Physician Responses to Financial Incentives: Evidence from Hospital Discharge Data

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PRELIMINARY AND INCOMPLETE: PLEASE DO NOT CITE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 o¤set 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 e¢ ciently 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 physicians are more likely to refer patients to lower-priced hospitals when insurers give them a …nancial incentive to do so. This particular mechanism is important for two reasons. First, hospital

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 di¤erent preferences. However, since patients have no reason to respond to the price paid by the insurer on their behalf, the price coe¢ cient is informative regarding physician responses to price di¤erences between hospitals. In

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.

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 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 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 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

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[14]

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

the other terms may be affected by both patient and insurer/physician preferences. The function $g(:)$ allows for flexible interactions between hospital quality and patient severity. $"_{ih}$ 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 $g(:)$ 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 $g(:)$ absorbed all unobservables known to the composite decision-maker that affected the hospital choice and could be correlated with price: i.e. that $g(:)$ addressed all price endogeneity issues. The remaining error term $"_{i;\,;h}$ 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:

$$_{;h} lp(c_i; h) = \hat{}_{h} lp(c_i; h) \tag{2}$$

$$_{d1;} = {}_{d1};\quad {}_{d2;} = {}_{d2} \tag{3}$$

$$g(q_h(s); s_i) = q_h + \; z_h x(s_i) \tag{4}$$

We make three different assumptions regarding the price coefficient $_{p;}$:

$$\begin{aligned} &(a) \quad {}_{p;} = {}_{p}; \\ &(b) \quad {}_{p;} = {}_{p;}\,; \\ &(c) \quad {}_{p;} = {}_{0} + {}_{1}{:}pcap \end{aligned} \tag{5}$$

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 $"_{i;\,;h}$ 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 $g(:)$ 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 $g(q_h(s); s_i) = q_h + \; z_h x(s_i)$, 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-pro…t hospitals and hospitals that o¤er 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 o¤ered. 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 su¢ cient to fully address the price endogeneity issues noted above. We therefore expect the estimated price coe¢ cient to be biased upwards.

The equations in (5) note that we begin by assuming a common price coe¢ cient across all insurers. We then allow this to di¤er across insurers and …nally in242 cienpr390(cgin)6lyer9444(in242TJ/F391

6.1 Logit Results

A summary of the results is reported in Table 5. The price coe¢ cients, price interaction terms and distance coe¢ cients are reported, together with the sample size, for each speci…cation. In each case the distance coe¢ cient is negative and highly signi…cant, with a magnitude that is consistent with estimates from the previous literature.[18] As expected, the price coe¢ cient seems to be biased upwards in the speci…cation using the full sample of labor/birth discharges. It is positive and signi…cant with a t value of approximately 5. When we restrict the sample to the least-sick women the coe¢ cient becomes negative (magnitude -0.017) and marginally signi…cant (standard error 0.009). Including interactions between price and insurer …xed e¤ects yields interesting results.

a¤ects choices more for sicker than for less-sick patients. When we add price-insurer interaction terms the interaction is again negative for Paci…care, although insigni…cant at p=0.05 and smaller in magnitude than for the healthier population. All other insurers' price coe¢ cients are positive; three out of …ve are statistically signi…cant. The third speci…cation, including a price-percent capitation interaction, tells the same story. Again we estimate a positive price coe¢ cient 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 coe¢ cient is positive even for insurers with 100% capitated payments to primary physicians.

We interpret the di¤erence 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 di¤erent sickness levels to weight price di¤erently, 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 …xed-util bene…t to vary across patients. The term $g(:)$ in the utility equation incorporates sickness-based variation in the weight placed on hospital quality. It seems unlikely that the price coe¢ cient 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 e¤ect 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 pro…t hospitals and with the number of nurses per bed at the hospital. The estimated coe¢ cients are almost always insigni…cantly di¤erent from zero.

Finally we consider the hospital …xed e¤ects estimated in the logit analyses. These are jointly signi…cantly di¤erent from zero in every speci…cation. Consider in particular the speci…cation that includes price and price interacted with the percent capitation in the insurer. The correlation between the coe¢ cients 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 …xed e¤ects from that model on hospital characteristics. We …nd that the number of nurses per bed is positively and signi…cantly related to demand for the hospital for both sickness groups. For sicker patients, an indicator for teaching hospitals also has a positive and signi…cant coe¢ cient; however this becomes insigni…cant when market …xed e¤ects 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 coe¢ cients, by insurer, separately for sicker and less-sick patients. We …nd little di¤erence between the two sets of estimates.

[22] In this regression we de…ne markets as Health Service Areas. These were originally de…ned 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 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 toenc a aame ceverity

7.2 The Inequalities Methodology

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

$$U_{i;\ ;h}(x^o; h;\ ) = \ _{p;}\ \ _{;h} lp(c_i; h) + g\ (q_h(s); s(a(c_i))) + \ _{d;}\ d(l_i; l_h) \tag{6}$$

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

$$U_{i;\ ;h}(x^o; h;\ ) = W_{i;\ ;h}(x; h;\ ) + "_{i;\ ;h} \tag{7}$$

Here x are the true inputs to the utility equation, x^o are the inputs observed by the econometrician and $"_{i;\ ;h}$ 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: $E("_{i;\ ;h} | I_{i;\ }) = 0$.

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

$$_{;h} lp(c_i; h) = \hat{}_h lp(c_i; h) \tag{8}$$

$$_{d;} = \ _d \tag{9}$$

$$g\ (q_h(s); s_i) = g\ (q_h(s); s(a(c_i))) \tag{10}$$

and the same three assumptions regarding the price coe¢ cient $_{p;}$ as in the logit analysis:

$$\begin{aligned} &(a)\ \ _{p;} = \ _p; \\ &(b)\ \ _{p;} = \ _{p;}\ ; \\ &(c)\ \ _{p;} = \ _0 + \ _1 {:}pcap \end{aligned} \tag{11}$$

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 coe¢ cient in the logit analysis; removing it from the logit speci…cations had little e¤ect on the results.[23] We now leave the function g (:) 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 coe¢ cient (which is assumed to be negative), incorporating its

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

magnitude into $_{p;}$ and g (:) and implying the following equation for observable utility:

$$U_{i;\ ;h}(x^o; h;\ ) = \ _{p;}\ \hat{\ }_h lp(c_i; h) + g\ (q_h(s); s(a(c_i))) - d(l_i; l_h) \tag{12}$$

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:

$$\alpha_p \sum_{:::i,} p(i_h;i_{h'};h;h')d(i_h;h;h')_+ \geq \sum_{:::i,} d(i_h;i_{h'};h;h')d(i_h;h;h')_+ \qquad (18)$$

$$-\alpha_p \sum_{:::i,} p(i_h;i_{h'};h;h')d(i_h;h;h')_- \geq -\sum_{:::i,} d(i_h;i_{h'};h;h')d(i_h;h;h')_- \qquad (19)$$

where $\sum_{:::i,}$ 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 α_p if the price term is positive (negative).

The method is very similar when we assume that $\alpha_{p,\ell}$ differs by insurer: the only difference is that we consider each insurer separately rather than pooling the data and summing over insurers ℓ. Under the assumption $\alpha_{p,\ell} = \alpha_0 + \alpha_1.pcap_\ell$; equation (17) becomes:

$$\alpha_0 \sum_{:::i,} p(i_h;i_{h'};h;h') + \alpha_1 \sum pcap \left[\sum_{h:::i,} p(i_h;i_{h'};h;h') \right] \geq \sum_{:::i,} d(i_h;i_{h'};h;h'). \qquad (20)$$

Each inequality now defines the area on one side of a line in two-dimensional $(\alpha_0; \alpha_1)$ space.

7.3 Inequality Results

Table 7 sets out the results of the inequalities analysis under the assumption that $\alpha_{p,\ell} = \alpha_p$. 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 α_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 (:) 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.

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 $g\ (:)$ 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 $_{;h}$

insurer characteristics. The equation we estimate is:

$$ {}_h = \sum w_{,h} x_{,h} + \varepsilon_h $$

where $w_{,h}$ is the (observed) share of hospital h's total charges that come from insurer and $x_{,h}$ are hospital and insurer characteristics. We include all diagnoses, rather than just women in labor, since ${}_h$ 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

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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

Table 2: Summary Statistics by Insurer

	2002 enrollment			Labor	% Prim	Pro...t	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
Paci...care	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 ...elds 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). "Pro...t 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 di¤erent hospital) and "Special Nursing Transfer" the probability of transfer to a special nursing facility (again at this or a di¤erent 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

Table 5: Logit Analysis Results

	All labor patients	Least sick patients	Sickest patients
Price			

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

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 proagnosean atient trea5gnoC sfxiu oC ssdriagnoses and thei1a1erity

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

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
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