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

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Abstract

The cost of quality improvement is an important issue in health care. Unfortunately, quality is difficult to measure and potentially confounded with productivity. We infer quality at hospitals in greater Los Angeles from the revealed preference of patients. The resulting measure – which we call "revealed quality" – embodies all aspects of the hospital experience which patients observe and value, potentially including patient amenities as well as clinical quality. We find that hospitals are highly differentiated in revealed quality, and that this quality measure is only modestly correlated with a standard measure of clinical quality (risk-adjusted mortality rates). We then determine the cost of revealed quality, appealing to heterogeneity in patient tastes and locations for exogenous quality variation. An inter-quartile increase in quality would raise costs by 48.2% at an otherwise average hospital. More productive hospitals supply higher revealed quality; when this relationship is ignored, the cost of quality is substantially understated. We also find that the cost of an inter-quartile increase in clinical quality is only 12.3%. Altogether, these findings suggest that non-clinical aspects of the hospital experience may be important determinants of both hospital demand 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 in U.S. hospitals totaled $697 billion in 2007, and have been growing faster than overall health spending [Hartman et al. (2009)].

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 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) attributes 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 cost of quality, leading a hospital to supply high quality. High-quality hospitals 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

[1]Skinner et al. (2006) suggest that changes over time in heart-attack survival and treatment costs may be explained by productivity differences across hospital regions.

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, appeals to the structure of firm costs and the nature of market equilibrium to identify firm demand, as do Berry et al. (1995) to sharpen demand estimates.

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 by their willingness to travel to distant hospitals.

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, Medicare insures these beneficiaries for almost all of the costs of inpatient care [Capps et al. (2003); Tay (2003)]. Thus, we need not measure patient out-of-pocket costs, nor address their probable relationship with quality levels; as a consequence, though, we are unable to measure the value of quality to patients.

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 their 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.

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:

$$C\left(Y, Q, W, K, A\right),$$

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 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 utility. 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] Utility may also vary with quality because of its

[2] We 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)].

impact on profits:

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

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 quantity 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 exogenous. 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 income 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 is exogenous, on the view that hospital quality is chosen by boards and managers who can set quality targets and whose effectiveness influences costs. More productive hospitals have lower fixed costs, lower marginal costs, or both.

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

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

The first term is the impact of quality on profits through hospital demand. Marginal utility also depends on the direct cost of quality, as well as any "warm glow" from quality.

A hospital's optimal quality $Q^*\left(P, \mathbf{X}, W, K, A, \gamma\right)$ depends on its productivity:

$$\frac{\partial Q^*}{\partial A} = \left(\frac{\partial^2 C}{\partial Y \partial A}\frac{\partial Y}{\partial Q} + \frac{\partial^2 C}{\partial Q \partial A}\right) \bigg/ \frac{\partial^2 U}{\partial Q^2} \geq 0 \tag{2}$$

Quality increases with productivity, if 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 One strategy for dealing with endogenous quality is to identify instruments that are correlated with quality but uncorrelated with productivity. Our model of quality supply suggests some candidates, in particular, factors affecting the marginal utility of quality in equation 1.

Marginal utility is influenced by consumer behavior. A large value of $\partial Y/\partial Q$ – which we refer to as the "quality responsiveness of hospital demand" – can increase marginal utility and thus quality. Intuitively, as more patients are on the quality margin, a given increase in quality draws more patients, raising profits.[3]

To measure consumer behavior, the demand shifters in **X** could be used. This vector is likely to be high-dimensional, given the importance of residential location in hospital demand [see, e.g., Luft et al. (1990)]. Moreover, the sign of the partial correlation between demand shifters and actual quality is often unknown *a priori*, so that the face validity of instruments can be difficult to assess.

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 the model. Productivity can be purged by evaluating each hospital's quality responsiveness at a common level $\widetilde{Q}$[4]:

$$\partial Y/\,\partial Q|_{\boldsymbol{Q}=\widetilde{\boldsymbol{Q}}} \tag{3}$$

Intuitively, this instrument identifies variation in the marginal utility of hospitals that are making decisions about quality from the same "starting point." This instrument is parsimonious yet potentially powerful. It has a clear interpretation, and a relatively clear relationship to actual quality. A disadvantage is that the instrument must be derived from an analysis of hospital

[3] Patients must be profitable at the margin. Pneumonia care, on which we focus, may not be as profitable as care for other conditions. We use quality as revealed by pneumonia patients as a proxy for quality for all patients. We also consider heart-attack patients in a sensitivity analysis. Reimbursement for coronary care is relatively generous [Horwitz (2005)].

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

choice; however, such an analysis may be needed to obtain a broad-based measure of quality.

Additional factors affect the marginal utility of quality. All else equal, a high output price P increases marginal utility and thus quality. High wages increase $\partial C/\partial Y, \partial C/\partial Q$ or both, thereby decreasing quality. In the empirical analysis below, we describe, assess and use instruments based on measures of output and input prices, as well as demand shifters and "exogenous quality responsiveness" $\partial Y/\partial Q|_{\boldsymbol{Q}=\tilde{\boldsymbol{Q}}}$.

Marginal costs may also be influenced by the capital stock. But capital appears in our cost function, thus failing to satisfy the necessary exclusion restriction.

Finally, greater altruism increases quality. Altruism 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 approach to measuring hospital quality is to specify and estimate a model of quality supply. Gertler and Waldman (1992) used this approach 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 approach 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.[5] The utility that patient i expects to obtain from hospital h consists of systematic and idiosyncratic components,

[5] A large body of evidence suggests that many patients exercise informed 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)].

denoted $\overline{U}_{ih}$ and ϵ_{ih}:

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

We further assume that all potential patients elect to receive care at some hospital and that idiosyncratic utility is i.i.d. type-1 extreme-valued. Following McFadden (1974), the likelihood that a hospital is a patient's utility-maximizing choice is:

$$l_{ih} = e^{\overline{U}_{ih}} \Big/ \sum\nolimits_{h'} e^{\overline{U}_{ih'}}, \tag{4}$$

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

$$Y_h \equiv Y\left(Q_h, \mathbf{X}\right) = \sum\nolimits_i l_{ih}$$

We specify systematic utility as:

$$\overline{U}_{ih} = \beta_d\left(\mathbf{X}_i\right) D_{ih} + \beta_q\left(\mathbf{X}_i\right) Q_h, \tag{5}$$

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, Medicare covers almost all inpatient costs for fee-for-service beneficiaries; hence, price does not appear in utility.

Revealed quality is an index of all aspects of the hospital experience known to, and valued by, patients.[6] 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 do not impose this restriction.

[6] The 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 $\boldsymbol{\beta}_{\mathbf{x},i}$ 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 $Q_h = \beta_{q,i}^{-1} \mathbf{X}_h \boldsymbol{\beta}_{\mathbf{x},i}$. 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 are informed about hospital volume/demand.

Because neither tastes nor quality is directly observed, 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 improvement based on the resulting distribution of Q_h, for example, from the 25th to the 75th percentile. Intuitively, the normalization does not affect the pth 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 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.[7]

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

$$\partial Y_h / \partial Q_h = \sum_i \beta_q(\mathbf{X}_i) l_{ih} (1 - l_{ih}) \tag{6}$$

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,

[7] A decreased distaste for distance would also allow for greater travel to high-quality hospitals. However, in the model, free parameters on all observed characteristics (including quality, as observed from patient behavior) allow not only for flexible estimates of the marginal rates of substitution between characteristics, but also for greater roles for observed characteristics in relation to idiosyncratic tastes. Intuitively, free parameters for both $\beta_d(\mathbf{X}_i)$ and $\beta_q(\mathbf{X}_i)$ allow for flexible estimates of both $\partial l_{ih}/\partial D_{ih}$ and $\partial l_{ih}/\partial Q_h$, as inspection of equation 6 shows.

setting quality at all hospitals equal to $\widetilde{Q}$, we have:

$$\left.\frac{\partial Y_h}{\partial Q_h}\right|_{\boldsymbol{Q}=\widetilde{\boldsymbol{Q}}} = \sum\nolimits_i \beta_q(\mathbf{X}_i)\left(\frac{e^{\beta_d(\mathbf{X}_i)D_{ih}+\beta_q(\mathbf{X}_i)\widetilde{Q}}}{\sum_{h'} e^{\beta_d(\mathbf{X}_i)D_{ih'}+\beta_q(\mathbf{X}_i)\widetilde{Q}}}\right)\left(1-\frac{e^{\beta_d(\mathbf{X}_i)D_{ih}+\beta_q(\mathbf{X}_i)\widetilde{Q}}}{\sum_{h'} e^{\beta_d(\mathbf{X}_i)D_{ih'}+\beta_q(\mathbf{X}_i)\widetilde{Q}}}\right)$$
$$= \sum\nolimits_i \beta_q(\mathbf{X}_i)\left(\frac{e^{\beta_d(\mathbf{X}_i)D_{ih}}}{\sum_{h'} e^{\beta_d(\mathbf{X}_i)D_{ih'}}}\right)\left(1-\frac{e^{\beta_d(\mathbf{X}_i)D_{ih}}}{\sum_{h'} e^{\beta_d(\mathbf{X}_i)D_{ih'}}}\right)$$

Heterogeneity in patient / hospital locations and thus D_{ih}, together with heterogeneity in tastes for quality and distance, leads to variation in the impact of higher quality on hospital demand which, as we discuss below, may be uncorrelated with productivity. Thus, our approach to measuring hospital quality yields a potential instrument for quality in the cost analysis.

3 Hospital Quality

To infer hospital quality, we analyze patient choice among hospitals in greater Los Angeles over 2000-2004. Good measures of clinical quality are 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 have carefully defined 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 in section 4.2. 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 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:

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

in which the variable $75+\ years_i$ equals one if a patient is at least 75 years old in the discharge abstract and zero otherwise, and $Female_i$ and $Black_i$.

The Charlson-Deyo index CDI_i is a widely used measure of health status based on 19 categories of co-morbidities [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 4 and 5, and is estimated by maximum likelihood. In our analysis, the Q_h terms are estimation parameters. Revealed quality is normalized to zero at Alhambra Hospital, and the taste for quality is normalized to 1 for white males under age 75 with mean income and health status. Like Tay (2003), we speed up estimation by restricting patient choice sets to the nearest 50 hospitals.

We estimate choice independently for each year, 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; residential zip code; age, gender and race; co-morbidities; payer; 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 geocoordinates 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)].[8] Pneumonia

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

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 excluded hospitals in the Ventura and Palm Springs Hospital Referral Regions [Dartmouth Medical School, The Center for the Evaluative Clinical Sciences (1998)], 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 excluded hospitals in Kaiser Permanente's integrated delivery system, because access to these facilities may have been limited. For pneumonia patients from 2000-2004, the market includes the 132 hospitals listed in the appendix. Revealed quality estimates change negligibly if we include all hospitals in metro LA in the choice analysis [Romley and Goldman (2008)].

Patient samples We analyze the hospital choices of Medicare fee-for-service patients who resided in metro LA's 5 counties and were admitted to a greater LA hospital with a principal diagnosis of pneumonia or acute myocardial infarction (i.e., heart attack).[9] 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, or whose reported zip code could not be matched to our zip-code database. Finally, we exclude patients who were less than 65 years old. Appendix table A1 reports summary statistics for the sample of pneumonia patients in 2002.

[9] The ICD-9 code for a pneumonia patient begins with the numbers *481*, *482*, *485*, *486* or *4838*. The ICD-9 code of heart-attack patients (whom we consider in a sensitivity analysis) begins with *410*.

3.2 Results

The choice behavior of pneumonia patients points to significant differentiation in revealed quality. To assess the extent of differentiation, hospital demand levels given actual quality are compared to counterfactual demand levels without any differentiation. Counterfactual demand is predicted based on the choice model, estimated patient tastes, and equal quality at all hospitals ($Q_h = \widetilde{Q} \forall h$). Using the year-2002 results reported in table 2, the correlation in hospital-level demands with and without differentiation is only +0.41. Predicted demand given the actual quality estimates is essentially perfectly correlated with observed demand, because revealed quality introduces hospital-level fixed effects into the conditional-logit choice model.

Our quality estimates have face validity. Our top two hospitals (Cedars Sinai and Hoag Memorial, as shown in appendix table A3) have consistently been identified in annual consumer surveys as having the highest quality and image in Los Angeles and Orange County.[10] In the 2002 survey, 33 hospitals in greater LA were never identified as a consumer's first choice for "best overall quality"; the median ranking of these hospitals on our revealed-quality measure was 94th place out of 129. We are also reassured that the quality estimates are invariant to alternative specifications [Romley and Goldman (2008)].

The revealed quality of hospitals in greater Los Angeles is stable over time. A regression of the annual estimates over 2000-2004 on hospital indicator variables accounts for 89% of the 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 embodies, and hospital choice is 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 ($\rho = -0.29$). Furthermore, using the negative of mortality to measure Q_h in the choice model, the correlation between actual and predicted hospital demand levels in 2002 is only +0.45 (shown at the bottom of appendix table A4).

This contrast between revealed and clinical quality is striking. Some of the contrast may have been attributable to incomplete information among pa-

[10] In particular, these hospitals have received Consumer Choice Awards from National Research Corporation (NRC), a health market research firm.

tients about clinical quality at hospitals. Incomplete information about clinical quality would magnify the role of non-clinical factors in hospital choice. This interpretation is consistent with evidence that standard metrics 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 and thus their willingness to travel for higher quality. Table 3 reports that white males 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.

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.

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. Costs are estimated based on clinical quality as well as revealed quality. We can therefore assess whether quality improvement based on a standard clinical measure understates the cost of quality based on all of the aspects of the hospital experience that patients observe and value.

4.1 Empirical approach

Costs Our model 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:

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

We analyze total short-run 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 define Medicare reimbursement rates under prospective payment [see, e.g., Athey and Stern (2002); 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.[11]

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 with the hospital-choice analysis. Because this analysis normalizes the level of revealed quality, Q_{ht} is not logged in the model. Thus, conventional economies of scale are undefined for revealed quality. Instead, quality impacts cost 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 earlier.

[11] We could also measure annual costs by aggregating total costs from quarterly financial reports submitted by hospitals to OSHPD. Based on this 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 quite low in comparison to prior studies [e.g., Carey (2000)].

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 are 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 $\boldsymbol{Z}_{ht}$. 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 A2 reports summary statistics for greater LA hospitals. All model covariates are de-meaned in the analysis. Before taking logs, variables are divided by their means in the 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 (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 implies that quality is correlated with unobserved productivity. 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:

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

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

$\boldsymbol{V}_{ht}$ 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 productivity controls include logged investment, logged capital, their squares and interaction, all interacted with year-level dummy variables. These time interactions allow investment policy to change with the economic environment.

We also consider the quality instruments described in section 2.1.

4.2 Results

Our main cost analyses are based on revealed quality. To begin with, we use the annual quality estimates from section 3.2.

In a first specification, we instrument for all quality-related covariates in the fixed-effects regression of costs. Exogenous quality responsiveness ($\partial Y / \partial Q|_{\boldsymbol{Q}=\tilde{\boldsymbol{Q}}}$), its square and its interactions with non-quality variables (such as case mix) serve as instruments. As table 4 shows, the parameter estimate $\widehat{\alpha}_Q$ is positive, but indistinguishable from zero at conventional levels of statistical significance.[12] 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 the canonical correlations test [Anderson (1951)].

A second specification uses Olley-Pakes-style controls for time-varying productivity, instead of instrumental variables. The linear quality parameter is now estimated to be positive ($\widehat{\alpha}_Q = 0.112$), and is highly significant. In addition, the productivity controls are jointly significant. There is also strong evidence of heterogeneity in hospital-cost fixed effects, and hence in the time-invariant component of hospital productivity. Hausman tests reject the models without productivity controls or fixed effects.

Yet fixed-effects regression can be biased if some covariates are more serially correlated than is any measurement error in them [Griliches and

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

Hausman (1986)]. As noted earlier, much of the variation over time in the quality estimates is attributable to sampling variability.

We therefore analyze costs with revealed quality treated as time-invariant. To do so, we average each hospital's annual estimates. The fixed-effects regression continues to include Olley-Pakes-style controls for time-varying productivity. This is our preferred specification in the subsequent analyses of the cost of quality improvement.

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

This regression does not identify quality parameters that do not involve interactions with time-varying variables, in particular, α_Q and α_{Q^2}. Time-invariant quality is subsumed, with time-invariant productivity, into the hospital-cost fixed effects. To estimate the remaining unknown parameters, we regress the unbiased estimates of the fixed effects from the cost regression on estimates of quality from the choice analysis [Wooldridge (2002)]. Table 5 reports the results.

We first instrument with exogenous quality responsiveness and its square. A model with both quality and its square is underidentified, as Gertler and Waldman (1992) found in analyzing latent quality at nursing homes. Imposing $\alpha_{Q^2} = 0$, the instruments have reasonable power for linear quality, with an F statistic of 12.6. Moreover, revealed quality increases with $\partial Y / \partial Q|_{\boldsymbol{Q}=\widetilde{\boldsymbol{Q}}}$, as our model of quality supply predicts. In the IV analysis, $\widehat{\alpha}_Q$ 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 $\partial^2 Y / \partial Q^2|_{\boldsymbol{Q}=\widetilde{\boldsymbol{Q}}}$; this 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, exogenous quality responsiveness may yield sharper identification in some applications. $\partial Y / \partial Q|_{\boldsymbol{Q}=\tilde{\boldsymbol{Q}}}$ measures the response of all patients, dealing parsimoniously yet precisely with the geography of the market. Indeed, table 5 shows the local demand shifters are less powerful than quality responsiveness in explaining actual quality. We do find that a hospital's revealed quality increases with the number and income of patients residing nearby (not shown in table).

Under either set of demand-based instruments, we are able to reject the hypothesis that the results of ordinary least squares are consistent for the IV results. Table 5 shows that $\widehat{\alpha}_Q$ is positive but much smaller and insignificant with OLS (specification 4). This bias is a consequence of a substantial positive correlation between revealed quality and productivity. Figure 3 shows this relationship, with productivity estimated by the residuals from specification 2 of table 5. Altogether, the IV results suggest that hospitals supply quality based on 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 $\partial Y / \partial Q|_{\boldsymbol{Q}=\tilde{\boldsymbol{Q}}}$ is independent of our revealed-quality measure. One might also worry that high-income patients tend to live in high-cost areas.[13] We consider the robustness of our identification, and additional instruments, in the next section.

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 (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

[13] We thank Robert Town for raising this issue.

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.[14]

Table 6 reports the results. Based on the exogenous quality responsiveness IV, the interquartile increase in revealed quality is estimated to increase costs by 48.2% at an otherwise average hospital, with a bootstrapped standard error of 16.2%. Using local demand shifters as instruments, this quality improvement raises costs by 51.2% (s.e. 14.8%). The cost of quality is substantially understated when we ignore the relationship between quality and productivity: based on OLS, cost increases by only 10.2% (s.e. 13.2%).[15]

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 correlated ($\rho = +0.80$) with revealed quality for pneumonia patients. Based on this 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, and also with a decreased emphasis on non-clinical aspects of quality, among relatively acute patients.

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%).

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

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

Input and output prices as instruments: As alternative instruments, we use the hospital-level wage index W_{ht} as a cost shifter and the Medicare area wage index as a proxy for the regulated output price, both averaged over 2000-2004.[16] The cost of quality improvement is (+54.1%); this is similar to the prior estimates, but imprecisely estimated (s.e. 179.9%).

Full set of instruments: Next, we consider both the price instruments and demand-based instruments (exogenous quality responsiveness and its square). This overidentified model cannot be rejected ($p = 0.27$). The cost of quality improvement is now 51.4% (s.e. 20.3%).

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 interacted 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%), and so is the standard error (23.5%).

Clinical quality We now assess the cost of clinical quality at hospitals. We again estimate the fixed-effects cost model with Olley-Pakes style 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 A5). As before, we regress the hospital-cost fixed effects on quality.

We instrument for clinical quality using exogenous quality responsiveness

[16] Medicare 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 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.

and its square; these instruments are now derived from the choice model with quality measured by pneumonia mortality (appendix table A4). We again cannot identify the quadratic quality parameter (as shown in the complete second-stage results in appendix table A6), and impose $\alpha_{Q^2} = 0$. In this IV analysis, the hypothesis that $\alpha_Q = 0$ cannot be rejected.[17]

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 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 section 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 suggest otherwise. 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. Moreover, 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 as well as clinical quality. We inferred the quality of hospitals in greater Los Angeles from the revealed preference of Medicare fee-for-service pneumonia patients. "Revealed quality" differentiates these hospitals, and is only moderately correlated with clinical quality, as measured by risk-adjusted pneumonia mortality rates. Some of this contrast may be attributable to limited information among patients about clinical quality at hospitals; if so, non-clinical factors would likely play a relatively smaller role in the choice behavior of better informed consumers.

[17] Costless quality also cannot be rejected when we instrument with local demand shifters.

Second, quality can appear to be cheap, if low-cost hospitals tend to offer high quality. Our preferred instruments again appeal to consumer behavior. We found that revealed quality is higher at hospitals whose demand is more quality responsive, and that an interquartile improvement in revealed quality would increase costs by 48.2% at an otherwise average hospital.

We also found a substantial positive correlation between revealed quality and productivity. This evidence is consistent with competition in revealed quality. In terms of cost, if the relationship between quality and productivity were ignored, the cost of an interquartile improvement in revealed quality would be substantially understated.

Finally, we considered the cost of hospital quality based on our clinical measure. We were unable to reject a model that treated clinical quality as exogenous. Based on this model, the cost of an interquartile reduction in mortality is only 12.6%.

Altogether, these results suggest that the patient perspective on quality includes aspects of the hospital experience unrelated to clinical quality, and that non-clinical quality is quite costly, both in absolute terms and in comparison to clinical quality. The latter conclusion would have been obscured, if we had ignored the relationship between revealed quality and productivity.

The welfare impact of improvements in non-clinical aspects of the hospital experience turns on their value to patients. Understanding this value is a worthwhile direction for further research.

The issue of value is related to concerns about the high cost of U.S. health care. This concern is reinforced by wide variation in hospital spending per patient within and across markets [Dartmouth Institute for Health Policy and Clinical Practice (2008)]. Our results suggest that hospitals compete by making costly investments in non-clinical aspects of the hospital experience. Efforts to contain costs might focus on such investments.

Productivity differences could also be important for cost containment, due to their role in the supply of revealed quality. A given quality reduction could yield greater cost savings at relatively low-quality, high-cost hospitals. Moreover, equalization of spending would likely result in unequal quality. To better understand the impact of productivity on quality, costs and welfare, quality supply must be analyzed. This is also a worthwhile direction for further research.

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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 frequently do not end on December 31, or even correspond to a full year.

We constructed calendar-year wages for each job classification (e.g., RNs) 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.

6.3 Cost of Quality Improvement

We estimated the costs of interquartile improvements 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:

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

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

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

in which Q_p is the pth quality percentile.

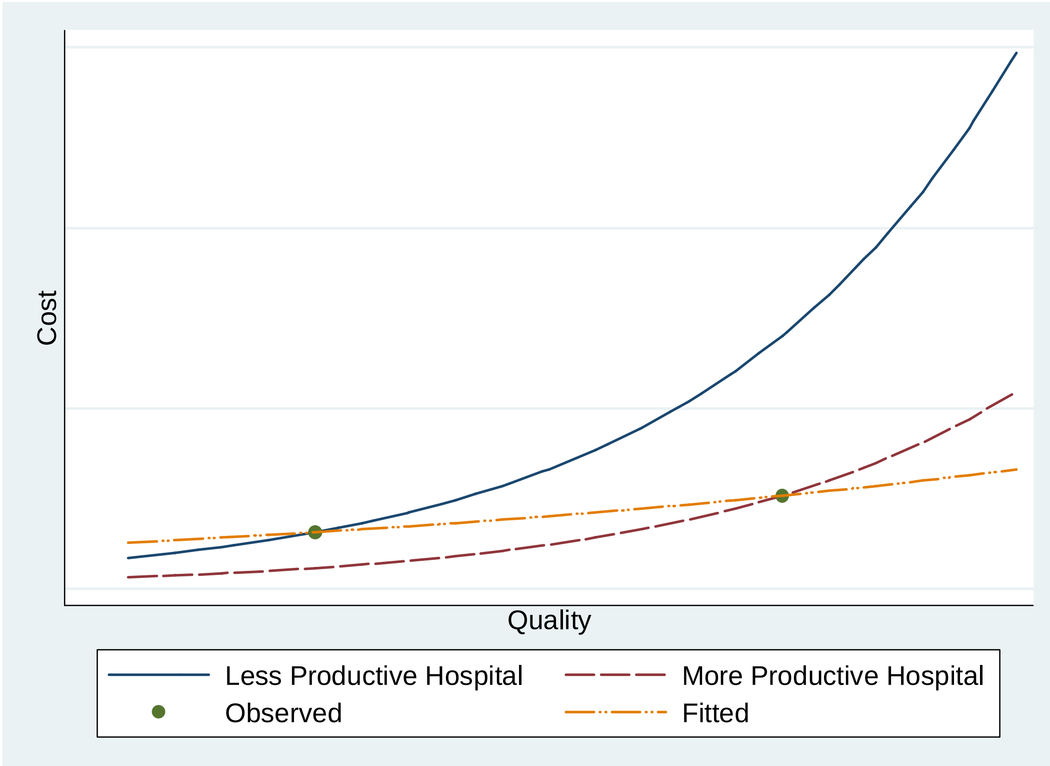

Figure 1:
Least squares understates cost of quality if
more productive hospital supplies higher quality

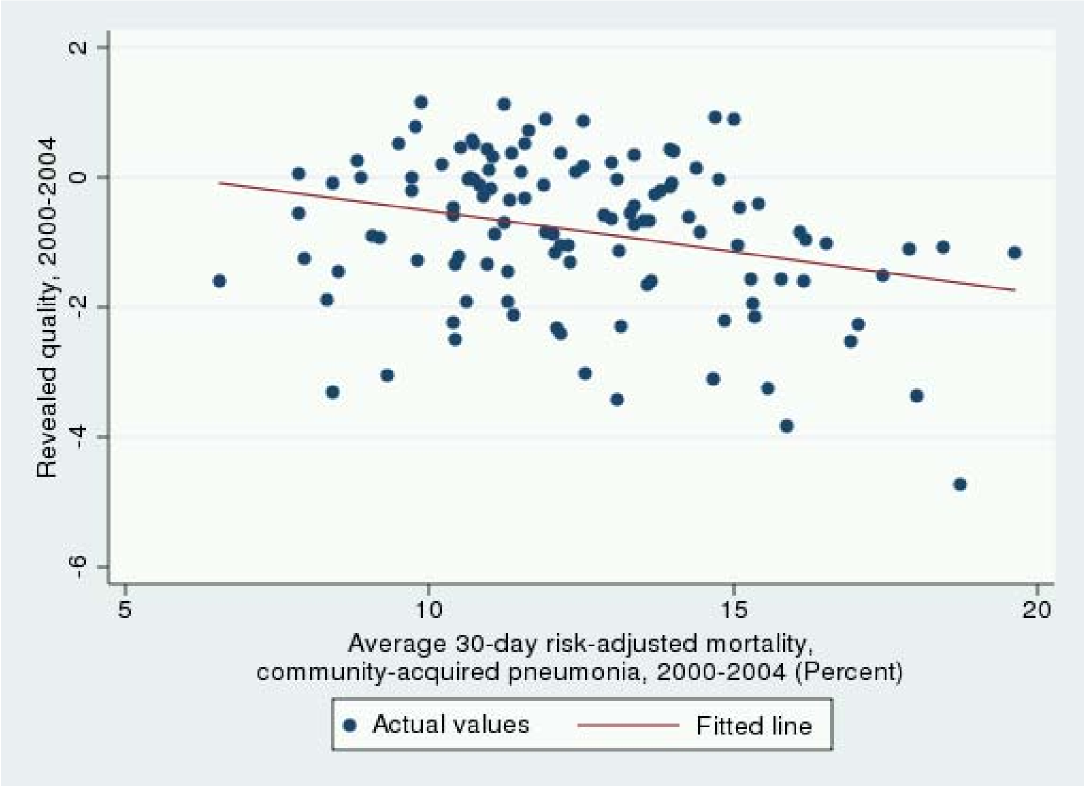

Figure 2:
Revealed quality versus clinical quality among hospitals in greater LA

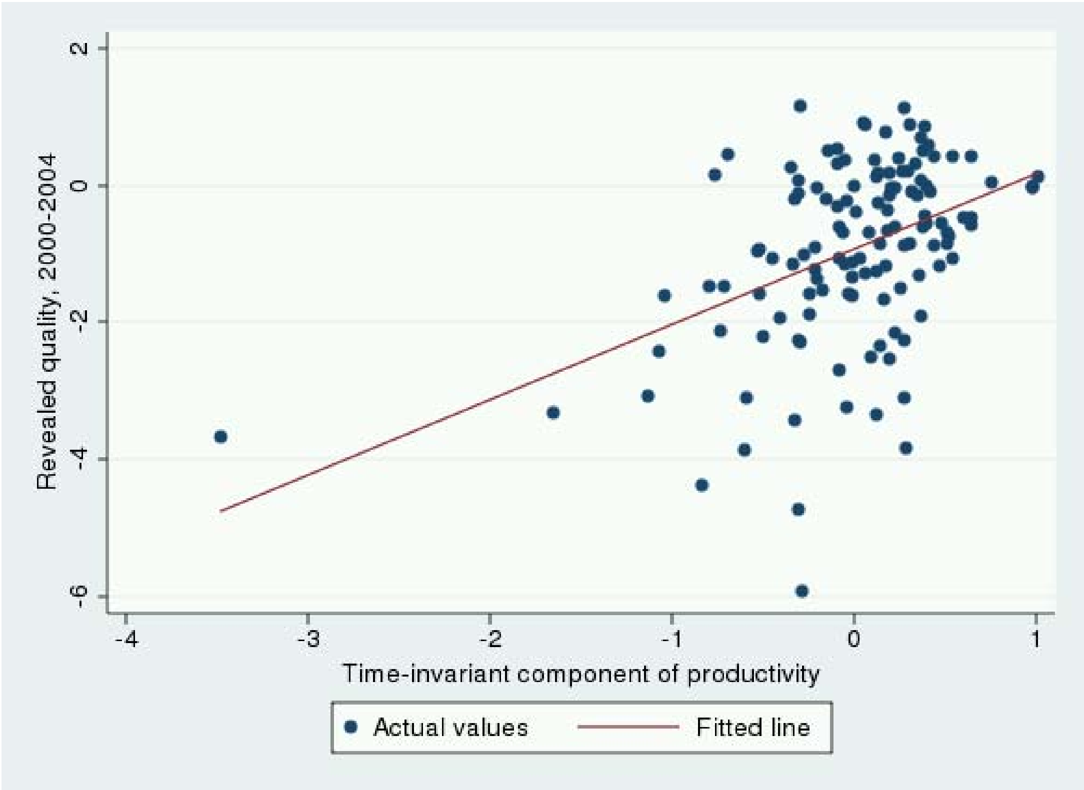

Figure 3:
Productivity and revealed quality among hospitals in greater LA

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 Revealed Quality

Taste parameter estimate (Standard error)	
Constant on distance, in miles	-0.594***
	(0.013)
Distance*75+ years old	-0.072***
	(0.013)
Distance*Female	0.024**
	(0.012)
Distance*Black	-0.069***
	(0.025)
Distance*Income ($000, demeaned)	0.001***
	(0.000)
Distance*Charlson-Deyo index (demeaned)	0.001
	(0.003)
Constant on quality	1.000
	(—)
Quality*75+ years old	0.339***
	(0.052)
Quality*Female	-0.023
	(0.037)
Quality*Black	-0.162**
	(0.069)
Quality*Income ($000, demeaned)	(0.037)
	0.021***
Quality*Charlson-Deyo index (demeaned)	0.032***
	(0.010)
Other statistics	
Number of patients	9008
Number of hospitals	129
Log likelihood	-16870.56
Correlation of observed and predicted hospital demand	1.00
Correlation given uniform quality	0.41

Notes: Analysis treats revealed quality as a parameter to be estimated for each hospital. Constant on quality is normalized as discussed in sections 2.2 and 3.1. 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
Baseline	
White male under 75 years old with mean income and Charlson-Deyo (co-morbidity) index	2.88 (0.07)
Deviation from baseline	
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.

Table 4: Fixed-Effects Regressions of Total Annual Inpatient Costs on Revealed Quality			
Specification			
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
Parameter Estimate (Standard Error)			
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)
$\ln Y_{ht} \cdot Q_{ht}$	0.04 (0.17)	0.01 (0.04)	-0.10 (0.09)
$\ln Y_{ht} \cdot \ln W_{ht}$	0.73 (0.63)	0.11 (0.37)	0.18 (0.41)
$\ln Y_{ht} \cdot \ln K_{ht}$	-0.05 (0.08)	0.01 (0.05)	0.02 (0.05)
$\ln Y_{ht} \cdot \ln CMI_{ht}$	-0.69 (1.19)	0.20 (0.42)	-0.07 (0.42)
$\ln Y_{ht} \cdot \ln CDI_{ht}$	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)	—
$Q_{ht} \cdot \ln W_{ht}$	-0.56 (0.47)	-0.06 (0.17)	-0.20 (0.21)
$Q_{ht} \cdot \ln K_{ht}$	0.03 (0.07)	0.01 (0.02)	0.02 (0.06)
$Q_{ht} \cdot \ln CMI_{ht}$	0.31 (0.88)	-0.43** (0.17)	-0.38 (0.31)
$Q_{ht} \cdot \ln CDI_{ht}$	-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)
$\ln W_{ht} \cdot \ln K_{ht}$	-0.05 (0.33)	0.06 (0.25)	0.10 (0.25)
$\ln W_{ht} \cdot \ln CMI_{ht}$	-2.04 (1.83)	-2.62** (1.19)	-2.40** (1.14)
$\ln W_{ht} \cdot \ln CDI_{ht}$	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)
$\ln K_{ht} \cdot \ln CMI_{ht}$	0.03 (0.34)	0.12 (0.29)	0.23 (0.29)
$\ln K_{ht} \cdot \ln CDI_{ht}$	-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)
$\ln CMI_{ht} \cdot \ln CDI_{ht}$	-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)
$t \cdot \ln Y_{ht}$	-0.03 (0.07)	0.00 (0.02)	-0.01 (0.02)
$t \cdot Q_{ht}$	0.01 (0.05)	-0.01 (0.01)	-0.01 (0.01)
$t \cdot \ln W_{ht}$	-0.15 (0.13)	-0.03 (0.07)	-0.01 (0.07)
$t \cdot \ln K_{ht}$	-0.01 (0.02)	-0.07*** (0.02)	-0.07*** (0.02)
$t \cdot \ln CMI_{ht}$	0.07 (0.33)	-0.17* (0.10)	-0.11 (0.09)
$t \cdot \ln CDI_{ht}$	-0.06 (0.30)	0.06 (0.06)	0.00 (0.06)
Other Statistics			
R squared	—	0.826	0.767
Number of hospitals	124	126	126
Number of hospital-years	589	591	591

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				
Specification				
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*	—
Parameter estimates and other statistics				
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, *p* value	0.155	<0.001	0.0031	—
Overidentification test, *p* value	—	0.16	0.94	—
Hausman test of OLS specification, *p* value	0.013	0.012	0.011	—
First-stage parameter estimates and weak identification F statistic				
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 *F* 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
Main results	
IV, quality responsiveness	+48.2% (16.2%)
IV, local demand shifters	+51.2% (14.8%)
OLS	+10.2% (13.2%)
Robustness checks	
Heart-attack patients	+26.0% (4.7%)
IV purged of income	+50.4% (15.8%)
Input and output prices as instruments	+54.1% (179.9%)
Full instrument set	+51.4% (20.3%)
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: Summary Statistics for Hospital Patients				
Patient characteristic	*Mean*	*SD*	*Min*	*Max*
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 A2: Summary Statistics for Hospitals		
Statistic	*Mean*	*SD*
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 A3: 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
Centinela 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	-2.11	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
Pacifica 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 A4: Results of Analysis of Hospital Choice in 2002
Based on Clinical Quality

Taste parameter estimate (Standard error)	
Constant on distance, in miles	-0.540***
	(0.012)
Distance*75+ years old	-0.090***
	(0.012)
Distance*Female	0.024**
	(0.011)
Distance*Black	-0.032
	(0.023)
Distance*Income ($000, demeaned)	-0.001**
	(0.000)
Distance*Charlson-Deyo index (demeaned)	0.002
	(0.003)
Constant on quality	0.084***
	(0.013)
Quality*75+ years old	0.002
	(0.011)
Quality*Female	-0.036***
	(0.013)
Quality*Black	-0.119***
	(0.022)
Quality*Income ($000, demeaned)	0.000
	(0.000)
Quality*Charlson-Deyo index (demeaned)	0.015***
	(0.003)
Other statistics	
Number of patients	8668
Number of hospitals	116
Log likelihood	-18547.50
Correlation of observed and predicted hospital demand	0.45

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. Standard errors appear in parentheses. * indicates statistical significance at the 10% level, ** at 5%, and *** at 1%.

Table A5: Fixed-Effects Regressions of Total Annual Inpatient Costs on Clinical Quality		
Specification		
Number	1	2
Time-varying quality	Yes	*No*
Controls for time-varying productivity	Yes	Yes
Parameter estimate (Standard error)		
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)
½ (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)
½ 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)
½ (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)
½ (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)
½ (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)
½ (ln CDI_{ht})^2	0.74 (1.02)	0.28 (0.69)
Linear time trend (t)	—	—
½ 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)
Other statistics		
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 A6: Regressions of Hospital-Cost Fixed Effects on Clinical Quality			
Specification			
Number	1	2	3
Quadratic quality	Yes	*No*	No
Instrument for quality	Yes	Yes	*No*
Instruments	Exogenous quality responsiveness	Exogenous quality responsiveness	—
Parameter estimates and other statistics			
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, *p* value	0.546	0.011	—
Overidentification test, *p* value	—	0.399	—
Hausman test of OLS specification, *p* value	0.191	0.186	—
First-stage parameter estimates and F statistic			
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)	—
F 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%.