Empirical Investigations of Contracting in Intermediate Markets

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EMPIRICAL INVESTIGATIONS OF CONTRACTING IN INTERMEDIATE MARKETS

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My doctoral research focuses on empirical investigations of contracting in intermediate markets and its effects. I am currently pursuing two research projects that together constitute the chapters of this dissertation. The first chapter focuses on contracting between hospitals and insurers and a pricing practice in place in Maryland. In the second chapter, which is joint work with Julie Holland Mortimer and Sylvia Hristakeva, we instead investigate contracting practices in the national television advertising market.

Chapter 1. In recent years researchers and policymakers have shown renewed interest in various types of health care reforms in the United States. In *"Welfare Effects of Using Hospital Rate Setting as an Alternative to Bargaining"* with Ayse Sera Diebel we investigate a potential health care reform. Prices paid by insurers to hospitals are determined by bilateral negotiations in all U.S. states except Maryland, where a unique all-payer rate setting health care regulation sets common prices for all insurers. Theory models of bilateral bargaining are unable to assign welfare effects when contracts are unobserved. We empirically analyze how a Maryland style regulation would affect overall welfare relative to bilateral bargaining, using the New Jersey health care market as an example. Using hospital-, insurer-, and patient-level data from 2010, we estimate a structural model of hospital and insurer demand, and simulate consumer and insurer responses to the new price regime. We find that replacing bargaining with all-payer rate setting increases total surplus in the market. However, not all agents benefit, and the effects depend on how the largest player in our market, Blue Cross Blue Shield (BCBS), sets premiums. If BCBS sets premiums à la Bertrand Nash, consumer surplus decreases, but joint hospital-insurer surplus increases by more. The number of uninsured increases by two percent. Surplus changes are robust to different pricing strategies of BCBS, that account for its non-profit status but, diminish the magnitude of surplus changes.

Chapter 2. In *"Contracts in the upfront market for national television advertising"* with Sylvia Hristakeva and Julie Holland Mortimer, we investigate unique pricing practices. We focus on advertising and treat it as an input to a firm's production process. The market of national television is of interest because it still commands the majority of advertising in the United States. Yet, firms face different costs when accessing the market for national television ads. Industry practices suggest that (legacy) firms with long histories of participation in the market benefit from favorable prices to reach the same audiences. We confirm empirically whether there are important differences in firms' costs to advertise nationally. Contracts between advertisers and networks are considered trade secrets, so we combine data on national ad placements and program viewership demographics with average ad prices in each program airing to perform our analysis. We find model-free evidence that firms who have longer relationships with broadcasters face lower prices in those networks. We use a structural model to quantify these price differentials, allowing for differences in firms' payoffs from advertising to different audiences. Preliminary results suggest that legacy firms obtain an 8% discount relative to non-legacy firms. This discount translates into a \$2 million efficiency that would be available to a non-legacy firm if it were to merge with a legacy firm.

To: Anyone who ever helped me.

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CHAPTER 1

WELFARE EFFECTS OF USING HOSPITAL RATE SETTING AS AN ALTERNATIVE TO BARGAINING (WITH AYSE SERA DIEBEL)

1 Introduction

Total expenditure on health care as a share of GDP increased from 5% in 1960 to 17.5% in 2014.[1] Today, hospital costs represent almost one-third of total health care expenditure, with high hospital prices and high hospital price growth being the main drivers of the increasing health care expenditure.[2,3] The increase in prices charged by hospitals to insurers has prompted a growing empirical literature that focuses on investigating the effect of hospital market power on negotiated prices. In 48 states hospitals and insurers negotiate prices bilaterally, and this literature has taken the bilateral bargaining in the market as given. An alternative model of hospital pricing is an all-payer rate setting regulation (APRS), in which a state agency sets hospital prices that are common to all insurers. The goal of this paper is to empirically analyze the welfare effects of replacing bilateral bargaining in the health care market with all-payer regulation.

While APRS regulations were historically used in many states, Maryland is the only state that currently implements an APRS system.[4] Compared to the rest of the United States Maryland has below average premiums and above-average quality of

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

[2] *https://www.cdc.gov/nchs/data/hus/hus15.pdf#094*

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

[4] West Virginia also regulates hospital prices, but the state government does so by setting price ceilings and price floors, and allowing hospitals to negotiate prices with insurers within these limits.

care. The success of the Maryland system and increasing policy interest in all-payer systems by other states, such as Vermont which recently voted to implement an APRS system[5], makes it crucial to investigate the welfare effects of adopting all-payer rate setting regulations.

We present a framework to analyze the effects of replacing bilateral bargaining with a Maryland-style all-payer regulation and investigate the effects of implementing a Maryland-style all-payer system in New Jersey.[6] We begin by estimating consumer demand for hospitals using detailed individual discharge data. Once we have hospital demand estimates, we calculate the expected utility from an insurer's network of hospitals. This first measure of expected utility is used to account for the fact that insurers only contract with a subset of hospitals in their market. We then estimate consumers' demand for insurance, including expected utility as an insurer characteristic. Given demand estimates and hospital price estimates from a Maryland-style pricing rule, we allow insurers to re-optimize their premiums and networks of hospital. We find that if New Jersey were to switch to a Maryland style APRS regulation, it would gain more than 2.2 billion dollars in producer surplus, where producer surplus is the combined surplus of hospitals and insurers.[7] The monetary value of the loss in consumer welfare would be about 700 dollars per consumer, or a loss of 1.7 billion dollars at the state level. This constitutes a gain of over 500 million dollars in total surplus. Along with these surplus changes, we see a 2.5% increase in the number of uninsured.

Our consumer surplus results suggest that when prices are negotiated through bilateral bargaining, BCBS leverages its market power to obtain lower prices from hospitals which are then passed on to consumers in the form of lower premiums. The lower

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

[6]New Jersey was chosen due to data availability of insurer hospital networks. Patient characteristics and hospital characteristics are not significantly different between the two states which also face similar costs of capital and labor.

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

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

Surplus for consumers can be broken down further into three groups of consumers: (i) those that stay with BCBS after a premium increase (ii) those that leave BCBS to another insurer (iii) those that stay with an insurer other than BCBS. Type (i) consumers lose a significant amount of surplus when BCBS's premiums increase. Type (ii) consumers also lose surplus because they face a higher premium from their new insurer (about $30 a month more than what consumers were previously paying to BCBS) and a more restrictive network. Type (iii) consumers see a significant gain in surplus, as the non BCBS plans are able to lower premiums by more than enough to offset the loss from changes to their hospital networks.

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

[8]BCBS is the largest private insurer in New Jersey with a 66% market share, and the United States with almost a 40% share of the market.

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

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

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

There is a growing literature on the formation of insurer-provider networks. Ho (2006) investigates the welfare impacts of restricted network formation and finds that consumer welfare would increase if health plans included all the hospitals in their

of last resort.

[11]Even the simple case of a monopoly supplier with unobservable contracts can reduce total surplus below that of monopoly. Once contracts have been established, even if those contracts achieve monopoly profits or the vertically integrated profits, a hospital and insurer can increase their bilateral profits by privately negotiating a reduction in their marginal transfer price which in turn lowers the retail price and shifts customers and profits away from rivals. The welfare effects of the renegotiation depend upon competition in the insurer market. See Dobson and Waterson (1997), von Ungern-Sternberg (1996), Chen (2003).

networks keeping prices and premiums fixed. While her conclusion is intuitive, it does not allow health plans to change premiums when they widen their networks. Ericson and Starc (2015) find that individuals' preference towards network breadth gets stronger with age. Shepard (2016a) looks at the effect adverse selection has on insurers' decisions to include a 'star' hospital in their network. He finds adverse selection provides a strong incentive to exclude a 'star' hospital but does not improve welfare. To our knowledge, there is no other work in the empirical literature that allows insurers to re-optimize their networks under a different price regime and set their premiums accordingly. In this paper, we follow this methodology to obtain the impacts of a counterfactual change in the price regime to an APRS system.

Our work is also related to the strand of literature that seeks to explicitly model the price negotiations between insurers and providers, normally in a Nash Bargaining framework.[12] These studies aim to uncover how surplus in the market is split between insurers and hospitals depending on their market power or leverage in the negotiation process. They find that hospitals in systems are able to set higher prices and extract a larger share of the market's surplus. More recent papers (Liebman (2016) and Ghili (2016)) were able to show the threat of exclusion to be important in determining price. Most papers that focus on bargaining rely upon at least one of the three following assumptions: (i) hospitals negotiate as systems and not individual entities; (ii) the hospital networks of insurers remain unchanged ; (iii) premiums are fixed. While these are necessary assumptions for computational reasons, we are not as restricted in our counterfactual analysis, because prices are the same for all insurers. This grants us greater flexibility in modeling insurer choices over individual hospitals and allowing insurer networks to change. We still must make a restriction in our equilibrium search where we fix the size of insurer networks. Thus we contribute to the literature analyzing bargaining and optimal decision making by focusing on total surplus changes due to the removal of bargaining.

[12] For recent papers that investigate price negotiation in the health care context, see Brooks et al. (1997), Gowrisankaran et al. (2015), Lewis and Pflum (2015), HaasWilson and Garmon (2011) , Dafny et al. (2016), Ho and Lee (2017) and Prager (2016).

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

2 Industry Background and Literature

Our paper is the first to empirically assess the effects of an all-payer system on welfare in the United States health care market.[13] Thus our paper is rooted in the literature that investigates government regulation in the hospital industry.[14] 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.[15] The findings of Dranove and Cone (1985) indicate that states with hospital rate setting experienced 1.32 percent smaller increases in expenses per admission. Melnick et al. (1981) conclude rate regulation lowers average and total hospital expenses. Thorpe and Phelps (1990) use data from New York State's all-payer system and find an annual growth of 1.9 percent in hospital costs when the price constraint is binding as opposed to a growth of 5.5 percent when it is not binding. Different from these previous studies, we investigate rate settings effects on consumer welfare and producer surplus which was not addressed by past authors[16].

Imposing Maryland APRS removes the price competition among hospitals, thus our work is related to the literature on hospital competition. While most theoretical re-

[13] Pauly and Town (2012) summarize past arguments for and against Maryland's APRS there has been no empirical work investigating possible reactions of the market.

[14] 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).

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

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

sults on competition and quality with variable prices are ambiguous, the theoretical literature on competition and quality when prices are regulated is clear. Gaynor et al. (2007) finds when price is above marginal cost, competition leads to more quality and improves consumer welfare but may have any impact on social welfare. Propper et al. (2004) support this theory with empirical findings showing that when the National Health Service of the United Kingdom removed price regulation and encouraged hospital competition, hospital quality decreased. Morrisey et al. (1983) and Garber and Phelps (1997) both present a theoretical framework under which rate review can be analyzed. These models see rate setting as a ceiling on the value of the service bundle produced by the hospital. If a binding ceiling is imposed, these models predict a reduction in quality while the impact on quantity is ambiguous. We refrain from the analysis of quality of care as the rate setting agencies also regulate hospital quality. Furthermore, there is little evidence in the empirical literature that DRG-based (Diagnosis-Related Group) payment systems such as APRS and prospective payment systems (PPS) reduce the quality of care.[17] We assume that hospital quality remains unchanged among the privately insured patients and investigate the change of price and network structure alone.

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

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

insurer profits.

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

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

Altman and Rodwin (1988) summarize the strategies to contain health care spending both by competition and by regulation. On the competition frontier, increasing consumer co-payments and deductibles were used to offset moral hazard, HMO competition, and prudent purchaser programs where large insurance plans received discounts from providers in return for a greater volume of patients were also used. Authors conclude that while competition may increase efficiency, it does not substantially reduce health care spending. On the regulatory frontier, federal and state governments pursued certificate-of-need programs, increase in quality and safety standards, hospital rate-setting, and prospective payment systems (PPS). Among these, hospital rate setting and PPS proved to be effective in cutting costs.[18] [19] The power of PPS to cut costs is encouraging for our analysis as PPS and Maryland APRS are similar in that price per admission to a hospital for a specific DRG is fixed.

Competition, both in the hospital market and in the health plan market, is expected to drive hospital costs down. High concentration of hospitals in the market encourages hospitals to cut costs as they compete on a price basis to be included in health

[18] 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). Eby and Cohodes (1985), Friedman and Coffey (1993), Sloan (1983a) all emphasize the relative success of mandatory rate setting in the context of cost containment.

[19] See citehadley1995hospital.

plan networks.[20] Competition among health plans is also expected to restrain hospital costs and control the quantity of the services provided.[21] Since health plans have large patient populations in geographically concentrated areas, they are expected to have leverage in negotiations and drive the hospital prices down. Their incentive to oversee the quantity and quality of services provided will prevent overuse and ensure patients get the exact care they need. However, hospital mergers, formation of hospital systems, and integration of hospital and physician groups led to an increased market power of particular provider groups that increased health care prices.[22] Our paper finds evidence that bargaining between insurers and hospitals does successfully lower costs for the consumer but at the expense of producer and total market surplus. The effects of regulation, specifically hospital rate setting are discussed next.

2.2 Hospital Rate Setting

Starting in the late 1960s and early 1970s, state governments began to implement mandatory rate setting programs where hospital rates or budgets were regulated. The purpose of hospital rate setting was to control hospital cost growth while reducing price discrimination and deterring cost shifting. More than half of the U.S. states adopted such programs on either mandatory or voluntary basis, and regulated the price paid to hospitals by insurers (payers) at the state level. The first mandatory hospital rate setting at the state level was implemented in 1971.[23] 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,

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

[21] See Hadley (1995).

[22] See Ho (2009) among others.

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

unit of payment (per diem, per case etc.), and methods for establishing rates (formula, budget review etc.).[24] 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 as this resulted in higher profits. Moreover, the pre-determined rate charged by a hospital was allowed to vary across payers and services.

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

Maryland's hospital rate setting program is the only remaining APRS system today. It is considered to be the most stable and most successful mandatory hospital rate setting program in the U.S. When the program was established, the cost of admission to a hospital was about 25 percent above the U.S. average while in 1993 this cost was 11 percent below the nation average. The rates in Maryland are determined by an independent state agency, the Health Services Cost Review Commission (HSCRC), in co-operation with the hospitals. By implementing an all-payer system in Maryland,

[24] See Sloan (1981) andSloan (1983b).

HSCRC aimed to[25] 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]

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.[27] These early papers that regress change in hospital expenses on a regulation dummy are usually criticized in several aspects.[28] 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

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

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

[27] Biles et al. (1980), Melnick et al. (1981), Sloan (1983b) 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).

[28] See, for example, Maddala (1986).

implement rate setting programs are the ones with transitory higher costs to begin with. To address this issue, they directly include the omitted variable in their regressions. Their findings indicate that while MA, NY, and MD have implemented such programs in response to high costs, this is not the case with WA and NJ. Therefore, regression to the mean does not greatly bias the result on the average effectiveness of the rate setting programs, however individual state results reported by Morrisey et al. (1983) are skewed. Antel et al. (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[29] 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 (1985) 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.[30] 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

[29]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.

[30]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)

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

There are two major conclusions of this literature. First, mature mandatory rate-setting programs led to a reduction in hospital cost growth.[31] Second, state level mandatory rate setting have been more effective than other regulatory programs both

[31] 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. (1983) Sloan (1983b).

in cost and non-cost aspects.[32] 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.

3 Data

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

We use SID data from New Jersey it covers 73 hospitals and 230,268 discharges in total. The patient zip code, diagnosis, treatment, insurance, age, sex, and charges are provided. We aggregate diagnosis to the 25 Major Diagnostic Categories (MDCs) as defined by the Centers for Medicare Services. All emergency room admissions are dropped as it is not likely these patients have any choice over the hospital to which they are admitted. This data is summarized in Table 1. We observe patients' zip codes and the hospitals they visited, therefore we are able to calculate the distance between a patient's residence location and hospital location. Average patient in our

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

data travels 10 miles to get care at a hospital. Females constitute 66.4% of all discharges due to the large number of pregnancies and childbirths. This paper focuses only on the non-elderly population (ages between 0 and 64) as people above 65 are likely to be enrolled in Medicare plans and we are concerned with private health plans only. Since all new-borns are considered as new patients in this dataset, the average patient is younger than expected.

Table 1.1: Patient Characteristics

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

Notes: N = 230,268 discharges.

Table 2 provides a summary of select variables from the hospital dataset.[33] We report information on 131 hospitals that operate Maryland and New Jersey. We observe ownership type (profit, non-profit), teaching status, system membership, total inpatient days, total number of admissions and services offered by each hospital among other variables.

The health plan dataset is at the national level and is constructed using various sources. The first four variables summarized in Table 3 come from AIS and Weiss Ratings Guide. To calculate premiums, we divided total premium revenue reported by each plan by the number of enrollees. Average premium per patient per month ranges from $66.7 to $1075.6 with an average of $384.6. The range is large since all types of plans (low-premium HMOs, high-premium indemnity plans etc.) are present in the dataset. In addition to premiums, we observe the age of the plan, the number of physicians who participated in the insurer's network of providers, and the total number of enrollees. The rest of the variables are created using NCQA reports on plan performance. This source reports type of each plan, which we aggregate to two

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

Table 1.2: Hospital Characteristics

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

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.

Table 1.3: Health Plan Characteristics

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

Notes: N = 473 health plans.

4 Model and Methodology

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

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.[34] 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 et al. (1995) (henceforth BLP) approach.

Hospital Demand:

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

$$u_{ihlm} = u(x_{hm}, v_{ilm}|\lambda, \theta) \tag{1.1}$$

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

$$u_{ihl} = u(x_h, v_{il}|\lambda, \theta) \geq u_{ih'l} = u(x_{h'}, v_{il}|\lambda, \theta) \tag{1.2}$$

In particular, let the specification for the utility be:

$$u_{ihl} = \theta x_h + \lambda x_h v_{il} + \epsilon_{ihl} \tag{1.3}$$

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:

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

$$s_h = \frac{exp(\theta x_h + \lambda x_h v_{il})}{\sum\limits_{k \in H_j} exp(\theta x_k + \lambda x_k v_{il})} \tag{1.4}$$

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

Since we observe the actual shares, we use maximum likelihood to obtain the parameter estimates $\hat{\lambda}$ and $\hat{\theta}$. Unlike our health plan demand model, this model does not account for unobserved characteristics or unobserved quality of hospitals.[35] We have very rich hospital characteristics data, therefore we assume that the 83 characteristics we use in estimation capture the quality of hospitals. Identification in this model comes from the variation in patients' hospital choice sets across insurers. In our model, patients' choice sets are defined by the set of hospitals in an insurer's hospital network. Results of this estimation are presented in Table 4.

Expected Utility:

Given the parameter estimates from the above estimation we can calculate the predicted utility of each individual of type i where types are defined by age-sex-zip code cells:[36]

$$\hat{u_{ihl}} = \hat{\theta} x_h + \hat{\lambda} x_h v_{il} + \epsilon_{ihl} \tag{1.5}$$

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

$$EU_{ij}(H_j) = \sum_l p_{il} log\left(\sum_{h \in H_j} exp(\hat{\theta} x_h + \hat{\lambda} x_h v_{il})\right) \tag{1.6}$$

where p_{il} is the probability that patient type i is hospitalized with diagnosis l and H_j

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

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

is the set of hospitals in insurer plan j.

We only observe insurer networks in New Jersey and Maryland and thus must compute networks for insurers of other states. We collected hospital networks of insurers from their websites in 2017 for 16 states[37] and use those networks to calculate expected utility for insurers other than Maryland and New Jersey. For the states where we don't observe exact insurer networks, we use the number of hospitals insurers contract with and calculate the average expected utility from a hospital network of that size taking into account the number of reported insurer contracts hospitals report. The average is calculated at the level of the individual of type i.

Health Plan Demand:

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

Conditional Logit:

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

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

$$u_{ijr} = \sum_k x_{jkr}\beta_k + \xi_{jr} + \epsilon_{ijr} \tag{1.7}$$

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

$$u_{ij} = \sum_k x_{jk}\beta_k + \xi_j + \epsilon_{ij} = \delta_j(x_j, \xi_j, \beta) + \epsilon_{ij} \tag{1.8}$$

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

$$s_j = \frac{e^{\delta_j}}{1 + \sum\limits_{g=1}^{G} e^{\delta_g}} \tag{1.9}$$

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

$$s_o = \frac{1}{1 + \sum\limits_{g=1}^{G} e^{\delta_g}} \tag{1.10}$$

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

$$\frac{s_j}{s_o} = e^{\delta_j} \Longrightarrow ln(s_j) - ln(s_o) = \delta_j \tag{1.11}$$

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

$$\delta_j = \sum_k x_{jk}\beta_k + \xi_j \tag{1.12}$$

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

$$\xi_j = \delta_j - \sum_k x_{jk}\beta_k = ln(s_j) - ln(s_o) - \sum_k x_{jk}\beta_k \tag{1.13}$$

The instruments should be orthogonal to this unobserved quality term, so we form the moment conditions as $E[\xi(\beta)'Z] = 0$. In applying iterative GMM, we use the "optimal" weighting matrix W which is the inverse of the variance of moment conditions. Therefore, the problem reduces to:

$$\min_\beta \xi(\beta)'ZWZ'\xi(\beta) \quad where \quad W = (E[Z'\xi\xi'Z])^{-1} \tag{1.14}$$

The analytical solution to this problem is:

$$\beta = (X'ZWZ'X)^{-1}(X'ZWZ'\delta) \tag{1.15}$$

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

BLP (1995) and Ho (2006):

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

Let the utility of patient i from plan j be:

$$w_{ijm} = \xi_{jm} + z_{jm}\lambda + \beta_2 prem_{jm} + \gamma_1 EU_{ijm}(H_{jm}) + \gamma_2 \frac{prem_{jm}}{y_i} + \eta_{ijm} \tag{1.16}$$

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

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

$$s_{jm} = \sum_i \frac{n_i}{n_m} s_{ijm}(\beta, \lambda, \gamma) \tag{1.17}$$

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

$$s_{\hat{ijm}}(\lambda, \gamma, \beta) = \frac{exp\left(\xi_{jm} + \beta_1 prem_{jm} + z_{jm}\beta + \gamma_1 EU_{ijm}(H_{jm}) + \gamma_2 \frac{prem_{jm}}{y_i}\right)}{1 + \sum_{k \in P_m} exp\left(\xi_{km} + \beta_1 prem_{km} + z_{km}\beta + \gamma_1 EU_{ikm}(H_{km}) + \gamma_2 \frac{prem_{km}}{y_i}\right)} \tag{1.18}$$

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

$$\delta^h = \delta^{h-1} + ln(s) - ln(\hat{s}) \tag{1.19}$$

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

5 Estimation Details and Results

5.1 Hospital Demand Results

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

$$u_{ihl} = \theta x_h + \lambda x_h \nu_{il} + \epsilon_{ihl} \tag{1.20}$$

Therefore, utility of patient i who goes to hospital h with diagnosis l depends on the hospital characteristics x_h and interaction of these characteristics with patient characteristics. Table 4 presents a subset[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 15.8%. Remaining co-variates are interactions of services offered by the hospital with the relevant MDCs. The results are intuitive. A patient diagnosed with a circulatory system disease has a strong preference for a hospital that offers cardiac surgery, while a patient with severe burns is more likely to go to a hospital that has a burn care unit.

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

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:

$$u_{ij} = \sum_k x_{jk}\beta_k + \xi_j + \epsilon_{ij} = \delta_j(x_j, \xi_j, \beta) + \epsilon_{ij} \tag{1.21}$$

where the observable plan characteristics x_j are plan premium per person per month, age of the plan, physicians per 1000 population, Weiss rating of the plan, three measures used by NCQA to obtain the 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 premiums are endogenous, we instrument for them using the average characteristics of other plans ($x_n, n \neq j$) in the same market commonly referred to as BLP style instruments. These characteristics are age, Weiss rating, number of physicians, and the NCQA score. These instruments satisfy the three traditional conditions of instrumental variables. They are relevant as they are correlated with premiums via competition and markups[39], they are uncorrelated with the error term, and they affect utility only through their impact on premiums. To further support the choice of

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

Table 1.4: Partial Hospital Demand Results

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

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

the instruments, we analyze two statistics. In the regression that includes both fixed effects, the first stage results report a partial R-squared of 0.77 and an F-statistic of 36.16. These statistics suggest a large portion of the unexplained variation in premiums come from the excluded instruments and the instruments are not weak since the F-statistic is greater than 10.[40]

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

The parameter estimates are reported in Table 5. The first and second column implement Berry (1994) with the difference coming from sample selection based on the expected utility. As previously mentioned we only observe insurer networks in New Jersey and Maryland in 2010 and thus restrict our sample in column 2 to only those states and add expected utility as an insurer characteristic. In column 3 we instead use the full sample with a single imputed average expected utility interacted with random coefficients. The fourth column is our final and preferred specification where expected utility is calculated by age-sex-zipcode groups and premium over income by zipcode is added to the specification. All specifications with expected utility report a positive coefficients showing that individuals value hospital networks offered by insurers. The price elasticities of insurers range from 3 to 0.6 with the average elasticity being 1.76 implying that \$100 a month increase in premiums would decrease the probability a plan is chosen by 33%.

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

Table 1.5: Health Plan Demand Results

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

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

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.[41]

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[42], depreciation, ownership status, and DRG fixed effects.[43] Results are reported in Table 6.[44] We use the results from column (4) while predicting prices for New Jersey. While the service rates (not the total charges) are set in Maryland, all service rates are given in units of time, as we are unable to capture these specifics in our data, we use the more accurate predictions we are able to obtain through the total charges regressions.

[41]Similar methods have been used by both Gowrisankaran et al. (2015) and Shepard (2016b).

[42]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.

[43]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.

[44]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 1.6: Maryland Pricing Rule

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

Notes: Results from GLM estimation. Robust clustered standard errors in parentheses (procedure-hospital clusters used in the first two columns, DRG-hospital clusters used in the last two columns). Teaching intensity is measured by resident-to-bed ratio. Elixhauser comordidity 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 sig-nificant at 5% level, * statistically significant at 10% level.

6 Analysis of the Welfare Impact of Price Regulation

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

6.1 Allowing for Re-optimization by Insurers

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

$$s_{j,h} = \sum_i \frac{n_i}{n_m} \frac{s_{ih}}{\sum_{k \in H} s_{ik}} \tag{1.22}$$

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

$$price_h = \sum_l p_{il} E(Price_i l) = \sum_l p_{il} s_{ihl} \hat{Price}_{ihl}^{NJ} \tag{1.23}$$

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

$$\pi_j = prem_j s_j(H_j, H_{-j}) - \sum_{h \in H_j} (s_{j,h}(H_j, H_{-j}) price_h) \tag{1.24}$$

Which gives us the standard first order condition as:

$$s_j(H_j, H_{-j}) + \sum_{h \in H_j} (prem_j - price_h) \frac{\delta s_{j,h}(H_j, H_{-j})}{\delta prem_j} = 0 \tag{1.25}$$

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

6.2 Equilibrium

As insurers' market shares depend not only on their own premiums and hospital networks but on other insurer networks and premiums, calculation of equilibrium is computationally infeasible as we would have to check every possible hospital combination of insurer hospital networks. Not only is it infeasible but there is the possibility of no equilibrium existing. Instead we approach our analysis in the following way:

1. Assign a number k_j to each insurer based on the number of hospitals an insurer includes of the two largest hospital systems.

2. Define N_j to be the set of hospitals an insurer does not include in his network plus k hospitals.

3. Calculate premiums for all $\binom{N_j}{k_j}$ combinations for a single insurer leaving other hospital networks fixed

4. Assign insurer j the hospital network with highest profits

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

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

6.3 Producer Surplus

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

$$R_j(H_j, H_{-j}) = M\left(s_j(H_j, H_{-j})\left[prem_j - \sum_{h\in H_j} s_{jh}(H_j)cost_h\right]\right) \tag{1.26}$$

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

$$cost_h = \sum_l p_l E(cost_l) = \sum_l p_l \sum_{h\in H_J} s_{hl}cost_{hl} \tag{1.27}$$

We calculate the producer surplus in the presence and in the absence of bargaining by summing individual insurer surplus. However, since we do not observe the prices hospitals charge insurers in the absence of our pricing rule (we do not observe insurer-hospital pair prices in New Jersey), we can only calculate the total producer surplus, or the combination of hospital and insurer surplus.[45] The total gain in producer surplus is $\$2,239,394,865$. The main component of gain in surplus comes from BCBS increasing its premiums. BCBS likely increase its premiums to account for higher prices from hospitals as it can no longer benefit from its market power when bargaining over prices. The removal of bargaining here also removes incentives for BCBS to cut

[45]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) and Dor et al. (2004) among others.

premiums in order gain market power to use as leverage against hospitals to obtain lower prices so it is no surprise we see almost a %40 increase in BCBS's monthly premiums. All other insurers, except the smallest, decrease premiums and increase market shares which also provides an increase in total producer surplus.

6.4 Consumer Surplus

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

$$CV_i = \sum_i \frac{n_i}{N} \frac{-1}{\alpha_i} \left[ln \sum_j exp(V_{ij}^{post}) - ln \sum_j exp(V_{ij}^{pre}) \right] \tag{1.28}$$

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

$$V_{ij} = \xi_j + z_j \hat{\lambda} + \hat{\beta}_2 prem_j + \hat{\gamma}_1 EU_{ij}(H_j) + \hat{\gamma}_2 \frac{prem_j}{y_i} \tag{1.29}$$

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

$$CV_{NJ} = M \frac{1}{n} \sum_{i=i}^{n} CV_i = M(-\frac{1}{\alpha_i}) \left[ln \sum_j exp(V_{ij}^{post}) - ln \sum_j exp(V_{ij}^{pre}) \right] \tag{1.30}$$

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

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

6.5 Blue Cross Blue Shield Counterfactuals

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

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

In our the final counterfactual where BCBS is not allowed to change its premiums, the increase in total surplus now comes from an increase in consumer and producer

Table 1.7: Welfare Results

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

surplus, the overall producer surplus increases by \$107 million and consumers gain \$7.5 million. Lastly, we observe that the percent of uninsured in the market falls by 1.46% percent.

7 Conclusion

As health care spending continues to increase, an important question is how to control the costs and spending. This paper empirically assess one method of controlling a substantial share of those costs, specifically hospitals prices. We use a Maryland-Style all-payer system, which has proven to be successful at reducing cost growth, to investigate how a change in price regime effects welfare within the health care market. We find that an all-payer system would increase total welfare and benefit producers at the expense of consumers. We argue the effects are driven by the largest insurer in the market (BCBS) losing the ability to negotiate price reductions from hospitals and pass those price reductions on to consumers. While state healthcare markets are very different, the presence of a large private insurer is common. As long as the large insurer is able to leverage its market power in negotiations with hospitals over price, we would expect to see similar results from the implementation of an APRS regulation.

We conclude with possible directions for future research. A straightforward extension could come from obtaining transaction prices between hospitals and insurers and further breaking down how the division of surplus changes at the hospital-insurer level. We also focus only on a static model with no adverse selection and do not allow any hospital or insurer to exit. In general, the implementation of an all-payer system is most effective over time and can result in exit of hospitals. While it is not the focus of this paper evaluating the long-run effects on welfare are also of significant interest.

APPENDIX1

1.A Data Appendix

Dataset for Hospital Demand:

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

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

Distance of a patient to a hospital is calculated as the distance between two latitude

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

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

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

and longitude coordinates which are centers of patient's zipcode and the hospital's latitude and longitude provided by the AHA. A patient's choice set consists of all the hospitals within its insurer's network.

Dataset for Health Plan Demand:

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

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

[49] All these datasets report data on 2010.

[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.

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 asthma, diabetes, heart attack, and mental health. Finally, the prevention score assesses measures such as timeliness of prenatal check ups, breast cancer screening and early immunizations.

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

Dataset for Price Regressions:

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

[52] $http://www.hscrc.state.md.us/hsp_Rates2.cfm$

[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

(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.

1.B Competition and Regulation in Health Care

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

Health care markets do not fit in the definition of perfect competition for many reasons. In particular, health care markets are characterized by asymmetric information, barriers to entry and exit, differentiated products, market power of providers and insurers. The seminal work by Arrow (1963) states that the health care markets suffer from market failures due to uncertainty and information problems. Patients know neither the care they need to receive nor the true costs of the care. They rely solely on their physicians when making choices about their treatment, and solely on their insurers when paying for the treatment they received. They are different than a consumer in a competitive market who chooses among alternatives with complete information. Furthermore, the incentive structure of the health care system leads to inefficiencies,

[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.

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[55] indicate that a profit maximizing hospital will not achieve the most efficient outcome like a competitive firm, especially when the well-being of the other agents in the market is considered. Given this nature and the form of financing of the health care sector, Altman and Weiner (1978) suggest regulation to be used as a second-best choice, a necessary solution even if not the most desirable one.

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

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

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

[57]PPS and state rate setting are similar in nature as they are both prospective payment systems that limit revenues and charges based on diagnosis-related groups (DRGs). Davis et al. (1990),

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.[58] These amendments also gave rise to utilization review to control the quantity and quality of medical procedures. If the Professional Standards Review Organizations (PSROs) reviewed a procedure and deemed it unneccesary, Medicare payments for that procedure could be denied to the hospital. Other controls implemented were Nixon administration's Economic Stabilization Program (ESP) and hospital rate and budget controls. ESP was implemented between 1971-1974 to slow price growth in the overall economy. Controlled hospital prices, wages, and input costs led to a decrease in expenditure. Price controls in the health care sector resulted in higher utilization and lower medi-

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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.

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

cal costs. Removal of ESP in 1974 along with the increase in economy-wide inflation partly due to the oil shocks resulted in a period of rapid price growth.

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

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

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

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

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

1.C Full Hospital Choice Model Estimates

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

Table A1: Hospital Demand Estimates

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

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

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

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

General Med/Surgical	0.821***	(0.224)
Obstetrics	-0.586***	(0.0435)
Cardiac IC	-0.111***	(0.0254)
Neonatal IC	-0.307***	(0.0227)
Neonatal Intermediate	-1.859***	(0.0440)
Burn Care	0.0337	(0.0379)
Birth Room	2.584***	(0.0483)
Blood Donor Hos	-0.566***	(0.0222)
Mammogram	-2.394***	(0.0359)
Adult Cardiology	-1.740***	(0.0533)
Diagnostic Catheterization	-0.416***	(0.0417)
Cardiac Catheterization	0.630***	(0.0228)
Cardiac Surgery	0.0379	(0.0320)
Cardiac Electrophysiology	-0.802***	(0.0348)
Cardiac Rehabilitation	-0.288***	(0.0242)
Chemotherapy	0.944***	(0.0650)
Optical Colonoscopy	1.485***	(0.0271)
Endoscopic Ultrasound	-0.235***	(0.0269)
Ablation of Esophagus	-0.628***	(0.0175)
ERCP	0.161***	(0.0201)
ESWL	0.461***	(0.0186)
Fertility Clinic	-0.594***	(0.0310)
Hemodialysis	-0.418***	(0.0302)
HIV-AIDS Services	0.373***	(0.0277)
Neurological Services	-0.329***	(0.0576)
Oncology	0.894***	(0.0714)
Othopedic	0.130***	(0.0390)
Diagnostic Radioisotope	-0.640***	(0.0502)
Full-field Mammography	0.472***	(0.0248)

Magnetic Resonance Imaging	-1.268***	(0.0383)
Multislice Spiral Tomography	0.680***	(0.0450)
Multislice Spiral Tomography64	1.929***	(0.0252)
Positron Emission Tomography	-0.286***	(0.0206)
Ultrasound	0.00672	(0.0533)
Heart Transplans	1.698***	(0.0511)
Kidney Transplanst	-0.675***	(0.0268)
Liver Transplanst	3.125***	(0.0492)
Lung Transplanst	-0.852***	(0.0586)
Tissue Transplanst	-0.102	(0.0524)
Virtual Colonoscopy	1.219***	(0.0281)
Women's Health Center	1.356***	(0.0329)
General Med/Surgical*Nervous	-2.452***	(0.187)
General Med/Surgical*Eye	1.456***	(0.407)
General Med/Surgical*Ear/Nose/Throat	0.648*	(0.270)
General Med/Surgical*Circulatory	-1.232***	(0.129)
General Med/Surgical*Hepatobiliary	1.823***	(0.175)
General Med/Surgical*Skin	0.325*	(0.164)
General Med/Surgical*Male Reproductive	0.732*	(0.345)
General Med/Surgical*Female Reproductive	0.210	(0.127)
General Med/Surgical*Childbirth	-1.710***	(0.0753)
General Med/Surgical*Multiple Sig Trauma	-0.108	(0.168)
Obstetrics*Female Reproductive	0.850***	(0.0382)
Obstetrics*Childbirth	0.348***	(0.0293)
Cardiac IC*Circulatory	0.225***	(0.0463)
Neonatal IC*Childbirth	0.0184	(0.0166)
Neonatal IC*Newborn	-0.0290	(0.0161)
Neonatal Intermediate*Childbirth	0.733***	(0.0309)
Neonatal Intermediate*Newborn	0.680***	(0.0293)

Burn Care * Burn	4.223***	(0.417)
Birth Room*Childbirth	1.072***	(0.0424)
Birth Room*Newborn	0.213***	(0.0309)
Blood Donor Hos*Circulatory	-0.0648*	(0.0318)
Blood Donor Hos*Blood Disorders	0.874***	(0.0715)
Mammogram*Subcutaneous Tissue	-0.104	(0.0812)
Adult Cardiology*Circulatory	1.036***	(0.125)
Diagnostic Catheterization*Kidney	0.407***	(0.0721)
Cardiac Catheterization*Circulatory	-0.255***	(0.0591)
Cardiac Surgery*Circulatory	2.292***	(0.0732)
Cardiac Electrophysiology*Circulatory	0.101	(0.0744)
Cardiac Rehabilitation*Circulatory	0.716***	(0.0428)
Chemotherapy*Ear/Nose/Throat	0.551*	(0.279)
Chemotherapy*Respiratory	-0.0913	(0.121)
Chemotherapy*Digestive	0.548***	(0.0997)
Chemotherapy*Heptobiliary	0.543***	(0.161)
Chemotherapy*Skin/Tissue	0.473***	(0.142)
Chemotherapy*Male Reproductive	1.199***	(0.287)
Chemotherapy*Female Reproductive	-0.812***	(0.103)
Chemotherapy*Blood	0.115	(0.296)
Optical Colonoscopy*Digestive	0.490***	(0.0449)
Endoscopic Ultrasound*Digestive	-0.137***	(0.0403)
Ablation of Esophagus*Digestive	0.0346	(0.0332)
ERCP*Digestive	-0.331***	(0.0395)
ERCP*Heptobiliary	-0.466***	(0.0711)
ESWL*Heptobiliary	-0.243***	(0.0550)
ESWL*Kidney/Urinary	-0.356***	(0.0475)
Fertility Clinic*Female Reproductive	-0.0904**	(0.0294)
Hemodialysis*Kidney	0.377***	(0.0591)

Neurological Services*Nervous	-0.349**	(0.121)
Oncology*Ear/Nose/Throat	-0.300	(0.271)
Oncology*Respiratory	-0.226	(0.141)
Oncology*Digestive	-0.596***	(0.0816)
Oncology*Heptobiliary	-0.754***	(0.131)
Oncology*Male Reproductive	-0.642**	(0.197)
Oncology*Female Reproductive	1.443***	(0.128)
Oncology*Blood	0.676*	(0.295)
Diagnostic Radioisotope*Ear/Nose/Throat	0.0559	(0.197)
Diagnostic Radioisotope*Respiratory	-0.649***	(0.108)
Diagnostic Radioisotope*Circulatory	-0.821***	(0.0866)
Full-field Mammography*Subcutaneoud Tissue	0.120	(0.0675)
Magnetic Resonance Imaging* Nervous	1.532***	(0.127)
Magnetic Resonance Imaging*Respiratory	0.778***	(0.0981)
Magnetic Resonance Imaging*Circulatory	0.699***	(0.0910)
Magnetic Resonance Imaging*Digestive	0.661***	(0.0679)
Magnetic Resonance Imaging*Male Reproductive	0.703***	(0.195)
Multislice Spiral Tomography*Nervous	1.326***	(0.0828)
Multislice Spiral Tomography*Respiratory	0.0334	(0.0638)
Multislice Spiral Tomography*Circulatory	-1.175***	(0.127)
Multislice Spiral Tomography64*Nervous	-0.0434	(0.0463)
Multislice Spiral Tomography64*Respiratory	0.113*	(0.0540)
Multislice Spiral Tomography64*Circulatory	-0.716***	(0.0420)
Positron Emission Tomography*Nervous	0.473***	(0.0316)
Positron Emission Tomography*Respiratory	0.284***	(0.0374)
Positron Emission Tomography*Circulatory	0.0971**	(0.0309)
Positron Emission Tomography*Subcutaneous Tissue	0.0382	(0.0415)
Ultrasound*Birth	-0.115*	(0.0514)
Heart Transplanst*Circulatory	0.734***	(0.0358)

Kidney Transplanst*Kidney	0.968***	(0.0470)
Liver Transplanst*Digestive	-0.0213	(0.0870)
Lung Transplanst*Respiratory	0.599***	(0.0921)
Tissue Transplanst*Subcutaneous Tissue	-0.0115	(0.0546)
Virtual Colonoscopy*Digestive	-0.107**	(0.0392)
Women's Health Center*Female Reproductive System	0.0215	(0.0530)
N	230268	

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

CHAPTER 2

CONTRACTS IN THE UPFRONT MARKET FOR NATIONAL TELEVISION ADVERTISING (WITH JULIE MORTIMER AND SYLVIA HRISTAKEVA)

1 Introduction

Firms contract with each other to access inputs of production and to reach customers. These contracts are often complex, aiming to align the incentives of the two parties. Economic theory indicates that the repeated nature of firms' interactions may be used to align these incentives. That is, static contracts may also depend on past relationships, learning, or reputation. As a result, firms with the same 'static characteristics' may face different contracts. This paper analyzes the contracts used in the television advertising market. The institutional practices in this market have established that past relationships influence firms' terms-of-trade; hence, firms may face different costs when accessing national television advertising.

Inter-firm contracts may affect competition in both upstream and downstream markets, and in turn total welfare. Commonly, firms that compete in a downstream market also face the same competitors in the input market. Theoretical work has analyzed how differences in input costs may affect market competition, firms' entry and investment decisions, and merger incentives (Tirole (1988)).[1] Furthermore, advertising itself may have strategic implications for shaping market competition. For example, Sutton (1991) proposes a model in which incumbents endogenously invest

[1] For example, DeGraba (1990) shows that variable input markets affect firms' choices of long-run production technology. Alternatively, firms may strategically attempt to limit competitors' access to an input of production (Eső et al. (2010)). In the television market, Dukes and Gal-Or (2003) develop a model to rationalize exclusive contracts between an advertiser and a network. We do not consider exclusive contracts because most advertising purchases are not subject to exclusivity arrangements.

in advertising, with the result that they maintain concentration in the market as it grows. In our setup, the structure of the market for national television advertising solidifies the advantages of incumbent firms that have previously established a relationship in the market. Importantly, we argue that the length of the relationship a firm has maintained with national television networks is an important driver of cost advantages in this market.

The competitive effects of accessing cheaper advertising have been considered by both academics and antitrust authorities. Porter (1976) raises the concern that national firms benefit from advertising nationally, and that this competitive advantage may create barriers to entry for small local firms. A similar concern was raised when the FTC challenged Procter & Gamble's acquisition of Clorox in 1957. In the market for liquid bleach, advertising is an important competitive instrument. The Commission was concerned that after the acquisition, Clorox would be able to access national advertising at a discount relative to its competitors; therefore, the merger would discourage competition and entry in that market.[2] Today, the Antitrust authorities would not consider such efficiencies as anti-competitive. Instead, they would be treated in the same way as, for example, distribution efficiencies (Mensch and Freeman (1990)). In this project, we do not explicitly model downstream competition, or the ways in which differences in the cost of advertising may affect market outcomes. Instead, we focus on documenting these cost differences.

Advertising is an important input in the production of most final products sold to consumers. Despite the recent increase in digital media and online advertising, television advertising still commands the majority of ad dollars spent.[3] National television ads accounted for $45 billion in 2016, with firms like Proctor & Gamble spending almost a billion dollars. Nevertheless, firms are not on equal ground when accessing this input market. Industry practices in the television advertising market

[2]During the 1950s and 1960s, firms purchased advertising by sponsoring television programming. As a result, larger firms were better positioned to access national television advertising. In the early 1960s, the networks changed the way they sell advertising to the practices used today. Several studies showed that once the market changed in the 1960s, large advertisers in broadcast networks stopped benefiting from discounts (Blank (1968) and Peterman and Carney (1978)).

[3]Digital advertising only reached parity with television in the last quarter of 2017 (Slefo (2017)).

have evolved so that firms often pay different prices to reach the same audience.

Price differences are so common that the industry refers to advertisers being either 'good money' or 'bad money'. The term 'good money' refers to advertisers who pay relatively high prices, while 'bad money' is commonly associated with legacy advertisers who receive grandfathered low prices. Industry practitioners suggest that continued relationships with an advertiser is the main driver of the price differentials, not the size of a firm's advertising budget.[4] As a consequence, legacy firms, which have long advertising relationships with networks, face lower costs for the same ad inventory.

The practice of rewarding legacy firms with lower advertising prices for the same program airing dates back to the beginning of the national television advertising market in the 1960s (Lotz (2007)). New clients negotiate prices during the first year in which they advertise in a network. All returning advertisers face prices that evolve as a percentage change from their 'base rate' (the price they paid in the previous year). The difference between legacy and non-legacy prices has emerged because negotiated prices for new businesses have been consistently higher than the prices paid by returning businesses. We refer to the lower costs faced by legacy firms as a 'legacy discount' in the remainder of the paper.

This work takes the first step in analyzing whether firms face different costs to access the input market for national television advertising. A challenge in studying inter-firm contracts is that firms consider these contracts as trade secrets, and data on the terms of the contracts are rarely available. We do not observe individual prices paid by firms. Thus, we rely on both reduced-form and structural approaches to document and quantify the presence of legacy discounts. We combine institutional knowledge of contracting practices with the input-sourcing decisions of firms to identify the value of continued relationships in the national market for television advertising.

Industry practitioners suggest that the size of legacy discounts is likely to be larger

[4] In 2005, a media spending audit uncovered that firms pay different prices for identical time and space in the market for national television advertising. In addition, the report concludes that these "price differentials are not associated with the size of firms' advertising budgets" (Bloom (2005)).

for broadcast rather than cable networks. Thus, we speculate that if legacy firms benefit from discounts on broadcast, then they will choose to reach a disproportionately larger fraction of their viewers on these networks. Controlling for firms' industries, budgets, and digital advertising strategies, we find that these patterns exist in the data. We interpret this as suggestive evidence of legacy discounts. We repeat the analysis for audiences with different demographic profiles to confirm the robustness of the result.

Given the reduced-form evidence, our analysis continues with a structural model in order to quantify the size of legacy discounts. The structural model uses average prices along with firm decisions of where and how much to advertise to identify these discounts. We assume that firms are making optimal advertising decisions after their budget is set exogenously and they do not take into account where or how competitors advertise. Results suggest an average legacy discount of about 8%.

We evaluate the role of these cost differences through the lens of efficiency gains from a merger. Firms typically refer to efficiency rationales as a primary justification for a merger; however, cost savings are hard to identify and measure.[5] Our setup identifies an input market where a merger may decrease firms' costs even if the firms operate in unrelated downstream markets. If the merging parties have different costs to access the market for national television advertising, then, according to industry practitioners, the newly-merged firm is able to purchase inventory at the lower price. A back-of-the-envelope calculation highlights the importance of these discounts for advertising firms and networks. Keeping average prices and firm advertising selections fixed, the results suggest that a merger between a legacy and a non-legacy firm will generate, on average, cost savings of at least $2 million through the lower cost to access the market for national television advertising. These benefits are a lower bound because the calculation does not allow the firm to re-optimize its advertising mix.

[5] Merger analyses highlight the tradeoff between potential production efficiencies and upward pricing pressures following a horizontal merger (Williamson (1968)). Most empirical work has focused on understanding how the change in competition following a merger influences prices or product characteristics (see Ashenfelter et al. (2014) for a survey). The evidence on cost savings from a merger is scarce due to the difficulties in identifying and measuring potential gains in efficiency. Ashenfelter et al. (2015) is an exception, where the authors analyze whether cost savings may offset the incentives to raise prices.

These cost savings will not be due to economies of scale or an improved bargaining position.

The question of what features of the market lead to the persistence of legacy discounts arises naturally. There are at least three potential rationales that we are pursuing in a separate project. For example, such price differentials may be explained by price discrimination or bargaining. In addition, industry practitioners suggest that demand uncertainty might be driving these price differentials. That is, legacy firms benefit from favorable bases as a “reward" for maintaining consistent business, even when demand is soft. One of the many unwritten expectations of the upfront market is that legacy firms are expected to maintain “consistent" spending with a network in order to keep benefiting from their grandfathered base rates (Lotz (2007)).

The nature of the market connects this project to two separate literatures; studies of two-sided markets, and studies of the role of advertising for market competition. Television networks connect viewers’ demand for programing on one side, and advertisers’ demand for audiences on the other side. The literature on two-sided markets carefully studies consumers’ choice and the incentives of media companies in balancing the two sides of the market. However the advertising side of the market has received less attention empirically.[6] Advertising competition is well-studied theoretically in setups that disregard firms’ input-sourcing choices (see Bagwell (2007) for a survey). In these cases, the effect of advertising on market structure and welfare depends on the way advertising influences consumers: whether it provides information or it affects consumers’ utility derived from the product.[7] Differences in firms’ costs

[6]Theoretically, Rochet and Tirole (2003) and Armstrong (2006) provide a framework for analyzing pricing incentives in two-sided markets. Anderson and Coate (2005) study equilibrium advertising levels and amount of programming in a setup where viewers incur a nuisance cost from ad exposure. Anderson and Gabszewicz (2006) provide a review of two-sided markets for advertising-sponsored media industries. Empirically, two-sided media industries are analyzed in the context of consolidation of local newspapers (Fan (2013)), network effects of Yellow Pages (Rysman (2004)), entry of radio stations (Berry and Waldfogel (1999)). Wilbur (2008) studies the national television market and finds that advertisers’ preferences influence networks’ choice of programming more strongly than viewers’ preferences. These studies provide a careful analysis of the consumer and media side of the problem, while using only aggregate demand for advertising.

[7]Doraszelski and Markovich (2007) extends our understanding of the role of informative and goodwill advertising for market structure to a dynamic setup. Most empirical studies focus on determining how consumers respond to advertising (Ackerberg (2001), Dubé et al. (2005), Shapiro (2018)). Researchers have also used data from firms’ advertising choices to infer information about

to advertise can affect the theoretical implications for both two-sided markets and advertising competition. For example, Doraszelski and Markovich (2007) show that the cost to advertise influences industry structure when advertising is persuasive. In this project, we do not model networks' optimal choices or downstream competition between firms. Instead, we attempt to infer unobserved information about contracts in the market for national television advertising.

The inherent hesitation of firms to provide information about their contracting practices and to share data on terms-of-trade and costs is an impediment to empirical analyses of inter-firm contracts and input costs. As a result, this project relates to the empirical works that rely on firms' observed choices and equilibrium assumptions to back out terms-of-trade and firm costs (Berto Villas-Boas (2007), Mortimer (2008b), Berry and Haile (2014), Hristakeva (2018)).

The rest of the paper is structured as follows: Section 2 covers the market for national television advertising, Section 3 explains the unique data set we use in estimation, Section 4 performs reduced for analysis of legacy discounts, Section 5 covers our discrete-continuous choice structural model, Section 6 discusses the estimation and parametrization of our structural model, and Section 7 covers the results.

2 Market for national television advertising

Networks sell national advertising inventory in two markets: the 'upfront' and the 'scatter.'[8] The scatter market sells ad slots close to the air date of a program. Prices are determined by the market, with little or no price discrimination between ad-

competition. Vilcassim et al. (1999) test different modes of conduct with respect to price and advertising competition. Dubé and Manchanda (2005) find that advertising has different effects on price competition depending on market size. Qi (2013) exploits market dynamics after the cigarette advertising ban of 1971 and concludes that such restrictions lead to a more concentrated industry structure. Chandra and Weinberg (2018) uses a merger in the U.S. brewing industry to analyze empirically the relationship between market structure and firms' advertising expenditures. Scott Morton (2000) and Ellison and Ellison (2011) study whether firms use advertising as an entry deterrent in the pharmaceutical industry. For earlier empirical cross-industry analyses of the association between advertising and entry refer to Bagwell (2007).

[8] Firms may also purchase ads in specific geographic regions through local affiliates. These ads are typically sold to local advertisers, such as car dealers, professional services, local retailers, political ads. Industry participants refer to these local markets as the 'spot' market. We do not observe local advertisements, and our focus throughout is on the national ads sold by the national networks.

vertisers. The scatter market, however, is relatively small, with broadcast networks (ABC, NBC, CBS, FOX, and CW) selling about 20% of their ad inventory on the scatter, and cable networks selling roughly half of their inventory through this market (Bollapragada et al. (2008)). Instead, most ad slots are sold through the upfront market.

The upfront market dates back to the 1960s and involves selling national television advertising for the upcoming season in advance. Each spring, between March and June, networks organize events to preview and promote their programming for the upcoming Fall television season. Advertisers attend the presentations and negotiate with networks over a programming mix for their ads. An important benefit of purchasing in the upfront market relates to the availability of programming. Popular television series often sell all their inventory in the upfront market, meaning that only restricted inventory is available in the scatter market. In addition to securing premium ad inventory, advertising firms typically receive discounts relative to the scatter market for purchasing in advance.[9] Firms with long advertising relationships also benefit from firm-specific legacy discounts.

In practice, most advertisers work with ad agencies to create advertising campaigns for their products, determine advertising budgets, and recommend a programming mix. Ad agencies also negotiate on behalf of their clients in the upfront market. The upfront typically proceeds in two steps (Lotz (2007)). First, agencies negotiate each client's 'program mix' allocation in a network.[10] The programming-mix negotiations are over blocks of ad slots that reach audiences with similar demographic profiles, rather than at the level of the individual commercial in a specific television show.

Once the programming mix is established, agencies negotiate prices. Prices are described as 'cost per mille' (CPM), or the cost to reach one thousand viewers. CPM rates vary by audience size and viewer demographics of the program, seasonality,

[9]Scatter rates commonly average roughly 15 percent higher than average upfront prices (Lotz (2007)).

[10]"Some clients are more involved and request to see mixes as the agency negotiates with the network." (Lotz (2007))

as well as, by advertiser. The price determination process differs between new and returning business. In the case of new accounts for a network, agencies separately negotiate a CPM for each new firm, which becomes its base rate for the following year's upfront. For all returning business, agencies negotiate a uniform percent increase (or rarely a decrease) that is applied to each firm's base rate to determine its price. These base rates reflect the prices firms paid in the previous upfront. For example, if Proctor & Gamble's (P&G) base rate with ABC in 2011 is $10, and ABC secures a 10% increase in prices in 2012, then P&G will pay a CPM of $11 in the 2012 upfront market.

The structure of this market suggests that price differentials may arise from differences in bargaining outcomes due to, for example, differences in advertising budgets or differences in bargaining abilities or positions of media buying agencies. Industry reports and narratives suggest that neither of these explanations are driving the market. In 2005, an auditor of media spending, Media Performance Monitor America (MPMA), analyzed actual prices paid by major U.S. advertisers.[11] The report documents the presence of price variation across firms for identical time and space in the upfront (Bloom (2005)). The findings show that firms may pay prices that are as much as 50% lower than the prices faced by firms on the other side of the distribution. The report further reveals that these deals are not associated with the size of the firm or the advertising agency.[12]

We do not observe the identities of the media buying agencies employed by each firm, and we assume that differentials across firms are not driven by the identity of the agency used during the upfront negotiations. The MPMA's report provides support for this assumption. In addition, industry participants report that the various agencies all secure similar percent increases (or decreases) during the upfront market. For example, over the last few years, viewership (as measured in gross ratings points) has decreased, while demand for television advertising has remained unchanged, leading to price increases for all firms regardless of agency.

[11] At the time, MPMA's clients accounted for $3 billion in advertising expenditure.

[12] Industry participants report that very recently, a few very large firms have been able to negotiate lower base rates despite having a shorter history with the networks.

Instead, practitioners suggest that prices for new businesses are, on average, higher than prices paid by firms with established base rates. As a result, variation in prices is associated with the length of an advertiser's relationship with networks in the upfront market. Typically, legacy firms, with long histories of participation in the upfront, benefit from low 'grandfathered' base rates; while newer firms have higher base rates, on average. The uniform price adjustments across all clients in the market suggest that the price differentials across firms persist over time. In the example above, ABC secured a 10% increase in its CPMs, and this percent increase is applied to all of its returning advertisers. Suppose that Netflix has a base rate of $20 in 2011. Then, Netflix's base rate in 2012 is $22. This example shows that P&G's percent discount vis-a-vis Netflix, in the upfront market, does not change over time: 50%. Given that broadcasters sell approximately 80% of their ad slots in the upfront, we expect that the benefits of lower pricing to legacy advertisers are disproportionately captured in broadcast programming.

The contracts in the market for national television advertising are further complicated by audience guarantees, firm and optionable buys, and multi-year arrangements. First, for all upfront purchases, the networks guarantee audience delivery. This implies that, if a program viewership is lower than the contracted expected viewership, then the networks provides additional ad spots. Alternatively, if the viewership is larger than predicted, then the advertiser captures these gains at no additional cost. To fulfill these audience guarantees, the networks reserve some inventory in advance, which may affect inventory availability and prices in the scatter market. Next, advertisers have some flexibility to adjust their upfront commitments. Typically, the commitments for the fourth quarter of the current year are considered 'firm' buys, whereas advertisers may cancel about 25% of the upfront commitments for the first quarter of the following year, and 50% for the second and third quarters. Historically, advertisers have not aggressively exercised this option, with cancellations only running between 10% and 15% (Wang et al. (2009)). Last, multi-year contracts may be associated with sporting events and event sponsorships. These practices do not directly affect the price determination process in the upfront market.

3 Data

The data for the project come from three sources: Rentrak Corporation, SQAD, and Kantar Media's Ad$pender.[13] In the television market, Rentrak collects viewership (i.e., ratings) data from over 13 million households and 29 million set-top cable boxes.[14] The demographic detail covers over 100 standard demographic variables for all members of each household (for example, gender, race, education, income, etc.). Rentrak combines these viewership data with information on ad placements. The information about each advertisement is extensive, describing the advertiser, industry, product, ad copy, timing, and placement of each ad (for example, Coca-Cola ran the 30-second "Let the World Come to Your Home" ad for Coca-Cola Classic during the 8:00pm showing of "16 and Pregnant" on MTV at 8:13:30pm on Tuesday, October 6, 2013, which was the third of four ads shown in the second ad break of that telecast). The Rentrak data also contain information on the corporate relationships across advertisers, identifying parent companies for brands across products in different industries.

Prices of ad spots are closely guarded by industry participants and are notoriously difficult to observe. SQAD is the sole provider of data on the prices that result from these transactions.[15] These transaction-level data, which SQAD calls 'NetCosts,' report the average transaction price for an ad spot in a specific telecast (for example, "16 and Pregnant" on MTV, shown at 8:00pm on Tuesday, October 6, 2013). The data contain information on reported prices separately for the upfront and scatter markets.

Information on the length of relationship between a parent company and a network is obtained from Ad$pender. Ad$pender collects information on advertising expen-

[13]After we collected the data for our analysis, Rentrak merged with ComScore.

[14]Unlike the Neilsen Company, which tracks 25,000 households using a 'PeopleMeter' to monitor which member of a household is viewing a telecast, Rentrak collects data for a much larger population at the level of each 'tune-in' of a remote control, but does not identify which household member is viewing a given telecast.

[15]In order to solve the information revelation problem, the transaction prices are reported as an average transaction price for telecasts for which advertisers from at least two agencies purchased a spot.

ditures for more than 3 million brands across media outlets: broadcast television, cable television, radio, magazines, and newspapers. The data include information on advertising expenditures starting in 1995, allowing us to track the length of a parent company's presence in the broadcast advertising market.

The final sample includes three years of pricing and detailed advertising data: January 2011 - December 2013. We focus the analysis on 30 networks for which we observe price, demographic information, and ad placements. These networks include the five broadcasters (ABC, CBS, CW, FOX, and NBC), and 25 cable networks. The cable networks are grouped into conglomerates according to their ownership structure during the sample period: Disney-ABC (ABC Family), ESPN (ESPN), Disney-ABC/Hearst Corporation (A&E, History, Lifetime), AMC Networks (AMC), Comcast (Bravo, MSNBC, Syfy, USA), Discovery Communications (Animal Planet, Discovery, TLC), Fox Entertainment Group (FX, Fox News), Scripps Networks (Food Network, HGTV, Travel Channel), Time Warner (CNN, TBS, TNT, TruTV), Viacom (BET, MTV, Spike).

We focus our analysis on firms' advertising choices in primetime programming. Primetime refers to the 8-11:00p.m. block of television programming; most television viewership and advertising expenditures are concentrated in primetime. Firms' primetime advertising reflects their ad-placement choices, while ad placements in non-prime time may be the result of audience deficiency guarantees. Large advertisers are the main participants in the upfront market. As a result, we focus on ad placements in primetime programming by large advertisers.

The final sample contains information on 95,472 unique telecasts (i.e., a program airing) and the input-sourcing advertising choices of 320 advertisers. These advertisers account for 80% of national television primetime advertisements during the sample period. An advertiser is defined at the brand level, and these 320 advertisers represent 191 unique parent companies. For example, the parent company Toyota Motor Corp owns three advertisers in the data: Lexus, Scion, and Toyota.

The information from Ad$pender allows us to construct a variable to track the length of parent company participation in the broadcast upfront market. Base rates are determined at the parent level and all brands of a parent company receive the same base rate. We use the Ad$pender data from 1995 and 1996 to determine whether a parent company has an established relationship with a broadcaster at the beginning of Ad$pender's sample. We define the year in which a company entered the broadcast upfront market as the first year in which we observe the parent company advertising in broadcast television, combined with 2 additional assumptions: 1. there are no gaps in spending greater than a year; 2. the broadcast spending by the company places in the top 90% of parent companies advertising in broadcast. We follow the same strategy to identify the year in which a firm entered the cable upfront market.

Data show that 56% of the parent companies have established relationships with a broadcaster at the beginning of Ad$pender's sample, and we can track the entry of the remaining companies. Table 2.1 summarizes the inferred year in which a parent company has an established relationship in the broadcast or cable network market. For 75% of the parent companies, the inferred entry in the broadcast and cable upfront market is the same. For most other companies, we infer that the parent company has longer uninterrupted relationships in the cable advertising market.

Ad$pender aggregates the information across all broadcasters and across all cable networks; thus, we can only infer when a parent company purchases ads from any broadcaster (or cable network), rather than the exact identities of the networks. The implicit assumption is that if a company's spending is significant for the broadcast (or cable) market, then the company purchases ads in the upfront and it advertises nn all broadcast (or cable) networks. We can confirm the plausibility of this assumption for the observed sample period using Rentrak data. On average, parent companies advertise in 24 of the 30 networks in a year. For the set of companies that advertise on broadcast, data show that, on average, they advertise in 3.8 of the 5 broadcasters, where the variation is created by the choice of whether or not to advertise on CW. In 64% of the 'parent company'-year observations, we see that parent companies advertise in all broadcasters' primetime programming.

Table 2.1 shows the variation in advertiser (brand) annual spending from Ad$pender. The average advertiser budget in the 5 broadcast networks is $49.7 million, while cable companies capture \$39.1 million per advertiser. The analysis focuses on primetime advertising, which constitutes 64% of advertisers' annual spending in broadcast television (35% for cable networks). During the sample period, national television advertising constitutes, on average, 77% of firms' total advertising spending. The other media outlets tracked by Ad\$pender capture firms' ad spending online, on the radio, in newspapers, and magazines.[16] We evaluate the match between our data sources by comparing the annual primetime spending reported in Ad\$pender with primetime spending constructed using average prices from SQAD and ad placements from Rentrak. The correlation between the two variables is 0.98, which confirms the match between our data sources.

To study firms' input-sourcing choices across different programming options, we rely on industry practices to define what constitutes a 'product' in the upfront market for national television advertising. The product purchased in this input market is the viewers reached through an ad, and its main characteristics are the size and demographic profile of viewership. In addition, the upfront market is characterized by block-buying. That is, advertisers purchase a programming mix rather than selecting ad placements in individual telecasts. We approximate this practice by aggregating telecasts into products using information on audience size and viewers' demographic composition.[17] We use a flexible clustering algorithm called affinity propagation described in detail in Appendix 2.A. The algorithm is run separately for each network conglomerate, using all viewer demographic variables to create clusters of similar shows.

The clusters help us aggregate the data in a meaningful way from the advertiser's perspective. Most previous analyses of the television market focus on viewers' choice of programing. Given that a consumer may watch only one telecast at a time, a timeline is typically introduced in these approaches. In contrast, we study firms' choices of advertising inputs, where the common currency is viewership. Thus, the

[16] The online spending reported in Ad\$pender includes only display advertising; search and broadband video are not included.

[17] The product definition also helps to resolve the dimensionality issues presented by the number of telecasts. The sample includes more than 2,600 telecasts for each month for each of the 30 networks.

Table 2.1: Summary Statistics

	mean	sd	med	min	max
broadcast relationship	2000	5.3	1996	1996	2011
cable relationship	1999	4.6	1996	1996	2011
Annual Advertiser Spending ($ millions)					
national broadcast TV	70.4	97.8	33.2	0.0	694.2
national broadcast TV, prime time	44.5	65.7	18.8	0.0	485.2
national cable TV	54.9	59.3	31.4	0.0	397.8
national cable TV, prime time	20.8	23.6	12.0	0.0	157.1
online	16.0	30.0	4.6	0.0	229.6
magazine	22.4	45.6	6.5	0.0	457.0
newspapers	2.2	5.3	0.0	0.0	53.1
radio	1.4	3.8	0.0	0.0	31.2
Product Definition					
# of telecasts (cluster)	23.3	19.4	18	1	94
# of clusters (conglomerate)	8.7	4.1	7	2	22
ratings	0.018	0.020	0.009	0.001	0.144
ratings (s.d. within cluster)	0.001	0.002	0.001	0.000	0.014
Product Definition Demographics					
male (single)	0.93	0.25	0.93	0.39	3.61
female (single)	0.94	0.27	0.94	0.41	3.29
age 18-24	1.09	0.20	1.06	0.56	1.80
age 65+	0.93	0.31	0.91	0.31	1.96
$100,000+	0.97	0.15	0.96	0.64	1.71
African American	1.06	0.29	0.99	0.55	2.49
Hispanic	0.86	0.34	0.77	0.39	2.51
Asian American	0.62	0.20	0.60	0.17	1.59
Advertiser Choices Across Clusters					
number of clusters (month)	42.1	26.9	38.0	1.0	122.0
number of ads in a cluster (month)	3.3	2.6	2.7	0.3	52.4

Advertiser spending (in millions) estimates and length of relationship are obtained from Ad$pender. The other variables are constructed using Rentrak data.

relevant characteristics of a product describe the audience size and types of viewers who may be reached through an ad.

The algorithm defines approximately 130 clusters (products) each month. For a given month, the telecasts of a network conglomerate are grouped into, on average, 9 clusters. The second panel of table 2.1 shows that a cluster combines information from 23.3 telecasts, on average. To create the ratings and demographic profiles of these products, we use the information of the “exemplar" telecast, which is the telecast that best describes the cluster to which it belongs. Cluster ratings measure the size of the audience reached by a program. The average cluster rating is 0.018, which suggests that the “exemplar" telecast of that cluster reached approximately 1.8 million households.

Television programming is diverse, and different shows appeal to different types of viewers. This is reflected in the demographic summary statistics across clusters in table 2.1. These indices measure the relative viewership of households with a specific demographic, compared to the viewership of all households with that demographic across the rest of the available programming. For example, if the male demographic index of a cluster is greater than 1, then this implies that the exemplar of that cluster attracts a disproportionate share of males relative to other telecasts airing at the same time. The demographic variables capture viewing by households, rather than the behavior of each member within the household. As a result, we use male (single) and female (single) demographics to describe the viewership patterns across gender.

Table 2.1 also shows summary statistics on advertisers' choices within a month. Data show that advertisers typically reach consumers in different programs. On average, an advertiser shows ads in 42.1 clusters (out of approximately 130 options), and conditional on advertising in a cluster, the average number of ads sent is 3.3.

4 Reduced-form analysis

Industry narratives suggest that there are large differences in the prices paid by different companies to reach the same audience, and that these differences are related to the length of the relationship between a firm and a network. Contractual agreements are closely guarded; hence, there are no reliable data that may directly identify the size of the grandfathered discounts. To our knowledge, the only study that relies on actual prices faced by different firms was published in 2005 by MPMA, an auditor of media spending in the U.S. The report documents that the spread in upfront prices can be as large as 50% and that the spread is not associated with firm size (Bloom (2005)). As a consequence, our first step is to check for data patterns that would suggest the presence of price differentials that are associated with the legacy status of a firm. In particular, we ask the following question: do companies with longer relationships with broadcasters advertise disproportionately more on broadcast than on cable networks?

Ideally, we would check whether a firm reaches disproportionately more viewers in a network when it has a longer historic relationship with that network. However, the Ad$pender data aggregate spending information to the level of 'broadcast spending' and 'cable spending.' The three major broadcasters (ABC, CBS, and NBC) established the upfront market in the 1960s. FOX enters the broadcast (and upfront) market in 1986, and CW in 2006. Broadcasters have been consistently selling approximately 80% of their prime-time programming during the upfront. In contrast, cable companies gradually enter the upfront starting in the 1990s and currently sell about 50% of their inventories during the upfront. These industry facts suggest that legacy discounts characterize the market for broadcast advertising and are of less importance for national cable advertising. Thus, the reduced-form analysis provides evidence of legacy discounts in the market for broadcast advertising relative to cable advertising.

Grandfathered rates depend on the parent company (P&G) rather than the advertiser (Tide). A parent company is defined as legacy if it advertised on broadcast in 1995 and 1996 as well as having no gap in spending greater than a year. The analysis compares the input-sourcing choices of legacy companies to those of companies that begin advertising with any broadcaster after 1996 (non-legacy firms). Even though a parent company faces a single price, it may have different advertising objectives across product categories. For example, P&G's brands span cleaning products (e.g. Tide), hair products (e.g. Head & Shoulders), non-prescription drugs (e.g. Dayquil), etc. These brands may target customers with different demographic profiles, while facing the same prices at the upfront. As a result, the unit of observation is constructed at the 'parent-category-month' level. This allows us to control for differences in the target audiences across product categories within the same parent company.

We measure advertising intensity on broadcast as the fraction of primetime viewers reached on broadcast networks. For each firm, the variable tracks the total number of primetime ads (weighted by ratings) shown on broadcast divided by the total number of primetime ads purchased in any of the tracked networks for the month. Table 2.2 shows that, on average, 45% of a firm's viewers are reached on broadcast programming.

If we find that legacy firms place a larger share of their ads in broadcast than non-legacy firms, these differences can be attributed to several factors:

1. the relative cost of advertising on broadcast networks is lower for legacy firms,

2. the relative value of the viewers reached on broadcast networks is higher for legacy firms,

3. the relative value of broadcast advertising depends on total advertising spending (and is correlated with the legacy status of the firm),

4. the relative value of broadcast programming (not captured through viewers' demographics) is higher for legacy firms,

5. the relative value of broadcast advertising depends on firm 'strategies' between television and digital advertising (and is correlated with the legacy status of the firm).

In order to assert that the first explanation is driving the results, we must take into account the other confounding factors. The reduced-form analysis compares firm input-sourcing choices in prime time to isolate comparable advertising inputs. However, advertising in broadcast and cable primetime programs may be imperfect substitutes because these media reach different audiences. To account for potential differences in the target audiences across legacy and non-legacy firms, we repeat the analysis for separate demographic variables described in table 2.2. In particular, we use demographics on gender, age, income, and race, and then test whether legacy firms reach a larger fraction of viewers (with that demographic profile) in broadcast than firms that have entered the broadcast advertising market after 1996.

Next, we control for parent company advertising expenditure, using the log of total advertising spending across all media outlets from Ad$pender. This variable controls for the possibility that firms with large advertising expenditures may have different payoffs from advertising in broadcast vis-a-vis cable. The control also captures the possibility that parents with large advertising expenditures may negotiate lower base rates irrespective of year of entry. We will not distinguish between the two rationales given the data available. However, as the MPMA report concludes that scale is not a key factor for prices, one may interpret the variable as a control for the correlation between firm advertising budgets and the benefit to advertising on broadcast. Table 2.2 summarizes this variable separately for legacy and non-legacy parent companies. The difference in spending is driven by differences in the number of brands produced by legacy firms. Data show that legacy firms often produce multiple brands within the same product category, while the pattern is not as prominent for non-legacy firms.

To address the confounding factor in (4.), we include category fixed effects. The analysis compares firms' advertising choices within an industry, separating firms by their legacy status. That is, we allow for category-specific unobserved benefits of reaching a viewer on broadcast (rather than cable). For example, the benefits from advertising on broadcast might differ between cleaning products and non-prescription drugs. This controls for the fact that legacy and non-legacy firms may be coming from different industries. Last, firms may have different strategies between television and digital advertising, so we include the share of digital advertising (as a fraction of total advertiser spending) as a control.

The confounding factors above raise the concern that legacy firms are different from non-legacy firms. If such unobservable differences are correlated with firms' returns to advertising on broadcast relative to cable in a way that is not captured by advertiser category, advertising budget, digital spending, and demographics, then the results presented below will be biased. The identifying assumption is that any remaining unobservable benefits to advertising on broadcast are independent of the length of relationship of a parent company in the broadcast market.

Another concern arises because firms make input-sourcing choices based on expected viewership, while our data track the actual demographic profile of a telecast. We assume that such differences affect all advertisers in the same way and these are not correlated with the legacy status of the firm.

The analysis asks whether the proportion of viewers reached in broadcast versus

Table 2.2: Reduced-form Variables

	mean	sd	med	min	max
dependent variables					
viewers reached in broadcast (fraction)	0.45	0.30	0.51	0.00	1.00
male (single)	0.43	0.29	0.48	0.00	1.00
female (single)	0.46	0.30	0.54	0.00	1.00
age 18-24	0.43	0.29	0.48	0.00	1.00
age 55-64	0.46	0.30	0.53	0.00	1.00
$100,000+	0.47	0.30	0.54	0.00	1.00
African American	0.41	0.28	0.46	0.00	1.00
Hispanic	0.41	0.29	0.46	0.00	1.00
Asian American	0.45	0.30	0.51	0.00	1.00
controls					
adv. expenditure (millions)	15.82	18.66	8.78	0.00	160.05
adv. expenditure (legacy,millions)	18.22	20.49	10.60	0.00	160.05
adv. expenditure (non-legacy, millions)	11.11	13.19	6.76	0.00	117.85
share of digital adv.	0.09	0.14	0.04	0.00	1.00
share of digital adv. (legacy)	0.09	0.13	0.04	0.00	1.00
share of digital adv. (non-legacy)	0.11	0.16	0.05	0.00	1.00

Advertiser spending estimates and length of relationship are obtained from Ad$pender.

cable networks varies with the legacy status of the parent company. Table 2.3 presents the results using all viewers to construct the dependent variable. Then, table 2.4 extends the results by comparing firm advertising choices across different demographic groups. The first row shows the variable of interest, and all regressions suggest that legacy firms reach a larger fraction of viewers on broadcast. Table 2.3 shows that the results do not change across specifications, which differ in the controls used. In columns (1) to (3) we add in each control one at a time: parent adverting expenditure, share of online advertising, and category fixed effects. The main specification is included in column (4) and it includes all controls.

The last column in table 2.3 repeats the analysis using data only for the last quarter of each year (September to December). In the upfront market firms purchase advertising portfolios in advance for the following season (purchase in June for advertising beginning in September). As a result, the contracts allow that some of the buys for January-June in the following year are 'optionable.' By repeating the reduced-form analysis for the part of the sample with 'firm' buys, we confirm that the patterns in the data are not driven by differences in demand volatility between legacy and non-legacy firms.

We also check the robustness of these results using viewer demographics to construct the dependent variable, and these results are reported in table 2.4. The first column replicates the results from table 2.3 using total ads weighted by ratings to construct the fraction of viewers reached on broadcast. The remaining columns use total ads weighted by both ratings and demographic indices to construct the dependent variable. Note that regressions may differ across demographics if the viewers watching broadcast programing have different demographic profiles from those watching cable networks. We find that the results are consistent across demographic profiles. Given this suggestive evidence, we proceed with a structural analysis that carefully models advertiser input-sourcing decisions.

Table 2.3: Model-free Evidence

	(1)	(2)	(3)	(4)	(5)
legacy firm=1	0.126***	0.101***	0.120***	0.085***	0.081***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.013)
firm adv. expenditure		0.059***		0.057***	0.061***
		(0.003)		(0.003)	(0.005)
share of online adv.			-0.230***	-0.229***	-0.222***
			(0.026)	(0.030)	(0.054)
constant	0.444***	-0.471***	0.469***	-0.431***	-0.535***
	(0.013)	(0.046)	(0.014)	(0.052)	(0.085)
month & year FE	yes	yes	yes	yes	yes
industry FE	no	no	no	yes	yes
observations	7678	7678	7678	7678	2618
adjusted R^2	0.050	0.113	0.062	0.259	0.249

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

The dependent variable in all regressions is the fraction of viewers reached in broadcast television. An observation is defined at the parent-category-month level.

5 Model

The model considers how firms use heterogeneous advertising inputs for the production of the final product sold to consumers. We focus on the careful analysis of firms'

Table 2.4: Model-free Evidence

	views	male (single)	female (single)	age 18-24	age 65+	\$100,000+	African Am.	Hispanic	Asian Am.
legacy firm=1	0.085***	0.083***	0.088***	0.082***	0.089***	0.091***	0.075***	0.079***	0.089***
firm adv. expenditure	0.057***	0.054***	0.060***	0.054***	0.059***	0.060***	0.051***	0.051***	0.056***
share of online adv.	-0.229***	-0.222***	-0.235***	-0.226***	-0.232***	-0.228***	-0.238***	-0.229***	-0.222***
constant	-0.431***	-0.398***	-0.475***	-0.406***	-0.454***	-0.459***	-0.377***	-0.362***	-0.418***
month & year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
observations	7678	7678	7678	7678	7678	7678	7678	7678	7678
adjusted R^2	0.259	0.253	0.262	0.255	0.264	0.266	0.239	0.252	0.255

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

The dependent variable in the first regressions is the fraction of viewers reached in broadcast television. The other regressions use the fraction of viewers with a specific demographic profile (by gender, age, and race) reached in broadcast. An observation is defined at the parent-category-month level.

choices to reach different audiences and the outlets selected to reach these viewers.[18] The model imposes that these decisions are non-strategic, as if firms operate in separate markets.

To define a product, we use the clustering algorithm described in Section 3. The approach combines telecasts into clusters using the demographic profile of viewers reached. This definition approximates the block-buying practice in the upfront market, and decreases the dimensionality of the problem, while preserving the variation in viewership characteristics across inputs.[19]

The market for national television advertising provides access to differentiated advertising inputs, that is, they may reach different viewers when advertising in different clusters. Thus, we consider two clusters with different demographic profiles as imperfect substitutes in the production of the final product sold to consumers. Patterns in the data reveal that firms typically show ads in multiple, but not necessarily all, clusters, and they often purchase several ad slots within the same cluster. As a result, we model firms' advertising payoffs with a function that accommodates mul-

[18] Advertising agencies select the advertising mix separately for each of their clients. The implicit assumption is that an agency maximizes the payoffs of each of its clients separately. We do not observe information on advertiser-agency relationships, and advertisers may employ several ad agencies to manage different ad campaigns. Industry practitioners confirm that the interests of advertising agencies and their clients are aligned.

[19] The model does not account for specific ad scheduling within a cluster. These choices may be important for the advertiser; however, such scheduling occurs months after the upfront market, and as a result, they do not provide information about advertising costs.

tiple discreteness and diminishing marginal returns to an input (advertising within the same cluster). Specifically, we borrow from the Multiple Discrete-Continuous Extreme Value literature (MDCEV, see Bhat (2008)). The model imposes that firms choose their advertising mix by maximizing payoffs subject to a budget constraint. First, define firm i's payoff from advertising in a set of clusters A_i as

$$\text{Payoff}(q_i) = \sum_{j \in [A_i, 0]} \exp(X_{ij}\beta_i + \epsilon_{ij}) \frac{((q_{ij}+1)^{\alpha_j} - 1)}{\alpha_j} \tag{2.1}$$

where q_{ij} is the number of ads that firm i shows to viewers of cluster j.[20] The α_j parameters govern firms' diminishing marginal returns to advertising in the same cluster. This implies that the value of showing an ad to the same (or similar) viewers may decrease with repetition. If all $\alpha_j = 1$, then the payoff function exhibits constant marginal returns. In this case, the model collapses to a standard discretechoice setup, where a payoff-maximizing firm will show ads only in the cluster(s) with the highest marginal benefit per dollar. Alternatively, as $\alpha_j \to 0$, the function collapses to $\log(q_{ij}+1)$. We refer to α_j as the *diminishing returns* parameters.

Firm i's payoff from using advertising input j is modeled by $\psi_{ij} = \exp(X_{ij}\beta_i + \epsilon_{ij})$, where the ψ_{ij} term captures firm i's value of reaching the audience of cluster j. To see this, suppose that the payoff function exhibits constant marginal returns ($\alpha_j = 1$ for $\forall j$), then ψ_{ij} tracks firm i's marginal benefits from advertising in cluster j. If firm i may choose between two inputs j and k (with unit prices, $\text{p}_j = \text{p}_k = 1$) and $\psi_{ij} > \psi_{ik}$, then firm i will choose to advertise in j. We describe this valuation with observable characteristics of firms and advertising inputs, X_{ij}, and an idiosyncratic shock, ϵ_{ij}. The shock is modeled as i.i.d. extreme value type I error with mean of zero and variance of σ^2. We refer to the parameters guiding ψ as *base value* parameters.

The payoff function takes into account that firms may use other media outlets to reach consumers, and this is captured through an outside option, $j = 0$. Similarly to discrete-choice models, the base valuation of the outside option is normalized to zero, that is, $X_{i0}\beta_i + \epsilon_{i0} = \epsilon_{i0}$; and its price is set to 1.

[20]We model advertisers' choices of programming mix for each month separately. Month subscripts are omitted for readability.

To complete the optimization problem, we impose that firm i's advertising expenditure may not exceed its advertising budget, B_i. The expenditure captures spending on national television combined with online, radio, newspapers, or outdoors advertising. The budget constraint is defined as

$$\mathrm{B}_i \geq \sum_{j \in A_i} (q_{ij}\mathrm{p}_{ij}) + q_{i0}\mathrm{p}_0 \tag{2.2}$$

where prices to advertise in primetime may vary by firm. As described in Section 2, these prices are described in terms of CPM costs and firms may have different discounts with respect to these CPM values: $\mathrm{p}_{ij} = \mathrm{audience}_j \mathrm{CPM}_{ij}$. So the budget constraint may be expressed as

$$\mathrm{B}_i \geq \sum_{j \in A_i} (q_{ij}(\mathrm{audience}_j \mathrm{CPM}_{ij})) + q_{i0}. \tag{2.3}$$

In this project we focus on understanding price differentials in the upfront market. As a result, we carefully analyze firms' input-sourcing choices of national television advertising. Firm strategic interactions in the product market and general economic conditions may influence firm decisions about the value of audience demographics and total advertising spending. However, we do not observe data on outcomes in the final-goods market, thus, the setup abstracts from interactions in the product market and takes overall television advertising budgets and demographic preferences as exogenous to the model.

The structure imposed on the payoff function allows us to decrease the dimensionality of the problem and makes estimation feasible. An alternative approach would be to find the payoff-maximizing "bundle" of programming without a functional-form assumption. This requires that we populate all possible bundles of clusters that a firm may choose. This approach is not well-suited in our setting for two reasons. First, we are modeling ' firms' choice across more than 100 clusters, which creates a dimensionality problem for the bundling approach. Second, a bundling approach would focus on the identities of the clusters in which a firm advertises and it will ignore any important information contained in the quantity choice. That is, it will impose that the marginal benefit from airing a second ad in a cluster is zero. Our approach allows us to take into account the discrete-continuous nature of the advertiser's problem in a tractable manner.

5.1 Likelihood function

Below we derive the likelihood function that reflects firms' optimal programming mix. Given the payoff function and the budget constraint defined in equations 1 and 3, firm i's optimization problem may be recast as

$$\mathcal{L}_i = \sum_{j \in [0, A_i]} \exp(X_{ij}\beta_i + \epsilon_{ij}) \frac{((q_{ij}+1)^{\alpha_j} - 1)}{\alpha_j} - \lambda\Big(\sum_{j \in [0, A_i]} (q_{ij}\text{price}_{ij}) - \mathrm{B}_i \Big) \tag{2.4}$$

where λ is the Lagrange multiplier associated with firms' budget constraints. The optimization problem allows that firms may purchase any combination of products. Thus we have the standard set of first order conditions (FOC) that depend on whether or not the product is purchased. If the product is purchased and the firm chooses to advertise in a cluster ($j \in [0, A_i]$), then the first order condition holds with equality. On the other hand if the firms chooses not to advertise in a cluster ($k \notin [0, A_i]$), then the conditions hold with an inequality. These first order conditions are given by

$$\begin{aligned} \frac{\exp((X_{ij}\beta_i + \epsilon_{ij}))}{\text{price}_{ij}}(q_{ij}+1)^{\alpha_j - 1} - \lambda = 0, \;\; \text{if } j \in [0, A_i] \text{ (i.e. } q_{ij} > 0) \\ \frac{\exp((X_{ik}\beta_i + \epsilon_{ik}))}{\text{price}_{ik}}(q_{ik}+1)^{\alpha_k - 1} - \lambda < 0, \;\; \text{if } k \notin A_i \text{ (i.e. } q_{ik} = 0) \end{aligned} \tag{2.5}$$

The first order conditions ensure that advertisers are buying products with the highest marginal utility per dollar. To see this assume some product 0 is always purchased and substitute in for λ to get the follow familiar equations that govern marginal rates of substitution between products.

$$\frac{\exp(X_{ij}\beta_i + \epsilon_{ij})}{\text{price}_{ij}}(q_{ij}+1)^{\alpha_j - 1} = \frac{\exp(X_{i0}\beta_i + \epsilon_{i0})}{\text{price}_0}(q_{i0}+1)^{\alpha_0 - 1}, \text{ if } j \in A_i \text{ (i.e. } q_{ij} > 0)$$
$$\frac{\exp(X_{ik}\beta_i + \epsilon_{ik})}{\text{price}_{ik}}(q_{ik}+1)^{\alpha_k - 1} < \frac{\exp(X_{i0}\beta_i + \epsilon_{i0})}{\text{price}_0}(q_{i0}+1)^{\alpha_0 - 1}, \text{ if } k \notin A_i \text{ (i.e. } q_{ik} = 0). \tag{2.6}$$

In order to simplify the above equations, we take logs and define V_{ij} as below:

$$V_{ij} = [(X_{ij}\beta_i) + (\alpha_j - 1)\log(q_{ij}+1)] - \log(\text{price}_{ij}) \tag{2.7}$$

We can now rewrite the Kuhn Tucker (KT) conditions by substituting in V to obtain

$$\begin{aligned} V_{ij} + \sigma\epsilon_{ij} &= V_{i0} + \sigma\epsilon_{i0} \text{ if } j \in [0, A_i] \\ V_{ik} + \sigma\epsilon_{ik} &< V_{i0} + \sigma\epsilon_{i0} \text{ if } j \notin A_i \end{aligned} \tag{2.8}$$

To complete the model we must specify the error structure. We skip the derivation of a general error structure[21] and instead specify an extreme value distribution for ϵ_k and assume ϵ_k is independent of X_k. We also assume the ϵ_k are independently distributed across alternatives with a scale parameter of σ. This assumption on the error term allows for a closed-form solution for the probability that an advertiser allocates expenditure to goods 0 to A_i.

$$\begin{aligned} P(q_0, q_1, ..., q_{A_i}, 0, 0, ..., 0) = |J| \int_{\epsilon_{i0}=-\infty}^{\epsilon_{i0}=\infty} &\left\{ \prod_{j \in [0, A_i]} \frac{1}{\sigma} \upsilon \left[\frac{V_{i0} - V_{ij} + \epsilon_{i0}}{\sigma} \right] \right\} \\ &* \left\{ (\prod_{k \notin [0, A_i]} \Upsilon \left[\frac{V_{i0} - V_{ik} + \epsilon_{i0}}{\sigma} \right] \right\} \frac{1}{\sigma} \upsilon \Big(\frac{\epsilon_{i0}}{\sigma} \Big) \end{aligned} \tag{2.9}$$

where υ is the standard extreme value density function and Υ is the standard extreme value cumulative distribution function. As shown in Bhat (2008) the Jacobian $|J|$ has the following closed form solution

[21] For the general derivation see Bhat (2008)

$$|J| = \left(\prod_{j \in [0,A_i]} \frac{1-\alpha_j}{p_j(q_{ij}+1)} \right) \left(\sum_{j \in [0,A_i]} \frac{p_j(q_{ij}+1)}{1-\alpha_j} \right) \tag{2.10}$$

Using this closed form of the Jacobian and integrating Equation 2.9 we can obtain a closed form expression of the probabilities

$$P(q_1, q_2, ..., q_M, 0, 0, ..., 0) = \frac{1}{p_0} \frac{1}{\sigma^{M-1}} |J| \left[\frac{\prod_{j \in [0,A_i]} \exp V_{ij}/\sigma}{(\sum_{j \in [0,A]} \exp V_{ij}/\sigma)^M} \right] (M-1)! \tag{2.11}$$

The expression above highlights that this model is just a discrete continuous choice extension of the multinomial logit model. To confirm, just set $\alpha = 1$, such that there are no diminishing returns to advertising in a cluster, and assume only a single product is purchased ($A_i = 0$), then the model collapses to the standard multinomial logit model.

6 Estimation and identification

The empirical analysis uses firms' advertising choices to infer information about the relative prices paid to reach viewers in a specific programming cluster. Such price differentials are prevalent in the upfront markets, where broadcast networks sell approximately 80% of their inventory. Only firms with relatively large advertising budgets participate in the upfront. As a result, the analysis uses data on the ad-placement choices of the top 191 parent companies.[22] The decision-making agent is defined at the 'parent company'-category level, and for the remaining of the paper we refer to this level of data aggregation as the advertiser.

Advertisers may reach customers through other media outlets as well. Firms may also rely on online, radio, newspapers, outdoors, or non-primetime cable advertisements. Thus, the outside option is defined as total spending in those media alternatives. We use data from Ad$pender to construct the monthly expenditure by

[22] A firm's decision of whether to participate in the upfront or to wait for the scatter market may have interesting implications; however, we cannot recover from the data how ad slots are purchased. The implicit assumption in the estimation is that legacy firms with large advertising budgets purchase primetime programming during the upfront.

advertiser, summarized in table 3.

Firms' choices across heterogeneous advertising inputs depend on four sets of parameters: those governing the base valuations (β), diminishing returns (α), the variance of the extreme value shocks (σ), and the coefficient of interest, introduced below, the legacy discount (δ). We first describe the parametrization approach, then we discuss the identification strategy.

The base valuation parameters capture firms' value of reach viewers in different clusters. To account for the size and demographic composition of the audience, we include household ratings and variables tracking whether a larger fraction of individuals with each of these characteristics is reached in that cluster: single female, presence of someone in the 18 to 24 age group, the presence of someone above 65 years of age, households with income over \$100,000, and race variables (African American, Hispanic, and Asian American). Additional controls include genre, network conglomerate fixed effects, advertiser category fixed effects, and month-year dummies to capture seasonality changes.

Advertisers spread their ad budgets across a range of programming clusters, which suggests there are diminishing returns to advertising in the same cluster. We use the following functional form

$$\alpha_j = \frac{1}{1 + \exp(\tilde{\alpha} X_j)} \tag{2.12}$$

which imposes that $\alpha_j \in (0, 1]$. For all television advertising clusters, we allow that α_j depends on the number of hours of programming combined in that cluster. Showing an additional ad in a specific cluster j has two effects. First, there may be marginal benefits of showing one more ad to the same viewers. Second, the additional ad may reach a different subset of viewers, as clusters combine multiple telecasts. We interpret the parameters governing the number of hours in a telecast as a proxy to the second effect. We estimate a separate α_0 for the outside option.

In the upfront market for national television advertising, firms purchase "access" to viewers and the cost to reach these viewers varies across firms. The variation in prices across firms is typically associated with the length of relationship between the firm and the network. Prices paid by new businesses have been consistently higher than those faced by returning businesses, which has established the difference between legacy and non-legacy prices. Unfortunately we do not observe individual firm prices. Instead, we allow that the prices faced by legacy and non-legacy firms to advertise on broadcast differ. We model the cost to firm i to reach the viewers of cluster j as

$$\text{price}_{ij} = \text{audience}_j \text{CPM}_{ij} = \text{audience}_j \text{CPM}_j \exp(\delta^b_{\text{legacy}}). \tag{2.13}$$

The exponential functional form ensures that prices are positive. The discount parameter, δ^b_{legacy}, allows that legacy firms benefit from lower prices in the broadcast advertising market. To match industry practices, the legacy discount is defined at the parent-company level, such that $\delta^b_{\text{legacy}} = 1$ if the parent-company has entered the broadcast upfront market prior to 1996 and cluster j is aired on a broadcast network. Thus, this parameter captures the relative price differences paid by legacy and non-legacy firms to advertise on broadcast rather than on cable.

The discount estimate does not change over time, which implies that relative price differences across broadcast and cable are preserved. This is consistent with industry practices, as prices in the upfront market adjust as uniform percentage changes. The implicit assumption is that, during our sample, all broadcast (and all cable) networks secured similar percent increases.

We acknowledge that the structure of the payoff function will play a role in the identification and interpretation of our parameter estimates. Below, we present an informal identification argument to highlight the variation in the data that drives the identification of each set of parameters.

In our setup, we observe both firms' choices of where and how much to advertise. The extensive margin of this choice (where to advertise) identifies the base parameters, while the intensive margin (how much to advertise) informs the diminishing returns parameters. First, variation in firms' programming mix pins down the base value parameters. These parameters depend only on the set of clusters selected and the intuition for the identification of these parameters is similar to standard discrete-choice arguments. Suppose that an advertiser may choose between showing one ad in two clusters with the same prices, she will choose to advertise in the cluster with the higher base value. As a result, if data suggest that firms are more likely to show ads in, for example, clusters appealing to younger audiences, then the estimation would infer that firms value reaching young viewers. Second, the diminishing returns parameters are identified through firms' decisions to allocate their budgets across the set of selected clusters. Consider a firm that sends ads in two clusters with the same base value parameters and prices. Differences in the number of ads placed in each cluster pins down the diminishing returns parameters.

Similarly to standard discrete-choice logit models, the base value and price estimates are scaled by the variance of the extreme-value shock; that is, all valuation parameters are β/σ and the price parameter equals $1/\sigma$. As a result, σ is identified through variation in average prices across clusters.

This paper focuses on documenting the presence of legacy discounts. The discount estimation exploits variation in the advertising mix between broadcast and cable networks across legacy and non-legacy advertisers. Conditional on ratings, demographics and other controls added in X, the discount parameter captures the difference in the likelihood that a legacy firm purchases advertising inputs from broadcasters.

Similarly to most empirical applications, we are faced with two concerns about prices: price endogeneity and measurement error. We observe data on average prices paid in the upfront market. These average prices may differ across telecasts according to the size of the audience reached, the demographic profile of the audience, the network, or some idiosyncratic characteristics of the telecast. We combine telecasts into clusters using detailed information on viewership, and the parameterization takes into account the fact that firms are able to reach different viewer profiles in different clusters. We also capture unobserved firm valuations from different networks and genres using fixed effects. Nevertheless, it is possible that reaching a young person in ABC is more valuable to advertisers than reaching a young person in A&E. This might be because the advertiser reaches different subsets of young people in these shows, or because the level of engagement differs across networks. The results presented assume that conditional on observables, any remaining unobservable components are not correlated with prices. We are working on extending the parameterization to capture advertisers' valuations more flexibly.

7 Results and interpretation

Below we discuss the parameter estimates of the advertiser payoff function. To interpret the legacy discount parameter, we use a simple back-of-the-envelope calculation that showcases the benefits from a legacy status with respect to efficiency gains from a merger.

Table 2.5 shows the results from two specifications that differ in the parametrization of the diminishing returns parameters, α. In the first column we allow that the return to sending an additional ad in a cluster of primetime programming depends on the number of hours of programming combined in the cluster. The specification also estimates a separate diminishing returns value for the outside option. Results show that $\alpha_j = \frac{1}{1+\exp(17.17-3.02*\log(\text{hours of programming}))}$, thus $\frac{\partial \alpha_j}{\partial \text{hours of programming}} > 0$. This is in line with our intuition that an additional ad in a cluster with many hours of programming may reach different subsets of viewers, so these inputs experience lower levels of diminishing returns (higher α_j). More importantly, the estimates suggest that the α parameters are close to zero for all primetime clusters. For example, the average cluster combines 18 hours of programming and this suggests that $\alpha_j = .0004$, and the α_j for the largest clusters is 0.013. For the outside option, we get $\alpha_0 = 0.02$. Given these results, we estimate a specification imposing that $\alpha_j \to 0$ and $\alpha_0 \to 0$. In this case, the payoff function collapses to $\sum_{j\in[0,A_i]} \exp(X_{ij}\beta_i + \epsilon_{ij}) \log(q_{ij}+1)$. The results are reported in the second column of table 2.5. The remainder of the discussion focuses on the results from this estimation.

Instead of normalizing the variance of the extreme value shock to 1, we estimate the σ parameter. In effect, this value determined the price coefficient for an advertiser, and it equals $\frac{1}{1.17} = 0.85$. Note that the base valuation parameters described below are scaled by the variance estimate as well.

The base value parameters reflect the payoffs to advertising in clusters with dif-

Table 2.5: Estimation Results of MDCEV Model

	(1) α parametrization	(2) $\alpha \to 0$
constant	-6.848	-7.154
	(0.126)	(0.116)
ratings	8.554	8.500
	(0.185)	(0.157)
income	0.645	0.647
	(0.213)	(0.187)
female (single)	-0.083	-0.084
	(.012)	(0.011)
age 18-24	0.765	0.764
	(0.031)	(0.024)
age 65+	-0.210	-0.211
	(0.019)	(0.020)
African American	0.016	0.016
	(0.009)	(0.008)
Hispanic	-0.039	-0.039
	(0.017)	(0.014)
Asian American	-0.337	-0.337
	(0.014)	(0.012)
α constant	17.175	-
	(0.015)	-
α log(hours of programming)	-3.024	-
	(0.243)	-
α broadcaster	40.853	-
	(0.012)	-
α outside option	3.809	-
	(0.138)	-
legacy discount	-0.084	-0.082
	(0.014)	(0.013)
σ	1.171	1.174
	(0.022)	(0.002)
ll	-1118018.152	-1143825.447
month FE	Yes	Yes
category FE	Yes	Yes
genre FE	Yes	Yes
conglomerate FE	Yes	Yes

Standard errors in parenthesis

ferent characteristics. The positive coefficient on ratings confirms that firms value advertising on clusters that reach more viewers. The coefficients on the demographic indices reflect how firms value the demographic mix of viewership. For example, the positive coefficients on viewers with income over $100,000 and viewers who are 18 to 24 years of age indicate that firms prefer advertising in clusters that reach a disproportionate share of those demographics. Alternatively, results imply that advertisers value less, shows that have an above average number of viewers over the age of 65. Note that the estimation uses a restricted set of demographics, as reported in table 2.5 because of high correlations between different demographic variables. For example, the correlation between viewers who are over 65 and those who are between the ages of 35-44 is -0.91. Thus, the negative coefficient on the demographic tracking viewers over 65 suggests that advertisers value placing advertisements in shows with lower concentrations of viewers over 65 years old.

We also include controls for network conglomerate, genre, advertiser category, and time period. As expected, we find that firms value more, the advertising inputs that are obtained from broadcast rather than cable networks, where ABC is the most preferred network in our data and A&E is the least. In terms of genre, results suggest that firms receive higher payoffs from advertising in action/adventure programming followed by reality, with the news genre being the least attractive.

The legacy discount estimates are negative. These suggest that a firm with long relationship in the broadcast market captures a 7.9% discount when advertising on broadcast relative to potential cable discounts.[23]

To evaluate the size of this discount, we perform a simple partial equilibrium calculation to quantify the dollar value of the differences between legacy and non-legacy firms. The exercise keeps average prices and firm programming mix fixed and calculates the cost savings to a firm if it changes its status from non-legacy to legacy. This type of adjustment may happen if, for example, a non-legacy firm merges with a legacy firm. In that case, the new firm will face the lower prices. The back-of-the-envelope calculation implies that the average non-legacy firm would save $2 million annually if the legacy discount applied to its advertising campaigns.

Another way to characterize these cost savings is to calculate the additional impressions (views that are not necessarily unique) the merged firm may purchase with-

[23]The legacy discount enters the price determination in a multiplicative way; as a result, its role in the indirect ‘utility’ function of a firm is analogous to a dummy variable identifying a legacy firm advertising in broadcast primetime programming. Hence, another interpretation of that variable is that legacy firms obtain higher payoffs from advertising on broadcast relative to cable networks. We present the preferred interpretation of the parameter estimate.

out increasing its budget. We use the average CPM and calculate the additional viewers that the firm may reach with these $2 million. This exercise suggest that these cost savings correspond to the value of 400 ads reaching 80 million viewers (at average CPM and average viewership).

Note that these efficiency gains from a merger are not due to economies of scale or an improved bargaining position. Instead, the legacy discounts are associated with the length of relationship of a firm in the broadcast market. The calculation presents a lower bound to such cost savings as we do not allow the merged from to re-optimize its advertising mix given the new prices. Despite its simplicity, the exercise shows the potential for important efficiency gains in the market for television advertising.

8 Conclusion

This paper investigates the existence of input discounts in the market for national television advertising. Importantly, industry practitioners assert these discounts are independent of the size of the firm but instead are reliant upon the length of relationship between the advertiser and television network. We first present a reduced-form model that confirms the existence of discounts. Next, we use detailed data on firms' input-sourcing decisions of where and how much to advertise in order to quantify the size of the discounts. We find the discount attributed to legacy firms is 7.9%. This suggest that a non-legacy firm will save, on average, $2 million on their current advertising strategies if it is able to capture the legacy discount.

Such efficiencies in accessing an inputs market are historically hard to identify as firms guard cost information closely. Still, firms largely refer to efficiency rationales as a main justification of mergers. While efficiencies certainly exist, it is unclear how they may affect firms' decisions on entry as well as downstream market competition. Identifying these efficiencies is an important first step in understanding how advantages in the input market may affect other aspects of firms' decision making processes.

APPENDIX2

2.A Affinity Propagation

This section provides an explanation of how products are defined. We cover the algorithm that is used (Affinity Propagation) and what specific data is used in the clustering algorithm. We use a clustering algorithm called Affinity Propagation as a means of grouping shows together. We chose Affinity Propagation because it endogenously selects the number of clusters as well as determining a single point that best represents the cluster, called an exemplar. The importance of these two properties will be discussed further after the explanation of the algorithm.

2.A.1 The Algorithm

Call $s(x_i, x_j)$ 'similarity' and define it as the negative euclidean distance between two points.

$$s(x_i, x_j) = -\sqrt{(x_{i1} - x_{j1})^2 + (x_{i2} - x_{j2})^2 ...} \tag{2.14}$$

Responsibility, $r(i, j)$ is how well suited x_i is to serve as an exemplar for x_j
Availability, $a(i, j)$ represents how appropriate it is for x_i to pick x_j as its exemplar

Algorithm

1. Compute $s(i, j)$ for all data points

2. Set $a(i, j) = 0 \; \forall i, j$

3. Update responsibility and availability with the following rule until convergence:

$$\forall i, j : r(i, j) = s(i, j) - max_{j':j' \neq j}[s(i, j') + a(i, j')] \tag{2.15}$$

$$\forall i, j : a(i, j) = \begin{cases} \end{cases} (2.16)$$

4. We then calculate clusters $c_i = argmax_j[a(i,j) + r(i,j)]$

As each data point would like to pick itself as the best example of a cluster that only contains a single data point, we must input a preference for each $s(i,i)$ which indicates how much each data point would like to be an exemplar. In our case we set this preference to the 35th percentile of similarity across the data points.

The function to be maximized can then be written as:

$$H(e) = -\sum_{n=1}^{N} s(e_n, x_n) + \sum_{m=1}^{N} \delta_m(e) \tag{2.17}$$

$$\delta_m(e) = \begin{cases} \\ 0 \text{else} \end{cases} \tag{2.18}$$

$$e* = argmin_{e \in e} H(e) \tag{2.19}$$

Where $e_n \in [1, ..., N]$ is the exemplar label which assigns each data point n to another data point e_n. This is our net similarity, or the total similarity between all points and exemplars given the preference of each point to be an exemplar.[24]

2.A.2 Application

For our application we take in demographics from the Rentrak data and normalize each demographic. This makes it so every demographic put into the $s(i,j)$ similarity calculation are equally weighted. The normalization is done as shown below:

$$\frac{DemoRating - DemoRatingMean}{DemoVariance} \tag{2.20}$$

These normalizations take place within each conglomerate, treating the major broadcast networks as their own conglomerates. We choose to normalize in this way because it mimics how firms buy advertising in the upfront market. Firms buy

[24]A technical point left out of this equation ensures that every point is assigned to only one exemplar and no cluster is allowed to exist without an exemplar.

blocks of advertising based on the demographics they want to reach and negotiate independently across networks.

2.A.3 List of demographics included in clustering algorithm

Below is a list of demographics used in clustering. As previously mentioned, demographics are measured at a household level and not the individual. This means if a white household that makes $45000 a year consists of one Man who is 35, one woman who is 39 and two female children ages 8 and 10, whenever a television is on they would be included in 17 demographics (A,M,W 18-49,25-54,35-64, White, $40000-$49999, Male Present in HH, Female Present in HH, Presence of Children 6-10, Presence of Children 3-10, Two Adults in HH, Two Children in HH). Because data is aggregated we include 73 demographics in our clustering algorithm. Demographics are listed below where A stands for ALL, M stands for Male, and F stands for Female.

A18-24, M18-24, W18-24, A18-34, M18-34, W18-34, A18-44, M18-44, W18-44, A18-49, M18-49, W18-49, M21-24, W21-24, M21-34, W21-34, A25-34, M25-49, W25-49, A25-54, M25-54, W25-54, A35-44, A35-64, M35-64, W35-64, A45-64, A55-64, A50+, M50+, W50+, A65+, M65+, W65+, African American, Hispanic, Asian American, White, Other (Race), $0-$19999, $20000-$29999, $30000-$39999, $40000-$49999, $50000-$74999, $75000-$99999, $100000-$124999, $125000-$149999, $150000-$174999, $175000-$199999, $200000-$249999, $75000+, $100000+, $125,000+, $150000+, $200000+, $250000+, Single Person in HH (Male), Single Person in HH (Female), Male Present in HH, Female Present in HH, Children Present in HH, No Children Present in HH, Presence of Children 3-5 in HH, Presence of Children 3-10 in HH, Presence of Children 6-10 in HH, Presence of Children 11-17 in HH, One Adult with Children in HH, One Child in HH, Two Adults in HH, Two Children in HH, Three Adults in HH, Three Children in HH, Four or More Adults in HH, Four or More Children in HH

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