MODELLING MEDICARE AS A PRICE SUBSIDY: ESTIMATION RESULTS

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I. SUMMARY OF TASK

INFORUM (INterindustry FORecasting at University of Maryland), as part of a contract for the Health Care Financing Administration, has re-examined the manner in which LIFT forecasts health services output and final demand.² Personal consumption expenditures (PCE) are the largest health services final demand category, thus, the way in which one models PCE will have a major impact on our forecasts. While influenced by many things, PCE is determined primarily by the level of personal income and changes in relative prices. Thus, how one models the effects of income and relative prices on PCE will greatly influence forecasts of PCE.

The current version of LIFT treats all government transfers as personal income. This is incorrect as some of these programs are in-kind transfers and some are price subsidies. Modelling a price subsidy as an income transfer leads to inaccurate forecasts. For example, one would expect the effects of an increase in Medicare benefits to be concentrated in health services. In the current version of LIFT, increased Medicare benefits translate into increased spending in **all** categories. This is because LIFT treats the increase in benefits as increased income.

Earlier work (Janoska 1994b) showed that modelling a price subsidy as an income transfer leads to inaccurate forecasts of the effects on PCE of changing the program. Janoska (1994b) gave several recommendations on how one could correctly model these price subsidy programs. The current work estimates a system of PCE equations that incorporates those recommendations in regard to the Medicare program. Toward this goal, we were to redefine the income concept used by the equations to exclude the value of Medicare payments. Similarly, the price variables used in the estimation and forecasts were to be redefined to adjust for the value of the Medicare subsidy.

All of the current work was conducted under a contract with the Health Care Financing Administration.³ Work conducted in support of task 11 also included several items not explicitly

¹I would like to thank Ralph Monaco, Clopper Almon and Lorraine Sullivan Monaco for invaluable assistance, guidance, and comments. I would also like to thank the Health Care Financing Administration for providing the financial support that made this work possible. As always, I take full credit and blame for all opinions and errors remaining in this work.

²LIFT (The Long-term Interindustry Forecasting Tool) was developed at the University of Maryland under the guidance of Clopper Almon. McCarthy (1991) presents an excellent overview of LIFT.

³The current work was done as part of task 11. All tasks were in support of contract 500-93-0007.

called for in the task description. These items included: reexamining the theory underlying the system of PCE equations; estimating the system with equations for Hospitals and Nursing homes; and deciding which equations could be improved with the addition of "non-economic" variables.

Most of these additional modifications to the PCE system were suggested by earlier work. For example, as part of task 1, we expanded the number of PCE categories from 78 to 80 $(Janoska^{1994a})⁴$ At the time of the expansion, we did not estimate the two new equations (*Hospitals* and *Nursing homes*) within the PCE system. This was done for expediency and not for theoretical reasons. In support of this task, we revised the regression software so that it would more readily adapt to increases in the number of PCE commodities.

Similarly, work done under task 4 suggested that the addition of non-income and non-price variables could improve the fit of the equations (Monaco 1994). In support of task 4, we allowed the real interest rate and residential construction activity to influence the composition of aggregate PCE. As part of the present task, we have modified the system by allowing other equation-specific variables to influence PCE. Additional variables used in the equations now include: the labor force participation rate, the over-85 population and housing stocks.

As part of task 11, we reexamined the underlying theoretical basis of the PCE system and modified our estimation procedure accordingly. Previously, the coefficient on the income variable was imposed via a soft-constraint (Devine 1983; Chao 1991), but our understanding of the theory implied that the value of this coefficient should be imposed exactly.⁵ The regression software was modified so that this parameter would be imposed exactly in all of the equations. As part of the examination of the underlying theory, we reviewed the composition of the various commodity groups and sub-groups to determine if alternate combinations and groupings produced more stable results.

The rest of this paper is organized as follows. Section two discusses the theory behind the system of equations. Section three discusses the data used in the estimation. Section four reviews the old estimation procedure and the changes that we implemented in support of this task. Section five presents the estimation. Section six contains concluding remarks.

II. A THEORY OF SYMMETRIC CONSUMPTION FUNCTIONS

There has been a long search for a system of demand equations derived explicitly from demand theory. With the exception of the Almon system (Almon 1979), all of these systems assume the existence of a representative agent. That is to say, the economy is populated by

⁴ For a list of the 80 PCE categories, please see Appendix A.

⁵See the reader to Almon (1994) for a more detailed discussion of how one imposes a soft-constraint. In short, a soft-constraint allows one to establish a trade-off between equation fit and his a-priori beliefs on the sign and magnitude of a parameter.

persons with identical utility functions and identical incomes. This means that distributional effects play no role in consumer spending decisions since all consumers have identical incomes. These systems can be thought of as belonging to one of the following types:

Systems derived from an explicit utility function. These include the linear expenditure system (Stone 1954) , the logarithmically-additive system (Houthakker 1960), and the doublelog additive system (Sato 1972).

Systems derived from an implicit or indirect utility function. These include the Rotterdam model (Barten 1969), the Translog model (Christensen, Joregenson and Lau 1975), and the Almost Ideal Demand System (AIDS) (Deaton and Muellbauer 1980).

Systems which are not derived from either an explicit or implicit utility function. This group includes the Almon system (Almon 1979).

The theoretical foundation of these systems is derived from demand theory. Ideally, a demand system must meet the following conditions (Deaton and Muellbauer 1988):

- **1. Adding Up:** The demand functions must exhaust the available income. Or, in other words, the sum of spending on all of the individual goods must equal total spending.
- **2. Homogeneity:** There must be no money illusion -- if all prices and income double, then demand must be unchanged.

It is a common, but incorrect belief among economists that absolute Slutsky symmetry is required for systems of market demand. Slutsky symmetry is the condition that the incomecompensated partial derivative of the demand for good X with respect to the price of Y must equal the income-compensated partial derivative of the demand for good Y with respect to the price of X. Slutsky symmetry must hold for any given individual. If one assumes the existence of a representative agent, then it also must be true that Slutsky symmetry holds for the system of market demand equations. However, if one relaxes this assumption and allows for differences among consumers in **either** their income level or their utility functions, absolute Slutsky symmetry does not hold. Among systems of demand equations, only the Almon system allows for these differences.

It is possible, however, to reduce the number of parameters to be estimated by assuming approximate Slutsky symmetry. Thus, we add the further condition that a demand system should have:

3. Approximate Slutsky symmetry: At the initial set of prices, the functions should possess exact Slutsky symmetry (Almon 1979).

All of the above systems meet these conditions, but the Almon system allows for more flexible price-income interactions than the other systems. Gauyacq (1985) examined the theoretical foundations, estimation techniques, and possible applications of these systems and found that "... only the Almon model is from a practical view, convenient for determination of disaggregated demand functions."

The system of PCE equations used by LIFT is based on the Almon theory as well as periodic cross-section and time-series analysis (Devine 1983; Chao 1991; Janoska 1994a). Devine (1983) expanded the Almon model to include cross-section estimations and performed the original empirical analysis. Chao (1991) improved the system's treatment of durable goods. Janoska (1994a) building on the work of Monaco (1984), expanded the system and added real interest rate and construction demand variables to the automotive and household durable expenditure categories. In related work, Pollock (1986) significantly improved the system for forecasting income variables used in the PCE system.

A two-step approach is used when estimating the equations. First, a cross-section analysis using data from the Consumer Expenditure Survey (CEX) estimates the effects of demographic, age, and income variables. Then, the parameters estimated in the cross-section analysis and data from the National Income and Product Accounts (NIPA) are used in a time-series analysis that estimates the effects on consumer spending caused by changes in relative prices, taste trends and business cycles. This two-step approach lets users of LIFT simulate the effects of different demographic projections on the U.S. economy, as well as the effects of different income distributions and relative prices.

We employ a two-step procedure for several reasons. One reason is to correct for definitional differences between the CEX and the NIPA. 6 The primary reason, however, we use the two-step method is the lack of price variation in a single year of cross-section data.

CROSS-SECTION ANALYSIS

The foundation of the system is the cross-section estimation that uses data from the CEX. The cross-section equation estimated for each expenditure category is of the form:

$$
C_i = (a + \sum_{j=1}^K b_j Y_j + \sum_{j=1}^L d_j D_j) * (\sum_{g=1}^G w_g n_g)
$$
 (1)

where:

- C_i = household consumption expenditures on good i,
 Y_i = the amount of per capita household "income" w
	- $=$ the amount of per capita household "income" within income category j,
- D_i = a zero/one dummy variable used to show membership in the j_{th} demographic group,

⁶The CEX only records out-of-pocket spending by households, while the NIPA uses a much broader definition of spending.

Conceptually, the above function has two components: consumption expenditures per "adult equivalent" and the "size" of the household in adult equivalents. Household per-capita income and demographic characteristics determine the value of the first component. The size of the household is determined by the second term. For the purposes of the cross-section work, the size of a household does not equal the number of people in the household, but is a function of the ages of the household members and the commodity under examination.

The cross-section estimation defined an "Adult" as an individual between the ages of 30 and 40 years. By definition, anyone in this age cohort equals one "adult." The effect of being a member of the other seven age cohorts on consumption is determined relative to the effect of this adult cohort. For example, according to our estimates, an additional infant in a household will not significantly increase the expenditures on alcohol by the household, but adding a person in their mid-twenties will increase household alcohol expenditures. Similarly, an additional twentyyear-old in the household will not increase the expenditures by the household on children's clothing, but a newborn will. In terms of adult equivalents, a newborn will count as less than one adult in the equation for alcohol expenditures, but will count as several adults in the equation forecasting children's clothing. Since the size of the weights for each age group is relative to the adult weight, we refer to them as Adult Equivalent Weights (AEW).

There are eight age cohorts (called gpops in LIFT) in the system. There are three cohorts of the "young," four cohorts of the "middle aged," and one cohort of the "elderly" (aged 65 or higher). The cohorts are given below:

- **Gpop1**: Age 0-5 years
- **Gpop2**: Age 5-15 years
- **Gpop3**: Age 15-20 years
- **Gpop4:** Age 20-30 years
- **Gpop5:** Age 30-40 years (This cohort is our Adult cohort.)
- **Gpop6:** Age 40-50 years
- **Gpop7:** Age 50-65 years
- **Gpop8:** Above 65 years

Some demographic dummy variables included in the cross-section estimation are:

- **Region**: North East, North Central, South and West.
- **Family Size**: One person, two person, three or four person, and five or more person households.
- **Education**: One if the household head was college educated.
- **Age of Household Head**: Households with heads: under 35; between 35 and 55; and over 55.

In addition to estimating the effects of the various demographic and age variables on consumption expenditures, the cross-section equations estimate five separate income parameters. A distinct marginal propensity to spend out of income is estimated for each income variable and cross-section commodity. This is known as a piecewise linear Engle curve (PLEC). The PLEC allows the effect of income to vary as per-capita household income rises. For example, a household in the lowest income bracket might spend only \$0.04 out of every dollar on jewelry, but a household in the highest income bracket might spend \$0.40 of every dollar of disposable income on jewelry. The pattern of expenditures might be reversed for some goods. For example, poorer households might have a higher propensity to consume used automobiles than do richer households.

The amount of income, Y_j , in each income bracket, J, depends on household income and the range or size of the bracket. Algebraically, this can be represented as:

$$
Y_j = \begin{matrix} &&B_{j} - B_{j\cdot 1} & \text{if} &&B_{j} \leq Y\\ &&Y - B_{j\cdot 1} & \text{if} &&B_{j\cdot 1} \leq Y \leq B_{j}\\ 0 & \text{if} &&Y \leq B_{j\cdot 1}\end{matrix}
$$

where:

 B_k = infinity, by definition.

For example, assume our bracket borders are set at \$ 0, \$1000, \$2000, \$3000, \$4000, and infinity. Then a household with a per-capita income of less than \$1000 would have all of its income attributed to the first income bracket. A household with a per-capita income of \$2500 would have the first \$1000 of per-capita income allocated to the first income bracket; the second \$1000 of per-capita income allocated to the second income bracket; and the last \$500 of percapita income allocated to the third income bracket. The income in each bracket becomes the Y_i used in equation **(3)** as the income variables.

For the boundaries given above, $B_0=0$, $B_1=1000$, $B_2=2000$, $B_3=3000$, $B_4=4000$, $B_5=$ infinity. Table 1 shows how a set of hypothetical per-capita incomes are allocated to the various income brackets, Y_j. **Table 1**

The table shows that income is allocated to the first bracket until the upper boundary of the bracket is reached or income is exhausted. If income remains, unallocated income is allocated to the second bracket until income is exhausted or the upper income boundary of the second income bracket is reached. This process continues until either all income has been allocated or we reach the final bracket, where the remaining income is allocated.

TIME-SERIES ANALYSIS

Using the cross-section parameters and the income distribution, a time-series variable, C^* , is constructed for each PCE category. C^* for any year equals consumption in that year assuming: no relative price movements, no changes in taste, and perfect complimentarity between the crosssection and time series data (Devine 1983). C^* captures the effects of the demographic and income variables across time. C^* is given by:

$$
C_i^* = a + \sum_{j=1}^K b_j Y_j + \sum_{j=1}^L d_j D_j \tag{2}
$$

Where :

 a,b,d,w = parameters from the cross-section estimation.

Similarly, the AEWs are used to construct a time-series of the adult equivalent population, WP_t . WP is given by:

$$
WP_{i,t} = \sum_{m=1}^{8} w_{i,m} N_{m,t}
$$
 (3)

where:

C* and WP are then used as variables in the time-series estimation of the consumption expenditure system.

The LIFT consumption system divides 80 categories of PCE into 10 Groups. Parameters are estimated as a system to insure cross-price symmetry and adding up (see the next sub-section for a discussion of the rationale behind these constraints). Each group then is divided into two or more sub-groups. The system is designed so that: (1) weak price effects occur between categories in different groups; (2) moderate price effects occur between categories in different sub-groups within a group; (3) and strong price effects occur between categories within a subgroup. The system imposes price effect symmetry between each group in the system and between each sub-group within a group.

We introduce the following notation before providing the general equation used in the timeseries estimation:

 $M =$ the number of groups,

 S_L = the sum of the budget shares of categories in group **L** in the base year, where the budget share is defined as the category's share of total PCE.

The time-series equation is written:

$$
\frac{q_{it}}{WP_{it}} = (a_i + b_i C_{it}^* + c_i \Delta C_{it}^*) \prod_{L=1}^M \left(\frac{P_{it}}{\overline{E}_{Lt}}\right)^{-S_L \lambda_{IL}}
$$
\n(4)

where:

The variables WP and C^* are determined from the parameters estimated in the cross-section work.

The earlier estimations (Devine 1983; Chao 1991; Janoska 1994a) imposed a "soft" constraint on the bi coefficients so that the system would satisfy the adding-up restriction described earlier. Each b_i was softly constrained so that the elasticity of consumption with respect to C_{it}^* equalled unity $(\eta_{C^*} = 1.0)^7$. After reviewing the literature, we decided that this coefficient should be imposed exactly via a "hard" constraint. The software was modified so that this parameter would be imposed automatically.

TREATMENT OF MEDICARE

Previous work on the LIFT PCE system treated Medicare payments as income (Devine 1983; Pollock 1986; Chao 1991; Janoska 1994a). Upon closer examination, it is apparent that the program functions as a price subsidy and not as an income transfer (Pauly 1986; Hurd 1990; Jacobs 1991; Janoska 1994b). Recent work has shown that treating Medicare as an income transfer incorrectly models the effect of the program. In general, modelling Medicare as an income transfer will understate the effect of a change in Medicare on medical PCE (Janoska 1994b).⁸ As outlined in Janoska (1994b), one can avoid this problem by modelling the program as a price subsidy. We model Medicare as a price subsidy by the following method:

Step 1. Redefine the income variable used by PCE system as follows:

(5) LIFT Disposable Income = NIPA Disposable Income - Medicare Benefits

⁷However, due the nature of soft-constraints, most of these elasticities did not equal 1.0 exactly.

⁸A-priori, we cannot determine if the income transfer modelling method over-states medical PCE demand. This depends on the own-price and income elasticities of the good. The Appendix to Janoska (1994b) shows this relationship.

Step 2. Redefine price deflators used by PCE system as follows:

$$
Medicare - Adjusted DEFLi = Ci * DEFLi
$$
 (6)

where C_i , the coinsurance rate, is given by:

$$
C_i = 1-subsidy rate_i = 1 - \frac{Nominal \ PCE_i - Medicine_i}{Nominal \ PCE_i}
$$
 (7)

Step 3. Estimate parameters for the current system of PCE equations, but use the newly defined disposable income and deflators as independent variables.

There are two possible sources of errors from this approach. The first is that we assume that the average coinsurance rate equals the marginal insurance rate across all individuals (Newhouse et al. 1979). This leads to errors in our estimated parameters since coinsurance rates vary across individuals and average coinsurance rates do not equal marginal rates. However, because we cannot measure the true marginal coinsurance rate, we assume that the average rate equals the marginal rate.

Our estimated price parameters will be inaccurate for another reason as well -- deductibles. Keeler et al. (1977) show that deductibles will lead to errors in the estimated price parameters, but the direction of bias cannot be determined a-priori. Keeler et al. (1977) and Newhouse et al. (1979) show that by either eliminating individuals with deductibles from the data set or lumping individuals together who have the same deductible, the bias is eliminated. These solutions could not be implemented because our data is aggregate and provides no information on deductibles. We acknowledge that our estimated parameters may be in error, but feel that the size of the bias is small relative to the improvement gained through modelling Medicare benefits as a price subsidy.

III. DATA

The data on which the cross-section consumption functions are estimated is the 1972-1973 Consumer Expenditure Survey (CEX) (Devine 1983).

The time-series data on PCE and NIPA-style deflators are gathered from published and unpublished National Income and Product Account (NIPA) data. Data on levels of Medicare funding by PCE category come from the National Health Expenditure Accounts (spreadsheet data from the Health Care Financing Administration). The Medicare-adjusted price deflators are constructed as shown in equations **(5)** and **(6)**.

The data for all age and demographic variables is gathered from published reports of the U.S. Census Bureau (Various Current Population Reports Series P-20 and P-25). Income distribution data comes from the Internal Revenue Service (various Statistics of Income reports).

IV. ESTIMATION PROCEDURE

This section discusses the procedure by which we estimate the system of equations. Comparisons between the old and new procedure are included. We first discuss the construction of the price deflators. Next, we describe how we incorporate the cross-section estimations into the time-series work. In the third sub-section, we discuss changes to the commodity group and sub-group structures that were undertaken as part of this task. In the next sub-section we discuss changes in the software that were implemented in support of this task. Next, we review the estimation technique. We then turn our attention to our use of "equation specific" variables. Last, we discuss the criteria we used in determining whether our equations were suitable for use in LIFT.

CONSTRUCTING PRICE DEFLATORS

The first step in estimating the equations given in **(4)** is the construction of the PCE category price deflators. For all categories (excluding PCE categories receiving Medicare funds, hereafter referred to as Medicare categories)⁹, price deflators were derived by rebasing the NIPA deflators so that $\text{DEFL}_{1972} = 1.00$. The first step in constructing the Medicare-adjusted deflators was to rebase the NIPA deflators so that $DEFL_{1972} = 1.00$. The second step was to apply equations **(6)** and **(7)**. 10

⁹These categories are: Ophthalmic and orthopedic goods (PCE15); Physicians (PCE64); Dentists and other professionals (PCE65); All hospitals (PCE66); and Nursing Homes (PCE80). Figures 1-10 show the deflators and the ratio of the Medicare-Adjusted deflator to the NIPA deflator.

 10 Under the old (or Medicare-as-a-transfer) procedure, all of the deflators would be derived from the NIPA PCE deflators and rebased so that $DEFl_{1972} = 1.0$.

Figure (1) Deflators for Ophthalmic goods **Note: All NIPA deflators = 1 in 1972**

Figure (2) Ratio of Deflators: Ophthalmic Goods

 90°

Dentists

Figure (7) Deflators for Hospitals Figure (8) Ratio of Deflators:

Hospitals

Figure (9) Deflators for Nursing Homes Figure (10) Ratio of Deflators:

INCORPORATING THE CROSS-SECTION RESULTS

Next, the weighted population and C^* variables are constructed using data on disposable income, population and Medicare transfers. The weighted populations were constructed from equation **(3)**.

For all PCE categories excluding Hospitals (PCE66) and Nursing homes (PCE80), we created these variables using the cross-section parameters estimated by Devine (1983). The cross-section parameters in the Hospitals (PCE66) equation and the Nursing homes (PCE80) equation are from Janoska $(1994a)^{11}$

REVISIONS TO COMMODITY GROUPS AND SUB-GROUPS

As part of task 11, we have revised some of the commodity groups -- either through addition/deletion of a PCE category from the group or by changing the sub-groups within the commodity group. For example, under the old system, Food off premise (PCE19) was a member of *Group 1, Food and Alcohol, off premise*. Under the new system, this category is in *Group 1, Food*. We list these changes from earlier work below:

 11 The old procedure used the cross-section weights estimated by Devine (1983) for all of the PCE categories.

Group 1: Food, Alcohol and Tobacco

Group 6: Medical Services

Group 7: Personal Services

Group 10: Reading and Education

CHANGES TO ESTIMATION SOFTWARE

The old software allowed for the imposition of "soft-constraints" when undertaking the estimation. Devine's work imposed a soft constraint on the coefficient associated with C^* so as to impose a C* -elasticity of one for every equation (see section II of this document). Our understanding of the theory was that there could be **no** trade-off between equation fit and the size of the C* parameter. Consequently, our work modified the software to impose these values via a "hard" constraint (i.e., imposed exactly) on the coefficient.

As part of the work allowing us to impose hard-constraints, we enhanced the software so that changing the form of the equations is easier. Using the old software, it was very difficult to change the form of an equation. For example, to estimate an equation without a time trend, one needed to impose a soft-constraint of zero on the time coefficient. Because we solve this nonlinear system in an iterative fashion, the estimated coefficients one obtains by imposing a softconstraint, differ from the results one obtains by estimating the equation without the variable (i.e., dropping it altogether).¹² For this reason, the software was revised to allow the user to specify the specific form each equation would take. This customization lets us impose a hard constraint of zero on any of the coefficients, thereby dropping the associated variable from the equation and

¹² Non-linear equations are sensitive to the starting values used when estimating the equation. By imposing a hard-constraint on the system, we change the initial values used. The results obtained using the soft-constraint are fairly close to the hard-constraint results and are almost certainly caused by this property of non-linear equations.

giving us seven different forms we could estimate.¹³ These are:

ESTIMATION TECHNIQUE

The system represented by **(4)** is difficult to estimate because of the interdependence of the parameters dictated by Slutsky symmetry and the adding-up constraint.¹⁴ To insure that these two conditions hold, the equations must be estimated as a system. This joint estimation, in turn, creates the problem of heteroscedasticity -- the variance of the error terms for each equation do not have the same value. This heteroscedasticity arises because we are forced to group the equations into a single estimation. Since the level of consumption for the different categories varies greatly, we expect that the variances of the error terms will vary, thereby violating the assumption of homoscedasticity. We correct for this heteroscedasticity by dividing the data for each category by an estimate of the standard deviation of the error term in the equation for that item prior to estimation (Johnston 1984). These estimates of the standard deviations are obtained by performing separate regressions of a linear version of the consumption function for each of the 80 categories.

The system represented by **(4)** is extremely nonlinear in the price terms. This nonlinearity increases the difficulty of estimating the system. We avoid this problem by iteratively estimating a linear version of the system. For purposes of illustrating this technique, suppose we have the following general nonlinear equation:

$$
Y_i = F(x_i, B) + U_i \tag{8}
$$

where Y_i and x_i are the observations of the dependent variable and the vector of independent variables in the ith period; U_i is the disturbance term in the ith period; and B is the vector of parameters to be estimated.

We select estimates of B to minimize the following:

$$
\sum_{i} \{Y_i - F(x_i, B)\}^2
$$
 (9)

 13 For a list of the commodities and the equation form used in the estimation, please see Appendix B.

¹⁴Slutsky symmetry requires that $\lambda_{IK} = \lambda_{KI}$.

We then employ the Gauss-Newton method to estimate iteratively the value of B by performing ordinary least squares regressions.15

Consider the following Taylor expansion of $F($) around B_0 , an estimate of B. We have

$$
F(x_i, B) = F(x_i, B_0) + F'(x_i, B_0) {B - B_0}
$$

= F(x_i, B₀) - F'(x_i, B₀)B₀ + F'(x_i, B₀)B (10)

where $F'(x_i, B_0)$ is the vector of first derivatives of F() with respect to B, evaluated at B_0 . If we substitute **(10)** into **(9)** we have:

$$
\sum_{i} \{ [Y_i - F(x_i, B_0) + F'(x_i, B_0)B_0] - F'(x_i, B_0)B \}^2
$$
 (11)

The expression within the brackets contains no unknown parameters. Likewise, $F'(x_i, B_0)$ is a vector that can be calculated for a given value of B_0 . It follows that the value of B that minimizes the expression **(11)** is the same as the value that results from performing an ordinary least squares regression of the expression in brackets on $F'(x, B_0)$. That is:

$$
Y_i - F(x_i, B_0) + F'(X_i, B_0) = F'(x_i, B_0)B
$$
 (12)

The estimate of B obtained from this regression is used to re-linearize equation **(8)**. Another regression is performed to obtain a second estimate of B. This iterative procedure continues until no further reductions are made in the sum of squared errors. Convergence is usually achieved within five or six iterations.

EQUATION-SPECIFIC VARIABLES

It is a long-established tradition that non-income and non-price variables play a key role in determining household PCE (Heien 1972; Denton and Spencer 1976; Devine 1983; Monaco 1984; Deaton et al. 1989; Chao 1991; Malley and Moutos 1993; Monaco 1994). Most of this work has focused on the effects of demographic and age variables, but some work has examined the effects of "other" variables (Devine 1983; Chao 1991; Malley and Moutos 1993; Monaco 1994). The LIFT PCE system has acknowledged these influences through the use of the cross-section effect variable, C^{*}, the adult equivalent weights, and equation-specific variables (Devine 1983). Devine included the following equation-specific variables:

Housing Demand Proxy Owner-occupied housing (PCE40) and Tenant-occupied housing(PCE41). A proxy for the speculative demand for housing. Calculated as the ratio

¹⁵ Our description of the Gauss-Newton method is a slight variation of the presentation found in Maddala (1977).

of the current price of owner-occupied housing to a three-year moving average of its price.

Natural Gas Price Control Dummy Natural gas (PCE46), Electricity (PCE45) and Fuel oil (PCE28). A dummy for Natural gas price controls. Equals one for the years 1974, 1975, 1976.

Mortality Rate Funeral expenses and other personal business expenses (PCE72). An attempt to capture the impact of increased longevity on funeral expenses. Expressed in deaths per thousand persons.

Availability of Used Cars Used cars (PCE02). A proxy for the potential stock of cars for the used car market. Equaled a three-year moving average of new car purchases lagged three years.

For our work, we felt that Devine's variables, except for the natural gas price control dummy, were inappropriate for our estimation. For example, the availability of used cars for market should be reflected in the price term and so this variable was rejected for theoretical reasons.

In our first attempt to estimate the system, we estimated all of the equations without the use of a time trend.¹⁶ Any commodity that appeared trended was examined to determine if there existed a known reason for the trend. For example, the growth in Nursing home expenditures (PCE80) was thought to be linked to the increased numbers of over-85 years of age persons. Unfortunately, we were forced to estimate the system with time trends included in some equations, and, for three of the commodities, were forced to add a second time trend. The equation-specific variables we used included:

Two-Year Moving Average of 3-month T-Bill Rate (Interest Rate) New Cars (PCE01), Used Cars (PCE02), and New and used trucks (PCE03). Calculated as a two-year moving average of the 3-month treasury bill rate. This variable attempted to capture the sensitivity of automobile financing to changes in the interest rate.

Residential Construction Activity (Construction) Furniture and mattresses (PCE06), Kitchen and other household durables (PCE07) and Durable furnishings, N.E.C. (PCE11). Equalled per-capita spending on Single-family residential construction (STR01) and Additions and alterations (STR04). Purchases of furniture, kitchen appliances and other miscellaneous household items often occur with a new house purchase and/or renovation of an existing structure.

Natural Gas Price Regulation Dummy (Dummy) Fuel oil (PCE28), Electricity (PCE45) and

 16 Devine (1983), Chao (1991) and Janoska (1993) included one or more time trends in their equations. This trend was incorporated in an attempt to capture systematic changes in demand that could not be attributed to price, income, age or demographics.

Natural gas (PCE46). Equaled 1 in all years of regulation (1973, 1974, 1975) and 0 in all others. This variable was an attempt to capture the effects of Natural gas price regulation during the early 1970's

Value of Housing Stock (Stock) Owner-occupied housing (PCE41) and Tenant-occupied housing (PCE42). Cumulative housing stock value adjusted for depreciation (2%). Owneroccupied housing (PCE41) is an imputed component of the NIPA. Our formulation is an attempt to bring this sector into a format similar to that used by the NIPA (Carr 1994).

Labor Force Participation Rate (Labor Parti) Net health insurance (PCE67) and Life insurance (PCE70). Equals the labor force participation rate. This variable is an attempt to capture the effect of increased labor force participation among women. Typically, life insurance is carried on the primary wage-earners in a household. Over time, second incomes have moved from being "extra" income to primary income. Consequently, households will probably purchase two policies (one for each wage-earner) when in the past households would have carried a single policy. We believe that a good proxy for this effect is the labor force participation rate.

Population 85 years and Older (Elderly) Hospitals (PCE66) and Nursing homes (PCE80). Equals population 85 years of age and older. Among the over-65 population, this group tends to use these services more frequently and intensely then those younger than 85 years of age (Harrison 1986; Waldo 1989). Because our equations combine the elderly into a single cohort, our system of weighted-populations cannot capture the "aging-of-the-aged" effect. This variable is an attempt to capture this effect.

Second Time Trend (Second time) Gasoline and oil (PCE27), Intercity railroad (PCE58) and Cleaning and laundering (PCE62). A second time trend beginning in 1982. Some unidentified structural change appears to have occurred in these sectors. This variable is an attempt to account for this change until the reasons for the change can be discovered.

ESTIMATION CRITERIA

Because the PCE equations eventually will be used in LIFT, they must be capable of generating reasonable forecasts as well as satisfying economic theory. We felt that each equation had to meet the following four criteria:

1. Non-Positive Own-Price Elasticity: Economic theory suggests that, except in the case of a Giffen good, quantity demanded of a good should be inversely related to its own price. Since, by assumption, none of the PCE categories are Giffen goods, any estimation that results in a category having a positive estimated own-price elasticity would have to be respecified and reestimated.

2. The size and magnitude of the coefficient on the ∆**C* must generate stable long-term forecasts**: This coefficient must either be positive or smaller in absolute value than the coefficient on the C^* term. If this did not hold, any long-run increase in income would reduce spending. At the level of dissagregation we use, such a property would lead to unreasonable forecasts. Consequently, if the estimated parameters did not meet this criteria, the system was respecified -- usually by changing the form of the equations.

3. The effect of time must be "small": Time was not allowed to change the absolute value of household consumption by more than 1 percent each year. This was to prevent the time trend from dominating the forecast.

4. Equation-specific variables must have the "correct" effect: In other words, the coefficient on these variables had to satisfy our a-priori beliefs on the variable's effect.

As we already mentioned, our first step was to estimate the system without a time trend in the equations. Those equations that fit poorly or did not satisfy the above four conditions were studied to determine if they required an equation-specific variable. For some of the categories that did not meet (1-4), we could find no equation-specific variable. We then estimated the system using alternate equation forms. This was possible because of the new estimation software.

Unfortunately, we were unable to find a set of equations that gave us non-positive own-price elasticities for all 80 PCE categories. Despite our efforts, we were forced to accept results with three categories (Auto repair (PCE53), Brokerage and investment counseling (PCE68), and Life insurance (PCE70)) having positive own-price elasticities. All of these estimated own-price elasticities are close to zero and may reflect inadequacies in the data.¹⁷

V. RESULTS

Traditionally, the regression statistic used in determining "goodness-of-fit" is the R-squared statistic. Under Ordinary-Least Squares (OLS) regression, the R-squared statistic shows the percentage of variation in the dependent variable that is explained by movements in the independent variables. Our equation is non-linear, and consequently, the R-squared statistic loses some of its meaning because it is no longer bounded between zero and one.¹⁸ While it is true that larger R-squared values indicate a "better" fit, the values become ordinal -- signifying better or worse, but not indicating the magnitude of improvement. The R-squared statistic is but one of many statistics on goodness-of-fit. The statistic we use is the Average Absolute Percentage

¹⁷ See Appendix D for a table of price elasticities.

¹⁸The calculation of the R-squared coefficient depends on the relationship between total sum of squares (TSS), residual sum of squares(RSS) and explained sum of squares (ESS). Under OLS, TSS = RSS + ESS. In a non-linear estimation, this relationship no longer holds, $TSS \neq ESS + RSS$.

Error (AAPE), since it gives information on both the direction and magnitude of changes in $fit.19$

It must also be remembered that because we are estimating the equations as a system, the software attempts to minimize the error of the system as a whole. Each category carries the same importance when the software attempts to solve equation **(11)**:

$$
\sum_{i} \{ [Y_i - F(x_i, B_0) + F'(x_i, B_0)B_0] - F'(x_i, B_0)B \}^2
$$
 (11)

For this reason, one must look at the AAPE of the system as a whole to determine whether or not one has obtained a "better" fit. Any improvement in the performance of the system, however, could be concentrated in a few categories while the majority of categories performed worse. Thus, one also must look at the AAPE by PCE category to determine whether the improved overall performance offsets any decline in individual equation performance.

We believe that the behavior of the system improved under the new method. This is true regardless of whether one examines the overall AAPE statistic or whether one looks at the AAPE's by PCE category. The new AAPE of the system is 9.71 percent versus the old AAPE of 9.86 percent -- a 1 percent improvement in performance. Forty-two of the categories had improved AAPE statistics and thirty-four categories had worse AAPE's. We list the improved sectors below with the health related categories in **bold**.

These forty-two categories account for over two-thirds of total PCE. The four health-care related categories -- Drug preparations (PCE31), Dentists and other professionals (PCE65), Hospitals (PCE66) and Nursing homes (PCE80) -- account for nearly three-quarters of healthrelated PCE. The two categories showing the largest improvement, Hospitals and Nursing homes, are health care related and improved by over one percent. In contrast, none of the commodities for which the AAPE grew saw an increase of over .750 percent.

Sectors with improved AAPE

¹⁹The average absolute percentage error (AAPE) is calculated as follows:

 \sum {Absolute Value(Predicted Level of PCE - Actual Level of PCE)/{Actual Level of PCE}/(# of observations). For a discussion of alternate measures-of-fit, see Newbold and Bos (1994) or Wilson and Keating (1994).

On the next page, we list the thirty-four categories with a larger AAPE (or worse AAPE).

Sectors with worse AAPE

Appendix C, contains the final parameters from the system. Due to the large number of price parameters, we only list the non-price parameters in Appendix A. The implied price and income elasticities from the estimated parameters are listed in Appendix D. Appendix E contains the estimated income and price-elasticities from the old method of modelling Medicare benefits. We present the following example showing how to read the tables in appendices D and E:

Sample Table From Appendix D **GROUP 6: MEDICAL SERVICES**

INSURANCE 4 DRUGS AND EQUIPMENT

Looking at the first PCE category, we see that *PCE64, Physicians* is a member of *Group 6: Medical Services* and is part of sub-group 1 *Dentists and Doctors* in Group 6. In 1992, 2.37 percent of total PCE was spent on Physicians. The category has an income elasticity (YELAS) of 1.244.²⁰ Physicians (PCE64) has an own-price elasticity (OWN) of -0.319. Looking at the values under the headings **SG #**, we see that a 1 percent increase in the cost of Physicians, leads to a -0.042 change in spending on the other categories in sub-group 1. The price increase in PCE64, causes spending in sub-group 2, *Facilities*, to increase 0.083 percent and also causes spending on sub-group 3, *Drugs and Equipment*, to fall -0.247 percent. Finally, the 1 percent increase in the price of PCE64 causes an increase of 0.153 percent on spending on sub-group 4, *Insurance*.

A casual examination of appendices D and E shows that the estimated elasticities for most of the categories are relatively unchanged. For example, the income elasticity of Tobacco (PCE29) was .267 under the old method, but under the new method it is .266. All of the PCE categories, with the exception of those in *Group 6: Medical Services*, show little change with the adoption of the new method of modelling Medicare benefits. In many ways, this is unsurprising, since our income variable is virtually unchanged and all of the revised price variables are in Group 6. Since we expect price effects between groups to be weak or non-existent, we hardly should be surprised when our empirical work validates our a-priori beliefs.

However, the estimated price elasticities in *Group 6: Medical Services* have changed a great deal. Under the new method, all of these categories are less elastic with respect to their own price. With the exception of categories in sub-group 3, *Drugs and Equipment*, the PCE categories exert less price-effects on categories within sub-group and outside their own sub-group. For example, under the old method, a 1 percent price increase in Hospitals (PCE66) caused a 1.113 percent increase in spending on sub-group 1, *Doctors and Dentists*, and a -0.752 decrease in spending on Nursing homes. Now, the same price increase will cause only a 0.146 increase in spending on sub-group 1, *Doctors and Dentists*, and a -0.457 decrease in spending on Nursing homes. This implies that the substitutability between Physicians and Hospitals and the complementarity between Hospitals and Nursing homes is lower than implied by the old method.

 20 An income elasticity of 1 means that, if income increases by 1 percent, spending increases 1 percent. Similarly, an own-price elasticity of -.5 means that, if the good's own price increased by 1 percent, spending on the good falls by one-half a percent.

VI. CONCLUDING REMARKS

This work is but the first step in modelling Medicare as a price subsidy. Our earlier work (1994b) showed that Medicare is not an income transfer program, but, instead functions as a price subsidy. The earlier work also suggested how one could model Medicare as a price subsidy. The current work has implemented those suggestions and we have obtained a better-fitting system of equations. The next step is to incorporate these equations into LIFT and determine their simulation properties.

One area of particular importance that these equations promise to improve is that the model will no longer treat Medicare as an income transfer. Thus, the effects of increased Medicare benefits will be concentrated in the health services categories of PCE. This should dramatically improve the simulation properties and capabilities of the model.

The current work points to other areas of the model that should be investigated. For example, the current task dealt exclusively with Medicare benefits. Medicaid benefits, an in-kind transfer to the poor (Smeeding and Moon 1980; Janoska 1994c), are still treated as an income transfer despite some evidence that this is an inappropriate treatment of the program (Janoska 1994b). Employer-provided insurance benefits are also treated as income by the model when theory suggests that these benefits be modelled as price subsidies to consumers.

Appendix A Personal Consumption Categories

DURABLE GOODS

MOTOR VEHICLES AND PARTS

- 1 New cars
- 2 Used cars
- 3 New & used trucks
- 4 Tires & tubes
- 5 Auto accessories & parts

FURNITURE & HOUSEHOLD EQUIPMENT

- 6 Furniture,mattresses,bedsprings
- 7 Kitchen, household appliances
- 8 China,glass&tableware,utensils
- 9 Radio,tv,records,musical instr.
- 10 Floor coverings
- 11 Durable housefurnishings, NEC
- 12 Writing equipment
- 13 Hand tools

OTHER DURABLES

- 14 Jewelry
- 15 Ophthalmic & orthopedic goods
- 16 Books & maps
- 17 Wheel goods & durable toys
- 18 Boats, rec vech., & aircraft

NON-DURABLE GOODS

FOOD AND ALCOHOL

- 19 Food, off premise
- 20 Food on premise
- 21 Alcohol, off premise
- 22 Alcohol, on premise

CLOTHING

- 23 Shoes & footwear
- 24 Women's clothing
- 25 Men's clothing
- 26 Luggage

OTHER NON-DURABLES

- 27 Gasoline & oil
- 28 Fuel oil & coal
- 29 Tobacco
- 31 Drug preparations & sundries
- 30 Semidurable housefurnishings
- 32 Toilet articles & preparations
- 33 Stationery & writing supplies
- 34 Nondurable toys, sport supplies
- 35 Flowers, seeds, potted plants
- 37 Cleaning preparations
- 36 Lighting supplies
- 38 Household paper products
- 39 Magazines & newspaper
- 40 Other nondurables -- identity

SERVICES

HOUSING

- 41 Owner occupied space rent
- 42 Tenant occupied space rent
- 43 Hotels, motels
- 44 Other housing

HOUSEHOLD OPERATION

- 45 Electricity
- 46 Natural gas
- 47 Water & other sanitary services
- 48 Telephone & telegraph
- 49 Domestic services
- 50 Household insurance
- 51 Other household operations:repair
- 52 Postage

TRANSPORTATION

- 53 Auto repair
- 54 Bridge, tolls, etc
- 55 Auto insurance
- 56 Taxicabs
- 57 Local public transport
- 58 Intercity railroad
- 59 Intercity buses
- 60 Airlines
- 61 Travel agents, other transportation services
- **MEDICAL SERVICES**
- 64 Physicians
- 65 Dentists & other professional services
- 66 Private & government hospitals
- 67 Health insurance
- 80 Nursing homes

OTHER SERVICES

76 EDUCATION

- 62 Laundries & shoe repair
- 63 Barbershops & beauty shops
- 68 Brokerage,investment counseling
- 69 Bank service charges &services w/o pay
- 70 Life insurance
- 71 Legal services
- 72 Funerals, other personal business services
- 73 Radio & tv repair
- 74 Movies, theater, spectator sports
- 75 Other recreational services
- 77 Religious & welfare services
- 78 Foreign travel by U.S. residents
- 79 Travel in U.S. by foreigners

Appendix B List of Customized Equations

Appendix B - Continued

Appendix C Final Estimates With Medicare as a Price Subsidy

Appendix C - Continued

Appendix D Estimated Price and Income Elasticities Under New Method

Appendix D - Continued

1 DURABLE PURCHASES 2 MAINTENANCE EXPENSES EXP. GASOLINE 3 PUBLIC TRANSPORTATION 4 GASOLINE

Appendix D - Continued

1 ADMISSIONS 2 RECREATIONAL NONDURABLES AND DUR 3 HOTELS ETC. 4 TRAVEL

GROUP 10: READING AND EDUCATION

1 READING 2 EDUCATION 3 RELIGIOUS

Appendix E Estimated Price and Income Elasticities Under Old Method

2 SERVICES AND INSURANCE 3 COMMUNICATION

Appendix E - Continued

1 DURABLE PURCHASES 2 MAINTENANCE EXPENSES EXP. GASOLINE 3 PUBLIC TRANSPORTATION 4 GASOLINE

Appendix E - Continued

1 ADMISSIONS 2 RECREATIONAL NONDURABLES AND DUR 3 HOTELS ETC. 4 TRAVEL

GROUP 10: READING AND EDUCATION

1 READING 2 EDUCATION 3 RELIGIOUS

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