

How Costly Is Hospital Quality? A Revealed-Preference Approach*

John A. Romley

University of Southern California and RAND Corporation

Dana P. Goldman

University of Southern California and RAND Corporation

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Abstract

We analyze the cost of quality improvement in hospitals, dealing with two challenges. Hospital quality is multidimensional and hard to measure, while unobserved productivity may influence quality supply. We infer the quality of hospitals in Los Angeles from patient choices. We then incorporate ‘revealed quality’ into a cost function, instrumenting with hospital demand. We find that revealed quality differentiates hospitals, but is not strongly correlated with clinical quality. Revealed quality is quite costly, and tends to increase with hospital productivity. Thus, non-clinical aspects of the hospital experience (perhaps including patient amenities) play important roles in hospital demand, competition, and costs.

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1 Introduction

In recent years there have been prominent calls for quality improvement in health care. The Institute of Medicine's report *Crossing the Quality Chasm* garnered national attention and spawned extensive research efforts devoted to measuring and improving quality [Institute of Medicine (2001)]. Yet quality improvement may be costly, and the value of quality in health care turns on its costs as well as its benefits [Cutler et al. (1998); Skinner et al. (2006)].

This paper focuses on the cost of quality improvement in hospitals. Expenditures on U.S. hospitals totaled \$718 billion in 2008, and have been growing faster than overall health spending [Hartman et al. (2010)].

There are two major potential challenges in understanding the cost of quality in hospitals. First, from a patient's point of view, quality embodies not only clinical quality, but all aspects of the hospital experience that patients observe and value. Much like the customers of an airline, hospital patients plausibly care about amenities such as good food, attentive staff and pleasant surroundings [Newhouse (1994)]. Prior empirical research has addressed the cost of clinical quality, but not amenities [Carey and Burgess, Jr. (1999); Picone et al. (2003)]. The cost of amenities may be substantial, yet good measures have been lacking.

Second, a hospital's quality may be confounded with its productivity. Some hospitals may produce at lower cost than others because their boards and managers are more effective, for example, in dealing with doctors who often enjoy substantial autonomy [Harris (1977)]. As an empirical matter, Zuckerman et al. (1994) attributed nearly 14% of total costs in U.S. hospitals to "inefficient" behavior. Such evidence is also consistent with heterogeneous productivity [Stigler (1976); Van Biesebroeck (2007)].¹

Productivity differences may be related to differences in quality, as well as quantity [Marschak and Andrews, Jr. (1944); Nerlove (1965)]. High productivity may lower the marginal cost of quality, leading a hospital to supply high quality. High-quality hospitals would then tend to be relatively low cost. Because productivity is not fully observed by researchers, quality can appear to be less costly than is truly the case.

Our approach to understanding the cost of hospital quality exploits the

¹Skinner et al. (2006) suggest that productivity differences have driven changes over time in heart-attack survival and treatment costs.

observed choice behavior of consumers in this industry. This approach is the mirror opposite of using supply behavior to understand demand. Thomadsen (2005), for example, appealed to the structure of firm costs and the nature of market equilibrium to identify demand at fast-food outlets.

To implement our approach, we first infer quality at hospitals in greater Los Angeles over 2000-2004 from the revealed preferences of Medicare fee-for-service patients with pneumonia, applying existing methods for choice among differentiated products with unobserved characteristics. Intuitively, patients reveal the quality of hospitals through their willingness to receive care at hospitals relatively far from home.

Pneumonia patients are more likely to exercise meaningful choice than patients with higher-acuity conditions (such as heart attacks.) Emergency transport to the hospital is relatively infrequent, and all hospitals are "in network." In addition, out-of-pocket costs do not vary across hospitals for Medicare fee-for-service patients [Capps et al. (2003); Tay (2003)]. Thus, we need not measure hospital prices, nor address their probable relationship with quality levels. As a consequence, however, we are unable to quantify the dollar value of quality to the patients studied.

We incorporate the resulting quality measure — which we refer to as "revealed quality" — into a hospital cost function. Our identification strategy again appeals to consumer behavior. To instrument for quality, we use the responsiveness of a hospital's demand to its quality level, obtained from the choice analysis and purged of the influence of actual quality. We also use demand shifters such as the average income of patients residing near a hospital, because such characteristics may affect willingness to travel to distant hospitals for better quality. These demand-based instruments affect a hospital's marginal utility in a simple model of quality competition.

We are then able to explore the patient perspective on hospital quality by comparing our broad revealed-quality measure to a standard measure of clinical quality, namely, risk-adjusted mortality rates for pneumonia. We also compare the costs of revealed and clinical quality.

We find that hospitals are highly differentiated in revealed quality, and that this broad quality measure is only moderately correlated with pneumonia mortality. We also find that an interquartile improvement in revealed quality would increase costs by 48.2% at an otherwise average hospital. Revealed quality was positively correlated with productivity; when this relationship is ignored, the cost of revealed quality is substantially understated, and statistically indistinguishable from zero. Finally, we find that the cost

of an interquartile reduction in pneumonia mortality is modest (only 12.6%). Altogether, these findings suggest that hospitals compete for patients based on costly non-clinical aspects of the hospital experience.

The rest of this paper is organized as follows. Section 2 presents our framework for measuring hospital quality and identifying its cost when productivity and quality are correlated. We analyze hospital quality in section 3 and hospital costs in section 4. Section 5 concludes with a discussion of the implications of our findings and directions for future research.

2 Framework

Our goal is to consistently estimate the short-run hospital cost function:

$$C(Y, Q, W, K, A),$$

in which Y is quantity, Q is quality, W is wages, K is capital, and A is productivity. With a focus on short-run costs, we need not assume that hospitals are in long-run equilibrium vis-a-vis capacity [Carey (2000)].

To determine the cost of quality, we must address two main issues. First, a patient's view of hospital quality may include non-clinical aspects of the hospital experience such as amenities, in addition to clinical quality. Yet good measures of amenities have been lacking. This hard-to-measure aspect of quality may be important to patients, and costly to hospitals.

Second, hospitals may decide how much quality to supply based on their productivity. Consequently, an analysis of hospital costs could be confounded insofar as researchers do not observe productivity. In particular, high-quality hospitals may tend to be relatively low cost, so that quality appears to be cheaper than is truly the case. This second issue could be a problem even if quality were well measured.

The rest of this section explains how patient choice behavior can help deal with endogenous quality, and how choice behavior can help measure quality.

2.1 Dealing with endogenous quality

We now show how unobserved productivity may confound estimates of the cost of quality, and then explain how the cost function can be identified.

Hospital productivity and quality supply Suppose that a hospital chooses its quality Q to maximize its utility. Hospital utility consists of expected profits Π and, potentially, quality:

$$U = \Pi + \gamma Q$$

A hospital is altruistic if $\gamma > 0$ [see, e.g., Newhouse (1970) and Lakdawalla and Philipson (2006)].² Hospital utility may also vary with quality because of its impact on profits:

$$\Pi = PY(P, Q, \mathbf{X}) - C(Y(Q, \mathbf{X}), Q, W, K, A),$$

in which P is the total price of a stay (including a patient's out-of-pocket cost and any third-party reimbursement), and Y is the quantity of stays (demand). It is natural to measure output by hospital stays, because we analyze where patients choose to stay, and hospitals are frequently reimbursed by the stay. For simplicity, the output price is not chosen by the hospital. Demand decreases in this price. An increase in a hospital's quality level may increase its demand ($\partial Y / \partial Q > 0$). All other demand shifters (e.g., quality and prices at other hospitals, and the distance to and characteristics of patients at various market locations) are included in \mathbf{X} .

Costs increase with output and wages W , and may increase with quality. Productivity A also affects costs, with more productive hospitals having lower fixed costs, lower marginal costs, or both. Productivity is assumed, for the sake of simplicity, to be unaffected by hospital quality. This assumption is nevertheless consistent with the view that hospital quality is chosen by boards and managers who can set quality goals and whose potentially heterogeneous effectiveness influences costs.³

In choosing quality, a hospital's marginal utility is:

$$\frac{\partial U}{\partial Q} = \left(P - \frac{\partial C}{\partial Y} \right) \cdot \frac{\partial Y}{\partial Q} - \frac{\partial C}{\partial Q} + \gamma \tag{1}$$

²We assume that the non-distribution constraint on a not-for-profit hospital does not bind. This simplification is consistent with some theory and evidence [Lakdawalla and Philipson (2006); Chakravarty et al. (2006)].

³If this assumption did not hold, a hospital's marginal utility of quality would still have to equal zero at an optimum, conditional on the productivity level induced in that optimum. Thus, quality and productivity could still covary across hospitals (albeit in an unknown direction), and an instrument for quality would still be needed.

The first term is the impact of quality on profits through hospital demand. A hospital's marginal utility also depends on its marginal cost of quality, as well as any "warm glow" from quality supply.

At an optimum, a hospital's quality $Q^*(P, \mathbf{X}, W, K, A, \gamma)$ depends on its productivity:

$$\frac{\partial Q^*}{\partial A} = \left(\frac{\partial^2 C}{\partial Y \partial A} \cdot \frac{\partial Y}{\partial Q} + \frac{\partial^2 C}{\partial Q \partial A} \right) / \frac{\partial^2 U}{\partial Q^2} \quad (2)$$

The second-order condition implies that the denominator of equation 2 is negative. Thus, quality increases with productivity, if and only if the numerator is also negative. This will tend to be the case insofar as productivity lowers the marginal cost of any quality-induced hospital stays, or of quality itself. Evidence suggests that hospital productivity can affect marginal costs. For example, there was substantial variation in nurse-to-patient ratios at California hospitals around the period that we study, and these ratios were not related to quality of care [Donaldson et al. (2001); Donaldson et al. (2005)].

A relationship between productivity and quality may confound estimates of the cost of quality, because researchers cannot fully observe productivity. Figure 1 illustrates the quality-cost relationship at a more and less productive hospital. If the observed data were fit by least squares, the cost of quality would be understated, because the high-quality hospital is also relatively low cost.

Identifying the cost of quality The preceding model of quality supply points to a major threat to identification of the cost function $C(Y, Q, W, K, A)$. Hospital quality may be correlated with a determinant of costs — productivity — that researchers do not observe.

One approach to identifying the cost function is instrumental variables. A valid instrument is correlated with, and therefore informative about, quality. An instrument for quality must not be perfectly correlated with any other determinant of costs; otherwise, the instrument will not contain any information that is specific to the cost of quality. Finally, a valid instrument must be uncorrelated with productivity.

The preceding model of hospital behavior suggests some potential correlates of quality, and thus candidate instruments. In particular, optimal quality $Q^*(P, \mathbf{X}, W, K, A, \gamma)$ is determined by a variety of factors that affect the marginal utility of quality to a hospital.

The demand shifters \mathbf{X} are of primary interest, because we wish to know

what can be learned about hospital costs from consumer behavior. Factors such as patient income may influence the taste for quality, and thus hospital choice. In high-income areas, for example, hospital demand might be relatively responsive to quality.

That is, $\partial Y/\partial Q$ — which we refer to as the "quality responsiveness of hospital demand" — might be relatively large. If so, a hospital's marginal utility of quality, shown in equation 1, would tend to be high. Intuitively, with a large number of patients on the quality margin, an increase in quality would draw many patients, raising profits and, in turn, quality supply.⁴

An alternative instrument based on consumer behavior is quality responsiveness itself. However, $\partial Y/\partial Q$ generally depends on a hospital's actual quality level, which is correlated with productivity under our model. Productivity can be purged by evaluating each hospital's quality responsiveness at a common level \tilde{Q} , i.e., $\partial Y/\partial Q|_{Q=\tilde{Q}}$.⁵ Intuitively, this derivative identifies variation in marginal utility for hospitals that are making decisions about quality from the same "starting point."

We also consider this derivative — which we refer to as "productivity-purged quality responsiveness" — as an instrument for hospital quality. This instrument is parsimonious yet potentially powerful, and has a clear interpretation. A disadvantage is that it must be derived from an analysis of hospital choice. Such an analysis may be needed to obtain an accurate measure of quality, as discussed in section 2.2.

Marginal costs $\partial C/\partial Q$ and $\partial C/\partial Y$ also affect a hospital's marginal utility in equation 1. These derivatives cannot serve on their own as instruments for quality. Estimates of the derivatives would require knowledge of the cost function, which is precisely the identification challenge that we confront.

Marginal costs are affected by wages and, in the short run, the capital stock. Yet these marginal cost shifters generally cannot instrument for quality. In a cross sectional analysis, variation in wages and capital serves to identify their respective impacts on costs. In a longitudinal setting, these cost impacts may be identified by variation in wages and capital within hospitals over time. Variation between hospitals could then lead to differences across hospitals in quality supply, and help to identify the cost of quality.

⁴Patients must be profitable at the margin. We use the choice behavior of pneumonia patients to estimate hospital quality. We also consider heart-attack patients in a sensitivity analysis. Reimbursement for coronary care is relatively generous [Horwitz (2005)].

⁵Gaynor and Vogt (2003) use a similar instrument for hospital demand in their analysis of pricing behavior.

A hospital's marginal utility of quality, and quality supply, are also affected by the output price. In section 4.2, we describe, assess and use instruments based on measures of output and input prices and capital, in addition to demand shifters and productivity-purged quality responsiveness $\partial Y / \partial Q|_{Q=\tilde{Q}}$.

Finally, a hospital's marginal utility of quality is affected by the degree of altruism γ . Altruism and quality supply may be relatively high among hospitals organized on a not-for-profit basis [Lakdawalla and Philipson (2006); Chakravarty et al. (2006)]. Nevertheless, we do not instrument with ownership, due to its potential correlation with productivity. Kessler and McClellan (2002), for example, find that costs are lower (conditional on measured quality of care) in markets with a larger share of for-profit hospitals.

2.2 Measuring quality

One strategy for measuring hospital quality is to specify and estimate a model of quality supply. Gertler and Waldman (1992) used this strategy to study nursing-home quality and its cost. Their analysis did not address unobserved productivity differences, as ours does. We do not estimate quality supply, but use our model to identify instruments. Hence, we are able to test whether hospital quality and productivity are correlated.

Our strategy is to infer hospital quality from the revealed preference of Medicare fee-for-service patients. Patients are assumed to choose the hospitals that maximize their utility.⁶ The utility that patient i expects to obtain from hospital h consists of systematic and idiosyncratic components, denoted \bar{U}_{ih} and ϵ_{ih} :

$$U_{ih} = \bar{U}_{ih} + \epsilon_{ih}$$

We further assume that all potential patients elect to receive care at some hospital and that idiosyncratic utility is distributed i.i.d. Type-1 Extreme Value. Thus, following McFadden (1974), the likelihood that a hospital is a

⁶A large body of evidence suggests that many patients exercise choice over hospitals [including, but not limited to, Luft et al. (1990), Mukamel and Mushlin (1998), Gowrisankaran and Town (1999), Kessler and McClellan (2000), Town and Vistnes (2001), Capps et al. (2003), Gaynor and Vogt (2003), Geweke et al. (2003), Tay (2003) and Ho (2006)]. While hospital choice is influenced by doctors as well as patients [Burns and Wholey (1992)], most patients report that the choice is effectively theirs to make [Wolinksy and Kurz (1984)].

patient's utility-maximizing choice takes the conditional logit form:

$$l_{ih} = e^{\bar{U}_{ih}} / \sum_{h'} e^{\bar{U}_{ih'}}, \quad (3)$$

and a hospital expects the following number of stays, i.e., demand:

$$Y_h \equiv Y(Q_h, \mathbf{X}) = \sum_i l_{ih}$$

We specify systematic utility as:

$$\bar{U}_{ih} = \beta_d(\mathbf{X}_i) D_{ih} + \beta_q(\mathbf{X}_i) Q_h, \quad (4)$$

in which D_{ih} is the distance between a hospital and a patient's home; Q_h is the hospital's "revealed quality"; and β_d and β_q are the tastes for each based on patient characteristics included in \mathbf{X}_i , for example, income.

As noted earlier, out-of-pocket costs do not vary across hospitals for the Medicare fee-for-service patients studied. Hence, price would affect the systematic utility of all choices equally, and so the numerator and denominator of equation 3 equally, and can simply be excluded from utility. Based on similar reasoning, patient characteristics influence choice only through any impact on the tastes for distance and quality.

Revealed quality is an index of all aspects of the hospital experience known to, and valued by, patients.⁷ Insofar as researchers do not observe Q_h , this term is the unobserved product characteristic in discrete-choice models of differentiated-products demand. In such analyses, tastes for the unobserved characteristic are usually treated as constant across consumers. We have not imposed this restriction, but instead allow tastes to vary with patient characteristics.

⁷The unidimensionality of revealed quality is restrictive in the following sense: Suppose that \mathbf{X}_h is a vector of 2 or more hospital characteristics and that $\beta_{\mathbf{x},i}$ is patient i 's tastes for these characteristics. Then $\beta_{X_j,i}/\beta_{X_k,i} = \lambda_{j,k} \forall i, j, k$ implies that $Q_h = \beta_{q,i}^{-1} \mathbf{X}_h \beta_{\mathbf{x},i}$. Aggregation of observed and unobserved hospital characteristics requires that the marginal rate of substitution between any characteristics be identical across patients. Gertler and Waldman (1992) implicitly make this assumption in analyzing the cost of nursing-home quality, which is also unobserved to researchers. (Alternatively, the assumption is that patients value a single nursing-home characteristic.) Relaxing such assumptions may be a worthwhile direction for future research.

Our approach does not preclude the possibility that large volumes lead to good outcomes through learning by doing [Luft et al. (1987); Gaynor et al. (2005); Gowrisankaran et al. (2006)]. Revealed quality embodies the high clinical quality resulting from a large volume, if patients have accurate beliefs about hospital volume / demand.

Because neither tastes nor quality is directly observed by researchers, the taste for revealed quality must be normalized for a reference group of patients. This normalization is arbitrary, yet still allows for an assessment of the cost of quality based on the resulting distribution of Q_h , for example, an improvement from the 25th to the 75th percentile. Intuitively, the normalization does not affect the p th percentile of $\beta_q(\mathbf{X}_i) Q_h$.

A normalization is also required on the level of quality for some hospital. Thus, *differences* in quality levels can be compared over time or across markets, if the normalization on the taste for quality is maintained. That is, the value of quality to the reference group, in relation to the dispersion of idiosyncratic tastes, must be constant.

A thought experiment and some data help clarify how hospital quality is revealed by patient choice behavior. Consider a group of patients within a neighborhood who must choose between a conveniently located hospital and a hospital farther from home. A substantial number of patients are willing to receive care at the distant hospital if and only if its quality is higher than that of the convenient hospital. As table 1 reports, only 40.6% of the pneumonia patients whom we study chose the nearest hospital, while slightly more than a third did not even choose one of the three nearest hospitals.

More formally, given the normalization on $\beta_q(\mathbf{X}_i)$ for members of the reference group, differences in quality between hospitals are identified by the degree to which these patients travel to distant hospitals. Then, given differences in quality levels, $\beta_q(\mathbf{X}_i)$ across all patients is identified by their relative willingness to travel for high quality.⁸

Under this choice model, the responsiveness of a hospital's demand to its own quality level is:

$$\partial Y_h / \partial Q_h = \sum_i \partial l_{ih} / \partial Q_h = \sum_i \beta_q(\mathbf{X}_i) l_{ih} (1 - l_{ih}) \quad (5)$$

As discussed in section 2.1, we use this derivative as an instrument for quality, but purged of the influence of a hospital's actual quality level. In particular, setting quality at all hospitals equal to \tilde{Q} , we have productivity-purged

⁸A decreased distaste for distance would also allow for greater travel to high-quality hospitals. However, in the model, free parameters on *all* observed choice factors (including quality, as revealed by patient behavior) allow not only for flexible estimates of the marginal rates of substitution between factors, but also for greater roles for *each* observed factor in relation to idiosyncratic tastes. Intuitively, free parameters for $\beta_d(\mathbf{X}_i)$ and $\beta_q(\mathbf{X}_i)$ allow for flexible estimates of $\partial l_{ih} / \partial D_{ih}$ and $\partial l_{ih} / \partial Q_h$, as shown in equation 5 for the latter.

quality responsiveness:

$$\begin{aligned} \frac{\partial Y_h}{\partial Q_h} \Big|_{Q=\tilde{Q}} &= \sum_i \beta_q(\mathbf{X}_i) \left(\frac{e^{\beta_d(\mathbf{X}_i)D_{ih} + \beta_q(\mathbf{X}_i)\tilde{Q}}}{\sum_{h'} e^{\beta_d(\mathbf{X}_i)D_{ih'} + \beta_q(\mathbf{X}_i)\tilde{Q}}} \right) \left(1 - \frac{e^{\beta_d(\mathbf{X}_i)D_{ih} + \beta_q(\mathbf{X}_i)\tilde{Q}}}{\sum_{h'} e^{\beta_d(\mathbf{X}_i)D_{ih'} + \beta_q(\mathbf{X}_i)\tilde{Q}}} \right) \\ &= \sum_i \beta_q(\mathbf{X}_i) \left(\frac{e^{\beta_d(\mathbf{X}_i)D_{ih}}}{\sum_{h'} e^{\beta_d(\mathbf{X}_i)D_{ih'}}} \right) \left(1 - \frac{e^{\beta_d(\mathbf{X}_i)D_{ih}}}{\sum_{h'} e^{\beta_d(\mathbf{X}_i)D_{ih'}}} \right) \end{aligned} \quad (6)$$

Heterogeneity in patient / hospital locations and thus D_{ih} , together with heterogeneity in tastes for quality and distance, may lead to variation in the impact of higher quality on hospital demand, and in turn to differences in the marginal utility of quality and, ultimately, quality supply. The variation in equation 6 may be uncorrelated with productivity, as we discuss below. Thus, our approach to measuring hospital quality may help to identify the cost of quality.

3 Hospital Quality

To estimate the revealed quality of hospitals, we analyze patient choice in greater Los Angeles over 2000-2004. A good measure of clinical quality is widely available for California hospitals during this period, making it possible to compare revealed quality to clinical quality. Los Angeles hospitals have been studied extensively, and we carefully define this market.

Our main analyses use revealed quality for pneumonia patients to proxy for quality among all patients. We also consider heart-attack patients in a sensitivity analysis. Hospital choice has been studied for both types of patients [Luft et al. (1990); Geweke et al. (2003); Tay (2003)].

3.1 Empirical approach

Model specification and estimation As we explained in section 2, a rich and well-specified model of hospital choice is central to our strategy for identifying the cost of quality. We allow tastes to vary with an extensive set of patient characteristics motivated by prior studies [see, e.g., Geweke et al. (2003) and Tay (2003)], and individual-level choices are observed. Thus, unobserved heterogeneity is less of a concern in our setting than in others.

We specify tastes for distance and quality as:

$$\beta_j(\mathbf{X}_i) = \beta_j + \beta_{j,75+years}75+years_i + \beta_{j,Female}Female_i \\ + \beta_{j,Black}Black_i + \beta_{j,Income}Income_i + \beta_{j,CDI}CDI_i, \quad j = d, q,$$

in which the variable $75+years_i$ equals one if a patient is at least 75 years old and zero otherwise, and $Female_i$ and $Black_i$ are defined similarly. Income and the Charlson-Deyo index CDI_i are de-meant.

This latter index measures health status based on 19 categories of comorbidities [see, e.g., Sokol et al. (2005)]. Each category is weighted according to risk of one-year mortality; the higher the score, the more severe the co-morbidity burden. Deyo et al. (1992) adapted the original Charlson index to be used based on ICD-9 codes from an administrative claims database, and validated their methodology using Medicare Part A claims data of 27,111 patients who underwent lumbar spine surgery.

The choice model consists of equations 3 and 4, and is estimated by maximum likelihood. In analyzing revealed quality, the Q_h terms are unknown parameters. The number of these parameters is fixed at the number of hospitals in the market; the parameter estimates are consistent in the number of patients, as are estimates of unobserved hospital characteristics in other studies [Town and Vistnes (2001); Gaynor and Vogt (2003); Ho (2006)].⁹ Revealed quality is normalized to 0 at one hospital (Alhambra Hospital), and the taste for quality is normalized to 1 for white males under age 75 with mean income and health status (i.e., $\beta_j = 1$). As in Tay (2003), our main analyses speed up estimation by restricting patient choice sets to the nearest 50 hospitals.

We estimate choice independently for each year studied, so that changes in hospital quality can be explored.

Data and variable construction Our primary data source is discharge abstracts for California hospital patients from the Office of Statewide Health Planning and Development (OSHPD). For each hospital stay, these abstracts identify the hospital from which a patient was discharged. The abstracts also report a variety of patient characteristics, including principal diagnosis;

⁹While unobserved quality interacts with observed patient characteristics in our choice model, the quality estimates remain consistent given the conditional-logit specification [McFadden (1974)].

5-digit residential zip code; age, gender and race; co-morbidities; payer type (e.g., Medicare fee-for-service); and source of admission (e.g., home).

We use reported co-morbidities to construct the Charlson-Deyo index [Quan et al. (2005)]. We use patient zip-code centroids and hospital geo-coordinates to measure the great-circle distance between patients and hospitals [ESRI (2001); California Office of Statewide Health Planning and Development (2006)]. We impute income from the 2000 Census (as described in the appendix.)

To measure clinical quality at hospitals, we use 30-day mortality rates for pneumonia patients, adjusted for patient health risk. OSHPD has estimated these rates for each of the years studied, using methods developed and validated by academic health researchers [Haas et al. (2000)].¹⁰ Pneumonia mortality is a good measure of clinical quality. Death is not uncommon, patients care about this outcome, and mortality is only weakly related to process-of-care quality measures [Werner and Bradlow (2006)]. Pneumonia mortality rates are available in 1 or more years for 89% of the hospitals in our market.

Market definition We define the greater LA hospital market based on the choices of Medicare fee-for-service patients. The definition begins with general acute-care hospitals located within, and chosen by residents of, the 5 counties comprising metro LA. We exclude hospitals in the Ventura and Palm Springs Hospital Referral Regions [Dartmouth Institute for Health Policy and Clinical Practice (2008)], as well as some remote hospitals. The revealed qualities of hospitals at these geographic extremes of Los Angeles were systematic outliers in exploratory analysis. We also exclude hospitals in Kaiser Permanente's integrated delivery system, because access to these facilities by the patients studied may have been constrained. For pneumonia patients from 2000-2004, the market included the 132 hospitals listed in appendix table A1. We consider alternative definitions of the market below.

Patient samples We analyze the hospital choices of Medicare fee-for-service patients who resided in metro LA and were admitted to a greater LA hospital with a principal diagnosis of pneumonia or acute myocardial

¹⁰OSHPD publishes two sets of rates based on alternative risk-adjustment models. We use the rates that account for "Do not resuscitate" orders.

infarction (i.e., heart attack).¹¹ We exclude patients who were not admitted from home, because in other settings (such as nursing homes) hospital choice may have been constrained or influenced by unobserved factors [Geweke et al. (2003)]. We also exclude patients whose age, gender or race was masked for privacy reasons; whose reported zip code could not be matched to our zip-code database; or whose nearest hospital was located outside greater LA. Finally, we exclude patients who were less than 65 years old. Appendix table A2 reports summary statistics for the sample of pneumonia patients in 2002.

3.2 Results

The choice behavior of pneumonia patients points to significant differentiation among hospitals in revealed quality. To assess the extent of differentiation, we compare hospital-level demand given actual quality to counterfactual demand in the absence of any quality differentiation. Demand is predicted based on the choice model, patient tastes, and hospital quality levels. Based on the actual quality estimates, demand is essentially perfectly correlated with observed demand, as table 2 shows (bottom of specification 1) for the year 2002.¹² Demand in the absence of quality differentiation fixes Q_h at \tilde{Q} at all hospitals.¹³ Table 2 shows a correlation of only +0.41 between hospital-level demand given actual quality, and demand in the absence of any quality differentiation. This limited correlation suggests that the patients studied view hospitals in greater Los Angeles as differentiated in quality.

The quality estimates (reported in appendix table A1) have face validity. Our top two hospitals, Cedars Sinai and Hoag Memorial, have consistently been identified in annual market surveys as having the highest quality and image in Los Angeles and Orange County.¹⁴ In the 2002 survey, 33 hospitals

¹¹The ICD-9 code for a pneumonia patient begins with the numbers 481, 482, 485, 486 or 488. The ICD-9 code of heart-attack patients (whom we consider in a sensitivity analysis) begins with 410.

¹²Revealed quality Q_h introduces hospital-level fixed effects into the conditional-logit analysis of each year of discharges. These fixed effects correspond to the reference group of patients whose taste for quality was normalized to 1. Maximum likelihood estimates of the fixed effects equate predicted choice probabilities (on average across patients) with observed market shares, and thus predicted with actual demand.

¹³Counterfactual demand is invariant to the choice of \tilde{Q} , as can be seen from inspection of equation 3.

¹⁴These hospitals have received Consumer Choice Awards from National Research Cor-

in greater LA were never identified as a household's first choice for "best overall quality"; the median ranking of these hospitals on our revealed-quality measure was 94th place out of 129 hospitals in 2002. We are also reassured that the quality estimates are robust to alternative specifications [Romley and Goldman (2008)].¹⁵

We estimate revealed quality levels independently for each year over 2000-2004, and find that quality at greater LA hospitals was stable over time. A regression of the annual quality estimates on hospital indicator variables accounts for 89% of the total variation. Much of the remaining variation is likely attributable to sampling variability. The average standard error of the quality estimates in 2002 is more than half the average standard deviation of hospital quality over time.

Revealed quality seems to embody, and hospital choice to be driven by, aspects of the hospital experience unrelated to clinical quality. Figure 2 shows revealed quality and risk-adjusted pneumonia mortality rates. Higher revealed quality is associated with lower mortality, yet the correlation is modest ($\rho = -0.29$). In addition, we re-analyze hospital choice in 2002 with quality measured by the negative value of mortality. Table 2 shows (bottom of specification 2) a correlation of +0.45 between actual and predicted hospital demand. This limited correlation with actual demand is comparable to that found in the absence of any differentiation in revealed quality.

This contrast between revealed and clinical quality is striking. Some of the contrast may have been attributable to incomplete information among patients about clinical quality at hospitals. Such incomplete information would magnify the role of non-clinical factors in hospital choice. This interpretation is consistent with evidence that measures of clinical quality are not strongly related to patients' overall ratings of their health care [Chang et al. (2006)].

The choice analysis also shows that patients differ in their tastes for quality, and their willingness to travel for it. Table 3 reports that white males

poration (NRC), a healthcare market research firm.

¹⁵We considered alternative definitions of the choice set in the year 2002 (all hospitals within 20 as well as 50 miles of patients). In another specification, we included patients whose nearest hospital was not in greater Los Angeles. Finally, we considered broader and narrower definitions of market geography [all hospitals in the 5 metro LA counties, as well as the LA County hospitals analyzed by Geweke et al. (2003)]. For each alternative, revealed-quality estimates were highly correlated ($\rho > +0.97$) with our benchmark estimates.

under age 75 with mean income and health status would travel an extra 2.88 miles for a hospital with revealed quality at the 75th percentile, rather than the 25th percentile. The same patients, only more affluent (1 standard deviation above mean income), would travel a mile farther for better quality. This greater willingness to travel for quality follows from both a stronger taste for quality ($\hat{\beta}_{q,Income} = 0.021$), and a lesser distaste for distance ($\hat{\beta}_{d,Income} = 0.001$), as shown in table 2.

Altogether, these results indicate that patients define hospital quality as more than just clinical quality. We therefore analyze the cost of hospital quality as revealed by patients. In doing so, we will assess whether heterogeneity in the willingness of patients to travel for quality is a source of variation in the quality levels that hospitals supply, and thus a potential source of identification for the cost of quality.

4 Costs

We analyze hospital costs across all patients, not only those with pneumonia. Our cost model and analyses allow for time-varying as well as time-invariant quality and productivity at hospitals. We consider a standard measure of clinical quality in addition to revealed quality. We can therefore compare the cost of clinical quality to the cost of our quality measure, which reflects all aspects of the hospital experience that patients observe and value.

4.1 Empirical approach

Costs Our model of short-run hospital costs is based on the translog [Christensen et al. (1973)]. This flexible functional form has been applied to a wide variety of firms, including hospitals [e.g., Cowing and Holtmann (1983); Zuckerman et al. (1994); Gaynor and Anderson (1995); Dor and Farley (1996)].

Hospital costs are specified as:

$$\begin{aligned}
\ln C_{ht} = & \alpha_0 + \alpha_Y \ln Y_{ht} + \alpha_Q Q_{ht} + \alpha_W \ln W_{ht} + \alpha_K \ln K_{ht} + \sum_j \alpha_{Z_j} \ln Z_{htj} \\
& + \frac{1}{2} \alpha_{Y^2} (\ln Y_{ht})^2 + \alpha_{Y,Q} \ln Y_{ht} \cdot Q_{ht} + \alpha_{Y,W} \ln Y_{ht} \ln W_{ht} \\
& + \alpha_{Y,K} \ln Y_{ht} \ln K_{ht} + \sum_j \alpha_{Y,Z_j} \ln Y_{ht} \ln Z_{htj} \\
& + \frac{1}{2} \alpha_{Q^2} Q_{ht}^2 + \alpha_{Q,W} Q_{ht} \ln W_{ht} + \alpha_{Q,K} Q_{ht} \ln K_{ht} + \sum_j \alpha_{Q,Z_j} Q_{ht} \ln Z_{htj} \\
& + \frac{1}{2} \alpha_{W^2} (\ln W_{ht})^2 + \alpha_{W,K} W_{ht} \ln K_{ht} + \sum_j \alpha_{W,Z_j} \ln W_{ht} \ln Z_{htj} \quad (7) \\
& + \frac{1}{2} \alpha_{K^2} (\ln K_{ht})^2 + \sum_j \alpha_{K,Z_j} \ln K_{ht} \ln Z_{htj} \\
& + \frac{1}{2} \sum_j \alpha_{Z_j^2} (\ln Z_{htj})^2 + \sum_j \sum_{k < j} \alpha_{Z_j, Z_k} \ln Z_{htj} \ln Z_{htk} \\
& - A_{ht} + \varepsilon_{ht}
\end{aligned}$$

We analyze total inpatient costs at greater Los Angeles hospitals over 2000-2004. Costs are measured by multiplying a hospital's total unadjusted charges in each year of the hospital discharge data, by its cost-to-charge ratio from each year of the "impact files" that defined Medicare reimbursement rates [see, e.g., Athey and Stern (2002) or Picone et al. (2003)]. These ratios reflect the costs of routine care from each hospital's most recent settled cost report to the Centers for Medicare and Medicaid Services [Medicare Payment Advisory Commission (2003a); Centers for Medicare and Medicaid Services (2009)]. Ratios specific to operating and capital costs are summed to obtain total costs.¹⁶

Quantity Y_{ht} is measured by the total number of patient stays in each year of the discharge data.

Quality Q_{ht} refers to either revealed or clinical quality. Revealed quality is measured from hospital-choice analysis. Because the level of revealed quality is normalized (as described in section 2), Q_{ht} is not logged in the model. Thus, conventional economies of scale are undefined for revealed quality. Instead, quality impacts costs in percentage terms. The second-order parameter α_{Q^2} allows this impact to vary as quality varies. Clinical quality at hospitals is measured by the negative value of risk-adjusted pneumonia mortality (as described in section 3.)

¹⁶Costs are also available from financial reports submitted by hospitals to OSHPD. Based on this alternative measure, revealed quality is costly at an average hospital (results available from authors upon request). However, the elasticity of costs with respect to discharges is low in comparison to prior studies [e.g., Carey (2000)]. This discrepancy may be attributable to problems with the quality of the financial data [Gaynor and Vogt (2003)].

We measure input prices W_{ht} using a Paasche wage index calculated relative to the average hospital over 10 job classifications [Gaynor and Vogt (2003)]. Hours worked and total wages were obtained from annual financial reports submitted to OSHPD; the appendix describes how hospital reporting periods are synchronized with calendar years.

Capital K_{ht} is measured by fixed assets net of accumulated depreciation, as reported in quarterly financial reports to OSHPD. We set capital in year t equal to the reported value at the end of the fourth quarter of year $t - 1$.

Additional determinants of costs are included in \mathbf{Z}_{ht} . As is common [e.g., Carey and Burgess, Jr. (1999)], we account for the complexity and relative resource intensity of a hospital’s care, as measured by annual all-payer case-mix indices from OSHPD. We also account for the health status of a hospital’s patients by averaging the Charlson-Deyo index across all discharges [see section 3.1]. Finally, we include a linear time trend that reflects any changes in the average level of revealed quality or other factors (see section 2.2).

Appendix table A3 reports summary statistics for greater LA hospitals. All model covariates are de-meanded in the analysis. Before taking logs, covariates are divided by their means in this table. We subtract the mean of quality (however defined), and set the time trend equal to 0 in 2002. Thus, the model’s first-order terms reflect costs at an average hospital in 2002 (e.g., α_Y measures returns to scale in quantity at such a hospital.)

Productivity With log costs linear in A_{ht} , higher productivity lowers the marginal cost of quality, and also hospital stays. Hence, our model of quality supply would imply that quality is correlated with unobserved productivity. Empirically, we are able to test this implication by comparing costs when quality is treated as exogenous, to costs when endogeneity is addressed.

Productivity is assumed to consist of time-invariant and time-varying components:

$$A_{ht} = A_h + \mathbf{V}_{ht}\boldsymbol{\alpha}_V, \tag{8}$$

in which A_h is the time-invariant component, and \mathbf{V}_{ht} is a vector of time-varying determinants. We use fixed-effects regressions to deal with the time-invariant component of productivity.

\mathbf{V}_{ht} may also affect hospital quality, or even quantity. Olley and Pakes (1996) use a flexible function of investment and capital to control for firm productivity, based on a dynamic investment model. Intuitively, a firm’s

optimal investment policy depends on state variables including productivity, capital and the economic environment. In cases of positive investment, a monotonic policy can be inverted for productivity, and the resulting function substituted for productivity in the empirical model.

In this spirit, we experiment with hospital's prior-year capital and current investment as proxies for the time-varying component of productivity. Investment is reported in quarterly financial reports, and aggregated into an annual flow. Our "Olley-Pakes-style" controls for productivity include logged investment, logged capital, their squares and interaction, all interacted with year-level indicator variables. These time interactions allow investment policy to change with the economic environment.

We also consider the quality instruments discussed in section 2.1. These instruments are described in the next section.

4.2 Results

Our main cost analyses are based on revealed quality. Table 4 shows the results of three fixed-effects regressions of the cost model in equation 7. We first treat hospital quality as time-varying, and address the potential relationship between quality and productivity using instrumental variables and productivity controls. We then consider time-invariant quality, while still allowing for time-varying productivity.

In the first specification in table 4, we use the annual quality estimates from section 3.2, and instrument for all quality-related covariates in the cost model. Productivity-purged quality responsiveness ($\partial Y / \partial Q|_{Q=\tilde{q}}$), its square and its interactions with non-quality covariates (such as case mix) serve as instruments. As the table shows, the linear quality parameter estimate ($\hat{\alpha}_Q$) is positive, but indistinguishable from zero at conventional levels of statistical significance.¹⁷ Likewise, none of the other quality parameters is significant. Statistical power is not strong here: the hypothesis that the model is underidentified cannot be rejected based on a canonical correlations test [Anderson (1951)].

In the second specification, quality is again time-varying, but we use controls for time-varying productivity (as discussed in the preceding subsection) instead of instrumental variables. Table 4 shows that the linear quality pa-

¹⁷We formally account for sampling variability in the quality estimates when we quantify the cost of improved quality in the next section.

parameter is now estimated to be positive ($\hat{\alpha}_Q = 0.112$), and highly significant. In addition, the productivity controls are jointly significant ($p < 0.001$). There is also strong evidence of heterogeneity in hospital-cost fixed effects ($p < 0.001$ for the hypothesis that all fixed effects equal zero). This evidence is consistent with persistent differences across hospitals in productivity. Hausman tests strongly reject the models without productivity controls or fixed effects ($p < 0.001$ in each case).

Yet fixed-effects regression can be biased if some covariates are more serially correlated than is any measurement error in them [Griliches and Hausman (1986)]. As noted in section 3.2, revealed quality is stable over time, and much of the variation that does exist is likely attributable to sampling variability.

Thus, in the third specification, we analyze costs with revealed quality treated as time-invariant ($Q_{ht} = Q_h \forall h, t$). To do so, we average each hospital’s annual quality estimates (see appendix table A1). This specification again includes controls for time-varying productivity. This is our preferred specification in the subsequent analyses of the cost of quality improvement.¹⁸

Under this approach, the results are reasonable on their face. As Table 4 shows for specification 3, constant returns to scale in quantity cannot be rejected, while a more resource-intensive case mix increases a hospital’s costs (though $\hat{\alpha}_{CMI}$ is imprecisely estimated). We also find that revealed quality is costlier when patients have greater health problems according to the Charlson-Deyo index ($\hat{\alpha}_{Q,CDI} = 0.576$).

When quality is time-invariant, the fixed-effects regression of the cost model in equation 7 does not identify quality parameters that do not involve interactions with time-varying covariates. In particular, α_Q and α_{Q^2} in equation 7 are not identified. Uninteracted quality Q_h is subsumed, with time-invariant productivity A_h , into the fixed effects for hospital costs. Specifically, denoting the fixed effect by φ_h , the cost model implies:

$$\varphi_h = \alpha_0 + \alpha_Q Q_h + \frac{1}{2} \alpha_{Q^2} Q_h^2 - A_h \tag{9}$$

To estimate the remaining unknown parameters, we regress unbiased estimates of the fixed effects from the cost regression on quality as estimated in the choice analysis [Wooldridge (2002)]. The results appear in table 5.

¹⁸As with the prior specification, the productivity controls are highly significant, and there is strong evidence of heterogeneity in hospital-cost fixed effects. These fixed effects now embody time-invariant quality.

We first instrument for quality with productivity-purged quality responsiveness and its square. A model with both quality and its square is underidentified, based on a canonical correlations test (specification 1 in table 5). Similarly, Gertler and Waldman (1992) could not identify the quadratic quality parameter in analyzing the cost of latent quality in nursing homes. When we impose $\alpha_{Q^2} = 0$, the instruments have reasonable power for linear quality, with a first-stage F statistic of 12.6 (specification 2). Moreover, revealed quality increases with $\partial Y / \partial Q|_{Q=\tilde{Q}}$, as our model of quality supply predicts.

In the corresponding IV regression, the table shows that the linear quality parameter estimate is significant, positive, and larger than when revealed quality is treated as time-varying (0.240 vs. 0.112). The results are quite similar if squared quality responsiveness is replaced as an instrument by $\partial^2 Y / \partial Q^2|_{Q=\tilde{Q}}$ (not shown in table); this latter variable affects the rate at which hospital utility diminishes with quality, and thus quality supply.

Next, we consider alternative instruments also related to hospital demand. Given that hospitals compete in localized markets, we use local demand shifters. These include the number of pneumonia patients in the choice analysis who resided within 2.5 miles of each hospital (including patients who chose other hospitals), and the average value among these patients of the characteristics included in the choice model (e.g., income), averaged over 2000-2004. The former affects the number of patients on the quality margin, while the latter were found in section 3.2 to affect patient willingness to travel for quality. The results are quite similar, as specification 3 of table 5 shows.

Local demand shifters do not require the estimation of a choice model. However, productivity-purged quality responsiveness may yield sharper identification in some applications. $\partial Y / \partial Q|_{Q=\tilde{Q}}$ measures the response of all patients, dealing parsimoniously yet precisely with the geography of the market. Indeed, the bottom of table 5 shows that quality responsiveness is more powerful than local demand shifters in explaining actual quality, with a first-stage F statistic of only 3.7 for the latter. We do find that a hospital's revealed quality increases with the number and income of patients residing nearby (not shown in table).

For either set of demand-based instruments, Table 5 shows that Hausman tests can reject the consistency of ordinary least squares. The table further shows that $\hat{\alpha}_Q$ remains positive but is much smaller and insignificant with OLS (specification 4). This negative bias is a consequence of a negative correlation between quality and the disturbance in equation 9, or $-A_h$. This

component of the hospital cost fixed effect is low when productivity is high. Thus, the substantial negative bias in $\hat{\alpha}_Q$ under OLS results from a positive correlation between revealed quality and productivity.¹⁹ Figure 3 shows this relationship (with productivity estimated by the residuals from specification 2). Altogether, the results suggest that hospitals supply quality based on both their demand responsiveness and their productivity.

Instruments based on hospital demand must be uncorrelated with hospital productivity in order to be valid. One might worry that productivity is related to where patients choose to live through its influence on hospital quality. Prior studies of the hospital industry have maintained that patient locations are uncorrelated with clinical quality at hospitals [e.g., Gowrisankaran and Town (1999); Kessler and McClellan (2000)]. We do not need to make such an assumption, because $\partial Y / \partial Q|_{Q=\tilde{Q}}$ is independent of our revealed-quality measure. One might also worry that high-income patients tend to live in high-cost areas.²⁰ We consider the robustness of our identification, and additional instruments, in the next subsection.

Cost of revealed quality improvement We now analyze the cost of improvement in revealed quality. In particular, we quantify the percentage change in costs given an interquartile increase in quality at a hospital with otherwise average characteristics in 2002 (see appendix for derivation). As in our preferred specification, revealed quality is measured (unless otherwise stated) by the average of the annual estimates for pneumonia patients.

Conventional standard errors do not account for sampling variability in the quality estimates [Murphy and Topel (1985)]. We therefore compute bootstrapped standard errors. To do so, we draw 500 patient samples with replacement from the initial hospital-choice sample. For each sample, we re-estimate the choice model, then the cost model, and finally the regression of cost fixed effects on linear quality. The standard deviation of the resulting cost estimates is used to estimate the standard error of the initial estimate.²¹

¹⁹If quality were unobserved, demand shifters could be used to test for bias in a cost function due to correlation between unobserved quality and observed covariates such as quantity. [Braeutigam and Pauly (1986)]. We re-estimate the preferred cost model with all quality terms excluded, and local demand shifters (described below) included. In a regression of the hospital-cost fixed effects, these time-invariant demand shifters are jointly statistically significant at a 10% level, consistent with endogenous quality.

²⁰We thank Robert Town for raising this issue.

²¹Bootstrapped errors were similar for 100 or 500 draws; we report the latter. To speed

Table 6 reports the results. Based on the productivity-purged quality responsiveness IV, the interquartile increase in revealed quality is estimated to increase costs by 48.2% at an otherwise average hospital in 2002, with a bootstrapped standard error of 16.2%. Using local demand shifters as instruments, this quality improvement increases costs by 51.2% (s.e. 14.8%).

The cost of quality is strongly biased toward when we ignore the preceding evidence that more productive (i.e., relatively low-cost) hospitals tend to supply higher quality. Based on OLS, cost appears to increase by an insignificant 10.2% (s.e. 13.2%). This finding suggests that analyses of costs or production in differentiated-products industries should address the potential relationship between a firm’s productivity and the characteristics of its product(s).

We now assess the robustness of the IV results.

Heart-attack patients: Pneumonia patients need not be representative of patients in general. In 2002, revealed quality based on heart-attack patients is strongly yet imperfectly correlated ($\rho = +0.80$) with revealed quality for pneumonia patients. Based on the heart-attack choice analysis, the estimated cost of an interquartile improvement in revealed quality is 26.0% (s.e. 4.7%). This lower cost is consistent with measurement error due to limited hospital choice among relatively acute patients. Such patients may also place greater emphasis on clinical quality, whose cost — which we analyze in the next subsection — may be relatively low.

IV purged of income: The cost of hospital quality could be biased upward if high-income patients tend to live in areas with high unobserved costs (i.e., low measured productivity), insofar as variation in hospital demand is driven by income-related variation in willingness to travel for quality. Again analyzing pneumonia patients, we exclude income from the set of local demand shifters. The estimated cost of quality improvement is almost unchanged (+50.4% vs. +51.2%).

Capital and input and output prices as instruments: As alternative instruments, we use the capital stock and hospital-level wage index W_{ht} as marginal cost shifters and the Medicare area wage index as a proxy for the output price.²² Each is averaged over 2000-2004 so that quality differences

up bootstrapping, we use revealed quality estimates for 2002 only. This simplification is likely to overstate standard errors, because averaging over time smooths the sampling variability of the quality estimates.

²²Medicare reimbursement for Medicare discharges depends on an area-level wage index, and also the hospital’s case and DRG mix, treatment of low-income patients, and presence

across hospitals are identified by variation between hospitals in the instruments, as discussed in section 2.1. Costs now increase by 56.3% with an interquartile quality improvement; this is similar to the prior results, but less precisely estimated (s.e. 24.7%).

Quality responsiveness, capital and prices as instruments: Next, we consider both the prior instrument set and productivity-purged quality responsiveness and its square. This overidentified model cannot be rejected ($p = 0.38$). The cost of quality improvement is now 51.6% (s.e. 17.7%).

Seismic ratings included in time-varying productivity: In controlling for time-varying productivity, we consider another potential determinant of hospital investment. After the 1994 Northridge earthquake, California strengthened its hospital safety requirements. Hospitals were required to evaluate and rate their buildings for seismic performance, and to submit the ratings to the state by 2001 [California Office of Statewide Health Planning and Development (2001)]. We interact the baseline productivity controls with the proportion of hospital buildings rated compliant with structural seismic safety standards. The cost of improved quality is higher under this specification (+69.6% vs. +48.2%), and so is the standard error (23.5% vs. 16.2%).

Clinical quality We now assess the cost of clinical quality at hospitals. We again estimate the fixed-effects cost model with controls for time-varying productivity.

The discussion here focuses on the specification in which annual risk-adjusted pneumonia mortality rates are averaged, and clinical quality is thus time-invariant. (The cost of clinical quality is modest when annual mortality is analyzed; see the complete cost-regression results in appendix table A4). As before, we regress the hospital-cost fixed effects on quality.

We instrument for clinical quality using productivity-purged quality responsiveness and its square. These instruments are now derived from the choice model with quality measured by pneumonia mortality (table 2, specification 2). We again cannot identify the quadratic quality parameter (as

of graduate medical education [Medicare Payment Advisory Commission (2008)]. This index can increase output prices more (or less) than commensurately with actual wages. Indeed, the Medicare index may overcompensate hospitals in high-cost areas such as Los Angeles [Medicare Payment Advisory Commission (2003b)]. We do not consider the other sources of variation in Medicare reimbursement. The associated hospital characteristics may be aspects of hospital quality [see, e.g., Tay (2003)], or driven by quality and thus productivity.

shown in appendix table A5), and therefore impose $\alpha_{Q^2} = 0$. In the corresponding IV regression, the hypothesis that $\alpha_Q = 0$ cannot be rejected.²³

Clinical quality is costly in an OLS regression, and a Hausman test cannot reject the consistency of OLS. Based on these results, the cost of an interquartile reduction in pneumonia mortality (from 14.0% to 10.7%) would increase costs at an otherwise average hospital by only 12.6% (s.e. 4.9%). In the previous subsection we found that an interquartile improvement in revealed quality would increase costs by 48.2%.

These results suggest that clinical quality is unrelated to productivity, and that the cost of clinical quality at hospitals may be modest. Prior research does not contradict the latter conclusion. Indeed, Picone et al. (2003) find that a 1-standard-deviation increase in hospital spending leads to only a 0.01-s.d. decrease in 6-month mortality among Medicare beneficiaries hospitalized with hip fracture, stroke, coronary heart disease or congestive heart failure. Carey and Burgess, Jr. (1999) find that higher costs are associated with higher, not lower, mortality and readmission rates at veterans' hospitals.

5 Conclusion

Given concerns about the quality of U.S. health care, this paper has investigated the cost of quality in hospitals, and dealt with two issues.

First, from the patient point of view, quality embodies all aspects of the hospital experience that patients value, potentially including amenities (such as good food, attentive staff or pleasant surroundings) in addition to clinical quality. We inferred the quality of hospitals in greater Los Angeles from the revealed preference of patients.

We found that "revealed quality" differentiates these hospitals. Furthermore, revealed quality was only moderately correlated with risk-adjusted mortality rates, suggesting that patients do care about non-clinical aspects of the hospital experience such as amenities [see also Goldman and Romley (2008)].

The second issue is that quality can appear to be cheap, if unobservably low-cost hospitals choose to supply high quality. To identify instruments for quality, we again appealed to consumer behavior. In particular, we used correlates of the impact of a hospital's quality level on patient choice and

²³Costless quality also cannot be rejected when we instrument with local demand shifters.

hospital demand. We found that revealed quality was higher at hospitals whose demand was more responsive to quality, consistent with competition in revealed quality.

Based on our quality responsiveness instrument, an interquartile improvement in revealed quality would increase costs by 48.2% at an otherwise average hospital. As we suspected, revealed quality was positively correlated with productivity. If the productivity-quality relationship had been ignored, the cost of an improvement in revealed quality would have been substantially understated (only 10.2%), and statistically indistinguishable from zero.

We also considered the cost of hospital quality based on clinical quality, as measured by risk-adjusted pneumonia mortality. The cost of an interquartile improvement in mortality was modest in comparison to the cost of revealed quality (12.6% vs. 48.2%). We were unable to reject the hypothesis that clinical quality was uncorrelated with productivity.

These findings should be interpreted with some caution. Our analysis focused on a relatively large group of patients who arguably exercised meaningful choice among hospitals, namely, Medicare fee-for-service patients with pneumonia. Yet these patients may not be representative in their preferences toward (or awareness of) various aspects of hospital quality. Nevertheless, our findings do suggest that hospitals compete for patients based on costly non-clinical aspects of the hospital experience.

The high cost of hospital quality implicates concerns about U.S. health spending [Goldman et al. (forthcoming)]. Spending on hospital patients varies widely within and across markets [Dartmouth Institute for Health Policy and Clinical Practice (2008)]. Efforts to contain hospital costs might focus on non-clinical spending.

Productivity differences would be relevant to cost containment. A given reduction in revealed quality could yield large savings from lower-quality hospitals, rather than higher-quality hospitals, given the relatively high costs of the former. The link between productivity and quality supply further implies that equalization of spending across hospitals would result in unequal quality for patients. To better understand the impact of productivity on quality and costs, quality supply must be analyzed. This is a worthwhile direction for further research.

Despite concerns about U.S. health spending, the high cost of hospital quality could be "worth it" if the benefits to patients are also large. Understanding the value of hospital quality is also a worthwhile direction for further research.

References

- Anderson, T. W. (1951). “Estimating Linear Restrictions on Regression Coefficients for Multivariate Normal Distributions.” *The Annals of Mathematical Statistics* 22(3):327–351.
- Athey, S., and S. Stern (2002). “The Impact of Information Technology on Emergency Health Care Outcomes.” *The RAND Journal of Economics* 33(3):399–432.
- Braeutigam, R. R., and M. V. Pauly (1986). “Cost Function Estimation and Quality Bias: The Regulated Automobile Insurance Industry.” *RAND Journal of Economics* 17(4):606–617.
- Burns, L. R., and D. R. Wholey (1992). “The Impact of Physician Characteristics in Conditional Choice Models for Hospital Care.” *Journal of Health Economics* 11(1):43–62.
- California Office of Statewide Health Planning and Development (2001). “Summary of Hospital Seismic Performance Ratings.” .
- California Office of Statewide Health Planning and Development (2006). “California Licensed Healthcare Facilities.” <http://gis.ca.gov/catalog/BrowseRecord.epl?id=29697> .
- Capps, C., D. Dranove, and M. Satterthwaite (2003). “Competition and Market Power in Option Demand Markets.” *RAND Journal of Economics* 34(4):737–763.
- Carey, K. (2000). “A Panel Data Design for Estimation of Hospital Cost Functions.” *Review of Economics and Statistics* 79(3):443–453.
- Carey, K., and J. F. Burgess, Jr. (1999). “On Measuring the Hospital Cost/Quality Trade-Off.” *Health Economics* 8(6):509–520.
- Centers for Medicare and Medicaid Services (2009). “The Provider Reimbursement Manual.” <http://www.cms.hhs.gov/manuals/PBM/list.asp> .
- Chakravarty, S., et al. (2006). “Does the Profit Motive Make Jack Nimble? Ownership Form and the Evolution of the U.S. Hospital Industry.” *Health Economics* 15(4):345–361.

- Chang, J. T., et al. (2006). "Patients' Global Ratings of Their Health Care Are Not Associated with the Technical Quality of Their Care." *Annals of Internal Medicine* 144(9):665–672.
- Christensen, L. T., D. W. Jorgenson, and L. J. Lau (1973). "Transcendental Logarithmic Production Frontiers." *Review of Economics and Statistics* 55(1):28–45.
- Cowing, T. G., and A. G. Holtmann (1983). "Multiproduct Short-Run Hospital Cost Functions: Empirical Evidence and Policy Implications from Cross-Section Data." *Southern Economic Journal* 49(3):637–653.
- Cutler, D. M., M. B. McClellan, and J. P. Newhouse (1998). "The Costs and Benefits of Intensive Treatment for Cardiovascular Disease." *Working Paper 6514*. Cambridge, MA: National Bureau of Economic Research.
- Dartmouth Institute for Health Policy and Clinical Practice (2008). *Tracking the Care of Patients with Severe Chronic Illness*.
- Deyo, R. A., D. C. Cherkin, and M. A. Ciol (1992). "Adapting a Clinical comorbidity Index for Use with ICD-9-CMA administrative Databases." *J Clin Epidemiol* 45(3):613–619.
- Donaldson, N., et al. (2005). "Impact of California's Licensed Nurse-Patient Ratios on Unit-Level Nurse Staffing and Patient Outcomes." *Politics, Policy and Nursing Practice* 6(3):198–210.
- Donaldson, N. E., D. S. Brown, and C. E. Aydin (2001). "Nurse Staffing in California Hospitals 1998-2000: Findings from the California Nursing Outcome Coalition Database Project." *Policy Politics Nursing Practice* 2(1):20–29.
- Dor, A., and D. E. Farley (1996). "Payment Source and the Cost of Hospital Care: Evidence from a Multiproduct Cost Function with Multiple Payers." *Journal of Health Economics* 15(1):1–21.
- ESRI (2001). "ESRI Data and Maps 2000." *Technical report*. Redlands, CA.
- Gaynor, M., and G. F. Anderson (1995). "Uncertain Demand, the Structure of Hospital Costs, and the Cost of Empty Beds." *Journal of Health Economics* 14(3):291–317.

- Gaynor, M., H. Seider, and W. B. Vogt (2005). “The Volume-Outcome Effect, Scale Economies, and Learning-by-Doing.” *American Economic Review* 95(2):243–247.
- Gaynor, M., and W. B. Vogt (2003). “Competition among Hospitals.” *RAND Journal of Economics* 34(4):764–785.
- Gertler, P. J., and D. M. Waldman (1992). “Quality-Adjusted Cost Functions and Policy Evaluation in the Nursing Home Industry.” *Journal of Political Economy* 10(6):1232–1256.
- Geweke, J., G. Gowrisankaran, and R. J. Town (2003). “Bayesian Inference for Hospital Quality in a Selection Model.” *Econometrica* 71(4):1215–1238.
- Goldman, D., and J. A. Romley (2008). “Hospitals As Hotels: The Role of Patient Amenities in Hospital Demand.” *Working Paper 14619*. Cambridge, MA: National Bureau of Economic Research.
- Goldman, D. P., M. Vaiana, and J. A. Romley (forthcoming). “The Emerging Importance of Amenities in Hospital Care.” *New England Journal of Medicine* .
- Gowrisankaran, G., V. Ho, and R. J. Town (2006). “Causality, Learning and Forgetting in Surgery.” Stanford University.
- Gowrisankaran, G., and R. J. Town (1999). “Estimating the Quality of Care in Hospitals Using Instrumental Variables.” *Journal of Health Economics* 18(4):747–767.
- Griliches, Z., and J. A. Hausman (1986). “Errors in Variables in Panel Data.” *Journal of Econometrics* 31(1):93–118.
- Haas, J., et al. (2000). “Community-Acquired Pneumonia 1996: Model Development and Validation.” *Technical report*. California Office of Statewide Health Planning and Development.
- Harris, J. E. (1977). “The Internal Organization of Hospitals: Some Economic Implications.” *Bell Journal of Economics* 8(2):467–482.
- Hartman, M., et al. (2010). “Health Spending Growth At A Historic Low In 2008.” *Health Aff* 29(1):147–155.

- Ho, K. (2006). “The Welfare Effects of Restricted Hospital Choice in the US Medical Care Market.” *Journal of Applied Econometrics* 21(7):1039–1079.
- Horwitz, J. R. (2005). “Making Profits and Providing Care: Comparing Non-profit, For-Profit, and Government Hospitals.” *Health Affairs* 24(3):790–801.
- Institute of Medicine (2001). *Crossing the Quality Chasm*. Washington, DC: National Academies Press.
- Kessler, D. P., and M. B. McClellan (2000). “Is Hospital Competition Socially Wasteful?” *Quarterly Journal of Economics* 115(2):577–615.
- Kessler, D. P., and M. B. McClellan (2002). “The Effects of Hospital Ownership on Medical Productivity.” *RAND Journal of Economics* 33(3):488–506.
- Lakdawalla, D., and T. Philipson (2006). “The Nonprofit Sector and Industry Performance.” *Journal of Public Economics* 90(8-9):1681–1698.
- Luft, H. S., S. S. Hunt, and S. C. Maerki (1987). “The Volume-Outcome Relationship: Practice-Makes-Perfect Or Selective Referral Patterns?” *Health Services Research* 22(2):157–182.
- Luft, H. S., et al. (1990). “Does Quality Influence Choice of Hospital?” *Journal of the American Medical Association* 263(21):2899–2906.
- Marschak, J., and W. H. Andrews, Jr. (1944). “Random Simultaneous Equations and the Theory of Production.” *Econometrica* 12(3/4):143–205.
- McFadden, D. (1974). “Conditional Logit Analysis of Qualitative Choice Behavior.” *Frontiers in Econometrics*. P. Zaremba, ed. New York: Academic Press. 105–142.
- Medicare Payment Advisory Commission (2003a). “Report to the Congress: Medicare Payment Policy.” .
- Medicare Payment Advisory Commission (2003b). “Report to the Congress: Variation and Innovation in Medicare.” .
- Medicare Payment Advisory Commission (2008). “Hospital Acute Inpatient Services Payment System.” .

- Mukamel, D. B., and A. I. Mushlin (1998). “Quality of Care Makes a Difference: An Analysis of Market Share and Price Changes after Publication of the New York State Cardiac Mortality Report Cards.” *Medical Care* 36(7):945–954.
- Murphy, K. M., and R. H. Topel (1985). “Estimation and Inference in Two-Step Econometric Models.” *Journal of Business and Economic Statistics* 3(4):370–379.
- Nerlove, M. (1965). *Estimation and Identification of Cobb-Douglas Production Functions*. Chicago, IL: Rand McNally.
- Newhouse, J. P. (1970). “Toward a Theory of Nonprofit Institutions: An Economic Model of a Hospital.” *American Economic Review* 60(1):64–74.
- Newhouse, J. P. (1994). “Frontier Estimation: How Useful a Tool for Health Economics?” *Journal of Health Economics* 13(3):317–322.
- Olley, G. S., and A. Pakes (1996). “The Dynamics of Productivity in the Telecommunications Equipment Industry.” *Econometrica* 64(6):1263–1297.
- Picone, G. A., et al. (2003). “Does Higher Hospital Cost Imply Higher Quality of Care?” *Review of Economics and Statistics* 85(1):51–62.
- Quan, H., et al. (2005). “Coding Algorithms for Defining Comorbidities in ICD-9-CM and ICD-10 Administrative Data.” *Medical Care* 43(11):1130–1139.
- Romley, J. A., and D. Goldman (2008). “How Costly Is Hospital Quality? A Revealed-Preference Approach.” *Working Paper 13730*. Cambridge, MA: National Bureau of Economic Research.
- Skinner, J. S., D. O. Staiger, and E. S. Fisher (2006). “Is Technological Change in Medicine Always Worth It? The Case of Acute Myocardial Infarction.” *Health Affairs* 25(2):w34–w47.
- Sokol, M. C., et al. (2005). “Impact of Medication Adherence on Hospitalization Risk and Healthcare Cost.” *Medical Care* 43:521–530.
- Stigler, G. J. (1976). “The Xistence of X-Efficiency.” *American Economic Review* 66(1):213–216.

- Tay, A. (2003). “Assessing Competition in Hospital-Care Markets: The Importance of Accounting for Quality Differentiation.” *RAND Journal of Economics* 34(4):786–814.
- Thomadsen, R. (2005). “The Effect of Ownership Structure on Prices in Geographically Differentiated Industries.” *RAND Journal of Economics* 36(4):908–929.
- Town, R., and G. Vistnes (2001). “Hospital Competition in HMO Networks.” *Journal of Health Economics* 20(5):733–753.
- Van Biesebroeck, J. (2007). “Robustness of Productivity Estimates.” *Journal of Industrial Economics* 55(3):529–569.
- Werner, R. M., and E. T. Bradlow (2006). “Relationship between Medicare’s Hospital Compare Performance Measures and Mortality Rates.” *Journal of the American Medical Association* 296(22):2694–2702.
- Wolinsky, F. D., and R. S. Kurz (1984). “How the Public Chooses and Views Hospitals.” *Hospital and Health Services Administration* 29(6):58–67.
- Wooldridge, J. M. (2002). *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT Press.
- Zuckerman, S., J. Hadley, and L. Iezzoni (1994). “Measuring Hospital Efficiency with Frontier Cost Functions.” *Journal of Health Economics* 13(3):255–280.

6 Appendix

6.1 Patient Income

Our approach to imputing patient income is motivated by Geweke et al. (2003). We first matched the five-digit zip code of a patient’s home to the five-digit Zip Code Tabulation Area (ZCTA) defined by the Census to approximate U.S. Postal Service zip codes. Where there was no match, we matched the patient to the ZCTA whose centroid was nearest to the centroid of her USPS zip code. We then estimated average income among black and non-black households headed by persons aged 65-74 and 75 or older

within the ZCTA. The Census reported the number of households within income intervals (e.g., \$35,000 to \$39,999), and we used the midpoint of each bounded interval (and a value of \$280,000 for the unbounded highest-income interval) to compute an average. Where there were no black households within a ZCTA, we used average income among all racial groups.

6.2 Hospital Wages

We measured hospital-level wages using the annual financial reports submitted to the California Office of Statewide Health Planning and Development. Our analysis of hospital costs is based on calendar years, while the financial reports are for reporting periods chosen by each hospital. These reporting periods do not always end on December 31, or even correspond to a full year.

We constructed calendar-year wages for each job classification (e.g., registered nurses) from the financial reports. Where a report spanned multiple calendar years, we apportioned labor hours and total wages to each year, according to the year’s share of total days within the reporting period. Where there were multiple apportioned reports for a calendar year, we aggregated across reports. Average wages were then obtained by dividing total wages by labor hours within calendar years.

6.3 Cost of Quality Improvement

We estimated the costs of an improvement in quality at a hospital with otherwise average characteristics. The resulting estimates are invariant to normalizations on the level and scale of revealed quality. Based on equation 7, the percentage impact of a marginal increase in quality on costs is:

$$100 \left\{ \alpha_Q + \alpha_{Q^2} Q_{ht} + \alpha_{Y,Q} \ln Y_{ht} + \alpha_{Q,W} \ln W_{ht} + \alpha_{Q,K} \ln K_{ht} + \sum_j \alpha_{Q,Z_j} \ln Z_{htj} \right\}$$

All covariates other than time have been de-meanded, and thus equal 0 for a hospital with average characteristics; time is defined to equal 0 in 2002. Thus, the marginal cost is $\alpha_Q + \alpha_{Q^2} Q_{ht}$ at a hospital with otherwise average characteristics in 2002. For the discrete quality change considered, the cost in percentage terms is:

$$100 \left\{ \exp \left[\alpha_Q (Q_{75} - Q_{25}) + \frac{1}{2} \alpha_{Q^2} (Q_{75}^2 - Q_{25}^2) \right] - 1 \right\},$$

in which Q_p is the p th quality percentile.

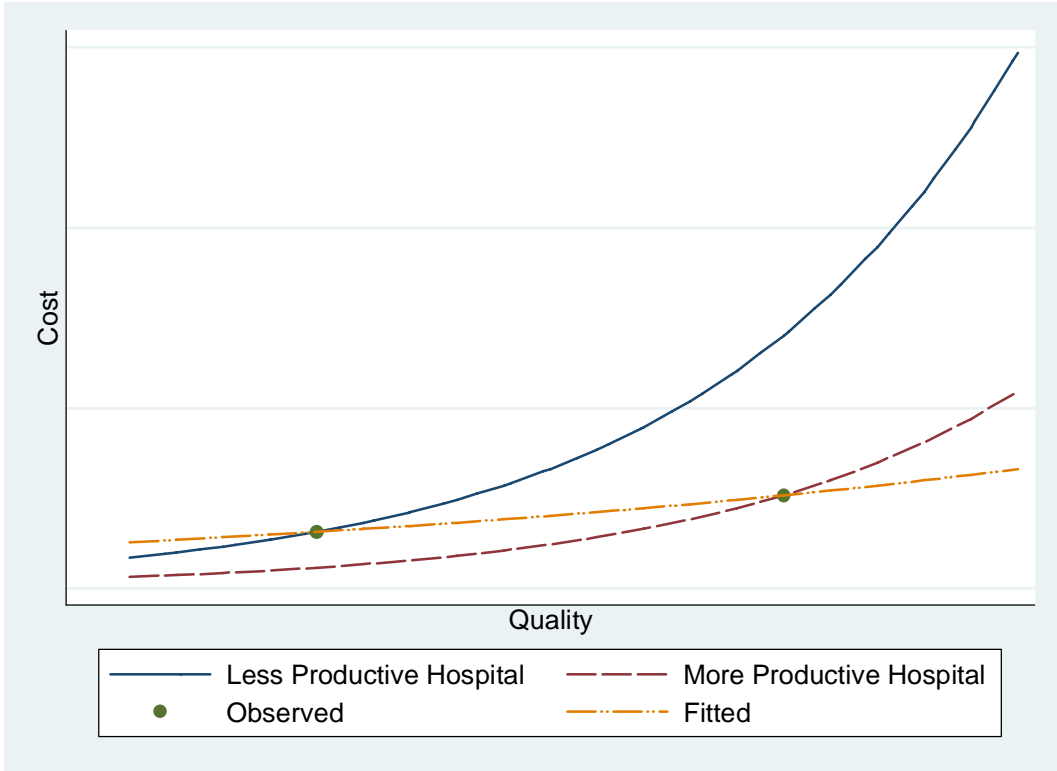


Figure 1:
**Least squares understates cost of quality if
more productive hospital supplies higher quality**

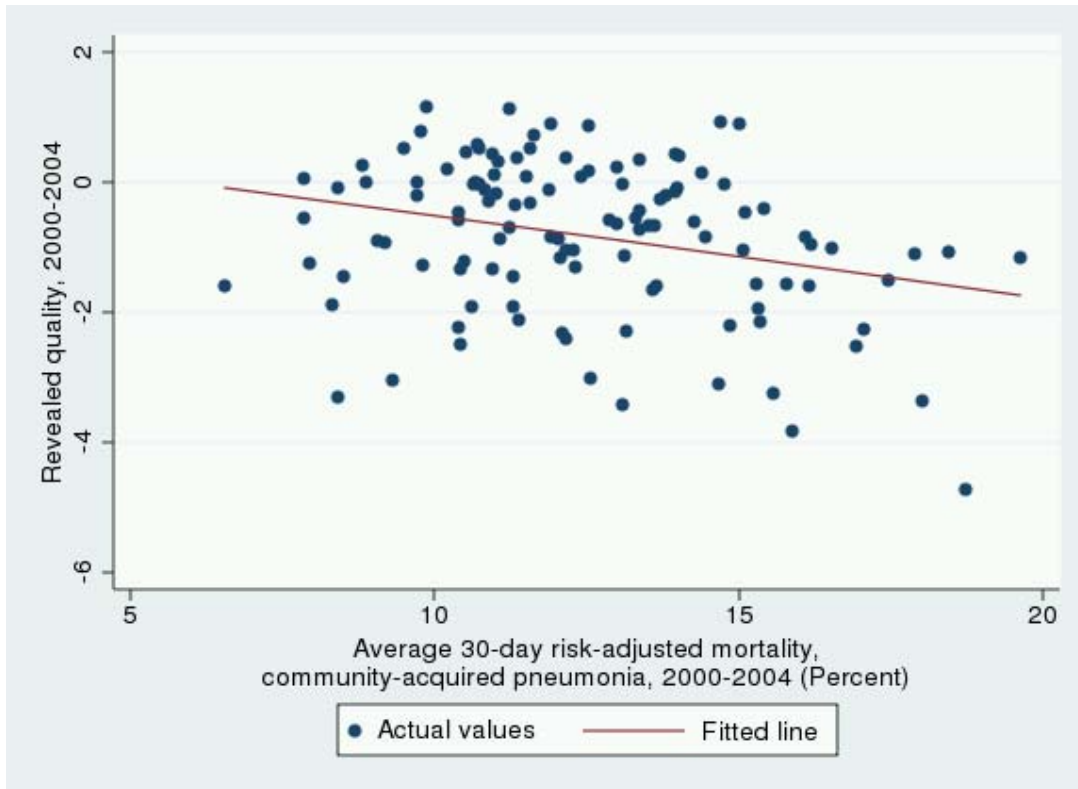


Figure 2:
Revealed quality versus clinical quality among hospitals in greater LA

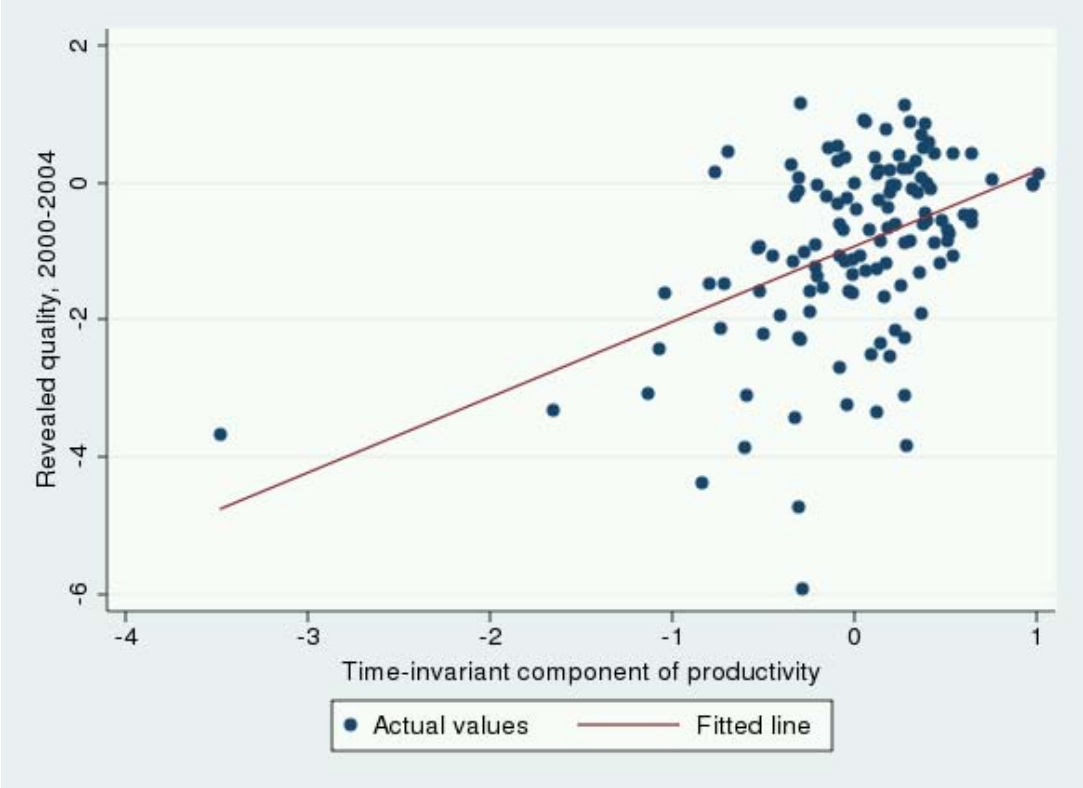


Figure 3:
Productivity and revealed quality among hospitals in greater LA

Table 1: Distance from Patient's Home and Hospital Choice	
Mean distance to nearest hospital (miles)	1.2
Mean distance to chosen hospital	2.8
Nearest hospital chosen	40.6%
2nd nearest hospital chosen	15.1%
3rd nearest hospital chosen	9.5%
Any other hospital chosen	34.8%

Note: Based on 2002 pneumonia patient sample.

Table 2: Results of Analysis of Hospital Choice in 2002 Based on Alternative Definitions of Quality		
<i>Specification</i>		
Number	1	2
Quality definition	Revealed quality	Clinical quality
<i>Taste parameter estimate (Standard error)</i>		
Distance, in miles	-0.594*** (0.013)	-0.540*** (0.012)
Distance*75+ years old	-0.072*** (0.013)	-0.090*** (0.012)
Distance*Female	0.024** (0.012)	0.024** (0.011)
Distance*Black	-0.069*** (0.025)	-0.032 (0.023)
Distance*Income (\$000, demeaned)	0.001*** (0.000)	-0.001** (0.000)
Distance*Charlson-Deyo index (demeaned)	0.001 (0.003)	0.002 (0.003)
Quality	1.000 (—)	0.084*** (0.013)
Quality*75+ years old	0.339*** (0.052)	0.002 (0.011)
Quality*Female	-0.023 (0.037)	-0.036*** (0.013)
Quality*Black	-0.162** (0.069)	-0.119*** (0.022)
Quality*Income (\$000, demeaned)	0.021*** (0.002)	0.000 (0.000)
Quality*Charlson-Deyo index (demeaned)	0.032*** (0.010)	0.015*** (0.003)
<i>Other statistics</i>		
Number of patients	9008	8668
Number of hospitals	129	116
Log likelihood	-16870.56	-18547.5
Correlation of observed and predicted hospital demand	1.00	0.446
Correlation given uniform quality	0.41	—

Notes: Specification 1 treats revealed quality as a parameter to be estimated for each hospital; these parameter estimates are reported in table A2. Coefficient on uninteracted revealed quality is normalized as discussed in sections 2.2 and 3.1. Clinical quality is the negative value of the risk-adjusted 30-day mortality rate for community-acquired pneumonia, averaged over 2000-2004 and measured in percentage points. Standard errors appear in parentheses. * indicates statistical significance at the 10% level, ** at 5%, and *** at 1%.

Table 3: Willingness To Travel for Revealed Quality at 75th Percentile, Rather than 25th Percentile	
Type of patient	Miles
<i>Baseline</i>	
White male under 75 years old with mean income and Charlson-Deyo (co-morbidity) index	2.88 (0.07)
<i>Deviation from baseline</i>	
Age 75 or older	3.85 (0.19)
Female	2.81 (0.12)
Black	2.41 (0.21)
Income +1 standard deviation above mean	3.94 (0.14)
Comorbidity +1 standard deviation above mean	3.05 (0.10)

Notes: Standard errors appear in parentheses. Based on 2002 pneumonia patient choice analysis (specification 1 of table 2.)

Table 4: Fixed-Effects Regressions of Total Annual Inpatient Costs on Revealed Quality			
<i>Specification</i>			
Number	1	2	3
Time-varying quality	Yes	Yes	No
Instrument for time-varying quality	Yes	No	—
Controls for time-varying productivity	No	Yes	Yes
<i>Parameter Estimate (Standard Error)</i>			
Constant	—	-0.33* (0.19)	-0.24 (0.19)
Log of total stays (ln Y_{ht})	0.68*** (0.22)	0.73*** (0.14)	0.90*** (0.14)
Revealed quality (Q_{ht})	0.22 (0.14)	0.11*** (0.04)	—
Log of wage index (ln W_{ht})	0.19 (0.27)	0.14 (0.19)	0.31 (0.22)
Log of capital (ln K_{ht})	0.13 (0.17)	—	—
Log of case-mix index (ln CMI_{ht})	0.01 (0.80)	0.49 (0.48)	0.45 (0.49)
Log of mean Charlson-Deyo index (ln CDI_{ht})	0.28 (0.46)	0.05 (0.25)	-0.02 (0.25)
$\frac{1}{2}$ (ln Y_{ht}) ²	-0.05 (0.26)	-0.09 (0.10)	0.00 (0.09)
ln Y_{ht} · Q_{ht}	0.04 (0.17)	0.01 (0.04)	-0.10 (0.09)
ln Y_{ht} · ln W_{ht}	0.73 (0.63)	0.11 (0.37)	0.18 (0.41)
ln Y_{ht} · ln K_{ht}	-0.05 (0.08)	0.01 (0.05)	0.02 (0.05)
ln Y_{ht} · ln CMI_{ht}	-0.69 (1.19)	0.20 (0.42)	-0.07 (0.42)
ln Y_{ht} · ln CDI_{ht}	0.33 (1.05)	-0.39* (0.23)	-0.05 (0.22)
$\frac{1}{2}$ Q_{ht} ²	-0.04 (0.19)	0.03 (0.02)	—
Q_{ht} · ln W_{ht}	-0.56 (0.47)	-0.06 (0.17)	-0.20 (0.21)
Q_{ht} · ln K_{ht}	0.03 (0.07)	0.01 (0.02)	0.02 (0.06)
Q_{ht} · ln CMI_{ht}	0.31 (0.88)	-0.43** (0.17)	-0.38 (0.31)
Q_{ht} · ln CDI_{ht}	-0.10 (0.83)	0.34*** (0.10)	0.58*** (0.16)
$\frac{1}{2}$ (ln W_{ht}) ²	-0.63 (0.73)	-0.07 (0.46)	-0.17 (0.46)
ln W_{ht} · ln K_{ht}	-0.05 (0.33)	0.06 (0.25)	0.10 (0.25)
ln W_{ht} · ln CMI_{ht}	-2.04 (1.83)	-2.62** (1.19)	-2.40** (1.14)
ln W_{ht} · ln CDI_{ht}	1.86 (1.16)	2.00** (0.88)	2.19** (0.91)
$\frac{1}{2}$ (ln K_{ht}) ²	0.05 (0.06)	0.00 (0.03)	0.00 (0.03)
ln K_{ht} · ln CMI_{ht}	0.03 (0.34)	0.12 (0.29)	0.23 (0.29)
ln K_{ht} · ln CDI_{ht}	-0.22 (0.24)	-0.10 (0.16)	-0.29* (0.16)
$\frac{1}{2}$ (ln CMI_{ht}) ²	1.48 (5.39)	1.94 (2.78)	1.31 (2.78)
ln CMI_{ht} · ln CDI_{ht}	-1.07 (2.02)	-0.58 (1.14)	-0.25 (1.17)
$\frac{1}{2}$ (ln CDI_{ht}) ²	0.50 (1.03)	0.37 (0.62)	-0.06 (0.63)
Linear time trend (t)	0.05 (0.03)	—	—
$\frac{1}{2}$ t ²	-0.08** (0.03)	-0.08 (0.09)	-0.10 (0.09)
t · ln Y_{ht}	-0.03 (0.07)	0.00 (0.02)	-0.01 (0.02)
t · Q_{ht}	0.01 (0.05)	-0.01 (0.01)	-0.01 (0.01)
t · ln W_{ht}	-0.15 (0.13)	-0.03 (0.07)	-0.01 (0.07)
t · ln K_{ht}	-0.01 (0.02)	-0.07*** (0.02)	-0.07*** (0.02)
t · ln CMI_{ht}	0.07 (0.33)	-0.17* (0.10)	-0.11 (0.09)
t · ln CDI_{ht}	-0.06 (0.30)	0.06 (0.06)	0.00 (0.06)
<i>Other Statistics</i>			
Number of hospitals	124	126	126
Number of hospital-years	589	591	591
R squared	—	0.826	0.767

Notes: Based on 2000-2004 pneumonia patient choice analyses. To preserve rank, specification 1 excludes 2 hospitals with a single annual quality estimate. Parameters for log capital and linear time trend are not separately identified from parameters for productivity controls (specifications 2 and 3). Productivity control parameters are not reported here but available from authors upon request. Parameters for quality and quality squared are not separately identified from fixed effects when quality is treated as time-invariant (specification 3). Standard errors are not corrected for sampling variability of revealed quality. * indicates statistical significance at the 10% level, ** at 5%, and *** at 1%.

Table 5: Regressions of Hospital-Cost Fixed Effects on Revealed Quality				
<i>Specification</i>				
Number	1	2	3	4
Quadratic quality	Yes	No	No	No
Instrument for quality	Yes	Yes	Yes	No
Instruments	Exogenous quality responsiveness	Exogenous quality responsiveness	Local demand shifters	—
<i>Parameter estimates and other statistics</i>				
Constant	-0.24 (0.27)	-0.02 (0.05)	-0.02 (0.05)	-0.01 (0.04)
Revealed quality	0.30** (0.12)	0.24*** (0.09)	0.25*** (0.09)	0.06 (0.05)
Quality squared	0.24 (0.30)	—	—	—
R squared	—	—	—	0.026
Canonical correlation underidentification test, <i>p</i> value	0.155	<0.001	0.003	—
Overidentification test, <i>p</i> value	—	0.16	0.94	—
Hausman test of OLS specification, <i>p</i> value	0.013	0.012	0.011	—
<i>First-stage parameter estimates and weak identification F statistic</i>				
Constant	-2.03*** (0.76)	-2.03*** (0.76)	-1.60 (3.18)	—
Exogenous quality responsiveness	0.03** (0.02)	0.03** (0.02)	—	—
Exogenous quality responsiveness squared	0.00 (0.00)	0.00 (0.00)	—	—
Number of patients residing within 2.5 miles of hospital	—	—	0.002* (0.001)	—
Percent of local patients who were age 75 or older	—	—	4.05 (2.78)	—
Percent female	—	—	-4.79 (3.37)	—
Percent black	—	—	0.27 (1.01)	—
Mean income	—	—	0.32* (0.17)	—
Mean Charlson-Deyo (co-morbidity) index	—	—	-0.17 (0.85)	—
Weak identification <i>F</i> statistic	1.001	12.598	3.683	—

Notes: Based on specification 3 in table 4. First stage for quality squared in specification 1 is not reported. Standard errors (heteroscedasticity-robust where appropriate) appear in parentheses. Standard errors are not corrected for sampling variability of revealed quality. * indicates statistical significance at the 10% level, ** at 5%, and *** at 1%.

Table 6: Cost of an Interquartile Improvement in Revealed Quality at Hospital with Otherwise Average Characteristics	
Specification	Percentage impact on costs
<i>Main results</i>	
IV, quality responsiveness	+48.2% (16.2%)
IV, local demand shifters	+51.2% (14.8%)
OLS	+10.2% (13.2%)
<i>Robustness checks</i>	
Heart-attack patients	+26.0% (4.7%)
Income excluded	+50.4% (15.8%)
Mean capital and input and output prices as instruments	+56.3% (24.7%)
Quality responsiveness, capital and prices as instruments	+51.6% (17.7%)
Seismic ratings included in time-varying productivity	+69.6% (23.5%)
Notes: Based on specification 3 in table 4 and instruments in table 5. Bootstrapped standard errors appear in parentheses.	

Table A1: Revealed Quality Estimates

Hospital	OSHPD ID	2002		2000-2004 Average	
		Level	Rank	Level	Rank
Alhambra Hospital	190017	0.00	30	0.00	34
Anaheim General Hospitals	301097	-1.54	91	-1.16	83
Anaheim Memorial Medical Centers	301098	-0.50	55	-0.26	48
Arrowhead Regional Medical Center	364231	-2.94	117	-3.83	128
Bellflower Medical Center	190066	-0.84	68	-0.87	70
Beverly Hospital	190081	0.37	13	0.00	35
Brea Community Hospital	301126	-2.31	110	-1.59	97
Brotman Medical Center	190110	-0.13	37	0.08	31
California Hospital Medical Center - Los Angeles	190125	-1.53	90	-1.14	81
Cedars Sinai Medical Center	190555	0.95	2	1.16	1
Centinel Hospital Medical Center	190148	0.15	24	0.16	27
Century City Hospital	190155	-0.03	33	-0.18	45
Chapman Medical Center	301140	-2.23	108	-2.21	109
Chino Valley Medical Center	361144	-1.00	76	-1.31	88
Citrus Valley Medical Center - Ic Campus	190413	-0.29	44	-0.32	50
Citrus Valley Medical Center - Qv Campus	190636	-0.67	60	-0.59	59
City Of Angels Medical Center-Downtown Campus	190661	-3.44	120	-3.07	121
City Of Hope National Medical Center	190176	-3.80	122	-3.02	119
Coast Plaza Doctors Hospital	190766	-1.34	84	-1.11	80
Coastal Communities Hospital	301258	-1.09	78	-1.01	76
College Hospital Costa Mesa	301155	-3.91	123	-3.01	118
Community & Mission Hosps Of Hntg Pk	190197	-1.75	100	-1.26	86
Community Hospital Of Gardena	190196	-0.99	75	-0.85	67
Community Hospital Of Long Beach	190475	-0.64	58	-0.46	54
Community Hospital Of San Bernardino	361323	-2.10	105	-3.43	125
Corona Regional Medical Centers	331152	-1.81	102	-2.19	107
Daniel Freeman Marina Hospital	190500	0.23	19	0.22	24
Daniel Freeman Memorial Hospital	190230	0.04	28	0.17	26
Doctors Hospital Of West Covina, Inc	190857	-4.27	125	-4.44	130
Doctors' Hospital Medical Center Of Montclair	361166	-1.24	82	-1.17	84
Downey Regional Medical Center	190243	0.11	26	0.22	23
East Los Angeles Doctors Hospital	190256	-0.66	59	-0.56	57
East Valley Hospital Medical Center	190328	-1.50	89	-1.66	100
Elastar Community Hospital	190685	-0.79	67	-0.54	56
Encino-Tarzana Regional Med Ctr-Encino	190280	0.44	11	0.38	18
Encino-Tarzana Regional Med Ctr-Tarzana	190517	0.25	18	0.45	13
Foothill Presbyterian Hospital-Johnston Memorial	190298	-0.54	57	-0.60	60
Fountain Valley Rgnl Hosps & Med Ctrs	301175	-0.51	56	-0.30	49
Garden Grove Hospital & Medical Center	301283	-0.84	69	-0.86	69
Garfield Medical Center	190315	0.17	22	0.26	22
Glendale Adventist Medical Center - Wilson Terrace	190323	0.47	10	0.52	10
Glendale Memorial Hospital & Health Center	190522	0.19	20	0.51	12
Good Samaritan Hospital-Los Angeles	190392	-0.12	36	0.32	21
Granada Hills Community Hospital	190348	-0.05	34	0.10	30
Greater El Monte Community Hospital	190352	-1.43	88	-1.35	90
Henry Mayo Newhall Memorial Hospital	190949	0.38	12	0.58	9
Hoag Memorial Hospital Presbyterian	301205	1.18	1	1.13	2
Hollywood Community Hospital Of Hollywood	190380	-3.71	121	-3.06	120
Huntington Beach Hospital	301209	-0.71	63	-0.68	64
Huntington Memorial Hospital	190400	0.82	4	0.88	5
Irvine Regional Hospital And Medical Center	304045	-0.43	51	-0.94	73
Kindred Hospital Brea	301127	Not in sample		-1.80	101
Kindred Hospitals - La Mirada, San Gabrl Val & Santa Ana	190449	Not in sample		-3.97	129
La Palma Intercommunity Hospital	301234	-1.27	83	-1.05	77
Lac/Rancho Los Amigos National Rehab Center	191306	-4.08	124	-3.70	126
Lakewood Regional Medical Center	190240	-0.78	66	-0.61	61
Lincoln Hospital Medical Center	190468	-5.32	128	-3.83	127
Little Company Of Mary Hospital	190470	0.78	5	0.85	6
Little Company Of Mary Hosps-San Pedro, Torrance & Harbor City	190680	0.13	25	0.44	14
Loma Linda University Medical Centers	361246	-0.98	73	-2.29	111
Long Beach Memorial Medical Center	190525	0.54	9	0.92	3
Los Alamitos Medical Center	301248	-0.28	43	-0.21	47

Los Angeles Co Harbor-Ucla Medical Center	191227	-1.64	96	-0.97	75
Los Angeles Co Martin Luther King Jr/Drew Med Ctr	191230	-1.56	93	-1.47	92
Los Angeles Co Usc Medical Center	191228	-2.88	116	-1.11	106
Los Angeles Community Hospital	190198	-2.23	109	-1.29	87
Los Angeles County Olive View-Ucla Medical Center	191231	-1.36	85	-1.23	85
Los Angeles Metropolitan Medical Centers	190854	-2.56	113	-2.33	112
Memorial Hospital Of Gardena	190521	-0.70	61	-0.57	58
Methodist Hospital Of Southern California	190529	0.35	14	0.33	20
Midway Hospital Medical Center	190534	-0.50	54	-0.04	38
Mission Community Hospitals	190524	-0.45	52	-0.48	55
Mission Hospital Regional Medical Center	301262	-0.36	48	-0.69	65
Monrovia Community Hospital	190541	-1.56	94	-1.86	102
Monterey Park Hospital	190547	-0.90	71	-0.89	72
Moreno Valley Community Hospital	334048	-1.05	77	-2.51	114
Motion Picture & Television Hospital	190552	-1.61	95	-1.60	98
Northridge Hospital Medical Center	190568	-0.24	42	0.01	33
Northridge Hospital Medical Center - Sherman Way	190810	-0.41	49	-0.35	51
Norwalk Community Hospital	190570	-2.13	107	-1.95	105
Orange Coast Memorial Medical Center	300225	-0.71	62	-0.63	62
Orange County Community Hospitals	301242	-3.17	119	-2.65	116
Orthopaedic Hospital	190581	-5.93	129	-5.73	132
Pacific Alliance Medical Center, Inc.	190307	-0.34	47	0.12	29
Pacific Hospitals Of Long Beach	190587	-0.01	31	-0.11	42
Pacific Hospital Of The Valley	190696	-1.42	86	-1.06	78
Parkview Community Hospital Medical Center	331293	-4.73	127	-4.72	131
Placentia Linda Hospital	301297	-1.55	92	-1.08	79
Pomona Valley Hospital Medical Center	190630	-0.89	70	-0.85	68
Presbyterian Intercommunity Hospital	190631	0.02	29	0.08	32
Providence Holy Cross Medical Center	190385	0.08	27	0.20	25
Providence Saint Joseph Medical Center	190758	0.58	7	0.71	8
Queen Of Angels/Hollywood Presbyterian Med Center	190382	-0.15	38	-0.19	46
Redlands Community Hospital	361308	-1.22	80	-2.52	115
Riverside Community Hospital	331312	-2.11	106	-3.24	122
Riverside County Regional Medical Center	334487	-2.04	104	-3.36	123
Robert F. Kennedy Medical Center	190366	-0.49	53	-0.45	53
Saddleback Memorial Medical Center	301317	-0.07	35	-0.40	52
San Antonio Community Hospital	361318	-0.72	64	-0.87	71
San Clemente Hospital & Medical Center	301325	-1.22	81	-1.53	94
San Dimas Community Hospital	190673	-1.68	98	-1.58	96
San Gabriel Valley Medical Center	190200	-0.18	40	-0.14	43
Santa Ana Hospital Medical Center Inc	301314	-2.51	111	-2.21	108
Santa Monica - Ucla Medical Center	190687	0.34	15	0.44	16
Santa Teresita Hospital	190691	-2.02	103	-1.47	91
Sherman Oaks Hospital And Health Center	190708	0.30	17	0.37	19
South Coast Medical Center	301337	-1.11	79	-1.35	89
St. Bernardine Medical Center	361339	-0.93	72	-2.27	110
St. Francis Medical Center	190754	-0.16	39	-0.09	40
St. John'S Hospital & Health Center	190756	0.61	6	0.77	7
St. Joseph Hospital - Orange	301340	-0.20	41	-0.15	44
St. Jude Medical Center	301342	-0.02	32	-0.03	37
St. Luke Medical Center	190759	-2.65	114	-0.96	74
St. Mary Medical Center	190053	0.16	23	0.40	17
St. Vincent Medical Center	190762	-0.32	45	-0.09	41
Suburban Medical Center	190599	-1.68	97	-1.14	82
Temple Community Hospital	190784	-2.51	112	-1.86	103
Torrance Memorial Medical Center	190422	0.92	3	0.92	4
Tri-City Regional Medical Center	190159	-2.81	115	-1.93	104
Tustin Hospital Medical Center	301357	Not in sample		-3.36	124
Ucla Medical Center	190796	0.58	8	0.52	11
University Of California Irvine Medical Center	301279	-1.43	87	-1.49	93
Usc Kenneth Norris, Jr. Cancer Hospital	191216	-4.31	126	-3.00	117
Usc University Hospitals	194219	-3.14	118	-2.42	113
Valley Presbyterian Hospital	190812	0.19	21	0.13	28
Verdugo Hills Hospital	190818	0.31	16	0.44	15
West Anaheim Medical Center	301379	-0.77	65	-0.74	66
West Hills Hospital & Medical Center	190859	-0.32	46	-0.05	39
Western Medical Center - Santa Ana	301566	-1.76	101	-1.57	95
Western Medical Center Hospital - Anaheim	301188	-1.69	99	-1.60	99
White Memorial Medical Center	190878	-0.41	50	0.00	36
Whittier Hospital Medical Center	190883	-0.99	74	-0.68	63

Table A2: Summary Statistics for Hospital Patients				
<i>Patient characteristic</i>	<i>Mean</i>	<i>SD</i>	<i>Min</i>	<i>Max</i>
75+ years old	75.1%	—	—	—
Female	57.1%	—	—	—
Black	7.6%	—	—	—
Income	\$43,930	\$17,400	\$5,000	\$155,660
Charlson-Deyo index (CDI)	2.1	1.8	0	15
Number of patients	9008			
Number of hospitals	129			

Notes: Based on estimation sample of pneumonia patients in 2002.

Table A3: Summary Statistics for Hospitals		
<i>Statistic</i>	<i>Mean</i>	<i>SD</i>
Total annual inpatient costs (million \$)	109.4	112.1
Annual stays, total	12072	8996
Wage index	1.005	0.207
Case-mix index (CMI), all stays	1.058	0.219
Mean Charlson-Deyo index (CDI), all stays	1.057	0.354
Year 2000	19.6%	—
Year 2001	20.1%	—
Year 2002	21.0%	—
Year 2003	20.0%	—
Year 2004	19.3%	—

Notes: Corresponds to specifications 2 and 3 of table 4.

Table A4: Fixed-Effects Regressions of Total Annual Inpatient Costs on Clinical Quality		
<i>Specification</i>		
Number	1	2
Time-varying quality	Yes	No
Controls for time-varying productivity	Yes	Yes
<i>Parameter estimate (Standard error)</i>		
Constant	-0.47** (0.20)	-0.32 (0.19)
Log of total stays (ln Y_{ht})	0.97*** (0.16)	0.94*** (0.15)
Revealed quality (Q_{ht})	0.004 (0.007)	—
Log of wage index (ln W_{ht})	0.30 (0.21)	0.12 (0.19)
Log of capital (ln K_{ht})	—	—
Log of case-mix index (ln CMI_{ht})	0.63 (0.50)	0.69 (0.49)
Log of mean Charlson-Deyo index (ln CDI_{ht})	0.32 (0.31)	0.07 (0.26)
$\frac{1}{2}$ (ln Y_{ht}) ²	0.01 (0.17)	0.09 (0.10)
ln Y_{ht} · Q_{ht}	-0.01 (0.01)	0.02 (0.04)
ln Y_{ht} · ln W_{ht}	-0.27 (0.39)	0.10 (0.37)
ln Y_{ht} · ln K_{ht}	0.10 (0.09)	-0.01 (0.06)
ln Y_{ht} · ln CMI_{ht}	0.49 (0.65)	0.36 (0.55)
ln Y_{ht} · ln CDI_{ht}	-0.34 (0.35)	-0.02 (0.21)
$\frac{1}{2}$ Q_{ht} ²	0.002* (0.001)	—
Q_{ht} · ln W_{ht}	0.05 (0.03)	0.01 (0.08)
Q_{ht} · ln K_{ht}	0.00 (0.00)	0.04 (0.03)
Q_{ht} · ln CMI_{ht}	0.03 (0.04)	-0.16 (0.16)
Q_{ht} · ln CDI_{ht}	-0.02 (0.02)	-0.08 (0.07)
$\frac{1}{2}$ (ln W_{ht}) ²	-0.21 (0.45)	-0.15 (0.45)
ln W_{ht} · ln K_{ht}	0.19 (0.26)	0.09 (0.25)
ln W_{ht} · ln CMI_{ht}	-1.58 (1.29)	-2.98** (1.24)
ln W_{ht} · ln CDI_{ht}	1.43 (0.99)	1.99** (1.01)
$\frac{1}{2}$ (ln K_{ht}) ²	-0.02 (0.04)	0.01 (0.03)
ln K_{ht} · ln CMI_{ht}	-0.02 (0.35)	-0.02 (0.31)
ln K_{ht} · ln CDI_{ht}	0.17 (0.21)	-0.08 (0.17)
$\frac{1}{2}$ (ln CMI_{ht}) ²	2.78 (3.04)	1.43 (2.90)
ln CMI_{ht} · ln CDI_{ht}	-1.10 (1.43)	-0.09 (1.19)
$\frac{1}{2}$ (ln CDI_{ht}) ²	0.74 (1.02)	0.28 (0.69)
Linear time trend (t)	—	—
$\frac{1}{2}$ t ²	0.03 (0.11)	-0.08 (0.09)
t · ln Y_{ht}	0.00 (0.02)	0.00 (0.02)
t · Q_{ht}	0.00 (0.00)	0.00 (0.01)
t · ln W_{ht}	0.03 (0.08)	-0.05 (0.07)
t · ln K_{ht}	-0.08*** (0.02)	-0.09*** (0.02)
t · ln CMI_{ht}	-0.08 (0.10)	-0.08 (0.09)
t · ln CDI_{ht}	-0.03 (0.07)	-0.04 (0.06)
<i>Other statistics</i>		
R squared	0.795	0.781
Number of hospitals	114	114
Number of hospital-years	530	550

Notes: Clinical quality is the negative value of the risk-adjusted 30-day mortality rate for community-acquired pneumonia, averaged over 2000-2004 and measured in percentage points.

Parameters for log capital and linear time trend are not separately identified from parameters for productivity controls. Productivity control parameters are not reported here but available from authors upon request. Parameters for quality and quality squared are not separately identified from fixed effects when quality is treated as time-invariant. * indicates statistical significance at the 10% level, ** at 5%, and *** at 1%.

Table A5: Regressions of Hospital-Cost Fixed Effects on Clinical Quality			
<i>Specification</i>			
Number	1	2	3
Quadratic quality	Yes	No	No
Instrument for quality	Yes	Yes	No
Instruments	Exogenous quality responsiveness	Exogenous quality responsiveness	—
<i>Parameter estimates and other statistics</i>			
Constant	-0.67 (1.17)	-0.02 (0.04)	-0.01 (0.04)
Revealed quality	0.24 (0.28)	0.10 (0.06)	0.04** (0.01)
Quality squared	0.19 (0.34)	—	—
R squared	—	—	0.049
Canonical correlation underidentification test, <i>p</i> value	0.546	0.011	—
Overidentification test, <i>p</i> value	—	0.399	—
Hausman test of OLS specification, <i>p</i> value	0.191	0.186	—
<i>First-stage parameter estimates and F statistic</i>			
Constant	-3.14* (1.64)	-3.14* (1.64)	—
Exogenous quality responsiveness	-0.06 (0.04)	-0.06 (0.04)	—
Exogenous quality responsiveness squared	0.00 (0.00)	0.00 (0.00)	—
<i>F</i> statistic	5.16	5.16	—

Notes: Based on specification 2 in table A5. First stage for quality squared in specification 1 is not reported. Standard errors (heteroscedasticity-robust where appropriate) appear in parentheses. * indicates statistical significance at the 10% level, ** at 5%, and *** at 1%.