Physician Responses to Financial Incentives: Evidence from Hospital Discharge Data

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October 2010

PRELIMINARY AND INCOMPLETE: PLEASE DO NOT CITE

1 Introduction

The health reforms signed into law in March 2010 include provisions to expand health insurance coverage, subsidize premiums and increase consumer choice. The costs of these provisions are partially offset by increased taxes and fees on various entities (including new Medicare taxes on high-income brackets and fees on medical devices and pharmaceuticals). In the long term, however, many policy-makers believe that cost controls rely on health insurance programs such as Medicare and Medicaid moving away from traditional fee-for-service payment systems, which reward providers that generate high service volume, towards systems that encourage them to use resources efficiently while still providing high-quality services. The reforms begin this shift by introducing provisions to make providers who are organized as accountable care organizations (ACOs) eligible, from 2012 onwards, to share in any cost savings they achieve for the Medicare and Medicaid programs. In addition the reforms introduce pilot arrangements under which physicians providing Medicaid services will receive bundled payments that pull together fees for the components of a particular episode of care. For example under these arrangements the obstetrician's and the hospital's payments for a labor and birth episode will be combined into a single fee that is shared by the providers. The goal of both initiatives is to identify and implement a provider payment system that reduces the growth in medical care costs by coordinating the number and type of services provided without compromising the quality of care.

The health policy literature has noted that similar cost control incentives are currently utilized by some health maintenance organizations (HMOs) in California and elsewhere.[1] However, relatively little is known about the effects of such incentive schemes. While numerous previous papers document low costs in HMOs compared to other insurance types, there is little evidence on the mechanisms used to reduce costs and the dimensions on which physicians respond to cost-control incentives. In this paper we use hospital discharge data from California to investigate whether

[1] See, for example, Hammelman et al (2009) for further information.

physicians are more likely to refer patients to lower-priced hospitals when insurers give them a financial incentive to do so. This particular mechanism is important for two reasons. First, hospital costs make up over 30% of national health care spending (Kaiser Family Foundation, 2007 data). Second, if hospital admissions are affected by their prices this has implications for their incentives in, and hence the likely outcome from, their negotiations with HMOs. This in turn affects their incentives both to invest in costly new technologies and also to engage in market-changing activities such as mergers since both are likely to impact these negotiations.

The process by which a patient chooses a hospital involves multiple players. Decisions are made by referring physicians in consultation with their patients. HMOs and other insurers attempt to influence physicians' choices through direct financial incentives and also less directly by making physicians' promotion on the pay scale contingent (formally or informally) on their management of costs. Direct financial incentives utilized in California include capitation contracts under which referring physicians bear financial risk for services they provide and global capitation contracts where they also bear risk for hospital services their patients receive from other providers. In 2003 73% of payments made to primary physicians by the six largest carriers in the data were capitation payments; the proportions varied substantially across carriers from 97% for Pacificare to 38% for Blue Cross.[2] However, both insurers and physicians face a trade-off between incentives to reduce costs and the impact of any negative health outcome on their reputation. The reputational problem may be less severe for less serious illnesses, where negative outcomes that affect reputation may be both less frequent and less dependent on whether the hospital is regarded as a high-quality provider and reimbursed as such.

This paper builds on the previous literature on hospital demand in order to test whether and how physicians respond to cost-control incentives. Previous papers consider the factors affecting patients' hospital choices in some detail but almost exclusively make the simplifying assumption that the patient makes her choice of hospital without any input from the insurer or the provider. In particular, the price paid by the insurer to the hospital is not included in the utility equation. We estimate models of hospital demand that allow this price to influence hospital choices. We use hospital discharge data for privately insured Health Maintenance Organization (HMO) enrollees from California in 2003 and focus on a single diagnosis: the labor/birth episode for pregnant women. We consider the implications of our results for the effects of the health reform's cost-control initiatives and also for hospital merger and investment analyses. The previous literature on hospital mergers (in which price is not included in the hospital choice equation) is likely to over-estimate price increases due to mergers. The previous demand models would also generate over-estimates of hospital incentives to invest in new, high-cost technologies.

We begin by estimating discrete choice logit models that mirror the previous literature but add price to the utility equation. We encounter price measurement issues that are discussed in detail below. In addition, it is important to include extensive controls for hospital quality to avoid price

[2] Our dataset does not distinguish between capitation and global capitation contracts. However, for reasons discussed below, physicians involved in either type of capitation contract have an incentive to reduce the costs of their patients' hospital inpatient stays.

endogeneity problems. We would ideally include interactions between hospital fixed effects and detailed measures of patient diagnosis or severity, since quality may vary across diagnoses within a hospital. Alternatively, the insurer / physician's preference for quality of the hospital may depend on the severity of the patient's illness. Fully flexible controls are not feasible in the logit model so we expect the price coefficient to be biased upwards. When we pool all labor and birth discharges we estimate a positive and significant coefficient on price. However, when we narrow the sample to the least sick women the price coefficient becomes negative, consistent with the hypothesis that price is correlated with unobserved quality of hospital and quality is more important for more severe medical cases. We then allow the price coefficient to vary by insurance carrier and find that the carriers with the highest proportion of payments to physicians made through capitation contracts have negative significant price coefficients while other carriers with a higher proportion of fee-for-service contracts have insignificant coefficients on price.

We develop a new methodology based on moment inequalities to address the price endogeneity issues inherent in the logit model. The identifying assumptions are that the hospital choice equation is additively separable in price and distance to the hospital and that the hospital chosen for each patient generates greater expected utility than any of the other hospitals in her choice set. Thus we can write down an inequality for each patient and each of her alternative hospitals (each hospital that is offered by her insurer, is within reasonable travel distance of her home, and that she did not choose). We identify pairs of patients who have the same severity and are enrollees in the same insurer but who chose different hospitals. By defining the alternative of each patient as the chosen hospital of the other and adding together the two patients' inequalities, we difference out the severity-hospital interaction terms from the utility equation. It is relatively straightforward to estimate bounds on the remaining terms. The methodology has the additional advantage that no distributional assumptions on the error terms are needed and errors of measurement in the right-hand-side variables are averaged out.

We estimate several inequality specifications each of which includes patient severity-hospital fixed effect interaction terms. We begin with a utility equation that is very close to the simplest logit specification, including an assumption that the price and distance coefficients are fixed across insurers. We then allow for cross-insurer variation in the price coefficient. For both equations we first use fairly broad definitions of severity, similar to our categorization of "sicker" and "less sick" patients in the logit analysis. The results are not very informative: for every insurer the bounds on the price coefficient are quite broad and do not determine its sign. We then address the endogeneity problem by defining severity at a much more detailed level. We also use a more detailed definition of the price variable. The results are much more informative. When we allow the price coefficients to differ across insurers the estimated bounds indicate negative price coefficients for the three insurers with the highest proportion of capitated payments. The remaining three insurers in our data have positive or unsigned price coefficients. We conclude that physicians in California do respond to hospital prices, particularly when they face financial incentives to do so. The incentive schemes introduced by the health reforms may be a means of controlling costs by redistributing patients towards lower-cost hospitals.[3]

Our analyses uncover the preferences of a composite agent, comprising the patient, the physician and the insurer. Our model does not attempt to separate out their different preferences. However, since patients have no reason to respond to the price paid by the insurer on their behalf, the price coefficient is informative regarding physician responses to price differences between hospitals. In addition the composite agent whose preferences we are able to recover is the right agent to consider if we wish to investigate the effect of changes in hospital characteristics on hospital market shares, since this is the agent that determines hospital choices. Thus while we are not able to identify the proportion of the choice made by the patient rather than the provider, for example, our estimates are relevant for hospital merger and investment analyses.

Finally we note that in addition to generating incentives for physician groups to control costs, the financial arrangements introduced by the 2010 health reforms, like those currently utilized in California, also introduce some risk of physician group bankruptcy. During the late 1990s many Californian physician groups that accepted capitation payments, some of which were well-established and well-known to patients, went out of business. Reports in the public press and the health policy literature noted that these groups often encountered problems with managing a significant amount of insurance risk, in addition to other challenges including reduced payment rates from employers (passed on to physicians by HMOs) and increased costs of new technologies.[4] In response to this wave of failures the California Legislature passed several managed care bills in 1999 which required physician groups to maintain positive working capital and positive tangible net equity and established a Department of Managed Health Care to oversee the financial condition of physician groups. Since then the financial stability of physician groups has improved (although the number of capitated HMO patients has fallen as some patients switched to other types of insurance such as PPO plans). If the accountable care organizations and bundling arrangements set up by the current health reforms are to be successful, policy makers need to fully understand the issues that caused these problems in California. We leave this as a topic for future research.

The remainder of the paper is structured as follows. In Section 2 we briefly discuss the previous literature on hospital choice and on managed care insurers' cost control efforts. Section 3 describes relevant features of the market, particularly those relevant to California and Section 4 describes the data. Section 5 sets out the full model we wish to analyze, Section 6 and 7 summarize the restrictions required for the logit and inequalities methods and set out their results, and Section 8 concludes.

[3] Given our limited price data, our estimated price coefficient in reality represents the interaction between the coefficient on the actual price paid to the hospital and $\frac{\delta_{\pi h}}{\delta_h}$ (the ratio between the fraction of the list price paid to the hospital by this insurer and the fraction reported as having been paid on average by all managed care plans). While not ideal, this estimate is sufficient for us to learn about physician responses to price differences between hospitals. For example, our finding that higher-percent capitation insurers have more negative coefficients implies either that physicians contracting with these insurers respond more to price than other providers or that these insurers negotiate lower discounts. The former interpretation of the results seems more credible than the latter.

[4] See Baumgarten (2004), Bodenheimer (2000) and Robinson (2001) for details.

2 Previous Literature

There are several relevant streams of previous literature. The first considers HMO gatekeeping and controls on utilization. A number of health policy papers describe the financial arrangements health plans make with physicians, often based on survey data and often focused on California (see, for example, Rosenthal et al (2001 and 2002) and Grumbach et al (1998a. and b.)). Glied (2000) summarizes the literature assessing whether managed care plans reduce utilization and/or costs relative to other insurers. Her summary suggests that HMOs reduce inpatient admissions and costs, although interpreting the results of the studies is often difficult because, for example, physician and patient preferences over intensity of treatment may differ across types of insurer.[5] There are a few more recent studies that consider similar questions. For example, Escarce et al (2001) study an HMO in Michigan offering both an HMO and POS product and find that the HMO, which requires referrals for specialty care, has lower physician and drug expenditures than the POS plan which does not. Gaynor, Rebitzer and Taylor (2004) look in more detail at how HMOs achieve cost savings. They analyze physician responses to group-based financial incentive contracts within a single HMO. They find that spending on medical utilization increases with the size of the physician group receiving group-based incentives. That is, spending is negatively correlated with the intensity of incentives to limit these expenditures. The correlation is greater for outpatient expenditures than for inpatient expenditures. However, there is little if any analysis of the mechanism used to reduce costs (for example, whether physicians move patients from high-cost to lower-cost providers).

The second relevant set of papers estimates discrete choice models of hospital demand. This is a substantial literature. Estimates from these papers have been used as inputs into hospital merger analyses and into models of the contracting process between hospitals and insurers; they are also important determinants of hospital investment incentives. Almost all of these models assume that the consumer chooses her hospital with no input from the insurer or physician (even if the insurer is an HMO): in particular, the price paid by the insurer to the hospital is rarely included in the utility equation. Examples of these papers include Luft et al (1990), Burns and Wholey (1992), Town and Vistnes (2001), Capps, Dranove and Satterthwaite (2003), Tay (2003) and Ho (2006), all of which either omit price entirely or include only the list price (and estimate a positive or unrealistically small negative price coefficient). See Gaynor and Vogt (2000) for a survey of the earlier papers in this literature. One exception is Gaynor and Vogt (2003) which uses assumptions to define a price index for each hospital that is included in the utility equation. However, that paper assumes away interactions between patient characteristics and the attributes of a particular hospital in determining procedures and therefore prices. It also does not consider the impact of physician incentives on the price coefficient.

Finally, our inequalities analysis is similar in spirit to previous papers that match treatment to control groups based on observable data and assume that unobserved information does not affect

[5] Gosden et al (1999) and Armour et al (2001) review the literature on the effects of financial incentives on physician behavior and come to similar conclusions.

response to treatment. The propensity score literature, and difference-in-differences analyses more generally, fall into this category. [Add references.]

3 Background on the Market

The 2003 California medical care market is described in detail in Baumgarten (2004). As noted there, most non-elderly consumers in California receive their health benefits through their employers who in turn contract with health insurers, particularly health maintenance organizations (HMOs) and preferred provider organizations (PPOs). The analysis in this paper focuses on HMOs because our data identifies the name of each patient's insurer, a key input into our analysis, only for HMO enrollees. HMOs place tighter restrictions on consumers' choices of providers than do PPOs. Each HMO contracts with a network of providers and enrollees are required to seek care only within that network.[6] As of December 2002, 21.4 million consumers in California (63% of the population) were enrolled in an insured HMO plan.

Four of the largest managed care insurers in the United States are based in California: Blue Cross, Health Net, Kaiser Permanente and Pacificare. The seven largest HMOs (Kaiser, Blue Cross, Blue Shield, Health Net, PacifiCare, Aetna and CIGNA) had 87.4% of the California HMO market at the end of 2002. Our analysis focuses on six of these seven: we exclude Kaiser Permanente (the largest HMO with 30.5% of the market in 2002) because the prices paid by this vertically integrated insurer to its hospitals are not observed in our data. There is considerable variation in HMO enrollment across markets, defined in Baumgarten (2004) as Health Service Areas (there are eleven of these in California).[7] Estimated HMO penetration ranges from 69% in the East Bay Area to 10% in northern California. Kaiser Permanente is the largest HMO in northern California and San Diego but Blue Cross is the largest in central California and Los Angeles. Pacificare's enrollment is concentrated in Los Angeles and San Diego while Health Net and Blue Cross have substantial numbers of enrollees in the Bay Area. This variation will help to identify the coefficients of interest in our model.

HMO networks contain both hospitals and physicians. In our application, each pregnant woman chooses an obstetrician from within the network and will be referred to one of the small number of network hospitals with which the obstetrician is affiliated. The patient's choice of obstetrician is informed by the list of affiliated hospitals, which is public information. While HMOs could, in theory, influence hospital referrals for their enrollees by defining narrow hospital networks, in practice this is not usually the case. Ho (2006) finds that on average over 80% of hospitals were included in each HMO's network in a sample of 43 large markets in 2003. Capps, Dranove and Satterthwaite (2003) report similar evidence.[8] Similarly, HMOs do not generally use hospital payment mechanisms that provide incentives either to control costs or improve quality. Most hospitals in California are paid

[6] In contrast, while PPO insurers also have provider networks, enrollees can go outside the network provided they are willing to make higher out-of-pocket payments to do so.

[7] We will use a different definition of markets in our estimation, based on the distance from each consumer's home zip code. See below for details.

[8] Our analysis conditions on the provider network of each HMO in our data.

by the insurance carrier on a per service or per diem basis. Capitation payment arrangements under which the hospital bore financial risk for the services provided, which at one point were common in California, had almost died out by 2003 (apparently due largely to the increase in hospital economic power generated by hospital system formation).[9]

Payment arrangements for physicians, in contrast, are often structured to generate cost-control incentives. There are two basic models of physician organization in California. The first (which is not considered in detail in our paper) is the Kaiser Permanente model under which the HMO contracts exclusively with particular medical groups, paying physicians a salary. The second model, known as the California Delegated Model, dominates in the market outside Kaiser. HMOs contract on a non-exclusive basis with medical groups or independent practice associations (IPAs).[10] Both types of physician groups tend to be very large, covering 50,000 lives and containing between 200 and 300 physicians on average. Physicians in medical groups are either employees or partners of the group. IPAs are organized differently: they are administrative organizations that contract with independent physicians or clinics and sign network contracts with health plans on behalf of their physicians. They exist primarily to negotiate and manage capitation contracts for their member physicians. In most cases the HMO pays a capitated (fixed) monthly rate to the medical group or IPA for every enrollee who uses it as his or her primary care clinic (the alternative is a fee-for-service payment arrangement).

The extent of financial risk passed to the medical group varies across capitated contracts. The monthly payment may be intended to cover only the cost of professional services provided by physicians within the group; the HMO makes separate payments to hospitals for providing secondary care. In other cases the capitation payment covers professional plus ancillary services (outpatient medical tests) and in still others (global capitation contracts) the capitation payment covers all services needed by the physician group's patients including inpatient hospital stays. Rosenthal et al (2001) surveyed physician organizations covering 80% of all Californians who obtained care through the delegated model in the years 1999-2000. They found that 84% of patient care revenue came from capitation rather than fee-for-service contracts, a little higher than the 73% reported in our data for 2003. 56% of revenues were from professional and ancillary capitation, 13% from professional service capitation and 15% from global capitation.

Physician groups with global capitation contracts have a clear incentive to refer their patients to lower-cost hospitals. Those paid through professional services capitation are likely to have similar incentives for several reasons. First, "shared risk arrangements" often apply to capitation contracts, under which a spending or utilization target is set and cost savings or overruns relative to the target are shared between the physician group and the HMO. Rosenthal et al (2001) note that 86% of professional or professional plus ancillary capitation revenues from medical groups surveyed, and 89% of those from IPAs, were contracts with shared hospital risk. Fee-for-service contracts did

[9] We control for the percent of the hospital's revenues that are capitated in some of our logit analysis specifications. In our inequalities analysis we exclude the hospitals that report receiving over 5% capitation payments in our data.

[10] Approximately two-thirds of patients covered by non-Kaiser physician organizations are in IPAs and one-third are in medical groups. See Rosenthal et al (2001) for data.

not involve shared hospital risk arrangements.[11] Incentives regarding hospital costs are therefore quite similar across all capitation contracts. In addition, physicians paid through professional and ancillary capitation have an incentive to utilize low-cost hospitals for outpatient visits and, since there are costs of maintaining relationships with hospitals, therefore for inpatient admissions too. Even when the capitation contract covers the most narrowly-defined set of services, obstetricians have incentives to choose low-cost hospitals because they often personally provide services in a hospital environment, implying that they can control their physician group's costs by locating themselves inside a low-cost hospital. Our dataset does not distinguish between professional service capitation and global capitation arrangements. We assume that physician groups facing capitation contracts of any kind have an incentive to be affiliated with and refer patients to lower-cost hospitals, while that incentive does not exist if the physician group receives fee-for-service payments.

If capitation arrangements are to influence hospital referral choices, however, cost-control incentives must be passed from the physician group to the individual physician. The connection is clear when the physician is a partner in a medical group since his or her own income is directly linked to the group's profitability but less clear for other physicians. Rosenthal et al (2002) consider this issue for physicians in both medical groups and IPAs, tracking the flow of financial incentives from physician organizations to physicians for the same set of California providers considered in their 2001 paper. Their findings are summarized in Table 1. The majority of physician groups receiving capitation payments pass financial risk on to individual physicians, in the form of either capitation-based compensation, cost-of-care bonuses or profit sharing. Grumbach et al (1998a) survey California IPAs and have similar findings. They also note that IPAs that are paid on a fee-for-service basis make fee-for-service payments to their member physicians; that is, there is generally no disconnect between the payment arrangement between the health plan and the IPA and that passed on to individual physicians.

Our dataset does not identify the physician or physician group referring each patient to hospital. However, we do observe the name of each patient's HMO and the percent of each HMO's primary services and other medical professional services that are capitated. In the analysis below we compare the importance of price in determining the hospital choice for patients enrolled in high-capitation insurers to its importance for those in low-capitation insurers. We expect obstetricians contracting with insurers that favor capitated payments to have a greater incentive to refer patients to low-cost hospitals.

We note that there are several dimensions on which the incentives generated by the California medical care system are similar to those introduced by the 2010 health care reforms. Capitation payments are similar in some respects to the payment bundling to be piloted in the Medicaid program. Both are intended to reduce the incentives, generated by fee-for-service payment systems,

[11] Similarly Robinson and Casalino (2001) surveyed and interviewed physician organizations contracting with Aetna U.S. Healthcare. They reported that in 1998 52% of commercial enrollees were covered by professional services capitation contracts coupled with arrangements under which financial responsibility for hospital costs was shared between the health plan and the physician organization. An additional 42% were covered by global capitation arrangements. This is in line with our data which indicate that in 2003, 91% of Aetna's payments to primary physicians were capitated.

to provide more services than necessary. Both reward physicians for referring patients to lower-priced hospitals. The difference is that bundled payments address these incentives within an episode of care while capitation payments address them both within and across episodes (presumably generating longer-term incentives). The Accountable Care Organizations set up by the reforms are also likely to generate incentives to control hospital costs. We therefore expect our analysis to be informative regarding the impact of the reforms on hospital inpatient costs. However we note that the physicians currently choosing to practice in groups receiving capitation payments represent a selected sample that is potentially pre-disposed towards responding to financial incentives. If true, and if there is no equilibrium change in the response function of agents as a result of the health care reforms, we would expect our results to represent an upper bound on the response of the universe of physicians.

4 The Dataset

We use four datasets. The first is hospital discharge data covering all patient discharges from hospitals in California in the year 2003 from the state's Office of Statewide Planning and Development (OSHPD). This provides information on each patient's zip code, demographic characteristics, health insurer, the hospital chosen and patient diagnosis details: both the "principal" diagnosis recorded as the major cause of admission and a list of up to 24 other diagnoses for each patient.[12] We link this to hospital financial data, also from OSHPD, and to hospital characteristics data from the American Hospital Association for 2003. Finally we have access to the State of California Department of Managed Health Care Annual Financial Reporting Forms for 2003. These include balance sheets, income statements and some information on enrollment, utilization and types of payment to providers for all HMOs in California.

We consider only admissions records for women in labor and only private HMO enrollees. We exclude Kaiser Permanente admissions because we do not observe prices for these enrollees. We consider only the six largest remaining insurers: these make up over 96% of the remaining observations in the data. We infer the hospital network of each HMO using the discharge data: we assume that a hospital is in the network if at least 3 patients are admitted from the particular insurer and outside the network otherwise. We check the implied network definitions against hand-collected data (described in detail in Ho (2006)) from seven California markets in 2003. The definition is conservative: that is, the networks implied by our methodology contain fewer hospitals than the networks in the hand-collected data and if an implied network contains a particular hospital it is also included in the hand-collected data in the vast majority of cases. Finally, we limit the size of each choice set by assuming, consistent with Kessler and McClellan (2000), that patients consider traveling up to 35 miles to visit a general hospital and up to 100 miles to visit a teaching hospital.

We do not observe the price charged to the insurer by the hospital. Instead our data includes the list price for every discharge. There is evidence that the list price contains meaningful information

[12] We have a Private Use version of the data in which patient zip code, age, race and gender are not masked.

on prices. As noted in Melnick (2004), list prices are essentially equivalent to the "rack rate" that hotels list for their rooms. They are a standard set of prices listed by hospitals in each year for all their services. All patients are quoted the same list price for the same service. However, only uninsured patients and some patients using an out-of-network provider are actually asked to pay the list price, and even they are frequently offered a discount by the hospital. Each insurance company has a contract with each provider in its network that defines a discount from the list price for its enrollees. We observe the average negotiated discount at the hospital level, calculated as the total contractual adjustments from private managed care payors divided by the total charges (the sum of list prices for all patients) for the relevant hospital-year. Both variables are recorded in the hospital's financial statements. Contractual adjustments are defined as "the difference between billings at full-established rates and amounts received or receivable from third-party payors under formal contract agreements".

Our price measure is calculated in two steps. First we find the expected list price for each patient-hospital pair, calculated as the average observed list price for a group of ex ante similar patients at the particular hospital, where our definitions of similar patients differ across our model specifications and are detailed below. We then multiply this ex ante measure of list price by 1 minus the average discount at the hospital level.[13]

We demonstrate below that there is meaningful variation in our price measure both across patients of different sickness levels and across hospitals. However, it is clearly subject to measurement problems. Potential problems with expectational error due to the fact that hospital admissions are made on the basis of ex ante expectations regarding prices, but we observe in the data their ex post realizations, are addressed by using the expected rather than observed list price. However there may also be specification error since we observe the discount at the hospital rather than the hospital-insurer level. Finally there is a trade-off between aggregation error, if our groups of similar patients for the expected list price calculation are defined too broadly, and measurement error if they are too narrow implying small sample problems. We return to these measurement issues below.

Different insurers may use different payment mechanisms to reimburse different hospitals in their networks. The possibilities are fee-for-service payments, per-diem payments under which the hospital receives a fixed number of dollars per day of inpatient stay, case-based (or D.R.G.) payments and capitation payments under which the insurer pays the hospital a fixed amount per patient per year to cover all needed care. We have some information at the hospital and insurer level on the payment mechanisms used but this information is not provided at the discharge level. 72% of hospitals report zero capitation payments in our data. Our logit analysis includes all hospitals, including those that receive capitation payments. We investigate their impact on the estimated coefficients in a robustness test that redefines price to be price*(1-percent of revenues received on a capitated basis). The results are available from the authors on request; they are very similar

[13] Gaynor and Vogt (2003) use a similar methodology, defining price as the observed list price multiplied by 1 minus the average discount.

to those from the baseline analysis. The inequalities analysis excludes a few hospitals reporting that more than 5% of their revenues are paid on a capitation basis; excluding all hospitals with non-zero capitation payments has very little effect on our results. Our data do not distinguish between fee-for-service and case-based payments but we expect case-based payments to be rare: they are predominately used by Medicare rather than private payors. The weighted average percent of payments that are made on a per-diem basis (where the weight is the number of enrollees in the plan) is fairly low at 21%. Two of the six carriers in our data, Aetna and Health Net, report no per-diem payments in 2003. Still, there is clearly some variation in the data in terms of payment mechanisms. Our methodology is valid under the assumption that the list price reported for a particular patient relates to the relevant payment mechanism for that patient.

For the logit analysis theory requires us to include every hospital in every patient's choice set. We exclude providers with fewer than 20 discharges since it is difficult to identify their fixed effect coefficients in the analysis but all others are included. The sample contains 88,157 patients and 195 hospitals.[14] The inequalities analysis has the advantage that we do not need to account for the patient's full choice set; pairwise comparisons between hospitals are sufficient for consistent estimation. We therefore exclude some hospitals with missing average discount data, whose values we fill in using regression analysis for the logits, in addition to dropping the small number of hospitals reporting that more than 5% of their revenues were paid on a capitation basis as noted above.[15] The inequalities analysis dataset contains 70,799 patients and 157 hospitals in total.

Table 2 sets out summary data on the six insurers included in the analysis; data for Kaiser Permanente is also included for comparison. These data give a broader picture of the insurers we consider than can be provided by our specific dataset. Since the effect of capitation payments on the price coefficient will be identified from variation across these six insurers, our goal here is to summarize the differences between them on other relevant dimensions. The first three columns provide enrollment data, showing that of the insurers we consider, Blue Cross, Blue Shield and Health Net have the largest commercial plan enrollment while Aetna and Cigna have the smallest. Pacificare, Blue Cross and Health Net, along with Kaiser, offer the largest Medicare plans. Blue Cross and Health Net are the only substantial players in the Medi-Cal and Healthy Families markets (the California equivalent of Medicaid), with Blue Cross being the largest. Every insurer in our dataset has over 70% of its enrollment in commercial plans. The fourth column of the table lists the number of labor discharges included in our analysis for each plan; the breakdown is approximately

[14] In fact there are 444 California hospitals in the American Hospital Association data. Considering only hospitals that treat women in labor from the six-largest non-Kaiser plans reduces the number to 213; the remaining 17 are hospitals for which we observe fewer than 20 discharges.

[15] The method used to fill in missing discount data for the logit regressions is as follows. For 7.5% of the hospitals in the sample we do not observe the discount for the calendar year but do observe discount data for both relevant fiscal years (from the annual financial statements; fiscal years vary across hospitals). We fill in the missing calendar year information using the predictions from a regression of calendar year discounts on fiscal year discounts and hospital characteristics (fixed effects for hospital systems, service type, control type, Hospital Referral Region, teaching hospitals and particular services provided and lagged numbers of doctors and beds, all as reported in the American Hospital Association data for 2003). The R^2 of the regression is 0.61. A further 12.1% of hospitals have missing discount data for the relevant fiscal years and the calendar year; in this case we use the predictions of a regression of calendar year discounts on hospital characteristics which has a R^2 of 0.49.

proportionate to the commercial enrollment numbers. Column 5 lists the percent of each HMO's primary services that are capitated.[16] There is considerable dispersion across insurers. Pacificare has the highest proportion of capitated payments for primary professional services, at 97%; Blue Cross has the lowest at 38%. The remaining columns of the Table demonstrate that insurers with a high percent of capitated payments are not obviously different from other insurers on dimensions such as profit margins, premiums per member per month, inpatient utilization and prescription drug costs. Blue Cross and Blue Shield, which have the lowest proportion of capitated payments, were historically different from other insurers. They were 501(c)(4) tax exempt as social welfare plans, acting as administrators of Medicare and providing coverage to state and federal government employees. Today, however, Blue Cross and Blue Shield companies are franchisees, independent of the association and each other. They are no longer tax exempt and may be for-profit corporations: in California Blue Cross is an investor-owned for-profit organization while Blue Shield is a not-for-profit company. Blue Cross, which dominates the Medi-Cal market, has a lower medical loss ratio (defined as medical and hospital expenses divided by premium revenues for the whole insurer) and similar inpatient utilization to other insurers in the market. Blue Shield has relatively high inpatient utilization figures but its premiums and medical loss ratio are relatively low and its profit margin is the third highest of those listed.

Table 3 provides summary statistics on the discharges in the dataset. The sample of labor admissions contains 88,157 patients, 195 hospitals and 6 insurers. There are 38 hospitals in the average patient's choice set. 27% of discharges are from teaching hospitals. The average price paid (approximated as list price*(1-average discount)) is $4,319 for labor admissions. The average length of stay is 2.5 days. The importance of the distance between the patient's home and her hospital is clear from the raw data. The average distance between a patient and a hospital in her choice set is 24.6 miles; the average distance to the chosen hospital is 6.7 miles. Distance will be an important variable in the utility equation estimated below.

The table also records means for three potential measures of outcomes: death while in hospital, transfer to an acute care setting (at this hospital or a different hospital) and transfer to a special nursing facility (again at either this or a different hospital). These are useful inputs to an initial investigation of the patterns in the data although we will not use them in our full model. The average probability of each event is low for labor admissions: 0.01% for death, 0.3% for acute care transfer and 1.5% for transfer to a special nursing facility. Table 4 demonstrates that the variation in price and in outcomes across patient ages and comorbidities is intuitive. Women giving birth who are aged over 40 have a significantly higher average price, significantly higher probability of acute care transfer and also a slightly higher probability of transfer to a special nursing facility although the latter is not significant.

[16] Capitation payments for primary professional services are defined in the HMO Annual Financial Statements as "capitation costs incurred by the reporting entity to primary care physicians, dentists and other professionals for the delivery of medical services". They include capitation payments to obstetricians. The statements also record capitation payments to other medical professional services, including support personnel such as nurses, ambulance drivers and technicians.

We use the Charlson score (Charlson et al, 1987) as a measure of patient severity: this assigns integer-valued weights (from 0 to 6) to comorbidities other than principal diagnosis where higher weights indicate higher severity. The weights are summed to generate a single integer-valued index. For example, patients with comorbidities indicating that they have diabetes or mild liver disease would receive a Charlson score of 1; those with renal disease or any malignancy would have a Charlson score of 2; those with a metastatic solid tumor or AIDS would have a Charlson score of 6. A patient with both diabetes and renal disease would have a score of 3. The index was developed by physicians and is widely used to measure severity based on diagnoses listed in patient records. Table 4 indicates that women with higher Charlson scores in our data had higher prices and higher probabilities of adverse outcomes than women with lower Charlson scores. All of these differences are significant at p=0.05. Our analysis will allow the Charlson score, interacted with other severity measures such as age and principal diagnosis, to affect preferences directly.

5 The Model

We assume that the utility equation determining patient i's admission to hospital h when her insurer is indexed π is made up of two components: the utility that the patient derives from visiting hospital h ($W_{i,h}$) and the combined preferences of the insurer and the referring physician (this utility is denoted $W_{\pi,h}$). The patient's preferences are affected by the distance from her home to the hospital and by the hospital's (observed and unobserved) characteristics. The physician and insurer may be influenced by distance and hospital characteristics and are likely also to take account of the price charged by the hospital to the insurer when they make their choice. The patient neither pays nor observes this price; we therefore assume that it does not affect $W_{i,h}$. We thus define the utility of the composite agent making the hospital choice to be:

$$W_{i,\pi,h} = W_{i,h} + wW_{\pi,h}$$

where w is the weight placed on physician/insurer preferences relative to those of the patient. We assume that the components of the utility equation generated by price and distance are each additively separable from those generated by other hospital and patient characteristics and therefore write:

$$W_{i,\pi,h} = \theta_{p,\pi}(\delta_{\pi,h} lp(c_i,h)) + g_\pi(q_h(s), s_i) + \theta_{d1,\pi} d(l_i,l_h) + \theta_{d2,\pi} d(l_i,l_h)^2 + \varepsilon_{i,\pi,h} \tag{1}$$

where $lp(c_i,h)$ is the expected list price for a patient with characteristics c_i at hospital h and $\delta_{\pi,h}$ is 1 minus the discount negotiated at the hospital-insurer level (this will be approximated in our model by 1 minus the average discount for the relevant hospital). The variable s_i is a measure of the severity of the patient's illness, $q_h(s)$ is a vector of perceived qualities of hospital h for different patient sickness levels s, l_i is patient i's location, l_h is hospital h's location and $d(.)$ provides the distance between the two. The first term in the equation (the price term) comes solely from $W_{\pi,h}$;

the other terms may be affected by both patient and insurer/physician preferences. The function $g_\pi(.)$ allows for flexible interactions between hospital quality and patient severity. ε_{ih} is an error term that is not observed by the econometrician. We assume that this is the utility equation which determines the hospital to which each consumer is referred. There is no outside option: we assume that patients in the discharge data do not have the option not to go to hospital.

The term $g_\pi(.)$ is likely to be important since it permits different physician / insurer preferences for quality for patients with different sickness levels. It also allows particular hospitals to have higher quality for some sickness levels than for others. We would ideally use variables such as patient age, diagnosis and co-morbidities to define very narrow severity groups and would interact them with hospital fixed effects. In that case we would assume that $g_\pi(.)$ absorbed all unobservables known to the composite decision-maker that affected the hospital choice and could be correlated with price: i.e. that $g_\pi(.)$ addressed all price endogeneity issues. The remaining error term $\varepsilon_{i,\pi,h}$ would then be econometrician measurement error (particularly in the price variable). Very detailed severity definitions are feasible for the inequalities analysis but not for the logits; the definitions used in estimation are provided below.

6 Logit Analysis

We begin by making the following assumptions:

$$\delta_{\pi,h} lp(c_i, h) = \hat{\delta}_h lp(c_i, h) \tag{2}$$

$$\theta_{d1,\pi} = \theta_{d1};\ \theta_{d2,\pi} = \theta_{d2} \tag{3}$$

$$g_\pi(q_h(s), s_i) = q_h + \beta z_h x(s_i) \tag{4}$$

We make three different assumptions regarding the price coefficient $\theta_{p,\pi}$:

$$\begin{aligned} (a)\ \theta_{p,\pi} &= \theta_p; \\ (b)\ \theta_{p,\pi} &= \theta_{p,\pi}; \\ (c)\ \theta_{p,\pi} &= \theta_0 + \theta_1.pcap_\pi \end{aligned} \tag{5}$$

Equations (2) - (3) state that the price is approximated by the expected list price multiplied by 1 minus the observed average discount and that the distance coefficients are assumed to be fixed across insurers. We further assume that $\varepsilon_{i,\pi,h}$ is an i.i.d. Type 1 extreme value error term. We will estimate the model using maximum likelihood.

It is not feasible to estimate a fully flexible $g_\pi(.)$ term using the logit methodology. In the inequalities analysis below we define over 100 patient severity groups; interacting these with all hospital fixed effects would imply estimating almost 20,000 coefficients. Equation (4) therefore follows the previous literature by defining $g_\pi(q_h(s), s_i) = q_h + \beta z_h x(s_i)$, hospital fixed effects plus interactions between hospital characteristics and patient characteristics that are known on admission and expected to be correlated with severity. The hospital characteristics included in z_h are the number of nurses per bed and indicators for teaching hospitals, for-profit hospitals and hospitals that offer transplant services (a proxy for high-tech hospitals). We also include a measure of the quality of labor and birth services: hospitals were rated on a scale from 0 to 1, where 0 indicated that no labor/birth services were provided and a higher rating indicated that a less common (assumed to be higher-tech) service was offered. The patient characteristics in x_i are the expected probabilities of death in hospital and of transfer to acute care setting or special nursing facility given the patient's age group, principal diagnosis and Charlson score. While these interactions, like those used in the previous literature, are sensible given the constraints imposed by the methodology, we expect them not to be sufficient to fully address the price endogeneity issues noted above. We therefore expect the estimated price coefficient to be biased upwards.

The equations in (5) note that we begin by assuming a common price coefficient across all insurers. We then allow this to differ across insurers and finally investigate whether there is a significant relationship between the percent of the insurer's payments to primary physicians that are capitated and the price coefficient. We define the expected list price to be the average list price for the particular hospital over patients with the same age (categories 11-19, 20-39, 40-49 and 50-64), principal diagnosis (21 categories for women in labor including, for example, "normal delivery", "previous Cesarean Section" and "early labor"), Charlson score and diagnosis generating the Charlson score. Both principal diagnosis and Charlson score are based only on diagnoses known on admission. For example two same-age, same-principal diagnosis women in labor, one with diabetes and the other with mild liver disease, would both have a Charlson score of 1 but would not be in the same group used to determine prices. However, if both had a Charlson score of zero implying no serious comorbidities, but one had a migraine and the other had a viral infection they would be assumed to have the same price.[17] We are constrained to using these fairly broad definitions of similar patients because we encounter small sample problems when we define narrower groups. We expect aggregation error in the price variable to affect our estimates.

We control for some additional variation in patient severity by restricting our attention to the least sick patients in the data, defined as women in labor who are aged 20-39, have a Charlson score of 0, and whose principal diagnosis and comorbidities are defined by obstetrical experts to be "routine". Our sample contains 43,742 of these patients. We repeat the estimation using the sickest patients in the data, defined as all women in labor other than those "least sick". We note, however, that the price coefficient is likely still to be biased upwards when we consider the restricted sample. The inequalities analysis below addresses both price endogeneity and aggregation error issues more fully.

[17] If the set of patients to be used to determine a patient's price in a particular hospital is empty, we expand the group of "similar" patients to include women in the same age category and with the same Charlson score and principal diagnosis. If this is also empty we expand it to include all same-age category same-principal diagnosis patients, then all same-principal diagnosis women. If this group is also empty we take the mean of the non-missing prices already calculated for the particular patient.

6.1 Logit Results

A summary of the results is reported in Table 5. The price coefficients, price interaction terms and distance coefficients are reported, together with the sample size, for each specification. In each case the distance coefficient is negative and highly significant, with a magnitude that is consistent with estimates from the previous literature.[18] As expected, the price coefficient seems to be biased upwards in the specification using the full sample of labor/birth discharges. It is positive and significant with a t value of approximately 5. When we restrict the sample to the least-sick women the coefficient becomes negative (magnitude -0.017) and marginally significant (standard error 0.009). Including interactions between price and insurer fixed effects yields interesting results. Insurers in the table are sorted by declining proportion of capitated payments to primary physicians. Blue Cross and Blue Shield, which have the lowest proportions of capitated payments, have small, positive and insignificant price coefficents. All four of the remaining HMOs have price coefficients less than 0 even though we have not fully controlled for severity-hospital interactions. The negative price coefficients are significant for Pacificare and Health Net, two of the three carriers that favor capitation the most (97% of payments for Pacificare and 80% for Health Net). The remaining carriers, Aetna and Cigna, have relatively small sample sizes (6291 and 8097 labor discharges respectively, compared to 15,479 for Pacificare and 16,950 for Health Net). This may help explain the larger standard errors on their price coefficients. When we remove the price-insurer interactions and instead include an interaction between price and the percent capitation in the insurer, the price coefficient is positive and the interaction term negative with almost twice the magnitude of the price coefficient. Both are significant at p=0.05.

We interpret the magnitudes of the coefficients by considering the average effects of changes in hospital characteristics on demand. Consider first the distance coefficient. We calculate the impact of a one mile increase in distance for hospital h, holding all else fixed, on the probability that a particular patient i visits that hospital. We then take the average over patients and a weighted average over hospitals. The average effect of the one mile distance increase is a 13.7% reduction in the probability that the hospital is chosen.[19] We also calculate elasticities: the average demand elasticity with respect to distance is -2.7. We conduct a similar exercise to evaluate the magnitude of the price effect. Consider Pacificare, the insurer with the most negative estimated price coefficient. The average effect of a $1000 increase in a hospital's price, holding all other prices constant, is a 5.2% reduction in the probability that the hospital is chosen.[20] The average elasticity with respect to price is much smaller than that with respect to distance at -0.25.

The results for the sickest population, as expected, are somewhat different. The price coefficient is now positive and significant, consistent with the hypothesis that unobserved within-hospital variation in quality (probably at the hospital-severity level) is positively correlated with price and

[18] See, for example, Gaynor and Vogt (2003) and Ho (2006).

[19] The average distance to the chosen hospital for the less-sick patients included in the sample is 6.45 miles; the standard deviation is 10.11 miles. The weighted average probability that a particular hospital is chosen is 2.7%, where the weight is the number of discharges.

[20] The average price for the less-sick patients in the sample is $3380; the standard deviation is $1870.

affects choices more for sicker than for less-sick patients. When we add price-insurer interaction terms the interaction is again negative for Pacificare, although insignificant at p=0.05 and smaller in magnitude than for the healthier population. All other insurers' price coefficients are positive; three out of five are statistically significant. The third specification, including a price-percent capitation interaction, tells the same story. Again we estimate a positive price coefficient and a negative interaction term (implying that insurers that favor capitated payments generate physician referrals that are more price-based than those of other physicians). However, the magnitudes are much more similar than for the healthier population and the implied overall price coefficient is positive even for insurers with 100% capitated payments to primary physicians.

We interpret the difference in results for the sick compared to the less-sick populations as indicating a more substantial endogeneity issue for the sicker population, rather than implying that choices are made for sicker patients with a smaller price elasticity of demand. Our reasoning is that, while we might expect patients with different sickness levels to weight price differently, in this application the insurer pays the price rather than the patient and we would not expect the insurer's willingness-to-pay for a fixed-util benefit to vary across patients. The term $g_{\pi}(.)$ in the utility equation incorporates sickness-based variation in the weight placed on hospital quality. It seems unlikely that the price coefficient should also vary across patients within a particular insurer.[21]

We conduct several robustness tests. First we investigate the importance of capitation payments to hospitals (rather than physicians) by interacting our price measure with 1 - the percent of hospital payments that are capitated. This has very little effect on the overall results. Second we add interactions between price and hospital characteristics such as indicators for teaching hospitals, hospitals providing transplant services and for profit hospitals and with the number of nurses per bed at the hospital. The estimated coefficients are almost always insignificantly different from zero.

Finally we consider the hospital fixed effects estimated in the logit analyses. These are jointly significantly different from zero in every specification. Consider in particular the specification that includes price and price interacted with the percent capitation in the insurer. The correlation between the coefficients from the analysis of less-sick and sicker patients is 0.71: that is, hospitals that are attractive to physicians referring less-sick women for their labor episodes tend also to be attractive options for sicker women. Table 6 reports the results of regressing the estimated hospital fixed effects from that model on hospital characteristics. We find that the number of nurses per bed is positively and significantly related to demand for the hospital for both sickness groups. For sicker patients, an indicator for teaching hospitals also has a positive and significant coefficient; however this becomes insignificant when market fixed effects are added to the regression.[22] This may indicate that sicker women are referred to hospitals in urban areas, where teaching hospitals

[21] We investigate this assumption in the inequalities analysis (which more fully addresses endogeneity issues) by estimating the price coefficients, by insurer, separately for sicker and less-sick patients. We find little difference between the two sets of estimates.

[22] In this regression we define markets as Health Service Areas. These were originally defined by the National Center for Health Statistics to be counties or clusters of contiguous counties that are relatively self-contained with respect to hospital care.

are also relatively common.

7 Inequalities-Based Methodology

7.1 Definitions of Severity and Price

The results of the logit analysis indicate that the price paid by the insurer does matter in determining patient referrals to hospital, at least for the least sick patients. However, the logit methodology does not fully control for variation in quality, or in preferences for quality, at the hospital-severity level that might explain the positive price coefficient for relatively sick patients. In addition we are compelled to use average prices within quite broadly-defined patient groups because narrower groups would contain small numbers of patients. Our next step is to develop an estimation method based on inequalities that addresses these issues. As noted above, the idea is to create an inequality for each patient and for each feasible alternative hospital that was not chosen. We then sum the inequalities of two same-insurer, same-severity patients whose chosen and alternative hospitals are switched. The severity-hospital interaction terms will be differenced out and it will be relatively straightforward to place bounds on the remaining terms. Since we have removed the interaction terms we no longer need to estimate their coefficients and can define them at a much more detailed level than was possible in the logit analysis.

This methodology relies on the assumption that the price measure varies within a hospital across patients who have the same insurer and the same severity level; otherwise the price terms would be differenced out along with the interaction terms. Severities are assumed to be defined in sufficient detail that the severity-hospital interactions absorb all unobserved variation that affects choices and might be correlated with price. The additional variation across patients in different price groups conditional on severity is therefore assumed not to affect choices except through the price variable itself. We now provide details of our severity and price definitions and consider whether these requirements are satisfied. Our definitions follow the advice of obstetrical experts at Columbia Presbyterian Hospital. As one input to the definitions, these experts assessed the list of principal diagnoses and co-morbidities in our data, assigning each a rank from 1 to 3 where 1 indicated a routine diagnosis (such as normal birth or immunization of the newborn) and 3 indicated something more serious. See Appendix 1 for a complete list.

We begin by using quite broad definitions of both severity and price that are similar to those used in the logit analysis. Severity is an interaction of the four age group categories defined above, Charlson score, dummies for the diagnosis generating the Charlson score, and dummies for the rank of the principal diagnosis. We do not make assumptions regarding the ordering of severities; instead we define dummy variables for different severity groups. Prices are defined in the same way as for the logits: they are averages for women with the same severity and the same principal diagnosis at the relevant hospital. We expect to encounter endogeneity and measurement problems here that are similar to those encountered in the logit analysis.

Our second specification addresses endogeneity and aggregation error concerns by using much narrower definitions of severity and price. Severity groups are now defined by the interaction between age, principal diagnosis, Charlson score, diagnosis generating the Charlson score and a sub-category defined by the rank of the most serious co-morbidity, other than principal diagnosis, that is listed in the discharge record. Prices are now averages for women with the same severity (as just defined) who also have the same number of most seriously-ranked co-morbidities. In the example above where two women have the same age and principal diagnosis and a zero Charlson score but one has a migraine (a rank 1 comorbidity) and one has a viral infection (rank 2), the women now have different severities and different prices. If neither women had a migraine but one had a viral infection and the other had a viral infection and also a thyroid disorder (both rank 2 comorbidities), they would be assumed to have the same severity but different prices. These definitions generate many more groups than those based on the logits. For example, for the first insurer in our data, there are 9 populated severity groups and 63 groups defining prices using the logit-based categories; there are 106 severities and 272 price groups under the more detailed definitions.

The obstetrical experts we interviewed advised us that these detailed price groups, conditional on severity, were unlikely to be important in terms of hospital choice. The price groupings are more detailed than those used for severity only in that they break out patients by the number of comorbidities of the highest rank as well as the identity of that rank. The number of similarly-ranked comorbidities is viewed as unimportant in determining referrals. While a physician might refer a pregnant woman with a comorbidity of rank 2 (such as hepatitis or a thyroid disorder) to a different hospital from a patient with only rank-1 comorbidities, this would be a hospital well-equipped to deal with high-risk pregnancies rather than the specific comorbidity, and the presence of two rather than one rank-2 comorbidities would not affect the referral decision. In contrast, our experts agreed that the number of comorbidities of a particular rank would be likely to affect the tests performed and drugs prescribed and therefore the price.

We test our assumptions by using an Analysis of Variance to consider whether price groups conditional on severity help explain variance in outcomes. We hypothesize that, if outcomes are not affected by this additional variation, it may be reasonable to assume that it also does not affect choices. The results indicate that, under our definitions, moving from severity to price groupings does not significantly increase the proportion of the variance in outcomes (the probability of death and of transfer to an acute care facility or a special nursing facility) that is absorbed in hospital-patient type groups. That is, we can hold outcomes fixed while allowing price to vary across groups of patients within a severity category. We also note that the Analysis of Variance indicates reasonable price variation across price groups conditional on severity. Moving from severity to price groupings explains an additional 12% of the variance in price (moving from 50% to 62% of the total variance). We take this to be sufficient evidence that our proposed definitions of severity and price groups are well-suited to our model. We now continue to the formal analysis.

7.2 The Inequalities Methodology

We begin by formalizing the interpretation of the unobservable $\varepsilon_{i,\pi,h}$ from equation (1) as econometrician measurement error. We assume that the econometrician's best estimate of the utility generated when patient i from insurer π visits hospital h is:

$$U_{i,\pi,h}(x^o, h, \theta) = \theta_{p,\pi}\delta_{\pi,h}lp(c_i, h) + g_\pi(q_h(s), s(a(c_i))) + \theta_{d,\pi}d(l_i, l_h) \tag{6}$$

where x^o is shorthand for the observable patient, hospital and insurer characteristics that affect utility, a indexes the severity groupings of patients and c their groupings for price. That is, we define $s_i = s\left(a\left(c_i\right)\right)$. The decision-making agent bases the hospital choice on utility $W_{i,\pi,h}(x, h, \theta)$, where:

$$U_{i,\pi,h}(x^o, h, \theta) = W_{i,\pi,h}(x, h, \theta) + \varepsilon_{i,\pi,h} \tag{7}$$

Here x are the true inputs to the utility equation, x^o are the inputs observed by the econometrician and $\varepsilon_{i,\pi,h}$ is measurement error (particularly in the price variable). We assume that the noise is mean-zero conditional on variables known when the choice is made: $E(\varepsilon_{i,\pi,h} \mid I_{i,\pi}) = 0$.

We complete the specification by making the following assumptions which are analogous to those in equations (2)-(5):

$$\delta_{\pi,h}lp(c_i, h) = \hat{\delta}_h lp(c_i, h) \tag{8}$$

$$\theta_{d,\pi} = \theta_d \tag{9}$$

$$g_\pi(q_h(s), s_i) = g_\pi(q_h(s), s(a(c_i))) \tag{10}$$

and the same three assumptions regarding the price coefficient $\theta_{p,\pi}$ as in the logit analysis:

$$\begin{aligned} (a)\ \theta_{p,\pi} &= \theta_p; \\ (b)\ \theta_{p,\pi} &= \theta_{p,\pi}; \\ (c)\ \theta_{p,\pi} &= \theta_0 + \theta_1.pcap_\pi \end{aligned} \tag{11}$$

Equations (8), (9) and (11) are essentially the same as for the logits. We remove the distance squared term for simplicity since it had a small estimated coefficient in the logit analysis; removing it from the logit specifications had little effect on the results.[23] We now leave the function $g_\pi(.)$ completely free (the only constraint we impose is additive separability from the price and distance terms). We also remove the distributional assumption on the error term and do not require it to be independently distributed across hospitals for a given individual and across individuals for a given hospital, as is required by the logit model. We have a free normalization so we divide through by the absolute value of the distance coefficient (which is assumed to be negative), incorporating its

[23] Results are available from the authors on request.

magnitude into $\theta_{p,\pi}$ and $g_\pi(.)$ and implying the following equation for observable utility:

$$U_{i,\pi,h}(x^o, h, \theta) = \theta_{p,\pi}\hat{\delta}_h lp(c_i, h) + g_\pi(q_h(s), s(a(c_i))) - d(l_i, l_h) \tag{12}$$

We describe first the methodology utilized under the assumption that $\theta_{p,\pi} = \theta_p$. We begin by ordering the hospitals from the highest to the lowest average price. For every hospital h we consider every patient i_h who is admitted to h in our data and every other hospital h' in her choice set. Our model implies the following inequality:

$$\begin{aligned}
\Delta W_{i_h,\pi,h,h'} &= W_{i_h,\pi,h}(x, h, \theta) - W_{i_h,\pi,h'}(x, h', \theta) && (13)\\
&= U_{i_h,\pi,h}(x^o, h, \theta) - U_{i_h,\pi,h'}(x^o, h', \theta) - (\varepsilon_{i_h,\pi,h} - \varepsilon_{i_h,\pi,h'}) && (14)\\
&= \theta_p(\hat{\delta}_h lp(c_{i_h}, h) - \hat{\delta}_{h'} lp(c_{i_h}, h')) + g_\pi(q_h(s), s(a(c_{i_h}))) - g_\pi(q_{h'}(s), s(a(c_{i_h})))\\
&\quad -(d(l_{i_h}, l_h) - d(l_{i_h}, l_{h'})) - \left(\varepsilon_{i_h,\pi,h} - \varepsilon_{i_h,\pi,h'}\right)\\
&\geq 0
\end{aligned}$$

For that (i_h, h, h') triple we find every patient $i_{h'}$ who is admitted to hospital h', whose choice set includes h and who has the same severity a, the same insurer π and a different group defining price c. We sum the inequalities of the two patients to difference out the $g_\pi(.)$ terms. Writing $\hat{\delta}_h lp(c_{i_h}, h) - \hat{\delta}_{h'} lp(c_{i_h}, h') = p(i_h, h, h')$, $d(l_{i_h}, l_h) - d(l_{i_h}, l_{h'}) = d(i_h, h, h')$ and $\varepsilon_{i_h,\pi,h} - \varepsilon_{i_h,\pi,h'} = \varepsilon(i_h, h, h')$:

$$\begin{aligned}
& \Delta W_{i_h,\pi,h,h'} + \Delta W_{i_{h'},\pi,h',h} && (15)\\
= \;& \theta_p\left[p(i_h, h, h') + p(i_{h'}, h', h)\right] - \left[d(i_h, h, h') + d\left(i_{h'}, h', h\right)\right] - \left[\varepsilon(i_h, h, h') + \varepsilon\left(i_{h'}, h', h\right)\right]\\
\geq \;& 0.
\end{aligned}$$

Finally we take expectations on the data generating process to construct an inequality that relates the price coefficient to differences in prices and differences in distances:

$$E\left[\theta_p(p(i_h, h, h') + p(i_{h'}, h', h)) \mid I_{i,\pi}\right] \geq E\left[d(i_h, h, h') + d\left(i_{h'}, h', h\right) \mid I_{i,\pi}\right] \tag{16}$$

Our first inequality for estimation is therefore:

$$\theta_p \sum_\pi \sum_{h,h'} \sum_{i_h, i_{h'}} (p(i_h, h, h') + p(i_{h'}, h', h)) \geq \sum_\pi \sum_{h,h'} \sum_{i_h, i_{h'}} \left(d(i_h, h, h') + d\left(i_{h'}, h', h\right)\right) \tag{17}$$

This generates a lower bound for θ_p if the price term is positive and an upper bound if the price term is negative.[24] We then add inequalities generated by interacting equation (15) with instru-

[24] We exclude from the analysis hospitals that have fewer than 50 switches with any other hospital in the analysis. When instruments are included, each pair of hospitals is required to have at least 50 switches whose value of the instrument is non-zero.

ments. We use four instruments defined by taking the positive and negative parts, respectively, of the distance difference terms defined above. That is, our instruments are: $d(i_h, h, h')_+, d(i_h, h, h')_-$, $d(i_{h'}, h', h)_+, d(i_{h'}, h', h)_-$. These are clearly correlated with the variables of interest; the additional inequalities will therefore create variation that helps identify the model. We assume they are perfectly observed by the econometrician and known to the decision-maker when choices are made. (There is no endogeneity problem in the usual sense: all unobservables that affect the decision-makers' choice are differenced out when we sum the inequalities of different patients.) We note that multiplying by the negative instruments will reverse the sign of the inequality. The inequalities generated by the first two instruments $d(i_h, h, h')_+$ and $d(i_h, h, h')_-$ are therefore:

$$\theta_p \sum_{\pi \ldots i_{h'}} p(i_h, i_{h'}, h, h') d(i_h, h, h')_+ \geq \sum_{\pi \ldots i_{h'}} d(i_h, i_{h'}, h, h') d(i_h, h, h')_+ \tag{18}$$

$$-\theta_p \sum_{\pi \ldots i_{h'}} p(i_h, i_{h'}, h, h') d(i_h, h, h')_- \geq -\sum_{\pi \ldots i_{h'}} d(i_h, i_{h'}, h, h') d(i_h, h, h')_- \tag{19}$$

where $\sum_{\pi \ldots i_{h'}}$ represents the same triple sum set out in equation (17) and $x(i_h, i_{h'}, h, h') = x(i_h, h, h') + x(i_{h'}, h', h)$. There are analogous inequalities for each of the two remaining instruments. Each defines a lower (upper) bound for θ_p if the price term is positive (negative).

The method is very similar when we assume that $\theta_{p,\pi}$ differs by insurer: the only difference is that we consider each insurer separately rather than pooling the data and summing over insurers π. Under the assumption $\theta_{p,\pi} = \theta_0 + \theta_1.pcap_\pi$, equation (17) becomes:

$$\theta_0 \sum_{\pi \ldots i_{h'}} p(i_h, i_{h'}, h, h') + \theta_1 \sum_{\pi} pcap_\pi \left[\sum_{h \ldots i_{h'}} p(i_h, i_{h'}, h, h') \right] \geq \sum_{\pi \ldots i_{h'}} d(i_h, i_{h'}, h, h'). \tag{20}$$

Each inequality now defines the area on one side of a line in two-dimensional (θ_0, θ_1) space.

7.3 Inequality Results

Table 7 sets out the results of the inequalities analysis under the assumption that $\theta_{p,\pi} = \theta_p$. The first column ("Broad groups") relates to the specification where severity and price are defined based on fairly broad groups of patients, similar to the logit analysis. The results are less informative than those from the logits: for each insurer we estimate a lower bound for θ_p that is negative and an upper bound that is positive. The reason is that this model imposes fewer restrictions than that estimated with the logit methodology. In particular, the logits placed a specific functional form on the $g_\pi(.)$ term which required us to estimate only around 200 coefficients (the hospital fixed effects plus 15 interactions between hospital and patient characteristics). In the inequalities methodology we allow for a free interaction of approximately 9 severity groups with 157 hospital fixed effects, implying around 1400 degrees of freedom.[25]

[25] The number of severities included varies by insurer; numbers reported are for Blue Shield.

The second column of the Table ("Narrow groups") defines severity and price on the more detailed level described above. We now have more degrees of freedom: for example for the first insurer the number of severities has increased from 9 to 106. However we have also increased the accuracy with which prices are measured and reduced the price endogeneity problem by allowing hospital quality to differ across a larger number of severity groups. The inequalities generate only an upper bound or only a lower bound for the price coefficient for most insurers. In spite of this, however, the results are quite informative. Higher-capitation insurers have more negative ranges for the price coefficient: in particular the coefficients for Pacificare, Aetna and Health Net are clearly negative while those for Blue Cross, Blue Shield and Cigna are not. We caveat the result for Cigna, which is inconsistent with the logit estimates, by noting that Cigna (like Aetna) has a relatively small sample size, with only 8,097 labor discharges in our data. We might therefore expect greater variance in the estimate for Cigna than for other insurers.[26]

These results indicate that insurers with over 75% of payments to primary physicians that are capitated have hospital referral processes that place a negative weight on prices. In contrast to the logit analysis, we did not need to subset by sickness level to generate this result. As a robustness test we repeated the inequalities analysis separately for less sick and sicker patients, using the same definitions as in the logits, and found that the price coefficients were not substantially different across the two groups. This is consistent with our assumption that, while the weight placed on hospital quality by the composite insurer/physician/consumer agent making the hospital choice might differ across patients with different sickness levels, that placed on price by the insurer/physician agent does not.

As expected, the price coefficient is more negative than that estimated in the logit analysis. To interpret its magnitude we again consider the effect of a $1000 price increase on the probability that a particular patient i visits hospital h. We then take the average of that effect over patients and a weighted average over hospitals. Again we consider Pacificare in particular. The logits implied a 5.2% reduction in the probability that the hospital was chosen on average. When we repeat the exercise using the upper bound of the range of values implied by the inequalities methodology (to generate a minimum estimate of the effect of the price change) we predict an 85.2% reduction in probability.[27] The implied price elasticity for Pacificare changes from -0.25 under the logits to -4.11 under the inequalities analysis. The inequalities clearly generate much larger effects than the logit analysis. They are also more in line with the previous literature: Gaynor and Vogt's (2003) price index approach generates an average price elasticity of demand of -4.85.

[26] Results for the specifications where $\theta_{p,\pi} = \theta_p$ and where $\theta_{p,\pi} = \theta_0 + \theta_1 .pcap_\pi$ are pending. Our preliminary specifications estimate a broad range of feasible values for (θ_0, θ_1).

[27] We assume that all other estimates from the logit analysis are correct. We repeat this analysis for Health Net, which has a slightly lower proportion of capitated payments than Pacificare. Under the logit analysis the $1000 price increase implies a 2.6% reduction in the probability that the hospital is chosen. The inequalities estimates imply a 40.7% reduction.

7.4 Potential Alternative Explanations

We consider several alternative possible interpretations of our results. First it is possible that, rather than higher-capitation insurers generating more price-sensitive referral decisions, Blue Cross and Blue Shield (the insurers with the lowest proportion of capitation payments) are different on some other dimension that affects hospital referrals in the manner observed. As noted above, Blue Cross and Blue Shield were historically different from other insurers in that they were focused on administering Medicare and providing coverage to state and federal government employees. However, the data in Table 2 indicate that the "Blue" plans are no longer major providers of Medicare services in California: in 2002 Blue Cross had only 252,000 Medicare enrollees and Blue Shield had only 67,000, compared (for example) to 672,000 for Kaiser and 386,000 for Pacificare. Blue Cross was a major provider of Medi-Cal coverage with just over 1 million of these enrollees, but 3.5 million of its 4.8 million enrollees were in its commercial plans. Blue Shield had no Medi-Cal enrollees; 2.2 million of its 2.3 million enrollees were in its commercial plans.[28] Blue Cross was a for-profit organization. Our assumption is that, while the historical differences between the "Blue" plans and other California insurers may be partly responsible for the variation in capitation payments used to identify our model, they are unlikely to generate differences in physician referral patterns directly. The fact that physicians in California are predominately members of large medical groups that contract on a non-exclusive basis with several insurers, implying that the physicians contracting with Blue Cross and Blue Shield are the same physicians contracting with other insurers, lends further support to our assumption.[29] In short, while it is possible that our results are generated by unobserved differences between insurers, it seems more likely that the observed variation in the proportion of payments to primary physicians that are capitated generates variation in responsiveness to price.

Goldman and Romley (2008) find evidence that hospital amenities such as food quality, staff attentiveness and "pleasant surroundings" play an important role in hospital demand. If these amenities are correlated with hospital prices, and insurers' capitation payments are correlated with their willingness to cater to patient preferences regarding these hospital characteristics, this might help to explain the results. However we expect the $g_{\pi}(.)$ function to control for this effect.

The use of discount data at the hospital level rather than the hospital-insurer level reduces the accuracy of the price variable. However, this would explain the more negative estimated price coefficients for higher-capitation insurers only if higher-capitation insurers negotiated smaller discounts from list prices (i.e. had higher values of $\delta_{\pi,h}$). We conduct an initial test of this possibility by using our average discount data at the hospital level, together with data on the share of each hospital's business that comes from each insurer, to estimate an equation relating discounts to hospital and

[28] See Baumgarten (2004) for details.

[29] In 2002, 10 physician organizations plus the two Kaiser Permanente medical groups had contracts to provide care for almost 80% of managed care enrollees. Blue Cross and Blue Shield, like other commercial insurers, contracted with many of these large groups. Consistent with this, in 2010 Blue Shield's website reported a huge California network of 34,800 physicians compared to a total of only around 66,000 physicians practicing in the state. (see Grumbach et al (2009) for details).

insurer characteristics. The equation we estimate is:

$$\delta_h = \sum_{\pi} w_{\pi,h} x_{\pi,h} \beta + \varepsilon_h$$

where $w_{\pi,h}$ is the (observed) share of hospital h's total charges that come from insurer π and $x_{\pi,h}$ are hospital and insurer characteristics. We include all diagnoses, rather than just women in labor, since δ_h is an average across all patients.[30] Our preliminary estimates indicate that high-capitation insurers may in fact negotiate larger discounts with hospitals than other insurers, all else equal. This result is reassuring in that the opposite correlation would be needed to reverse or invalidate our results. Future iterations of the model will investigate the variation in discounts across insurers in more detail.

Finally, it is possible that some price endogeneity or measurement error problems remain. However, either issue would imply an upwards bias on the estimated price coefficients, i.e. that insurers and physicians were in reality more influenced by price than our estimates suggest. We do not expect either issue to be more severe for lower-capitation insurers, so this is unlikely to explain the estimated cross-insurer differences in price sensitivities.

8 Conclusion

We have analyzed the price sensitivity of the combined insurer/physician/patient agent making hospital choices using two methodologies: a multinomial logit analysis and an analysis based on inequalities. The inequalities method has the advantages of controlling for price endogeneity and price measurement issues more fully than the logits, but the disadvantage of identifying a range of feasible values for the price coefficient rather than a point estimate. Both methodologies indicate that the price coefficient is negative for patients whose insurers make predominately capitation-based payments to physicians but not for other patients. The inequalities analysis indicates that these results hold on average for all women in labor, not just the least sick. Our results are preliminary: in particular we have more work to do on the inequalities analysis. However, the results generated to date have important implications for the coming health reforms, which introduce similar financial incentives for physicians providing Medicare and Medicaid services.

[30] We would ideally also include all insurers contracting with hospital h. Unfortunately the list price variable is not observed for Kaiser; for this reason Kaiser is excluded from the analysis.

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Table 1: Compensation Schemes and Bonuses/Withholds from Primary Care Physicians in California

Method	Medical Groups	Independent Practice Assocns
Capitation-based compensation	21%	87%
Salary	41%	0%
Fee-for-service	39%	13%
	All Physician Groups	
Cost of care bonuses	17%	
Profit sharing	48%	

Notes: All data in the table is reported in Rosenthal et al (2002). The authors surveyed physician organizations covering approximately 87% of all Californians enrolled in managed care plans (excluding Kaiser). Data were collected through structured interviews between May 1999 and June 2000. The paper does not provide a breakdown of the data on cost of care bonuses and profit sharing by type of physician organization.

Table 2: Summary Statistics by Insurer

	2002 enrollment			Labor	% Prim	Profit	Tax	Premium	Admin	Medical	Inpatient utilizn		Prescrip
	Commerc	Medicare	Medi-Cal	discharg	Capitn	Margin	Status	pmpm	expense	loss ratio	discha	days	drugs
Aetna	485,787	37,312	0	6,291	0.91	6.71%	FP	152.42	19.33	86.2%	38.4	139.8	23.15
Blue Cross	3,486,358	251,299	1,099,044	25,038	0.38	7.78%	FP	186.86	21.22	78.9%	38.4	142.4	20.92
Blue Shield	2,231,350	67,049	0	16,302	0.57	5.25%	NFP	146.33	22.72	83.5%	50.3	176.4	20.51
Cigna	634,568	0	0	8,097	0.75	-0.81%	FP	-	27.07	84.6%	39.8	137.1	15.63
Health Net	1,665,221	101,317	349,826	16,950	0.80	4.86%	FP	184.92	18.60	86.3%	39.0	137.8	21.08
Pacificare	1,543,000	386,076	0	15,479	0.97	3.62%	FP	149.92	24.51	88.4%	44.5	156.5	20.48
Kaiser	5,790,348	671,858	104,844	0		-1.50%	NFP	163.44	5.23	97.7%	49.1	158.1	0.44

Notes: Data on the six insurers included in our analysis and on Kaiser Permanente; the latter is excluded from our later analysis because the prices paid to hospitals are not reported. Source for all fields except Labor discharges and % primary capitation: Baumgarten (2004). 2002 enrollment provided separately for commercial plans, Medicare plans and Medi-Cal/Healthy Families plans. "Labor discharg" is the number of discharges in the data sample used in our analyses. "% Prim Capitn" is the percent of payments to primary providers made on a capitated basis in 2003 (source: State of California Department of Managed Health Care Annual Financial Reporting Forms, 2003). "Profit Margin" is net income (after taxes and including investment income) divided by revenues for entire insurer in 2002, "Admin expense" is per member per month administrative expenses for entire insurer in 2002, "Medical loss ratio" is medical and hospital expenses divided by premium revenues for entire insurer in 2002. Inpatient utilization and prescription drug data are for commercial plan only in 2002: "discha" is dicharges per 1000 members, "days" is acute days per 1000 members and "Prescrip drugs" is outpatient prescription drug expenses per member per month.

Table 3: Summary Statistics by Discharge

	Labor only	
	Mean	Std. Devn.
Number of patients	88,157	
Number of hospitals	195	
Number of insurers	6	
Hospitals per patient choice set	38	
Teaching hospital	0.27	
Distance to all hospitals (miles)	24.6	25.6
Distance to chosen hospital	6.7	10.3
List price	$13,312	$13,213
List price*(1-discount)	$4,317	$4,596
Length of stay	2.54	2.39
Died	0.01%	0.004%
Acute transfer	0.3%	0.02%
Special Nursing Transfer	1.5%	0.04%

Notes: Summary statistics for dataset comprising private enrollees of the six largest HMOs excluding Kaiser who are admitted for labor-related diagnoses. "Died" is the probability of death while in hospital, "Acute Transfer" the probability of transfer to an acute care setting (in this or a different hospital) and "Special Nursing Transfer" the probability of transfer to a special nursing facility (again at this or a different hospital). "Std Devn" for "Died", "Acute transfer" and "Special Nursing Transfer" are calculated under the assumption that the 0/1 variable is binomially distributed.

Table 4: Prices and Outcomes by Patient Type

		N	Price*(1-disc)	Acute Transfer	Special Nursing
Age					
	<40	84130	4269 (4488)	0.3% (0.0%)	1.49% (0.0%)
	>40	4027	5310 (6373)	0.5% (0.1%)	1.54% (0.2%)
Signif diff			0.000	0.009	0.797
Charlson					
	0	86326	4276 (4501)	0.3% (0.0%)	1.5% (0.0%)
	1	1753	6079 (7060)	0.6% (0.2%)	2.3% (0.4%)
	>1	78	10022 (15186)	5.1% (2.5%)	12.8% (3.8%)
Signif diff (0 to 1)			0.000	0.005	0.003
Signif diff (1 to >1)			0.000	0.000	0.000

Notes: Labor diagnosis only. See notes to Table 2 for variable definitions. Standard deviations in parentheses; for Acute Transfer and Special Nursing these are standard errors calculated assuming that the 0/1 variables are binomially distributed. Charlson scores assign weights to comorbidities (known on admission to hospital) other than principal diagnosis where higher weight indicates higher severity. Value 0-6 are observed in the data. "Signif diff" states significance level at which we cannot reject the hypothesis that the means in the two samples are the same; these are the results of a t-test for price*(1-discount) and a z-test assuming two binomial distributions for Acute Transfer and Special Nursing.

Table 5: Logit Analysis Results

	All labor patients	Least sick patients			Sickest patients		
Price	0.010** (0.002)	-0.017* (0.009)		0.069** (0.014)	0.012** (0.002)		0.028** (0.006)
Price interactions:							
% Capitated				-0.127** (0.016)			-0.025** (0.008)
Pacificare			-0.077** (0.01)			-0.006 (0.006)	
Aetna			-0.011 (0.016)			0.021** (0.008)	
Health Net			-0.038** (0.01)			0.007 (0.005)	
Cigna			-0.021 (0.014)			0.004 (0.007)	
Blue Shield			0.018 (0.011)			0.024** (0.004)	
Blue Cross			0.008 (0.011)			0.014** (0.003)	
Distance	-0.215** (0.001)	-0.215** (0.002)	-0.215** (0.002)	-0.215** (0.002)	-0.217** (0002)	-0.216** (0.002)	-0.216** (0.002)
Distance squared	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)
$z_h x_i$ controls	Y	Y	Y	Y	Y	Y	Y
Hospital F.E.s	Y	Y	Y	Y	Y	Y	Y
N	88,157	43,742	43,742	43,742	44,059	44,059	44,059

Notes: N is the number of patients. Least sick patients are defined as those aged 20-39, with zero Charlson scores and both principal diagnoses and all comorbidities defined by obstetrical experts to be "routine" (see Appendix 1 for details). Sickest patients are all other patients. $z_h x_i$ are interactions between observed hospital characteristics (indicators for teaching hospitals, for profit hospitals and hospitals that offer transplants, the number of nurses per bed and a variable that summarizes the quality of labor services provided) and patient characteristics (the probabilities of death while in hospital, transfer to an acute care facility and transfer to a special nursing facility conditional on principal diagnosis, age category and Charlson score, all of which are known to the patient ex ante). Price and distance coefficients are reported from multinomial logit demand analysis.

Table 6: Regression of Hospital Fixed Effects on Characteristics

	Least sick patients		Sickest patients	
	Coefft (S.E.)	Coefft (S.E.)	Coefft (S.E.)	Coefft (S.E.)
Teaching hospital	0.466 (0.454)	0.411 (0.436)	0.686** (0.334)	0.482 (0.317)
Nurses per bed	0.929** (0.339)	1.279** (0.322)	0.647** (0.260)	0.855** (0.244)
For profit hospital	-0.054 (0.371)	-0.368 (0.370)	-0.041 (0.289)	-0.436 (0.285)
Offers transplants	-0.686 (0.584)	-0.850 (0.547)	-0.243 (0.435)	-0.206 (0.404)
Quality of labor services	-0.026 (0.404)	-0.188 (0.377)	0.072 (0.303)	0.019 (0.279)
Constant	-1.685** (0.455)	-1.917** (0.420)	-3.023** (0.351)	-3.128** (0.322)
HSA fixed effects	No	Yes	No	Yes
R^2	0.023	0.191	0.042	0.221
N	182	182	182	182

Notes: Results of OLS regressions of the hospital fixed effects estimated in the logit demand analysis (results reported in table 4, specification including price and price interacted with insurer percent capitation) on hospital characteristics. "Least sick patients" and "sickest patients" are defined as in Notes to Table 4. "Teaching hospital", "For profit hospital" and "offers transplants" are dummies for hospitals with the relevant characteristics. "Nurses per bed" is the number of nurses per bed in the hospital. "Quality of labor services" takes values from 0 to 1, where 0 indicates that no labor services are recorded in the American Hospital Association data for 2003 as being provided and 1 indicates that the least commonly-offered labor service is recorded as being offered by the hospital. "HSAs" are Health Service Areas: these were originally defined by the National Center for Health Statistics to be counties or clusters of contiguous counties that are relatively self-contained with respect to hospital care.

Table 7: Results of Inequalities Analysis

	% capitated	Broad groups [θ_{LB},	θ_{UB}]	θ_{point}	Narrow groups [θ_{LB},	θ_{UB}]
Pacificare	0.97	[-3.32,	147.13]		[-,	-0.74]
Aetna	0.91	[-2.13,	102.72]		[-,	-1.07]
Health Net	0.80	[-4.34,	229.75]		[-,	-0.34]
Cigna	0.75	[-9.39,	119.24]		[2.17,	-]
Blue Shield	0.57	[-8.71,	83.08]		[-1.26,	4.18]
Blue Cross	0.38				[-,	2.04]

Notes: Results of inequalities analysis. We include 157 hospitals in total. Estimated coefficient is the ratio of the price coefficient to the distance coefficient in the utility equation, where prices are measured in $000 and distance in tens of miles. "Broad groups": patient severity is defined by age category, Charlson score, inputs into Charlson score and rank of principal diagnosis (see Appendix 1 for details of rankings); price is defined in further detail, breaking out the rank of principal diagnosis into individual diagnoses. "Narrow groups": both severity and price are defined in more detail. Now severity is defined by age category, Charlson score, diagnosis inputs into Charlson score, identity of principal diagnosis and maximum rank of comorbidities (1, 2, 3 where 1 are routine and 3 are serious). Price is defined by breaking out the maximum rank of comorbidities by the number of comorbidities of the highest rank.

Appendix: Categorization of Co-Morbidities by Severity

We asked obstetrical experts at Columbia Presbyterian Hospital to assign a rank to each co-morbidity listed in our discharge data covering privately insured patients admitted for a labor/birth episode in California in 2003. Ranks were numbered from 1 to 3, where 1 indicated a routine diagnosis that would not affect patient treatment in any significant way, 2 indicated a more severe diagnosis and 3 indicated the most severe conditions that would have a substantial effect on the patient's treatment during the labor/birth admission. The list of diagnoses and their assigned ranks is given below. The number of patients with each co-morbidity is also provided. (A single patient may have more than one co-morbidity.)

Diagnosis	# patients	% patients	Rank (1-3)
1. Tuberculosis	9	0	3
2. Septicemia (except in labor)	42	0.02	2
3. Bacterial infection; unspecified sit	668	0.32	2
4. Mycoses	28	0.01	2
6. Hepatitis	119	0.06	2
7. Viral infection	643	0.3	2
8. Other infections; including parasiti	70	0.03	2
9. Sexually transmitted infections (not	19	0.01	2
10. Immunizations and screening for inf	12,523	5.93	1
22. Melanomas of skin	10	0	3
23. Other non-epithelial cancer of skin	6	0	3
24. Cancer of breast	18	0.01	3
26. Cancer of cervix	14	0.01	3
28. Cancer of other female genital orga	2	0	3
32. Cancer of bladder	1	0	3
33. Cancer of kidney and renal pelvis	2	0	3
35. Cancer of brain and nervous system	5	0	3
36. Cancer of thyroid	24	0.01	3
37. Hodgkins disease	8	0	3
38. Non-Hodgkins lymphoma	5	0	3
39. Leukemias	3	0	3
41. Cancer; other and unspecified prima	4	0	3
44. Neoplasms of unspecified nature or	14	0.01	3
46. Benign neoplasm of uterus	1,110	0.53	1
47. Other and unspecified benign neopla	275	0.13	1
48. Thyroid disorders	1,266	0.6	2
49. Diabetes mellitus without complicat	9	0	2
50. Diabetes mellitus with complication	35	0.02	3
51. Other endocrine disorders	81	0.04	2
52. Nutritional deficiencies	22	0.01	1
53. Disorders of lipid metabolism	11	0.01	2
55. Fluid and electrolyte disorders	554	0.26	2
56. Cystic fibrosis	1	0	3
57. Immunity disorders	8	0	2
58. Other nutritional; endocrine; and m	703	0.33	2
59. Deficiency and other anemia	1,542	0.73	1
60. Acute posthemorrhagic anemia	215	0.1	2
61. Sickle cell anemia	59	0.03	3
62. Coagulation and hemorrhagic disorde	338	0.16	2
63. Diseases of white blood cells	37	0.02	2
64. Other hematologic conditions	9	0	2
76. Meningitis (except that caused by t	9	0	3
77. Encephalitis (except that caused by	1	0	3

Diagnosis	# patients	% patients	Rank (1-3)
78. Other CNS infection and poliomyelit	3	0	3
79. Parkinsons disease	2	0	3
80. Multiple sclerosis	28	0.01	3
81. Other hereditary and degenerative n	10	0	3
82. Paralysis	8	0	3
83. Epilepsy; convulsions	146	0.07	3
84. Headache; including migraine	174	0.08	1
85. Coma; stupor; and brain damage	6	0	3
87. Retinal detachments; defects; vascu	5	0	2
88. Glaucoma	3	0	2
89. Blindness and vision defects	17	0.01	2
90. Inflammation; infection of eye (exc	10	0	1
91. Other eye disorders	4	0	1
92. Otitis media and related conditions	16	0.01	1
93. Conditions associated with dizzines	27	0.01	1
94. Other ear and sense organ disorders	21	0.01	1
95. Other nervous system disorders	103	0.05	2
96. Heart valve disorders	540	0.26	3
97. Peri-; endo-; and myocarditis; card	19	0.01	3
98. Essential hypertension	581	0.27	2
99. Hypertension with complications and	18	0.01	3
101. Coronary atherosclerosis and other	1	0	3
102. Nonspecific chest pain	21	0.01	2
103. Pulmonary heart disease	7	0	3
104. Other and ill-defined heart diseas	12	0.01	3
105. Conduction disorders	28	0.01	3
106. Cardiac dysrhythmias	193	0.09	3
107. Cardiac arrest and ventricular fib	2	0	3
108. Congestive heart failure; nonhyper	1	0	3
114. Peripheral and visceral atheroscle	3	0	3
117. Other circulatory disease	187	0.09	2
118. Phlebitis; thrombophlebitis and th	74	0.04	2
119. Varicose veins of lower extremity	4	0	1
120. Hemorrhoids	186	0.09	1
121. ther diseases of veins and lymphat	18	0.01	2
122. Pneumonia (except that caused by t	66	0.03	2
123. Influenza	21	0.01	1
125. Acute bronchitis	13	0.01	1
126. Other upper respiratory infections	190	0.09	1
129. Aspiration pneumonitis; food/vomit	6	0	2
130. Pleurisy; pneumothorax; pulmonary	42	0.02	3
131. Respiratory failure; insufficiency	12	0.01	3
133. Other lower respiratory disease	79	0.04	2
134. Other upper respiratory disease	19	0.01	2
135. Intestinal infection	37	0.02	1
136. Disorders of teeth and jaw	5	0	1
138. Esophageal disorders	101	0.05	2
139. Gastroduodenal ulcer (except hemor	1	0	2
140. Gastritis and duodenitis	24	0.01	1
141. Other disorders of stomach and duo	13	0.01	1
142. Appendicitis and other appendiceal	67	0.03	2
143. Abdominal hernia	94	0.04	1

Diagnosis	# patients	% patients	Rank (1-3)
144. Regional enteritis and ulcerative	55	0.03	2
145. Intestinal obstruction without her	41	0.02	2
146. Diverticulosis and diverticulitis	2	0	2
147. Anal and rectal conditions	16	0.01	1
148. Peritonitis and intestinal abscess	8	0	3
149. Biliary tract disease	401	0.19	2
151. Other liver diseases	84	0.04	2
152. Pancreatic disorders (not diabetes	41	0.02	2
153. Gastrointestinal hemorrhage	12	0.01	3
154. Noninfectious gastroenteritis	61	0.03	1
155. Other gastrointestinal disorders	390	0.18	2
156. Nephritis; nephrosis; renal sclero	11	0.01	2
157. Acute and unspecified renal failur	8	0	3
158. Chronic renal failure	2	0	3
159. Urinary tract infections	838	0.4	1
160. Calculus of urinary tract	216	0.1	1
161. Other diseases of kidney and urete	191	0.09	2
162. Other diseases of bladder and uret	15	0.01	2
163. Genitourinary symptoms and ill-def	97	0.05	1
167. Nonmalignant breast conditions	14	0.01	1
168. Inflammatory diseases of female pe	837	0.4	1
169. Endometriosis	94	0.04	1
170. Prolapse of female genital organs	3	0	1
171. Menstrual disorders	5	0	1
172. Ovarian cyst	297	0.14	1
173. Menopausal disorders	3	0	1
174. Female infertility	6	0	1
175. Other female genital disorders	448	0.21	1
176. Contraceptive and procreative mana	5,442	2.58	1
177. Spontaneous abortion	20	0.01	1
178. Induced abortion	9	0	1
179. Postabortion complications	98	0.05	2
180. Ectopic pregnancy	11	0.01	2
181. Other complications of pregnancy	16,871	7.99	2
182. Hemorrhage during pregnancy; abrup	755	0.36	3
183. Hypertension complicating pregnanc	2,388	1.13	2
184. Early or threatened labor	3,223	1.53	2
185. Prolonged pregnancy	5,103	2.42	1
186. Diabetes or abnormal glucose toler	3,501	1.66	2
187. Malposition; malpresentation	3,375	1.6	1
188. Fetopelvic disproportion; obstruct	3,061	1.45	2
189. Previous C-section	2,592	1.23	1
190. Fetal distress and abnormal forces	2,586	1.22	1
191. Polyhydramnios and other problems	5,086	2.41	2
192. Umbilical cord complication	10,393	4.92	1
193. OB-related trauma to perineum and	3,157	1.49	1
194. Forceps delivery	273	0.13	1
195. Other complications of birth; puer	26,576	12.58	1
196. Normal pregnancy and/or delivery	83,408	39.48	1
197. Skin and subcutaneous tissue infec	66	0.03	1
198. Other inflammatory condition of sk	92	0.04	1
200. Other skin disorders	182	0.09	1

Diagnosis	# patients	% patients	Rank (1-3)
201. Infective arthritis and osteomyeli	2	0	2
202. Rheumatoid arthritis and related d	5	0	2
203. Osteoarthritis	2	0	1
204. Other non-traumatic joint disorder	23	0.01	1
205. Spondylosis; intervertebral disc d	212	0.1	1
206. Osteoporosis	3	0	2
208. Acquired foot deformities	3	0	1
209. Other acquired deformities	6	0	1
210. Systemic lupus erythematosus and c	7	0	2
211. Other connective tissue disease	93	0.04	2
212. Other bone disease and musculoskel	35	0.02	2
213. Cardiac and circulatory congenital	42	0.02	2
214. Digestive congenital anomalies	2	0	2
215. Genitourinary congenital anomalies	240	0.11	2
216. Nervous system congenital anomalie	5	0	2
217. Other congenital anomalies	47	0.02	2
218. Liveborn	1	0	1
219. Short gestation; low birth weight;	2	0	2
224. Other perinatal conditions	6	0	2
225. Joint disorders and dislocations;	5	0	2
226. Fracture of neck of femur (hip)	2	0	2
228. Skull and face fractures	3	0	2
229. Fracture of upper limb	9	0	2
230. Fracture of lower limb	8	0	2
231. Other fractures	15	0.01	2
232. Sprains and strains	21	0.01	1
233. Intracranial injury	6	0	3
234. Crushing injury or internal injury	6	0	3
235. Open wounds of head; neck; and tru	5	0	2
236. Open wounds of extremities	3	0	2
237. Complication of device; implant or	21	0.01	2
238. Complications of surgical procedur	138	0.07	2
239. Superficial injury; contusion	55	0.03	1
240. Burns	2	0	2
242. Poisoning by other medications and	5	0	2
244. Other injuries and conditions due	45	0.02	2
245. Syncope	27	0.01	2
246. Fever of unknown origin	58	0.03	2
247. Lymphadenitis	5	0	2
249. Shock	3	0	3
250. Nausea and vomiting	32	0.02	1
251. Abdominal pain	185	0.09	1
252. Malaise and fatigue	15	0.01	1
253. Allergic reactions	194	0.09	2
255. Administrative/social admission	13	0.01	1
256. Medical examination/evaluation	1	0	1
257. Other aftercare	37	0.02	1
259. Residual codes; unclassified	1,537	0.73	1
650. Adjustment disorders	11	0.01	1
651. Anxiety disorders	129	0.06	1
652. Attention-deficit, conduct, and di	3	0	1
654. Developmental disorders	2	0	1

Diagnosis	# patients	% patients	Rank (1-3)
655. Disorders usually diagnosed in inf	1	0	1
657. Mood disorders	397	0.19	2
658. Personality disorders	5	0	2
659. Schizophrenia and other psychotic	8	0	2
660. Alcohol-related disorders	13	0.01	2
661. Substance-related disorders	164	0.08	2
663. Screening and history of mental he	410	0.19	1
670. Miscellaneous disorders	684	0.32	2