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ESTIMATING A HOUSEHOLD PRODUCTION FUNCTION: HETEROGENEITY, THE DEMAND FOR HEALTH INPUTS AND THEIR EFFECTS ON BIRTHWEIGHT

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Estimating A Household Production Function: Heterogeneity, The Demand for Health Inputs and Their Effects on Birthweight*

1. Introduction

In the last decade there has appeared an extensive body of empirical work concerned with the allocation of family resources. The framework underlying many of these analyses of the determinants of labor supply, fertility, health and other family behavior is the household production model introduced by Becker (1965). Despite the emphasis of this framework on the distinction between production technology and preference orderings, none of the empirical studies based on this approach has attempted to disentangle the household's technology from its "tastes." Since the predictions embodied in the reduced-form-demand equations for market goods, derived from the household production model, are no different from the predictions contained in demand equations from the conventional multi-person consumer demand model (in which all observable goods enter the utility function directly), the distinct implications of the household production approach have not yet been exploited empirically.

In one field, health, the household production framework appears particularly applicable. The notion of an underlying technology, i.e., biological processes, is well-accepted and attention to quantifying health conditions has narrowed the potential set of important health inputs. While economists have employed the household production approach in this domain, the major focus of empirical work has been on the demand for health inputs, chiefly medical services (Goldman and Grossman, 1978, Friedman and Leibowitz, 1979). Estimates of the technical/biological effects of such inputs on health, constrained by the limited availability of data on inputs, have been obtained from "hybrid" health equations which contain one or two health inputs and prices and income variables on the right-hand side (Edwards and Grossman, 1979). Moreover, these latter studies as well as those in the medical literature have ignored the endogeneity

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of the (self-selected) health inputs and have thereby implicitly assumed that the population does not differ with respect to exogenous health endowments.[1] Yet it would appear that innate differences loom large in the distribution of health across individuals and that at least some of these fixed characteristics are known to individuals, who act upon that knowledge.

In this paper we estimate a (household) health production function using information on one important early health indicator, birthweight, and a set of behavioral variables considered to be the important determinants of birth outcomes in the medical literature--prenatal medical care, working and smoking by the mother while pregnant, the number of births of the mother and her age. In section 2 we describe a household production model to interpret the hybrid-type health equation and to assess the effects of health heterogeneity on health behavior and its consequences for the estimation of the health technology. We describe the data and the estimation strategies employed to take into account heterogeneity in section 3. Section 4 discusses the estimates of the reduced-form effects of parental income, schooling, race, health programs and prices on the demand for the health inputs. Section 5 reports estimates of the birthweight production function. Statistical tests are performed of functional form and of heterogeneity bias as well as of one version of the complete household production/consumption model. Section 6 discusses estimates of the effect of child health endowments on input demand behavior. Our results indicate that OLS estimates of the birthweight production function are significantly contaminated by heterogeneity bias. In particular, neglect of heterogeneity appears to lead to a substantial underestimate of the beneficial effects of early prenatal care on the weight of a baby at its birth. The negative effects of the mother's smoking while pregnant on fetal growth are also importantly understated.

2. The Household Production of Health

a. Health Production, Input Demand and Hybrid Functions

Assume that a household's preference orderings over child health, H, n X-goods, and m - n Y-goods which affect child health can be characterized by the utility function, subject to the usual properties:

(1) $$U = U(X_i, Y_j, H) \qquad i = 1,\ldots,n,; \; j = n + 1,\ldots,m$$

Let the production of child health by the household be described by the production function:

(2) $$H = \Gamma(Y_j, I_k, \mu) \qquad k = m + 1,\ldots,r$$

where the r - m I_k are health inputs which do not augment utility other than through their effects on H (medical care, for example), and μ represents family-specific health endowments known to the family but not controlled by them, e.g., genetic traits, environmental factors.[2]

The budget constraint for the household in terms of the r purchased goods is:

(3) $$F = \sum_t Z_t p_t \qquad t = 1,\ldots,r$$

where F is exogenous money income, the p_t are exogenous prices and Z = XUYUI. The household model as depicted is characterized by joint production (Pollak and Wachter, 1975) in the sense that a subset of goods Y (smoking, for example) both affects child health and contributes to utility directly.[3] For simplicity, only one production process is discussed, but the model can be easily generalized to depict many processes without changing its major implications.

The household's reduced-form demand functions for the r goods, including the r - n health inputs, derived from the maximization of (1), subject to (2) and (3), are:

(4) $Z_t = S_t(p, F, \mu)$ $t = 1,\ldots,r$

The reduced-form demand function for the health outcome may be written analogously:

(5) $H = \psi(p, F, \mu)$

Empirical applications of health production models have chiefly focused on estimating input demand functions, such as (4), or reduced-form health equations, such as (5). Since the properties of (4) are identical to those from models which posit that there is no household production of health and the reduced-form health equation embodies few, if any, restrictions implied by the model, these studies do not really make use of the notion of an underlying household health technology, nor do they provide information on that technology.

While estimates of reduced forms such as (4) or (5) are useful in both providing policy-relevant parameters and for prediction, econometric applications which have been concerned with the relationships between health and health inputs have been hampered by the limited availability of data on health inputs and have consequently estimated equations ("hybrids") with less desirable properties. These hybrid equations have the form:

(6) $H = \theta(Y_m, p_\ell, F, \mu)$ $\ell = 1,\ldots,m-1, m+1, \ldots, r$

i.e., one input, say Y_m, and the <u>determinants</u> of all other inputs, p_ℓ, F and μ are regressed against a measure of health. The "effects" of health input Y_m, usually medical care, estimated from an equation like (6) is interpreted as if it were the relevant production function relation. However, it can be readily shown that the partial θ_{Y_m} in (6) embodies both the technological properties of the health production function and the characteristics of the household's preferences. Thus, the "hybrid" effect of a health input on health, controlling for prices and income, is generally a biased estimate of the true technical relationship (other inputs held constant) embodied in the health production function, where the sign and magnitude of the bias depend on the properties of (1).[4]

b. Heterogeneity and the Health Technology

The data requirements and estimation problems involved in separating out both the characteristics of the utility function and the underlying health technology are clearly formidable (see Barnett, 1977 and Pollak and Wachter, 1977). However, the notion that the health production inputs are behavioral variables also implies that even if only information on the technology of health production were desired, having measures of all important behavioral inputs and the health output would not be adequate to describe the health technology. The difficulty arises chiefly from the presence of exogenous health factors which can be known to individual households but which are unobserved by the researcher.[5]

Consider the relationship between a small change in the input Y_m and child health estimated from (2) in a population in which μ is distributed randomly. From (1) and (2), this association can be approximated by:

$$\frac{dH}{dY_m} = \Gamma_{Y_m} + \left(\frac{dY_m}{d\mu}\right)^{-1} \tag{7}$$

where

$$\frac{dY_m}{d\mu} = -\Gamma_\mu\left(\sum_{n+1}^{m} S^c_{jm}(U_{Y_jH}+U_{HH}\Gamma_{Y_j}) + \sum_{1}^{n} S^c_{im}U_{X_iH} + \sum_{m+1}^{r} S^c_{km}U_{HH}\Gamma_{I_k}\right)$$
$$- U_H\left(\sum_{n+1}^{m} S^c_{jm}\,\Gamma_{Y_j\mu} + \sum_{m+1}^{r} S^c_{km}\,\Gamma_{I_k\mu}\right)$$

and the S^c_{ij} are the compensated price effects from the relevant demand functions (4) and the Γ_x are the marginal products of the factors in (2).

As can be seen, the observed input-constant relationship between Y_m and H will not correspond to the true marginal product, Γ_{Y_m}. Moreover, the "bias", given by the second term in (7), will depend on i) the properties of the utility function, ii) the marginal products of all inputs, iii) how μ affects health directly and iv) how μ affects the marginal products of the controllable inputs.

In the study of health, heterogeneity bias is most likely to affect measurements of the effectiveness of "remedial" medical care.[6] Many pregnant women, for example, have information on health endowments from prior histories of pregnancy complications or of prior birth outcomes reflecting low child health which may alter their use of prenatal care. Indeed, it is not unlikely that women who have prior medical problems may be the ones most likely to be using prenatal medical services and to have such problems again. Inferences from non-experimental data about the health technology and the value of remedial measures may be misleading, therefore, if these inferences do not take into account the interdependence of the levels of health inputs and preference orderings that occur because of exogenous health heterogeneity.

3. Data and Estimation Strategies

The 1967, 1968 and 1969 U.S. National Natality Followback Surveys, described in U.S. DHEW (1978), appear to meet most of the data requirements for estimating the health technology associated with birth outcomes. These national probability samples of approximately 10,000 legitimate, live births, for the three years combined, contain information on the birthweight and gestation period for each birth, on the schooling attainment of both parents, the income of the husband, and three retrospectively obtained aspects of the mother's behavior while pregnant that are potentially linked to infant health at birth--smoking, working and prenatal medical care--in addition to data on age at birth and birth order (parity). While no data on input costs or prices are provided, the survey does provide information on the county of residence of the mother at the time of the birth, enabling us to merge local-area price, health program and labor force variables with the individual micro data. The sample size for non-multiple births, available for analysis, is 9621.

The weight of a child at birth or birthweight and birthweight standardized for gestation length are used in this study as two indicators of child health. Both child health outcome variables are linked in an extensive medical literature to infant survival and to the prospects of subsequent child growth and development.[7] Recently two distinct health effects of low birthweight and "prematurity" have been noted in the medical literature: a relatively transitory trauma associated with delivery and its immediate consequences, and more permanent side effects that contribute to elevated risks of later childhood morbidity and mortality (Beck and van den Berg, 1975). The latter more permanent effect appears to be related to the rate of weight gain of the fetus to birth. To obtain a measure of the latter, an infant's actual birthweight was divided by the expected birthweight conditional on the infant's gestation, predicted by a fetal growth function estimated as a cubic function from the sample data.[8]

The endogenous or behavioral variables considered to have a direct, technical or biological relationship with birthweight (the arguments in (2)) are the number of months the mother worked while pregnant, the number of months of elapsed pregnancy before the mother visited a medical doctor (DELAY), the number of cigarettes smoked per day by the mother while pregnant (SMOKING), the order of the current live birth (BIRTHS) and the age of the mother at birth (AGE).[9] All of these variables have been identified (usually in isolation) as significant correlates of birthweight in the medical literature. We note that the mother's age in this context is a choice variable as it refers to the point in her life cycle at which she is choosing to have a child. In preliminary specifications and tests of the health production function, the number of months the mother worked while pregnant never appeared to be a significant determinant of birth outcomes. In the reported specifications we consequently omit this variable.

To augment the set of exogenous variables in the data, we collected and merged with the household data SMSA- or state-level information on input and goods prices, health infrastructure, public expenditures and labor market conditions. The added variables are: hospital beds per-capita, per-capita governmental health expenditures, the per-capita number of hospitals and health departments with family planning, medical doctors and obstetrician-gynecologists, the unemployment rate for women aged 15-59, the general unemployment rate, the percent of persons employed in service, government, and manufacturing industries, the per-pack cost (including excise taxes) of cigarettes, the sales tax per pack on cigarettes, the price per quart of milk, and the size of the SMSA for inhabitants of SMSAs. The data sources for these areal variables are described in Rosenzweig and Schultz (1982).

The generalized functional form used for the health production function is the transcendental logarithmic (translog), which can be viewed as a local second-order approximation to any production function. The technological specifications employed also assume that log birthweight and the log of standardized birthweight differ according to whether or not the mother is black. We can thus test for differences in infants' weight at birth by race, conditional on input levels. The generalized birthweight and standardized birthweight production functions are thus given by:

$$\text{(8)} \quad \text{L BIRTHWEIGHT} = \gamma_0 + \frac{1}{2}\sum_{ij}\sum \beta_{ij} Y_i Y_j + \sum_i \beta_i Y_i + \gamma_1 \text{ BLACK} + \mu + \varepsilon$$

where the prefix L denotes the logarithm of the respective variable, and the Y are LDELAY, LSMOKING, LBIRTHS, LAGE, μ is the unobserved health endowment "effect," ε is a random error, the β_{ij} and γ_i are estimated production parameters, and $\beta_{ij} = \beta_{ji}$.

As we have shown, the error term in (8), containing μ, is likely to be correlated with the Y_i, and therefore, ordinary least squares estimates of the β_{ij} parameters are inconsistent. Consistent estimates of the health production function (8) could be obtained in a number of ways utilizing information from the full structure of production and utility system, including estimation of a complete structural demand system enabling the identification of the underlying preference parameters (Barnett, 1971; Pollack and Wachter, 1977). Given the absence of data on (or variation in) the prices of all inputs and of all household expenditures, consistent estimates are obtained here by using two-stage least squares (TSLS), where estimates from the first-stage log linear input demand equations for the four behavioral input variables, Y_i, are employed to obtain second-stage estimates of the health production parameters.[11] Since the price, income and education variables that determine input demands are by assumption orthogonal to the exogenous health endowment, they serve as instruments to identify the health technology.[12] For comparative purposes and to perform statistical tests (Durbin (1954)) of heterogeneity bias, OLS estimates are also obtained. The log-linear first-stage equations include, in addition to the set of state and SMSA-level exogenous variables specified, a set of schooling level

Table 1

Variable Descriptions and Sample Characteristics

Variable	Definition	Mean	Standard Deviation
Health Outcomes (in Natural Logarithms):			
Birthweight	Weight of infant at birth in grams	8.08	.215
Standardized Birthweight	Birthweight divided by predicted birthweight based on infants gestation (x100). See text.	-.0136	.173
Health Input Behavior (in Natural Logarithms):			
Doctor Delay	Number of elapsed months of pregnancy before mother consulted a doctor or nurse	.865	.521
Smoking	Number of cigarettes smoked per day by mother while pregnant	.834	1.25
Births	Number of live births born to mother	.713	.638
Age	Age of mother at birth	3.19	.214
Exogenous Individual Characteristics:			
Mother's Education by Cateogry: (less than 9 years is omitted category)			
High School Incomplete (9-11 years)		.229	.420
High School Complete (12 years)		.445	.497
College Incomplete (13-15 years)		.143	.350
College Complete (16 or more)		.088	.283
Father's Education by category: (less than 9 years is omitted category)			
High School Incomplete (9-11 years)		.191	.393
High School Complete (12 years)		.378	.485
College Incomplete (13-15 years)		.146	.353
College Complete (16 or more)		.159	.365
Black	One if mother is black	.185	.388
Income	Log of Husband's life cycle (experience equals ten years) annual income. See footnote 13.	8.65	.725
Exogenous Area Characteristics:			
Metropolitan	One if located in Standard Metropolitan Statistical Area	.701	.458
City Size	Population in SMSA in 1970 ($x10^{-3}$)	1351.	2091.
Hospital Beds	Number of hospital beds per capita ($x10^{2}$) 1965, state level	.465	.109

Table 1 continued

Variable	Definition	Mean	Standard Deviation
Health Expenditures	Local governmental health and hospital expenditures in thousands of dollars per capita, 1965, at state or SMSA level	.0203	.0226
Family Planning in Health Dept.	Number of hospitals with family planning services per capita, 1969, at state or SMSA level ($x10^5$)	.486	.871
Family Planning in Hospitals	Number of hospitals with family planning services per capita, 1969, at state level ($x10^5$)	.300	.158
Population per M.D.	Number of persons per medical doctor, 1969, at state or SMSA level	1422	687.
Obstetrician-gynecologists per capita	Number of obstetricians-gynecologists per capita at state or SMSA level ($x10^4$)	.801	.234
Female Unemployment Rate	Proportion of women in labor force, age 15-59 unemployed, 1970, at state level	.0526	.0104
General Unemployment Rate	Proportion of the labor force unemployed, 1970, at state level	.0476	.0092
Share of Jobs in Services	Percent of persons employed in serivces, 1970,at state level (x10)	77.8	15.3
Share of Jobs Manufacturing	Percent of persons employed in manufacturing, 1970, at state level (x10)	260.	72.9
Share of Jobs in Government	Percent of persons employed in government, 1970, at state level (x10)	160.	29.0
Cigarette Price	Price of cigarettes (exclusive of sales tax), cents per pack, 1967-69, at state level	34.6	3.38
Sales Tax	Retail sales tax on cigarettes 1967-69, at state level	.582	.493
Milk Price	Retail price of milk per quart, 1970 , at state level	27.0	2.23
1967	One if birth occurred in 1968	.330	.470
1968	One if birth occurred in 1969	.331	.471

dummy variables for the husband and wife, the race variable, and a measure of husband's income which is standardized for years of potential labor market experience.[13] Table 1 defines the variables used and reports their sample means and standard deviations.

While the two-stage procedure achieves consistency and allows for flexibility in the specification of the health technology, estimates are not efficient because the reduced-form cross-equation restrictions implied by the model are ignored. Such restrictions, however, cannot be imposed without specifying the exact form of the utility function (1). Moreover, closed form analytic solutions for the demand equations cannot be obtained without sacrificing the flexibility in either or both of the specifications of the production and utility functions. One production and utility system which yields such solutions, and thus exact cross-equation restrictions, is that in which both functions are described by the Cobb-Douglas form.[14] Since if the birthweight technology is Cobb-Douglas, $\beta_{ij} = 0$ for all i and j in (8), the translog function can be used to test this restriction on the health technology. Conditional on its acceptance, we can then exploit potential efficiency gains by estimating jointly the production function and the demand system implied by the Cobb-Douglas form of the utility function.

4. Estimates of the Reduced Form Demand Equations

The first four columns of Table 2 report the first stage log-linear input demand equations used to estimate the birthweight production functions. While in many cases the estimates are relatively precise, the R^2's of the equations are relatively low, ranging from .033 for smoking to .119 for delay of prenatal care. The input demand equations appear reasonable in the context of prior studies of household behavior, with parental schooling levels and income evidently significant determinants of health-related

Table 2

Estimates of Log Linear Input and Birth Characteristic Demand Equation[1]

Independent Variables	Log of Doctor Delay (1)	Log of Smoking (2)	Log of Births (3)	Log of Age (4)	Log of Birthweight (5)	Log of Birthweight Standardized for Gestation (6)
Mother's Education:						
High School Incomplete	-.0914	.201	-.185	-.0813	-.0109	-.0162
	(4.46)	(3.91)	(7.33)	(9.59)	(1.23)	(2.26)
High School Complete	-.215	-.0585	-.300	-.0005	.00392	-.00306
	(10.5)	(1.14)	(11.92)	(.06)	(.44)	(.43)
College Incomplete	-.259	-.0900	-.380	.0148	.00916	.000826
	(10.5)	(1.46)	(12.6)	(1.45)	(.86)	(.106)
College Complete	-.257	-.145	-.447	.0797	.0135	.00505
	(8.92)	(2.01)	(12.6)	(6.69)	(1.08)	(.50)
Father's Education:						
High School Incomplete	-.0115	.192	-.272	-.1144	-.00720	-.00606
	(.60)	(3.99)	(11.47)	(14.3)	(.86)	(.90)
High School Complete	-.099	.0441	-.355	-.1143	-.00989	-.00829
	(5.23)	(.93)	(15.3)	(14.6)	(1.21)	(1.25)
College Incomplete	-.116	-.0366	-.387	-.1208	-.00350	-.00641
	(5.14)	(.64)	(13.9)	(12.9)	(.355)	(.81)
College Complete	-.149	-.0423	-.262	-.0473	-.0144	-.0166
	(5.95)	(.08)	(8.53)	(4.57)	(1.33)	(1.90)
Log of Husband's Life Cycle Income	-.079	.0667	.0640	.0107	.00989	.00490
	(9.30)	(3.12)	(6.10)	(3.01)	(2.67)	(1.64)
1967	-.084	.149	.0247	.0068	.00658	-1.0157
	(6.81)	(4.80)	(1.62)	(1.32)	(1.22)	(3.62)
1968	-.074	.0787	-.0156	-.0049	.00536	-.0124
	(6.00)	(2.54)	(1.03)	(.952)	(1.0012)	(.29)
Metropolitan Residence	-.052	.0853	-.0342	.00966	-.0169	-.0130
	(3.15)	(2.04)	(1.67)	(1.40)	(2.33)	(2.22)
*SMSA Size ($x10^9$)	-.0229	27.2	1.03	3.10	-.171	1.46
	(.01)	(3.25)	(.25)	(2.24)	(.12)	(1.26)
Health Expenditures	.00815	.300	-.469	-.240	.155	.0784
	(.03)	(.37)	(1.16)	(1.77)	(1.09)	(.66)
Health Dept. Family Planning	-.2266	4228.	-2414.	-586.	-143.0	134.
	(2.40)	(1.79)	(2.08)	(1.50)	(.35)	(.41)
Cigarette Price (x100)	.186	-7.56	8.93	.410	1.07	2.03
	(.07)	(1.06)	(2.57)	(.35)	(.87)	(2.05)
Cigarette Price Squared ($x10^4$)	-.690	12.10	-13.6	.339	-1.43	-3.04
	(.16)	(1.11)	(2.55)	(.19)	(.76)	(2.00)
Milk Price (x103)	-.129	10.92	.0587	.392	-1.74	-3.30
	(.05)	(1.51)	(.016)	(.33)	(1.39)	(-3.26)
Hospital Family Planning	385.9	22280.	-3942.	83.3	-1822.	-131[illegible].
	(.101)	(2.37)	(.86)	(.05)	(1.12)	(1.00)
Population Per Doctor ($x10^5$)	.298	-2.74	1.81	.120	.141	.2851
	(.371)	(1.36)	(1.83)	(.36)	(.40)	(1.01)
OBYGYN Per Capita	604.	246.	98.4	202.	-98.3	202.
	(1.74)	(.28)	(.23)	(2.11)	(.65)	(1.67)
Manufacturing Jobs ($x10^3$)	-.169	-.0612	-.484	.0524	-.0379	-.0702
	(1.15)	(.17)	(2.70)	(.87)	(.60)	(1.37)
Black	.142	-.300	.252	.0042	-.06701	-.0426
	(10.01)	(8.40)	(14.4)	(.72)	(10.85)	(8.58)
Service Jobs ($x10^3$)	-.348	-1.55	-1.54	-.675	-.359	-.447
	(.61)	(1.09)	(2.19)	(2.85)	(1.42)	(2.23)
Government Jobs ($x10^3$)	-.431	-1.3	-1.151	.0462	-.111	-.143
	(1.34)	(1.40)	(2.93)	(.35)	(.80)	(1.27)
General Unemployment ($x10^3$)	1.88	5.66	-1.58	-.0664	.250	-.392
	(1.48)	(1.77)	(1.01)	(1.26)	(.453)	(.88)
Female Unemployment	.017	-6.71	1.40	-.262	.627	1.12
	(.014)	(2.26)	(.96)	(.53)	(1.22)	(2.70)
Hospital Beds Per Capita	5.02	14.38	11.7	9.86	2.47	3.60
	(.83)	(.95)	(1.58)	(3.95)	(.94)	(1.71)
Sales Tax on Cigarettes (x100)	-.0126	-4.60	-1.30	.676	-.842	.00199
	(.98)	(1.42)	(.82)	(1.29)	(1.505)	(.44)
Intercept	1.89	1.25	-.376	3.09	7.88	-.269
	(3.98)	(1.05)	(.65)	(15.7)	(38.3)	(1.62)
R^2	.1188	.0332	.1103	.1070	.0269	.0240
F	43.94	11.18	40.42	39.05	9.03	8.02
SEE	2266.	14287.	3432.	389.1	428.4	277.8
Health Endowment Elasticity[2]	.182	-.00643	.297	.0754		
	(10.4)	(.15)	(13.9)	(10.5)		

[1] Absolute value of t ratios in parentheses beneath regression coefficient.

[2] For interpretation of the health endowment elasticity, see section 6 of the text and footnote 16.

behavior along with the local-area health infrastructure. The results indicate that mothers (and fathers) with at least a completed high school education seek prenatal care earlier in their pregnancies than do parents with lower schooling attainment. Husband's income also shortens this delay in care; however a rise in income by 10 percent reduces the delay by less than one-percent. Govenment expenditures on hospitals and health care and urbanization also appear to hasten prenatal care.

Smoking by mothers during their pregnancies is related to the mother's education according to an inverted U shaped pattern, in which mothers who did not complete high school appear to smoke more frequently than do mothers in other educational groups. Increases in husband's income, however, increase smoking by the wife while she is pregnant, although the income elasticity is again small (.07). Smoking is lower where sales taxes on cigarettes are higher, whereas the effect of the pretax price of cigarettes is weak and nonlinear. Metropolitan residents also tend to smoke more.

The reduced-form equations for number of births and maternal age at birth are consistent with findings obtained in earlier studies of U.S. fertility--more educated women tend to have fewer births and to have them later in their lifetime, while husband's income is positively and significantly correlated with cumulative fertility and negatively with maternal age. The income elasticity of fertility is comparable in magnitude to that for prenatal care and smoking. Mothers living in urban environments have lower fertility, and in those regions where industries that employ women are concentrated--services, government, and manufacturing--cumulative fertility is also lower. Most interestingly, the local availability of family planning services in health departments (and perhaps in hospitals), while not significantly associated with maternal age of childbearing, is related to lower levels of cumulative fertility. Later childbearing appears to occur in metropolitan areas and regions with greater availability of hospital beds and obstetricians per capita.

The reduced-form input demand equations also indicate statistically significant behavioral differences between black and white mothers with respect to three of the four health-related inputs, which are not accounted for by racial differences in the socioeconomic variables or in the price determinants. Pregnant black women appear to postpone seeking prenatal care about 11 days more than do similarly located white mothers of similar income and educational attainment. However, pregnant black women appear to smoke nearly a third fewer cigarettes than do pregnant white women. Black mothers also appear to have one-fourth more live births but to be only slightly older than white mothers. The extent to which these differences in "input" demand behavior account for the well-documented lower birthweight of black than of white infants can be ascertained from the production function estimates reported below. Discussion of the reduced-form birthweight equations in columns 5 and 6 of Table 2 are postponed until after the presentation of these latter results.

5. Estimates of Infant Health Production Functions

Ordinary least squares (OLS), two-stage least squares (TSLS), and three-stage least squares (3SLS) estimates of the Cobb-Douglas and translog production functions for birthweight and standardized birthweight are reported in Table 3. Application of the Durbin (1954) test for the endogeneity of the behavioral inputs indicates that heterogeneity bias in the OLS production function coefficients is statistically significant in all specifications. The computed test statistics for the Cobb-Douglas specification are 3.44 for birthweight and 2.44 for birthweight standard-

Table 3

Estimates of Household Production Functions for Birth Characteristics: Translog and Cobb Douglas Specifications[a]

Dependent Variable:	Log of Birthweight					Log of Birthweight Standardized for Gestation				
Model Specification:	Translog		Cobb-Douglas		Cobb-Douglas System	Translog		Cobb-Douglas		Cobb-Douglas System
Estimation Technique:	OLS (1)	TSLS (2)	OLS (3)	TSLS (4)	3SLS (5)	OLS (6)	TSLS (7)	OLS (8)	TSLS (9)	3SLS (10)
Explanatory Variables (in logs)										
Delay of Doctor (LDELAY)	.0401	1.39	-.00178	-.0682	-.0680	.0443	.585	.000973	-.00216	-.00330
	(.50)	(.90)	(.41)	(2.84)	(2.82)	(.69)	(.37)	(0.28)	(.11)	(.17)
Smoking (LSMOK)	.0145	2.17	-.0241	-.0256	-.0234	.00657	2.01	-.0221	-.0456	-.0469
	(0.44)	(1.82)	(13.9)	(2.08)	(1.88)	(.25)	(1.66)	(-15.9)	(4.59)	(4.71)
Births (LPAR)	-.199	-3.12	.0217	.0413	.0394	-.179	-1.66	.0211	.0130	.0132
	(-2.26)	(1.77)	(4.88)	(2.09)	(1.97)	(2.52)	(.93)	(5.87)	(.81)	(.82)
Age (LAGE)	.905	9.03	.0125	-.0202	-.0178	.462	5.86	.0148	-.0139	-.0191
	(2.66)	(1.70)	(0.98)	(.48)	(.42)	(1.69)	(1.09)	(1.42)	(.40)	(.56)
Delay* Smoke	.00132	.0725				-.00115	.148			
	(0.38)	(.57)				(.41)	(1.13)			
Delay* Births	.0165	.333				.0120	-.0207			
	(1.89)	(1.40)				(1.71)	(.09)			
Delay* Age	-.0129	-.542				-.0147	-.209			
	(0.51)	(1.12)				(.72)	(-.43)			
Smoke* Births	-.00166	.0535				-.00247	-.00611			
	(.47)	(.41)				(.86)	(-.045)			
Smoke* Age	-.0114	-.797				-.00880	-.813			
	(1.10)	(1.87)				(1.07)	(1.88)			
Births* Age	.0729	.958				.0671	.576			
	(2.55)	(1.58)				(2.91)	(.94)			
$1/2\ Delay^2$	-.0121	-.0324				-.00525	-.0328			
	(.95)	(.08)				(.51)	(-.08)			
$1/2\ Smoke^2$	-.00002	.166				.00179	.271			
	(.10)	(.81)				(.42)	(1.30)			
$1/2\ Births^2$	-.0368	-.415				-.0338	-.249			
	(2.50)	(.85)				(2.85)	(.60)			
$1/2\ Age^2$	-.280	2.70				-.147	-1.70			
	(2.67)	(1.66)				(1.70)	(1.03)			
Black	-.0869	-.0314	-.0806	-.0815	-.0804	-.057	.0013	-.0594	-.0647	-.0650
	(14.8)	(1.04)	(-15.7)	(10.2)	(9.99)	(-12.1)	(.04)	(-12.8)	(9.99)	(10.0)
Intercept	6.67	-6.66	8.06	8.21	8.20	-.728	-.0992	-00471	.0734	.0921
	(12.3)	(.77)	(199.)	(56.5)	(56.2)	(1.67)	(1.14)	(-1.44)	(.62)	(.79)
R^2	.0461		.0444			.0458		.0444		
F	30.96	7.67	89.47	42.71	64.14[b]	30.76	3.95	89.07	26.24	61.65[b]

[a] absolute value of t ratios in parentheses beneath regression coefficients.

[b] F computed for system of 4 input equations and production function (82 free parameters)

ized for gestation. The appropriate critical F value, assuming that the first-stage input demand and production function residuals are jointly normally distributed (Wu, 1973), is 2.37 at the 5 percent level for 4 and 9000 degrees of freedom. The test statistics are 8.05 and 15.05 for the respective translog specifications, both well exceeding the critical F value of 1.85.

Comparisons of both the OLS and TSLS residuals across the alternative functional specifications indicate that the ten additional quadratic and interaction terms embodied in the translog functional form are not jointly statistically significant. The F values for birthweight and standardized birthweight computed from the OLS residuals are 1.68 and 1.57 respectively, whereas the critical value at the 5 percent level is 1.85; the additional non-linear terms increase the magnitude of the residual variance in the TSLS translog specification.

The existence of bias in the OLS coefficient estimates and the statistical rejection of the more complex functional form in favor of the restrictive Cobb-Douglas specification suggests that there are potential and achievable efficiency gains from estimating the birthweight technology as part of the system of demand equations derived from the Cobb-Douglas utility function. The 3SLS estimates of the Cobb-Douglas function are reported in columns (5) and (10); estimates of the set of demand functions are reported in Appendix Tables A and B. While the coefficients and their standard errors are nearly identical to those obtained using the less efficient two-stage procedure, the set of cross-equation restrictions implied by the Cobb-Douglas production/utility variant of the model are rejected by the data. All of these tests thus imply that we cannot reject the hypothesis that the birthweight technology is Cobb-Douglas, but we can reject the hypotheses that there is no heterogeneity bias in the production function estimates and that preference orderings are described by the Cobb-Douglas utility function.

Comparison of the OLS and TSLS Cobb-Douglas birthweight results indicate that the neglect of health heterogeneity can importantly affect the inferences drawn from estimates of the effects of self-selected health inputs. Delay in use of medical care during a woman's pregnancy appears to have no appreciable effect on birthweight according to the OLS estimates (column 3, Table 3), whereas the TSLS estimates suggest a statistically significant deleterious effect of delay that is almost forty times the OLS point estimate. Parity has almost twice as large a beneficial effect on birthweight according to the TSLS estimates than indicated by OLS, although the magnitude is small; a fourth birth would weigh three percent more than a second birth. Smoking, on the other hand, has a substantial negative effect on birthweight that is evidently robust to estimation technique.

With respect to the TSLS point estimates, the Cobb-Douglas smoking effects are slightly higher than those obtained from direct correlational studies for birthweight. The consensus of those studies (DHEW, 1980) attributes a 200 gram deficit to mothers who smoke. In our sample, the one-third who continued to smoke after they knew they were pregnant smoked on average 14 cigarettes a day. According to our estimates, the birthweight of infants for the average smoker would be seven percent or 230 grams less than that of the nonsmoking mother. A 5 month increase in the sample mean delay in seeking prenatal care has a similar effect on birthweight, decreasing it by 260 grams or 8 percent. Age, however, appears to exert little or no effect on birthweight in the Cobb-Douglas specification.

In the standardized birthweight equations several additional insights emerge. First, the beneficial effects of prenatal care are no longer evident, whether or not heterogeneity is taken into account. Prenatal medical care and associated drug therapies evidently have their primary effect on birthweight by extending gestation, but this care does not have a substantial effect on the rate of growth of the fetus. Second, smoking by the mother while pregnant appears to increase gestation; since when birthweight is standardized for gestation the effect of smoking is increased by 78 percent relative to its effect on birthweight based on the Cobb-Douglas TSLS estimates. This pronounced retarding effect of smoking on fetal growth has not been noted in the epidemiological literature, and is also nearly masked in our OLS estimates in Table 3 (DHEW, 1980).

The translog specification, although rejected in favor of the nested Cobb-Douglas form, reveals significant non (log) linear effects of age and substantial age interactions with other inputs that are in accord with the descriptive clinical literature. From the (preferred) TSLS estimates it appears that the best age for a mother to bear a child is 24, which happens to be the sample mean. At age 20 mothers have babies who have 4.4 percent lower birthweight, while at age 30 mothers have babies who have 6.7 percent lower birthweight. Smoking has an increasing deleterious effect on birthweight among older mothers, probably because of the cumulative nature of smoking on the mother's and child's health and the lifetime persistence of smoking. A larger number of births, according to the translog TSLS estimates, is associated with lower birthweight, but this is counterbalanced by a large positive age-birth interaction effect. Having a fourth birth at age 20 is not associated with as favorable an outcome as having this fourth birth at age 30. Thus, the age interactions permitted by the translog specification approximate the health effects of different patterns of birth spacing, as well as total number of births and input use.

The TSLS output elasticities for the health inputs derived from Table 3 and the input demand equation estimates together shed some light on the black-white differences in birthweight noted in the literature and evident in the reduced-form demand equations reported in columns (5) and (6) of Table 2. Those equations indicate that black infants weigh 6.7 percent less at birth and 4.3 percent less standardized for gestation, conditional on individual socioeonomic characteristics of the mother and father as well as the area-level variables. In the TSLS Cobb-Douglas specifications of the birthweight production functions, however,Blacks have 8 percent lower birthweight and 5 to 6 percent lower rates of fetal growth, holding constant input behavior.[15] The differentials in smoking, timing of prenatal care, and fertility, net of location and socioeconomic characteristics of blacks and whites also reported in Table 2 do not account for black-white differences in birth characteristics. However, it is notable that the more flexible translog TSLS estimates eliminate half of the black/white birthweight differential and account for nearly all the racial differences in birthweight standardized for gestation. These latter findings suggest that the lower birthweight of black infants, given their mother's input behavior, is due to shorter gestation and not due to lower rates of fetal growth. Methods for increasing gestation for black infants may, therefore, warrant increased study, such as obtaining earlier preuatal care.

6. The Health Endowment Effect and the Behavior of the Mother

The residuals from the TSLS birthweight production function estimates, conditioned on the inclusion of all significant inputs, contain the exogenous child health endowment effect and an error component which was unforeseen by the mother and by assumption did not affect her prenatal behavior.

Thus, regressions of the health input levels chosen by the mothers on the TSLS birthweight residuals provides estimates of the effects of the health endowment on input demand behavior which, though biased to zero because of the measurement error, should yield the correct sign of the relationships.[16] These estimates are reported for each input in the bottom row of Table 2.

As previously shown, it is difficult to predict how input demand varies with the exogenous component of child health without information on both the health technology and on preference orderings. We conjectured, however, that a major source of bias in the OLS birthweight production function estimates was remedial behavior by mothers who could anticipate a pregnancy that would yield a less healthy (low birthweight) baby. The endowment estimate for the timing of prenatal care (DELAY) supports this interpretation--mothers whose babies have lower-than predicted birthweight, given the level of inputs, evidently seek prenatal care earlier. This remedial behavior suggests why epidemiological correlational studies have not always found a beneficial "effect" of the timing of prenatal care on birthweight (Eisner et al. 1979); indeed our OLS estimates replicate this misleading conclusion.

The endowment effects estimates also indicate that while the smoking behavior of mothers does not vary significantly with child health endowments, an increase in the birthweight endowment does appear to increase parity. Moreover, while our production function estimates indicate that changes in the age of the mother have only weak effects on the weight of the child at birth, women with more favorable health endowments appear to bear children at significantly lower ages. Population heterogeneity may thus wholly account for the observed negative correlations between mother's age over 18 and birthweight reported in epidemiological studies (Eisner et al. 1979).

7. Conclusion

Much of the information on the human biological mechanisms through which behavior affects health must by necessity come from non-experimental data which link health related activities or inputs to health outcomes. The principal insight offered by the household production literature is that these biological processes (the health technology), to the extent that they are perceived, condition health "input" choices made by households, along with prices and income. As a consequence, if there are exogenous variations in endowment health which are known to individuals but not to the researcher (health heterogeneity), the observed correlations between input behavior and health cannot be used to derive causal conclusions. Estimates of the health technology must therefore be obtained from a behavioral model in which inputs affecting health are themselves choice variables. Despite the emphasis of the household production model on the role of technology, econometric applications of this framework have not provided estimates which disentangle the relevant technologies from preference orderings. The medical literature concerned with depicting health technology, on the other hand, has ignored the estimation problems associated with household optimization in the presence of exogenous health heterogeneity.

In this paper we have attempted to bridge these two literatures by directly estimating the health technology pertaining to the "production" of birthweight and fetal growth in a model in which maternal behavior is responsive to variations in prices, income and exogenous health endowment. The empirical analysis, based on a probability sample of over 9,000 legitimate births in the United States between 1967 and 1969, suggested that inferences concerning the effects of health inputs are sensitive to whether or not heterogeneity is taken into account. In particular, heterogeneity appeared to almost completely mask a significant positive impact on child health of early prenatal medical care and to underestimate the significant negative effects of maternal smoking on the rate of fetal growth, an important indicator of the subsequent health of children.

Two important caveats concerning our results must be kept in mind. First, and most obviously, the estimates may be sensitive to the omission of relevant behavioral determinants of birthweight correlated with those included in our data (drugs, consumption of alcohol). More importantly, the area-level program and price variables used here as instruments to identify the health technology may not be independent of health endowments. Government health programs may be established to serve groups in the population that are known by the government to have distinctly different health endowments or environments. Alternatively, individuals may migrate to regions according to which region has lower prices for preferred inputs and/or available programs. In either instance, estimates of input productivities and prices and program effects based on regional price and program information could be inconsistent, as the regional variables would no longer be independently distributed with regard to health heterogeneity.

FOOTNOTES

[1]Examples of ordinary least-squares estimates of hybrid-type functions in which a measure of child health is the dependent variable and behavioral inputs, prices, education and income are regressors are found in Harris, (1982), and Lewit, (1982). Inman (1976) uses maximum likelihood logit to estimate child health production functions using dichotomous measures of morbidity. These functions contain, in addition to the use of medical services, measures of lagged child health and family income per person as "inputs." Of the two variables representing the use of doctor care, only number of "curative" doctor visits is treated as endogenous ("preventive" visits, time spent with children, family income and lagged health are assumed to be exogenous).

[2]Realizations of health outcomes may have a stochastic component, but this will be unknown to the family decision-makers at the time when decisions are made. Whether or not risk enters the process of optimization will thus depend on the form of (1). Variations in μ, however, will generally affect decisions and, as shown below, have important econometric implications. Our estimation procedure, described below, is appropriate whether or not household decisions take into account uncertainty.

[3]The model also captures, in its general form, possible interactions between "quality" and quantity of children, as in Becker and Lewis (1973), since one Y_j can represent the number of children. For a discussion of the predictive content of models which assume interactions between family size and investments in children, see Rosenzweig and Wolpin (1980).

[4]Ignoring the μ-term for a moment, it can be demonstrated that the single-input hybrid relationship between the input Y_m and health from (6) can be written as:

$$\theta_{Y_m} = \Gamma_{Y_m} + (S^c_{mm})^{-1}[\sum_{n+1}^{m-1} \Gamma_{Y_j} S^c_{jm} + \sum_{m+1}^{r} \Gamma_{I_k} S^c_{km}]$$

where S^c_{vm} is the compensated price effect p_m on input v. Since $S^c_{mm} < 0$ and the S^c_{jm} and S^c_{km} terms, j, k ≠ m, are unlikely to sum to a negative number, given the Cournot aggregation condition, if we define the r − n inputs such that they have non-negative marginal products, then $\Gamma_{Y_m} > \theta_{Y_m}$.

[5]The problem of heterogeneity in unobserved exogenous factors (not omitted control variables) perceived by decision-makers has been well-developed in the literature pertaining to the estimation of production functions for farms or firms (Fuss and McFadden, 1978, Mundlak and Hoch, 1965). This problem has not been treated to our knowledge in estimating household production functions.

[6]Inman (1976) found that mothers for whom preventive doctor visits were most effective in reducing the incidence of child morbidity tended to utilize preventive care more often.

[7]Chi-squared tests were applied to maximum likelihood probit regressions of child mortality (whether or not the sample child died between its birth and the time of the survey) and transforms of birthweight. The addition of quadratic or higher order polynomials in birthweight did not significantly alter the explanatory power of the mortality equation, nor the log-linear birthweight coefficient.

[8]The equation is: $\underset{(7.7)}{\text{birthweight} = 10107} - \underset{(10.0)}{1042 \text{ weeks}} + \underset{(10.4)}{37.8 \text{ weeks}^2} - \underset{(10.9)}{.398 \text{ weeks}^3}$ $R^2 = .227$ where the absolute value of t-statistics are reported in parentheses.

[9]The variable DELAY was set equal to the sample mean gestation period (39 weeks) if no prenatal medical care was sought (one percent of the sample) and to 4 weeks if "immediate" care was received upon learning of the pregnancy. The number of cigarettes smoked per day was set equal to one for non-smoking women in order to avoid undefined log-values. Since a large proportion of sample did not smoke (66 percent), tests of the sensitivity of the estimates to this scaling assumption were performed. While the LSMOKING coefficients did change according to the minimum values selected, statistical significance levels and other input coefficient values were unaltered. The sample mean smoking effects, reported below, conform closely to estimates obtained using linear specifications of the production technology (Leontief and Generalized Leontief-Diewert) (Rosenzweig and Schultz, 1982).

[10]Examples, based on univariate associations, are medical care (Shah and Abbey (1971), Rosenwaike (1971) and Iba et al. (1973)), smoking by mothers (Hebel et al. (1971) and wife's work (Coombs et al. (1969)).

[11]An alternative estimation strategy which could provide consistent estimates of the health production function in the presence of heterogeneity would make use of differences in birth outcomes and parental behavior

between births within the same family. Such a technique would require longitudinal data or good retrospective information on prior births to implement and requires the assumption that (perceived) μ is constant across all births in the same household, ruling out modifications in expectations through experience. This technique can only be applied, of course, to families with at least two live births and would suffer from the imprecision of estimates obtained from most individual "fixed effects" models.

[12]We assume that education, controlling for the significant inputs, plays no direct role in the production of birth outcomes. Tests of this overidentification restriction with respect to the mother's education, reported elsewhere (Rosenzweig and Schultz, 1981), indicate that inclusion of this variable directly in the health production function does not statistically reduce the appropriate standard error of estimate.

[13]The log income measure for each husband was obtained by adding the residual from the estimated log income function

$$\ln Y = \underset{(188.9)}{6.65} + \underset{(48.6)}{.178ED} + \underset{(33.2)}{.0730EX} - \underset{(21.1)}{.00148EX^2} \qquad R^2 = .24 \quad SEE\ .403 \quad n = 9621$$

(t values in parentheses)

where ED = years of schooling, EX = age + ED −7, to the predicted value of $\ln Y$ with EX set at 10 years.

[14]When (1) and (2) are Cobb-Douglas, the demand equations for all goods and health inputs have the following form: $\ln Z_j = \delta_j + \sum_{k=1}^{r} e_{jk} \ln P_k + f_j \ln F$ where $e_{jk} = -1$ for $j = k$, $e_{jk} = 0$ for $j \neq k$, $f_j = f_k = 1$. A subset of the complete Cobb-Douglas utility production demand system is estimated below that includes the production function and the health input demand equations. The cross-equation restrictions for this subsystem are also tested.

[15]Separate estimates of white and non-white birthweight production functions as well as separate normalizations of birthweight for gestational age are explored in Rosenzweig and Schultz (1982). Reductions in sample size reduced the precision in estimates for both groups; the hypothesis that input coefficients differed significantly across the two racial groups could not be rejected.

[16]The difference between the actual and predicted health outcome, based on actual input levels and consistent TSLS estimates of the birthweight production function parameters, approximates the health endowment, with a random error. Regressing the logarithms of the behavioral inputs on this calculated residual of the health production function yields the reported estimate of the elasticity between anticipated exogenous health endowment and the input response of parents. But since the calculated residual measures the health endowment with the error, this estimate of the elasticity of inputs with respect to health endowment is biased toward zero.

Appendix Table A

Three Stage Least Squares Estimates for Input Demands

for Determining Birthweight from Cobb Douglas Production-Utility System*

Explanatory Variables	Log Doctor Delay	Log Smoking	Log Births	Log Age
Log of Husband's Income	-.0789	.0674	.0641	.0105
	(9.35)	(3.17)	(6.12)	(2.98)
1967	-.0851	.151	.0244	.0068
	(-6.94)	(4.86)	(1.60)	(1.32)
1968	-.0748	.0781	-.0155	-.0049
	(6.13)	(2.52)	(1.02)	(.96)
Metropolitan Residence	-.0203	.0737	-.0330	.0055
	(1.45)	(2.36)	(1.79)	(.87)
SMSA Size ($x10^9$)	.161	.244	-4.84	1.56
	(.05)	(3.55)	(1.43)	(1.37)
Mother's Education:				
High School Incomplete	-.0867	.201	-.184	-.0810
	(4.28)	(3.90)	(7.33)	(9.55)
High School Complete	-.212	-.0478	-.300	.0003
	(10.5)	(.93)	(11.9)	(.04)
College Incomplete	-.258	-.0840	-.380	.0155
	(10.6)	(1.36)	(12.6)	(1.52)
College Complete	-.259	-.135	-.448	.0810
	(9.10)	(1.87)	(12.7)	(6.79)
Father's Education:				
High School Incomplete	-.0120	.198	-.274	-.115
	(.63)	(4.10)	(11.6)	(14.4)
High School Complete	-.0963	.0413	-.355	-.114
	(5.15)	(.87)	(15.3)	(14.6)
College Incomplete	-.118	-.0463	-.388	-.120
	(5.25)	(.81)	(13.9)	(12.8)
College Complete	-.146	-.0411	-.265	-.0469
	(5.89)	(.66)	(8.63)	(4.54)
Black	.131	-.309	.251	.00512
	(9.50)	(8.89)	(14.4)	(.87)
General Unemployment Rate	.111	-.262	-.104	.0358
	(1.93)	(1.86)	(.74)	(.75)
Female Unemployment Rate			.861	-1.01
			(.68)	(2.33)
Population per MD ($x10^5$)	-.436			
	(.59)			
OBGYN per capita	637.			
	(2.72)			
Health Expenditures	-.155			
	(.53)			
Hospital Beds	8.20			
	(1.65)			
Cigarette Price		.195		
		(1.53)		
Health Dept. Family Planning			-1875.	-1011.
			(1.82)	(2.89)
Hospital Family Planning			-2530.	2159.
			(.58)	(1.46)
Service Jobs ($x10^3$)			-.231	-.0521
			(3.94)	(2.63)
Government Jobs ($x10^3$)			-.101	.0004
			(3.16)	(.04)
Manufacturer Jobs ($x10^3$)			-.0598	-.0021
			(3.98)	(.40)
Intercept	1.71	-.458	1.21	3.27
	(21.0)	(.95)	(9.04)	(72.2)

*Production function estimates from system reported in column (5) Table 3. Absolute value of asymptotic t values reported in parentheses beneath regression coefficients.

Appendix Table B

Three Stage Least Squares Estimates for Input Demands for Determining Standardized Birthweight from Cobb Douglas Production-Utility System*

Explanatory Variables	Log Doctor Delay	Log Smoking	Log Births	Log Age
Log of Husband's Income	-.0775 (9.15)	.0598 (2.82)	.0624 (5.97)	.0100 (2.85)
1967	-.0834 (6.74)	.160 (5.19)	.0266 (1.75)	.0074 (.41)
1968	-.0739 (6.00)	.0758 (2.47)	-.0160 (1.06)	-.0051 (.99)
Metropolitan Residence	-.0232 (1.64)	.0803 (2.60)	-.0309 (1.67)	.0060 (.97)
SMSA Size ($x10^9$)	.617 (.19)	.215 (3.15)	-5.47 (1.62)	1.39 (1.22)
Mother's Education:				
High School Incomplete	-.0885 (4.33)	.205 (4.03)	-.184 (7.33)	-.0806 (9.51)
High School Complete	-.211 (10.3)	-.0474 (.93)	-.300 (11.9)	.0004 (.05)
College Incomplete	-.257 (10.5)	-.0866 (1.42)	-.380 (12.6)	.0153 (1.51)
College Complete	-.255 (8.87)	-.141 (1.97)	-.448 (12.7)	.0805 (6.76)
Father's Education:				
High School Incomplete	-.0102 (.53)	.194 (4.04)	-.274 (11.6)	-.115 (14.4)
High School Complete	-.0972 (5.16)	.0447 (.94)	-.355 (15.3)	-.114 (14.6)
College Incomplete	-.117 (5.18)	-.0404 (.72)	-.388 (13.9)	-.120 (12.7)
College Complete	-.151 (6.04)	-.0240 (.39)	-.265 (8.63)	-.0457 (4.42)
Black	.132 (9.55)	-.312 (8.98)	.251 (14.4)	.00472 (.80)
General Unemployment Rate	.138 (2.39)	-.346 (2.48)	-.104 (.74)	.035 (.74)
Female Unemployment Rate			.861 (.68)	-1.07 (2.48)
Population per MD ($x10^5$)	-.493 (.65)			
OBGYN per capita	567. (2.39)			
Health Expenditures	-.126 (.42)			
Hospital Beds	9.34 (1.85)			
Cigarette Price		.196 (1.54)		
Health Dept. Family Planning			-1874. (1.82)	-1007. (2.88)
Hospital Family Planning			-2530. (.58)	2186. (1.48)
Service Jobs ($x10^3$)			-.231 (3.94)	-.0482 (2.43)
Government Jobs ($x10^3$)			-.101 (3.16)	.0012 (.11)
Manufacturer Jobs ($x10^3$)			-.0598 (3.98)	-.0015 (.31)
Intercept	1.69 (20.6)	-.361 (.75)	1.22 (9.09)	3.28 (72.3)

*Production function estimates from system reported in column (5) Table 3. Absolute value of asymptotic t values reported in parentheses beneath regression coefficients.

REFERENCES

Becker, G., "A Theory of the Allocation of Time," Economic Journal 75, September 1965, 493-517.

Barnett, W.A., "Pollak and Wachter on the Household Production Function Approach," Journal of Political Economy 85, October 1977, 1073-1082.

Beck, G.J. and B.J. van den Berg, "The Relationship of the Rate of Intra-uterine Growth of Low-birthweight Infants to Later Growth," Journal of Pediatrics Vol. 86, No. 4: April 1975, 504-511.

Becker, G. and H.G. Lewis, "On the Interaction Between Quantity and Quality of Children," Journal of Political Economy 82, April/May 1974, S279-S288.

Chernichovsky, D. and D. Coate, "An Economic Analysis of the Diet, Growth, and Health of Young Children in the United States," National Bureau of Economic Research Working Paper No. 416, December 1979.

Coombs, L., R. Freedman, and K. Namboodiri, "Inferences About Abortion From Foetal Mortality Data," Population Studies 23, July 1969, 247-265.

Durbin, J., "Errors in Variables," Review of the International Statistical Institute 22, 1954, 23-32.

Edwards, L. and M. Grossman, "Adolescent Health, Family Background, and Preventive Medical Care," National Bureau of Economic Research Working Paper No. 398, October 1979.

Eisner, V., J.V. Brazie, M.W. Pratt, and A.C. Hexter, "The Risk of Low Birthweight," American Journal of Public Health Vol. 69, No. 9, September 1979, 887-893.

Friedman, B. and A. Leibowitz, "Family Bequests and the Derived Demand for Health Inputs," Economic Inquiry XVII, July 1979, 419-434.

Fuss, M. and D. McFadden, Production Economics: A Dual Approach to Theory and Applications, Vol. 1 and 2, Amsterdam: North Holland Publishing, 1978.

Goldman, F. and M. Grossman, "The Demand for Pediatric Case: An Hedonic Approach," Journal of Political Economy 86, April 1978, 259-280.

Harris, J., "Prenatal Medical Care and Infant Mortality," in V. Fuchs, ed., Economic Aspects of Health, Chicago: Chicago University Press, 1982.

Hemminki, E. and B. Starfield, "Prevention of Low Birth Weight and Preterm Birth: Literature Review and Suggestions for Research Policy," Milbank Memorial Fund Quarterly/Health and Society Vol. 56, No. 3, Summer 1978, 339-361.

Hebel, R., G. Entwisle, M. Tayback, "A Risk Adjustment Technique for Comparing Prematurity Rates Among Clinic Population," HMSHA Health Reports 86, October 1971, 946-952.

Iba, B.Y., J.D. Niswander, and L. Woodville, "Relation of Prenatal Care to Birthweights, Major Malformations, and Newborn Deaths of American Indians," Health Services Reports 88, October 1973, 697-701.

Inman, R.P., "The Family Provision of Children's Health: An Economic Analysis," in R. Rosett, ed., The Role of Health Insurance in the Health Services Sector, New York: Columbia University Press, 1976.

Lewit, E., "The Demand for Prenatal Care and the Production of Healthy Infants," in I. Sirageldin (ed.), Research in Human Capital and Development, Volume III, 1982.

Mundlak, Y. and I. Hoch, "Consequences of Alternative Specifications in Estimation of the Cobb-Douglas Functions," Econometrica 33, November 1965, 814-828.

Pollak, R. and M. Wachter, "The Relevance of the Household Production Function and Its Implications for the Allocation of Time," Journal of Political Economy 83, April 1975, 255-277.

_____, "Reply: Pollak and Wachter on the Household Production Approach," Journal of Political Economy 85, October 1977, 1083-1086.

Rosenwaike, I., "The Influence of Socioeconomic Status on Incidence of Low Birthweight," HMSHA Health Reports 86, July 1971, 641-649.

Rosenzweig, M.R. and T.P. Schultz, "The Behavior of Mothers as Inputs to Child Health," in V. Fuchs, ed., Economic Aspects of Health, Chicago: Chicago University Press, 1982.

_____ and T.P. Schultz, "Education and the Household Production of Child Health," Social Statistical Section, Proceedings of the American Statistical Association, 1981.

_____ and K.I. Wolpin, "Testing the Quantity-Quality Fertility Model: The Use of Twins as a Natural Experiment," Econometrica 48, January 1980, 227-240.

Shah, F.K. and H. Abbey, "Effects of Some Factors on Neonatal and Post-Neonatal Mortality," Milbank Memorial Fund Quarterly 49, January 1971, 33-57.

U.S. Department of Health, Education and Welfare, National Center for Health Statistics, Standardized Micro-Data Tape Transcripts, DHEW Publication No. (PHS) 78-1213, June 1978.

U.S. Department of Health and Human Services, The Health Consequences of Smoking for Women: A Report of the Surgeon General, Office of the Assistant Secretary for Health, Office of Smoking and Health, Washington, D.C., 1980.

Wu, De-Min, "Alternative Tests of Independence Between Stochastic Regressors and Disturbances," Econometrica, 41, July 1973, 733-750.