0.018	0.125	-0.015
	(0.086)	(0.087)	(0.125)	(0.012)
Consumer Satisfaction	-0.149*	-0.157*	-0.012	
	(0.085)	(0.094)	(0.098)	
Treatment	-0.232	0.066	0.122	
	(0.162)	(0.160)	(0.166)	
Prevention	-0.013	0.123	-0.565***	0.215***
	(0.125)	(0.141)	(0.205)	(0.038)
NCQA Accreditation	-3.036**	0.081	-2.123	
	(1.299)	(1.314)	(1.878)	
Expected Utility	-	-	0.261**	0.106*
			(0.118)	(0.062)
Constant	-12.807**	-0.776	-12.18	-2.131**
	(5.165)	(5.248)	(7.481)	(1.062)
Large Plan FE	No	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
R^2	0.395	0.517	0.941	

Notes: Results from GMM estimation. N = 520 health plans. Clustered standard errors (at the state level) in parentheses. First three columns follow Berry (1994), last column follows BLP (1995). *** statistically significant at 1% level, ** statistically significant at 5% level, * statistically significant at 10% level.

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.

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 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[40], depreciation, ownership status, and DRG fixed effects.[41] Results are reported in Table 6.[42] 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, almost all of the explanatory power in rate regressions come from service fixed effects. This suggests hospitals take into account specifics of each procedure/service rather than hospital characteristics while setting their rates. As we are unable to capture these specifics in our data, we use the more accurate prediction 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 counter factual of setting a single price per hospital and allowing hospitals and insurers to set prices individually.

[40]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.

[41]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.

[42]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.

Table 6: Maryland Pricing Rule

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

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. Insurers maximize a standard profit function by choosing networks and premiums:

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

Which gives us the first order condition as:

$$s_j(H_j, H_{-j}) + \sum_{h \in H_j} (prem_j - price_h) \frac{\delta s_{j,h}(H_j, H_{-j})}{\delta prem_j} = 0 \tag{26}$$

where $price_h$ is the average expected cost of including a hospital in an insurers network

$$price_h = \sum_l p_l E(Price_l) = \sum_l p_l s_{hl} \hat{Price}^N J_{hl} \tag{27}$$

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.

As shares depend not only on insurers 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. 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

The Blue Cross Blue Shield plan will not change its network, as by assumption it covers all hospitals. The remaining insurers can deviate by adding or subtracting a hospital and would earn extra profits 42,300. So a yearly fixed fee of contracting would enforce our equilibrium. However as contract interdependency is built into this model we can not rule out profitable multilateral deviations.[43] We must also include that insurers are setting their networks and premiums based on the expected networks and premiums of other insurers and that contracts may not be renegotiated if expected networks do not match actual networks.

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:

$$R_j(H_j, H_{-j}) = \sum_g \left(n_g s_{gj}(H_j, H_{-j}) \left[prem_j - p_g \sum_{h \in H_j} s_{gh}(H_j) cost_h \right] \right) \tag{28}$$

where $cost_h$ is the expected costs incurred by hospital h

$$cost_h = \sum_l p_l E(cost_l) = \sum_l p_l \sum_{h \in H_J} s_{hl} cost_{hl} \tag{29}$$

We calculate the producer surplus in the presence and in the absence of price discrimination. 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 $\$1,604,420,555$. The main cause for this gain in surplus is that BCBS increases its premiums drastically. BCBS exploits their power from being the sole provider of hospitals and increases premiums which lowers their total market share but greatly increases their surplus generation. All other insurers, except the smallest, decrease premiums and increase market shares which also provides an increase in total producer surplus.

6.2 Consumer Surplus

The compensating variation is used to measure the change in consumer's welfare after price regulation 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

[43] See Rey and Verge (2004)

[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.

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

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

$$V_{ij} = \xi_j + z_j\hat{\lambda} + \hat{\beta}_1 EU_j + \hat{\beta}_2 prem_j + \hat{\gamma}_1\nu_i EU_j(H_j) + \hat{\gamma}_2\frac{prem_j}{y_i} \tag{31}$$

Compensating variation is then the market size times the integral of compensating variation over the distribution of ν and is given by

$$CV_{NJ} = M\int CV_i dP_\nu(\nu) \tag{32}$$

where M is market size. Applying this to the random-coefficients model we calculate the compensating variation by simulation. Specifically for each draw of ν, the compensating variation is calculated. Simulated compensating variation is then the average of these compensating variations.

$$CV_{NJ} = M\frac{1}{n}\sum_{i=i}^{n} CV_i = M - \frac{1}{\alpha_i}\left[ln\sum_j exp(V_{ij}^{post} - ln\sum_j exp(V_{ij}^{pre})\right] \tag{33}$$

where $\alpha_i = \beta_2 + \gamma_2 y_i$.

Overall, consumers lose \$288 each and the total surplus loss for consumers equals \$720 million. Along with a large loss in surplus we see that the percent uninsured for all of New Jersey would increase by more than 5%. The loss comes partially from the shift of insurers to lower cost hospitals which generally are valued at a lower expected utility for consumers, however the main portion of the loss comes from the increase in BCBS premiums and consumers unwillingness to switch from BCBS to another plan.

6.3 Blue Cross Blue Shield Counterfactuals

As mentioned previously, BCBS is the dominant firm in our market of interest and has the largest impact on both producer and consumer surplus. We therefore simulate two more counterfactuals to exposit their

Table 7: Welfare Results

	BCBS Network Size Fixed	BCBS Markup Fixed	BCBS No Change
Δ PS	1,604,420,555	1,083,340,362	-6,590,194
Δ CS	-723,915,091	-290,389,450	18,341,204
Δ BCBS Surplus	1,386,357,630	961,169,248	-76,403,147
Δ Other Insurer Surplus	218,062,925	122,171,114	69,812,953
Δ Uninsured	5.06%	2.03%	-0.46%

importance in New Jersey. First, we allow BCBS to change its premiums to a constant price over cost ratio which is calculated using BCBS of Maryland data. Second, we do not allow BCBS to change at all, we hold both its premiums and network fixed.

Setting New Jersey's price over marginal cost ratio to what we observe in Maryland helps to account for BCBS acting as a nonprofit firm, but more importantly it helps us get an idea of how the increased costs from BCBS no longer being able to bargain affect the market. We see that the magnitudes of both changes in producer and consumer surplus lessen although we still have an overall gain in surplus in the market. The decrease in consumer surplus is about $290 million or approximately $116 per person and still is 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 a little more than 2% but still is lower than when all firms competed in a Bertrand Nash game.

In the final counterfactual where BCBS is not allowed to change its network or premiums, the source of increase in total surplus now comes from an increase in consumer surplus and a relatively small decrease in producer surplus. While all insurers other than BCBS increase their producer surplus, the overall producer surplus falls by $6.5 million due to the losses incurred by BCBS. Since other insurers switch away from relatively expensive hospitals, now all patients who visit these hospitals visit them through BCBS who cannot raise its premiums to counteract the higher costs. Lastly, we observe that the percent of uninsured in the market falls by about half a percent.

7 Conclusion

While literature has focused on mergers of hospitals having a negative effect on competition by increasing bargaining power, the U.S. Robinson Patman Act also disallows price discrimination where the effect may lessen competition. This paper argues that the current price discrimination present in the health care market is detrimental to overall welfare. Our results highlight the importance of investigating price discrimination in the health care industry and their effects on competition. To the best of our knowledge this is the first paper to empirically allow insurers to not only set premiums but also partially re-optimize their network of hospitals offered.

Many authors have stated that rate setting does not have the same effects in every state.[45] It is also important to remember that consumer welfare depends not only on price but on quality and quantity of the services received which we are unable to model, we can only apply our welfare gains to a static model where hospitals and patients do not act differently under the new price regime. However, we still highlight the possibility of large potential welfare gains from a move towards more uniform pricing. Further research would be useful, especially in a setting where prices from bargaining could be observed, to more precisely breakdown welfare between hospitals and insurers.

[45] For a thorough and specific analysis of why Maryland's regulation may not work in other states see Pauly and Town (2012).

8 Appendix

8.1 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 Arizona, Kentucky, Maryland, New Jersey and Washington 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 and hospital's zip codes. A patient's choice set consists of all the hospitals any other patient in his zip code visited that year.

Dataset for Health Plan Demand:

The first four specifications of health plan demand reported in Table 5 use nationwide health plan data. In these models, 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

[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 my 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.

information is used to determine which plans offer commercial business. We work only with these plans as 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 25 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

[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$_{R}ates2.cfm$

year 2010. Our second dependent variable, the total charges per patient, is available from the SID files. 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.

8.2 Full Model Estimates

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

[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.

Table A1: Hospital Full Demand Model Estimates

Variable	Coefficient	Variable	Coefficient
Distance (miles)	-0.076*** (0.0001)	Breast cancer screening/ mammograms	-0.082*** (0.012)
Distance squared	0.0001*** (0.00001)	Cardiology services	-0.025* (0.012)
Foundation - hosp	0.489*** (0.013)	Diagnostic catheterization	0.161*** (0.014)
HMO - hospital	0.777*** (0.023)	Interventional cardiac catheterization	0.284*** (0.011)
PPO - hospital	-0.397*** (0.014)	Adult cardiac surgery	-0.328*** (0.011)
Indemnity - hospital	-3.095*** (0.047)	Adult cardiac electrophysiology	0.056*** (0.011)
Number of beds	-0.0002*** (0.00003)	Cardiac Rehabilitation	0.093*** (0.009)
Medical/surgical care	-0.772*** (0.026)	Chemotherapy	0.600*** (0.014)
Obstetrics care	0.044** (0.017)	Computer assisted orthopedic surgery	-0.300*** (0.007)
Medical/surgical intensive care	0.330*** (0.015)	Dental services	-0.280*** (0.008)
Cardiac intensive care	0.199*** (0.008)	Optical Colonoscopy	0.150*** (0.007)
Neonatal intensive care	0.640*** (0.008)	Endoscopic ultrasound	0.083*** (0.009)
Burn care	0.159*** (0.013)	Ablation of Barrett's esophagus	0.109*** (0.007)
Physical Rehabilitation care	0.142*** (0.007)	Endoscopic retrograde cholangiopancreatography (ERCP)	0.312*** (0.011)
Alcohol/drug abuse care	-0.365*** (0.011)	Fertility clinic	-0.539*** (0.016)
Psychiatric care	-0.260*** (0.007)	Extracorporeal shock waved lithotripter (ESWL)	0.220*** (0.008)
Skilled nursing care	-0.496*** (0.011)	Geriatric services	-0.005 (0.008)
Intermediate nursing care	-0.254*** (0.013)	Health screenings	-0.059*** (0.014)
Acute long term care	0.190*** (0.014)	Hemodialysis	-0.011 (0.008)
Alzheimer Center	0.039** (0.014)	HIV-AIDS services	0.493*** (0.008)
Arthritis treatment center	-0.356*** (0.015)	Indigent care clinic	-0.061*** (0.009)
Birthing room	0.254*** (0.016)	Linguistic/translation services	0.156*** (0.010)
Blood Donor Center Hospital	0.820*** (0.012)	Neurological services	0.547*** (0.013)

Table A1: Hospital Full Demand Model Estimates continued

Variable	Coefficient	Variable	Coefficient
Occupational health services	-0.255*** (0.009)	Proton beam therapy	0.121*** (0.015)
Oncology services	-0.172*** (0.018)	Shaped beam radiation system	-0.286*** (0.012)
Orthopedic services	-0.097*** (0.014)	Stereotactic radiosurgery	0.136*** (0.009)
Pain Management Program	0.076*** (0.009)	Robotic surgery	0.476*** (0.008)
Palliative Care Program	0.014 (0.009)	Rural health clinic	-0.662*** (0.014)
Inpatient palliative care unit	0.016* (0.008)	Sports medicine	-0.176*** (0.007)
Electrodiagnostic services	-0.188*** (0.007)	Tobacco Treatment Services	-0.220*** (0.008)
Prosthetic and orthotic services	0.290*** (0.008)	Bone Marrow transplant services	0.361*** (0.016)
Primary care department	-0.003 (0.009)	Heart transplant	-1.431*** (0.016)
Psychiatric geriatric services	-0.193*** (0.009)	Kidney transplant	0.056** (0.018)
Computed-tomography (CT) scanner	-0.262*** (0.032)	Liver transplant	0.218*** (0.015)
Diagnostic radioisotope facility	0.127*** (0.015)	Lung transplant	-0.291*** (0.023)
Full-eld digital mammography	-0.304*** (0.009)	Tissue transplant	0.920*** (0.021)
Magnetic resonance imaging (MRI)	-0.489*** (0.014)	Virtual colonoscopy	0.072*** (0.009)
Intraoperative magnetic resonance imaging	0.496*** (0.010)	Women's health center	0.281*** (0.010)
Multislice spiral computed tomography <64 slice	0.007 (0.012)	Neonatal intermediate care	-0.074*** (0.009)
Multislice spiral computed tomography 64+ slice	0.403*** (0.008)	Medical/surgical care*Eye	-0.616** (0.233)
Positron emission tomography (PET)	-0.238*** (0.010)	Medical/surgical care* Ear, nose, mouth and throat	-0.129*** (0.113)
PET/CT	-0.176*** (0.008)	Medical/surgical care* Circulatory system	0.730*** (0.084)
Single photon emission computerized tomography (SPECT)	-0.113*** (0.008)	Medical/surgical care* Hepatobiliary and pancreas	1.815*** (0.140)
Ultrasound	0.258*** (0.020)	Medical/surgical care* Skin, subcutaneous tissue, breast	0.870*** (0.111)
Image-guided radiation therapy	0.352*** (0.010)	Medical/surgical care* Male reproductive system	2.481*** (0.327)
Intensity-Modulated Radiation Therapy (IMRT)	-0.082*** (0.012)	Medical/surgical care* Female reproductive system	3.499*** (0.192)

Table A1: Hospital Full Demand Model Estimates continued

Variable	Coefficient	Variable	Coefficient
Medical/surgical care*	1.936***	Cardiac rehabilitation*	-0.012
Pregnancy, childbirth and puerperium	(0.125)	Circulatory system	(0.024)
Medical/surgical care*	0.677**	Chemotherapy*	0.945***
Multiple significant trauma	(0.234)	Ear, nose, mouth and throat	(0.113)
Obstetrics care*	2.113***	Chemotherapy*	0.0008
Pregnancy, childbirth and puerperium	(0.031)	Respiratory system	(0.044)
Obstetrics care*	2.198***	Chemotherapy*	-0.009
Newborn and other neonates	(0.029)	Digestive system	(0.035)
Cardiac intensive care*	0.182***	Chemotherapy*	-0.089
Circulatory system	(0.025)	Hepatobiliary and pancreas	(0.060)
Neonatal intensive care*	0.043***	Chemotherapy*	0.171**
Pregnancy, childbirth and puerperium	(0.009)	Skin, subcutaneous tissue, breast	(0.065)
Neonatal intensive care*	0.066***	Chemotherapy*	0.906***
Newborn and other neonates	(0.009)	Male reproductive system	(0.107)
Neonatal intermediate care*	0.113***	Chemotherapy*	-0.055
Pregnancy, childbirth and puerperium	(0.010)	Female reproductive system	(0.040)
Neonatal intermediate care*	0.141***	Chemotherapy*	0.188
Newborn and other neonates	(0.010)	Blood disorders	(0.111)
Burn care*Burns	5.154***	Optical colonoscopy*	0.420***
	(0.260)	Digestive system	(0.020)
Alcohol/drug abuse care*	4.618***	Endoscopic ultrasound*	0.052*
Alcohol/drug induced mental disorders	(0.060)	Digestive system	(0.022)
Psychiatric care*	4.391***	Ablation of Barrett's esophagus*	-0.014
Mental diseases and disorders	(0.080)	Digestive system	(0.017)
Alzheimer Center*	-1.474***	ERCP*Digestive system	-0.272***
Mental diseases and disorders	(0.062)		(0.025)
Birthing room*	0.668***	ERCP*Hepatobiliary and pancreas	-0.431***
Pregnancy, childbirth and puerperium	(0.021)		(0.044)
Birthing room*	0.602***	ESWL*Hepatobiliary and pancreas	-0.061*
Newborn and other neonates	(0.021)		(0.031)
Blood Donor Center*	0.240***	ESWL*Kidney and urinary tract	-0.076**
Circulatory system	(0.023)		(0.027)
Blood Donor Center*	0.800***	Fertility Clinic*	0.033
Blood and blood forming organ disorders	(0.061)	Female reproductive system	(0.022)
Breast cancer screening/mammograms*	0.140**	Hemodialysis*	0.036
Skin, subcutaneous tissue and breast	(0.045)	Kidney and urinary tract	(0.030)
Adult cardiology services*	-0.115**	HIV-AIDS services*	0.373***
Circulatory system	(0.036)	Infectious and parasitic DDs	(0.035)
Diagnostic catheterization*	0.297***	Neurological services*	1.347***
Kidney and urinary tract	(0.039)	Nervous system	(0.060)
Interventional cardiac catheterization*	0.284***	Oncology services*	0.357**
Circulatory system	(0.036)	Ear, nose, mouth and throat	(0.130)
Adult cardiac surgery*	1.535***	Oncology services*	0.071
Circulatory system	(0.033)	Respiratory system	(0.055)
Adult cardiac electrophysiology*	0.329***	Oncology services*	0.203***
Circulatory system	(0.033)	Digestive system	(0.042)

Table A1: Hospital Full Demand Model Estimates continued

Variable	Coefficient	Variable	Coefficient
Oncology services*	0.258***	Multislice spiral computed tomography	-0.140***
Hepatobiliary and pancreas	(0.071)	<64 slice*Respiratory system	(0.040)
Oncology services*	0.116	Multislice spiral computed tomography	-0.574***
Skin, subcutaneous tissue, breast	(0.070)	<64 slice*Circulatory system	(0.035)
Oncology services*	0.231*	Multi-slice spiral computed tomography	0.492***
Male reproductive system	(0.109)	64+ slice*Nervous system	(0.025)
Oncology services*	0.563***	Multi-slice spiral computed tomography	-0.010
Female reproductive system	(0.049)	64+ slice*Respiratory system	(0.025)
Oncology services*	0.808***	Multi-slice spiral computed tomography	-0.277***
Blood disorders	(0.137)	64+ slice*Circulatory system	(0.023)
Medical/surgical care*	-0.302***	PET/CT*Nervous system	0.439***
Nervous system	(0.051)		(0.019)
Psychiatric geriatric services*	-0.439***	PET/CT*Respiratory system	0.127***
Mental diseases and disorders	(0.028)		(0.021)
Diagnostic radioisotope facility*	0.644***	PET/CT*Circulatory system	-0.046**
Ear, nose, mouth, throat	(0.131)		(0.017)
Diagnostic radioisotope facility*	-0.073	PET/CT*Skin, subcutaneous tissue,	0.079**
Respiratory system	(0.056)	breast	(0.029)
Diagnostic radioisotope facility*	-0.271***	Ultrasound*Pregnancy, childbirth,	0.126***
Circulatory system	(0.044)	and puerperium	(0.026)
Full-field digital mammography*	-0.024	Heart transplant*	0.732***
Skin, subcutaneous tissue, breast	(0.034)	Circulatory system	(0.020)
MRI*Nervous system	0.773***	Kidney transplant*	0.903***
	(0.065)	Kidney and urinary tract	(0.026)
MRI*Respiratory system	0.105*	Liver transplant*	0.219***
	(0.050)	Digestive system	(0.024)
MRI*Circulatory system	-0.457***	Lung transplant*	0.889***
	(0.041)	Respiratory system	(0.032)
MRI*Digestive system	0.334***	Tissue transplant*	0.315***
	(0.037)	Skin, subcutaneous tissue, breast	(0.031)
MRI*Male reproductive system	0.628***	Virtual colonoscopy*	0.115***
	(0.102)	Digestive system	(0.018)
Multislice spiral computed tomography	-0.191***	Women's health center*	-0.012
<64 slice*Nervous system	(0.039)	Female reproductive system	(0.025)

Notes: Standard errors in parantheses. *** statistically significant at 1% level, ** statistically significant at 5% level, * statistically significant at 10% level.

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