Competition and Quality Choice in Hospital Markets*

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While hospital quality is typically measured using clinical outcomes, patients are likely to also value non-clinical attributes such as hospital amenities. As a result, using clinical outcome measures to evaluate whether competition policy effectively encourages higher hospital quality will not provide a complete picture if hospitals compete along non-clinical dimensions. We examine the causal impact of competition on both a hospital's level of demand-shifting quality and clinical quality. We find that demand-shifting quality is increased for all patients when competing for managed care patients while the impact of competition for Medicare patients is mixed. Clinical quality also improves with competition for managed care patients but declines with competition for Medicare patients. Competition appears to affect clinical quality through the selective networking practices of managed care while direct competition for patients largely affects other non-clinical quality attributes.

I. INTRODUCTION

Competition can provide a strong incentive to improve product quality, but this is not always the case. A substantial theoretical literature on the relationship between competition and product quality (e.g., Dorfman and Steiner, 1954; Dranove and Satterthwaite, 1992) has established a fairly robust prediction that increased competition will cause firms to provide higher quality as long as competition does not cause the elasticity of demand faced by the firm with respect to price to increase by more than its elasticity of demand with respect to quality.[1] In other words, the impact of competition depends on whether the presence of additional sellers causes consumers to become more or less responsive to differences in quality compared to price.

When considering competition between hospitals, however, several important characteristics of the market further complicate the relationship between competition and quality.

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[1] Gaynor (2006) provides a nice discussion of the relevance of this literature within the context of the hospital market.

First, given the prominent role of managed care organizations (MCOs), where a patient receives treatment is likely to depend on both the patient's (and/or physician's) preferences as well as the provider network established by the MCO. As a result, a hospital's optimal price and quality level will respond to both consumer tastes and the criteria used by MCOs to determine network inclusion. Second, the notion of quality represented in the theory literature differs from that typically considered in health care settings. In the theory literature, quality represents every non-price product attribute that determines a consumer's overall valuation for a product or service. This is quite different from the usage of the term quality in the health care literature where it generally represents some professional standard of care, which often determined by practitioners. Third, a significant portion of patients receive public insurance (e.g., Medicare) so may respond to quality differently than privately insured patients. Hospitals that compete more strongly for one of these patient groups might choose to invest more heavily in the services important to that group, possibly even resulting in a lower quality level for the other group.[2] Moreover, the administratively set prices of Medicare may further alter the incentives for hospitals to invest in services for Medicare patients versus privately insured patients.

Though the quality of care defined in a medical sense—i.e., *clinical quality*—would almost certainly influence a patient's valuation of a particular hospital's services, a lack of medical understanding and imperfect information about the relevant clinical quality levels of hospitals may prevent patients from being particularly responsive to differences in clinical quality.[3] Given that insurance causes most patients to be exceptionally price inelastic consumers, however, hospitals are still likely to invest in other non-price characteristics that patients value. In contrast, MCOs are much better informed about the relative clinical quality levels of hospitals and the importance of clinical quality to long run health, but are also more responsive to price differences. Since MCOs pay for the medical care received by their enrollees their decisions to include a hospital in their provider network are heavily influenced by the prices they can negotiate with the hospital. However, given their longer-run relationship with their enrollees, they may also seek out hospitals that can provide the most effective

[2]Mirroring the quality versus price tradeoff, the optimal investment in quality across consumer types will change if competition causes the elasticity with respect to quality to increase for one group but not the other.

[3]Existing empirical evidence is scant, but the literature on the impacts of hospital report cards (e.g., Dranove and Sfekas, 2008) suggests that consumers' response to clinical quality is limited.

care and help to minimize future health care expenditures for the patients. The relative importance to MCOs of price versus clinical quality will determine whether increased competition between hospitals to be included in MCO provider networks encourages lower prices and/or higher clinical quality.

Empirical studies of hospital competition, which typically focus on price effects, are generally careful to try to control for any differences in the relative attractiveness of hospitals to patients (examples include, Town and Vistnes, 2001; Capps et al., 2003; Lewis and Pflum, 2015; Ho, 2009; Gowrisankaran et al., 2015). However, these studies do not examine the impact of competition on the decisions of hospitals to invest in improving their attractiveness to consumers or the degree to which hospitals may substitute toward such investments at the expense of clinical quality improvements. Although improving clinical quality is an important policy objective, focusing on clinical quality alone does not paint a complete picture of how competition in hospital markets impacts hospital incentives or overall welfare. In this paper we seek to complete the picture by examining the causal impact of competition on a hospital's quality as perceived by patients. That is, we empirically model the demand for hospital services and identify how competition affects demand-shifting quality, which we refer to as *revealed quality*. We then compare and contrast these results with the causal impact of competition on several clinical outcomes (in-hospital mortality rates) and explore the relationships between these two notions of quality; i.e., the degree to which patients consider clinical quality when making their choice of hospital for treatment.

To identify how hospitals alter revealed quality we estimate the relative utility that patients receive from hospitals as a function of the level of market competition and managed care penetration using a panel of discharges for California from 2000 to 2010. Since preferences may differ across patients we perform the estimation separately by illness type as well as payer type (i.e., HMO or Medicare). We utilize the Herfindahl-Hirschman Index (HHI) as our measure of market competitiveness and control for the endogeneity of price and market structure using a control function approach. We are particularly interested in examining whether competition for patients of one payer-type might have a differential effect on quality investments to other payer-types. As a result, we compute separate HHI measures for HMO and traditional Medicare patients and allow both measures to influence the utility of each payer type.

We find that the impact of competition depends on the patient group that hospitals are competing over. Hospitals increase their revealed quality when facing a more competitive environment for HMO patients. For example, a hospital will respond to a 250 point decrease in the HHI for HMO patients by increasing its demand shifting quality enough so that the average HMO patient will be 6% to 20% more likey to choose that hospital.[4] Moreover, competition for HMO patients generates spill-over effects as Medicare patients also find such hospitals to be of higher quality. In contrast, HMO patients experience a decrease in revealed quality when hospitals face a more competitive environment for Medicare patients even though Medicare patients view such hospitals more favorably. Such an outcome would be expected if a lower HHI for Medicare patients caused the elasticity of demand with respect to quality to increase for Medicare patients but not for HMO patients. In this case, hospitals would find it profitable to substitute towards investments in quality for Medicare patients, possibly at the expense of investment in quality for HMO patients. Consistent with this, we additionally find that hospitals located in markets with higher proportions of Medicare patients are viewed less favorably by HMO patients and more favorably by Medicare patients.

Similar to Gowrisankaran and Town (2003), when we switch to examining clinical quality, we find that mortality rates for both privately and publicly insured patients decrease when hospitals face a more competitive environment for HMO patients while increasing significantly when facing a more competitive environment for Medicare patients. This is somewhat surprising since basic theory implies that firms competing in markets where prices are regulated (such as Medicare) will compete through attempts to offer superior quality. Gowrisankaran and Town offer a potential explanation — if the profit margin on Medicare patients is sufficiently low, greater competition for these patients can make it more profitable for the hospital to give up on investing to attract Medicare patients and focus more on the higher-margin MCO patients. By studying revealed quality separately from clinical quality, however, our findings reveal an alternative explanation. Hospitals facing more competition do continue to use quality to compete for Medicare patients but they do so by offering higher levels of non-clinical quality. Moreover, as we find that patients' choice of hospitals is relatively unresponsive to improvements in clinical quality, increased competition for Medicare patients appears to cause hospitals to substitute away from investing in clinical quality so that

[4]In hospital markets each hospital will have a slightly different HHI reflecting the difference in the hospitals' markets that come from the spatial distribution of patients and hospitals. See Section IV.B for an explanation of how we calculate HHIs.

they can spend more on other amenities that improve their revealed quality. We do not see the same result for HMO patients because HMOs are able to evaluate the clinical quality level of hospitals more effectively than individual patients, giving hospitals the incentive to keep clinical quality levels high when competing for inclusion in HMO provider networks.

The remainder of the paper is organized as follows. Section II provides some background on the theoretical predictions and the approaches taken in the empirical literature. In Section III we present the data used in the analysis and then outline our empirical approach in Section IV. The evidence for the impact of competition on revealed quality is presented in Section V while Section VI examines the direct impact of competition on health outcomes. In Section VII we analyze the degree of overlap between revealed and clinical quality. Lastly, section VIII concludes with some final remarks.

II. Background and Related Literature

Over the last few decades hospital markets have undergone tremendous change that, if anything, has accelerated in recent years with the passage of the Affordable Care Act (ACA). On the payer side there has been enormous growth in managed care from Health Maintenance Organizations (HMOs) and Preferred Provider Organizations (PPOs) at the expense of traditional indemnity insurance. The provider networks these managed care organizations (MCOs) built were initially fairly narrow in the 1990s to generate more cost competition but were broadened following a backlash by patients. Today the ACA and its health exchanges have generated a shift back to the narrow provider network model for many insurance plans while indemnity plans have all but disappeared and represent less than 1% of the employer sponsored insurance market (Kaiser Family Foundation and Health Research and Education Trust, 2012). At the same time, the provider-side of the market has experienced an unprecedented wave of consolidation, especially since the passage of the ACA, as thousands of hospitals have been acquired by systems. Roughly 60% of all acute-care hospitals now belong to a system and the proportion continues to grow.

The literature has extensively studied how these changes have impacted hospital market power, and it has been well documented that reductions in competition result in higher hospital prices (Dranove et al., 1993; Lynk, 1995; Melnick et al., 1992; Brooks et al., 1997; Connor et al., 1998; Simpson and Shin, 1998; Dranove and Ludwick, 1999; Keeler et al., 1999; Town and Vistnes, 2001; Capps et al., 2003; Gaynor and Vogt, 2003; Cuellar and Gertler, 2005; Melnick and Keeler, 2007; Ho, 2009; Lewis and Pflum, 2015; Gowrisankaran et al., 2015). In contrast, significant debate continues over how these changes in MCO and hospital market structure have impacted hospital quality. The theoretical literature provides some guidance here, but, due to the many complexities of the hospital market, a variety of outcomes are possible. Empirical studies examining the impact of competition on clinical outcomes have also yielded varying results.

Fundamental insights on the topic come from Dorfman and Steiner (1954), who's predictions can be interpreted to imply that a monopolist's optimal level of price and quality will depend on the relative magnitudes of its elasticities of demand with respect to price and quality.[5] Following this logic, if increased competition in a market causes hospitals' residual demand to become more elastic to both price and quality, then hospitals respond by offering higher (lower) quality whenever the elasticity of demand with respect to quality increases in magnitude by more (less) than the elasticity with respect to price. Dranove and Satterthwaite (1992) analyze the optimal quality and price when hospitals are profit maximizing and consumers receive noisy signals for quality and price. Similar to Dorfman and Steiner (1954) they find that the effect of competition on quality choice depends on how it alters the price elasticity of demand compared to the quality elasticity of demand.

In cases where reimbursement rates are administratively set (as they are for Medicare patients), firms can only compete through quality, so quality levels might be expected to improve when competition increases (Pope, 1989).[6] However, as Brekke et al. (2011) highlight, this will only be true if the additional patients attracted by higher quality are profitable to serve (i.e., the payment for treatment exceeds the cost of treating the marginal patient). To make matters more complex, hospitals typically receive revenues from both publicly- and privately-insured patients. To the extent that hospitals can selectively invest in the quality of service provided these different groups, an increase in competition for privately insured patients might lead hospitals to substitute resources away from publicly insured patients in order to improve quality for private patients (and vice versa). For components of quality that can-

[5]While the original model considers investments in advertising, this is conceptually equivalent to investments in demand-shifting quality.

[6]Though not exactly representing a change in service quality, Bloom, Propper, Seiler, and Reenan (2015) examine the impact of competition on managerial quality for hospitals in the United Kingdom's National Health Service, which like Medicare uses administrative rates, and found that managerial quality is increasing with competition.

not be targeted to specific patient groups, hospitals are forced to compromise on their quality choice by providing a level of quality that differs from what they would provide if facing either payer type alone (Ma and McGuire, 1993; Glazer and McGuire, 2002).[7]

Empirical investigations of these relationships between competition and quality have largely examined how clinical outcomes vary with market concentration as measured by the Herfindahl-Hirschman Index (HHI).[8] Many studies only capture a descriptive relationship, ignoring the fact that the HHI is potentially endogenous as hospital's market shares depends in part on its quality level.[9] Others, such as Kessler and McClellan (2000), Gowrisankaran and Town (2003) and Kessler and Geppert (2005) avoid the endogeneity of HHI by estimating a utility model based on distances and use the predicted HHI derived from these predicted market shares as their measure of competitiveness.[10] The results have been mixed. Gowrisankaran and Town (2003), Shen (2003) and Propper, Burgess, and Green (2004) find evidence that competition may increase mortality for certain groups of patients while Kessler and McClellan (2000) and Kessler and Geppert (2005) uncover evidence that competition may improve quality by decreasing mortality rates.[11] Rather than considering just one or two outcomes, Mutter, Wong, and Goldfarb (2008) examined 38 distinct clinical outcomes and processes of care and found that competition increases the value for some measures while decreasing the value for others.[12]

The contradictory findings of previous empirical studies could result from differences in clinical measures or methodology, or from the fact that some studies such as Kessler and McClellan (2000) and Propper et al. (2004) focus on competition for publicly insured patients (paying regulated prices) while others such as Gowrisankaran and Town (2003) and Sari (2002) consider competition for privately insured patients (paying un-regulated prices).

[7]These studies find that the compromised level of quality can be beneficial when the public payer's payments are too low, however, it also creates incentive for the public payer to free-ride on the private payer.

[8]Shen (2003) and Mutter et al. (2008) also use the number of hospitals within a fixed distance as a measure of competition. Ho and Hamilton (2000) examined the impact of mergers and acquisitions of hospitals by systems on mortality, 90-day readmissions for heart attack patients and discharge times for normal newborns.

[9]The use of HHI in hospital markets also presents an added problem with respect to how the market is defined. We take a similar approach to that taken by Kessler and McClellan (2000), Gowrisankaran and Town (2003), Tay (2003), among others in defining hospital markets. The details are provided in section IV.A.

[10]Kessler and McClellan (2000) and Kessler and Geppert (2005) both utilize information on the distance to suitable substitute hospitals to avoid assuming independence of irrelevant alternatives to predict hospital choice while Gowrisankaran and Town (2003) utilize the direct distance between a patient and hospital.

[11]Gowrisankaran and Town (2003) find that competition for HMO patients increases clinical quality (decreases mortality) while competition for Medicare patients decreases clinical quality.

[12]The above discussion does not represent a comprehensive list of the research on hospital competition and quality choice. See Gaynor (2006) for a detailed review of the literature.

It could also be that most hospitals do not compete purely through clinical outcomes, and the dimensions of quality over which they do compete may be only loosely correlated with the outcome measures used. Romley and Goldman (2011) find evidence consistent with this view in a study examining the cost of hospital quality. Specifically, Romley and Goldman identify the demand-responsiveness of patients by calculating the change in demand with respect to a change in revealed quality evaluated at a common quality level for all hospitals. They find that quality (as perceived by patients diagnosed with pneumonia or AMI) is higher at hospitals that have more elastic demand but that risk-adjusted mortality was only moderately correlated with revealed quality. We take a similar approach in that we estimate the revealed quality of hospitals, but we utilize panel data and instrument for market structure to ascertain the causal effect of competition on demand-shifting quality so that we can relate this to the impact of competition on clinical outcomes. Addressing the endogeneity of HHI is particularly important when examining revealed quality since higher quality hospitals will necessarily have a higher market share, so that even exogenous increases in quality could be incorrectly attributed to competition. We adopt an IV control function approach in which we instrument for actual HHIs using "predicted HHIs" generated with predicted market shares from a utility model based on distances only (i.e., the measure of competition developed by Kessler and McClellan (2000)).

III. Data

We primarily use the patient discharge abstracts and hospital financial disclosure reports from the California Office of Statewide Health Planning and Development (OSHPD). We collect data for the even years between 2000 and 2010, inclusive. We also utilize hospital system status, which comes from the American Hospital Association's (AHA) annual survey of hospitals. We link the AHA and OSHPD data using the hospitals' Centers for Medicare and Medicaid (CMS) provider number. We exclude from the analysis Veteran's Administration and military hospitals, Shriner's hospitals for crippled children as well as psychiatric, chemical dependency, and long-term care hospitals. In the second stage demand estimation we further limit the sample to hospitals in the San Francisco Bay area, the Los Angeles basin and San Diego.

The OSHPD discharge abstracts contain just under 4 million discharges per year for

TABLE 1—DISCHARGE COUNTS

Major Diagnostic Category	Top 5 HMO			Medicare		
	Total	Mean	S.D.	Total	Mean	S.D.
Circulatory System	63,247	116	(98)	178,019	214	(182)
Digestive System	59,151	108	(91)	80,787	99	(82)
Respiratory System	28,761	54	(42)	92,724	111	(81)
Nervous System	24,101	47	(40)	56,341	75	(60)

Notes: Summary statistics are at the hospital-year level except totals, which reflect the entire sample.

all acute care hospitals in the state of California for these years. For each hospital discharge, these reports identify characteristics of the patient such as gender, age, and insurer type (e.g., private, Medicare fee-for-service, Medi-Cal, etc.), characteristics of the patient's illness (e.g., Major Diagnostic Category (MDC), Diagnosis Related Group (DRG), diagnostic and procedure codes), and the reports identify the hospital from which the patient was discharged and source of admission (e.g., home, transfer from another hospital, etc.). We include only discharges having a diagnosis belonging to either the circulatory, digestive, respiratory, and nervous systems and further limit the sample to include only patients whose source of admission is from home, whose home zip code is within California and within a 75 minute drive of the hospital, who are more than 24 hours old, and who are 75 years of age and younger because older patients may have significantly different preferences from the typical patient under 75 who is likely not receiving extraordinary end-of-life treatment.

We estimate the model (details provided in the next section) separately using patients insured with either traditional Medicare or insured with one of the five largest HMOs in California. Medicare patients have the option of visiting any hospital that accepts Medicare while HMO plans form restrictive hospital networks. As a low quality hospital may also be low cost it could be more attractive to an HMO. In consequence, if low quality hospitals are more likely to be in provider networks than high quality hospitals while both are erroneously included in a patient's choice set, then the low quality hospital will have a higher market share and appear to be higher quality by the econometrician. Although we lack data on actual hospital-MCO contracts, we observe to which HMO an HMO patient belongs and use this information to piece together an HMO's likely network by observing which hospitals treat patients from a particular HMO. To reduce the possibility of misidentifying HMO networks we restrict the sample of

HMO patients to those enrolled with one of the five largest HMOs, which together account for about 85 percent of all HMO patients in the data. We include a hospital in an HMO's provider network (a patient's choice set) if it has at least 50 non-ER discharges from that HMO. ER patients are excluded from identifying networks since patients admitted through the ER may not have had a choice of hospital.[13]

Table 1 provides summary statistics for the discharge data for each of these patient groups. The table reports the total number of discharges included in the patient group as well as hospital-level summary statistics for the number of discharges for each MDC. As indicated by the relatively large standard deviations, there is considerable heterogeneity in the number of patients treated by hospitals with the largest treating thousands of patients and the smallest treating only a couple dozen from any particular MDC-patient group pair. The number of patients for the four MDCs also drops considerably with less than a third as many patients treated for a diagnosis of the nervous system as are treated for a diagnosis of the circulatory system. Medicare is the largest of the two groups for all of the diagnostic categories with hospitals often treating twice as many patients from Medicare for a particular MDC.

We use data from the OSHPD Financial Reports paired with the discharge abstracts to estimate the average case-weighted price per HMO discharge. Because OSHPD reports both the gross charges (the list price for the services offered) and the net revenues (the actual amount received reflecting contractual discounts) as aggregates for each payer type (private, Medicare, Medicaid, etc.), the reimbursements are calculated by multiplying the deduction ratio for privately insured, manage care (MC) patients, which is the net revenues divided by the gross charges for private MC patients, against the total gross charges for all HMO discharges divided by the total diagnosis-related group (DRG) case-mix weight for these discharges. That is, the average case-weight adjusted price per discharge for HMO inpatient care is calculated as:

$$\text{Avg. Price Per Case-Weight Adjusted HMO Discharge} =$$
$$\frac{\text{Net Rev. for Private MC}}{\text{Gross Chrg. for Private MC}} \times \frac{\text{Total Charges for HMO Discharges}}{\text{Total DRG weight of HMO Discharges}}.$$

DRG weights come from the CMS final rules files for the year of the discharge.

[13] Using other cut-off values to identify networks did not alter the results in any meaningful way since we already restricted the sample to the 5 largest HMOs.

Table 2 provides summary statistics for the hospital market characteristics. We assemble two measures of HHI, one based on patients belonging to one of the largest 5 HMOs and one based on traditional Medicare patients. The HHIs are hospital-specific as they represent weighted averages of zip code level HHIs where zip codes are weighted based on the proportion of a hospital's expected demand originates from that zip code (details provided below in Section IV.B). The shares % HMO, % PPO, % Medicare, and % Medicaid represent the share of patients in a hospital's market (not the share of patients that visit a hospital) and are all tabulated at the zip code level and weighted based on the individual hospital demand proportions in the same manner as the HHIs. The statistics show that the two HHIs are very similar across insurer types and MDCs. HMO markets are marginally more concentrated than Medicare markets because not all hospitals treat HMO patients every year. The HHIs also indicate that markets are quite concentrated with the least concentrated markets still having HHIs above 0.220.

Medicare patients represent the largest share of patients on average while about 20 to 25 percent of patients in a market are insured by an HMO on average. PPOs represent the smallest share of insurance type, averaging less than 10 percent while Medicare ranges from 12 to 18 percent across the MDCs. Across hospital markets, however, there is tremendous variation in all of the insurance types with each of the insurance types not present in at least one hospital market. In the following section we outline our empirical approach and provide details for how this data is utilized.

IV. EMPIRICAL APPROACH

A. *Hospital Choice*

As our focus is on how competition impacts a hospital's choice of demand-shifting quality we begin with the patients' hospital choice problem. In choosing from which hospital to receive treatment, patients balance the relative value of the hospitals' quality characteristics with how convenient it is to travel to the different hospitals. Patient i's utility from receiving treatment at hospital h at time t can thus be specified as

$$U_{iht} = \mathbf{X}_{it}\mathbf{A}\mathbf{D}_{iht} - \beta P_{iht} + \mu_{ht} + \epsilon_{iht}, \tag{1}$$

TABLE 2—HOSPITAL SUMMARY STATISTICS

MDC	Mean	S.D.	Min.	Max.
All				
Log avg. price per case-weight adjusted discharge	8.968	0.765	4.588	12.211
Circulatory system				
HHI_{HMO}	0.548	0.147	0.297	1.000
$\text{HHI}_{\text{Medicare}}$	0.490	0.157	0.220	0.990
% HMO	0.223	0.138	0.000	0.719
% PPO	0.079	0.074	0.000	0.629
% Medicare	0.486	0.166	0.000	0.847
% Medicaid	0.121	0.101	0.000	0.567
Digestive system				
HHI_{HMO}	0.531	0.162	0.274	0.998
$\text{HHI}_{\text{Medicare}}$	0.510	0.170	0.222	0.994
% HMO	0.249	0.144	0.000	0.762
% PPO	0.119	0.103	0.000	0.643
% Medicare	0.361	0.146	0.000	0.781
% Medicaid	0.144	0.115	0.000	0.574
Respiratory system				
HHI_{HMO}	0.538	0.155	0.267	1.000
$\text{HHI}_{\text{Medicare}}$	0.529	0.176	0.230	0.997
% HMO	0.224	0.137	0.000	0.750
% PPO	0.074	0.076	0.000	0.598
% Medicare	0.457	0.174	0.000	0.843
% Medicaid	0.175	0.138	0.000	0.692
Nervous system				
HHI_{HMO}	0.523	0.146	0.259	1.000
$\text{HHI}_{\text{Medicare}}$	0.512	0.154	0.240	0.992
% HMO	0.216	0.129	0.000	0.738
% PPO	0.085	0.080	0.000	0.621
% Medicare	0.429	0.163	0.000	0.884
% Medicaid	0.126	0.104	0.000	0.639

Notes: Summary statistics are at the hospital-year level.

where $\mathbf{X}_{it}$ is a vector of patient characteristics (age, race, gender, income level), $\mathbf{D}_{iht}$ is a vector of distance and relative location metrics for patient i and hospital h; P_{iht} is patient i's out-of-pocket cost for treatment at hospital h; the μ_{ht} represent hospital h's revealed quality; and ϵ_{iht} is the idiosyncratic patient-hospital error all at time t. The parameter matrix $\mathbf{A}$ represents the patients' preferences for the location characteristics.

We include in $\mathbf{D}$ both the travel time and travel time squared to the hospital and allow for separate coefficients on travel time for discharges that originate in a hospital's emergency room versus those that do not. These are all interacted with patient characteristics age, gender, race, and income level. To soften the assumption of independence of irrelevant alternatives (IIA), we also include an indicator identifying whether the hospital is one of the five closest hospitals among those in i's choice set and an indicator identifying whether hospital h is among the 5th to 15th closest hospitals within i's choice set, all at time t. The vector $\mathbf{D}$ additionally includes an indicator identifying if the hospital is the closest to a patient when the patient is admitted through the emergency room. There is typically very little difference in the travel times to the five closest hospitals in California;[14] consequently, we found no significance in the value of the closest hospital for non-emergency discharges in comparison to the next five closest hospitals. The relative distance indicators are not interacted with patient characteristics.

The quality term μ represents the hospital's revealed quality index, or quality isoquant, achieved from the mix of attributes that affect each patient's hospital choice. These quality attributes include service quality, availability of technology and equipment, hospital amenities, and expected health outcomes. In principle all of these dimensions of quality can be directly included in the utility function if observable, but many are likely not observable or at best not perfectly observable.

Since market conditions, such as the concentration of hospitals or the mix of insurance providers, change from year to year and influence a hospital's choice of quality, we parametrize μ_{ht} as

$$\mu_{ht} = \mathbf{\Gamma}\mathbf{C}_{ht} + \mathbf{\Delta}\mathbf{F}_{ht} + \mu_h, \tag{2}$$

where $\mathbf{C}_{ht}$ is a vector of measures of market competitiveness that could also affect a hospital's choice of quality and $\mathbf{F}_{ht}$ is a vector of noncompetitive market characteristics that could affect a hospital's choice of quality (by altering the marginal benefit of quality); all for hospital h at time t. We also include a hospital fixed effect, μ_h, to capture any remaining, unobserved, time-invariant attributes of hospital quality.

Plugging (2) into the patient's utility function yields the parameterized utility function:

$$U_{iht} = \mathbf{X}_{it}\mathbf{A}\mathbf{D}_{iht} - \beta P_{iht} + \mathbf{\Gamma}\mathbf{C}_{ht} + \mathbf{\Delta}\mathbf{F}_{ht} + \mu_h + \epsilon_{iht}. \tag{3}$$

[14] This is because of the large number of hospitals in the San Francisco/Oakland, San Diego, and Los Angeles metropolitan areas.

In this representation of utility the parameters in $\mathbf{\Gamma}$ indicate the amount the patients' utility changes when the hospital adjusts its quality based on the competitive pressures indicated by $\mathbf{C}_{ht}$ and $\mathbf{\Delta}$ indicate the amount the patients' utility changes when the hospital adjusts its quality in response to non-competitive market characteristics $\mathbf{F}_{ht}$.[15] As the objectives and constraints of government and privately owned hospitals likely cause them to respond to market characteristics differently we allow the parameters to differ based on whether the hospital is publicly or privately owned.

We utilize two HHIs as our measures of competitive pressure, $\mathbf{C}_{ht}$. As the impact of competition for privately insured patients (whose reimbursements can vary with the degree of competition) and publicly insured patients (whose reimbursements will not vary) could be different we include an HHI based on the HMO patients in the market and an HHI based on the Medicare patients. These HHIs will not be the same for a given hospital because of differences in the distributions of patients within a market and differences in which hospitals treat Medicare or HMO patients; i.e., not every general acute care hospital has a contract with every HMO.

The vector $\mathbf{F}_{ht}$ includes several market characteristics that do not reflect differences in the competitiveness of a market, but are likely associated with the marginal benefit for quality. The first is the number of patients that have that hospital in their choice set as a measure of the size of the market. Larger markets increase the potential returns to investing in quality and hospitals that treat more patients may be able to provide higher quality through learning-by-doing. Larger markets can also potentially support more hospitals generating systematic differences in the concentration of larger versus small markets. The second and third characteristics are the proportion of all patients in the hospital's market that are insured by an HMO or PPO. Both types of MCO form provider networks and HMOs in particular are typically able to negotiate lower reimbursement prices compared to other forms of insurance by making hospitals compete over inclusion in their network. A large number of patients insured by managed care in a hospital's market could put pressure on a hospital to keep costs low causing it to select lower overall quality than it otherwise would if quality enhancements result in higher costs.

[15]Note that in this specification one cannot interpret the parameters of $\mathbf{\Gamma}$ and $\mathbf{\Delta}$ as i's taste for quality as could be done in a standard utility model since they capture both i's taste and the amount of quality adjustment by the hospital that results from the corresponding characteristic.

We additionally include the proportion of patients in the hospital's market that are insured by Medicare and the proportion insured by Medicaid. Again, the reimbursements by Medicare, and especially Medicaid, are typically lower than those from private insurance companies. Moreover, as these payments are not negotiated but administratively set based on the average cost of care adjusted for case severity and geographic factors these reimbursements are not influenced by the relative value of a hospital to patients. In consequence, the only benefit to quality enhancements for these patients comes from their demand responsiveness and not from changes in reimbursement rates. All of these proportions are calculated as weighted averages by zip code and represent shares of all patients in the market, not just the share of patients that are treated at a particular hospital (details of the weighting are provided below in subsection IV.B).

Patients select hospitals based on their preference for location and travel time characteristics compared to hospital quality; therefore patients are unlikely to choose hospitals that are too far away as the difference in value between hospitals h and k ($\mathbf{B}[\mathbf{D}_{iht} - \mathbf{D}_{ikt}]$) can potentially be quite large. Examining the data supports this notion as nearly 98 percent of all discharges that originate from in-state are from zip codes that are less than a 75 minute drive from the hospital.[16] With this in mind, for tractability we restrict choice sets to include every hospital within a 75 minute drive of a patient's zip code centroid.[17,18] As Medicare patients have the option of visiting any hospital that accepts Medicare we include in a Medicare patient's choice set every hospital observed treating Medicare patients (within a 75 minute drive of the patient's zip code centroid). We include in an HMO patient's choice set every hospital flagged as belonging to the provider network of that patient's HMO that is also within a 75 minute drive of the patient's zip code centroid.

Since all patients in our data choose a hospital we assume that there is no outside option and that ϵ_{iht} is drawn from a type-1 extreme value distribution and are i.i.d. across patients but not necessarily independent for a patient across time.[19] We further assume that patients choose the hospital that maximizes their utility. With these assumptions, following McFadden

[16]The average and median travel times to chosen hospitals are about 20 and 15 minutes, respectively.

[17]Travel time is calculated using the Google Maps API which takes into account traffic patterns, speed limits, and stop lights

[18]Kessler and McClellan (2000) define choice sets as all hospitals within 35 miles and all teaching hospitals within 100 miles. Tay (2003) defines choice sets as all hospitals within 50 miles from the patents' home zip code centroid and alternatively as the 50 closest hospitals. Romley and Goldman (2011) also restrict patient choice sets to the nearest 50.

[19]We do not observe individual patients, but allow for the ϵ to be correlated within a zip code across time.

(1974), the probability that a patient chooses hospital h takes the conditional logit form

$$\pi_{iht} = \Pr[h = 1 \mid \mathcal{H}_{it}] = \exp\{U_{iht}\} \Bigg/ \sum_{k \in \mathcal{H}_{it}} \exp\{U_{ikt}\} \,, \tag{4}$$

where $\mathcal{H}_{it}$ is the set of hospitals in i's choice set at time t. Eq. (4) is estimated via maximum likelihood. The model is estimated separately for insurance type and major diagnostic category (see Section III for details on the specific insurance types and MDCs used).

B. Hospital HHI: Measurement and Instruments

The Herfindahl-Hirschman Index is commonly used as a measure of market competitiveness throughout the industrial organization literature generally and with respect to hospital markets specifically. When market shares are represented as decimal values between 0 and 1 the index takes a value of 0 to 1 as well and more competitive markets will have a lower HHI compared to less competitive markets. The advantage of the index is that it incorporates both the number of hospitals in the market as well as the market shares of those hospitals. For these reasons we include in the vector $\mathbf{C}_{ht}$ two HHIs: one based on HMO patients and one based on Medicare patients. Although the HHI is a convenient measure of competition, defining a market's boundary in order to calculate market shares is not as straightforward in hospital markets as in other product markets. One difference is that hospitals are spatially distributed, generally drawing patients from slightly different populations that are better thought of as overlapping markets rather than one large market. A second difference is that hospitals may offer different services or specializations that effectively represent separate markets.

To account for the spacial distribution of hospitals we calculate hospital-specific HHIs based on patient flows for HMO and Medicare patients by taking the average of the zip code-level HHIs weighted by the proportion of a hospital's expected demand that a zip code represents.[20] In this way further zip codes contribute much less to a hospital's HHI than nearby zip codes and the HHI is not limited to any fixed distance measure.[21] To help mitigate the service

[20]The weighting is performed using the expected proportion of patients based on eq. (7) described below. Basing the weights on the actual proportion of patients is problematic because any zip code from which no patient visits a particular hospital will then have zero weight in that hospital's HHI calculation even if it is near the hospital. This can happen when the population of a particular zip code is relatively small or there are even closer hospitals to that zip code.

[21]Choice sets are limited to hospitals within a 75 minute drive, but zip codes at this distance form a hospital represent an exceedingly small proportion of their demand so have very little weight in the HHI calculation.

mix differences of hospitals we calculate HHIs separately by MDC and estimate the choice model using only patients from that MDC.

In addition to the challenges associated with defining hospital markets, the HHIs for a hospital's market are endogenous since they include the hospital's own market share. As our objective is to identify changes in quality that are a result of market competitiveness, the endogeneity of own market share is particularly problematic. Hospitals that are perceived to be higher quality by patients will necessarily have a higher market share since market shares identify quality in the logit model of utility. Consequently, any increase in quality that occurs for reasons unrelated to competition will alter alter the HHI and be incorrectly attributed to a change in competition.[22]

To correct for the endogeneity of own market share we take the same approach used by Petrin and Train (2010) and instrument for the HHIs using a control function approach.[23] That is, we use a control function to condition on the part of the HHI_{mht}, $m \in \{\text{HMO}, \text{Medicare}\}$, that depends on ϵ_{iht} in (3).[24] By including the control function, the remaining variation in HHI_{mht} is independent of the error and the estimates will be consistent.[25] We could alternatively utilize the market share inversion approach developed by Berry (1994) and Berry, Levinsohn, and Pakes (1995) and used by Goolsbee and Petrin (2004) and Chintagunta, Dubé, and Goh (2005), to remove the endogeneity from the non-linear choice model and deal with it in linear regressions, but the control function approach is simpler to implement and more efficient in this application since we have individual-level data.[26]

As with 2SLS, correcting endogenous instruments using a control function approach is done through two stages. In the first stage we estimate each HHI_{mht} as linear functions of the exogenous hospital characteristics, $\mathbf{F}_{ht}$ in (3), that affect utility, other exogenous variables $\mathbf{Z}_{ht}$ that do not affect utility but impact HHI_{mht}, and a single unobservable term ν_{mht}; i.e., we express each HHI_{mht} as

$$\text{HHI}_{mht} = \Theta \mathbf{F}_{ht} + \Omega \mathbf{Z}_{ht} + \nu_{mht}. \tag{5}$$

[22]To avoid the issue of endogenous market structure, Kessler and McClellan (2000) and Gowrisankaran and Town (2003) calculate a hospital's HHI using predicted market shares based on hospital and patient locations.

[23]Ferreira (2010); Guevara and Ben-Akiva (2006, 2012) have also utilized a control function approach to correct for endogeneity in discrete choice models.

[24]In a linear model the control function approach and two-stage least squares will yield the same estimates.

[25]See Wooldridge (2010) for more details.

[26]See Kim and Petrin (2010) for a detailed explanation of how the two approaches to dealing with endogeneity in a non-linear choice model differ and their advantages over one another.

As $\mathbf{F}_{ht}$ and $\mathbf{Z}_{ht}$ are exogenous, they are independent of both ν_{mht} and ϵ_{iht}, which are not independent of one another. To capture the relationship between ν_{mht} and ϵ_{iht} we decompose the ϵ_{iht} into the parts that can be explained by the ν_{mht} and a residual yielding

$$\epsilon_{iht} = \text{CF}(\nu_{mht}) + \tilde{\epsilon}_{iht},$$

where CF(ν_{mht}) are the *control functions*. The simplest approximation of this control function, and the one that we use, is the linear function CF$(\nu_{mht}) = \eta_m \nu_{mht}$. By including the fitted residuals $\hat{\nu}_{mht}$ as estimates for ν_{mht} in (6) we recover consistent estimators of Γ, the coefficients on our HHI measures in C_{ht}. The second-stage, patient utility we therefore estimate is

$$\begin{aligned} U_{iht} = {} & \mathbf{X}_{it}\mathbf{AD}_{iht} - \beta P_{iht} + \mathbf{\Gamma C}_{ht} + \mathbf{\Delta F}_{ht} \\ & + \mu_h + \eta_1 \hat{\nu}_{\text{HMO},ht} + \eta_2 \hat{\nu}_{\text{Medicare},ht} + \tilde{\epsilon}_{iht}, \end{aligned} \tag{6}$$

where the $\tilde{\epsilon}_{iht}$ are distributed i.i.d. type 1 extreme value and the $\hat{\nu}_{mht}$ are the normally distributed. For ease of exposition we will refer to this two-step estimation as 2SCL for two-stage conditional logit as it is analogous to 2SLS in a linear IV model.

The instruments we use for the HHIs are based on the counterfactual experiment that all hospitals in the market supply the same level of quality and charge the same price so that hospital choice is simply a function of relative distances. This is the measure of market concentration first developed by Kessler and McClellan (2000) and additionally used by Gowrisankaran and Town (2003). Formally, we assume that patients only consider the distances of the hospitals in their choice set by estimating

$$U_{iht} = \mathbf{X}_{it}\mathbf{AD}_{iht} + \epsilon_{iht}, \tag{7}$$

where the variables are the same as in eq. 1. Let $\hat{\rho}_{hkt}$ denote the predicted proportion of hospital h's patients that it receives from zip code k at time t; $\mathcal{K}_h$ denote the set of all zip codes in which hospital h receives some patients where $\sum_{k\in\mathcal{K}_h} \hat{\rho}_{hk} = 1$; $\mathcal{H}_k$ denote the set of hospitals in the choicest of a patient residing in zip code k; and π_{kht} denote the predicted market share (or choice probability) for hospital h in zip code k at time t. The predicted HHIs (denoted as predHHI_{mht}) for insurance type m hospital h at time t are defined as

$$\text{predHHI}_{mht} = \sum_{k \in \mathcal{K}_h} \hat{\rho}_{kmht} \cdot \sum_{j \in \mathcal{H}_k} \pi^2_{kmjt}. \tag{8}$$

In addition to the predHHI_{mht} we include the fraction of patients in the hospital's market that are insured by an HMO, PPO, traditional Medicare, and Medicaid, as well as the number of patients within a 10 and 25 mile radius, which are the exogenous instruments from the second-stage choice model. All of these instruments except the number of patients within 10 and 25 miles are weighted by zip codes based on predicted proportion of overall demand similar to the HHI_{mht} and predHHI_{mht} while the number of patients is unweighted so that it represents a measure of the size of the total market. Larger patient populations will allow for more entry resulting in a lower HHI, independent of quality.[27]

C. Out-of-pocket Costs: Measurement and Instruments

As is a common problem in the literature that estimates a hospital choice model we do not observe individual patient out-of-pocket costs. We are, however, able to estimate the case-mix adjusted price per discharge by insurance type (i.e., HMO, traditional Medicare) and can include this in (3) as a proxy for out-of-pocket costs. In this case, the parameter β represents a composite of the patients' disutility from paying for care and the proportion of the price that they are responsible for paying out-of-pocket. For example, if patients pay 1 percent of the price out-of-pocket on average then $\beta = 0.01 \times \kappa$ where κ is the true disutility of money. As there is considerable variation in the case-mix adjusted price across hospitals it is likely that patient out-of-pocket costs will vary substantially as well and, in consequence, represent an important determinant of hospital choice (for privately-insured patients).

Even if it only represents a proxy for the patients' out-of-pocket costs, the case-mix adjusted price per discharge is endogenous (perhaps even more than would be the out-of-pocket costs) so we utilize two instruments and control functions based on the residuals of the linear first-stage regressions to control for this endogeneity. The first instrument is the total

[27]Larger markets also allow hospitals to make additional investments in service offerings; consequently hospitals in a growing market may improve their quality while new hospitals are simultaneously entering the market. Dranove et al. (1992) discuss how this simultaneity makes it difficult to identify quality investment that is a result of competition and investment that is a result of market growth. We include a measure of the market size in the utility model to capture quality changes that come from the extent of the market while the competition term captures quality changes that come from the degree of competition.

additional willingness-to-pay by enrollees to have a hospital in their choice set based on the counterfactual experiment that all hospitals provide the same level of quality and charge the same price so that hospital choice is simply a function of relative distances (see the appendix for a detailed derivation of the instrument). Patients will be willing to pay more in premiums to have those hospitals that are nearby in their insurer's provider network so hospitals located in a more centralized location relative to the distribution of patients will be able to secure higher prices.

Our second instrument is simply the HHI of the insurer-side of the market. As reimbursement prices are established via bilateral negotiations between insurers and hospitals, hospitals will be able to secure higher prices if there are more substitution opportunities between insurers and lower prices when there are few insurers in the market (or few insurers hold a large proportion of all patients in a market). As with the HHI_{mht}, predHHI_{mht}, and the insurance penetration rates, we calculate each of these instruments at the zip code level and take the weighted average based on the predicted proportion of overall demand each zip code represents for each hospital.

V. Revealed Quality Results

Table 3 reports the revealed quality estimates for the hospital and market characteristics and the log of the case-weight adjusted price from the hospital utility model for each of the four diagnostic categories using HMO patients.[28] To provide a sense of the scope of the endogeneity problem the specifications in Panel A do not control for the endogeneity of price or market structure so are the estimates from standard conditional logits (CL) while the specifications in Panel B are the 2SCL IV estimates. The standard errors in parentheses are clustered by zip code and for the 2SCL estimates, additionally corrected to account for the noise in the first-stage residual following Karaca-Mandic and Train (2003).[29] At the bottom of each 2SCL specification we additionally report the first-stage Cragg-Donald Wald F statistics (Cragg and Donald, 1993). All of the values are above 10, which is the cut-off proposed by Staiger and Stock (1997) for determining whether instruments are strong or weak.[30] A straightforward

[28]Each specification additionally includes travel time and relative location measures as described in Section IV.A as well as hospital fixed effects. Complete travel time estimates are reported in the appendix.

[29]Karaca-Mandic and Train (2003) develop a correction for standard errors in a two-step estimation that follows Murphy and Topel (1985) but allows for a nested data structure.

[30]Stock and Yogo (2005) develop a set of critical values based on the number of endogenous variables and exogenous instruments. They find that using a critical value of 10 is close to a test with approximately a 5% significance level when there

way of assessing whether the price and HHIs are in fact endogenous is through the control function. If the estimates for the control function are statistically significant, then that is strong evidence in favor of the endogeneity of the variables (Kim and Petrin, 2015). In almost all 2SCL specifications the coefficients on the control functions are significant at the 5% level or lower.[31]

The first parameter estimate reported in Table 3 is the log of the average case-weighted price. Affirming that prices are endogenous (correlated with the unobservable, idiosyncratic utility of the patient), the un-instrumented CL estimates are positively biased while the magnitude of the 2SCL IV estimates are 3 to 10 times larger. Nevertheless, similar to results found in the literature (e.g., Gowrisankaran et al., 2015), the IV estimates still indicate that patients are quite price inelastic as would be expected given their insurance status. When evaluated at the mean choice probability, the estimates imply a price elasticity of about 0.5.[32]

Each market characteristic is allowed to vary based on the ownership type (private or non-Federal government), however, we only report the results for private hospitals.[33] The first four market characteristics represent the non-competitive characteristics as they are largely a function of patient characteristics within the market and independent of the level of competition between hospitals.[34] The last two market characteristics are the two HHIs and represent the competitive market characteristics as they are a function of the number and quality of hospitals in the market.

The estimates are relatively consistent across the four MDCs, but there is some variation in magnitude with those for diagnoses of the circulatory system generally exhibiting the lowest effect and those for diagnoses of the digestive system exhibiting the largest effect. The coefficients on HHI_{HMO} and $\text{HHI}_{\text{Medicare}}$ clearly illustrate the importance of controlling for the endogeneity of market structure. In all cases, the 2SCL IV estimates are all significantly dif-

are few instruments, but is too conservative when there are more instruments. They do not calculate a critical value when there are 3 endogenous variables and 4 instruments, though the critical F statistic when there are 3 endogenous variables and 5 instruments is 9.53. These values are only suggestive, however, as they are based on linear 2SLS models having homoskedastic disturbances.

[31]The estimates for the control function for price diagnoses of the circulatory system and the control function for HHI_{HMO} for diagnoses of the respiratory system are significant at the 10 percent level.

[32]A 1 unit increase in log price, or 100 percent increase in price, lowers the choice probability by about 0.01, or 50 percent of the mean choice probability of 0.02.

[33]We have also allowed the estimates to vary based on the profit status of the private hospital. However, the estimates were extremely similar so we pooled the two types of hospital together. These additional estimates are available upon request.

[34]To some extent the relative portion of HMO to PPO patients may be a function of hospital costs, but are still likely not affected by marginal changes in hospital quality over time.

TABLE 3—REVEALED QUALITY BY MAJOR DIAGNOSTIC CATEGORY BASED ON HMO PATIENTS

	Major Diagnostic Category							
	Circulatory		Digestive		Respiratory		Nervous	
Panel A: CL	(a)		(b)		(c)		(d)	
Log CW Price	-0.041	(0.026)	-0.073^{**}	(0.023)	-0.101^{**}	(0.038)	-0.066^{*}	(0.032)
% HMO	0.622^{*}	(0.247)	1.455^{**}	(0.271)	1.894^{**}	(0.332)	2.021^{**}	(0.390)
% PPO	-0.004	(0.234)	0.418^{+}	(0.214)	0.033	(0.319)	-0.541	(0.349)
% Medicare	-1.286^{**}	(0.190)	-1.150^{**}	(0.202)	-2.304^{**}	(0.249)	-1.183^{**}	(0.246)
% Medicaid	-0.646^{+}	(0.370)	-0.927^{*}	(0.374)	-0.838^{*}	(0.394)	-1.304^{*}	(0.516)
$1-\text{HHI}_{\text{HMO}}$	-2.742^{**}	(0.305)	-1.742^{**}	(0.292)	-1.012^{*}	(0.436)	-0.761^{+}	(0.406)
$1-\text{HHI}_{\text{Medicare}}$	1.130^{**}	(0.319)	0.917^{**}	(0.289)	0.302	(0.407)	0.345	(0.367)
# Hospitals	115		119		114		110	
Panel B: 2SCL	(e)		(f)		(h)		(i)	
Log CW Price	-0.454^{**}	(0.113)	-0.641^{**}	(0.152)	-0.376^{*}	(0.152)	-0.392^{*}	(0.163)
% HMO	0.171	(0.431)	2.310^{**}	(0.616)	2.413^{**}	(0.617)	2.531^{**}	(0.674)
% PPO	-0.089	(0.345)	0.796^{+}	(0.468)	0.324	(0.486)	-0.923^{+}	(0.561)
% Medicare	-1.581^{**}	(0.274)	-1.559^{**}	(0.415)	-2.718^{**}	(0.472)	-1.955^{**}	(0.449)
% Medicaid	0.754	(0.670)	-0.293	(0.874)	-0.132	(0.551)	-0.039	(0.945)
$1-\text{HHI}_{\text{HMO}}$	2.509^{+}	(1.319)	8.040^{**}	(1.909)	4.769^{**}	(1.553)	7.112^{**}	(2.428)
$1-\text{HHI}_{\text{Medicare}}$	-1.444	(1.361)	-7.212^{**}	(1.621)	-3.123^{*}	(1.446)	-4.861^{*}	(2.018)
CF(Log Price)	0.412^{**}	(0.111)	0.558^{**}	(0.150)	0.273^{+}	(0.149)	0.315^{*}	(0.159)
CF(HHI_{HMO})	-5.444^{**}	(1.331)	-10.047^{**}	(1.894)	-6.243^{**}	(1.553)	-8.378^{**}	(2.494)
CF($\text{HHI}_{\text{Medicare}}$)	2.320^{+}	(1.339)	7.787^{**}	(1.672)	3.248^{*}	(1.505)	5.201^{*}	(2.040)
# Hospitals	115		119		114		110	
Cragg-Donald Wald F statistic for excluded instruments								
	21.82		14.17		16.80		10.60	

Notes: Each specification additionally includes travel time and relative location measures as described in Section IV.A as well as hospital fixed effects. Standard errors in parentheses are clustered by zip code. The standard errors for the IV estimates are additionally corrected to reflect the noise from the first stage estimation following Karaca-Mandic and Train (2003).
Significance levels:
$** : p < 0.01$
$* : p < 0.05$
$+ : p < 0.10$

ferent and of opposite sign from the CL estimates. The 2SCL coefficient estimates for % HMO and HHI_{HMO} indicate that HMO patients generally have higher utility for hospitals located in areas that have a higher proportion of HMO patients and/or in areas where the hospital market serving HMO patients is less concentrated.[35] These findings likely reflect the incentive hospi-

[35]To be clear, patients do not necessarily prefer hospitals that treat a higher proportion of HMO patients, which would be endogenous. Rather, this result indicates that hospitals located in markets in which there is a higher proportion of HMO patients are also more desirable from the perspective of HMO patients.

tals have to cater to specific types of patients when they represent a larger share of population or when hospitals face more competition for those patents. In contrast, HMO patients have a much less favorable view of hospitals that are located in areas with proportionally more Medicare patients or in areas that exhibit lower concentration in the market for Medicare patients. It is possible that hospitals serving larger Medicare populations or facing more competition for these patients may have a limited ability to invest in quality due to the relatively low reimbursement rates paid by Medicare. Alternatively, the results could reflect hospitals substituting away from characteristics valued by HMO patients towards those valued by Medicare patients, which we might expect if Medicare patients exhibited higher quality elasticities of demand, for example. Market penetration rates of PPOs or Medicaid are also included as controls but exhibit no consistent or significant relationship with patient utility.

To provide some sense of importance for the impact that competition has on revealed quality we evaluated how much a 250 point decrease in HHI (increase in competition) impacts the probability that a hospital is chosen for treatment by an average patient.[36] The top panel of Table 5 presents the impact based on the average patient in one of the five largest HMOs while the bottom panel is based on the average Medicare patient. The HMO patients estimates indicate that a hospital experiencing a 250 point decrease in HHI_{HMO} would be about 6 percent more likely to be chosen for treatment by the average HMO patient having a diagnosis of the circulatory system and almost 20 percent more likely to be chosen by the average HMO patient having a diagnosis of the digestive system. A hospital experiencing a 250 point decrease in $\text{HHI}_{\text{Medicare}}$ has an opposing impact of similar magnitude for HMO patients. For example, an HMO patient having a diagnosis of the circulatory system is about 3.5 percent less likely to choose such a hospital while an HMO patient having a diagnosis of the digestive system is nearly 18 percent less likely to choose such a hospital.

Table 4 provides the revealed-quality results for when the model is estimated using Medicare patients. We do not include the log of the average, case-weight adjusted price since Medicare patients effectively have the same (expected) out-of-pocket costs regardless of what hospital they visit, but the specifications are otherwise identical to the HMO patient specifi-

[36]Recall that the marginal effect of the logit is $m_j = \beta_j p(1-p)$ where p is the choice probability and β_j is the coefficient for explanatory variable j. As a result, the marginal effect represents a partial derivative and the change in choice probability resulting from a change in HHI is not a consequence of a change in the number of hospitals available to a patient nor does it reflect the fact that if one hospital's HHI were to go up the HHIs for nearby hospitals would also likely change.

TABLE 4—REVEALED QUALITY BY MDC BASED ON MEDICARE PATIENTS

	Major Diagnostic Category							
	Circulatory		Digestive		Respiratory		Nervous	
Panel A: CL	(a)		(b)		(c)		(d)	
% HMO	-0.715^{**}	(0.127)	-0.799^{**}	(0.154)	-0.657^{**}	(0.160)	-0.503^{*}	(0.197)
% PPO	-0.126	(0.170)	-0.106	(0.184)	0.140	(0.199)	0.277	(0.251)
% Medicare	0.224^{+}	(0.134)	0.328^{+}	(0.169)	0.546^{**}	(0.168)	0.553^{**}	(0.176)
% Medicaid	0.184	(0.202)	0.352^{+}	(0.208)	0.719^{**}	(0.223)	0.477^{+}	(0.274)
$1 - \text{HHI}_{\text{HMO}}$	-0.240^{**}	(0.074)	-0.137	(0.100)	-0.238^{**}	(0.070)	-0.160^{*}	(0.082)
$1 - \text{HHI}_{\text{Medicare}}$	-0.390^{+}	(0.228)	-0.953^{**}	(0.249)	-0.618^{*}	(0.250)	-0.440^{+}	(0.256)
# Hospitals	155		154		158		147	
Panel B: 2SCL	(e)		(f)		(h)		(i)	
% HMO	-0.843^{**}	(0.191)	-0.661^{**}	(0.250)	-0.469^{+}	(0.241)	-0.263	(0.331)
% PPO	0.110	(0.230)	-0.154	(0.201)	0.379	(0.283)	0.523	(0.337)
% Medicare	0.134	(0.171)	0.276	(0.208)	0.140	(0.254)	0.379	(0.274)
% Medicaid	0.125	(0.271)	0.077	(0.292)	0.329	(0.282)	0.684^{+}	(0.405)
$1 - \text{HHI}_{\text{HMO}}$	-0.752	(0.823)	0.006	(1.256)	2.532^{*}	(1.049)	3.103^{+}	(1.654)
$1 - \text{HHI}_{\text{Medicare}}$	2.301^{*}	(1.097)	1.569	(1.199)	2.012^{*}	(0.915)	2.290	(1.404)
$\text{CF}(\text{HHI}_{\text{HMO}})$	0.105	(0.844)	-0.358	(1.272)	-2.723^{*}	(1.083)	-3.184^{+}	(1.705)
$\text{CF}(\text{HHI}_{\text{Medicare}})$	-2.714^{*}	(1.090)	-2.303^{+}	(1.217)	-2.956^{**}	(0.956)	-3.103^{*}	(1.483)
# Hospitals	136		135		131		115	
Cragg-Donald Wald F statistic for excluded instruments	21.82		14.17		16.80		10.60	

Notes: Each specification additionally includes travel time and relative location measures as described in Section IV.A as well as hospital fixed effects. Standard errors are clustered by zip code. The standard errors for the IV estimates are additionally corrected to reflect the noise from the first stage estimation following Karaca-Mandic and Train (2003).
Significance levels:
$** : p < 0.01$
$* : p < 0.05$
$+ : p < 0.10$

cations and include travel time and relative location measures as described in Section IV.A as well as hospital fixed effects. The estimates are almost a mirror image of those for HMO patients, indicating that Medicare patients generally place a higher value on hospitals located in areas with larger share of Medicare patients (though the estimates are not statistically different from zero in the 2SCL IV specifications), but lower utility for those hospitals in markets that have proportionally more HMO patients. Opposite perceived quality effects for HMO and Medicare patients would suggest that hospitals are actively trading-off quality characteristics that appeal to each group depending on the relative market presence the patient-types. There

TABLE 5—PERCENTAGE DIFFERENCE IN CHOICE PROBABILITY FOR 250 POINT DECREASE IN HHI

	Major Diagnostic Category			
	Circulatory	Digestive	Respiratory	Nervous
Top 5 HMO Patient				
$1 - \text{HHI}_{\text{HMO}}$	6.12	19.61	11.63	17.32
$1 - \text{HHI}_{\text{Medicare}}$	-3.52	-17.59	-7.62	-11.84
Medicare Patient				
$1 - \text{HHI}_{\text{HMO}}$	-1.84	0.02	6.20	7.57
$1 - \text{HHI}_{\text{Medicare}}$	5.65	3.85	4.93	5.59

Notes: All variables are based on patients belonging to the indicated diagnostic category and insurer type. The percentage change in choice probability is evaluated at the mean of the data and the average choice probability is approximately 0.02 or 2% for each of the MDCs and insurer types.

is no consistent or significant relationship between perceived hospital quality and the market penetration rates of PPOs.

Interestingly, with diagnoses of the respiratory and nervous systems the 2SCL IV estimates indicate that competition for HMO patients generate positive spill-over effects for Medicare patients who find these hospitals to be more attractive as well. The estimates for all four MDCs also indicate that Medicare patients view hospitals that experience an increase in competitive pressure for Medicare patients to be more valuable, though the impact of competition is less than that observed with HMO patients. For example, the results in Table 5 show that a 250 point reduction in $\text{HHI}_{\text{Medicare}}$ for a hospital would increase the probability the average Medicare patient chooses that hospital by about 5 percent for each of the four MDCs in contrast to the 6 to 20 percent change observed with HMO patients following a 250 point decrease in HHI_{HMO}. As Medicare patients having a diagnosis of the respiratory or nervous system also view hospitals that face a more competitive environment for HMO patients as more valuable, a 250 point reduction in HHI_{HMO} would increase the choice probability by about 6 to 7 percent for these diagnoses, respectively. In summary, hospitals in markets with greater competition for HMO patients tend to be viewed more favorably by HMO patients and sometimes even by Medicare patients, while hospitals that face greater competition for Medicare patients are more attractive to Medicare patients but less attractive to HMO patients.

VI. Competition and Health Outcomes

The findings from the previous section suggest that competition causes hospitals to alter their level of service quality as perceived by patients, and that these quality adjustments differ across patient types and depend on which type of patients hospitals are competing for. To better understand how these adjustments to perceived quality might compare with the adjustments to clinical quality that are typically studied in the literature, we now adapt our identification approach to estimate the causal impact of competition on observed mortality rates. We specifically examine in-hospital mortality rates related to 4 different conditions commonly considered in the literature: AMI, heart failure, pneumonia, and acute stroke. To accomplish this we specify an individual-level model of mortality in which the patient's risk of dying depends, among other things, on the concentration of the local hospital market.

We assume that a patient having observable personal and disease attributes X_{it} choosing hospital h having clinical quality μ_{ht} at time t will die if $m^*_{iht} > 0$ where

$$m^*_{iht} = \alpha + \mathbf{B}\mathbf{X}_{it} + \mu_{ht} + \epsilon_{iht},$$

and ϵ_{iht} represents an idiosyncratic component to i's treatment at hospital h. The vector of observable patient and disease characteristics $\mathbf{X}_i$ includes the patient's travel time and travel time squared to the treating hospital, that patient's age, gender, ethnicity, and primary payer type;[37] as well as several observable characteristics of the discharge: the log of the number of procedures performed, the percentage of the diagnoses that were present on admission, a dummy indicating if the discharge included palliative care, and the APR-DRG mortality risk code.[38] We assume that the idiosyncratic component to i's treatment at h, ϵ_{iht}, are i.i.d. type I extreme value.

We follow a similar strategy used when estimating hospitals' revealed quality and decompose μ_{ht} as

$$\mu_{ht} = \mathbf{\Gamma}\mathbf{C}_{ht} + \mathbf{\Delta}\mathbf{F}_{ht} + \mu_h,$$

where, as in eq. (2), $\mathbf{C}_{ht}$ is a vector of competitive measures ($\text{HHI}_{\text{HMO},ht}$ and $\text{HHI}_{\text{Medicare},ht}$),

[37] Controlling for payer type is important because patients may select one form of insurance over another due to their overall level of health prior to experiencing an illness.

[38] The APR-DRG mortality risk is a categorical variable taking an integer value between 0 and 4 and is generated using QI SAS, version 4.5, provided by AHRQ and are more generally used to generate risk-adjusted quality statistics for hospitals.

$\mathbf{F}_{ht}$ is a vector of non-competitive measures (%HMO, %PPO, %Medicare, and %Medicaid), and μ_h is hospital h's time-invariant contribution to mortality. With this decomposition the latent variable m^* can be expressed as

$$m^*_{iht} = \alpha + \mathbf{B}\mathbf{X}_{it} + \mathbf{\Gamma}\mathbf{C}_{ht} + \mathbf{\Delta}\mathbf{F}_{ht} + \mu_h + \epsilon_{iht}, \tag{9}$$

and given the distribution of ϵ the probability of dying during treatment takes the logit form:

$$\Pr(m^*_{iht} > 0) = \Big[1 + \exp\big\{-\alpha - \mathbf{B}\mathbf{X}_{it} - \mathbf{\Gamma}\mathbf{C}_{ht} - \mathbf{\Delta}\mathbf{F}_{ht} - \mu_h\big\}\Big]^{-1}. \tag{10}$$

An important issue with eq. (9) is that the unobservable characteristics of a patient's illness severity may be correlated with the patient's choice of hospital. For example, a more severely ill patient will likely choose a higher quality hospital. Gowrisankaran and Town (1999) examine this possibility and conclude that GLS estimates of hospital quality are inconsistent because of just such a correlation between illness severity, mortality, and hospital choice. In consequence, each element of both $\mathbf{C}_{ht}$ and $\mathbf{F}_{ht}$ as well as μ_h are all endogenous since they are the values for the chosen hospital. Moreover, as with revealed quality, the HHI_{mht} have the additional degree of endogeneity that come from the inclusion of own market share since hospitals that are of higher clinical quality may have higher market shares as a result, reversing the direction of causality in (9).

To control for this endogeneity we again utilize a control function approach. We use the expected values of predHHI_{mht} as instruments for the two HHIs and the expected values of %HMO, %PPO, %Medicare, and %Medicaid as instruments for their actual values where expectations are over predicted hospital choice probabilities from the model in (7) that only considers distance traveled. That is, we use as instruments for the HHI_{mht}, the HHI_m of the hospital chosen by patient i at time t the expected value for predHHI_{mht} defined as:

$$\mathbb{E}_i[\text{predHHI}_{mht}] = \sum_{k \in \mathcal{H}_i} \pi_{it}(k) \times \text{predHHI}_{mkt}, \tag{11}$$

where $\mathcal{H}_i$ is the set of hospitals in i's choicest and $\pi_{it}(k)$ is the probability that patient i, upon falling ill at time t chooses hospital k. Note that expectations are at the patient-level since the expected value is a function of that patient's choice probabilities. The instruments for each of the insurer percentages is similarly defined as

$$\mathbb{E}_i[\%\text{InsType}_{iht}] = \sum_{k \in \mathcal{H}_i} \pi_{it}(k) \times \%\text{InsType}_{kt}. \tag{12}$$

With these instruments we estimate for each of the six endogenous variables, $y \in \{\mathbf{C}, \mathbf{F}\}$, the first-stage model

$$y_{iht} = \Theta \mathbf{X}_{it} + \Omega \mathbf{Z}_{iht} + \nu_{iht}, \tag{13}$$

where the $\mathbf{X}_{it}$ are the patient and disease characteristics from (9), $\mathbf{Z}_{iht}$ is the set of exogenous instruments defined by (11) and (12), and ν_{iht} is an i.i.d. normally distributed disturbance term; and use the fitted error terms, $\hat{\nu}_{iht}$, as the control functions in (9). Lastly, we treat the μ_h as nuisance parameters and condition them out by estimating (9) as a conditional logit.

Table 6 reports the coefficient estimates for the HHIs.[39] All of the non-Federal hospitals used in the revealed quality estimation of the previous section are included and, as before, we allow the impact of competition to differ based on whether the hospital is privately owned or a state hospital, but only the estimates for the private hospitals are reported. We pool patients of both insurance types together since the patient and disease characteristics should have the same affect on patient mortality, but we allow the market conditions to impact mortality differently. Panel A in Table 6 reports the estimates without controlling for the endogeneity of market structure or hospital choice while Panel B reports the 2SCL IV estimates. Panel B also reports the Cragg-Donald Wald F statistics, which show that the instruments are particularly strong with the lowest F statistic being slightly greater than 19.

As with revealed quality, correcting for the endogeneity of HHI is important. The CL estimates frequently imply that mortality is not affected by competition; however, reinforcing the findings of Gowrisankaran and Town (2003), the 2SCL IV estimates indicate that mortality declines as the market for HMO patients becomes more competitive while increasing as the market for Medicare patients becomes more competitive. The impact of competition does not appear to differ by patient, suggesting either that hospitals do not selectively target investments related to clinical between HMO and Medicare patients, or that any such targeted investments

[39]See the appendix for the complete set of coefficient estimates.

TABLE 6—THE IMPACT OF COMPETITION ON MORTALITY RATES

	AMI		Heart Failure		Pneumonia		Acute Stroke	
Panel A: CL	(a)		(b)		(c)		(d)	
Top 5 HMO Patient								
$\times(1-\text{HHI}_{\text{HMO}})$	-1.272	(1.233)	-0.520	(1.248)	-1.464	(1.042)	0.960	(1.060)
$\times(1-\text{HHI}_{\text{Medicare}})$	0.508	(1.815)	3.223	(2.283)	3.475^{*}	(1.635)	-0.054	(1.542)
Medicare Patient								
$\times(1-\text{HHI}_{\text{HMO}})$	0.719^{+}	(0.378)	-0.068	(0.306)	0.459^{*}	(0.230)	0.446	(0.340)
$\times(1-\text{HHI}_{\text{Medicare}})$	0.254	(0.671)	0.205	(0.547)	0.478	(0.464)	0.046	(0.614)
# Discharges	12,421		27,260		22,434		14,543	
# Hospitals	166		166		167		161	
Panel B: 2SCL	(e)		(f)		(g)		(h)	
Top 5 HMO Patient								
$\times(1-\text{HHI}_{\text{HMO}})$	-3.532^{+}	(1.932)	-2.184	(1.828)	-3.699^{**}	(1.319)	-3.661^{+}	(1.934)
$\times(1-\text{HHI}_{\text{Mcare}})$	11.512^{+}	(6.306)	4.975	(5.390)	13.534^{**}	(3.575)	1.948	(4.920)
Medicare Patient								
$\times(1-\text{HHI}_{\text{HMO}})$	-1.503	(1.504)	-1.794	(1.375)	-1.720^{*}	(0.830)	-4.219^{*}	(1.646)
$\times(1-\text{HHI}_{\text{Mcare}})$	11.175^{+}	(6.030)	2.119	(4.947)	10.454^{**}	(3.219)	2.187	(4.743)
CF(HHI_{HMO})	2.232	(1.537)	1.742	(1.401)	2.265^{**}	(0.854)	4.836^{**}	(1.676)
CF($\text{HHI}_{\text{Medicare}}$)	-11.119^{+}	(6.078)	-2.084	(4.988)	-10.307^{**}	(3.255)	-2.158	(4.770)
# Discharges	12,421		27,260		22,434		14,543	
# Hospitals	166		166		167		161	
Cragg-Donald Wald F statistic for excluded instruments								
	19.686		45.154		51.623		30.13	

Notes: The data include discharges for both HMO and Medicare patients pooled together. Standard errors in parentheses are clustered by hospital but not corrected to reflect estimated data from the first-stage. Significance levels:
$** : p < 0.01$
$* : p < 0.05$
$+ : p < 0.10$

have little impact on in-hospital mortality.[40]

In addition to having a different sign, competition for Medicare patients also has a much larger impact on mortality rates than competition for HMO patients. To provide a more comparable measure of the effects, Table 7 reports the impact that a 250 point decrease in HHI has on the mortality of an average patient having the specified diagnosis. Competition has the largest effect on mortality for heart failure, which has an average mortality rate of 19.5

[40]While many treatment investments benefit all patients, hospitals could choose, for example, to discharge one group faster than the other. Such treatment differences do not appear to affect in-hospital mortality, but could still impact other clinical quality metrics such as 30-day mortality rates or readmission rates.

TABLE 7—PERCENTAGE DIFFERENCE IN MORTALITY FOR 250 POINT DECREASE IN HHI

	AMI	Heart Failure	Pneumonia	Acute Stroke
HMO Patient				
HHI_{HMO}	-7.178	-10.649	-9.900	-0.521
$HHI_{Medicare}$	19.567	35.365	35.631	3.86
Medicare Patient				
HHI_{HMO}	-4.029	-9.904	-6.58	-1.273
$HHI_{Medicare}$	19.123	29.521	30.738	3.562
Avg. Mortality	43.3	19.5	31.8	45.6

Notes: The data include discharges for both HMO and Medicare patients pooled together. Standard errors in parentheses are clustered by hospital but not corrected to reflect estimated data. Significance levels:
$** : p < 0.01$
$* : p < 0.05$
$+ : p < 0.10$

percent. At this rate, a 250 point decrease in HHI_{HMO} will decrease the probability of dying by about 10 percent (1.9 percentage points) while a 250 point decrease in $HHI_{Medicare}$ will increase the probability of dying by a sizable 30 percent (8.8 percentage points). The relative impact of competition for HMO versus Medicare patients on mortality for AMI and pneumonia is similar. Although some coefficients are imprecisely estimated, the results of Tables 6 and 7 fairly consistently suggest that competition for Medicare patients substantially reduces clinical quality for all patients, while competition for HMO patients results in somewhat better clinical outcomes for all.

VII. HEALTH OUTCOMES AS DEMAND SHIFTERS

We have shown that hospitals adjust both their revealed quality and clinical quality when faced with increased competition, but in some cases they move in opposite directions. To examine this discrepancy, we now more carefully investigate the relationship between these two notions of quality by estimating the degree to which hospital mortality rates influence patients' hospital choice. While modeling patient indirect utility as a function of HHI (as in Section V) allows us to identify the causal impact of competition on hospital revealed quality, it does not reveal the specific dimensions of hospital quality that are affected by competition. To determine whether clinical quality is a hospital attribute patients use when selecting a hospital we can include it directly in the patient indirect utility function and observe what effect this has on the estimated revealed quality directly associated with competition. To illustrate, suppose that clinical quality (measured by in-hospital mortality) is the only attribute hospitals use to compete for patients. In this case, if we include the in-hospital mortality rate directly in the indirect utility function along with the HHIs, then we will no longer find a relationship between the HHIs and revealed quality since the HHIs only affected revealed quality through the mortality rate. If instead, the mortality rate is not a dimension of quality considered by patients when selecting a hospital for treatment, then its coefficient will be close to zero and we will still observe a strong, statistically significant relationship between the HHIs and revealed quality.

As we analyze the impact of competition using multiple MDCs we include only the mortality rate related to the corresponding MDC directly in the patients' indirect utility function (6); i.e., we include the in-hospital mortality rates for AMI and heart failure when estimating the model using diagnoses relating to the circulatory system; the in-hospital mortality rate for pneumonia when estimating the model using diagnoses relating to the respiratory system; and the in-hospital mortality rate for acute stroke when estimating the model using diagnoses relating to the nervous system. Hospitals that are in high demand for other reasons may also disproportionally attract more high-risk patients. To control for this potential endogeneity we utilize risk-adjusted mortality rates generated by version 4.5 of the Agency for Healthcare Research and Quality's (AHRQ) QI SAS software.[41] Table 8 reports the estimation results. All specifications are identical to those reported in Table 3, but only the estimates for the HHIs and mortality are reported. To ease comparison, we present the original estimation results from Table 3 when the mortality rate is not included next to the new results based on the inclusion of the mortality measure.

In general, hospital mortality rates appear to have very little impact on patients' choice of hospital. Moreover, including mortality rates in the utility function does not change the estimated coefficients on our HHI measures, suggesting that competition does not influence hospital choice through clinical quality. For HMO patients the mortality rates for AMI and acute stroke have the expected sign (higher mortality rates indicates lower revealed quality), but there is no apparent relationship between revealed quality and the mortality rate for pneu-

[41] A couple hospitals had an insufficient number of observations relating to these mortality measures to generate a risk-adjusted mortality rate so in those cases we utilize the observed mortality rate. We additionally tried a specification in which we included an indicator variable for when the risk-adjusted mortality rate could not be computed to verify that the use of an un-adjusted mortality rate did not affect the results and the results were the same.

TABLE 8—REVEALED PREFERENCES FOR CLINICAL OUTCOMES BY MAJOR DIAGNOSTIC CATEGORY

	Major Diagnostic Category					
	Circulatory		Respiratory		Nervous	
Panel A: Top 5 HMO, 2SCL	(a)		(b)		(c)	
$1 - \text{HHI}_{\text{HMO}}$	2.509^{+}	2.585^{*}	4.769^{**}	4.793^{**}	7.112^{**}	7.310^{**}
	(1.319)	(1.279)	(1.553)	(1.485)	(2.428)	(2.243)
$1 - \text{HHI}_{\text{Medicare}}$	−1.444	−1.438	-3.123^{*}	-3.251^{*}	-4.861^{*}	-5.108^{**}
	(1.361)	(1.343)	(1.446)	(1.431)	(2.018)	(1.869)
AMI/Pneumonia/Stroke		-0.191^{+}		0.005		-0.286^{*}
		(0.101)		(0.165)		(0.144)
Heart Failure		0.304^{*}				
		(0.122)				
Panel B: Medicare, 2SCL	(d)		(e)		(f)	
$1 - \text{HHI}_{\text{HMO}}$	−0.752	−0.787	2.532^{*}	2.534^{*}	3.103^{+}	3.083^{+}
	(0.823)	(0.805)	(1.049)	(1.038)	(1.654)	(1.634)
$1 - \text{HHI}_{\text{Medicare}}$	2.301^{*}	2.385^{*}	2.012^{*}	2.008^{*}	2.290	2.277
	(1.097)	(1.096)	(0.915)	(0.912)	(1.404)	(1.394)
	(0.445)	(0.443)	(0.466)	(0.460)	(0.296)	(0.297)
AMI/Pneumonia/Stroke		0.003		−0.032		0.009
		(0.059)		(0.104)		(0.102)
Heart Failure		0.107				
		(0.071)				

Notes: Each specification additionally includes travel time and relative location measures as described in Section IV.A as well as hospital fixed effects. Standard errors are clustered by zip code and corrected to reflect the noise from the first stage estimation following Karaca-Mandic and Train (2003). Significance levels:
$** : p < 0.01$
$* : p < 0.05$
$+ : p < 0.10$

monia and a positive relationship between revealed quality and the mortality rate for heart failure. This latter finding suggests that the risk-adjustment process may not fully account for all of the risk factors or that there are other hospital characteristics, which are associated with higher mortality rates for heart failure, that attract patients. Even when there are statically significant relationships between mortality and revealed quality, the implied elasticities are extremely small. For example, when evaluated at the mean of the data, the implied elasticity for AMI mortality is -0.08; i.e., a 10% increase in mortality for AMI will decrease demand by about 0.8%. The low elasticity with respect to mortality could occur because patients may not be aware of the differences in mortality rates across hospitals or understand the degree to which hospitals contribute to a patient's mortality.

For Medicare patients there is no apparent relationship between revealed quality and the mortality rates. In all cases the point estimates are quite close to zero (the standard errors are also relatively small) suggesting that Medicare patients do not consider the relative mortality rate differences between hospitals when selecting a hospital for treatment.

It is somewhat surprising that patients do not appear to place much, if any, weight on the relative mortality rate of the hospitals when selecting a hospital for treatment given that, in addition to our findings of a relationship in Section VI, the literature has also identified a relationship between competition and mortality (e.g., Kessler and McClellan, 2000; Gowrisankaran and Town, 2003; Kessler and Geppert, 2005). One may be concerned that we do not find a relationship between hospital choice and mortality because the mortality rates are for specific diagnoses while the hospital choice model is estimated using patients that have any diagnosis within the same MDC. However, it is likely the case that if a hospital has a lower mortality rate for a particular diagnosis it is able to provide higher clinical quality for related diagnoses as well. Supporting this conjecture, there is a relatively high degree of correlation between the four mortality measures indicating that hospitals that have higher clinical quality in one dimension are generally higher quality in other dimensions as well so that the mortality rates function as strong proxies for other related measures of clinical quality. Moreover, most of the evidence on hospital report cards indicates that if patients do respond to report cards, which try to provide clear, comparable information on hospital clinical quality, that response occurs when there are substantial differences in patients' priors and the report card rating (Dranove and Sfekas, 2008). The marginal changes to a hospital's mortality rate that occur during the timespan of the panel may be too small to generate a measurable demand response.

What these results suggest instead is that a hospital likely adjusts its clinical quality as a result of competitive pressure for network inclusion and not as a means of attracting marginal patients. Illustrating this point, in a discussion of how hospitals can gain leverage vis-à-vis insurers, Janie Patterson, senior vice president at Conifer Health Solutions says that "...payors are placing more emphasis on quality of care, and if a hospital doesn't meet a certain standard a payor may not even want a contract with that hospital (Oh, 2010)." In this way, HMOs and their selective contracting practices are important for generating incentives for hospitals to improve clinical quality while competition for patients directly appears to result in quality improvements on other, non-clinical dimensions.

VIII. CONCLUSIONS

The pressure generated by competitive forces is generally considered to be a valuable, if not essential, mechanism for encouraging firms to provide higher quality products at lower prices. Competition can only be effective, however, if demand is sufficiently responsive to both price and quality, which may not always be true in the market for hospital services. To further complicate the impact of competition, the concept of clinical quality that is so important to health providers and health policymakers represents only one component of the overall set of non-price amenities (i.e., service qualities) over which hospitals may compete. In this paper we more carefully investigate the relationships between clinical quality and overall quality as perceived by patients (and/or their physicians), and examine how the levels of clinical and perceived quality offered by hospitals is affected by the degree of competition in the local hospital market.

The results indicate that competition affects both revealed and clinical quality, but in different ways. Competition for HMO patients results in both higher revealed and clinical quality for HMO and Medicare patients alike while competition for Medicare patients generates lower clinical quality for both types of patient but somewhat higher revealed quality for Medicare patients. The impact that competition has on clinical quality is consistent with the findings of Gowrisankaran and Town (2003) who posit that this effect is driven by hospitals substituting away from lower profit margin Medicare patients to higher-margin privately insured patients. Our results suggest that instead of substituting away from Medicare patients when facing a more competitive environment, hospitals increase quality in those dimensions that have higher demand elasticity at the expense of clinical quality, which does not exhibit much elasticity. In contrast, HMOs' interest in high-quality care for their enrollees and their use of selective contracting combine to make each hospital's demand more elastic with respect to clinical quality.

Our findings provide a new perspective on the role of HMOs and have important implications for competition policy. Together, the results suggest that the main impact of competition on clinical quality comes through the selective networking practices of HMOs that make HMO patient demand responsive to both price and clinical quality. Unfortunately, the health exchanges and standardized coverage tiers required by the ACA has increased price competition between HMOs and could undermine the benefit of competition by weakening the incentive to improve clinical quality. Similarly, "Any Willing Provider" laws that emphasize prices and weaken the ability of HMOs to exclude hospitals based on their clinical quality will also eliminate the mechanism through which competition encourages higher clinical quality. On the other hand, competition for patients will still provide strong incentives to improve revealed quality so policies that increase patient awareness and understanding of the clinical differences between hospitals should better allow competition to generate the desired outcomes of higher clinical quality.

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APPENDIX A. INSTRUMENTS FOR OUT-OF-POCKET COSTS

We use two instruments for a patient's out-of-pockets cost, the HHI of the HMO market and the added value to a patient of having a hospital included in his provider network. Like hospital HHIs, the HMO HHI is calculated at the zip code level as the sum of the market shares squared for the HMO patients that seek treatment that year. For each hospital we then take the weighted sum of all zipped level HMO HHIs for all zip codes within a 75 minute drive of the hospital. The weighting is based on the proportion of a hospital's total demand that is expected to come from that zip code using a hospital choice model in which utility is a function of relative travel times only (eq. 7) as done with the hospital HHIs and insurance market shares.

Our measure of added value is based on the option-demand framework developed by Capps et al. (2003) and is analogous to what they refer as the market's willingness-to-pay for having access to a hospital. To avoid problems with endogenous quality we use the basic choice model defined by eq. (7), in which patients select hospitals based only on their relative distance. Patient i's interim utility of having hospital h in his choice set $\mathcal{M} = \{1, 2, \ldots, M\}$ can be expressed as

$$V(\mathcal{M} \mid H, X_i, D_{ih}) = E\left[\max_{m \in \mathcal{M}} \{U(H_m, X_i, D_{ih})\}\right] = \ln\left[\sum_{m \in \mathcal{M}} \exp\{U(H_m, X_i, , D_{ih})\}\right],$$

where H is the vector of all H_m. Hospital h's contribution to patient i's interim utility derived from MCO m's network $\mathcal{M}$ can therefore be expressed as

$$\begin{aligned} \Delta_h V(\mathcal{M} \mid H, X_i, D_{ih}) &= V(\mathcal{M} \mid H, X_i, D_{ih}) - V(\mathcal{M} \setminus h \mid H, X_i, D_{ih}) \\ &= \ln\left(\frac{1}{1 - s_h(\mathcal{M} \mid H, X_i, D_{ih})}\right), \end{aligned} \tag{A-1}$$

where $s_h(\mathcal{M} \mid H, X_i, D_{ih})$ is the probability that hospital h is chosen by patient i when included in network $\mathcal{M}$ given by the logit demand specification:

$$s_h(\mathcal{M} \mid H, X_i, D_{ih}) = \frac{\exp\{U_{ih}\}}{\sum_{m \in \mathcal{M}} \exp\{U_{im}\}}.$$

There is no outside option because the data contain only those patients which have become sufficiently ill that they choose to visit a hospital. Integrating (A-1) over the population distribution of patient attributes, diseases, and patient locations produces the *ex ante* value of including hospital h in network M. Let $F(X_{it}, D_{iht})$ denote the joint cumulative distribution of patient characteristics, diseases, and locations of all patients who will visit a hospital, then the total *ex ante* value (in utils) for inclusion of hospital h in MCO m's network is

$$\Delta_h W_m(\mathcal{M}) = N_m \int_{X,D} \ln\left(\frac{1}{1 - s_h(\mathcal{M} \mid H, X_i, D_{ih})}\right) dF(X_i, D_{ih}), \tag{A-2}$$

where N_m is the number of enrollees with MCO m sufficiently ill that they visit a hospital in the choice set. We calculate $\Delta_h W_m(\mathcal{M})$ for each hospital and each year and use this as the instrument.

Appendix B. Additional Coefficient Estimates

TABLE B1—REVEALED QUALITY TRAVEL TIME PARAMETER ESTIMATES FOR HMO PATIENTS

	Major Diagnostic Category							
	Circulatory		Digestive		Respiratory		Nervous	
	β	(s.e.)	β	(s.e.)	β	(s.e.)	β	(s.e.)
Case Weight								
×Travel Time	0.170^{+}	(0.092)	0.345^{*}	(0.158)	0.414^{*}	(0.176)	0.824^{**}	(0.195)
×Travel Time Sqrd.	0.144	(0.095)	−0.193	(0.172)	−0.128	(0.184)	-0.407^{*}	(0.172)
×ER×Travel Time	0.508^{**}	(0.147)	−0.334	(0.209)	-0.417^{+}	(0.213)	-0.646^{**}	(0.232)
×ER×Travel Time Sqrd.	-0.487^{**}	(0.173)	0.383	(0.237)	0.210	(0.234)	0.405^{+}	(0.230)
1 – 17 Yrs.								
×Travel Time	-15.231^{**}	(2.276)	-19.123^{**}	(1.840)	-17.212^{**}	(2.011)	-15.614^{**}	(1.785)
×Travel Time Sqrd.	8.410^{**}	(2.213)	3.611^{+}	(2.022)	1.154	(2.503)	4.037^{*}	(1.914)
×ER×Travel Time	-10.788^{**}	(3.406)	-4.477^{**}	(1.657)	−1.540	(2.141)	−3.091	(2.257)
×ER×Travel Time Sqrd.	2.849	(3.344)	2.565	(2.054)	0.227	(2.893)	−1.567	(2.641)
18 – 34 Yrs.								
×Travel Time	-18.593^{**}	(1.820)	-19.181^{**}	(1.499)	-20.824^{**}	(2.042)	-18.344^{**}	(1.685)
×Travel Time Sqrd.	7.450^{**}	(2.038)	5.863^{**}	(1.566)	7.974^{**}	(2.280)	7.170^{**}	(1.813)
×ER×Travel Time	-4.887^{*}	(1.935)	-3.259^{*}	(1.418)	−2.102	(2.085)	−2.148	(1.988)
×ER×Travel Time Sqrd.	0.920	(2.394)	1.214	(1.710)	−1.496	(2.541)	−1.008	(2.373)
35 – 64 Yrs.								
×Travel Time	-19.721^{**}	(1.677)	-19.275^{**}	(1.411)	-19.135^{**}	(1.802)	-18.606^{**}	(1.684)
×Travel Time Sqrd.	6.901^{**}	(1.970)	5.817^{**}	(1.441)	5.173^{*}	(2.086)	6.438^{**}	(1.776)
×ER×Travel Time	-3.978^{*}	(1.687)	-3.545^{**}	(1.299)	-3.623^{*}	(1.744)	−2.369	(1.886)
×ER×Travel Time Sqrd.	−0.898	(2.136)	1.369	(1.583)	0.693	(2.168)	−1.492	(2.217)
≥65 Yrs.								
×Travel Time	-20.574^{**}	(1.694)	-20.344^{**}	(1.681)	-19.684^{**}	(2.240)	-20.592^{**}	(1.954)
×Travel Time Sqrd.	6.722^{**}	(1.967)	6.018^{**}	(1.894)	3.816	(2.920)	6.974^{**}	(2.057)
×ER×Travel Time	−2.338	(1.835)	-3.205^{+}	(1.666)	−2.666	(2.350)	−2.141	(2.394)
×ER×Travel Time Sqrd.	−3.379	(2.509)	0.605	(2.200)	−1.272	(3.124)	−2.322	(3.031)
Income								
×Travel Time	12.791^{**}	(2.643)	9.804^{**}	(2.120)	10.354^{**}	(2.817)	10.101^{**}	(2.269)
×Travel Time Sqrd.	-10.678^{**}	(3.107)	-5.341^{*}	(2.148)	-5.455^{+}	(3.223)	-6.314^{**}	(2.399)
×ER×Travel Time	-5.469^{*}	(2.743)	0.606	(2.327)	−2.372	(2.912)	−3.226	(2.943)
×ER×Travel Time Sqrd.	6.865^{*}	(3.314)	−2.219	(2.678)	2.060	(3.511)	3.132	(3.264)
Closest 5	0.547^{**}	(0.113)	0.542^{**}	(0.110)	0.564^{**}	(0.132)	0.681^{**}	(0.115)
6th to 10th closest	0.505^{**}	(0.073)	0.466^{**}	(0.075)	0.507^{**}	(0.089)	0.525^{**}	(0.078)
ER×Closest	0.119	(0.080)	0.084	(0.075)	0.121	(0.083)	0.036	(0.084)
#Pat. within 10 mi.	-0.185^{*}	(0.076)	-0.978^{**}	(0.149)	-0.526^{**}	(0.178)	0.203	(0.263)
#Pat. within 25 mi.	0.021^{**}	(0.005)	0.090^{**}	(0.011)	0.036^{**}	(0.013)	0.011	(0.022)

Notes: Standard errors are clustered by zip code. Significance levels:
$** : p < 0.01$
$* : p < 0.05$
$+ : p < 0.10$

TABLE B2—REVEALED QUALITY TRAVEL TIME PARAMETER ESTIMATES FOR MEDICARE PATIENTS

	Major Diagnostic Category							
	Circulatory		Digestive		Respiratory		Nervous	
	β	(s.e.)	β	(s.e.)	β	(s.e.)	β	(s.e.)
Case Weight								
×Travel Time	0.382^{**}	(0.061)	0.214^{+}	(0.118)	0.331^{**}	(0.104)	0.683^{**}	(0.151)
×Travel Time Sqrd.	−0.052	(0.059)	−0.068	(0.130)	−0.063	(0.104)	-0.300^{*}	(0.132)
×ER×Travel Time	0.143	(0.097)	−0.103	(0.157)	-0.653^{**}	(0.130)	-0.589^{**}	(0.170)
×ER×Travel Time Sqrd.	-0.219^{+}	(0.120)	0.074	(0.181)	0.368^{**}	(0.141)	0.346^{*}	(0.176)
1 – 34 Yrs.								
×Travel Time	-19.193^{**}	(1.747)	-17.314^{**}	(1.692)	-15.928^{**}	(2.447)	-18.920^{**}	(1.964)
×Travel Time Sqrd.	8.058^{**}	(2.068)	8.204^{**}	(1.743)	6.331^{**}	(2.381)	9.206^{**}	(1.825)
×ER×Travel Time	−1.491	(2.122)	-4.690^{*}	(1.995)	-6.583^{**}	(2.508)	-5.632^{*}	(2.411)
×ER×Travel Time Sqrd.	−2.520	(2.858)	0.166	(2.295)	1.325	(2.881)	0.103	(2.684)
35 – 64 Yrs.								
×Travel Time	-21.361^{**}	(1.208)	-20.994^{**}	(1.159)	-20.586^{**}	(1.509)	-21.127^{**}	(1.402)
×Travel Time Sqrd.	8.215^{**}	(1.342)	9.217^{**}	(1.227)	7.713^{**}	(1.538)	10.123^{**}	(1.435)
×ER×Travel Time	-4.213^{**}	(1.304)	-2.950^{*}	(1.233)	-4.312^{**}	(1.278)	-4.430^{**}	(1.437)
×ER×Travel Time Sqrd.	0.678	(1.835)	−0.835	(1.591)	0.674	(1.678)	−0.856	(1.839)
≥65 Yrs.								
×Travel Time	-22.308^{**}	(1.245)	-21.423^{**}	(1.221)	-21.979^{**}	(1.434)	-22.984^{**}	(1.410)
×Travel Time Sqrd.	8.963^{**}	(1.390)	8.256^{**}	(1.337)	8.447^{**}	(1.505)	10.303^{**}	(1.463)
×ER×Travel Time	-4.033^{**}	(1.381)	-2.661^{*}	(1.251)	-3.832^{**}	(1.343)	-3.830^{*}	(1.493)
×ER×Travel Time Sqrd.	−0.416	(1.928)	−1.529	(1.595)	0.161	(1.782)	−1.061	(1.917)
Income								
×Travel Time	12.602^{**}	(1.915)	10.040^{**}	(1.767)	10.616^{**}	(2.225)	13.164^{**}	(2.140)
×Travel Time Sqrd.	-9.656^{**}	(2.105)	-6.806^{**}	(1.880)	-6.799^{**}	(2.221)	-9.694^{**}	(2.149)
×ER×Travel Time	−1.356	(2.376)	0.054	(2.152)	1.678	(2.370)	−0.241	(2.556)
×ER×Travel Time Sqrd.	2.225	(3.114)	1.056	(2.667)	−1.316	(2.862)	1.200	(3.054)
Closest 5	0.605^{**}	(0.100)	0.628^{**}	(0.106)	0.697^{**}	(0.114)	0.656^{**}	(0.111)
6th to 10th closest	0.441^{**}	(0.074)	0.467^{**}	(0.076)	0.511^{**}	(0.085)	0.449^{**}	(0.081)
ER×Closest	0.081	(0.081)	0.056	(0.076)	0.133^{+}	(0.080)	0.110	(0.077)
#Pat. within 10 mi.	0.094^{**}	(0.024)	0.332^{**}	(0.103)	0.263^{**}	(0.069)	0.642^{**}	(0.095)
#Pat. within 25 mi	0.009^{**}	(0.002)	0.008	(0.008)	0.004	(0.005)	−0.002	(0.007)

Notes: Standard errors are clustered by zip code. Significance levels:
$** : p < 0.01$
$* : p < 0.05$
$+ : p < 0.10$

TABLE B3—THE IMPACT OF COMPETITION ON MORTALITY RATES

	AMI		Heart Failure		Pneumonia		Acute Stroke	
2SCL	(e)		(f)		(g)		(h)	
Top 5 HMO Patient								
$\times(1-\mathrm{HHI}_{\mathrm{HMO}})$	-3.532^{+}	(1.932)	-2.184	(1.828)	-3.699^{**}	(1.319)	-3.661^{+}	(1.934)
$\times(1-\mathrm{HHI}_{\mathrm{Mcare}})$	11.512^{+}	(6.306)	4.975	(5.390)	13.534^{**}	(3.575)	1.948	(4.920)
Medicare Patient								
$\times(1-\mathrm{HHI}_{\mathrm{HMO}})$	-1.503	(1.504)	-1.794	(1.375)	-1.720^{*}	(0.830)	-4.219^{*}	(1.646)
$\times(1-\mathrm{HHI}_{\mathrm{Mcare}})$	11.175^{+}	(6.030)	2.119	(4.947)	10.454^{**}	(3.219)	2.187	(4.743)
Top 5 HMO Patient×Gov't Hosp.								
$\times(1-\mathrm{HHI}_{\mathrm{HMO}})$	-3.556	(6.790)	-8.240	(9.701)	-1.829	(5.213)	0.529	(4.700)
$\times(1-\mathrm{HHI}_{\mathrm{Mcare}})$	-3.791	(6.845)	13.375	(10.613)	4.885	(6.219)	2.540	(6.992)
Medicare Patient×Gov't Hosp.								
$\times(1-\mathrm{HHI}_{\mathrm{HMO}})$	1.452	(1.200)	0.317	(1.021)	-0.724	(0.800)	4.085^{**}	(1.219)
$\times(1-\mathrm{HHI}_{\mathrm{Mcare}})$	7.969^{**}	(2.498)	2.853	(1.886)	4.414^{**}	(1.536)	2.163	(2.191)
%HMO	-3.141	(2.362)	2.608	(2.229)	4.594^{**}	(1.728)	-1.748	(2.077)
%PPO	-7.384^{*}	(3.246)	2.976	(2.872)	-1.076	(2.658)	-4.618	(3.256)
%Medicare	-3.012	(2.427)	1.606	(2.079)	-3.587^{+}	(2.130)	6.573^{**}	(2.322)
%Medicaid	-17.688^{**}	(3.601)	-23.826^{**}	(2.945)	-7.135^{+}	(3.934)	-11.212^{**}	(3.806)
Travel Time	-0.021^{**}	(0.007)	-0.011^{+}	(0.006)	-0.022^{**}	(0.006)	-0.031^{**}	(0.008)
Travel Time Surd.	0.000	(0.000)	0.000	(0.000)	0.000^{*}	(0.000)	0.000^{**}	(0.000)
Palliative care	1.852^{**}	(0.068)	2.326^{**}	(0.051)	2.476^{**}	(0.049)	2.703^{**}	(0.067)
Patient Age								
18-34	0.258	(0.494)	0.543	(0.335)	0.654^{**}	(0.217)	-0.060	(0.274)
35-64	0.397	(0.494)	0.535	(0.332)	0.911^{**}	(0.215)	-0.187	(0.275)
65+	0.631	(0.494)	0.880^{**}	(0.331)	1.191^{**}	(0.212)	-0.106	(0.273)
Female	-0.044	(0.047)	-0.153^{**}	(0.040)	-0.106^{**}	(0.039)	-0.046	(0.052)
Race								
Black	-0.216^{+}	(0.112)	-0.434^{**}	(0.083)	-0.169^{+}	(0.091)	-0.630^{**}	(0.119)
Native American	-13.662	(463.741)	-0.175	(0.666)	-0.315	(0.778)	-13.991	(460.995)
Other	0.971	(1.177)	-1.116	(0.862)	-1.484	(0.945)	-3.436^{*}	(1.401)
Unknown	-0.213^{**}	(0.060)	-0.263^{**}	(0.055)	-0.230^{**}	(0.052)	-0.072	(0.065)
APR-DRG Risk Index								
1	-3.970^{**}	(0.241)	-2.925^{**}	(0.216)	-3.107^{**}	(0.165)	-3.157^{**}	(0.138)
2	-2.883^{**}	(0.101)	-2.015^{**}	(0.082)	-1.726^{**}	(0.076)	-1.763^{**}	(0.096)
3	-1.348^{**}	(0.079)	-0.685^{**}	(0.073)	-0.394^{**}	(0.070)	-0.263^{**}	(0.094)
4	0.547^{**}	(0.077)	0.821^{**}	(0.071)	1.017^{**}	(0.074)	2.021^{**}	(0.104)
Log # Diagnostic Codes	-1.040^{**}	(0.072)	-0.689^{**}	(0.063)	-0.698^{**}	(0.060)	-1.363^{**}	(0.069)
Log # Procedure Codes	0.295^{**}	(0.034)	0.651^{**}	(0.032)	0.855^{**}	(0.036)	0.862^{**}	(0.046)
% Present on Admission	-0.749^{**}	(0.161)	-2.315^{**}	(0.166)	-1.447^{**}	(0.163)	-0.567^{*}	(0.222)
CF($\mathrm{HHI}_{\mathrm{HMO}}$)	2.232	(1.537)	1.742	(1.401)	2.265^{**}	(0.854)	4.836^{**}	(1.676)
CF($\mathrm{HHI}_{\mathrm{Medicare}}$)	-11.119^{+}	(6.078)	-2.084	(4.988)	-10.307^{**}	(3.255)	-2.158	(4.770)
CF(%HMO)	4.323^{+}	(2.443)	0.097	(2.292)	-1.230	(1.794)	2.375	(2.199)
CF(%PPO)	7.378^{*}	(3.404)	-0.967	(2.994)	1.144	(2.775)	4.545	(3.387)
CF(%Medicare)	2.349	(2.501)	-3.350	(2.150)	1.673	(2.183)	-8.456^{**}	(2.410)
CF(%Medicaid)	11.520^{**}	(3.798)	17.798^{**}	(3.095)	5.290	(3.992)	6.872^{+}	(3.980)
# Discharges	12,421		27,260		22,434		14,543	
# Hospitals	166		166		167		161	
Cragg-Donald Wald F statistic for excluded instruments								
	19.686		45.154		51.623		30.13	

Notes: The data include discharges for both HMO and Medicare patients pooled together. Standard errors in parentheses are clustered by hospital but not corrected to reflect estimated data. Significance levels:
$** : p < 0.01$
$* : p < 0.05$
$+ : p < 0.10$