DETERMINANTS OF PEDIATRIC CARE UTILIZATION*

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ABSTRACT

The purpose of this paper is to understand the determinants of utilization of pediatric care—care rendered to children by all physicians. Multivariate techniques are employed to examine four measures of pediatric care utilization in a national sample of children between the ages of 1 and 5. These measures are the probability of contacting a physician within the past year, the probability of obtaining a preventive physical examination within the past year, the number of office visits to physicians in private practice by children with positive visits, and the average quality of these visits.

The role of children's health in the determination of economic and social well-being is a subject of increasing concern for medicine, social science, and public policy. Numerous studies have demonstrated that adults' earnings and life expectancy depend on their schooling, health, and ability. Others suggest important causal relationships from health to cognitive development at early stages in the life cycle, from both these variables to years of formal schooling completed, and from schooling to adults' health.[1] A common theme in these studies as well as in the massive literature on the effects of

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1 For a partial survey of the literature on relationships among earnings, schooling, health, and intelligence of adults and children, see Grossman [19] and Edwards and Grossman [12].

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home environmental variables on children is that well-being at later stages in the life cycle depends on well-being at early stages.

The purpose of this paper is to understand the determinants of utilization of pediatric care—care rendered to children by all physicians. Appropriate pediatric care is a vehicle for maintaining children's health and an object of government policy via programs such as Medicaid, the neighborhood health center program, maternal and child health services, and children and youth projects. Despite these programs, there are substantial variations, especially according to race and socioeconomic class of parents, in utilization of pediatric care services [34, 46, 5]. These variations have led to proposals by Newberger, Newberger, and Richmond [35], Keniston and the Carnegie Council on Children [27], and Marmor [30] to restrict a national health insurance system, at least initially, to rather complete coverage of prenatal and pediatric care. Bills with this aim have been introduced in Congress by Senator Jacob K. Javits and Congressman James H. Scheuer, both of New York.

In this paper, we use multivariate techniques to identify the main sources of variation in the decision to obtain pediatric care, the number of pediatric visits to physicians, and the composition of visits among various types of physicians. Our research addresses a basic question put forward by the Harvard Child Health Project [23, Vol. I, p. 43]: "What basic forces influence the use of medical services by children?" This question must be answered in order to improve the primary-care system for children. The selection of variables to analyze is guided by models of utilization of physicians' services that have been developed by economists and sociologists. The resulting estimates of demand functions for pediatric care are not based on one particular model. Instead, the insights contained in several models are used to shed light on the most effective means of increasing utilization by certain groups of children and to provide useful information for calculations of the effect of national health insurance on the total cost of pediatric care. The data source for the demand estimates is a representative sample of all children in the United States—the 1971 health survey conducted by the National Opinion Research Center and the Center for Health Administration Studies of the University of Chicago. Previous studies in this area have used samples in specific cities in the United States (for example, Haggerty, Roghmann, and Pless [21]; Inman [24]; Goldman and Grossman [17]) or have examined a small number of determinants for a national sample (for example, Friedman and Leibowitz [14]).

ANALYTICAL FRAMEWORK

Whenever decision-makers such as firms or households must allocate scarce resources among competing goals, economists can provide useful insights into their behavior. Parent-child relationships clearly involve such allocation. That parents wish to increase the current and future economic well-being of their children is an assumption that is surely consistent with the behavior of most parents in the United States, notwithstanding reported instances of child abuse and neglect. And even though it is not easy to define what is meant by the "well-being" of children, factors such as their health, intelligence, school performance, school attainment, social behavior, and lifetime earnings undoubtedly play an important role. To enhance any of these components of children's welfare, parents must allocate to their children some part of their own scarce resources—goods and services purchased in the market, or their own time.

Our analytical framework is based on two propositions. One is the above notion that parents must allocate scarce resources between a child's well-being (the child's life "quality") and other competing goals. These competing goals include not only the parents' own consumption, but also the number and the consumption of other children in the family. Thus the framework builds upon the important distinction between the quantity and "quality" of children that is stressed in much of the literature on the economics of fertility and optimum family size (for example, Becker and Lewis [8], Willis [50], O'Hara [39]). The second proposition, embedded in the household production function approach to consumer behavior, is that consumers produce their basic objects of choice with inputs of goods and services purchased in the market and their own time (Becker [7], Lancaster [29], Muth [33]). This insight is of particular relevance in dealing with children's health, cognitive development, and other aspects of their well-being because parents obviously do not buy these objects of choice directly in the market.

In the specific instance of children's health, one can conceive of it being formed according to a multivariate production function. This production function would involve such factors as the child's genetic endowment, his or her previous health history, various kinds of medical services, parents' time, nutrition, housing quality, air pollution, and home environmental factors that are shaped to a large extent by parents. The production function interacts with parents' income, their preferences, various prices, and the number of children in the family to determine the level of health of each child. In more formal economic language, this interaction generates a demand curve for children's health. It also generates demand curves for endogenous inputs in the production function such as medical care, nutrition, and parents' time. The number of children enters these functions because the more children there are in a family, the more costly it is to raise their average level of health.

Within the preceding general framework, we employ the insights in several specific models to study the utilization of pediatric care. Since the consumer's time is required to produce health and obtain medical care, the relevant price in the demand function for care contains both a money price component and a time price component [20, 36, 37, 1, 2, 42]. In the instance of pediatric care, since the mother typically is responsible for the child, the opportunity cost of one hour of time can be evaluated by her actual or potential hourly wage rate (w) [24, 16, 18]. Thus, the "shadow price" of a visit to a physician for pediatric care (π_v) is

$$(1) \qquad \pi_v = p + wt$$

where p is the money price of the visit (the payment to the physician) and t is the sum of the time spent traveling to reach the physician and return home and waiting to see the physician at the source of care.[2]

In most studies, the measure of utilization of physicians' services by nonhospitalized patients is the annual number of visits to physicians.[3] The number of visits, however is not the ideal dependent variable to employ in demand function estimates. In any given year a substantial fraction of the population does not visit a physician. For example, in the group of preschool children between the ages of 1 and 5 that is analyzed in this paper, approximately 26 percent did not see a physician in 1970. It is plausible that consumers confront substantial entry costs in the medical care market due to imperfect information (discussed in more detail below). Thus, the decision to obtain care and the number of visits should be treated as separate dependent variables.[4]

Even among patients with positive visits, the number of visits is not a completely accurate measure of total services. If possible, one should distinguish between preventive and curative (remedial) services because these two services are likely to be separate inputs in the health production function and to be associated with different kinds of health output [24, 16]. With the type of care held constant, the average quality or productivity of a visit might vary among physicians [15, 36, 37, 13, 17]. Quality differences can be traced in turn to different levels of investment in human capital by physicians. For instance, medical schooling, internships, and residency-training programs can differ in quality; and physicians may or may not

2 If the trip to the source of care is made by a mode of transportation other than walking, the direct cost of the trip would be included in the shadow price of the visit.

3 Contacts between physicians and patients who are not hospitalized can occur in physicians' offices or private clinics, hospital emergency rooms, hospital outpatient departments, neighborhood health centers or other clinics not associated with hospitals, schools or work health-service departments, patients' homes, and by telephone. We exclude health-service department, home, and telephone contacts in this section and in our empirical work. For a more complete discussion of this point, see the following section.

4 For an elaboration of this argument, see Newhouse and Phelps [36].

obtain primary-practice status in a specialty, board certification in that specialty, faculty status, and memberships in peer professional societies.

One implication of the existence of quality differences is that the relevant money price variable is quality-adjusted price ($\hat{p} = p/q$, where q is quality per visit). A second implication, which is stressed by Goldman and Grossman [17], is that there are separate demand curves for the quantity (measured in terms of visits) and quality of pediatric care with somewhat different properties. This proposition follows if visits and quality enter the production function of child health as separate variables. It is particularly relevant in the presence of a "fixed cost" of a visit. Such a cost is independent of the quality of a visit and coincides with the time or forgone earnings price of a visit in equation (1). Goldman and Grossman show that the magnitude and in some instances the direction of the fixed-cost effect can differ from the corresponding quality-adjusted price effect in a given demand function.[5]

Studies that investigate aspects of children's well-being or quality[6] in the context of intergenerational transfer models make predictions about differences in demand curves for pediatric care between high- and low-income families [14, 25, 9, 11, 49]. In these studies, the family's time horizon is divided into two periods: a period during which children are dependent upon their parents for financial support, and a period during which children are financially independent. It is assumed that the quality of a given child depends *solely* on his or her lifetime wealth, which parents can affect in two ways. They can make investments, including health investments, in the child's human capital in the period of dependence, and they can make a financial transfer (a bequest) to the child at the onset of the period of independence. The marginal rate of return on an investment in human capital diminishes with the amount invested, while the marginal rate of return on a financial transfer is independent of the size of the transfer.

The final ingredient in the intergenerational transfer models is the solvency constraint that parents cannot leave net debts to their children or that the financial transfer cannot be smaller than zero. This implies a two-regime specification of demand functions for children's health and for health inputs such as pediatric care. Parents who do not make financial transfers

5 Specifically, the price of quality relative to the price of a visit is directly related to the quality-adjusted price of a visit and inversely related to the fixed costs of a visit. An increase in quality-adjusted price induces consumers to substitute away from quality and toward visits. Although visits need not rise absolutely, the ratio of visits to quality will be positively related to quality-adjusted price. A rise in the fixed cost of a visit would lead consumers to substitute quality for visits. Consequently, the fixed cost and quality-adjusted price variables would have opposite effects on the demand for quality. For derivations and qualifications of these propositions, see Goldman and Grossman [17].

6 The reader is cautioned not to confuse the concept of quality of children with the concept of quality of pediatric care.

are members of Regime 1, while parents who do make financial transfers are members of Regime 2. The demand functions in the two regimes have different properties. In particular, parents' income has a positive effect on pediatric care in Regime 1, but no effect in Regime 2. The higher the parents' income, the more likely it is that they are members of Regime 2. Therefore, income should have a positive effect on pediatric care utilization at relatively low income levels, but should have no effect (or a weaker effect) at relatively high income levels.

Other aspects of the processes by which health and medical services are produced and supplied in the household and in the market suggest additional determinants of pediatric-care utilization. Parents' schooling is an obvious example of a home environmental factor in the production function of children's health. Recent studies have established the importance of mother's schooling in particular in the determination of childen's health and pediatric-care utilization [28, 14, 21, 24, 44, 11, 17]. Several mechanisms by which this variable affects utilization have been identified, but the relative importance of each remains an open issue. Michael [32] argues that schooling is a positive correlate of efficiency in the production of many household commodities. Suchman [47, 48], Rosenstock et al. [43], and Andersen [3] advance the hypothesis that schooling is related to specific knowledge of appropriate health practices.[7] These same authors also suggest that it determines attitudes or preferences toward health and medical care. Slesinger [44] finds that health knowledge and attitudes are significant predictors of pediatric care in a sample of black children in Washington, D.C. On the other hand, Haggerty, Roghmann, and Pless [21] find no impact of these variables on care in a sample of children of all races in Rochester, New York.[8]

Many persons have pointed out that physicians play a rather unique role in the market for medical care services. This has led to theoretical discussions and empirical estimates of the "availability effect." By this is meant the notion that the physician can directly influence the demand for his or her services. Existing estimates of the availability effect pertain to utilization by the population at large or by adults. In their interstate model of the market for physicians' services, Fuchs and Kramer [15] report that the elasticity of physicians' visits per capita with respect to physicians per capita is approximately equal to .4. This estimate is obtained from a demand curve for visits in which income and the money price of a visit are held constant.

7 The distinction between general efficiency and specific knowledge of health practices is analogous to the distinction between general and specific on-the-job training first introduced by Becker [6].

8 The effect of schooling on the demand for care is ambiguous whether it reflects general efficiency, specific health knowledge, or preferences. This follows because the demand for care is derived from the more basic demand for health.

This finding is not direct evidence in favor of the availability effect. For example, the travel, waiting, inconvenience, and information costs of obtaining physicians' services should fall as the number of physicians per capita rises. Yet many persons would argue that the elasticity is too large to be explained entirely by this factor. Moreover, in a study that controls for travel and waiting time, May [31] finds a statistically significant availability effect. His estimate, however, is only half as large as that of Fuchs and Kramer.

DATA AND ESTIMATION

The Data

Our data set is the 1971 health survey conducted by the Center for Health Administration Studies and the National Opinion Research Center of the University of Chicago (the NORC sample). This is national sample of the noninstitutionalized population of the United States in which the inner-city poor, the aged, and rural farm residents are overrepresented. It contains information on socioeconomic characteristics, health insurance coverage, health status, and utilization of various kinds of medical care services during the calender year 1970 for 11,822 adults and children from 3,880 families.[9]

The empirical analysis is restricted to utilization of physicians' services by preschool children ages 1 through 5. Infants under 1 are eliminated because we wish to focus on pediatric care for the health problems that are encountered beyond the first year of life. These problems are very different from those of infants, as reflected by mortality rates that are as high for infants as for persons ages 55 to 64 and very low beyond age 1. Infants are not analyzed as a separate group because the sample size is too small to permit reliable coefficient estimates. Children beyond age 5 are excluded since our primary interest is in pediatric care initiated by the parents, and care received by children in this older age group may be dictated in part by school regulations. Moreover, this procedure takes account of the differences in the nature of health conditions at the preschool as compared to the school stage of a child's life cycle. Finally, the group ages 1 through 5 is of special interest because inadequate pediatric care at this stage is likely to have a particularly detrimental influence on the child's current and future health.

Due to the considerable interest in the low level of economic and social well-being of blacks relative to whites, part of the empirical work is focused on an analysis of black-white differences in the utilization of pediatric care. The NORC sample is well suited for such an analysis because the oversampling of the inner-city poor resulted in a sample that is 32 percent

9 For a detailed description of the sample, see Andersen, Lion, and Anderson [4].

black. The comparable figure for the population of the United States is approximately 12 percent.[10] Mexican, Puerto Rican, Oriental, and American Indian children are omitted from the empircal work. These groups are extremely small, and their parents might behave in different ways than either blacks or whites.

The sample is further limited by the exclusion of children who do not live with their mother or for whom the mother's years of formal schooling is unknown. This reflects our concern with the role of the mother in the determination of pediatric care utilization.[11] Note that children who live with their mother but not their father are included in our sample. Finally, observations are omitted if a dependent variable is unknown. This occurs *only* in the case of the average quality of visits to physicians in private practice. The final sample size is 839 children, of which 511 are whites and 328 are blacks.

Measurement of Variables

Table 1 contains definitions of the dependent, independent, and intermediate variables in the demand functions for pediatric care. The intermediate variables are used to construct some of the independent variables. Tables A1 and A2 in the appendix contain pooled and race-specific unweighted means and standard deviations of the dependent and independent variables. The demand functions are concerned with contacts between physician and children who are not currently hospitalized and who have to travel to reach the physician (ambulatory contacts).[12] The most comprehensive measure of these contacts (*USE*) is a dichtomous variable that equals one if a child had at least one ambulatory contact with a physician in 1970 and equals zero if a child had no contacts. By definition, ambulatory contacts can take place in physicians' offices or private clinics, hospital emergency rooms, hospital outpatient departments, and neighborhood health centers or other public clinics not associated with hospitals. Excluded are contacts while a child is hospitalized, contacts in a child's home, contacts in school health-service departments, and telephone contacts between

10 The oversampling of the aged is not relevant for our analysis except that there are fewer children in the NORC sample than in a random sample of all families in the United States. The degree of oversampling of rural farm residents is very small. Nine percent of the sample reside on farms, compared to 7 percent of the U.S. population.

11 When there are unknown values of independent variables other than mother's schooling, the race-specific weighted mean value of the relevant variable is substituted. The weights employed correct for oversampling and make the means representative of the population of the United States. Throughout this paper the term *weighted mean* is used to denote a mean that is corrected for oversampling. The term *unweighted mean* is used to denote a mean that is not corrected for oversampling.

12 We exclude contacts between children and ophthalmologists in this paper.

parents and physicians. We focus on ambulatory care because relatively few children are hospitalized, visits in school health departments rarely are initiated by parents, there is no information in the sample on telephone contacts, and home visits have declined in importance over time.[13]

Preventive pediatric care (*PREVENT*) is measured by a dichotomous variable that equals one if a child had a physical examination within the past year because it was time to have an examination, and equals zero otherwise. Thus, *PREVENT* equals zero if a child had an examination within the past year because he or she was ill, because it was required, or if a child did not have an examination within the past year. It is intended to measure discretionary preventive care that is initiated, at least in part, by parents.[14]

The other two dependent variables (VISITS and *QUAL*) pertain to pediatric care rendered by private-practice physicians in their office. This source of care is emphasized because detailed information is available on the characteristics of the physicians who delivered it and on their fees. Characteristics are available because parents were asked to identify by name all physicians who saw their children during 1970. The type of primary practice and board-certification status of these physicians were obtained from the American Medical Association Directory. Since parents frequently do not know the names of physicians who saw their children at other sites, there is little information on such physicians. Therefore, when *VISITS* or *QUAL* is the dependent variable, children with no office visits to physicians in private practice (*VISITS*) are excluded from the regressions. There are 420 children in the sample of those with positive visits, of whom 336 are whites and 84 are blacks.

Quality per visit (*QUAL*) is estimated from mean office prices of five types of physicians seen by children in the NORC sample (see Table 2). It is expressed as an index number with the quality of a visit to a general practitioner set equal to one. Thus if a child in a given family made all of his or her visits to a board-certified pediatrician, quality per visit would equal 1.362 for that child. In cases where the child saw more than one type of physician, quality per visit is defined as a weighted average of the quality of each type, where the weights are the percentage of visits to that type. Even if the higher fees associated with visits to board-certified specialists do not solely reflect quality in some objective sense, the demand functions for quality convey useful information. In particular, by showing the factors that

13 According to data in Andersen, Lion, and Anderson [4], home visits accounted for 11 percent of total out-of-hospital physician visits in 1958 for the population as a whole. The corresponding figure in 1970 was 2 percent. For children under age 5, home visits accounted for 1 percent of total out-of-hospital visits in 1970.

14 The mean difference between *PREVENT* and a variable that equals one if a child had an examination for preventive reasons or because it was required within the past year is very small.

TABLE 1
DEFINITION OF VARIABLES

Variable Name	Definition
A. *Dependent Variables*	
1. *USE*	Child visited a physician during 1970 = 1
2. *PREVENT*	Child had a physical exam for preventive reasons during 1970 = 1
3. *VISITS*	Annual number of visits to physicians in private practice
4. *QUAL*	Average quality of a visit to physicians in private practice
B. *Intermediate* (*) and *Independent Variables*	
1. *DFAMINC*	Deflated annual family income in thousands of dollars
2. *DY6*	Deflated annual family income ≥ $6,000 = 1
3. *DY11*	Deflated annual family income ≥ $11,000 = 1
4. *DEXPEND*(*)	Deflated annual expenditures, including health insurance benefits, for visits to physicians in private practice
5. *QUALVISITS*(*)	Annual number of quality-adjusted visits to physicians in private practice: *QUALVISITS* = *QUAL* × *VISITS*
6. *DQUALPRICE*(*)	Deflated quality-adjusted price of a visit to a physician in private practice: *DQUALPRICE* = *DEXPEND*/*QUALVISITS*
7. *DNETPRICE*	Deflated net quality-adjusted price of a visit to a physician in private practice: *DNETPRICE* = (coinsurance rate) × *DQUALPRICE* (used only when *QUAL* or *VISITS* is the dependent variable)
8. *MEDICAID*	Medicaid recipient = 1 (used only when *QUAL* or *VISITS* is the dependent variable)
9. *INS*	Child had office-visit insurance coverage = 1 (used only when *USE* or *PREVENT* is the dependent variable)
10. *WELFARE*	Welfare recipient = 1 (used only when *USE* or *PREVENT* is the dependent variable)
11. *MEDUCAT*	Years of formal schooling completed by mother
12. *KNOW*	A measure of the parents' knowledge of signs of disease
13. *TASTE*	A measure of the parents' taste for medical services or attitude toward the value of medical services
14. *HO*	Child hospitalized during 1970 = 1
15. *RAD*	Number of days during 1970 that child's activity was restricted due to illness or injury
16. *HG, HF, HP*	Evaluation of child's health by parent: *HP* = 1 if health is poor; *HF* = 1 if health is fair; *HG* = 1 if health is good; omitted class if health is excellent

TABLE 1 (*Continued*)

Variable Name	Definition
17. *WTIME*(*)	Usual waiting time in the office per visit to usual source of care
18. *TTIME*(*)	Round-trip travel time per visit to usual source of care
19. *NLF*(*)	Mother did not work during 1970 = 1
20. *DMWAGE*(*)	Deflated mother's actual hourly wage if she worked and predicted hourly wage if she did not
21. *DWT*	Deflated travel and waiting time cost per visit: $DWT = DMWAGE \times (TTIME + WTIME)$
22. *DWTNLF*	Interaction between deflated travel and waiting time cost and labor force status: $DWTNLF = NLF \times [DMWAGE \times (TTIME + WTIME)]$
23. *DELAY*	Usual number of days, except for emergencies, that child has to wait to get an appointment with usual source of care
24. *WALK*	Mode of transportation to usual source of care is walking = 1; omitted class if mode is by car, by taxi, or by public transportation
25. *NOREG*	Child has no regular source of care = 1
26. *SSMSA, URBAN, RURALNF, FARM*(*)	Size of place of residence: *SSMSA* = 1 if location is in some SMSA other than the 10 largest SMSAs in the country; *URBAN* = 1 if location is in an urban area that is not part of an SMSA; *RURAL* = 1 if location is in a rural area and not a farm; *FARM* = 1 if location is a farm; omitted class is location in one of the 10 largest SMSAs in the country
27. *MD*	Number of nonfederal physicians per hundred population in the primary sampling unit
28. *MDSSMSA, MDURBAN, MDRURALNF, MDFARM*	Interactions between residence and number of nonfederal physicians per hundred population in the primary sampling unit: $MDSSMSA = MD \times SSMSA$; $MDURBAN = MD \times URBAN$; $MDRURALNF = MD \times RURALNF$; $MDFARM = MD \times FARM$
29. *AC*	Age of child
30. *NC*	Number of children in the family
31. *MALE*	Child is male = 1
32. *BLACK*	Race of child is black = 1

determine the choice of relatively high-priced physicians, the demand estimates can be used to predict how the total cost of pediatric care would be affected by alternative government policies.

We discussed the roles of family income, fixed cost, quality-adjusted

TABLE 2
MEAN OFFICE PRICES BY TYPE OF PHYSICIAN[a]

Type	Weighted Mean Price	Price Relative to Price of General Practitioner
Board-certified pediatrician	$10.80	1.362
Nonboard-certified pediatrician	9.65	1.217
Board-certified specialist other than pediatrician	13.57	1.711
Nonboard-certified specialist other than pediatrician	11.71	1.477
General practitioner	7.93	1.000

a The weights employed correct for oversampling and make the means representative of the population of the United States.

price, mother's schooling, knowledge of appropriate health practices, taste for medical services, and physicians per hundred population in the primary sampling unit in the demand functions in the first section. Therefore, in the remainder of this section we clarify some of the definitions of independent variables in Table 1 and comment briefly on the effects of certain variables and on alternative specifications of the equations to be estimated. To take account of differences in the cost of living among areas, money family income in 1970 is deflated by the Bureau of Labor Statistics' [10] estimate of the annual costs of an intermediate budget for an urban four-person family to obtain deflated family income (*DFAMINC*). The BLS cost-of-living variable is available for 40 cities and four nonmetropolitan areas (Northeast, North Central, South, and West). Where possible, the primary sampling units in the NORC survey were matched with the cities in the BLS survey. For rural primary sampling units, the region-specific nonmetropolitan area cost figure was used. The same cost-of-living variable was employed to obtain the other deflated variables in Table 1.[15]

In some of the multivariate estimates in the following section, where the results are reported, deflated family income is entered as a continuous variable. In others, two marginal income variables (*DY*6 and *DY*11) are entered. This enables us to test the proposition derived from the intergenerational transfer model that the income effect should diminish as

15 Obviously, there are errors of measurement in the cost-of-living variable. Results obtained with undeflated variables (not shown) are, however, very similar to the estimates presented in the following section on "Results."

income rises. The coding scheme for the income dummy variables was selected because it divides the sample into three groups of roughly equal size (deflated family income less than \$6,000; deflated family income between \$6,000 and \$10,999; and deflated family income equal to or greater than \$11,000).

The deflated quality-adjusted price of an office visit to a physician in private practice (*DQUALPRICE*) is measured as deflated annual expenditures, including health insurance benefits, for visits to these physicians divided by quality-adjusted visits (*QUALVISITS*). Following Newhouse and Phelps [36, 37] and Goldman and Grossman [17], we assume that cross-sectional variations in quality-adjusted price primarily can be traced to imperfect information due to positive costs of search. As Newhouse, Phelps, and many others have stressed, the relevant price in the demand function is net quality-adjusted price (*DNETPRICE*), defined as gross quality-adjusted price multiplied by the coinsurance rate for physician office visits *by children* specified in the family's health insurance policy. If the family had a policy with no deductible that covered its children, the coinsurance rate is computed as out-of-pocket outlays for visits to physicians in private practice by a given child divided by total outlays. If the family had a major medical policy with a deductible that had not been exceeded, the coinsurance rate is set equal to one. If the deductible was exceeded, the coinsurance rate is obtained directly from the policy for those policies that were verified with insurance companies by NORC. In the case of nonverified major medical policies, the coinsurance rate is set equal to 20 percent, the most common value in the verified policies. Of course, the coinsurance rate equals one when there is no health insurance for doctor-office visits by children.[16]

If a family receives Medicaid benefits (*MEDICAID*), net price nominally is zero. Not all physicians, however, will accept Medicaid recipients as their patients. Inclusion of the dummy variable *MEDICAID* controls for this factor. Of course, the impact of Medicaid on pediatric care utilization is of considerable interest and importance for public policy.

Net price and Medicaid cannot be employed as independent variables in the use and preventive-care functions. Net price cannot be computed when a child has had no office visits. Receipt of Medicaid benefits is mechanically related to a dependent variable such as use because a child cannot receive benefits if he or she had no use. Therefore, in the use and preventive-care functions, net price is replaced by a dummy variable that

16 Keeler, Newhouse, and Phelps [26] show that it is extremely difficult to define the appropriate net price variable when a policy contains a deductible. Our procedure is identical to the one used by Newhouse and Phelps [37] and Phelps [42]. Newhouse and Phelps [36] exclude observations with a deductible that has not been met. We have not pursued this option because our main focus is not on the net price effect.

equals one if a child has doctor-office-visit insurance (*INS*), regardless of whether health insurance benefits were actually received. Medicaid is replaced by a dummy variable that equals one if a family had welfare income (*WELFARE*), regardless of whether Medicaid benefits were actually received. These variables are designed to capture the potential impacts of health insurance for doctor-office visits and the welfare system on the use of pediatric care and on preventive care.

Knowledge of signs of disease (*KNOW*), taste for medical care or attitudes toward the value of medical care (*TASTE*), and the child's health are potential correlates of mother's schooling (*MEDUCAT*) and mechanisms by which the gross effect of schooling on pediatric care might operate. The child's health is included here because of evidence that health and mother's schooling are positively related (for example, Edwards and Grossman [12]). Under fairly weak assumptions, Grossman [20] and Phelps [41] show that the quantity of medical care demanded will rise as health falls. Note that in our framework, the parents' basic object of choice is the child's ultimate level of health at the age when he or she becomes financially independent. Even with current health held constant, income, prices, and other variables can affect pediatric care by means of their effects on ultimate health.

Knowledge of signs of disease (*KNOW*) is based on the answers to 10 questions such as: Is shortness of breath after light exercise a sign of cancer? Are open sores or ulcers that do not heal a possible sign of cancer? Is unexplained loss of weight a possible sign of tuberculosis? Correct answers are given higher scores than are incorrect ones, and the final variable measures the parents' total score on the 10 questions. It is used as a proxy for their health-specific knowledge. Taste for medical care or attitudes toward the value of medical care (*TASTE*) is based on the answers to six questions such as: Do you agree or disagree that, if you wait long enough, you can get over most any disease without getting medical aid? Do you agree or disagree that modern medicine can cure almost any illness? Do you agree or disagree that some home remedies are still better than prescribed drugs for curing illness? Responses that indicate favorable attitudes toward the value of medical services are scored higher, and a total score on the six questions is computed.[17] The child's health is measured by whether the child was hospitalized during 1970 (*HO*), by the number of restricted-activity days due to illness or injury during 1970 (*RAD*), and by the parents' evaluation of the child's health (*HP, HF, HG*). These variables are all negative correlates of good health and should have positive effects on utilization.[18]

17 For more detailed descriptions of the variables *KNOW* and *TASTE*, see Andersen [3].

18 In the preventive-care equation, good health and utilization might be positively related rather than negatively related. In a production function context, such a relationship indicates reverse causality from preventive-care inputs to health outcomes. In a more

The deflated hourly wage rate of mothers who worked in 1970 is calculated as deflated annual earnings in 1970 divided by the product of weeks worked in 1970 and usual hours worked per week. If the mother did not work in 1970, her wage is estimated from a race-specific regression of the natural logarithm of the hourly wage rate of working mothers on mother's years of formal schooling, mother's years of experience in the labor market (defined as mother's age minus her years of formal schooling completed minus six years), years of experience squared, and the number of children in the family (a positive correlate of interruptions in the labor market experience).

The actual or predicted wage rate is multiplied by the sum of round-trip travel time per visit to the child's usual source of medical care and usual waiting time to see the physician at that source to obtain the deflated time or fixed cost of a visit (*DWT*). The regression specification of the demand function allows for the estimation of a time cost effect for mothers who work (given by the coefficient of *DWT*) and a time cost effect for mothers who do not work (given by the sum of the coefficients of *DWT* and *DWTNLF*). The time cost effect is allowed to vary with labor force status because the shadow value of time of a mother who does not work exceeds *her* potential market wage rate. In turn, her potential wage might differ from the actual wage of a working mother with similar *measured* characteristics.

The net price of an office visit and the time or forgone earnings price do not fully reflect all costs that families incur to receive pediatric services. In addition, there are transporation costs, inconvenience costs, and information costs. Transportation costs are proxied by a dummy variable that equals one if the mode of transportation to the usual source of care is walking (*WALK*). Obviously, this variable is a negative correlate of these costs. Information and inconvenience costs arise because of imperfect knowledge about many aspects of the pediatric care market. For example, mothers do not have complete information about the characteristics of physicians, the nature of their practices, and their fees. Information and inconvenience costs are reflected in part by the absence of a regular source of care (*NOREG*) and by the usual number of days, except for emergencies, that a child has to wait to get an appointment with the usual source of care (*DELAY*).[19]

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mechanical context, relatively healthy children are not likely to have undergone their most recent physical examination because they were ill. Thus, the health effects in the preventive-care function should be interpreted with caution.

19 If a child did not have a regular source of care, his or her parents were not asked about travel or visiting time. For such children, waiting or travel time is set equal to the race-specific mean value of the relevant variable. This procedure does not introduce biases because equations fit with the subsample of children who had a regular source of care are almost identical in all respects to the ones presented in the "Results" section below.

The coefficients of the number of nonfederal physicians per hundred population in the primary sampling unit in which a given child resides (*MD*) provide estimates of the size of the availability effect in the market for pediatric care. Pauly [40] argues that the availability effect is due in part to demand manipulation by physicians in the presence of imperfect information. It follows that the availability effect should be larger in large metropolitan areas where consumers have more physicians to choose from and less information on any given physician. To test this proposition, the physician variable is interacted with size of place of residence (*SSMSA, URBAN, RURALNF, FARM*). This procedure also supplies useful insights concerning the effects of policies to reallocate the existing stock of physicians or to increase the stock in certain areas.[20] It should be noted that significant *MD* coefficients need not solely reflect an availability effect due to demand manipulation by physicians. Alternative explanations are discussed when the results are presented in the following section.

The final four variables in the empirical analysis are the number of children in the family (*NC*), the child's age (*AC*), the child's sex (*MALE*), and the child's race (*BLACK*). An increase in the number of children in a family increases the cost of raising their average level of health and lowers the quantity of pediatric care demanded.[21] Among preschool children, visits to physicians fall with age and are larger for males than for females (for example, National Center for Health Statistics [34]). The male-female differential reflects differences in the health problems encountered by preschool boys as compared to preschool girls. These problems might not be completely captured by the measures of children's health in Table 1. The race dummy variable controls for differences in pediatric care utilization between black and white children that are not due to differences in the other independent variables. We are particularly interested in estimating the portion of the gross (no other variable held constant) difference between the black and white mean values of a given dependent variable that can be explained by differences between black and white mean values of the independent variables.

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20 It might be argued that the number of general practitioners in private practice and the number of pediatricians in private practice are better indexes of availability of pediatric care than the number of nonfederal physicians. On the other hand, the former two variables do not measure the availability of public care. The latter component is reflected in part by nonfederal physicians who work in hospitals and in public clinics not connected with hospitals.

21 The number of children is an endogenous variable, but to treat it in such a manner is beyond the scope of this paper. In a somewhat different context, Tomes [49] reports similar estimates of demand functions for children's schooling whether the number of children is treated as exogenous or endogenous.

Estimation Techniques

Since the dependent variables for ambulatory use of physician services (*USE*) and for a preventive physical examination within the past year are dichotomous variables, dichotomous logit *USE* and *PREVENT* functions are estimated by the method of maximum likelihood. This technique assumes, for example, that the probability that the *i*th child had an ambulatory contact with a physician (θ_i) is given by the logistic function

$$(2) \qquad \theta_i = 1/(1 + e^{-ae^{-bx_i}})$$

where x_i is a vector of independent variables and b is a vector of logit coefficients. After fitting (2), we compute the marginal effect of X_i on θ_i (the change in θ_i due to a one-unit change in x_i) as

$$(3) \qquad (\partial\theta_i/\partial x_i) = b\theta_i(1 - \theta_i)$$

These computations are made at the unweighted sample mean value of θ_i. They are very similar to computations made at the weighted sample mean value (not shown). We also have fitted *USE* and *PREVENT* functions by ordinary least squares and have obtained identical results in terms of signs and statistical significance of all variables.

Demand functions for visits (*VISITS*) and quality (*QUAL)* are estimated by ordinary least squares. A potential problem in these equations arises because the quality-adjusted price variable (*DQUALPRICE*) is identical to observed price (the ratio of expenditures to visits) divided by quality (QUAL). Therefore, errors of measurement in quality or in visits are negatively correlated with errors of measurement in net price. Under certain conditions this will lead to an overestimation in absolute value of the net price elasticities of quality and visits if the demand functions are fitted by ordinary least squares. This same bias arises in the context of a search model in which quality-adjusted price is an endogenous variable that falls as the optimal amount of quality or visits rises. Both factors suggest an estimation procedure in which *QUALPRICE* is predicted by a set of instrumental variables. Yet we have found in preliminary work that demand functions for quality and visits fitted by two-stage least squares do not differ much from ordinary least squares estimates. Therefore, we rely on ordinary least squares estimation in this paper.

We do not present separate equations for white and black children because for three of the four dependent variables the hypothesis of equality between sets of coefficients for white and black children was accepted at the 1 percent level of significance.[22] The hypothesis was rejected for quality, but

22 Specifically, we performed a Chow test of the hypothesis that slope coefficients but not intercepts for white and black children are the same. For *USE* and *PREVENT* the test was based on ordinary least squares regressions rather than on logit functions.

the sample of black children for whom quality can be computed is too small (n = 84) to permit reliable coefficient estimates. Moreover, the parameter estimates of the quality function for the pooled sample are similar to those for the white sample.

RESULTS

Maximum likelihood dichotomous logit equations for the dependent variables *USE* and *PREVENT* are given in Table A3 in the appendix. Ordinary least squares multiple regression equations for the dependent variables *VISITS* and *QUAL* are given in Table A4 in the appendix. The discussion of the results is focused around the effects of six independent variables or related sets of independent variables on the four dependent variables. The variable sets are as follows: (1) family income; (2) net price and related variables (Medicaid recipient, welfare recipient, presence of health insurance for physician visits); (3) mother's schooling and its correlates (knowledge of signs of disease, taste for medical services, child's health status); (4) time costs and other indirect costs (no regular source of care, mode of transportation to the source or care, appointment delay); (5) physicians per hundred population and its interactions with size of place of residence; and (6) other family and child characteristics (child's age, child's sex, number of children in the family). After the results are discussed, there is an analysis of differences between black and white mean values of the dependent variables.

Effects of Independent Variables

1. Family Income. Panel A of Table 3 contains coefficients of family income. In preliminary estimation, no evidence was found of a diminishing income effect in the visit or quality equation. Therefore, the income measure in the final estimates of these two equations is the continuous deflated family income variable (*DFAMINC*). On the other hand, evidence was found of diminishing income effects in the use and preventive-care equations. Therefore, the marginal family income dummy variables for deflated family income equal to or greater than $6,000 (*DY*6) and equal to or greater than $11,000 (*DY*11) are employed in the final estimates of the logit functions.

According to the coefficients of *DY*6, children from families with an income between $6,000 and $10,999 are more likely to have had an ambulatory contact with a physician and a preventive physical examination than children from families with an income under $6,000. As shown by the coefficients of *DY*11, however, use and preventive care are approximately the same for children from families with an income of $11,000 or over as for children from families with an income between $6,000 and $10,999. These

TABLE 3
COEFFICIENTS OF FAMILY INCOME AND INCOME ELASTICITIES

	Dependent Variables			
	VISITS	*QUAL*	*USE*	*PREVENT*
A. *Coefficients of Family Income*[a]				
DFAMINC	.175	.004	—	—
	(4.12)	(2.45)		
DY6	—	—	1.07	.110
			(2.10)	(2.16)
DY11	—	—	.063	−.034
			(1.11)	(−0.69)
B. *Income Elasticities*[b]				
WHITE	.398	.036	—	—
BLACK	.284	.021	—	—
TOTAL	.379	.033	—	—

a *Source:* Appendix Tables A-3 and A-4. t-ratios are in parentheses. The critical t-ratios at the 5 percent level of significance are 1.64 for a one-tailed test and 1.96 for a two-tailed test. For *USE* and *PREVENT*, marginal effects (and asymptotic t-ratios) from maximum likelihood estimates of dichotomous logit functions are given.

b Computations were made using income coefficients from the total sample and relevant unweighted means of the white, black, and total samples, respectively.

findings are consistent with the prediction of an intergenerational transfer model in which financial transfers from parents to children cannot be negative and are subject to a constant rate of return if they are positive. By assumption, investments in children's human capital, including health, are subject to a diminishing marginal rate of return. Consequently, parents who make financial transfers would not increase health investments as their income rises.

To be sure, there are alternative interpretations of the diminishing income effect. For example, the marginal rate of return on health investments might diminish at a more rapid rate than the marginal rates of return on other kinds of investments in children's human capital. Alternatively, since pediatric care has a positive income elasticity (see Panel B of Table 3), a family's entry price into the pediatric care market (that price at which it is willing to consume a positive amount of the good) is a positive function of income. In this context, the diminishing income effect might simply reflect little variation in entry prices above a certain income.

Deflated family income has positive and statistically significant regression coefficients in the demand curves for visits and quality. As shown in Panel B of Table 3, the income elasticity of visits is much larger than the income elasticity of quality. When total sample mean values of income, visits, and quality are used to compute these elasticities, the income elasticity of visits is .38 and the income elasticity of quality is .03. Similar conclusions emerge when the computations are based on mean values of white children or mean values of black children.[23] Goldman and Grossman [17] report that pediatric visits are more responsive to income than the quality of these visits in a sample of New York City residents. They attribute this result to the presence of a fixed (time) cost component in the total cost of a visit, which causes the shadow price of quality to rise at a more rapid rate with income than the shadow price of a visit. Our results also might be due in part to the rather narrow range of variation in quality (coefficient of variation = 18.26 percent) relative to visits (coefficient of variation = 127.31 percent) in the NORC sample.

Regardless of the way in which specific income effects are interpreted, a clear message of Table 3 is that family income is an important determinant of pediatric care utilization. This finding controls for variables that could contribute to an observed gross relationship such as net price, mother's schooling, family size, and race. The finding should be contrasted with the insignificant effect of family income on physicians' services for adults in almost all studies cited in this paper.

2. *Net Price and Related Variables*. Deflated net price (*DNETPRICE*) has a negative and statistically significant regression coefficient in the demand curve for quality (see Table 4). The same variable has an insignificant negative regression coefficient in the demand curve for visits. In their quality-quantity (visit) substitution model, Goldman and Grossman [17] show that an increase in net price raises the price of quality relative to that of visits and causes the ratio of quality to visits to fall. If one accepts the null hypothesis that net price has no impact on visits, then our findings are consistent with this prediction. Note, however, that the price elasticity of visits exceeds the price elasticity of quality in absolute value (−.11 vs. −.04 at the total sample means in Panel B of Table 4). This result is not consistent with the quality-quantity substitution model.

The coefficients of the Medicaid dummy variable suggest that families who receive Medicaid benefits do not behave as if they faced a zero net price. For example, the coefficient of Medicaid in the visit equation shows that a child who received Medicaid benefits made approximatly one fewer

23 The computations of income elasticities are based on unweighted sample mean values. Computations based on weighted sample mean values are very similar to the unweighted estimates. The same comment applies to the price elasticities presented in Panel B of Table 4.

TABLE 4
COEFFICIENTS OF NET PRICE AND RELATED VARIABLES
AND NET PRICE ELASTICITIES

	Dependent Variables			
	VISITS	*QUAL*	*USE*	*PREVENT*
A. *Coefficients of Net Price and Related Variables*[a]				
DNETPRICE	−.082	−.008	—	—
	(−1.14)	(−2.73)		
MEDICAID	−.936	−.115	—	—
	(−0.84)	(−2.56)		
INS	—	—	−.068	.002
			(−1.33)	(0.05)
WELFARE	—	—	.139	.109
			(2.31)	(1.87)
B. *Net Price Elasticities*[b]				
WHITE	−.104	−.041	—	—
BLACK	−.116	−.036	—	—
TOTAL	−.106	−.039	—	—

a *Source:* Appendix Tables A-3 and A-4. t-ratios are in parentheses. The critical t-ratios at the 5 percent level of significance are 1.64 for a one-tailed test and 1.96 for a two-tailed test. For *USE* and *PREVENT*, marginal effects (and asymptotic t-ratios) from maximum likelihood estimates of dichotomous logit functions are given.

b Computations were made using price coefficients from the total sample and relevant unweighted means of the white, black, and total samples, respectively.

visit than one would predict by extrapolating the demand curve to the point where net price is zero. Although the one-visit differential is not statistically significant, the large and negative quality differential is statistically significant. Indeed, children who received Medicaid benefits made fewer visits and had visits of lower average quality than did children whose families paid the *mean* price in the sample of non-Medicaid recipients.[24] An explanation of these findings is that some physicians in private practice are reluctant to accept Medicaid recipients as their patients. In particular, the

24 Suppose that the demand curve for visits is $VISITS = a + b_1 DNETPRICE + b_2 MEDICAID$, where $b_1 < 0$. Let the subscripts m and n denote mean values of a given variable for Medicaid recipients and other children, respectively. Then, $b_2 = VISITS_m - VISITS_n + b_1 DNETPRICE_n$. Since $DNETPRICE_n$ = \$6.64, b_2 equals − .936, and b_1 equals −.082, $VISITS_m - VISITS_n$ equals − .392. Along similar lines, $QUAL_m - QUAL_n$ equals − .062.

TABLE 5
COEFFICIENTS OF MOTHER'S SCHOOLING AND CORRELATES[a]

Dependent Variable	Correlates Omitted	Correlates Included							
	MEDUCAT	*MEDUCAT*	*KNOW*	*TASTE*	*HO*	*RAD*	*HG*	*HF*	*HP*
USE	.034	.040	−.002	−.011	.183	.024	.061	.147	.199
	(4.08)	(4.39)	(−0.18)	(−1.14)	(1.74)	(4.20)	(1.39)	(1.42)	(1.00)
PREVENT	.038	.035	−.017	.007	−.101	.004	−.061	−.113	−.369
	(4.57)	(4.03)	(−2.00)	(0.82)	(−1.29)	(1.67)	(−1.52)	(−1.26)	(−1.40)
VISITS	−.511	−.279	.158	.002	.043	.036	.897	2.788	16.749
	(−4.28)	(−2.39)	(1.36)	(0.00)	(0.00)	(1.41)	(1.57)	(2.42)	(6.84)
QUAL	.003	.003	.010	.003	.118	.001	.034	.008	−.021
	(0.67)	(0.60)	(2.17)	(0.63)	(3.06)	(0.69)	(1.50)	(0.17)	(−0.20)

a *Source:* Appendix Tables A-3 and A-4. Equations with correlates omitted (not shown) hold all other variables constant. *t*-ratios are in parentheses. The critical *t*-ratios at the 5 percent level of significance are 1.64 for a one-tailed test and 1.96 for a two-tailed test. For *USE* and *PREVENT*, marginal effects (and asymptotic *t*-ratios) from maximum likelihood estimates of dichotomous logit functions are given.

sizable quality differential can be attributed to the failure of many Medicaid reimbursement schedules to recognize physician speciality (for example, Sloan, Mitchell, and Cromwell [45]).

The dummy variable for receipt of welfare income in 1970 (*WELFARE*) has positive and statistically significant effects on *USE* and *PREVENT*. Thus, there is a sharp contrast between the role of Medicaid in the visit and quality equations and the role of welfare in the use and preventive-care equations. The welfare program, of which Medicaid is an integral part, encourages poor families to take their children to a physician at least once during a year and to take their children for a preventive physical examination. These same families, however, encounter substantial barriers when they try to see specialists or to make a relatively large number of pediatric visits to physicians in private practice.

The dummy variable denoting whether or not the child has health insurance coverage for doctor-office visits has an insignificant negative effect on the decision to use ambulatory care and an insignificant positive effect on the decision to obtain preventive care. For several reasons these results are not surprising. Health insurance policies typically do not cover preventive care. The presence of health insurance is an imperfect measure of net price, especially if the policy contains a deductible. Moreover, net price is not a significant predictor of the number of visits.

3. *Mother's Schooling and Correlates of Schooling.* Table 5 contains coefficients of mother's schooling and coefficients of variables that we have identified as correlates of mother's schooling. These variables are the parents' knowledge of signs of disease (*KNOW*), the parents' taste for medical care (*TASTE*), and the child's health (*HO, RAD, HG, HF, HP*).[25] When the correlates are held constant, mother's schooling has positive effects on *USE, PREVENT,* and *QUAL* and has a negative effect on *VISITS*. Except in the case of quality, these relationships are statistically significant. When the correlates are excluded, the same signs and the same pattern of statistical significance emerge. The negative coefficient of schooling on the number of visits is, however, much larger in absolute value. Put differently, the absolute value of the visit coefficient falls by approximately 40 percent when the correlates are held constant. The source

25 In addition to knowledge of appropriate health practices, taste for medical care, and the child's health, other independent variables can be regarded as closely related correlates of mother's schooling. For example, a negative effect of mother's schooling on the number of children in a family has been found in many studies. To cite another illustration, schooling raises the actual or potential market wage rate and therefore influences the time cost of a visit. Thus our selection of the closely related correlates is somewhat arbitrary. Of course, the schooling effects in Table 5 that control for knowledge, taste, and health status also control for the effects of all other independent variables in the basic equations. The same comment applies to the schooling effects in the table that do not control for knowledge, taste, and health status.

of this reduction is that mother's schooling is negatively related to the measures of poor health (*HO, RAD, HG, HF, HP*). In turn, these variables have positive effects on the number of visits.

The finding that the number of visits falls as mother's schooling rises is somewhat surprising. It contradicts the positive relationship between these two variables in the U.S. Health Interview Survey reported by Friedman and Leibowitz[14]. Moreover, the negative effect of schooling on visits in Table 5 is rather large in absolute value, even after the correlates are held constant. Specifically, a one-year increase in schooling is associated with a reduction in visits equal to three-tenths of one visit. Thus, children of mothers with a college education make approximately one fewer visit per year than children of mothers with a high school education.

A full explanation of the negative relationship between visits and schooling in the NORC sample is both difficult and challenging, but a number of relevant factors can be mentioned. At an empirical level, the finding is not due to a failure to control adequately for mother's labor force status with the interaction variable between time cost and labor force status (*WTNLF*). When a dummy variable for mother's labor force status is directly entered in the regression, the coefficient of schooling is almost the same as in Table 5. Another empirical consideration is that our visit variable excludes telephone contacts, while Friedman and Leibowitz's variable includes these contacts. Goldman and Grossman [18] show that telephone contacts rise with mother's schooling in a sample of New York City residents. Indeed, a doctor may be willing to rely on a well-educated mother's description of the child's symptoms, her ability to follow his directions and to monitor the child's progress, whereas he may encourage a less educated mother to bring the child to his office for a visit and possibly a follow-up visit. Therefore, the substitution of telephone contacts for office visits might be expected to increase as mother's schooling increases.

At a theoretical level, Michael [32] has described the impact of a "neutral" improvement in efficiency in the production of all household commodities due to schooling. With money income held constant, he shows that the demand for inputs associated with a given commodity would fall with schooling if the income elasticity of the commodity were less than one. We find that the income elasticity of visits is less than one (see Panel B of Table 3), so that the negative schooling coefficient is consistent with the predictions of Michael's model.

An additional insight into the schooling effect is gained by viewing the observed number of visits (z) as the product of the probability of positive ambulatory contacts in a year (θ) multiplied by the number of visits conditional on positive use (v):

(4) $$z = \theta v$$

Differentiation of equation (4) with respect to mother's schooling (s) yields

$$\partial z/\partial s = \theta(\partial v/\partial s) + v(\partial\theta/\partial s) \tag{5}$$

According to the use equation in Table 5, $\partial\theta/\partial s$ equals +.040, and according to the visit equation, $\partial v/\partial s$ equals −.279. Therefore, if $\partial z/\partial s$ is evaluated at the total sample mean values of θ and v, it equals +.012. This derivative equals −.029 at the white sample mean values, and it equals +.034 at the black sample mean values. Put differently, more educated mothers are more likely to take their children to a physician at least once a year, but these mothers take their children to the physician fewer times per year given positive use. The computations of $\partial z/\partial s$ imply that the relationship between schooling and visits might well be positive if children with no visits were included in the regression. In fact, Friedman and Leibowitz [14] include such children in their visit regressions.[26]

A final consideration revolves around the relationships among mother's schooling, children's health, and the use of preventive-care services. To the extent that the health proxies are imperfect measures of health status, mother's schooling might capture part of the negative effect of good health on utilization of curative pediatric care services. In addition, mother's schooling has a positive effect in the preventive-care function, and preventive and curative care might be negatively related.[27]

With regard to the effects of the correlates of mother's schooling, in the use, visit, and quality equations, 14 of the 15 coefficients of the correlates of poor health are positive.[28] Thus, these three measures of pediatric care utilization rise as the child's health declines. Two of the health variables are significant in the use equation (*HO* and *RAD*); two are significant in the visit equation (*HF* and *HP*); and one is significant in the quality equation (*HO*). The parents' taste for medical care (*TASTE*) never is significant. The parents' knowledge of signs of disease (*KNOW*) is positively related to visits

26 We are indebted to Arleen Leibowitz for helping us to reconcile our findings with hers. She points out that the "selectivity biases" that arise when one estimates labor force participation and hours of work equations for married women might also arise when one estimates use and visit equations. In future research we plan to take account of selectivity biases by using estimation methods developed by Hanoch [22].

27 We have explored the last proposition with a crude estimate of the number of curative visits for the sample of children with positive visits. The estimation is defined as *NETVISITS* = *VISITS* − *PREVENT*. We have regressed *NETVISITS* on the same set of variables that enter the visit equation and *PREVENT*. The coefficient of *PREVENT* in this equation is −1.179 (t = −2.03). The coefficient of mother's schooling, however, is only slightly smaller than in Table 5. Specifically, it equals − .272 (t = −2.26). Clearly, more refined measures of preventive medical and nonmedical inputs and an allowance for the "lagged effect" of preventive inputs on health output are required to understand fully the impact of mother's schooling on the number of visits.

28 For an interpretation of the four negative health coefficients in the *PREVENT* equation, see fn. 18.

TABLE 6
COEFFICIENTS OF TIME COST AND OTHER INDIRECT COSTS OF A VISIT[a]

Dependent Variable	*DWT*	*DWTNLF*	*DELAY*	*WALK*	*NOREG*
USE	−.004	−.012	−.003	.183	−.245
	(−0.50)	(−1.40)	(−0.84)	(1.96)	(−3.65)
PREVENT	−.012	.007	.005	−.125	.051
	(−1.66)	(0.75)	(1.82)	(−1.72)	(0.65)
VISITS	.124	.037	−.032	3.140	−1.115
	(1.08)	(0.26)	(−0.80)	(2.58)	(−0.25)
QUAL	.003	−.003	.001	−.052	.003
	(0.69)	(−0.52)	(0.57)	(−1.06)	(0.57)

a *Source:* Appendix Tables A-3 and A-4. *t*-ratios are in parentheses. The critical *t*-ratios at the 5 percent level of significance are 1.64 for a one-tailed test and 1.96 for a two-tailed test. For *USE* and *PREVENT*, marginal effects (and asymptotic *t*-ratios) from maximum likelihood estimates of dichotomous logit functions are given.

and quality, but is negatively related to the probability of positive use and to the probability of a preventive physician examination within the past year. The quality and preventive-care effects of *KNOW* are statistically significant. There is little evidence that the mother's schooling effect operates via this variable because schooling has no impact on quality and has a positive impact on the probability of a preventive physical examination.

4. *Time Cost and Other Indirect Costs.* Table 6 contains coefficients of the time cost of a pediatric visit (*DWT*), coefficients of the interaction between this variable and the mother's labor force status (*DWTNLF*), and coefficients of other indirect cost variables. Goldman and Grossman [17] show that an increase in the time or fixed cost of a visit causes a substitution away from visits and toward quality. Empirically, they indicate that the time cost of a visit has a negative effect on the number of pediatric visits and a positive effect on the quality of a visit in a sample of New York City families. Inman [24] also reports a negative relationship between the number of pediatric visits and the time cost of a visit in a sample of Washington, D. C., families. We do not find evidence of a negative time cost coefficient in the demand curve for visits in Table 6. Indeed, the coefficient of *DWT* is positive, but not statistically significant. We do find a positive time cost effect in the demand curve for quality for mothers who work, but the estimated coefficient is not statistically significant. The effect of time cost on

quality for women who do not work, given by the sum of the coefficients of *DWT* and *DWTNLF*, is equal to zero.

Our failure to uncover a negative time cost effect in the demand curve for visits is puzzling. It is not due to a failure to control adequately for differences in the value of time between mothers who work and those who do not by means of the interaction variable *DWTNLF*. The time cost coefficients in the four equations in Table 6 are hardly altered when a dummy variable for mother's labor force status is included in the equations as an additional independent variable. The dummy variable itself has no effect on visits. One way to reconcile the theory with our empirical results is to recognize that the time parents spend with their children in the household is an additional input in the health production function. In this context, an increase in the wage rate raises the price of time relative to the price of a visit and generates a substitution toward visits in the production of a given amount of health.[29] In comparing our results to those of Inman [24] and Goldman and Grossman [17], it should be kept in mind that theirs pertain to samples in particular cities, while ours pertain to a national sample.

An important result in Table 6 is that the time cost of a visit for mothers who work has a negative and statistically significant effect on the probability that a child obtained a preventive physical examination within the past year. The probability of an ambulatory contact within the past year also is negatively related to the time cost of mothers who work, but the coefficient is not statistically significant. These results are noteworthy because the decisions to contact a physician and to take a child for a preventive examination probably have a larger discretionary component from the mother's point of view than the decision with regard to the number of visits given positive use. The latter decision depends at least to some extent on the physician. At the total sample mean values, a one dollar per visit increase in the time cost of a visit for mothers who work lowers the probability of

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29 To fit the above model, one would have to include the mother's actual or potential wage rate, the time cost of a visit, and the net price of pediatric care as separate variables in the demand curve for visits. We have not attemptd to estimate such an equation because of potential multicollinearity problems due to interrelationships among the wage rate, the time cost of a visit, and the mother's schooling. Note that Nichols, Smolensky, and Tideman [38] and others have argued that travel and waiting time are endogenous variables that are selected by choosing a physician to minimize the cost of a visit, by trading more travel and waiting time per visit for a lower money fee, and by search. No reverse causality from visits to time per visit is created by the fee-time tradeoff. Search to acquire information about travel and waiting time would introduce reverse causality from an increase in visits to a reduction in time, but this factor could not explain the sign of our estimated time-cost effect. If mothers with high wage rates lived closer to specialists than to general practitioners, the relationship between time cost and quality might reflect in part a nonrandom locational distribution of physicians and families. The nature of locational patterns could not, however, account for the positive relationship between time costs and visits in the NORC sample.

obtaining preventive care by 1.2 percentage points. The corresponding reduction for women who do not work equals 0.5 percentage points, which is consistent with the notion that the cost of time of mothers who work exceeds that of mothers who do not work. As shown, however, by the coefficient of *DWTNLF* in the *PREVENT* equation, the difference between these two effects is not statistically significant.

With regard to the other independent variables in Table 6, the direct cost of transportation to the usual source of care is proxied in a negative manner by a dummy variable that equals one if the mode of transportation is walking (*WALK*). The transportation cost of a visit, like the time cost, is a fixed cost that does not depend on quality. Therefore, the number of visits should fall and the quality per visit should rise as transportation cost rises. Consequently, the dummy variable *WALK* should raise visits and lower quality, which is consistent with the coefficients in Table 6. The absence of a regular source of care (*NOREG*) has a negative and significant coefficient in the *USE* equation, but is not a significant variable in the other three equations. Finally, appointment delay (*DELAY*) does not appear to be an important nonprice rationing mechanism in the pediatric care market.

5. *Physician per Hundred Population and Residence Interaction.* Table 7 shows coefficients of physicians per hundred population in the primary sampling unit (*MD*) with and without the interactions between this variable and size of place of residence (*MDSSMSA, MDURBAN, MDRURALNF, MDFARM*). When the interactions are included, the coefficient of *MD* gives the effect of an increase in this variable in large metropolitan areas. These areas are defined as the ten largest SMSAs in the United States. The coefficient of a given *MD*-residence interaction variable indicates the difference between the *MD* effect in large metropolitan areas and the *MD* effect in the given area. In the use or preventive-care equation, there is a statistically significant interaction effect between *MD* and size of place of residence at the 5 percent level. In the visit or quality equation, however, the interaction effect is not statisticaly significant.[30]

According to the results in Table 7, not only is there no interaction effect in the visit equation, but also no *MD* effect. On the other hand, *MD* has a positive and statistically significant effect in the demand curve for quality. In the use and preventive-care equations, which contain significant

30 Specifically, in the logit functions chi-square tests of the null hypothesis that no member of the set of four interaction variables has a nonzero effect result in a chi-square of 11.36 in the use equation and 16.56 in the preventive-care equation. The F-statistic from testing the same hypothesis in the visit or quality regression is 1.37 for visits and 1.70 for quality. Note that the interaction variables are retained in the basic regression specification in Table A4, although they are not statistically significant. The coefficients and t-ratios of the other independent variables are, however, altered only slightly by the inclusion of the *MD*-residence interactions.

TABLE 7
COEFFICIENTS OF PHYSICIANS PER HUNDRED POPULATION WITH AND WITHOUT RESIDENCE INTERACTIONS[a]

Dependent Variable	No Interactions *MD*	With Residence Interactions *MD*	*MDSSMSA*	*MDURBAN*	*MDRURALNF*	*MDFARM*
USE	.156 (0.34)	.595 (1.17)	−.713 (−1.98)	−.316 (−0.34)	1.844 (1.81)	−.769 (−0.44)
PREVENT	2.121 (5.22)	2.508 (5.51)	−.716 (−2.24)	−1.441 (−1.61)	1.378 (1.70)	1.376 (0.90)
VISITS	−1.398 (−0.26)	−.122 (0.00)	−9.178 (−1.76)	−15.403 (−1.43)	−1.751 (−0.17)	9.202 (0.46)
QUAL	.712 (3.30)	.626 (2.70)	.048 (0.22)	−.888 (−2.03)	.105 (0.24)	.340 (0.41)

a *Source:* Appendix Tables A-3 and A-4. Equations with interactions omitted (not shown) hold all other variables constant. The coefficients and *t*-ratios of these other variables are altered only slightly by the exclusion of the *MD*-residence interactions. *t*-ratios are in parentheses. The critical *t*-ratios at the 5 percent level of significance are 1.64 for a one-tailed test and 1.96 for a two-tailed test. For *USE* and *PREVENT*, marginal effects (and asymptotic *t*-ratios) from maximum likelihood estimates of dichotomous logit functions are given.

interactions, the relationship between a given *MD* variable and the probability of an ambulatory-care contact or the probability of a preventive physical examination is positive in eight out of ten cases. The two exceptions are that the probability of an ambulatory contact falls as the physician stock rises in farm areas (shown by the sum of the coefficients of *MD* and *MDFARM*) and in SMSAs other than the ten largest (shown by the sum of the coefficients of *MD* and *MDSSMSA*). The *MD* coefficients are uniformly larger in the ten largest SMSAs than in other SMSAs or other urban areas. The coefficients are smaller in the ten largest SMSAs than in rural nonfarm areas, and there are no significant differences between effects in farm areas and in the ten largest SMSAs.

In his penetrating survey of the sources of the availability effect in the medical care market, Pauly [40] deals in some detail with a model in which physicians manipulate the demand curve for their services in the presence of imperfect information. This model contains the implication that the availability effect should be larger in a sample of consumers with positive utilization than in a sample of all consumers. Moreover, it gives no foundation for expecting an availability effect in an equation that explains the probability of contacting a physician or the probability of obtaining a preventive physical examination. Therefore, there is little evidence in Table 7 in support of an information manipulation model of the availability effect in the pediatric care market. Further, in a study that includes all persons in the NORC sample, May [31] reports an insignificant availability effect if persons with no visits are excluded from the sample. If they are included, however, the effect is significant.

Sherwin Rosen has proposed an explanation of the availability relationships in studies like May's and ours. He argues that there will be relatively more specialization in areas where physicians are more numerous. Thus, board-certified pediatricians in areas where physicians are more numerous will be more highly skilled than board-certified pediatricians in general. Hence quality per physician depends on the number of physicians in a local market as well as on their characteristics. In the context of our estimated equations, an increase in the *MD* variable may be viewed as a reduction in net quality-adjusted price. According to Table 4, there is no significant relationship between net price and visits, and there is a significant relationship between net price and quality per visit. Therefore, the signs of the *MD* coefficients in the demand functions for visits and quality are in agreement with the signs of the net price coefficients.

Along similar lines, the relationship between *MD* and the probability of an ambulatory contact or the probability of a preventive examination might simply reflect the greater incentive to use services as true net price falls. Alternatively, the *MD* variable might be negatively related to the information, inconvenience, and other kinds of entry costs in the pediatric care market. These costs are not reflected perfectly by factors such as the time cost of a visit and the absence of a regular source of care. As they fall, the probability of use of services rises. For reasons that are not entirely clear, the entry-cost effect is important in large metropolitan areas, where the physician-population ratio is relatively high, and in rural nonfarm areas, where the physician-population ratio is relatively low. Perhaps the magnitude of this effect is related to the variation in the physician-population ratio within an area as well as to its absolute level.

6. *Other Family and Child Characteristics.* Table 8 contains coefficients of the child's age (*AC*), the child's sex (*MALE*), and the number of children in the family (*NC*). In general, the effects of age and sex replicate the results of other studies and do not merit additional discussion. The number of children in the family is negatively related to all four measures of pediatric care. Except in the quality demand function, the coefficients of this variable are statistically significant. The most straightforward interpretation of the family-size effect is that the more children there are in a family, the more costly it is to raise their average level of health. To the extent that the

TABLE 8
COEFFICIENTS OF OTHER FAMILY AND CHILD CHARACTERISTICS[a]

Dependent Variable	*NC*	*AC*	*MALE*
USE	−.052	−.044	.046
	(−4.78)	(−2.93)	(1.13)
PREVENT	−.031	−.047	.069
	(−2.89)	(−3.46)	(1.83)
VISITS	−.581	−.651	1.449
	(−3.41)	(−3.46)	(2.68)
QUALITY	−.008	−.010	−.028
	(−1.20)	(−1.26)	(−1.30)

a *Source:* Appendix Tables A-3 and A-4. *t*-ratios are in parentheses. The critical *t*-ratios at the 5 percent level of significance are 1.64 for a one-tailed test and 1.96 for a two-tailed test. For *USE* and *PREVENT*, marginal effects (and asymptotic *t*-ratios) from maximum likelihood estimates of dichotomous logit functions are given.

TABLE 9
DIFFERENCE IN *USE*, *PREVENT*, *VISITS*, AND *QUAL* BETWEEN WHITE AND BLACK CHILDREN[a]

Variable	Gross Difference	Net Difference	Explained Difference[c]
USE[b]	.242	.143	.099
	(7.25)	(3.42)	
PREVENT[b]	.060	.019	.041
	(1.81)	(0.14)	
VISITS	.926	−.129	1.055
	(1.29)	(−0.16)	
QUAL	.003	−.051	.054
	(0.11)	(−1.60)	

a *t*-ratios are in parentheses. The critical *t*-ratios at the 5 percent level of significance are 1.64 for a one-tailed test and 1.96 for a two-tailed test.

b Differences are based on ordinary least squares estimates.

c Explained Difference = Gross Difference − Net Difference.

number of childen and their quality, measured in part by health, are simultaneously determined, these relationships reflect *planned* substitution away from quality and toward numbers by some parents.

Race Differences in Pediatric Care Utilization

Table 9 contains gross and net differences between white and black mean values of the probability of an ambulatory contact with a physician, the probability of a preventive physical examination, the number of visits, and the quality of a visit. The net difference equals the negative of the coefficient of the race dummy variable (*BLACK*) in a multiple regression that controls for all other independent variables that were discussed above. The gross difference equals the race coefficient in a simple regression that does not hold constant these other variables. For reasons mentioned in note 32, the use and preventive-care differences are taken from multiple regression equations rather than from logit equations.

According to the gross differences, white children have higher mean values of all four dependent variables than do black children. Only the use and preventive-care differentials, however, are statistically significant. According to the net differences, only in the case of use of ambulatory care is there a positive and significant race effect with all other variables held constant.[31] An important result in Table 9 is that the significant gross differences in *USE* and in *PREVENT* are much larger than the net differences. The gross difference in the probability of use between white and black children equals 24.2 percentage points, while the net difference equals 14.3 percentage points. The gross difference in the probability of a preventive physical examination is 6.0 percentage points, while the net difference is 1.9 percentage points. These findings indicate that differences in characteristics other than race between white and black families explain part of the differences in use of care and in preventive care between white and black children. Indeed, in a statistical sense differences in these characteristics fully explain the preventive care differential.

Table 10 shows how much of the white-black differences in use of care and in preventive care can be accounted for by specific factors or sets of factors. More specifically, the coefficients of ordinary least squares regressions of *USE* or *PREVENT* and the differences in mean values of independent variables between white and black children are used to obtain the estimates in Table 10.[32] These estimates show how much of the gross difference in *USE* and *PREVENT* between white and black children

31 As shown in Table A3, identical conclusions emerge from the coefficients of the race dummy variable in the logit functions.

32 Ordinary least-squares equations are employed instead of logit equations because the *observed* race-specific mean value of *USE* or *PREVENT* lies on the regression line.

TABLE 10
POSITIVE AND NEGATIVE COMPONENTS OF THE DIFFERENCE IN *USE* AND *PREVENT* BETWEEN WHITE AND BLACK CHILDREN

Component	Contribution to Difference in *USE*	Contribution to Difference in *PREVENT*
A. *Explained Difference*		
Family income ≥ $6,000	+.034	+.033
Family income ≥ $11,000	+.012	−.006
Welfare recipient	−.043	−.024
Mother's schooling	+.039	+.027
Number of children	+.054	+.026
Insurance coverage	−.008	−.0001
Knowledge	−.001	−.020
Taste	−.015	+.011
Child's health	+.004	+.014
Time cost	+.011	+.008
Delay	−.004	+.009
Walk	−.016	−.004
No regular source of care	+.008	+.004
Physicians per hundred population	+.023	−.044
Age of child	+.005	+.007
Child is male	+.001	+.001
Total	+.099	+.041
B. *Net Difference*	+.143	+.019
C. *Gross Difference (A + B)*	+.242	+.060

disappear if black children are given the same mean values of the independent variables as white children.

Several results in Table 10 are noteworthy. Whether use or preventive care is the dependent variable, the positive family-income distribution component is almost entirely offset by the negative welfare component. For instance, in the case of use of services, the income-distribution component (the sum of the two family-income components) amounts to a positive differential of 4.6 percentage points, while the welfare component amounts to 4.3 percentage points. For preventive care, the corresponding figures are a positive income-distribution component of 2.7 percentage points and a negative welfare component of 2.4 percentage points. Put differently, the welfare program, which is aimed specifically at low-income families, is an effective policy tool for eliminating income-related differences in the utilization of certain kinds of pediatric care between black and white children. Table 10 also reveals that mother's schooling and the number of childen in the family make extremely large contributions to the black deficits in use of services and in preventive care. Suppose that mother's schooling and family size were equalized between blacks and whites by increasing years of formal schooling completed by black mothers by one year and by reducing the number of children in black families by one child. These changes would reduce the black deficit in the probability of preventive care by 5.3 percentage points, which would result in a gross deficit of less than 1 percentage point.

Table 9 contains the findings that black children make more visits and have a larger average quality than white children with all other variables held constant. These findings might reflect aspects of a selectivity process. Black children are less likely than white children to have had at least one physician contact during the past year. Among children with positive contacts, blacks are much more likely to have had visits at "public care" sites (hospital emergency rooms, hospital outpatient departments, and public clinics not connected with hospitals) than in physicians' offices. Therefore, the parents of black children with positive office visits might have a strong preference for pediatric care as opposed to other goods. Alternatively, their children might have been in worse health, which is not fully reflected by the available health measures. The statement concerning the propensity of blacks to use the public-care sector is based on a multiple regression analysis of the ratio of public visits to total visits (private plus public) for children with positive contacts (not shown). In general, this propensity cannot be explained by the independent variables that have been employed in this paper. The determinants of the decision to use public care and the quality of this care as opposed to private care are subjects to explore in future research.

SUMMARY AND IMPLICATIONS

In this study multivariate techniques have been employed to examine four measures of pediatric care utilization for children between the ages of 1 and 5. These measures are the probability of contacting a physician within the past year, the probability of obtaining a preventive physical examination within the past year, the number of office visits to physicians in private practice by children with positive visits, and the average quality of these visits. The most important empirical results and their policy implications are indicated below.

Family income has positive and statistically significant effects on all four dependent variables. The net quality-adjusted price of a pediatric office visit has negative effects on the number of visits and on the average quality of these visits, although the former relationship is not statistically significant. Since the income elasticity of office visits exceeds the price elasticity, it might be more efficient to increase these visits by means of direct cash subsidies rather than by means of national health insurance. This conclusion would be modified if the aim of government policy is to stimulate the demand for quality because the net price elasticity of quality is slightly larger than the income elasticity. Regardless of the specific aim of national health insurance, a plan that pays a fixed percentage of the fee of a visit would increase the demand for specialists relative to general practitioners. Such a plan might be more costly than one that caused the relative demand for visits to rise if the supply elasticity of visits exceeded that of quality.

The welfare program, of which Medicaid is an integral part, is an effective method of raising the probability of an ambulatory contact and the probability of a preventive physical examination for children from low-income families. Indeed, the welfare program almost completely eliminates income-related differences in these two indexes of pediatric care between white and black children. Poor families who receive Medicaid benefits encounter substantial barriers, however, when they try to take their children to specialists or to make a relatively large number of pediatric visits to physicians in private practice. This suggests that certain modifications in the incentive structure of Medicaid reimbursement formulas might be desirable.

An increase in the number of physicians per capita in an area has no impact on the number of visits, but has positive impacts on the quality of pediatric visits, on the probability of an ambulatory contact, and on the probability of a preventive physical examination. These relationships are particularly important in large metropolitan areas and in rural nonfarm areas. Such findings have obvious implications for government policies to raise the stock of physicians in certain areas or to reallocate the existing stock.

Mother's schooling and the number of children in a family are extremely important determinants of pediatric care utilization. Family size discourages utilization of services, however measured. Mother's schooling is a positive correlate of the probability of an ambulatory contact and the probability of obtaining a preventive physical examination, but it is a negative correlate of the number of visits. Black-white differences in use of services would be dramatically altered by eliminating black-white differences in mother's schooling and in family size.

We began this paper by indicating that our research would address a fundamental question put forward by the Harvard Child Health Project [23, Vol. I, p. 43]: "What basic forces influence the use of medical services by children?" Based on our analysis of the probabilities of use of services and of preventive care, the two basic forces are mother's schooling and the number of children in a family. Yet from both a positive and a normative point of view, it is not clear that differences due to schooling and to family size are a legitimate concern of public policy. From a positive point of view, the large changes in schooling or in family size that are required to eliminate black-white differences might be extremely costly to achieve. Moreover, in the case of schooling in particular, the mechanisms by which this variable operates still are not firmly established. Until these mechanisms are pinpointed more precisely, the appropriate kinds of government intervention cannot be identified. From a normative point of view, the results of our study and others indicate that black families have more children and spend less on the medical care and other quality aspects of each child, with income and market prices held constant. If these outcomes reflect planned decisions made with relatively complete information, they should not be a legitimate concern of public policy. Of course this conclusion must be modified if the decisions are made in the context of imperfect information or if they are due in part to racial discrimination.

We conclude this paper with an empirical observation and a proposal for future research. The empirical observation is that policies to reduce variations in family income and in the net price of pediatric care might have little or no impact on the substantial variations in care due to the strong effects of mother's schooling and family size. The proposal is for future research directed toward explaining the sources of black-white differences in family size and the effects of schooling and family size on pediatric care. Given government interest in increasing the utilization of pediatric care, such research would be beneficial in the evaluation and selection of alternative government intervention strategies.

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TABLE A-1
UNWEIGHTED MEANS AND STANDARD DEVIATIONS OF THE TOTAL SAMPLE

	White		Black		Pooled	
Variable	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
USE	.714	.452	.473	.500	.620	.486
PREVENT	.346	.476	.287	.453	.323	.468
MALE	.530	.500	.515	.501	.524	.500
NC	2.965	1.728	4.165	2.509	3.434	2.149
AC	3.190	1.351	3.354	1.347	3.254	1.351
MEDUCAT	11.711	2.689	10.654	2.480	11.298	2.658
DELAY	3.644	7.291	1.763	5.098	2.908	6.583
NOREG	.082	.275	.116	.320	.095	.294
WALK	.024	.145	.137	.321	.068	.237
DWT	2.913	2.628	4.000	3.932	3.338	3.243
DWTNLF	1.813	2.197	2.357	3.003	2.026	2.555
MD	.102	.053	.137	.038	.116	.051
MDSSMSA	.041	.062	.083	.068	.057	.067
MDURBAN	.015	.031	.002	.011	.010	.026
MDRURALNF	.015	.030	.002	.015	.010	.026
MDFARM	.003	.014	.001	.007	.002	.012
INS	.305	.461	.149	.357	.244	.430
WELFARE	.076	.256	.439	.497	.218	.413
DY6	.793	.406	.390	.489	.635	.482
DY11	.339	.474	.092	.289	.242	.429
KNOW	14.598	2.325	13.187	1.855	14.046	2.260
TASTE	11.708	2.328	10.005	1.772	11.043	2.284
HO	.082	.275	.058	.234	.073	.260
RAD	4.809	10.180	2.597	7.879	3.944	9.405
HG	.386	.486	.481	.493	.423	.490
HF	.041	.199	.072	.255	.054	.223
HP	.012	.108	.017	.123	.014	.114
BLACK					.391	.488
n	511		328		839	

TABLE A-2
UNWEIGHTED MEANS AND STANDARD DEVIATIONS OF SAMPLE WITH A POSITIVE NUMBER OF VISITS TO PHYSICIANS IN PRIVATE PRACTICE

	White		Black		Total	
Variable	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
VISITS	4.807	6.282	3.881	3.842	4.621	5.883
QUAL	1.211	.222	1.208	.219	1.210	.221
DFAMINC(000)	10.947	7.286	6.295	4.339	10.016	7.046
DNETPRICE	6.081	4.090	5.510	4.338	5.967	4.142
MALE	.569	.496	.512	.503	.557	.497
NC	2.676	1.516	3.191	1.973	2.779	1.628
AC	3.021	1.385	3.155	1.410	3.048	1.390
MEDUCAT	12.207	2.568	11.339	2.400	12.033	2.556
DELAY	3.714	7.417	.890	1.823	3.149	6.777
NOREG	.042	.200	.036	.187	.041	.197
WALK	.031	.170	.172	.374	.059	.232
DWT	2.834	2.651	3.145	1.892	2.896	2.519
DWTNLF	1.639	1.901	1.854	2.343	1.682	1.996
MD	.103	.055	.132	.039	.109	.054
MDSSMSA	.037	.059	.086	.067	.046	.064
MDURBAN	.014	.030	.004	.018	.012	.029
MDRURALNF	.017	.032	.002	.013	.014	.030
MDFARM	.004	.016	.001	.005	.003	.014
MEDICAID	.060	.237	.274	.449	.102	.304
KNOW	14.591	2.387	13.204	1.695	14.314	2.331
TASTE	11.885	2.297	10.016	1.597	11.514	2.299
HO	.107	.310	.048	.214	.095	.294
RAD	5.898	11.000	5.607	13.428	5.840	11.510
HG	.392	.488	.452	.501	.404	.490
HF	.054	.226	.083	.278	.060	.237
HP	.015	.121	.012	.109	.014	.119
BLACK					.200	.401
n	336		84		420	

TABLE A-3
MAXIMUM LIKELIHOOD ESTIMATES OF DICHOTOMOUS LOGIT *USE* AND *PREVENT* FUNCTIONS[a]

	USE			*PREVENT*		
Independent Variable	Logit Coefficient	Asymptotic t-ratio	Marginal Effect	Logit Coefficient	Asymptotic t-ratio	Marginal Effect
MALE	.193	1.13	.046	.314	1.83	.069
NC	−.222	−4.78	−.052	−.142	−2.89	−.031
AC	−.188	−2.93	−.044	−.215	−3.46	−.047
MEDUCAT	.171	4.39	.040	.161	4.03	.035
DELAY	−.011	−0.84	−.003	.022	1.82	.005
NOREG	1.077	−3.65	−.254	−.572	−1.72	−.125
WALK	.775	1.96	.183	.233	0.65	0.51
DWT	−.015	−0.50	−.004	−.054	−1.66	−.012
DWTNLF	−.052	−1.40	−.012	.030	0.75	.007
MD	2.525	1.17	.595	11.468	5.51	2.508
MDSSMSA	−3.027	−1.98	−.713	−3.275	−2.24	−.716
MDURBAN	−1.342	−0.34	−.316	−6.590	1.61	−1.441
MDRURALNF	7.827	1.81	1.844	6.303	1.70	1.378
MDFARM	−3.263	−0.44	−.769	6.290	0.90	1.376
INS	−.290	−1.33	−.068	.011	0.05	.002
WELFARE	.588	2.31	.139	.499	1.87	.109
DY6	.454	2.10	.107	.501	2.16	.110
DY11	.268	1.11	.063	−.156	−0.69	−.034

BLACK	−.692	−2.97	−.163	−.111	−0.47	−.024
KNOW	−.007	−0.18	−.002	−.079	−2.00	−.017
TASTE	−.047	−1.14	−.011	.034	0.82	.007
HO	.778	1.74	.183	−.460	−1.29	−.101
RAD	.101	4.20	.024	.017	1.67	.004
HG	.259	1.39	.061	−2.77	−1.52	−.061
HF	.624	1.42	.147	−.519	−1.26	−.113
HP	.843	1.00	.199	−1.686	−1.40	−.369
Constant	.028			−2.253		
Chi-square	254.87			173.35		
n	839			839		

a The critical t-ratios at the 5 percent level of significance are 1.64 for a one-tailed test and 1.96 for a two-tailed test. The marginal effects are evaluated at the sample means.

TABLE A-4
ORDINARY LEAST SQUARES ESTIMATES OF *VISITS* AND *QUAL*[a]

Independent Variable	*VISITS* Regression Coefficient	*VISITS* t-ratio	*QUAL* Regression Coefficient	*QUAL* t-ratio
DFAMINC (000)	.175	4.12	.004	2.45
DNETPRICE	−.082	−1.14	−.008	−2.73
MALE	1.449	2.68	−.028	−1.30
NC	−.581	−3.41	−.008	−1.20
AC	−.651	−3.46	−.010	−1.26
MEDUCAT	−.279	−2.37	.003	0.60
DELAY	−.032	−0.80	.001	0.18
NOREG	−1.115	−0.79	.033	0.57
WALK	3.140	2.58	−.052	−1.06
DWT	.124	1.08	.003	0.69
DWTNLF	.037	0.26	−.003	−0.52
MD	−.122	−0.00	.626	2.70
MDSSMSA	−9.178	−1.76	.048	0.22
MDURBAN	−15.403	−1.43	−.888	−2.03
MDRURALNF	−1.751	−0.17	.105	0.24
MDFARM	9.202	0.46	.340	0.41
MEDICAID	−.936	−0.84	−.115	−2.56
BLACK	.129	0.17	.051	1.60
KNOW	.158	1.36	.010	2.17
TASTE	.002	0.00	.003	0.63
HO	.043	0.00	.118	3.06
RAD	.036	1.41	.001	0.69
HG	.897	1.57	.034	1.50
HF	2.788	2.42	.008	0.17
HP	16.749	6.84	−.021	−0.20
Constant	6.492		.970	
Adj. R^2	.219		.094	
F	5.69		2.74	
n	420		420	

a The critical t-ratios at the 5 percent level of significance are 1.64 for a one-tailed test and 1.96 for a two-tailed test.