Shadow prices for a physician's services

ROBERT J. BRENT

Department of Economics, Fordham University, Bronx, NY 10458, USA

This paper presents a method for determining shadow prices for a physician's services on the basis of actual prices charged. The Ramsey rule is used as the shadow-pricing formula. This is combined with the physician's profit-maximizing condition to produce an expression for the social prices in terms of the price elasticities of demand for the third parties paying for the services. On the basis of implicit estimates of the elasticities for a hospital plastic surgeon in the USA, it was found that roughly half (between 42 and 59 cents of every dollar charged) was not relevant for social-valuation purposes.

1. INTRODUCTION

In the health-care evaluation field, it is usually the case that market prices are used as the basis for valuing the costs of health procedures and programmes, even though many have recognized the distinction between costs and charges (Drummond et al., 1987). Much of the literature does not adopt a social perspective. In other contexts, using payments to reflect costs may have been appropriate. But, for a social cost–benefit analysis, we must acknowledge the well-known market imperfections that exist somewhat inherently (Arrow, 1963) and those that exist as a consequence of government and third-party involvement in the financing of health-care expenditures.

Some work has been carried out in the USA to estimate the shadow (or optimal social) prices for hospital products (e.g. Harris, 1978); but this includes only a part of the patient's total bill. Excluded is the charge for any physician services. Moreover, the patient's bill is not usually what is paid to the hospitals. Third parties are often involved. (Such payments accounted for 74.5% of personal health expenditures in 1985, and 76.7% in 1990; see Health Insurance Association of America (1991, Table 4.4)). Third parties in the USA pay what they consider to be an 'appropriate' amount. Since the early 1970s, what Medicare and other private insurers have considered to be appropriate is the physician's 'customary, prevailing and reasonable charges' (the CPR), which are rates based on the past bills of the particular physician, adjusted for the fee typically charged in the local area of the physician. In 1975, it was estimated by Showstack et al. (1979) that approximately 130 of 169 million persons with private coverage for physician care were subject to the CPR pricing system.

This paper provides estimates of the shadow prices for the services provided by a hospital physician under the CPR system. The theory will be applied to the case of a plastic surgeon's services in a large, north-eastern teaching hospital in the USA. We keep the notion of cross-subsidization that occurs for hospital products. In our context the cross-subsidization appears as price discrimination, charging different prices for similar services to different individual users (or rather, third-party representatives of the individual users). The aim is to uncover the shadow prices in such a way that there is a bridge built between the prices actually charged by the hospital physician and those that would be considered socially optimal.

The literature on the actual pricing practices of physicians/surgeons is very extensive. Some analysts assume that doctors behave as if in a competitive environment (e.g. Feldstein, 1970), while others view doctors as working under monopoly (e.g. Newhouse, 1970). No matter what we assume about the state of competition for the plastic surgeon, the crucial aspect is that these studies assume profit-maximizing behaviour. Other approaches do exist. Ruffin and Lehigh (1973) develop a model based on charity which has good explanatory power. The 'target-income hypothesis' has also been advocated, which implies satisficing rather than maximizing behaviour. In this context the study by Sweeney (1982) is important, for it tries to estimate the target income directly to see if actual earnings approach this target figure. It finds that, in large urban areas like the one in which our study takes place, the targets far exceed actual
incomes and 'the probability that target income pricing takes place is minute'.\textsuperscript{1} Pauly and Satterthwaite's (1981) findings also reject the target-income hypothesis in favour of the theory of increasing monopoly. Steinwold and Sloan (1974) present a general test in the context of a mark-up pricing framework that allows many different hypotheses of physician behaviour to be included. Because demand variables exert a definite impact on fees as well as costs, they conclude that profit-maximizing behaviour best fits the facts. We take the view that all the empirical support for the profit-maximization model makes this a useful first approach to employ to model actual behaviour. If empirically valid findings are not obtained using this model, then subsequently other approaches can be tried.

The literature on shadow-pricing theory is equally extensive. We will be basing our analysis on the Baumol and Bradford (1970) approach and the follow-up papers, as summarized by Atkinson and Stiglitz (1980, pp. 400–11). This views the social-pricing decision as one in which health-care services are provided to maximize social welfare subject to a sector's profits constraint. The results are the familiar Ramsey (1927) shadow-pricing rules expressed in terms of (inverse) price elasticities of demand. The only difference in our analysis is that we will distinguish the category of user as well as the category of service. In the process, our shadow prices for particular services will have the property that they vary according to the third party paying for them.

In the context of shadow pricing for developing countries (see Brent, 1990) it has been found useful to work in terms of 'accounting ratios', i.e. shadow prices as ratios of their market prices. Because the accounting ratio (AR) expresses the adjustments for market imperfections in a quotient form, it enables practitioners to take one set of estimates for shadow prices and adapt them for differences in time and place. For example, in the circumstance where there are regional differences in market prices, one area's market prices can be multiplied by the AR found in another area to obtain an estimate of the shadow prices in local values. Similarly, if there is inflation, the current market price in any year can be multiplied by the AR found in the base year to form an estimate of the current shadow price. As we shall see in Section II, both the shadow-pricing rules and the physician's profit-maximizing conditions contain prices solely in price-elasticity terms, albeit in different forms. The accounting ratios therefore turn out to be very simple relations of the price elasticities.

\textsuperscript{1}See Sweeney (1982), p 611.
\textsuperscript{2}Note that estimates of price elasticities are available, such as those in Newhouse and Phelps (1976). But these relate to individual price elasticities, and not those of particular third-party payers.
\textsuperscript{3}In this formulation of the problem, we have kept matters as general as possible. Thus, the total-cost function relates to both the individual involved as well as the type of service provided. It may well be that costs do vary by individual, when standard services require more physician time for some individuals than others. In this case, by definition, services are not the same and therefore differences in prices charged would not constitute 'price discrimination'. However, for our purposes, it is essential only that prices vary by individual and service. For ease of notation and interpretation, we have used the double subscript for i and j for C (and T) as well. If in practice costs do not vary by individual, the data will reflect this. But this will not affect the nature of the empirical results. In the second-best world in which we are operating, taxes and subsidies will not be set optimally. Thus, it will not matter how T is indexed as they do not vary in the problem.

Since a knowledge of the elasticities of demand by category of user is vital to determine the shadow prices, and no estimates exist for the categories for which we are concerned,\textsuperscript{2} an attempt is made to provide indirect estimates of the necessary elasticities. This is achieved by exploiting the well-known relation between marginal revenue and the price elasticity of demand. So when physicians maximize profits, they set their prices in line with their estimates of the elasticities. In Section III we show how, from information on physician prices, approximations of costs, and knowledge of the third party and type of service involved, implicit estimates of the elasticities can be found. Section IV then applies the theory to the context of shadow pricing for the services of a hospital plastic surgeon. The summary and conclusions appear in Section V.

II. THE METHOD FOR DETERMINING THE SHADOW PRICES

Let p stand for a shadow price, q for a market price, i be any individual (i runs from 1 to n) and Z_{ij} be the amount of the jth good or service purchased by the ith individual (j runs from 1 to m). The shadow prices will be derived within a framework that has the public sector maximizing a welfare function W subject to a profits constraint. W is a function of individual utilities U_i. When these individuals maximize their utilities subject to their budget constraints, the direct-utility functions can be replaced by their indirect-utility functions V_i. Since the prices for the outputs are to vary by individual, the social prices will also vary by individual. The indirect-utility function for a representative individual i can therefore be denoted by V_i(p_{ij}, q_{ij}, M_i), for all j, where M_i is an individual's income. The objective function is then the indirect social-welfare function V represented by

\[ V = V(V_1, \ldots, V_n, \ldots, V_n) \]  

Production is to be undertaken by multiproduct firms whose profits are constrained by the social decision maker to be equal to \Pi_0. The difference between the revenues obtained and costs incurred for all the outputs, net of any taxes or subsidies \text{\textit{T}_ij}, must equal the profits target. The profits constraint for the firm is therefore

\[ \sum_{i=1}^{n} \sum_{j=1}^{m} p_{ij} Z_{ij} - C_{ij}(Z_{ij}) + T_{ij} = \Pi_0 \]  

where \text{\textit{C}_{ij}}(Z_{ij}) indicates the total cost function.\textsuperscript{3}
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The problem is to maximize \( V \) as defined by Equation 1 subject to the profits constraint expressed in Equation 2. The Lagrangean \( L \) for this problem is

\[
L = V + \lambda \left[ \sum_{i=1}^{m} \sum_{j=1}^{m} p_{ij} Z_{ij} - C_{ij}(Z_{ij}) + T_{ij} - \Pi_0 \right]
\]

(3)

where \( \lambda \) is the shadow price of any revenues received by the public sector.

We will assume that the goods and services have independent demands. In our context this relates to the individual demands in such a way that the \( Z_{ij} \)'s depend solely on the \( p_{ij} \). The first-order conditions with respect to the \( p_{ij} \) are

\[
\frac{\partial L}{\partial p_{ij}} = \left[ \frac{\partial V}{\partial V_i} - \alpha_i Z_{ij} \right] + \lambda \left[ \frac{p_{ij} - c_{ij}}{\partial Z_{ij}/\partial p_{ij} + Z_{ij}} \right] = 0
\]

(4)

where \( c_{ij} \) is the marginal cost and \( \alpha_i \) is an individual's marginal utility of income \((\partial V/\partial V_i)\) by Roy's identity. The following three definitions will be useful. The social marginal utility of income for individual \( i \), i.e. \((\partial V/\partial V_i)\), is to be denoted by \( \beta_i \); the percentage premium given to any revenue received by the public sector over the social value given to any income received by an individual in the private sector, i.e. \((\lambda - \beta_i)/\lambda \) will be represented by \( K_{ij} \), and the price elasticity of demand by individual \( i \) for good or service \( j \), i.e. \(-Z_{ij}/\partial p_{ij}(p_{ij}/Z_{ij}) \), will be defined as \( e_{ij} \). Note that because the \( \partial Z_{ij}/\partial p_{ij} \) are negative, the price elasticities are being defined as positive numbers. Using these definitions, Equation 4 can be simplified to be

\[
1 - c_{ij}/p_{ij} = \frac{(p_{ij} - c_{ij})/p_{ij} = K_{ij}/e_{ij}}
\]

(5)

This is the so-called Ramsey rule, which requires that a product's shadow price exceed its marginal cost according to the inverse of the price elasticity of demand. The only difference to the usual formulations is that the elasticities vary by individual as well as by service.

Equation 5 specifies how the shadow prices should be set. But, the prices actually charged by the firms for their services are to be those that correspond with the profit-maximizing level of output. Equating marginal revenue to marginal cost involves (again regarding the elasticities as positive) \( c_{ij} = q_{ij}(1 - 1/e_{ij}) \), which on rearranging becomes

\[
1 - c_{ij}/q_{ij} = \frac{(q_{ij} - c_{ij})/q_{ij} = 1/e_{ij}}
\]

(6)

Inspection of Equations 5 and 6 shows that the shadow-pricing and the market-pricing relations have the \( e_{ij} \) in common.\(^4\) It is therefore not surprising that the ratio of the two sets of prices, the accounting ratio for physician services \( AR_{ij} \), takes a simple form

\[
AR_{ij} = p_{ij}/q_{ij} = (e_{ij} - 1)/(e_{ij} - K_{ij})
\]

(7)

Equation 7 highlights two important cases when market prices would be socially optimal in our framework. Firstly, there will be no difference between shadow prices and market prices, the \( AR_{ij} \) will be unity, when the price elasticities approach infinity. This result is consistent with the well-known proposition from welfare economics, that under perfect competition (where demand is perfectly elastic) the prices charged are socially optimal (Pareto efficient). Secondly, the \( AR_{ij} \)'s will be unity when the \( K_{ij} \)'s are equal to 1. From the definition of \( K_{ij} \), it can be seen that this occurs when the revenue constraint is so strong (\( \lambda \) approaches infinity) as to swamp the distribution term. Market prices would then be optimal precisely because they are profit maximizing and ensure that the government obtains the highest revenue possible.

Estimation will be based on Equation 7. This has two variables, \( e_{ij} \) and \( K_{ij} \). In the next section we will explain a method for obtaining estimates of the elasticities, that is derived only from the profit-maximization condition, Equation 6. This leaves us needing estimates for the \( K_{ij} \). Thus, the accounting ratio method that this paper provides is conditional on the values for \( K_{ij} \). From Equation 7, we see

\[
\frac{\partial AR_{ij}}{\partial K_{ij}} = \frac{(e_{ij} - 1)/(e_{ij} - K_{ij})}{(e_{ij} - 1)/(e_{ij} - K_{ij})^2}
\]

(8)

This is positive if \( e_{ij} > 1 \). Thus, for elastic demands, the higher the value of \( K_{ij} \), the greater will be the estimate of the \( AR_{ij} \).

In the application, the issue of the variability of \( K_{ij} \) is handled by first setting the distribution weights.\(^5\) This means that there will be just a single value for \( K_{ij} \), as it becomes independent of \( i \). We then supply best estimates for \( K_{ij} \) and perform a sensitivity analysis around this value.

III A METHOD FOR OBTAINING IMPLICIT ESTIMATES OF THE PRICE ELASTICITIES

From Equation 6, we see that \( (q_{ij} - c_{ij})/q_{ij} = e_{ij}^{-1} \). The left-hand side of this expression can be used to obtain estimates of the \( e_{ij} \). That is, if the physician tries to maximize profits, the excess of the price over the marginal cost, relative to the price charged, will uncover the (inverse of the) price elasticities. Let us now explain our method for obtaining these implicit estimates.

We begin by rewriting Equation 6 as an estimation equation in a regression format:

\[
\frac{q_{ij} - c_{ij}}{q_{ij}} = \alpha_0 + \alpha_i e_{ij}^{-1} + U_{ij}
\]

(9)

Here the \( \alpha_i \) are linear coefficients, \( \alpha_0 \) is the constant term, and \( U_{ij} \) is the random-error term. Because we do not have information on the \( c_{ij}^{-1} \), we intend to replace the elasticities by a series of dummy variables, \( D_{ij} \). There is one dummy

\(^4\)Strictly, we are assuming here that the inverse-elasticity rule applies to the shadow prices in terms of actual demand elasticities, which is what appears in the firm's profit-maximization condition.

\(^5\)For a full explanation of the distribution-weights methodology, see Brent (1979, 1980 and 1984)
variable for each distinct third-party payer according to each service that is provided. These take the value of 1 whenever the physician faces (charges) a particular third party i for a specified service j. The actual estimation will therefore take place with

\[ \frac{q_{ij} - c_{ij}}{q_{ij}} = d_0 + d_j D_{ij} + U_{ij} \] (10)

Clearly, the actual estimation equation involves setting

\[ d_0 + d_j D_{ij} = \alpha_0 + \alpha_j e_{ij}^{-1} \] (11)

From the theory of Section II, Equation 6, we saw that the relation between the excesses over marginal costs and the inverse elasticities was exact. Thus the \( \alpha_j \)'s should all be equal to one, and \( \alpha_0 \) be zero. By construction, the dummy variables \( D_{ij} \) are all to be set equal to unity when they apply. Hence, Equation 10 reduces to:

\[ d_0 + d_j = e_{ij}^{-1} \] (12)

The result is that the regression coefficients attached to the dummy variables, when added to the value of the constant term, provide the implicit estimates of the inverse elasticities.

**IV. AN APPLICATION OF THE SHADOW PRICING METHOD**

The cornerstones of the shadow-pricing methodology outlined in Section II are the values for the \( e_{ij} \). Here we provide estimates for the services of a plastic surgeon who is located in a department of a large, north-eastern, city teaching hospital.

As Equation 10 indicates, we need data on the \( q_{ij} \)'s and \( c_{ij} \)'s (and the dummy variables \( D_{ij} \)). Information on the prices actually charged was easy to find. The surgeon in the appointment book recorded the price billed for each service to each third party. But knowledge of the marginal costs of particular services to individual users was not listed. What was recorded was the actual payments received from the third parties. If we assume that the third parties themselves try to estimate the \( c_{ij} \), and that they make payments only to this extent, then the rates set by the third parties approximate the particular marginal costs. This is the approach adopted here, and so the specifications of the items that make up the dependent variable will be:

- \( q_{ij} \): the bill to the third party i for service j
- \( e_{ij} \): the payment received from third-party i for service j

The sample consists of 766 payments billed and received over the period 1986-88. The list of services supplied and third-party payers that help specify the dummy independent variables appear in Table 1, and are defined in a footnote.\(^6\)

Two features of the data need to be noted. Firstly, the list of third parties contains only those for which the CPR system was relevant. Excluded are those, such as Medicaid and Workers' Compensation, which impose their own schedule of fees. Thus, all of the sample consists of cases where the prices actually charged were privately (profit) motivated and not reflections of what they were allowed to charge. Recall that our AR formulae were predicated on the profit-maximization assumption. Secondly, all the cases were ones for which 'assignment' was accepted, i.e. the physician elected to be paid directly by the carrier and agreed to accept in full the amount that the carrier determined as reasonable.\(^7\) With no liability being placed on the patient, the payment received by the physician constitutes the total amount that the third party is reimbursing the service. This makes credible the use of the payments by the third-parties as measures of the marginal costs, as no part of the costs are allocated to the patient.

<table>
<thead>
<tr>
<th>Services involved</th>
<th>Number in sample</th>
<th>Third-party payers</th>
<th>Number in sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hospital surgery</td>
<td>75</td>
<td>Medicare</td>
<td>143</td>
</tr>
<tr>
<td>Office surgery</td>
<td>34</td>
<td>GHI</td>
<td>189</td>
</tr>
<tr>
<td>Consultations</td>
<td>247</td>
<td>HIP</td>
<td>154</td>
</tr>
<tr>
<td>Follow-up visits</td>
<td>221</td>
<td>Blue Cross</td>
<td>75</td>
</tr>
<tr>
<td>Mix of services</td>
<td>97</td>
<td>Empire</td>
<td>18</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Union</td>
<td>27</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Joint</td>
<td>21</td>
</tr>
<tr>
<td>Others (5)</td>
<td>92</td>
<td>Others (27)</td>
<td>139</td>
</tr>
<tr>
<td>Total</td>
<td>766</td>
<td>Total</td>
<td>766</td>
</tr>
</tbody>
</table>

\(^6\)The following abbreviations were used in Table 1: 'Consultations' involve both office and hospital consultations; mix of services combines both a consultation or visit with a surgical procedure; GHI is the Group Health Insurance Plan of New York; HIP is the Health Improvement Plan of Greater New York; and Joint means that two third-party payers were involved with the one bill (one of them, almost always, was Medicare).

\(^7\)On assignment rates for Medicare, see McMillan et al. (1985).
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Estimates of the AR’s will be constructed in three steps:

1. Equation 10 will be estimated using ordinary least squares (OLS) to obtain values for the $d_0$ and $d_1$ coefficients. The estimates are reported in Table 2.

2. The OLS estimates of $d_0$ and the $d_1$ coefficients will be summed and inverted, as required by Equation 12, to produce estimates of the elasticities. The $e_i$'s are shown in Table 3.

3. Finally, the elasticity estimates will be fed into Equation 7 to solve for the AR values conditional on the values for $K_i$. Table 3 presents the AR results for a range of values for $K_i$.

Estimates of the regression coefficients

It turned out that the plastic surgeon mainly acted as if price discrimination took place only by third-party user and not by category of service. This finding follows from the fact that entering a user-dummy variable $D_i$ and a service-dummy variable $D_j$ in a multiplicative form to produce a $D_{ij}$ produced results that were statistically inferior to those where the service-dummy variables were included on their own. Equation 1 in Table 2 shows the estimates for the categories of user that were relevant. Each third-party had a coefficient that was significant at all within the 1% confidence level. The overall fit of the equation (judged by the $R^2$) was such that 11% of the variation in the premium charged over marginal costs was explained by the users listed. The $F$-value indicates that there was a very small probability (less than 1%) of obtaining these results by chance. When estimation took place in multiplicative form, some of the coefficients attached to the user/service dummies were significantly different from zero (at 5% levels and higher) and the overall fit was much reduced.

The only service that was statistically significant was whether a consultation was involved. Consultations had their impact in an additive rather than a multiplicative form. Thus Equation B in Table 2 shows the regression which has all the user dummies and includes, in addition, a dummy variable to record the impact of whether a consultation was the service in question. All the user variables maintained their significance levels, and the overall fit was better (the $R^2$ was 15%).

Because there is much discussion in the literature of the inflationary consequences of the CPR payments system (see, for example, Yelt, 1985), it was decided that it would be useful to include a time-dummy variable in the regressions. Roughly half of the observations related to the final year in the sample, and we formed a dummy variable, Y88, which took the value of 1 when the surgeon’s service took place in 1988, and took the value 0 for the years 1986 and 1987. Equation C of Table 2 reports the results for this regression, which included all the variables in Equation B and had Y88 in addition. The Y88 variable had a statistically significant impact at within the 1% level and raised the overall explanatory powers of the regressions by about 1%. Thus, the plastic surgeon did receive a higher payment over time.

Table 2 Estimates of the individual coefficients

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient $(d_0)$</th>
<th>t-value</th>
<th>Coefficient $(d_1)$</th>
<th>t-value</th>
<th>Coefficient $(d_2)$</th>
<th>t-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.2681</td>
<td>10.6460</td>
<td>0.3022</td>
<td>11.8964</td>
<td>0.3304</td>
<td>12.5339</td>
</tr>
<tr>
<td>Medicare</td>
<td>0.3196</td>
<td>9.1017</td>
<td>0.3150</td>
<td>9.1520</td>
<td>0.3255</td>
<td>9.4987</td>
</tr>
<tr>
<td>GHI</td>
<td>0.2751</td>
<td>8.3426</td>
<td>0.2931</td>
<td>9.0261</td>
<td>0.2911</td>
<td>9.0371</td>
</tr>
<tr>
<td>HIP</td>
<td>0.1529</td>
<td>4.4329</td>
<td>0.1628</td>
<td>4.8098</td>
<td>0.1653</td>
<td>4.9215</td>
</tr>
<tr>
<td>Blue Cross</td>
<td>0.1897</td>
<td>5.4026</td>
<td>0.1966</td>
<td>4.7576</td>
<td>0.2073</td>
<td>5.0461</td>
</tr>
<tr>
<td>Empire</td>
<td>0.2138</td>
<td>2.9124</td>
<td>0.2294</td>
<td>3.1866</td>
<td>0.2616</td>
<td>3.6353</td>
</tr>
<tr>
<td>Union</td>
<td>0.1417</td>
<td>2.2972</td>
<td>0.1502</td>
<td>2.4843</td>
<td>0.1616</td>
<td>2.6899</td>
</tr>
<tr>
<td>Joint</td>
<td>0.2003</td>
<td>2.9173</td>
<td>0.1905</td>
<td>2.8314</td>
<td>0.1971</td>
<td>2.9517</td>
</tr>
<tr>
<td>Consulting</td>
<td>-0.1277</td>
<td>-5.6695</td>
<td></td>
<td></td>
<td>-0.1184</td>
<td>-5.2637</td>
</tr>
<tr>
<td>Year = 1988</td>
<td>Summary</td>
<td>$\bar{R}^2 = 0.1133$</td>
<td></td>
<td>$\bar{R}^2 = 0.1484$</td>
<td></td>
<td>$\bar{R}^2 = 0.1621$</td>
</tr>
<tr>
<td></td>
<td>statistics</td>
<td>F = 14 8856</td>
<td></td>
<td>F = 17 5807</td>
<td></td>
<td>F = 17 3567</td>
</tr>
</tbody>
</table>

8It might seem that explaining 11% of the variation would appear to be a poor result. But cross-sectional data are being used, and we are dealing with this in an extremely parsimonious fashion. We are not including any of the real-world activities which must have had an impact, such as whether the physician applied for payments late, whether the description of the service was clearly stated, etc. As long as these factors were random, and independent of the variables that we did include in the regressions, our results would still be valid.

9For example, the counterpart of Equation A, where the users interact with a dummy variable whenever a consultation service was involved, produced a regression where only two of the user/service variables were significant at within the 5% level, and the $R^2$ was only 0.0140
Table 3. Estimates of the elasticities and accounting ratios (based on Equation C)

<table>
<thead>
<tr>
<th>Variable</th>
<th>( e_{ij} )</th>
<th>Lower bound ( K = 0.0909 )</th>
<th>Best estimate ( K = 0.2481 )</th>
<th>Upper bound ( K = 0.3590 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medicare</td>
<td>1.5246</td>
<td>0.3659</td>
<td>0.4110</td>
<td>0.4501</td>
</tr>
<tr>
<td>GHI</td>
<td>1.6090</td>
<td>0.4012</td>
<td>0.4475</td>
<td>0.4872</td>
</tr>
<tr>
<td>HIP</td>
<td>2.0173</td>
<td>0.5281</td>
<td>0.5750</td>
<td>0.6135</td>
</tr>
<tr>
<td>Blue Cross</td>
<td>1.8598</td>
<td>0.4861</td>
<td>0.5335</td>
<td>0.5729</td>
</tr>
<tr>
<td>Empire</td>
<td>1.6892</td>
<td>0.4312</td>
<td>0.4782</td>
<td>0.5181</td>
</tr>
<tr>
<td>Union</td>
<td>2.0325</td>
<td>0.5318</td>
<td>0.5786</td>
<td>0.6170</td>
</tr>
<tr>
<td>Joint</td>
<td>1.8957</td>
<td>0.4963</td>
<td>0.5436</td>
<td>0.5829</td>
</tr>
</tbody>
</table>

(about 3% higher).\(^10\) But, the important point here is that this upward adjustment had minimal impact on the user dummies that were included with Y88. All the user dummies were interacted with the time-dummy variable Y88 and none of these cross-product terms were significant. The F-test of whether the set of interaction terms as a whole made a difference was insignificant. Thus it was the intercept of the regression equation that was shifted, not the slope coefficients.

Estimates of the elasticities and accounting ratios

Equation 12 explains how to obtain the elasticity estimates from the regression coefficients. Column 2 of Table 3 displays the results. The coefficient estimates come from the equation with the best statistical fit, i.e. Equation C. Thus, the variable coefficients in Equation C were added to the constant term (0.3022) and inverted to produce the elasticity estimates. We have just seen that all the individual third-party user coefficients were significant at within 1% level. This means that the elasticities that are derived from them should also be given a high degree of confidence. Because all the regression coefficients in Table 2 had positive signs, the \( e_{ij} \)'s are all positive, in line with the way we defined them in Section II. The results shown in Table 3 indicate that the plastic surgeon’s services were price elastic for all third-party payers. The \( e_{ij} \)'s were all significantly different from unity within the 1% level.\(^11\) The fact that the elasticities were greater than unity is consistent with our assumption that the physician tried to maximize profits. That is, with elasticities above unity, the marginal revenues are positive. So the marginal revenue equals marginal cost condition for each physician takes place at a positive output level.\(^12\) The estimates therefore support the underlying theory behind our implicit elasticity method.

The final step involves using Equation 7. We have the elasticity estimates. All we need now is values for the \( K_i \)'s. We proceed as follows. In our context, where paying for the services is by third-party insurers on behalf of individuals and not by the individuals paying direct, we could expect that distribution was not an issue for social pricing. All insurers have a mix of high- and low-income insurers and no group would therefore be particularly socially deserving. (Recall that Medicaid cases are not in our sample). One third-party’s payments would carry an equal (unity) weight to that for any other third-party insurer. With \( \beta_i = 1(\forall i) \) the formula for \( K \) becomes independent of \( i \) and equal to: \( (\lambda - 1)/\lambda \). The crucial parameter then is \( \lambda \), the shadow price of government funds.

In most studies by the World Bank of the shadow price of government funds of LDC’s, \( \lambda \) is considered to be about 3 (see Brent, 1990). As LDCs have greater capital (and other) market imperfections than the USA, we would expect lower values than this. Jones et al. (1990, pp. 28–30), in a survey of the empirical values of \( \lambda \) for the USA, put the plausible range of values between 1.01 and 1.56. They suggest that a value in the middle of the range, i.e. 1.33, ‘may serve as a reasonable approximation for the parameter’. Thus, we will choose 1.33 as our ‘best estimate’, and use the endpoints of their range to fix the lower and upper bounds for \( \lambda \). These values in turn fix the critical values for \( K: K = 0.0909 \) is the lower bound, \( K = 0.2481 \) is the best estimate, and \( K = 0.3590 \) is the upper bound. Consequently, we present three sets of results in Table 3 for the \( AR_{ij} \), corresponding to the three different values for \( K \). This range of estimates for \( K \), and hence for the \( AR \)'s, is not greater than the other

\(^{10}\)Although the coefficient for Y88 in estimation Equation 3 was negative this does not mean that the physician received lower prices in 1988. The dependent variable is \( 1 - c_{ij}/q_{ij} \) So it is minus \( c_{ij}/q_{ij} \) that is being regressed on Y88. Consequently the negative sign on Y88 reverses the negative sign on the dependent variable. Hence the share given to physicians was raised in that year.

\(^{11}\)This follows because the only way that the elasticities could be less than unity is if the coefficients in Table 2 are greater than unity, which is not the case (the 99% confidence interval never includes unity as an element for any of the third-party payers).

\(^{12}\)It was Arrow (1963) who questioned the profit-maximization assumption for health care because the price elasticity of demand was usually estimated to be less than unity. Note that our elasticity estimates relate to individual firms/physicians and not to industry as a whole.
variables typically tested by sensitivity analysis in health-care evaluations.

The estimates for the accounting ratios are (like the elasticities) also in line with our a priori expectations for the plastic surgeon. They are less than unity, signifying that the social value of the services are less than the prices actually charged. Furthermore, the AR estimates do vary by category of user. As predicted by Equation 8, with all third-party demands found to be price elastic, the AR estimates are higher, the higher the value for K. On the basis of the set of best estimates in Table 3, we see that AR vary from 41 cents for every dollar charged to Medicare, to 58 cents for every dollar charged to Union.

V. SUMMARY AND CONCLUSIONS

Given the existence of non-competitive pricing in the health-care sector, we must always be suspicious of regarding the actual prices charged as good indicators of social value. In our study of the shadow prices for the services of a plastic surgeon, the best estimates showed that, depending on the third-party payer involved, the accounting ratios varied between 0.41 and 0.58. So, between 42 and 59 cents of every dollar charged was not relevant for social-valuation purposes. Even if we take the upper-bound estimates, the accounting ratios would only be 4% higher. The message of this paper is the following: not only should a social cost–benefit analysis that entails physician services make significant downward adjustments to any prices listed, the adjustment should also be different according to which entity (third party) is being charged the particular prices. However, given that the variation in accounting ratios is 17 percentage points (between 41 and 58) which is small relative to the 42 percentage points difference between the highest AR and the market price (100–58), a case can be made for using an average adjustment of halving the market price when precise data are not available, or when the project being evaluated is non-marginal.

The estimates of the shadow prices were based on a straightforward extension to the theoretical framework established by Baumol and Bradford. This specified the social prices as functions of the user-price elasticities of demand for each service provided by the physician. By exploiting the fact that under profit maximization there is a relation between these user-price elasticities and the prices actually charged by a physician, a link was established between the two sets of prices, social and actual, via the price elasticities.

Because values of the user-price elasticities were not known, a method for deriving the elasticities were formulated. This was based on the idea that if the physician maximized profits, there would be a linear relation between the extra charged over marginal costs, relative to the price actually charged, and the inverse of the elasticities. By using dummy variables to represent the particular user (and service) involved, and obtaining data on the prices charged and the marginal costs, it was possible to construct a regression equation which had the inverses of the elasticities constituting the fixed parameters. The estimates of the regression coefficients, when inverted, thereby produced the implicit estimates of the elasticities.

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