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# Hedonic Adjustment of Hospital Services Price Inflation: An Application to Medicare Prices

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## Abstract

### Hedonic Adjustment of Hospital Services Price Inflation:

### An Application to Medicare Prices

We apply hedonic methods to adjust the prices of hospital services for changes in attributes. We look at data from the Health Care Financing Administration (HCFA) and from the American Hospital Association (AHA) to see if changes in patient and hospital characteristics can explain some of the variation in charges for several specific hospital services provided in 1989 and 1990, to Medicare patients from New York State. Our hedonic specification uses outcomes measures not generally available previously. We find that taking into account changes in characteristics leads one to revise estimates of the change in prices for specific services. In general, this leads to a reduction in the measure of pure price change.

# Hedonic Adjustment of Hospital Services Price Inflation

## 1. Introduction.

For the past several years there has been considerable concern about the growth in expenditures for hospital services. Hospital services comprise about 40% of total spending on health care, and these expenditures are growing at rates comparable to the rate of growth of health care spending overall. (Levit et. al., 1994).

One would like to know whether this increase in expenditure was due to an increase in prices for hospital services, and increase in quantity consumed, or a combination of the two. Such a decomposition requires a price or quantity index. Moreover the indexes must be constructed in a way that distinguishes between pure price changes and price changes that are induced by changes in product or service attributes. The measurement of changes in product characteristics is a difficult task in any industry and is especially difficult with hospital services and health care in general. Nevertheless a proper price index must account for the impact of these changes on price change in order to avoid an overstatement (or understatement) of the true price change.

Our purpose here is to identify product characteristics or attributes that can be used to adjust changes in price of a treatment provided in a hospital. In our hedonic regressions, we use a number of more or less standard variables as price determining characteristics, including type of hospital, location, whether it is a teaching hospital, etc. In addition, we use excess mortality rates as a measure of the efficacy of services provided by the hospital. Outcome indicators such as mortality rates have received considerable attention as an indicator of quality.[1] This paper is (to our knowledge) the first to attempt to link outcomes variables to prices for services.

Our empirical work is based on charges for Medicare services for the years 1989 and 1990, as provided by HCFA. This data is augmented by data from the American Hospital Association (AHA) on hospital characteristics. In the hedonic regressions, the single most

[1] See for example, Geigle and Jones (1990) and Fleming (1990).

important price determining characteristic is length of stay. Other effects are important, though significance (and even sign) may vary across DRG's, suggesting difficulty in generalizing the results. Measures of patient illness severity are typically positive and significant, although the magnitude of the effects vary across Diagnostic Related Groups (DRG's). Location effects are important; rural hospitals typically charge less for given services. Coefficients on some variables--the outcomes measures, the medical school affiliation indicator variable, and the proportion of administrators out of total employees--vary in statistical significance across DRG's. Because our focus is on output prices we construct output price indexes with and without a hedonic adjustment to illustrate the importance of product characteristics in determining prices. Our results indicate that changes in the characteristics of the services provided is a very important factor in explaining changes in the charges for services. In six of the 8 DRG's we considered, hedonic adjustment results in a reduction of the rate of inflation. In one case, the adjustment is enough to change inflation to deflation.

This paper is organized as follows. Section 2 is a discussion of the conceptual problems in measuring output, prices and changes in prices for this industry. Section 3 is a discussion of the statistical methodology implementing the hedonic method. Section 4 is a discussion of the results, and section 5 is a brief summary.

## 2. Output Price Indexes.

Generally, the underlying theory of an output price index as set out in Archibald (1977), Diewert (1983) and Fisher and Shell (1974), presumes a profit maximizing competitive firm. An application of the theory to the hospital industry is not immediately obvious because many hospitals are operated on a non-profit basis.

From the perspective of index number theory we are interested in whether one can aggregate the prices charged by profit and non-profit hospitals into a single output price index. To accomplish this, several assumptions are necessary: First, the output prices must be exogenous to individual firms. Second, firms must use these output prices to decide how much output to produce and how to produce it. Third, each hospital type must be efficient in the sense that it operates on its production possibility frontier.

Regarding the first assumption, there are two considerations. First, there is some degree of competition between hospitals, though it is generally agreed that this takes the form of non price competition more often than price competition. Second, and more important, is the fact that most

hospital bills are paid for by third parties. These payers negotiate with hospitals for the prices that they will pay for treatments. In fact, one could argue that, given the increasing prominence of third party payers, especially Medicare, these negotiations likely increase the degree of price competition among hospitals. Because these negotiations cover all the treatments that a hospital may provide, the price is exogenous when considering the transaction for a given treatment between a hospital and a patient covered by a given third party payer. For Medicare at least, it is not unreasonable to consider output prices as exogenous.

Regarding the second assumption, there is some potential concern as to whether it is appropriate to model non-profit institutions as making the same sorts of cost and output trade offs as for-profit firms. Several views of the behavior of non-profit firms can be found in the literature, see for example Weisbrod (1975) or Newhouse (1970). Three institutional differences are of particular importance in comparing the behavior of non-profit to for-profit hospitals. First, there is no owner's claim on the surplus of non-profits, which of course does not imply that they do not seek to accumulate a surplus. Second, there is the possibility that non-profit hospitals may have objectives different from for-profit institutions and these may cause non-profits to produce output bundles that are systematically different from the output bundles produced by for-profit institutions. Third, non-profit hospitals may receive charitable contributions which can reduce the need to pay for inputs through revenue generation and they face a zero corporate tax rate.

At issue is whether these institutional differences lead to systematically different output and production choices by non-profit institutions. Evidence on this point is slim, but consider Needham (1978):

> "The behavior of non-profit organizations, such as hospitals, educational institutions and government departments, can be explained in terms very similar to those applicable to industrial firms.....There are, moreover, many similarities between the factors determining the behavior of non-profit organizations and industrial firms and differences between the two type of organizations may often be more apparent than real...."

Accordingly, to ensure that output prices are unaffected by organizational type, we assume that that the charitable contributions and zero corporate tax rate enjoyed by the non-profit hospitals are used to reduce input costs in lump sum fashion and not to charge lower (or subsidized) output prices.

That non-profit hospitals might produce output bundles different from those of for-profit hospitals is a possibility that, as shown below, ties into our third assumption above that each hospital type must be efficient in the sense that it operates on its production possibility frontier.

The equally efficient assumption is necessary to compare the impact of a relative price changes on the output of a firm. Furthermore, the assumption has empirical support.[2]

The apparent equality of efficiency in the provision of service allows us to characterize the different output bundles provided by each hospital type as solely deriving from differences in the their respective production possibility frontiers. While both hospital types may provide the same service, say treatment for pneumonia, the characteristics of the service might be different owing to the different objective functions and the consequent differences in the ways that inputs are transformed into outputs. However, these differences in objectives and resources affect only the inframarginal or average levels of the attributes of services, not the marginal decisions on attribute loading in the services.

Consider a hospital that transforms the input vector $v$ into the output vector $x$. The difference between the quantity-quality decisions of a for-profit and a non-profit hospital can be viewed as affecting the way inputs are transformed into outputs. Let $a$ denote the hospital type characteristic. A hospital's production relationship can be characterized as

$$F(v,a) = \{y | (v,a,x) \in T\} \text{for given } v \text{ and } a$$

where T is the technology set and denotes the $x$ that can produce $y$. $F(v,a)$ is thus the set feasible outputs for a given quantity of inputs conditioned by the hospital type.

The conceptual output price index is based on a firm's revenue function. Define the revenue function for a hospital as

$$R(p,v,a) = \max_x \{px | x \in F(v,a)\}.$$

Clearly, the value of $x$ that solves the above problem will vary with $a$. However, because the optimal point in both cases is determined by the tangency of each production possibility frontier with the same price plane, the marginal values must be the same.

The conceptual output price index between periods 0 and 1, for given hospital type $a$, is given by

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[2] In fact, studies find that on average both types of hospitals are inefficient; that is, they do not use the minimum quantity of inputs to produce a given level of output. See for example Register and Bruning (1987).

$$I(p^0, p^1, v^r, a) = \frac{R^r(p^1, v^r, a)}{R^r(p^0, v^r, a)} \tag{2.1}$$

where r denotes the reference period for the determination of the relevant technology set and input vector. If r is equal to 0 then the index takes a Laspeyres perspective and if r is equal to 1 then the index takes a Paasche perspective. We can aggregate these indexes to obtain an industry index, conditioned by the various organizational forms. Because the above framework applies to the inclusion of any product characteristic, it forms the conceptual foundation for our approach to hedonic adjustment. (For an application of this framework to the construction of superlative index numbers see Fixler and Zieschang (1992))

Index number makers of course have to come up with a way of computing the index $I(p^t, p^{t-1}, v^r, a)$ above. Most statistical agencies do so by setting r equal to t-1, ignoring $a$ (competitive firms are assumed), and using the Laspeyres index formula to obtain:

$$I_L(p^t, p^{t-1}, v^{t-1}) = \frac{p^t \cdot x^{t-1}}{p^{t-1} \cdot x^{t-1}}. \tag{2.2}$$

$$= \sum_i \frac{p_i^t}{p_i^{t-1}} \times s_i^{t-1};\ s_i^{t-1} = \frac{p_i^{t-1} x_i^{t-1}}{\sum_i p_i^{t-1} x_i^{t-1}}.$$

The second form of the Laspeyres index shows that it is a revenue share weighted average of the price relative, the ratio of prices in each period. Observe that by definition the denominator in (2.2) is equal to the one in (2.1). The numerator is an unobservable lower bound estimate of the numerator in (2.1). It follows that the index in (2.2) is a lower bound to the index in (2.1) and therefore potentially understates the true level of inflation.

To capture the role of organizational type as well as other characteristics, one can write the Laspeyres perspective version of the index in (2.1) as:

$$I(p^t, p^{t-1}, a^{t-1}, v^{t-1}) = \frac{R^{t-1}(p^t, a^{t-1}, v^{t-1})}{R^{t-1}(p^{t-1}, a^{t-1}, v^{t-1})}. \tag{2.3}$$

The vector $a$ contains attributes of the product (service) that affect the price of the product whose production requires inputs; organizational type can be viewed as one such attribute. Again this index is unobservable and it could be estimated by the Laspeyres index given by:

$$\hat{I}_L(p^t, p^{t-1}, a^{t-1}, v^{t-1}) = \frac{\hat{p}^t \cdot x^{t-1}}{p^{t-1} \cdot x^{t-1}} \qquad (2.4)$$

where the "hat" denotes an estimated price adjusted for changes in product characteristics.

In practice, we observe statistical agencies taking several approaches to quality adjustment of price indexes. One approach, for example, is to factor out changes in production costs associated with any product price change: For a new product, one would subtract from the total change in price any change in the production costs associated with the change in product characteristics. In another approach, one would adjust prices using hedonic methods: One could use an estimated statistical relationship between product characteristics and price to adjust price for changes in characteristics.

To implement the hedonic approach, we require a specification of the appropriate output, prices, and characteristics. In the case of hospital services, each specification presents interesting conceptual difficulties.

It is not at all obvious how one ought to measure the service output provided by a hospital. Researchers have used a number of measures of output, including the treatment-of-illness episode, total patient days, and the number of patient discharges. The treatment of illness episode is very attractive theoretically: one would aggregate data on all heath expenditures associated with a specific illness, including (for example) multiple admissions to various types of health care providers, doctors charges, total spending on prescriptions, and so on. However, it is the least practical basis for output measurement because of the lack of data following specific patients through the health care system.[3]

We measure output in terms of discharges, stratified according to service intensity. More specifically, we view a hospital as producing a vector of outputs, where each element in the vector corresponds to the number of cases in a particular class of treatments, which we set to be the DRG classification used by HCFA. In terms of the optimization problem set out earlier the $x_i$ are bundles of services for hospital treatments as indicated by the DRG. Each DRG category contains a set of treatments and these treatments are the service products of the hospital.

Identifying the output price presents additional difficulties. The prices paid by private patients, private third party (insurers), and government are not necessarily the same. Private

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[3] In fact, one could not construct an Producer Price Index in this view because the PPI is industry-based and therefore cannot account for expenditures associated with a given treatment that occur in different industries.

patients generally pay list prices. Private third party payers often negotiate contracts for special discounts from these list prices. Government rates may be set by fiat. The Medicare Prospective Payment System (PPS) is a Federal legally-mandated pricing formula that dictates the compensation for services, though Medicare reimbursement practices vary from state to state. Thus, there are often several prices associated with a specific service, with the price varying according to the identity of the purchaser. It follows that in constructing an index, one must take into account that payment practices generally vary by the identity of the payer.[4]

In the case of Medicare sales, one might suppose that the existence of a Medicare pricing formula creates little variation in prices for a given treatment in a given hospital. Empirically, this is not the case. Figure 1 plots the distribution of the log of charges from a given hospital, for patients from DRG 89 (Simple Pneumonia and Pleurisy), who in addition have the same primary diagnosis. The highest charges in the sample are more than a factor of 100 greater than the lowest charges in the sample. Clearly the use of a pricing formula does not equate charges for all patients in DRG 89 in this hospital. (We observe similar results for the other DRG's we examine in this study.)

In the case of hospital services, measuring changes in product characteristics is an extremely complex undertaking. From an economic perspective, hospitals choose the level of attributes that they wish to provide with perhaps lower bounds being set by state or regulatory agencies. The achievement of the desired level of quality involves the consumption of inputs and therefore costs. The implication is that one can identify the impact of changes in product characteristics on price through the change in the costs associated with the improvement. This notion is consistent with the general empirical finding that there is a positive relationship between quality and price. (See, for example, Stiglitz (1987)).

However, simply identifying quality with inputs (costs) may provide insufficient emphasis on the consequences of the quality of the treatment for the patient. Accordingly, measures of quality can be supplemented by (or based on) the outcomes associated with a treatment. The most prominent measures of treatment outcomes are the morbidity and mortality rates associated with particular treatments.

There are varying opinions about how these outcomes measures should be related to price. On the one hand, one could argue that better outcomes should be associated with higher

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[4] Catron and Murphy (1996) show that the PPI for hospital treatments vary by payer.

prices: Lower mortality or morbidity is a good that is obtained by greater resource usage, and this leads to higher prices. (An implicit assumption in this view is that hospitals are operating efficiently so that additional expenditures are efficacious.) On the other hand one could argue that better outcomes are associated with lower prices: Bradbury et. al (1994) argue that effective care (good decision making, good use of resources) consumes fewer resources, implying that costs and therefore charges (price) should be lower. Because staff (inclusive of physicians) perform all of the activities associated with a treatment well they reduce the costs of mistakes and complications and thereby effectively establish a positive correlation between outcomes (quality) and price.

There are certain traps to be avoided with the selection of outcomes measures. In particular, the outcome measure must be germane to the population under analysis. Mortality rates, for example, are not necessarily informative for DRG's where mortality is a very rare event.

Given that mortality is (one) relevant measure of the success of outcomes, there are additional issues in its interpretation. It is well known that most measures of health status are correlated with economic and demographic factors such as income, race, and age. For example, poor patients tend to be sicker on admission than wealthy patients, as poor patients are more likely to delay obtaining medical care at the onset of illness. Thus it is common to adjust indicators for demographic and economic characteristics when such data are available. See, for example, DesHarnais et. al. (1990) for a discussion of issues in adjustment of mortality rates for patient risk and an example of how adjustments are calculated.

In addition, in-hospital mortality rates are sometimes criticized as being vulnerable to manipulation by hospitals. In principle, hospitals could screen admissions and perform opportunistic discharges to systematically affect these rates. One might be able to minimize the impact of this type of opportunistic behavior by including deaths thirty or sixty days after discharge when calculating mortality rates. On the other hand, using longer horizons to calculate mortality rates adds noise to the signal: The likelihood of post-discharge mortality is influenced by the quality of care received by the patient outside the hospital, over which the hospital may have little control. This is another area where "illness episode" data -- linking patient records across types of providers, following the course of their treatment -- could resolve some basic questions.

Table 4 provides a list of the variables we use as price-determining characteristics. Our input intensity variables, such as the Nurse-to-Bed ratio (Nurs2bed) are intended to capture an "attentiveness" dimension to treatment. The hospital related variables such as medical school

affiliation capture dimensions of product attributes that are related to type of personnel, location, management, etc. The remaining variables, such as length of stay, concern characteristics of treatment. With these variables and the attentiveness variables it is not unambiguously clear whether quality is associated with increases or decreases in their levels. The reason is analogous to that in the case of the relationship between outcomes and prices. For example, increases in the length of stay for some treatments may not indicate increases in the quality of treatment, as when there are complications, while for other treatments it does as when there are improvements in procedures that allow earlier discharges..

## 3. Methodology.

The statistical methodology that we follow is straightforward. First, we winnow patient records so as to insure a degree of uniformity of diagnosis across patients. We then use the mortality model developed by the Health Care Financing Administration to estimate a logit regression between patient characteristics and in-hospital mortality for a given DRG. We use these results to calculate our outcomes measure, excess mortality by hospital by DRG. We then specify a hedonic regression that relates hospital charges to service characteristics, hospital characteristics, and input usage. The results are then used to estimate an adjusted charge, which takes into account that the characteristics of services change over time.

### *3.1 Data Sources*

The data for this study is assembled from a number of sources.

Patient data is obtained from the HCFA QC-MEDPAR file.[5] We were provided with over 20 million patient records for the years 1989 and 1990, covering all Medicare admissions of patients who lived in New York state for those years. From those files, we extract records of patients whose treatment fit into any one of the eight target DRG's, as well as information related to the medical histories of these patients. Our price variable, total charges, also comes from this file. Total charges is the amount billed to HCFA (actually to one of its fiscal intermediaries such as Blue Cross) from the hospital and it includes non covered charges. As with any third party payment, there may be a difference between the charge and the actual reimbursement. In the

[5] The acronym stands for "Quality of Care- Medicare Provider Analysis and Review." The file consists of summaries of Medicare billing statements for all Medicare hospitalizations in a given year.

case of HCFA, reimbursement is complicated by the fact that it often consists of two parts: one part is associated with the patient charge and the other part is a lump sum payment made at the end of the year for some aspects of activity over the course of the year. For example, a service provided by a teaching hospital with higher charges may initially receive a reimbursement that is less than the charge. However, teaching hospitals are likely to receive a substantial year end adjustment to compensate for that part of the charge arising from training and medical education expenses—this adjustment serves to reduce the initial gap between charges and reimbursement. Total charges therefore are a better measure of the price of the service than reimbursements.[6]

Lemrow et. al. (1990) provide a listing of the most frequently observed DRG's. From this listing, we selected DRG's for which mortality is not a rare event: our target DRG's comprise every DRG from Lemrow's list with a raw mortality rate of 4% or higher. Table 1 provides a listing of the DRG's that we select for further analysis.

Hospital data were assembled from files provided by HCFA and the American Hospital Association. The HCFA Provider of Services file was used to locate information on ownership characteristics, location, and medical school affiliation. The American Hospital Association provided data on skilled labor inputs, including usage of registered nurses, total nursing staff, number of residents, and the number of administrators, as well as size measures.

*3.2 Sample Selection*

Prior to conducting the empirical analysis, several steps were taken to insure that the patient records included in the analysis of each DRG were of similar nature and severity. These steps involved dropping records from the analysis if they did not meet certain criteria that are discussed below.

The starting point for the sample was the population of Medicare patients residing in New York state. Our first selection was to drop from further analysis patients who did not receive treatment from a hospital in New York state. In the case of DRG 89, for example, this lead to a reduction of our sample size of approximately 4% in each year.

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[6] Nother (1988) also uses the HCFA data on charges as prices. To substantiate this treatment, she cites HCFA Program Information Letter no. 81-28, March 31, 1981, which states that the charge data "can be considered reasonable indicators of the overall relative differences in prices charged by hospitals for similar types of diagnoses."

Our HCFA-based logit specification includes dummy variables indicating whether the patient had a previous hospitalization up to six months prior to a given admission. As we did not have data from 1988, we had to drop from the 1989 data patients who were admitted prior to July 1 of 1989, for whom we could not generate a 6-month previous admission history. This selection cut the 1989 sample roughly in half.

Further selections were conducted on the basis of diagnostic information. Because each DRG is itself an aggregation of lower-level International Classification of Diseases (ICD) codes (9th revision) each DRG exhibits a degree of heterogeneity in severity and characteristics of patient illness. If ignored, this heterogeneity adds noise to the estimated relationships. We used sample selection criteria to reduce the degree of patient heterogeneity in our hedonic regressions.

For example, for each patient in DRG 89, we had information on the primary and secondary diagnoses. We tabulated the various primary diagnoses observed in the remaining data from 1989, and kept only those observations which had the single most frequent primary diagnosis. Data from 1990 was similarly selected to conform with the 1989 sample. For DRG 89, these selections reduced our effective sample size by just under 30%.

The next selection involved tabulation of all secondary diagnoses included in the remaining patient records. At various points in our empirical work, we include dummy variables indicating the presence of specific secondary diagnoses. To eliminate potential singularity problems, and to keep the patient population as homogenous as possible, we dropped from the analysis patient records containing what we designated as rare secondary diagnoses. A secondary diagnosis was considered rare if there were fewer than 50 patient records with that diagnosis in the remaining sample. For DRG 89, this final selection reduced our effective sample by an additional 30% in each year.

For the hedonic regressions and the computation of our outcome measures, we require hospital specific data. Some of the required information was not available for a number of hospitals in our sample; patients from these institutions were dropped from the hedonic regression. Further, the calculation of some hospital - specific outcomes measures required comparing features of the hospital experience with the overall population experience. Some hospitals treated so few patients that such comparisons were suspect. Hence we drop patients from hospitals that treated fewer than 4 patients per year in a given DRG.

Table 2 provides a summary of our data screening as applied to DRG 89. In 1989, the initial sample was 22,284, while the effective sample for the logit regressions was 4,267. After

matching patient records to hospital information, we had 3,131 observations available for the hedonic regression. Similar adjustments were made for each of the eight DRG's in this study and the last column in Table 1 provides the number of observations available for the final hedonic regression.

*3.3 Excess Mortality Rates*

We use the results of the HCFA mortality model (U. S. Department of Health and Human Services, 1991) to derive a measure of excess mortality by DRG for each hospital in our sample. In that model patient characteristics include variables describing previous admission history, presence of specific secondary diagnoses, patient age, type of admission (emergency, elective, or urgent), the sex of the patient, and whether the hospital is an urban or rural hospital. The HCFA model estimates a relationship between the patient characteristics and the likelihood of in-hospital mortality.

In order to implement the HCFA mortality model, we were required to construct variables describing the number and severity of previous admissions for each patient for the six months immediately prior to a given admission. We used the detailed description of the HCFA admission characteristics in order to identify ICD codes associated with specific severity classes, and then reviewed our tapes for information on previous admissions for given patients. As we had available patient data from data tapes from the 1989 and 1990, we were able to reconstruct these variables for all patient admissions during the last eighteen months of our sample.

To help to control for varying severity of illness (and hence varying likelihood of mortality) associated with varying diagnoses, we include in the logit regression a series of dummy variables keyed to the secondary diagnoses present in the patient record. Every secondary diagnosis present in the patient records remaining in our final data set receives its own dummy variable in this regression. The number of dummy variables included on the right hand side of this regression hence varies from as few as eight in the less populous DRG's to as many as 40 in the more populous DRG's.

If the experience at a given hospital is no different from the average experience for the entire DRG, then the expected number of mortalities for a hospital is obtained by summing across patients at the hospital the probability of mortality given by the HCFA model. The excess mortality rate is just the difference between the actual number of deaths at hospital t, N(t), and the expected number of deaths given patient characteristics, E[N(t)]. A certain amount of chance variation of the actual mortality rate about the expected mortality rate is expected, hence it is

useful to normalize the difference by the standard error of the expected mortality rate $\sigma_{N(t)}$. Thus, our final excess mortality rate D(b) is measured as

$$D(b) = ( N(t) - E[ N(t) ] ) / \sigma_{N(t)} .$$

*3.5 The Hedonic Regression.*

The hedonic regression relates patient charge to variables thought to be useful in explaining the variation in charges. In applying the hedonic approach, one would take, say, a set of k characteristics, measured by a set of variables $a = \{a_j, j=1, 2, \ldots , k\}$, and estimate the functional relationship between price and these variables, $E[ p \mid a ] = f( a )$. $E[ p \mid a ]$ is the expected price of the product conditioned on the characteristic vector $a$. A linear regression of log of price on the attributes is estimated for some output price i:

$$\ln p_i = a_i'\beta + e_i, \qquad (3.1)$$

where $e_i$ is an error term with $E[ e_i \mid a_i ] = 0$, and a finite variance. Table 3 is a list of the right hand side variables in the hedonic regression.

The use of the excess mortality rate as a dependent variable in this regression presents some statistical problems. The use of estimates of parameters from the logit regression to construct the excess death rate D(b) means that this variable contains some measurement error. Formally, D(b) can be written as

$$D(b) = D(\beta) + [ D(b) - D(\beta) ],$$

where the bracketed term gives the measurement error involved in using estimates of $\beta$ in place of $\beta$ itself in the calculation.

Our model thus corresponds to the classical errors in variables model. Note that our estimated parameter b is distributed $\mathcal{N}( \beta, \Sigma )$, and so by the delta method (Serfling, 1980) we have $D(b) \sim \mathcal{N}( D(\beta), \nabla D' \Sigma \nabla D)$, where $\nabla D$ is the gradient of D. Following Gleser (1992), we can use this information in a GLS framework to generate consistent estimates of the desired parameters and consistent standard errors for hypothesis testing. The results in Table 5 for the hedonic regressions are reported using the Gleser - adjusted estimates and standard errors.

*3.6 The Price Indexes*

To demonstrate the importance of distinguishing between a price change induced by product characteristic change and a price change caused by market dynamics (pure price change), we construct two price indexes for each of the DRGs, one with and one without an adjustment for changes in quality. To illustrate, consider the price relative for service i, measured from

period 0 to period 1, which is calculated as $p_{i,1} / p_{i,0} = \pi_{i,1,0}$. This relative is an element in the unadjusted price index To adjust a price relative for product and outcomes changes over time, we calculate a "quality index" $\Theta_{i,1,0}$ and then use the adjusted price relative to construct the quality adjusted price index

$\Theta_{i,1,0}$ measures the change in price from period 0 to period 1 that our model attributes to a change in the underlying characteristics of the services in DRG i. We use the estimated parameters of the hedonic equation to construct this measure. Let $a_{i,1}$ be the levels of the price determining characteristics in period 1. The expression for $\Theta$ is thus

$$\Theta_{i,0,1} = \theta_{i,1} / p_{i,0}$$

where

$$\theta_{i,k} = \exp\{ a_{i,k}' \hat{b} \}$$

The vector $\hat{b}$ represents the estimated values of the parameters $\beta$ from the hedonic regression (3.1). The price, $\theta_{i,k}$ represents the price $\hat{p}$ in (2.4).

The adjusted price relative for DRG i is then calculated as $\pi^*_{i,1,0} = \pi_{i,1,0} / \Theta_{i,1,0}$, which simplifies to $\pi^*_{i,1,0} = p_{i,1} / \theta_{i,1}$.

We construct price indexes for the 8 DRG's by first taking the geometric average of 1989 patient charges that match on the primary diagnosis code and the first secondary diagnosis code. (The order in which the diagnosis codes appear on the patient record indicates relative importance.). We then find corresponding treatments in 1990. If there is more than one match, we again take the geometric mean. Formally, for some DRG suppose that in t there is a set of prices indexed by i, each having $n_j$ secondary diagnoses; we then have

$$p_{i,t} = \left( \prod_j p_{i,j,t} \right)^{1/n_j}.$$

Consequently, the price relative for a particular set of primary and secondary diagnosis codes within a DRG may be formed as a ratio of the geometric means of charges. After computing all of the price relatives within a DRG, we then aggregate them by taking a share weighted geometric mean, where the shares are the fraction of total charges in the DRG in 1989. Using the notation above, the DRG price index is written as

$$I = \prod_i \left(\pi_{i,90,89}\right)^{w_i}$$

where

$$w_i = \frac{p_{i,89}}{\sum_i p_{i,89}}.$$

Our purpose is to adjust the nominal rates of inflation for changes in product characteristics. To calculate the adjusted DRG price index, each relative in I is divided by the relative of the estimated 1990 price from the hedonic regression to the 1989 price. The estimated 1990 price for the i'th DRG, $\hat{p}_{i,90}$, is constructed according to the above equation for $p_{i,t}$, using the same aggregation procedure within a DRG. The adjusted index simplifies to

$$I = \prod_i \left(\pi^*_{i,90,89}\right)^{w_i}$$

## 4. Results.

This section reports on the results for the hedonic regression, and the hedonic price index for each of the eight component DRG/ICD treatments included in this study.

### *4.1 The Hedonic Regression*

The results for the hedonic regression are given in Table 4 and note that the P-values are given below each reported coefficient. The hedonic regressions appear to fit prices well: the simple correlation between the estimated 1989 price and the actual 1989 price in each DRG is approximately 0.9.[7]

Hospitals affiliation appears to be significantly related to charge. In the regression, dummy variables for non-profit and government affiliation indicate whether those institutions have higher or lower charges than average. (The excluded category is private, for-profit institutions.) Government hospitals tend to charge less than average prices. Nonprofit hospitals tend to charge more than average, but the difference is only occasionally significant.

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[7] Since we use a GLS estimator, the usual measures of fit are misleading.

Other hospital characteristics are significantly related to price. Larger hospitals tend to have higher charges. Rural hospitals tend to have lower charges. Medical school affiliation is significant in only two of eight cases; the coefficient is positive in both cases.

We have two measures of the intensity of resource usage. Higher ratios of residents to beds are always positively and significantly related to charges. The nurse to bed ratio is ambiguously related to charges overall. In two of the eight DRG's, we observe a significant relationship between charge and nurse-to-bed ratio, but the two cases are of opposite sign.

Further exploring the role of inputs, the ratio of RN's to nurses is generally positively related to charges, but the effect is only significant in one case. A higher ratio of administrators to employees is generally negatively related to costs.

The excess mortality rate to which we paid considerable attention is significant in but two of eight cases, DRGs 14 and 296, and this is at a less than 1% level of significance. The sign in both cases is positive, as it is for every DRG except 127 where it is negative but with a very high P-value. As mentioned earlier, a positive correlation between mortality rates and prices would be expected when better care and consequently better outcomes are associated with the consumption of fewer resources.

Specific patient characteristics are significantly related to charges. The complexity of the case, measured by the number of secondary diagnoses present in the patient record, is significantly positively related to charges. Cases involving surgical procedures have higher charges than cases with no surgical procedures. Length of stay is a very significant determinant of charges, with longer stays related to higher charges. In fact, length of stay is the only variable that unquestionably belongs in each regression.

*4.2 Adjusted Price Changes*

Table 5 compares the simple price relatives for each DRG to the adjusted price relatives as determined by the hedonic regression.

The simple index formula shows great dispersion in the rates of inflation across services. Before adjustment, we see inflation rates varying from -1% to +32%. For every service, adjustment reduces the rate of change in prices. After adjustment, inflation rates vary from -6% to +14%. Looking at the last line in Table 5, accounting for changes in product characteristics reduces the overall inflation rate from 11.5% to 6.0%.

## 5. Summary.

In this paper we have sought to establish how one can adjust changes in the prices of hospital treatments for changes in product characteristics. We find that product characteristics matter in explaining even short run changes in hospital prices. There are important changes in the characteristics of the all of the services we look at. Accounting for these changes in characteristics leads to downward revisions in the estimate of pure price change for these services. In one cases, hedonic adjustment is enough to change the sign of the measured price change.

It is clear from our results that properly accounting for changes in product characteristics can have a significant impact on the implied changes in output of the hospital industry.[8] Nominal spending on hospital care in 1989 was $231.8 billion, and spending in 1990 was $256.5 billion. For the sake of an example, suppose that our unadjusted rate of inflation of 11.5% per year and our quality adjusted rate of 6% were representative of price changes in all DRG's, for both Medicare and non-Medicare sectors. With 11.5% inflation, total output of hospital services *decreased* by about 0.8%. If the pure price change was instead 6%, then the output of hospital services *increased* by about 4.3%.

We find that there is large variation across services in the factors that are important in explaining price changes, and even in the sign with which some factors enter the hedonic regression. In particular, there seems to be no uniform relationship between outcomes measures and price. Thus extrapolating the empirical results for our specific services to hospital services generally is difficult. In regard to the role of mortality, our results suggest that there is a positive correlation between quality and price; a low mortality rate is directly related to price because lower resources are consumed as a result of a "better" provision of services.

These results are of broad interest to economists studying output and productivity in the hospital services industry, as well as to policy makers generally. Our figures give a rough idea of the magnitude of the proportion of price change that may be attributed to changes in the quality of services. The size of this adjustment is economically highly significant.

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[8] A property of index number is that they satisfy the product test: the product of a price index and its corresponding quantity index equals the ratio of values (expenditures) for the relevant periods. An implicit quantity index can be obtained by dividing the value ratio by the price index.

Table 1.

DRG's Selected for Analysis

| DRG Code | Primary Diagnosis (IDC Code) | Title | Number of Cases in 1989 |
|---|---|---|---|
| 127 | 4280 | Heart Failure & Shock | 8620 |
| 89 | 486 | Simple pneumonia & pleurisy, age ≥ 70 and / or complication and / or co-morbidity | 3131 |
| 14 | 4349 | Specific cerebovascular disorders except transient ischemic attack | 3581 |
| 296 | 2765 | Nutritional & miscellaneous metabolic disorders, age ≥ 70 and / or complication and / or comorbidity | 1413 |
| 88 | 496 | Chronic obstructive pulmonary disease | 721 |
| 174 | 5789 | Gastrointestinal hemorrhage, age ≥ 70 and / or complication and / or comorbidity | 925 |
| 148 | 1533 | Major small & large bowel procedures, age ≥ 70 and / or complication and / or comorbidity | 300 |
| 210 | 82021 | Hip & Femur procedures except major joint, age ≥ 70 and / or complication and / or comorbidity | 842 |

*in Lemrow et. al (1990), out of

Table 2.

Sample Selection, DRG 89.

| Category | 1989 |
|---|---|
| Total Records | 22,284 |
| Patients in New York Hospitals | 21,397 |
| 6 Month history available | 8,723 |
| Largest Primary Diagnosis | 6,263 |
| Absent rare secondary diagnoses | 4,267 |
| Minus low volume hospitals or hospitals with incomplete data | 3,131 |

Table 3.

Variables used in Hedonic Regression

| Variable Name | Description |
|---|---|
| GOV | 1 if hospital is controlled by Government, 0 otherwise |
| NOPRO | 1 if hospital is organized as private, non-profit |
| SIZE | Average number of employees at hospital |
| RURAL | 1 if hospital is rural, 0 otherwise |
| MEDSCHOOL | 1 if hospital is affiliated with a medical school, 0 otherwise |
| RN/NURSE | Ratio of number of registered nurses to total number of nurses employed |
| NURS2BED | Total number of nurses divided by number of beds |
| ADMIN/EMP | Number of administrators employed as a proportion of total employment |
| RES/BEDS | Number of residents in hospital divided by number of beds |
| EXCESS | Excess mortality rate |
| SECPRSNT | Number of secondary diagnoses present in patient record |
| SURGICAL | Number of surgical codes present in patient record |
| LOS | Patient length of stay in hospital. (Log) |

Table 4

Hedonic Regression Results

| Variable | DRG 210 | DRG 296 | DRG 14 | DRG 127 | DRG 174 | DRG 148 | DRG 88 | DRG 89 |
|---|---|---|---|---|---|---|---|---|
| Constant | 6.654 | 6.487 | 6.362 | 6.410 | 6.412 | 5.846 | 6.083 | 6.548 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| GOV | | | -0.163 | -0.255 | -0.076 | | | -0.208 |
| | | | (0.002) | (0.000) | (0.529) | | | (0.000) |
| NOPRO | 0.069 | 0.059 | 0.051 | -0.016 | 0.134 | 0.261 | 0.164 | 0.002 |
| | (0.112) | (0.144) | (0.022) | (0.203) | (0.001) | (0.063) | (0.008) | (0.932) |
| SIZE | 0.013 | 0.004 | 0.022 | 0.015 | -0.007 | -0.019 | 0.031 | 0.015 |
| | (0.160) | (0.565) | (0.000) | (0.000) | (0.482) | (0.624) | (0.002) | (0.000) |
| RURAL | -0.070 | -0.280 | -0.274 | -0.171 | -0.067 | | -0.202 | -0.167 |
| | (0.465) | (0.000) | (0.000) | (0.000) | (0.290) | | (0.000) | (0.000) |
| MEDSCHOOL | -0.052 | 0.087 | 0.053 | 0.085 | 0.096 | 0.074 | 0.100 | 0.080 |
| | (0.164) | (0.002) | (0.001) | (0.000) | (0.017) | (0.623) | (0.030) | (0.000) |
| RN/NURSE | 0.130 | -15.475 | 0.123 | 0.184 | 0.315 | 0.127 | 0.133 | 0.099 |
| | (0.409) | (0.067) | (0.031) | (0.000) | (0.021) | (0.840) | (0.364) | (0.043) |
| NURS2BED | 0.006 | 0.087 | 0.000 | 0.003 | 0.000 | 0.056 | 0.004 | -0.004 |
| | (0.209) | (0.000) | (0.815) | (0.005) | (0.913) | (0.000) | (0.342) | (0.015) |
| ADMIN/EMP | -7.854 | 0.056 | -7.084 | -8.777 | -1.763 | 30.349 | -29.270 | -11.474 |
| | (0.179) | (0.000) | (0.063) | (0.000) | (0.888) | (0.492) | (0.003) | (0.000) |
| RES/BEDS | 0.108 | 0.010 | 0.064 | 0.051 | 0.057 | 0.052 | 0.066 | 0.065 |
| | (0.000) | (0.671) | (0.000) | (0.000) | (0.000) | (0.004) | (0.000) | (0.000) |
| EXCESS | 0.009 | 0.049 | 0.015 | -0.003 | 0.010 | 0.060 | 0.026 | 0.007 |
| | (0.450) | (0.000) | (0.007) | (0.415) | (0.469) | (0.346) | (0.156) | (0.163) |
| SECPRSNT | 0.027 | 0.820 | 0.016 | 0.015 | 0.013 | 0.052 | 0.025 | 0.022 |
| | (0.086) | (0.000) | (0.012) | (0.000) | (0.538) | (0.244) | (0.024) | (0.000) |
| SURGICAL | 0.011 | | 0.012 | 0.041 | 0.058 | 0.118 | 0.010 | 0.021 |
| | (0.502) | | (0.035) | (0.000) | (0.000) | (0.030) | (0.445) | (0.000) |
| LOS | 0.770 | | 0.829 | 0.819 | 0.800 | 0.737 | 0.872 | 0.822 |
| | (0.000) | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |

P-Values in Parentheses.

*Variable removed from specification due to singularity problems.

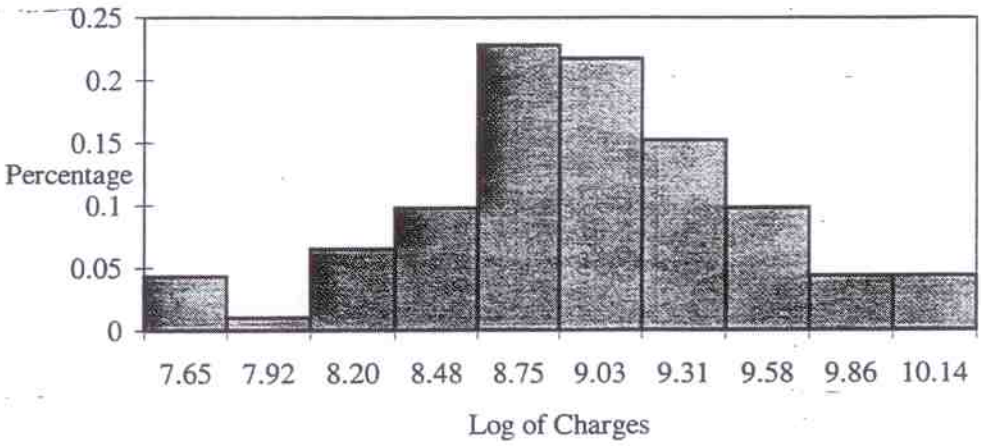
Table 5.

Changes in Adjusted and Unadjusted Price Indexes

| DRG | Simple Price Index | Quality Adjusted Price Index |
|---|---|---|
| 210 | 1.069 | 0.997 |
| 296 | 1.139 | 1.060 |
| 14 | 1.194 | 1.100 |
| 127 | 1.093 | 1.111 |
| 174 | 1.064 | 1.089 |
| 148 | 1.325 | 1.139 |
| 88 | 0.989 | 0.940 |
| 89 | 1.082 | 1.058 |
| Geometric Mean | 1.115 | 1.060 |

Figure 1.

The Distribution of Charges: DRG 89.



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