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The Effect of Endogenous Health Inputs on the Relationship between Health and Education

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Abstract—This paper extends the analysis of the relationship between health and schooling by examining the impact of education on the choice of medical care inputs and the subsequent relationship between these inputs and overall health. In particular, we examine the productive effects of education on health as well as the allocative effects of education on the consumption of curative and preventive medical care and other lifestyle choices. In addition to the significant positive productive influence of education on health, we find that the allocative efficiency of education is significantly positive. Unlike most work in this area, we model illness during the consumption period to obtain more accurate estimates of demand for medical care and, consequently, health. Additionally, controlling for unobserved heterogeneity, a possibility accounted for in few previous studies, has a substantial impact on the estimates. [*JEL* I1] © 1998 Elsevier Science Ltd. All rights reserved

1. INTRODUCTION

IN VARIOUS studies, educational attainment, or years of schooling, is found to be strongly correlated with health status. The associated policy implications motivate both health economists and education researchers to better understand the relationship between health and schooling. If a direct causal relationship between education and health exists, then a transfer of resources to education may be an effective way of increasing the health status of a population.[1] Similarly, if education affects the selection of beneficial and detrimental health inputs, then improvements in education may have an additional indirect impact on the production and maintenance of good health.

While many studies support the view of a direct causal relationship between education and health status, questions about the mechanisms through which schooling affects health remain. In our paper, we extend the analysis of the causal relationship along three dimensions. First, in order to examine the impact of education on health, we jointly estimate the demand for several inputs to the health production function and the subsequent relationship between these inputs and overall health. The inputs include both curative and preventive medical care, as well as smoking and physical exercise. Having measured education's allocative influence on medical care and lifestyle decisions, we measure the productive and allocative efficiency of education in producing health by including education, the endogenous inputs, and interactions between the two as explanatory variables in the health production function. Secondly, we demonstrate that annual observations of medical care use depend crucially on an individual's level of illness during the year. We model the level of illness during the observation period in order to control for differences in health flows (in addition to health stocks) as determinants of medical care consumption variation. Finally, we allow for the effects of latent variables, such as preferences for care or unobserved health, on the observed illness, input demand, and general health of an individual. We use a flexible semi-parametric random effects estimator to account for the unobserved heterogeneity. Our study indicates a highly significant productive effect of education on health as well as an indirect allocative effect through education's impact on the consumption of health inputs.

Section 2 briefly reviews the literature analyzing the relationship between education and health, discusses the empirical results in support of a direct causal relationship, and describes a dynamic, stochastic model of the demand for health and health inputs. The empirical model and the data used to estimate the empirical model are described in Section 3. Section 4 details the results and provides tests for validity of the findings. Section 5 concludes with a discussion of how our study contributes to a better understanding of the health-schooling correlation.

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2. MOTIVATION

In this section we begin by listing alternative theories and subsequent research concerning the observed correlation between health and education. Having chosen to focus on the direct causal relationship, we then explain avenues through which education may directly and indirectly affect health. Finally, we present the theoretical framework that motivates the empirical model (discussed in detail in Section 3) and emphasize the need to model illness during the period of measured medical care consumption.

2.1. Health and Schooling Literature

Although the vast majority of empirical studies explaining differences in health find that an individual's education level has a large and significant positive contribution (regardless of whether health is measured by mortality, morbidity, or self-evaluation), there are alternative views about why the correlation exists. The alternative views can be grouped according to three structural relationships that generate a positive correlation. The first view supports a direct causal effect whereby schooling enhances the production of health (Auster *et al*., 1969; Grossman, 1976; Grossman and Joyce, 1987; Taubman and Rosen, 1982; Berger and Leigh, 1989; Behrman and Wolfe, 1989; Kenkel, 1991, 1995). The second view supports a spurious relationship where unobserved variables such as one's preferences or upbringing affect both health and education in the same direction (Rosenzweig and Schultz, 1983). Another example of an unobserved variable generating the spurious correlation is the rate of time discount, as was argued in studies of the correlation between cigarette smoking and schooling (Fuchs, 1982; Farrell and Fuchs, 1982). The third view is often referred to as reverse causality; a better health status enables one to achieve a higher level of education (Edwards and Grossman, 1979; Shakotko *et al*., 1981; Shakotko and Grossman, 1982; Perri, 1984; Wolfe, 1985; Berger and Leigh, 1989).

The purpose of our paper is not to prove or disprove any of the theories, for the health-schooling correlation is most likely a combination of these explanations. Rather, we intend to quantify the effects of education on preventive and curative medical care consumption, smoking, and exercise, the effects of each input on the production of health, and the direct effect of education on health holding all inputs constant. To this end, we focus on the direct causal relationship between schooling and health and make no attempt to model educational attainment.[2]

2.2. Avenues for Correlation: Productive and Allocative Efficiency

The most notable champion of the direct causal relationship between schooling and health is Michael Grossman. Grossman not only makes a tremendous contribution with his theoretical work on the demand for health and health care (Grossman, 1972), but he also provides an empirical investigation into the correlation between health and schooling (Grossman, 1976). In the latter study, he shows that a statistically significant effect of schooling on health remains after controlling for a large number of other variables, including family background, health status in high school, income, job satisfaction, and scores on physical and mental tests. Unlike the relationship between income and health, which is positive at low levels of income but much weaker or nonexistent at average or higher levels (Auster *et al*., 1969), Grossman finds that the positive effect of additional schooling continues to exist at high levels of education.

Assuming a direct positive relationship, through what mechanisms might education improve one's health status? A positive relationship exists between an individual's education and the productivity of his time in the labor market. If education (or the human capital of an individual) affects the productivity of his time favorably in productive activities in the labor market, it may be expected to do so in other productive activities as well (Becker, 1965; Michael, 1973, among others). Furthermore, if education raises the productivity of one's time in non-market production, it thereby lowers the costs or increases the efficiency of non-market production, ceteris paribus. This notion of *productive* efficiency implies that additional education allows an individual to obtain a better health status from a given set of health inputs. Grossman contends that the inputs may include not only medical care, but also housing, diet, recreation, cigarette smoking, alcohol consumption, and other lifestyle choices.

Kenkel (1995) attempts to isolate the notion of productive efficiency by testing the effect of education on the marginal products of other health inputs. For example, he examines whether a more educated person derives greater benefits from a healthy behavior such as regular exercise or good eating habits.[3] In addition to a significant positive contribution of education holding inputs constant, the results indicate that, for some health measures, schooling increases the positive marginal product of several healthy inputs and lessens the negative marginal product of some unhealthy inputs. However, systematic empirical support for the theoretical predictions was not found.

There is another reason to expect a positive effect of education on health production. As Welch (1970) and Michael (1973) explain, the level of education may affect the productivity of the individual for the same reasons that the level of technology affects the productivity of the firm. Just as technology represents the acquisition and adoption of new knowledge or new productive techniques, education represents exposure to knowledge and the development of a receptive attitude toward the use of new information. The individual chooses the productive techniques and selects the market goods and services with which he combines his own time to produce commodities. Similarly, the level of his managerial skill and the proficiency with which he purchases and uses market goods influence the level of efficiency in his nonmarket production. This notion of *allocative* efficiency suggests that a more educated person is likely to select more efficient inputs with which to produce health.

Kenkel (1991) uses direct measures of health knowledge to examine the role of allocative efficiency in the health-schooling correlation. In other words, he examines the hypothesis that schooling improves the choice of health inputs or health behavior by improving an individual's health knowledge. The study demonstrates that, although the relationship between schooling and health behaviors is partially explained by differences in health knowledge, most of schooling's effects remain after controlling for these differences. Kenkel's work provides evidence that allocative efficiency is a possible explanation for the health-schooling correlation.

The above discussion of the health-schooling correlation considers only the efficiency effects of education on health production. An additional explanation is that educated individuals simply recognize and enjoy the benefits of improved health – they have a greater taste for health relative to other goods. If so, they may be more likely than less educated people to eat nutritious meals, to engage in physical exercise, and to avoid smoking and dangerous activities. We might also expect individuals with more education to demand more preventive and curative care, ceteris paribus. This argument focuses on the demand for health while the efficiency arguments focus on the supply or production of health. In this paper, we measure the productive and allocative efficiency effects of education on health.

2.3. Theoretical Framework

The literature describing the demand for medical care, or health inputs in general, follows predominantly from Grossman's 1972 contribution where it is assumed that individuals demand health for both consumption and investment purposes. Consumption of medical care alleviates current disutility associated with illness by reducing the number of unhealthy days; medical care also influences one's health stock which determines future utility.

Grossman refers to the direct utility of health as health services or the flow of health. Alternatively, we follow the works of Heffley (1982), Hey and Patel (1983), Viscusi and Evans (1990), Gilleskie (1998), which specify health state dependent utility functions, and model transitions between the alternative states of health. We distinguish the health *state* or the flow of health (i.e., illness) from the health *stock* or stock of health (i.e., health status). The per-period health state transition probabilities define the probability of a specific number of ill or well periods over a specified length of time or, in Grossman's words, the flow of services from a given stock of health. Two examples demonstrate our reasons for distinguishing between health state (illness) and health stock (general health level). First, consider two individuals with an excellent general health level. One individual experiences two cases of flu and a broken arm over the course of the year, while the other does not fall ill at all during the year. Due to differences in illness (but not overall health status) we might expect to observe differences in medical care consumption. Secondly, consider two individuals with the same health status at the beginning of the year and the same illnesses throughout the year. If curative medical care is expected to improve or at least maintain one's health status, then we expect the individual with more medical treatment to have a better health status at the end of the year than the individual with less treatment.

Because medical care decisions are made sequentially and depend on expectations of future contraction of and recovery from illness, we describe the optimization problem of an individual using a daily, stochastic, discrete choice, dynamic programming framework. Let h_t denote the illness state of an individual in period t. Each period individuals choose whether to seek preventive medical treatment if well ($h_t = 0$), or curative medical treatment if ill ($h_t = 1$). The model is flexible enough to also include lifestyle decisions such as whether to smoke and to exercise. In addition to providing utility (or disutility), decisions each period directly impact the individual's budget constraint and expectations of future health states and health stocks.

The probabilistic transition between ill and well health states involves both exogenous biological factors and individual behavior. That is, the transition probability from a state free of illness in period t to an ill state in period $t + 1$, denoted $\gamma(\cdot)$, is a function of one's stock of health and his behavior during period t. The probability of recovering by period $t + 1$ from an illness in period t (i.e., a transition from an ill state at t to a well state at $t + 1$) is also a function of the stock of health and behavior, and is denoted $\rho(\cdot)$. A health production function governs the evolution of the health stock. The stock of health in period $t + 1$, H_{t+1}, depends on the health stock in period t, H_t; the illness state in period t, h_t; behavior during period t (medical care consumption, M_t, and lifestyles, L_t); and biological deterioration (or depreciation) resulting from age. The production technology allows for differential efficiency by education levels, E_t, in converting the inputs into improved health. More specifically, the household production technology follows a Markov process and is defined by

$$H_{t+1} = H(H_t, h_t, M_t, L_t; E_t). \quad (1)$$

Because the health stock influences future illness states and evolves according to per-period behavior, the stock of health with which an individual enters a period is a state variable. That is, the value of each alternative chosen during period t is different depending on the value of one's health stock at the beginning of the period. We use the Bellman (1957) value function formulation to define the value of current and future utility for each possible illness state at time t. The expected lifetime utilities of an individual who is well in period t or ill in period t are

$$V^{\text{well}}(H_t) = U^{\text{well}}(C_t,M_t,L_t)$$
$$+ \beta[(1 - \gamma(H_t,M_t,L_t))V^{\text{well}}(H_{t+1}) + \gamma(H_t,M_t,L_t)V^{\text{ill}}(H_{t+1})] \quad (2)$$
$$V^{\text{ill}}(H_t) = U^{\text{ill}}(C_t,M_t,L_t)$$
$$+ \beta[(\rho(H_t,M_t,L_t))V^{\text{well}}(H_{t+1}) + (1 - \rho(H_t,M_t,L_t))V^{\text{ill}}(H_{t+1})]$$

where β is the discount factor. Individuals receive utility from a composite consumption good, C_t, which equals per-period income minus expenditures on health inputs and savings.[4] Individuals may also receive direct utility (or disutility) from the health inputs themselves. Note that current period utility does not depend on the stock of health directly but on the current period health state (ill or well). The present value of discounted utility, however, does depend on one's stock of health through its influence on the transitions between health states in the future.

The demand equations derived from this framework are observationally equivalent to the traditional demand for health model developed by Grossman and adopted in much of the demand for medical care literature – with one exception. Here, the level of illness during the period is allowed to influence the decision to seek medical care and the production of health. Aggregating behavior to one year, the level of illness during the year influences annual consumption of medical care and health levels at the end of the year. The theoretical model that distinguishes between health states and health stock provides a better motivation for the empirical model that follows because it emphasizes the importance of illness, or departures from the well state, in the consumption of health inputs and the subsequent production of health.

2.4. Implications of the Theory

The model implies that biological determinants, including past health, age, race, gender, and exposure to illness, govern the transitions between health states. Departures from the well state and consumption of health inputs, in turn, affect the accumulation of health capital. The health capital, or health stock, determines future illness. Thus, the important aspects of the model include the level of illness, consumption of health inputs, and production of health.

An increase in the costs of medical care consumption decreases the quantity of medical care demanded; however, future benefits of positive health flows encourage its consumption. Thus, the relative magnitudes of the costs and benefits, including the direct utility (or disutility) of medical care consumption, determine the demand for medical care.

We might expect to observe positive returns to investment in preventive medical care over time, but it is difficult to conjecture about the effect of today's consumption of curative medical care on tomorrow's stock of health. If two individuals are identical in all respects, more medical care should provide positive returns, albeit, perhaps at a decreasing rate. This conjecture implies that medical care has more value than simply alleviating pain while ill; it increases rates of recovery or restores individuals to a healthy state. However, simple regressions of health on the number of medical care visits reveal that additional visits decrease one's health status. Consequently, in order to measure the benefit of curative care, it is important to account for illness, or increased susceptibility to illness, which may result in increased consumption of medical care. Our attempts to do so empirically are described in the next section.

Focusing on education's effect on health, we hypothesize that additional years of schooling improve the ability of an individual to obtain a better health status from the same set of inputs (productive efficiency). Furthermore, we believe that education influences the selection of health inputs and thereby has an additional indirect effect on one's health status (allocative efficiency). The total derivative of the health production function, $H(\cdot)$, decomposes the total effect of education into the two parts. That is,

$$\frac{\partial H(M,L,E)}{\partial E} = \frac{\partial H}{\partial E} + \sum_{n=1}^{N_m} \frac{\partial H}{\partial M_n}\frac{\partial M_n}{\partial E} + \sum_{n=1}^{N_\ell} \frac{\partial H}{\partial L_n}\frac{\partial L_n}{\partial E} \quad (3)$$

where N_m is the number of endogenous health care inputs and N_ℓ is the number of endogenous lifestyle inputs. The first term measures the productive efficiency of an additional year of education; the latter two terms measure the allocative efficiency. We present and discuss quantative results in Section 4.

3. DATA AND EMPIRICAL SPECIFICATION

3.1. The Data

To empirically analyze the relationship between education and health described in the theory above, we make use of the detailed health and health care data in the 1987 National Medical Expenditure Survey (NMES). Although the NMES data do not permit analysis of educational attainment or changes in health status over time, they do allow for measurement of both the productive and allocative effects of education. That is, we are able to study the direct, productive effect of education on the production of health as well as the indirect, allocative effect of education on health through the demand for curative and preventive medical care because both the quantity and type of these health inputs are observed.

The survey covers the civilian, non-institutionalized population and is designed to provide a large representation of population groups of special policy interest. These groups include poor and low income families, the elderly, the functionally impaired, and Black and Hispanic minorities. The major components of NMES contain information to make national estimates of health status, use of health services, insurance coverage, expenditures, and sources of payment for the civilian population of the US during the period from January 1 to December 31, 1987. Each family in the household survey was interviewed four times over a period of 16 months to obtain information about the family's health and health care during 1987. Baseline data on household characteristics, employment, and insurance were updated at each interview, and information was obtained on illnesses, use of health services, and health expenditures for each family member. The sample used in this paper is made up of 12,095 individuals between the ages of 25 and 65 who have complete data with which to estimate the empirical model (see Table 1).

3.2. The Empirical Model

An empirical model that captures the daily decision-making behavior described above (and that can be estimated using annual data) is difficult to develop. The theoretical model indicates that current illness and expectations of future illness influence the consumption of medical care and other health inputs. In order to explain this consumption, we require a variable that captures the annual (negative) flow of services of a given health stock. Because illness duration data (the number of days an individual is ill) are missing or unreliable in the NMES data, we measure an individual's level of illness during the year by his annual number of illness episodes.[5] Because we use data that are aggregated to one year (therefore, losing the sequential and contingent nature of contraction of and recovery from illness), we have chosen to explain variations in the number of episodes by differences in biological factors only (i.e., reduced form). More specifically, we model the number of illness episodes in year t, I_t, as a function of one's health stock at the end of year $t-1$, H_{t-1} and a vector of exogenous characteristics at t, X_t. That is,

$$I_t = I(H_{t-1}, X_t). \tag{4}$$

According to theory, the number of periods of ill health influence demand for health inputs. Thus, both the number of curative medical care visits and the number of preventive visits in year t, M_t^c and M_t^p, are functions of the number of illness episodes in year t, I_t. The input demand equations are also a function of the number of years of schooling, E_t; a vector of exogenous characteristics, X_t; and a set of additional exogenous variables, Z_t, other than the biological determinants of illness (e.g., prices of medical care, health insurance, and attitudes about medical care effectiveness). Thus,

$$M_t^j = M^j(H_{t-1}, I_t, E_t, X_t, Z_t),\ j = c,p. \tag{5}$$

A physician office visit associated with a particular illness episode is considered curative medical care; a routine physical examination in a doctor's office with no explicit illness prompting the visit is preventive care. Similarly, lifestyles[6] are modeled as $L_t = L(H_{t-1}, I_t, E_t, X_t, Z_t)$.

We model one's health stock, H_t, as a function of past health, the numbers of each health input, education, and other exogenous individual characteristics, where

$$H_t = H(H_{t-1}, I_t, M_t, L_t, E_t, X_t). \tag{6}$$

Unfortunately, the NMES reports a measure of health status at only one point during the 1987 calendar year. The lack of longitudinal information requires that we use a proxy for past health, H_{t-1}. Natural candidates include measures of initial health stock such as birth weight or parent's health status, but these measures are not available in the dataset. Thus, we use the number of chronic conditions (among stroke, cancer, heart disease, gall bladder disease, high blood pressure, hardening of the arteries, rheumatism, and diabetes) and a measure of body mass (weight in kilograms divided by height in meters squared) as proxies for past health. The variable measuring one's health stock at the end of the year, H_t, is self-reported health status. Thus, we model probabilities of being in excellent, good, fair, and poor health status.[7] In the health production equation,

Table 1. Sample selection information

Selection criteria	Remaining sample size: Full sample	Males	Females
NMES participants	38446	18094	20352
aged 25–65 years	17041	7752	9289
with a completed Health Status Questionnaire	14764	6714	8050
and valid responses for key variables	12377	5826	6551
and not pregnant during the survey period	12095	5826	6269

education is allowed to affect health status directly (measuring productive efficiency) and indirectly through the consumption of health inputs (measuring allocative efficiency). We also allow for interactions between the health inputs and education.

Having described the equations to be estimated, we estimate three separate models.

1. We estimate each equation separately treating illness and health inputs as exogenous explanatory variables (Model 1).
2. Using appropriate exclusion restrictions, we estimate the illness equation, include its predicted value in the medical inputs equations and, similarly, include the predicted value of the inputs in the health production function (Model 2).
3. We estimate the equations jointly allowing for correlation across all outcomes using a discrete factor random effects estimator (Model 3).

Although we report some results from all three estimation approaches, we prefer the third approach because it eliminates endogeneity bias and allows behavior to depend on unobserved heterogeneity without imposing a distribution on the unobservables.

We incorporate permanent unobserved heterogeneity in Model 3 by allowing each equation to depend on a common unobserved factor μ. The equations are linked by dependence on the common factor, which is treated as a random effect and is integrated out of the model. We follow Mroz and Guilkey (1992) and Heckman and Singer (1984) in approximating the distribution of μ by a step function. The points of support of the distribution, the factor loadings in each equation, and the probabilities associated with each point of support are estimated jointly with the other parameters.[8]

3.3. Identification and Model Detail

Because the degree of illness during the year (measured by the number of illness episodes over the year) influences the demand for medical care, exclusion restrictions are required for identification. In the illness equation (Equation (4)) we measure past health by dummy variables for each chronic condition reported, as opposed to a variable measuring the total number of chronic conditions which enters the other equations.[9] Because preventive and curative visits are endogenous inputs to the production of health, we also require variables that influence the medical care decisions that do not directly affect the production of health. The theory provides a set of a priori restrictions including prices of the inputs and other economic variables. However, prices of medical care are available only for individuals who sought care, thus providing only a truncated distribution of the actual prices faced by all individuals. Indicators of regional or state variation in medical care prices is not useful because the data only distinguish residences by four regions of the country. We do, however, control for health insurance which affects the out-of-pocket price an individual faces. We classify individuals as having either private health insurance (employer-provided or privately-purchased), public health insurance, or no health insurance. The equation that explains health insurance is identified by attitudes about risk and prices of insurance. We also include in the consumption equations a variable to indicate whether the individual has a usual source of care. This variable may serve as an indicator of health knowledge; people with a regular source of medical care have more information about location and availability of medical services. Alternatively, it may capture time costs associated with medical care consumption. Other economic variables that may affect medical care consumption but not the production of health include income, employment, and sick leave provisions. We make no attempt to model participation in the work force and therefore do not include these endogenous variables in estimation.

The empirical model focuses on the total number of illness episodes (the flow of health throughout the year), curative and preventive medical care treatment, and the stock of health. Additional equations for the endogeneity of health insurance, smoking, and exercise are also included.[10] Table 2 details the moments of the dependent variables. A multinomial logit model is used to estimate the probability of being in excellent, good, fair, or poor health, with good health being the comparison group. Given the discrete, non-negative nature of the number of episodes, curative visits, and preventive visits, each is modeled using an ordered logit framework.[11] The health insurance equation is multinomial logit, and the smoking and exercise equations are binary logits.

Table 3 describes the sample moments of the explanatory variables in the model. In addition to the health and economic variables discussed above, demographic variables include age, gender, race, education, marital status, family size, metropolitan area, and geographic region.[12] Table 3 also includes variables describing attitudes toward doctors and health risks.

4. RESULTS AND DISCUSSION

4.1. Estimation Results

Tables 4 and 5 display the estimates and significance of education and input coefficients from the three estimated models of health production: a model with no controls for unobserved heterogeneity (Model 1), a model with predicted values of endogenous variables included as regressors (Model 2), and a model with controls for several sources of endogeneity or unobserved heterogeneity (Model 3).[13] Since it is difficult to obtain a thorough understanding of a variable's effect from the estimated parameters alone, we also discuss simulations based on the parameter estimates in order to provide additional interpretation.

In Model 1, the linear and quadratic direct effects of education are significant for explaining the prob-

Table 2. Proportions and moments of dependent variables

	Males (5826)	Females (6269)
Health insurance		
Private health insurance	78.94	75.18
Public health insurance	5.41	11.10
Uninsured	15.65	13.72
Episodes of illness		
Prob of 0 episodes	24.58	15.68
1–2	43.68	36.43
3–5	25.42	31.86
6–10	5.80	14.02
11 +	0.51	2.01
Mean (std. dev.)	2.02 (2.07)	3.02 (2.75)
Curative visits		
Prob of 0 visits	48.42	37.93
1	16.39	16.38
2	9.68	10.53
3–5	12.24	15.68
6–10	6.81	9.75
11–15	2.63	3.94
16 +	3.83	5.79
Mean (std. dev.)	2.80 (6.68)	3.88 (7.72)
Preventive visits		
Prob of 0 visits	77.88	61.70
1	13.32	21.22
2	4.29	8.69
3 +	4.51	8.39
Mean (std. dev.)	0.44 (1.28)	0.80 (1.69)
Lifestyles		
Smoke now	35.77	30.29
Exercise regularly	65.17	48.96
Health status		
Excellent	30.93	24.17
Good	52.39	54.75
Fair	13.89	17.96
Poor	2.80	3.13

ability of being in excellent health among males. The estimates indicate that higher levels of education improve the probability of excellent health relative to good health. The quadratic term alone significantly decreases the probability of being in fair health relative to good health. Among females, only the higher order polynomials in education are significant and indicate that education decreases the probability of being in fair health relative to good health.

The only significant medical input variables among both males and females include the indicator of sixteen or more annual curative care visits for all health outcomes and the indicator of three or more preventive visits explaining fair health relative to good health. From the theory, we hypothesize that curative care should improve one's health status once we control for differences in illness; that is, curative care is a positive input to the production of health. We include the indicator of a large number of visits because we expect that several visits during the year is indicative of a serious illness that requires multiple visits and one that is not captured by our illness severity measure (i.e., number of episodes). Thus, a larger number of curative care visits may be associated with an unobserved severe illness which, in turn, may lead to predictions of health stock depreciation rather than improvements in it's production. The signs on the indicator of a large number of visits are, therefore, as we expected. However, the signs on dummy variables indicating the number of curative visits if less than sixteen, although insignificant, do not indicate that curative care improves one's health.

Despite the lack of significance in most cases, the coefficients on preventive visits do indicate a positive effect on the production of health at low levels of care for females. Three or more preventive visits, however, decrease the probability of being in excellent health. Again, more than two preventive visits may indicate the existence of a current chronic condition that requires routine visits to a physician for regular check-ups. The chronic condition, in turn, may negatively affect the evolution of health. The only significant interaction between medical care inputs and education indicates that preventive care visits are more likely to decrease the probability of poor health among males as education increases. Smoking significantly decreases the probability of being in excellent health and increases the probability of being in fair health relative to good health among both men and women. As expected, regular exercise has a significant opposite effect.

How robust are the estimates to controls for endog-

Table 3. Proportions and moments of independent variables

Variable	Males (5826)		Females (6269)	
	Mean	StDev	Mean	StDev
Demographic variables				
Age #	41.84	11.59	43.68	11.84
Highest grade completed #	12.73	3.17	12.33	2.86
Black, non-Hispanic	0.16	0.36	0.21	0.40
Hispanic	0.09	0.28	0.09	0.28
White or Asian *	0.76	0.43	0.71	0.45
Single	0.24	0.43	0.32	0.47
Family size #	3.15	1.59	3.14	1.57
19 Largest SMSA *	0.27	0.44	0.26	0.44
Other SMSA	0.47	0.50	0.48	0.50
Rural	0.26	0.44	0.26	0.44
South *	0.35	0.48	0.38	0.49
Northeast	0.19	0.40	0.20	0.40
Midwest	0.25	0.43	0.24	0.43
West	0.20	0.40	0.18	0.39
Economic variables				
Have usual source of care	0.74	0.44	0.82	0.38
Family income #	40934.92	31593.13	36892.27	31572.75
Employed	0.86	0.34	0.65	0.48
Sick leave (and employed)	0.48	0.50	0.37	0.48
Health variables				
Body mass index #	26.04	4.19	25.54	5.66
No. of chronic conditions ever #	0.64	1.11	0.85	1.21
Attitude variables				
Can get well without doctor	0.55	0.50	0.47	0.50
Home remedy is better than Rx	0.25	0.44	0.29	0.45
Luck is a big part of recovery	0.10	0.30	0.09	0.28
Too healthy to need insurance	0.12	0.32	0.08	0.27
Insurance is not worth the cost	0.23	0.42	0.19	0.39
More than average risk taker	0.31	0.46	0.16	0.36

Note: A number sign (#) indicates a continuous variable. All other characteristics are dummy variables. For discrete characteristics with more than two categories, each category is listed and an asterisk (*) indicates the omitted category in subsequent regression equations. Also, some variables listed above are not used in the empirical models, but provide a description of the sample. Responses to each attitude question are missing for about 2% of males and females. A missing dummy is included in the empirical analysis.

eneity of the input decisions, illness, and health insurance? In Model 2 the predicted values of the input variables are used to explain variations in health rather than assuming that the inputs are exogenous; predictions of illness and health insurance are also included. This method of correcting the endogeneity bias, however, results in the loss of significance of many variables. In fact, the coefficients on education, although insignificant, indicate that the direct effect of education is to decrease the probability of being in excellent health and to increase the probability of being in fair or poor health relative to good health. We find that Model 2 predicts a significant positive effect of preventive care (less than three visits) on the production of health among females. The results indicate, however, that curative medical care improves the probability of excellent health, while also increasing the probability of fair and poor health among men. Among females, curative care decreases the probability of excellent health.

Model 3 attempts to correct for endogeneity bias by estimating the health production, input demand, illness, and health insurance equations jointly and allowing them to be correlated through unobserved heterogeneity. The significance of several variables increases, but the qualitative results are similar to Model 1. The direct effect of education remains significant and increases the probability of excellent health and decreases the probability of fair and poor health. Preventive care becomes significant, and we find that two preventive care visits are better than one among females. Ironically, however, zero preventive care visits are better than one such visit. The coefficient on the number of curative visits (if less than sixteen) is insignificant, with an indicator of sixteen or more visits significantly decreasing the probability of excellent health. Despite only small quantitative differences, Model 3 is preferred to both Model 1 and Model 2, as indicated by the log likelihood values of each model. Likelihood ratio tests indicate that Model 3 provides the best fit of the data among the three models.

Table 4. Health status equation results-males

	Model 1 No unobserved heterogeneity			Model 2 Predicted endogenous values			Model 3 Unobserved heterogeneity		
	Exc	Fair	Poor	Exc	Fair	Poor	Exc	Fair	Poor
Education	–0.160 (0.056)	–0.043 (0.061)	–0.134 (0.137)	–0.135 (0.154)	–0.156 (0.173)	–0.076 (0.433)	–0.158 (0.057)	–0.046 (0.064)	–0.157 (0.160)
Education^2/10	0.108 (0.023)	–0.056 (0.028)	–0.048 (0.064)	0.048 (0.062)	0.143 (0.074)	0.145 (0.193)	0.112 (0.023)	–0.068 (0.029)	–0.073 (0.073)
No. of curative visits (if ≤ 15)	–0.001 (0.087)	0.046 (0.079)	0.033 (0.133)	0.322 (0.269)	0.190 (0.224)	0.894 (0.462)	–0.015 (0.088)	0.101 (0.085)	0.228 (0.159)
No. of curative visits^2 (if ≤ 15)	–0.003 (0.004)	0.000 (0.004)	0.010 (0.007)	–0.031 (0.027)	–0.009 (0.021)	–0.058 (0.042)	–0.001 (0.004)	–0.003 (0.004)	0.002 (0.008)
> 15 curative visits	–0.712 (0.235)	0.439 (0.210)	1.054 (0.369)	–0.694 (0.368)	1.128 (0.383)	3.890 (1.006)	–0.806 (0.242)	0.690 (0.230)	1.847 (0.470)
No. of curative visits *Education	–0.001 (0.006)	0.000 (0.005)	–0.007 (0.010)	–0.014 (0.016)	0.003 (0.013)	0.002 (0.020)	–0.001 (0.006)	0.000 (0.006)	–0.011 (0.011)
No. of preventive visits (if ≤ 2)	–0.125 (0.403)	0.117 (0.420)	0.807 (0.758)	–2.014 (1.254)	0.307 (0.910)	–1.867 (1.467)	–0.286 (0.410)	0.899 (0.475)	3.392 (1.156)
No. of preventive visits^2 (if ≤ 2)	–0.076 (0.128)	0.028 (0.156)	0.133 (0.342)	0.489 (0.454)	0.476 (0.368)	1.579 (0.571)	0.007 (0.133)	–0.244 (0.177)	–0.442 (0.454)
> 2 preventive visits	–0.327 (0.216)	–0.075 (0.192)	–0.491 (0.375)	–0.812 (0.351)	–0.084 (0.393)	–1.632 (0.904)	–0.491 (0.226)	0.572 (0.262)	2.017 (0.826)
No. of preventive visits *Education	0.015 (0.026)	–0.019 (0.028)	–0.131 (0.049)	0.066 (0.072)	–0.083 (0.049)	–0.131 (0.081)	0.009 (0.026)	–0.011 (0.029)	–0.154 (0.057)
Smoke	–0.507 (0.072)	0.342 (0.095)	0.339 (0.223)	–3.606 (1.589)	7.670 (1.928)	8.839 (5.310)	–0.401 (0.084)	0.091 (0.116)	–0.296 (0.293)
Exercise	0.609 (0.074)	–0.803 (0.092)	–1.693 (0.247)	2.351 (2.435)	–3.838 (2.953)	–9.465 (7.985)	0.591 (0.076)	–0.777 (0.099)	–1.613 (0.294)
Log likelihood		–33120.254			–34761.172			–32988.328	

Note: Absolute values of standard errors are in parentheses.

4.2. Simulations

In order to evaluate the quantitative implications of the parameter estimates, we present simulations (in Table 6) of the health probabilities based on the preferred model (Model 3) with heterogeneity.[14] The table displays the direct or productive effect of education, health inputs, and illness. The first two rows of the table indicate that predictions from the model closely match the sample proportions. The first set of simulations reveal that, on average, increases in the number of years of schooling improve the probability of excellent health and decrease the probabilities of fair or poor health. For example, twelve years of education versus eleven years improves the probability of excellent health by a little over 8% for both males and females, ceteris paribus. Four additional years of education after graduation from high school increase the probability of excellent health among males and females by 50% and 44.5% respectively.

Having one versus zero curative visits appears to decrease the probability of excellent health and to increase the probability of fair or poor health, but the result is not statistically significant. We find a similar result with preventive care, but find that the negative effect of one preventive care visit is half as large for females as for males. Smoking significantly decreases the probability of excellent health by 21.3% among males and 24.4% among females. Regular exercise improves the probability of excellent health by 52.9% for males and by 60.6% for females. Two versus one illness episodes during the year significantly decreases the probability of excellent health by 7.8% and by 11.8% among males and females.

The simulated behavior indicates the direct, productive effects of education and various inputs. Knowledge of the total effect of education requires that we also analyze the effect of education on the consumption of health inputs. Simulations of the effect of different levels of education are presented in Tables 7 and 8. (Additional parameter estimates from Model 3 are presented in the Appendix. Results for all models and all variables are available from the authors.) Among males, education has little effect on the probability of a particular number of visits or the average number of visits; visits fall slightly as education rises. Among females, increases in education

Table 5. Health status equation results-females

	Model 1 No unobserved heterogeneity			Model 2 Predicted endogenous values			Model 3 Unobserved heterogeneity		
	Exc	Fair	Poor	Exc	Fair	Poor	Exc	Fair	Poor
Education	–0.128 (0.140)	0.179 (0.139)	0.130 (0.313)	–0.214 (0.243)	0.163 (0.238)	0.380 (0.570)	–0.177 (0.143)	0.242 (0.145)	0.312 (0.345)
Education^2/10	0.073 (0.148)	–0.336 (0.153)	–0.478 (0.349)	0.093 (0.208)	–0.278 (0.214)	–0.659 (0.491)	0.121 (0.151)	–0.403 (0.158)	–0.693 (0.384)
Education^3/100	0.004 (0.047)	0.099 (0.050)	0.177 (0.115)	–0.012 (0.057)	0.091 (0.060)	0.280 (0.129)	–0.009 (0.048)	0.118 (0.052)	0.245 (0.126)
No. of curative visits (if ≤ 15)	–0.066 (0.084)	–0.049 (0.062)	0.004 (0.117)	–0.294 (0.197)	0.467 (0.153)	0.727 (0.286)	–0.077 (0.085)	–0.025 (0.063)	0.077 (0.129)
No. of curative visits^2 (if ≤ 15)	0.003 (0.003)	0.001 (0.003)	–0.001 (0.006)	0.009 (0.017)	–0.011 (0.011)	–0.022 (0.022)	0.004 (0.003)	0.000 (0.003)	–0.004 (0.007)
> 15 curative visits	–0.388 (0.202)	0.434 (0.180)	1.563 (0.322)	–1.197 (0.385)	2.240 (0.386)	3.423 (0.916)	–0.453 (0.207)	0.538 (0.189)	2.004 (0.377)
No. of curative visits *Education	0.001 (0.006)	0.005 (0.005)	0.008 (0.008)	0.005 (0.011)	–0.006 (0.009)	–0.020 (0.011)	0.001 (0.006)	0.005 (0.005)	0.007 (0.008)
No. of preventive visits (if ≤ 2)	0.023 (0.331)	–0.559 (0.336)	–0.405 (0.654)	0.251 (0.935)	–2.136 (0.829)	–0.124 (1.604)	–0.346 (0.364)	0.024 (0.397)	2.007 (0.944)
No. of preventive visits^2 (if ≤ 2)	–0.042 (0.098)	0.181 (0.113)	0.137 (0.250)	0.076 (0.360)	0.462 (0.307)	0.021 (0.633)	0.084 (0.112)	0.001 (0.132)	–0.429 (0.307)
> 2 preventive visits	–0.059 (0.159)	–0.261 (0.143)	–0.345 (0.262)	–0.136 (0.416)	–0.862 (0.426)	0.490 (0.929)	–0.350 (0.202)	0.246 (0.236)	2.042 (0.642)
No. of preventive visits *Education	0.017 (0.023)	0.009 (0.022)	0.000 (0.043)	–0.008 (0.054)	0.061 (0.048)	0.033 (0.075)	0.015 (0.023)	0.012 (0.023)	–0.016 (0.048)
Smoke	–0.475 (0.079)	0.206 (0.085)	0.244 (0.198)	–2.279 (1.997)	3.110 (2.511)	7.203 (6.038)	–0.430 (0.081)	0.141 (0.089)	–0.042 (0.226)
Exercise	0.666 (0.070)	-0.525 (0.080)	–1.356 (0.220)	3.010 (2.167)	–1.741 (1.983)	–6.997 (4.771)	0.676 (0.071)	–0.541 (0.082)	–1.437 (0.244)
Log likelihood		–40072.711			–41945.316			–39900.023	

Note: Absolute values of standard errors are in parentheses.

from lower levels decrease the average number of curative visits, but increase the number at higher levels of education. The average number of preventive visits among males increases by 3.2% with an additional year of schooling beyond eleven and by 13.9% with four additional years beyond twelve. Among females, these increases are 8.5% and 27.3%.

Finally, smoking is 9.1% less likely for male high school graduates than for those with eleven years of schooling. Females with similar levels of education are only 6.4% less likely to smoke. Males with sixteen years of education as opposed to twelve years are 50.2% less likely to smoke. The corresponding figure for females is 42.6%. The probability of regular exercise increases with education among males, but the positive effect tapers off at higher levels of education. Females, on the other hand, are consistently more likely to exercise with higher levels of schooling.

4.3. The Total Effect of Education

Although the simulations provide further analysis of the empirical results, we are most interested in measuring the productive and allocative effects of education on health. The following empirical results refer to Equation (3) in Section 2. In order to determine the effect of one additional year of education (as opposed to the empirical derivative of Equation (3)), we simulate the effects of a one year change in the observed years of education. To evaluate the productive effect of an additional year of education on the probability of each health outcome, we compare the simulated probabilities of a particular health status under observed levels of schooling and the simulated probabilities of that health status after increasing the observed level of schooling by one year for each individual. We calculate the allocative effect of one additional year of education by simulating probabilities of the different input measures before and after increasing the observed level of schooling by one year ($\partial M_n/\partial E$ and $\partial L_n/\partial E$). We multiply each percentage change by the percentage change in the probability of each health outcome with one additional curative or preventive visit, when an individual is a smoker and not, and when an individual exercises regularly and not ($\partial H/\partial M_n$ and $\partial H/\partial L_n$).

Table 6. Health status simulations-productive effects of education, inputs, and illness

	Males				Females			
	Exc	Good	Fair	Poor	Exc	Good	Fair	Poor
Actual distribution	0.309	0.524	0.139	0.028	0.242	0.547	0.180	0.031
Predicted distribution	0.309	0.518	0.139	0.034	0.243	0.534	0.175	0.048
Effect of education								
Education = 8	0.207	0.515	0.231	0.047	0.167	0.464	0.278	0.090
Education = 11	0.244	0.548	0.172	0.036	0.201	0.542	0.204	0.053
Education = 12	0.264	0.552	0.151	0.033	0.218	0.560	0.178	0.044
Education = 16	0.396	0.507	0.076	0.021	0.315	0.561	0.098	0.026
Education = 18	0.493	0.443	0.048	0.016	0.384	0.513	0.076	0.027
Effect of inputs								
Curative visits = 0	0.326	0.523	0.125	0.027	0.260	0.540	0.169	0.031
Curative visits = 1	0.318	0.522	0.133	0.028	0.249	0.545	0.171	0.035
Curative visits = 2	0.310	0.521	0.140	0.029	0.240	0.548	0.174	0.038
Curative visits = 3	0.301	0.521	0.148	0.030	0.232	0.550	0.177	0.042
Curative visits = 4	0.292	0.521	0.155	0.032	0.225	0.551	0.179	0.045
Curative visits = 5	0.283	0.521	0.162	0.034	0.219	0.550	0.182	0.048
Preventive visits = 0	0.319	0.527	0.132	0.023	0.249	0.549	0.177	0.025
Preventive visits = 1	0.278	0.505	0.171	0.045	0.234	0.527	0.176	0.063
Preventive visits = 2	0.254	0.518	0.168	0.060	0.244	0.491	0.182	0.084
Preventive visits = 3	0.224	0.535	0.172	0.069	0.193	0.539	0.177	0.091
Not a smoker	0.333	0.499	0.132	0.036	0.262	0.522	0.167	0.049
Smoker	0.262	0.557	0.151	0.030	0.198	0.563	0.192	0.046
No regular exercise	0.227	0.539	0.186	0.047	0.183	0.553	0.201	0.063
Regular exercise	0.347	0.517	0.114	0.022	0.294	0.531	0.147	0.028
Effect of illness								
Episodes = 1	0.321	0.528	0.124	0.026	0.279	0.561	0.136	0.025
Episodes = 2	0.296	0.533	0.141	0.030	0.246	0.564	0.158	0.032
Episodes = 3	0.275	0.533	0.157	0.035	0.219	0.560	0.181	0.040

Note: Simulations are based on estimated results from Model 3.

The simulations discussed earlier indicate that when every individual's observed education level is replaced with a *specific* level of education, higher levels improve the probability of excellent health (Table 6). Despite this, increasing the observed years of schooling *by one* for each individual reduces the probability of excellent health by 6.5% among males (Table 9). However, this finding does not indicate that education is detrimental to health. The probabilities of good health increase by 6.2% under the scenario and the probabilities of fair and poor decrease by 5.8% and 14.7%. Among females, the productive effect of a one year increase in years of schooling is an improvement in the probability of excellent health by 17.7%. Among males, the allocative effect of education serves to increase the probability of excellent health by 3.0%; the allocative effect among females is 9.9%. Given these figures, the combined effect (productive + allocative effect) of one additional year of education is a decrease in the probability of excellent health by 3.5% among males and an increase in the probability of excellent health by 27.6% among females. As is also shown in the table, the total effect of an additional year of education is an increase in the probability of good health and a decrease in the probabilities of fair and poor health.[15]

As explained in Section 2, we model an individual's level of illness throughout the year and allow it to influence medical care consumption and health production. In order to evaluate the effect of illness on the education results of interest, we re-estimated Model 3 without an equation for illness and restricted the coefficient on illness to zero in the relevant equations. The effect of the omission is to greatly reduce the allocative effect of education for males, but produces only small differences in both the productive and allocative effect of education for females. Because the original Model 3 included an equation for the number of episodes, the effects of unobservables on illness behavior were allowed to influence the estimated distribution of unobserved heterogeneity. By omitting the illness equation and by not controlling for illness, we find that the estimated effects of education, through the consumption of health inputs, diminish.

4.4. Unobserved Heterogeneity

Allowing for an unspecified, but estimated, distribution of unobserved heterogeneity improves the fit of the empirical model. Two points of support of the discrete distribution provide the best fit (as opposed to three or more points of support); the direction of influence of the estimated unobserved heterogeneity makes sense in each equation. The estimated weight

Table 7. Health inputs simulations-males

Number of curative visits	0	1	2	3–5	6–10	11–15	16 +	Ave
Actual distribution	0.484	0.164	0.097	0.122	0.068	0.026	0.038	2.796
Predicted distribution	0.490	0.169	0.096	0.119	0.064	0.024	0.038	2.532
Education = 8	0.480	0.169	0.097	0.121	0.066	0.026	0.040	2.642
Education = 11	0.486	0.169	0.097	0.120	0.065	0.025	0.039	2.572
Education = 12	0.488	0.169	0.097	0.119	0.064	0.025	0.038	2.550
Education = 16	0.496	0.169	0.096	0.118	0.062	0.024	0.036	2.460
Education = 18	0.500	0.169	0.096	0.117	0.062	0.023	0.035	2.416
Number of preventive visits	0	1	2	3 +	Ave			
Actual distribution	0.779	0.133	0.043	0.045	0.441			
Predicted distribution	0.782	0.131	0.042	0.045	0.397			
Education = 8	0.810	0.116	0.036	0.038	0.340			
Education = 11	0.793	0.125	0.040	0.043	0.376			
Education = 12	0.787	0.128	0.041	0.045	0.388			
Education = 16	0.761	0.140	0.046	0.052	0.442			
Education = 18	0.747	0.147	0.050	0.057	0.474			
Lifestyles	Smoking		Exercise					
	Yes	No	Yes	No				
Actual distribution	0.358	0.642	0.652	0.348				
Predicted distribution	0.358	0.642	0.652	0.348				
Education = 8	0.537	0.463	0.578	0.422				
Education = 11	0.460	0.540	0.643	0.357				
Education = 12	0.418	0.582	0.658	0.342				
Education = 16	0.208	0.792	0.689	0.311				
Education = 18	0.113	0.887	0.688	0.312				

Note: Simulations are based on estimated results from Model 3.

on each mass point is 35.9% and 64.1% for males and 41.6% and 58.6% for females.[16] Table 10 provides simulations for the entire sample (unconditional on unobserved heterogeneity) and conditional on each unobserved type. While we can never be sure of the correct interpretation to place on the unobserved heterogeneity that characterizes individuals, we can tell a story that substantiates the estimated distribution and subsequent predicted behavior. For example, the estimated unobserved characteristics of type 1 individuals depict them as more likely to be in poorer health and to be uninsured or have public insurance. They are also less likely to report illnesses and to seek medical attention. They are more likely to smoke and males are less likely to exercise. Perhaps individuals of type 1 have less knowledge about the detrimental effects of lifestyles such as smoking or the beneficial effects of exercise and regular medical care and, therefore, smoke more, exercise less, seek less care, and are in worse health. Another interpretation is that individuals of type 1 have a higher rate of time preference. That is, they discount the future more; they are more myopic. They do not consider the effects of lifestyles and consumption of medical care on future behavior and, thus, exhibit the observed behavior. Despite the interpretation, the use of a discrete factor random effects estimator to capture unobservables that might be influencing the outcomes of interest is an effective method of purging the estimates of endogeneity bias while also providing a description of behavior that is consistent with unobservable characteristics of individuals.

5. CONCLUSIONS

Previous literature about the health-schooling correlation focuses on either the direct causal relationship between education and health, the possible effect of unobservables, or the effect of health on educational attainment. As such, the focus of these studies has been either to determine causality or to investigate the possibility of a spurious correlation between the two outcomes. Furthermore, previous analyses of the direct effect of educational attainment on health status lend strong support for a positive correlation, but few have modeled the endogenous contribution of health inputs in a model of health production. Even less common is the distinction between curative and preventive medical care as inputs to the production of health.

In this paper we explore the possibility of medical care and lifestyle behaviors as intervening variables in the relationship between health and schooling. Although data limitations prevent us from modeling

Table 8. Health inputs simulations-females

Number of curative visits	0	1	2	3–5	6–10	11–15	16 +	Ave
Actual distribution	0.379	0.164	0.105	0.157	0.097	0.039	0.058	3.880
Predicted distribution	0.380	0.173	0.106	0.154	0.094	0.037	0.056	3.502
Education = 8	0.371	0.173	0.107	0.156	0.096	0.038	0.059	3.605
Education = 11	0.383	0.173	0.106	0.154	0.093	0.037	0.056	3.473
Education = 12	0.384	0.173	0.106	0.153	0.093	0.036	0.055	3.454
Education = 16	0.380	0.173	0.106	0.154	0.094	0.037	0.056	3.505
Education = 18	0.371	0.173	0.107	0.156	0.096	0.038	0.059	3.607
Number of preventive visits	0	1	2	3 +	Ave			
Actual distribution	0.617	0.212	0.087	0.084	0.800			
Predicted distribution	0.620	0.211	0.086	0.082	0.713			
Education = 8	0.707	0.181	0.061	0.051	0.506			
Education = 11	0.647	0.204	0.078	0.071	0.645			
Education = 12	0.625	0.210	0.084	0.080	0.700			
Education = 16	0.557	0.225	0.104	0.115	0.891			
Education = 18	0.548	0.226	0.107	0.120	0.917			
Lifestyles	Smoking		Exercise					
	Yes	No	Yes	No				
Actual distribution	0.303	0.697	0.490	0.510				
Predicted distribution	0.303	0.697	0.490	0.510				
Education = 8	0.383	0.617	0.420	0.580				
Education = 11	0.361	0.639	0.468	0.532				
Education = 12	0.338	0.662	0.484	0.516				
Education = 16	0.194	0.806	0.547	0.453				
Education = 18	0.117	0.883	0.577	0.423				

Note: Simulations are based on estimated results from Model 3.

Table 9. Total effect of one additional year of education on health outcomes

	Percentage change in health		
	Total effect	Productive effect	Allocative effect
Males			
Excellent	−3.48	−6.47	3.00
Good	6.22	6.18	0.04
Fair	−9.68	−5.76	−3.92
Poor	−19.65	−14.71	−4.94
Females			
Excellent	27.62	17.70	9.92
Good	4.73	7.12	−2.38
Fair	−40.96	−35.43	−5.53
Poor	−38.61	−41.67	3.06

all avenues that may lead to a positive correlation between health and schooling, the data richness of the NMES allows us to distinguish between the productive and allocative effects of education by modeling the consumption of several health inputs including curative medical care and preventive medical care. Observations of illness during the year allow us to model illness events that trigger consumption of these inputs. Our empirical results provide three conclusions. First, we confirm the significant productive effect of education on health status. Although an additional year of education appears to reduce the probability of excellent health slightly among males, it improves the probability of good health and reduces the probability of fair and poor health considerably. Among females, the productive effect of an additional year of schooling increases the probabilities of excellent and good health and decreases the fair and poor health probabilities. In addition to this direct effect of schooling on health, education indirectly affects the

Table 10. Simulations by unobserved types

	Males				Females			
	Health status							
	Exc	Good	Fair	Poor	Exc	Good	Fair	Poor
Sample	0.309	0.518	0.139	0.034	0.243	0.534	0.175	0.048
"Type" 1	0.226	0.491	0.207	0.076	0.183	0.509	0.210	0.098
"Type" 2	0.355	0.534	0.102	0.009	0.285	0.552	0.150	0.013
	Average number of visits or episodes							
	Curative visits	Preventive visits	Illness episodes	Curative visits	Preventive visits	Illness episodes		
Sample	2.532	0.397	2.022	3.502	0.713	3.001		
"Type" 1	2.055	0.054	1.548	3.110	0.089	2.066		
"Type" 2	2.800	0.589	2.289	3.782	1.157	3.666		
	Health insurance							
	Private	Public	Uninsured	Private	Public	Uninsured		
Sample	0.791	0.054	0.156	0.754	0.111	0.135		
"Type" 1	0.616	0.099	0.285	0.623	0.141	0.237		
"Type" 2	0.889	0.028	0.083	0.847	0.090	0.063		
	Lifestyles							
	Smoke now		Exercise regularly		Smoke now		Exercise regularly	
	No	Yes	No	Yes	No	Yes	No	Yes
Sample	0.642	0.358	0.348	0.652	0.697	0.303	0.510	0.490
"Type" 1	0.506	0.494	0.405	0.595	0.634	0.366	0.509	0.491
"Type" 2	0.719	0.281	0.316	0.684	0.742	0.258	0.512	0.488

Note: Simulations are based on estimated results from Model 3.

health outcomes of individuals by influencing the allocative efficiency with which people of varying education levels select and use inputs to produce health. An additional year of schooling increases the allocative efficiency for both genders. Among males, education has the largest positive influence through consumption of curative medical care inputs. Among females, education's greatest influence is on increased exercise and decreased smoking. Overall, the combined impact of the productive and allocative effects of completing one more year of school for males is a 3.5% decrease in the probability of excellent health and a 19.6% decrease in the probability of poor health. An additional year improves the probability of excellent health by 22.6% for females and decreases the probability of poor health by 35.6%.

Secondly, controlling for unobserved heterogeneity has a substantial impact on the parameter estimates. Our method improves the efficiency of the estimates as evidenced by results from Model 1 and Model 3. We also demonstrate that this method of controlling for unobservables that lead to endogeneity bias in the estimates is superior to the method of using the predicted values of endogenous inputs (Model 2). Unlike other studies that have studied the effect of unobservables or spurious correlation, we do not impose a distribution on these latent variables and, instead, estimate the distribution using a discrete factor method that lets the data dictate its form.

Finally, our estimates reveal that failing to model the illness level of an individual over the period of observation (in this case, one year) can lead to misleading predictions of the effects of medical inputs. While we are not completely satisfied with our measure of illness during the year, namely the number of episodes of illness over the year, we find these results promising. We intend to further our interest in modeling the severity of illness by incorporating specific diagnoses and duration of illness as the data permit.

NOTES

1. In one of the earliest empirical studies, Auster *et al*. (1969) estimated the contribution of several variables, including medical services, education, income, and cigarette consumption, to death rates across states. Their calculations suggested that an improvement in population mortality rates could be achieved through a marginal transfer of expenditures from medical services to education.
2. We are unable to explain educational attainment because the dataset that we use contains a panel of

only one year. Additionally, parental background information, often used to explain accumulation of schooling, is not available for prime age individuals in the sample.

3. The data for his study are drawn from a sample of residents of Alameda County, California. The survey elicited information on seven lifestyle practices associated with good health (the "Alameda Seven") including eating breakfast regularly, maintaining proper weight, not snacking between meals, never smoking cigarettes, engaging in regular physical activity, consuming moderate or no amounts of alcohol, and getting 7–8 hours of sleep regularly.
4. Although we do not specify the budget constraint here, it is a function of income, medical care prices, health insurance characteristics, and prices associated with consumption of different lifestyles.
5. Ideally we would like a measure of the duration and severity of illness as well as the number of episodes during the survey period. While the NMES asks about lengths of illnesses, there are many missing values for this variable. The NMES also records the International Classification of Diseases, 9th Edition (ICD-9) code for all reported illnesses. It is difficult, however, to aggregate the specific illness diagnoses to a measure of annual severity of illness during the year.
6. Because we want to measure both the productive and allocative efficiency of education, health inputs are distinguished by curative and preventive medical care, smoking, and exercise. We recognize that lifestyle decisions regarding, for example, alcohol consumption and drug use, may also influence one's health status. In fact, many analyses in the empirical health literature have sought to explain the influence of different inputs, including the "Alameda seven", alcohol consumption, cigarette smoking, drug use, physical activity, job activities and exposure, seat belt use, and conventional medical care, on the production of health. (Although the many articles are too numerous to list, most of the works cited in this paper provide references to these and similar articles.) While each of these inputs may prove to be an important determinant of health, it is difficult to model the endogenous consumption of each input due to data constraints and computational restrictions. No datasets provide information on all of these inputs and most contain information on only one or two at a time. Estimation of these demands also requires a considerable amount of data detail in order to provide enough variables that allow for identification of all the parameters in the model. Consequently, we model the demand for curative and preventive care as well as other behaviors that are observed in the NMES data (i.e., smoking and exercise). We interpret the results with caution given possible omitted lifestyles associated with production of health.
7. There are concerns in the literature about the subjective measurement error associated with self-reported health status. Problems with self-reporting may be exacerbated by correlation with education level. Other possible measures of health that have been used in different studies include restricted activity days, absences from work, work or functional limitations, blood pressure, and weight. We choose not to focus on these other measures for several reasons. First, restricted activity days and absences from work measure the flow of health services from a given level of health stock. Additionally, they accumulate over the same period of observation as medical care consumption. As such, they do not measure one's overall general level of health, but rather, the endogenous decisions of an individual during an episode of illness. (See Gilleskie (1998) for a model of medical care consumption and work absenteeism during an illness episode.) Secondly, measures of work or functional limitations capture one aspect of health, but not the notion of overall general health. There is also some concern that non-working individuals have psychological and economic incentives to report such limitations in order to rationalize or legitimize not working (Bound, 1991). Finally, blood pressure is not used because it is not available in the dataset and we use weight (or body mass index) this year as a proxy for past health because of its persistence characterized by gradual positive and negative fluctuations.
8. The results in the paper from Model 3 have two points of support in the heterogeneity distribution. Three points of support did not provide a significant improvement in the fit over two points of support. The model is identified without exclusion restrictions because of the nonlinearity of the discrete factor specification, but as indicated below we have imposed some exclusion restrictions to provide additional identification. The Appendix contains further detail about the method used in Model 3.
9. Other variables that may serve as better exclusion restrictions such as parental health or previous medical care use are not available.
10. Initial conditions, such as the body mass index and the number of chronic conditions, are determined by behavior up to the first observation period. Because we have no data on the determinants of behavior prior to the survey, we cannot explain the initial conditions as endogenous outcomes. Attempts to model the reduced form determinants of our proxies for past health were unsuccessful due to a lack of identifying variables and lack of convergence given the large number of parameters in the jointly estimated model.
11. Estimated separately, likelihood ratio tests indicate that a multinomial logit model or the two-part model used extensively in the health care literature are slightly better models to explain these outcomes. However, we were unable to obtain convergence due to the large number of parameters in the model with multiple multinomial logit equations and a lack of exclusion restrictions prevented us from pursuing the two-part model.
12. If family composition and location are chosen jointly with other modeled behaviors, then they may be correlated with unobserved factors and create endogeneity bias. However, we allow them to enter the model and presume that they will not contaminate the results.
13. Likelihood ratio tests indicate that full interactions with a female dummy (or estimation on split samples) are warranted and, thus, results are shown by gender.
14. We simulate behavior of each individual allowing the individual to maintain all of his observed characteristics except for the variable of interest in the simulation. We integrate over the estimated heterogeneity distribution and average behavior over the entire sample.
15. One explanation for our finding that the productive efficiency of education (i.e., the effect of education holding all inputs constant) is negative is the omission of important health inputs. That is, if we fail

to include inputs that explain differences in health and that are influenced by education, then our measurement of the productive efficiency of education includes the effects transmitted through the omitted variables. One example is stress. Stress is likely to have a negative effect on health levels. Stress is also likely to increase with higher levels of education (i.e., higher stress jobs).

16. Each mass point is a particular value of the unobserved variable within its distribution. We can loosely interpret the two mass points as representing two types of individuals. That is, consider two observed age categories (e.g., below and above age 45) within a distribution of ages among the population. We could refer to an individual in the sample who falls into one of these age categories as either young or old.

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APPENDIX A

Appendix

Let B be the set of all behaviors of interest in this model. That is, B includes the health status outcome, the number of curative visits, preventive visits, and illness episodes, an indicator of smoking and regular exercise, and the health insurance outcome. Let J_b define the number of outcomes associated with each behavior $b, b = 1, \ldots, B$. Finally, an indicator d^j_{bn} identifies the observed outcome for each individual n in the sample of size N. That is, $d^j_{bn} = 1$ if individual n is observed to have outcome j for behavior b; zero otherwise. More specifically, individual n may be observed to be in excellent health status, for example. In this case, the probability of a particular health outcome, j, is

$$p(d^j_{bn} = 1|\mu) = \frac{\exp(\boldsymbol{A}_b\alpha_{bj} + \rho_{bj}\mu)}{\sum_{j'=1}^{J_b} \exp(\boldsymbol{A}_b\alpha_{bj'} + \rho_{bj'}\mu)} \tag{A1}$$

where J_b indicates the number of health outcomes and A_b is the vector of explanatory variables defined in Equation (6) of Section 3.

Let Θ denote the vector of parameters in the model, including the points of support of the distribution of unobserved heterogeneity, μ, and the factor loadings, ρ_{bj}. The contribution of individual n to the likelihood function, conditional on μ, is

$$\mathcal{L}_n(\Theta|\mu) = \prod_{b=1}^{B} \left[\prod_{j=1}^{J_b} p(d^j_{bn} = 1|\mu)^{d^j_{bn}}\right]. \tag{A2}$$

Unconditional on the permanent heterogeneity component μ, the likelihood contribution of individual n is

$$\mathcal{L}_n(\Theta,\theta) = \sum_{m=1}^{M} \theta_m \mathcal{L}_n(\Theta|\mu_m) \tag{A3}$$

where θ is the vector of probabilities of the M points of support of the heterogeneity distribution.

Finally, the likelihood function for a sample of size N is

$$\mathcal{L}(\Theta,\theta) = \prod_{n=1}^{N} \mathcal{L}_n(\Theta,\theta). \tag{A4}$$

Table A1. Input equation results for education variables

	Males		Females	
Curative visits				
Education	–0.010 (0.016)		–0.089 (0.044)	
Education^2/10			0.034 (0.018)	
Preventive visits				
Education	0.081 (0.179)		–0.294 (0.163)	
Education^2/10	–0.026 (0.177)		0.403 (0.166)	
Education^3/100	0.007 (0.054)		–0.120 (0.051)	
Smoke now-yes				
Education	0.225 (0.045)		0.316 (0.056)	
Education^2/10	–0.178 (0.019)		–0.184 (0.023)	
Regular exercise-no				
Education	–0.220 (0.043)		0.075 (0.046)	
Education^2/10	0.065 (0.018)		–0.004 (0.019)	
Health insurance	Public	Uninsured	Public	Uninsured
Education	–0.314 (0.235)	0.237 (0.198)	–0.124 (0.210)	0.365 (0.196)
Education^2/10	0.010 (0.252)	–0.444 (0.204)	0.035 (0.228)	–0.618 (0.201)
Education^3/100	0.009 (0.082)	0.124 (0.064)	–0.060 (0.077)	0.191 (0.064)

Note: These estimates are from Model 3.
Absolute values of standard errors are in parentheses.