Estimating Interdependence between Health and Education
in a Dynamic Model

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Abstract

This paper investigates to what extent and through which channels that health and education are interdependent. We develop a dynamic programming model of joint decisions of young men on schooling, work, home, health expenditure, and savings. The structural framework explicitly models two existing hypotheses on the positive correlation between health and education. The estimation results strongly support the interdependence between health and education. On average, an individual who has been sick before age 21 has 1.08 less years of schooling compared with those who are healthy. Moreover, a twenty-year-old individual with four more years of education would be about 6 percent less likely to be sick given that he is healthy and spends nothing on health. Policy experiments indicate that a high school health expenditure subsidy would have a larger impact on education and wellbeing than a college tuition subsidy.

Key Words: dynamic model, health, education, indirect inference.
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1. Introduction

The highly positive correlation between health and education has been well documented in numerous literatures.¹ This finding is robust even after controlling for different measures of socio-economic status, such as income and race, and regardless of whether health levels are measured by mortality rates, self-reported health status, or physiological indicators of health.

This paper studies the existing two competing explanations of this correlation.² The first explanation argues that education improves health by raising economic conditions in per capita income so that a higher expenditure in health is possible, and/or by increasing knowledge of health issues (Grossman 1975; Kenkel 1991; Rosenzweig and Schultz 1991; Lleras-Muney 2005). This explanation suggests that more education is the cause of better health. The second explanation argues the reverse causality, i.e., better health results in more education; healthier students may be more efficient in studying (Perri 1984, Currie and Hyson 1999). Better health may also increase the demand for education because of longer life expectancy (Gan and Gong 2004; Soares 2005; Jayachandran and Lleras-Muney 2009).

Clearly, these two explanations may not be mutually exclusive (Grossman 2000). The purpose of this paper is to study to what extent and through which channels that health and education are interdependent. In this paper, we estimate a dynamic programming model of joint decisions of young men on schooling, work, home health expenditure, and savings. The structural framework explicitly models the correlation between health and education in the existing theoretical hypotheses, and thus the structural approach provides us a possibility to evaluate relative importance of alternative hypotheses. Moreover, the estimated model is used to evaluate the effects of policies such as financial support in health expenditure and/or in college education on an individual’s education, wealth, health and wellbeing.

Previous empirical studies on the correlation between health and education are

¹ See Grossman and Kaestner (1997) for an extensive review.
² A third explanation argues the existence of a “third factor” that affects both health and education in the same direction. For example, Fuchs (1982) states that time discount rates could be an explanation for the correlation between health and education: patient people would highly value future income and health—and thereafter invest more in education and spend more time and money on activities related to health—while impatient people would invest less in education and health.
typically based on the models with a static setting. The static setting creates at least two
problems. First, since schooling and health are inherently endogenous, finding the proper
and reliable instruments for either health or schooling is often difficult.\(^3\) Second, a typical
static model will have difficulty in describing individuals who may have distinctive paths
even if they experience similar shocks. For example, a low academic ability creates a
higher risk of reaping the wage benefits of schooling, and a higher probability of failing a
grade. When facing a negative health shock, an individual with a lower academic ability
may choose to drop off school. His path in consumption, health status, and working,
therefore, may differ systematically from those who have high academic abilities but face
similar negative health shocks.

This paper develops a dynamic model in an uncertain environment. The model
allows heterogeneity in work skills, study skills, and health status for youth aged 16.\(^4\) The
heterogeneity may be either innate or a result of prior parental and youth investment
behavior. The model contains a number of channels that can account for interactive
effects between health and education. First, the model allows the possibility that
education may affect the chance of getting sick, as more educated people are more
efficient producers of health.\(^5\) In addition, since an individual’s wage depends on his
education, the individual’s education has an indirect effect on his health expenditure. In
both cases, more education may lead to better health.

Second, health is assumed to affect academic performance. The probability for an
individual to pass or fail a grade depends not only on his academic ability but also on his
health. Better health improves the productivity of the study and hence might increase the
educational attainment. Similarly, the model also assumes that health affects
productivities at work and at home and therefore affects wages at work and output in

\(^3\) Another concern about the instrumental variable method is that it provides an estimate for a specific
group, i.e., people whose behavior can be manipulated by the instrument (Angrist and Krueger, 2001).
\(^4\) The sample selection of individuals above age 16 is based on the Fair Labor Standards Act (FLSA),
which restrains children under the age 16 from working under conditions that affect their schooling
and health.
\(^5\) The efficiency effect, discussed in detail by Grossman (2000), can take two forms: productive
efficiency and allocative efficiency. Productive efficiency pertains to a situation in which the more
educated obtain a larger health output from given amounts of endogenous (choice) inputs. Allocative
efficiency pertains to a situation in which schooling increases information about the true effects of the
input on health (Kenkel 2000). Allocative efficiency will improve health to the extent that it leads to
the selection of a better input mix.
Third, health is assumed to affect survival rate. Sickness decreases the survival rate and thus reduces the effective time discount rate, which may result in less school attendance since the individual values his current consumption more at the expense of investment in the future. Although the reduction in survival rate and thus a reduction in effective time discount rate may be viewed as the third factor (Fuchs 1982, also see footnote 2) that reduces both health and education, the reduction in survival rate is still caused by health.

Finally, an individual’s future health status is dependent on his past and current health status. The individual is assumed to be constantly at risk of sickness. Past and current health status affects future health because they contribute to the level of the individual’s physical and mental states. Grossman (1972) suggests health to be a stock variable. Allowing past and current health status to affect future health status captures an important aspect of health as a stock variable.

The model is estimated using data from the 1979 youth cohort of the National Longitudinal Surveys of Youth (NLSY79). For a representative sample of youth beginning at age 16, the data set provides longitudinal information on school enrollment, grade transcripts, work status, wages, assets, sickness, and the duration of sickness.

Estimation of the model strongly supports the interdependence between health and education because the coefficients that correspond to two hypotheses are all significantly estimated. In particular, the estimated sickness function indicates that an individual’s probability of being sick is affected by his education, health expenditure, his previous health status. A twenty-year-old individual with four more years of educational attainment would be about 6 percent less likely to be sick given that he is healthy and spends nothing in health. Moreover, health has a substantial effect on an individual’s mortality rate, wage, home production, and academic success in school. Indeed, health plays an extremely important role in determining an individual’s education. On average, an individual who has been sick before age 21 has 1.08 less years of schooling compared with those who are healthy.

Finally, the estimated model is used to perform two policy experiments: a college tuition subsidy and a high school health expenditure subsidy. To assess the efficiency of
the policies, we let these two experiments have the same per capita cost. The results reveal that a high school health expenditure subsidy would have a larger impact on education and wellbeing than a college tuition subsidy. Specifically, an annual $2,000 college tuition subsidy will favor healthy individuals: those who have high academic ability will have the largest increase in their wellbeing while those who have low academic ability will have the largest increase in their years of schooling. By contrast, a subsidy of high school health expenditure of the same cost will favor sick individuals, especially those sick and having high academic ability will have the largest increases in both schooling years and wellbeing.

Since the NLSY does not contain direct observations on health expenditure, the model has to infer the health expenditure from the individual’s trajectory of asset accumulation and his choice decisions such as work and school attendance. A key assumption for identifying the unobserved health expenditure is that only the individuals whose incomes are above a minimum level spend on health. Below this minimum level, the individual’s primary concern is the consumption of necessary commodities. The minimum income level is exogenous to the individual, although it is estimated as a parameter in the structure model. The identification of health expenditure is achieved by comparing the different paths of asset accumulation among high-income groups who spend on health and low-income groups who do not.

The estimation of the model applies the method of indirect inference (Gourieroux, Monfort, and Renault, 1993; Keane and Smith, 2004) and the method of simulation and interpolation by Keane and Wolpin (1994). Typically, dynamic discrete choice models are estimated using maximum likelihood (ML) or method of moments (MOM). When the number of alternatives is large, evaluation of choice probability required by ML or MOM is computationally burdensome, because the choice probability is a high dimensional integral over stochastic factors that affect the individual’s utility at each alternative. In addition, unobserved initial conditions, unobserved state variables, and variables with missing data may also create computational problems. In this paper, many initial conditions and state variables are unobserved. Asset information for 1979-1984 and 1991 and transcript records beyond high school are missing.

The idea of indirect inference is to use a descriptive statistical model to summarize
the statistical properties of the observed and simulated data from the structural economic model. Then the structural parameters are chosen so that the coefficients of the descriptive statistical model in the simulated data match as closely as possible those in the observed data. Since the indirect inference method uses simulated data, it avoids the need to construct the choice probabilities while provides a practical simulation-based approach to deal with this “curse of dimensionality” problem and missing data problem. However, the implementation of indirect inference method in a discrete choice model encounters a problem due to the non-smooth objective function. Keane and Smith (2004) suggest using continuous latent variables which are smooth functions of the structural parameters to substitute the discrete choice variables. Their method proves to be effective in practice.

The paper is organized as follows. Section 2 presents the model, its basic structure, solution method, estimation method, and parameterization. Section 3 describes the data. Section 4 presents the estimation results and describes the policy applications. Section 5 concludes the paper.

2. Model

The model corresponds to the decision problem of a young man beginning at age 16. At each period, he decides to be in one of the three states: work, schooling, or staying at home. In addition, he chooses the amounts of health expenditure and saving. This section presents the structure of the model with the environment settings, the solution of the model, and the estimation method.

2.1. Basic structure

2.1.1. Choice set

The element of an individual’s choice set at each period $t$ consists of a combination of activity choice $d^1_t$, asset $d^2_t$, and health expenditure $d^3_t$. The individual chooses one of the three states: work, schooling, or staying at home. The activity choice vector $d^1_t$ hence has three dummy variables: $d^1_{1,t} = 1$ if the individual chooses to work at period $t$, otherwise $d^1_{1,t} = 0$; $d^1_{2,t}$ and $d^1_{3,t}$ correspond to going to school or staying at home.
Their values are similarly defined as \( d_{i,t}^j \). At each period \( t \), \( \sum_{j=1}^{3} d_{i,t}^j = 1 \).

In addition, the individual at each period will choose the level of assets. To improve the tractability of the problem, the continuous asset level is discretized into \( K \) fixed number of discrete levels of savings, \( \{\Delta A^1, \Delta A^2, \ldots, \Delta A^K\} \), where \( A \) is the level of assets, and \( \Delta A_{t+1} = A_{t+1} - (1 + r)A_t \). The asset choice vector \( d_{i,t}^2 \) includes \( K \) mutually exclusive alternatives, with \( \sum_{k=1}^{K} d_{k,t}^2 = 1 \), i.e., \( d_{k,t}^2 = 1 \) if \( \Delta A^k \) is chosen, otherwise \( d_{k,t}^2 = 0 \). It is necessary to point out that net borrowing is allowed since \( \Delta A \) may be less than zero.

Finally, the continuous health expenditure is also divided into the \( M \) fixed number of discrete levels that are not less than zero: \( \{h^1, h^2, \ldots, h^M\} \). Denote \( 1 \times M \) vector \( d_{i,t}^3 \) as the decision on the level of health expenditure with \( \sum_{m=1}^{M} d_{m,t}^3 = 1 \), i.e., \( d_{m,t}^3 = 1 \) if \( h^m \) is chosen, otherwise \( d_{m,t}^3 = 0 \).

In summary, given the three choice vectors \( d_{i,t}^1, d_{i,t}^2, \) and \( d_{i,t}^3 \), the number of the individual’s choice set at each period \( t \) is \( 3 \times K \times M \).

### 2.1.2. Environment settings

In order to understand how the individual chooses alternatives in response to the current information set and stochastic shocks, it is useful to first describe the environment settings.

Individuals differ in their skill endowments, health status, and schoolings. At each age, individuals make choices among mutually exclusive and exhaustive alternatives on activities of schooling, work, or home, on net savings, and on health expenditure. The health status and incomes from work and home have stochastic elements that are known to the individuals prior to the current-period decision but are unknown prior to the beginning of the current period. Although the individuals do not know if they will succeed in school before making the decision of whether to attend school, they know the probability of passing or failing the grade. Individuals may take divergent paths of schooling, work, home, savings, and health expenditure because of the cumulative effects.
of various shocks, and because they have heterogeneous skill endowments and heterogeneous initial health status.

Figure 1 illustrates the order in which stochastic shocks happen and the timing of an individual’s choices on alternatives. At the beginning of period $t$, the individual’s health status (sick or healthy) is known, and the random shocks to wage and home production are realized. Then the individual chooses alternatives from amongst a combination of activity choices (job participation, school attendance, or staying at home), the levels of savings and health expenditure. If he enrolls in school, the individual will receive a shock for the grade, which will impact his success in passing the grade. At the end of period $t$, the agent will get a health shock, which, together with his prior educational attainment and current health expenditure, will determine his health at period $t+1$. The whole pattern at period $t$ is repeated at period $t+1$.

### 2.1.3. Dynamic programming

The individual is assumed to maximize the present discounted value of lifetime utility from age 16 ($t=1$) to a known terminal age, $t = T$. The value function at $t$ is given by:

$$V_t(\Omega_t) = \text{Max} \ E \left[ \sum_{s=t}^{T} \delta^{t-s} u(c_s) P_{s|t} \Omega_t \right],$$

where $E$ is the expectation operator, $\delta$ is the subjective time discount factor, and $u(c_s) = c_s^{1-\rho} / (1 - \rho)$ is the contemporary utility at period $s$. $P_{s|t}$ is the conditional survival rate at period $s$ based on the information set at period $t$, $\Omega_t$. The information set, known at the beginning of period $t$, includes age, education, work experience, health, accumulated assets, and contemporaneous shocks from wage and home production. The maximization of the objective function (1) is achieved by choices of the optimal sequence of feasible control variables $\{d_s^1, d_s^2, d_s^3\}$, given current realizations of stochastic shocks.

The budget constraint for the individual is given by:

$$c_t + \Delta A_{t+1} = w_t \ast d_{t,1}^1 + e_t \ast d_{t,1}^1 - ec \ast I(\text{edu}_t > 12) \ast d_{t,1}^2 - h_t,$$

where $w_t$ is wage, $e_t$ is home production including compensation for not working, $ec$ is the cost of education beyond high school, $h_t$ is the health expenditure, and $edu_t$ is the
level of educational attainment. \( I(\cdot) \) is the indicator function which equals one if the argument holds and zero otherwise. The cost of education is assumed to be zero when \( \text{edu} \) is less than or equal to 12 years (completion of high school). Note that in this paper, educational attainment and years of schooling are two different concepts. Years of schooling are the total years that the individual has attended school, while educational attainment is the effective years of schooling, i.e., the total years of schooling minus the number of grades that the individual fails.

Health expenditure, such as spending on appropriate nutrition, vacation, and health clubs, affects an individual’s survival. To make the model tractable, we do not model the individual’s choice decision on health insurance and its subsequent effect on the individual’s behavior.\(^6\) As stated above, the identification of health expenditure comes from a threshold of income. Only after the income is larger than this threshold will the individual spend on health. More specifically, let \( \text{NIB} \) be the income boundary such that the health expenditure is strictly positive, if \( rA_t + w_t d^1_{1,t} + e_t d^1_{3,t} > \text{NIB} \), and zero otherwise.\(^7\) It should be noted that although people with an income below the threshold will not spend on health, they still have chances implied by random shocks to back to healthy status from sickness.

Initial conditions include the values of state variables by the beginning of age 16: health status, the duration of prior sickness, the years of work experience, and the level of assets accumulated. Both work experience and the level of assets at age 16 are assumed to be zero.

### 2.1.4. Probability of sickness

Health status (healthy or sick) is uncertain prior to the next decision horizon. The

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\(^6\) Insured and uninsured people show many differences in behaviors related to health, including seatbelt use, diet, and exercise. Moreover, both the supply and demand for insurance depend on health status, which confounds the causal effect between insurance coverage and health. Indeed, evidence that access to health insurance causes better health is limited (Newhouse 1993; Levy and Meltzer, 2001; Fang, Keane and Silverman, 2008).

\(^7\) We do not impose a minimum level of consumption or consumption floor in the model as in Hubbard, Skinner and Zeldes (1995). Since the NLSY79 does not collect consumption and health expenditure information, it is impossible to simultaneously identify both the consumption floor and the income threshold of positive health expenditure. We focus on the individual’s unobserved health expenditure.
health status for an individual in the next period is assumed to depend on his age (age),
health expenditure, educational attainment, and current health. Define the latent health
status as:

\[ H_{t+1}^* = \beta_1 \text{age}_{t+1} + \beta_2 h_t + \beta_3 \text{edu}_{t+1} + D_t \left( \beta_4 + \beta_5 \text{s}l_t \right) + \varepsilon^S_{t+1}, \tag{3} \]

where \( \beta \)'s are parameters. \( D_t \) is an indicator for health status at period \( t \), i.e., \( D_t = 1 \) if the
individual is sick at period \( t \), otherwise \( D_t = 0 \). \( \text{s}l_t \) is the duration of prior sickness or the
number of continuous years that the individual has been sick up to period \( t \).\(^8\) If an
individual is currently sick, his previous sickness, measured by \( \text{s}l_t \), may affect his
succeeding health status. However, if an individual is currently healthy, his previous
sickness is simply assumed to have no impact on his succeeding health status. The
parameter \( \beta_3 \) reflects the idea that more educated people may have better knowledge of
health issues and thereby refrain from activities that are harmful to health. \( \varepsilon^S_{t+1} \) is the
serially independent standard normal distribution. Then:

sick or \( D_{t+1} = 1 \) if \( H_{t+1}^* > 0 \),
not sick or \( D_{t+1} = 0 \) if \( H_{t+1}^* \leq 0 \).

It is important to note that \( H_{t+1}^* \) in equation (3) is related to but different from the
health capital of Grossman (1972). To model Grossman’s health capital, \( H_{t+1}^* \) would
have to depend on \( H_t^* \). Since both \( H_{t+1}^* \) and \( H_t^* \) are unobserved, such a model would
be very difficult to estimate. Instead, we use an observed binary variable \( D_t \) and an
accumulative stock variable \( \text{s}l_t \) to approximate \( H_t^* \). Compared with the effect of most
current health status \( D_t \), our estimation results show that the effect of \( \text{s}l_t \) is very small.

2.1.5. Survival rate

An individual’s survival rate is assumed to be affected by his current health status, \( D_t \),
and the duration of prior sickness, \( \text{s}l_t \). The mortality rate \( m_t \) is given by:

\[ m_t = \frac{P_{t+1} - P_t}{P_t} = \begin{cases} \hat{m}_t e^{a_0 + D_t(a_1 + a_2 \text{s}l_t)}, & \text{if } \hat{m}_t e^{a_0 + D_t(a_1 + a_2 \text{s}l_t)} < 1, \\ 1, & \text{otherwise} \end{cases} \tag{4} \]

where \( \hat{m}_t \) is the mortality rate of the life table at period \( t \). Parameters \( a_0, a_1 \) and \( a_2 \)

\(^8\) Equation (9.5) below shows how the value of \( \text{s}l_t \) is calculated.
measure the effect of health on the individual’s mortality. Both \( \alpha_1 \) and \( \alpha_2 \) are expected to be positive. The mortality rate function in (4) implies that if the individual recovers from a previous period of illness, his current mortality risk will not be affected by his sickness during the previous periods. However, if he is currently sick, the number of continuously sick years up to the current period will affect his current mortality risk. The survival rate at \( t \), conditional on being alive at \( s \), can thereby be written as:

\[
P_{sg} = \begin{cases} 
\prod_{j=s}^{s-1} (1 - m_j), & \text{as } s > t \\
1, & \text{as } s = t.
\end{cases}
\] (5)

Note here the identification of the mortality difference between the sick and the healthy is not from mortality risks at the individual levels. The current sample is too small to have enough observed deaths to allow reliable estimates.\(^9\) Rather, the identification comes from implied behavioral difference that leads to observed difference in outcomes.

### 2.1.6. Probability of passing a grade

When an individual enrolls in school, he may pass or fail a grade. As in Heckman and Singer (1984), Keane and Wolpin (1997), and Eckstein and Wolpin (1999), we categorize individuals into different types to handle the unobserved heterogeneity of skill endowments in study and work. We assume that the individual may have a high academic ability (a high study type, denoted as 1) or a low academic ability (a low study type, denoted as 2). Whether he passes or fails a grade depends on his academic ability and educational attainment at the beginning of the decision horizon. The duration of his prior sickness may also affect his school performance if he is currently sick. In addition, if school attendance is not continuous, reentry into school may increase the chance of poor performance, caused by, for example, knowledge depreciation or psychic factors of studying with younger cohorts. Let \( \Phi_t^* \) be the latent academic performance variable\(^{10}\):

\(^9\) From 1979 to 1994, there were only 19 deaths in the sample.

\(^{10}\) In the early version of this paper (Gan and Gong 2007), the latent academic performance variable is only a function of study type and health. That model matches the average years of schooling very well, but it unsuccessfully fits the decreasing pattern of percent grade failing. Parameter estimates are robust to this alternative model specification.
\[ \Phi_i^* = \sum_{k=1}^{2} \xi_0 I(\text{study type} = k) + D_i (\xi_1 + \xi_2 s_l_i) + \xi_3 e_d u_i, \]
\[ + \xi_4 I(e_d u_i \geq 10) + \xi_5 I(d_{2,i-1} \neq 1) + \varepsilon_i^G, \]

where coefficients \( \xi_0 \) and \( \xi_2 \) indicate that individuals of different study types may differ in their academic performances. Coefficients \( \xi_3 \) and \( \xi_4 \) capture the linear effect and nonlinear effect of the previous education. Specifically, the nonlinear effect is given by a dummy variable indicating whether the individual’s effective years of schooling is no less than 10 years. The inclusion of the effect of educational attainment on academic performance reflects the fact that the percentages of people failing grades differ substantially and systematically by grade, which will be addressed in detail in the following section (see section 3.5 and table 4). Coefficient \( \xi_5 \) captures the reentry cost (a dummy variable indicating whether the individual attended school in the previous period). It is expected that coefficients \( \xi_1 \) and \( \xi_2 \) are negative since health may negatively affect the individual’s academic performance by affecting the quality of learning.

The serially independent random shock \( \varepsilon_i^G \) follows a standard normal distribution. Then:

- pass if \( \Phi_i^* > 0 \),
- fail if \( \Phi_i^* \leq 0 \).

### 2.1.7. Wage

Assume that the logarithm of the wage is a linear function of education (or effective schooling years), \( e_d u_i \), work skill, work experience, \( e_p_i \), which is measured by cumulative years worked, age, health, and idiosyncratic shock \( \varepsilon_i^w \):

\[
\ln w_i = \sum_{k=1}^{2} \gamma_{0k} I(\text{work type} = k) + \gamma_1 e_d u_i + \gamma_2 e_p_i + \gamma_3 e_p_i^2 + \gamma_4 a g_e_i,
\]
\[ + D_i (\gamma_5 + \gamma_6 s_l_i) + \gamma_7 I(e_p_i = e_p_{i-1}) + \varepsilon_i^w. \]

The inclusion of work types reflects differences in unobserved work skill endowments on wages. The high work type is denoted as 1 and the low work type is denoted as 2. The parameter \( \gamma_7 \) is the adjustment cost if the individual doesn’t work in the previous period. 

\[\footnote{The unobserved random variable may include the individual’s level of motivation in study and the quality of his teachers.}\]
Again, we assume that the individual’s previous health status may affect his wages if he is currently sick. Note that the wage rate is typical, except for the health terms.

2.1.8. Home production

The output of home production is unobserved to econometrician, but observed to the individuals. Any output that the individual produces to lower the household expenditure and any compensation he may receive when staying at home are included as the output of home production. To make it simple, the home production function is assumed to depend only on an individual’s health:

\[ e_t = \bar{e} + D_t (\phi_1 + \phi_2 s_l) + \varepsilon_{\alpha}, \]  

where \( \bar{e} \) is constant and \( \phi_1 \) and \( \phi_2 \) are parameters. The shocks \( \varepsilon_{\alpha} \) in the home production equation (8) and \( \varepsilon_w \) in the wage equation (7) are serially independent and follow joint normal distributions: \( Var(\varepsilon_w) = \sigma_w^2 \), \( Var(\varepsilon_{\alpha}) = \sigma_{\alpha}^2 \), and \( Cov(\varepsilon_w, \varepsilon_{\alpha}) = \sigma_{we} \).

2.1.9. Evolution of the state space variables

The state space of this dynamic programming model at period \( t \) is:

\[ \Omega_t = \{edu_t, ep_t, A_t, D_t, s_l, d_{-1}, d_{-1}, d_{-1}, d_{-1}, e_t, \varepsilon_t\}. \]

Note that both the grade shock \( \varepsilon^G_t \) and the health shock \( \varepsilon^S_t \) are not included in the state space. As described in the environment settings and in Figure 1, \( \varepsilon^G_t \) is only certain to the individual after the choice decision on school attendance has been made. The health shock \( \varepsilon^S_t \), on the other hand, is known to the individual prior to the choice decisions and its information is reflected in the sickness dummy, \( D_t \).

It is important to describe how the elements of the state space evolve. We only describe the first five elements of the state space. The evolution of the rest elements is either obvious or independent across years. We start with \( edu_t \). As noted earlier, educational attainment is different from the years of schooling in this paper. The individual’s years of educational attainment increase by one year at period \( t+1 \) if and only if he attends school at period \( t \) and passes the grade, i.e.,
\[ edu_{t+1} = \begin{cases} 
edu_t + 1, & \text{attending school and passing the grade} \\
edu_t, & \text{otherwise} 
\end{cases} \]  
(9.1)

The individual’s work experience \( ep_{t+1} \) increases one year if and only if he works at period \( t \):

\[ ep_{t+1} = ep_t + d_{t,t}^1. \]  
(9.2)

The individual’s assets at period \( t+1 \) are the sum of his assets at the beginning of period \( t \) and his choice of saving level at period \( t \):

\[ A_{t+1} = (1 + r)A_t + \sum_{k=1}^{K} \Delta A^k d_{k,t}^2. \]  
(9.3)

As illustrated in Figure 1, the sickness dummy at period \( t+1 \), \( D_{t+1} \), takes value at the end of \( t \), after the occurrence on health expenditure choice at \( t \) and the realization of health shock and grade shock conditional on school attendance at the end of \( t \)(see equation (3) and Figure 1). Namely,

\[ D_{t+1} = \begin{cases} 
1, & \text{if sick at } t+1 \\
0, & \text{if healthy at } t+1. 
\end{cases} \]  
(9.4)

The variable \( sl_t \) measures the duration of continuous sickness up to period \( t \) (not including period \( t \)). In particular, \( sl_{t+1} \) evolves as the following:

\[ sl_{t+1} = D_t (sl_t + D_t). \]  
(9.5)

From equation (9.5), \( sl_{t+1} = 0 \) if \( D_t = 0 \). Suppose the individual is sick at period \( t \) and period \( t-1 \), but not sick at period \( t-2 \), then his \( sl_{t-1} \) is 0, \( sl_t \) is 1, and \( sl_{t+1} \) is 2.

### 2.2. Solution method

The maximization problem is set in a dynamic programming framework. The value function can be written as the maximum over alternative-specific value functions, each of which obeys the Bellman equation:

\[ V_i(\Omega_i; \Psi) = \max_{\Omega_r} \left\{ V'_i(\Omega_r; \Psi) \right\}, \]  
(10)

where \( \Psi \) is the parameter set of the structural model. \( \Gamma \) is the Cartesian product set of alternatives \( \mathcal{Z} = d^1 \times d^2 \times d^3 \), which consists of \( 3 \times K \times M \) elements. The value function of the \( i \)th alternative, \( V'_i(\Omega_i; \Psi) \), is given by:
The terminal value function of the $i$th alternative is given by:

$$V^i_t(\Omega, \Psi) = u'(\Omega, \Psi) + \delta(1-m_t) E[V_{t+1}(\Omega_{t+1}, \Psi|\Omega_t, Z_t^i = 1)]$$

$$\equiv u'(\Omega, \Psi) + \delta(1-m_t) E \max_{j=1}^d \{V^*_t(\Omega, \Psi|\Omega_t, Z_t^j = 1)\} \quad t < T \quad (11)$$

The terminal value function of the $i$th alternative is given by:

$$V^i_T(\Omega, \Psi) = u'(\Omega, \Psi) + \delta(1-m_T) E[V_{T+1}^*(\Omega_T, \Psi|\Omega_T, Z_T^i = 1)] \quad t = T \quad (12)$$

In both (11) and (12), $u'(\Omega, \Psi)$ represents the contemporary utility if the $i$th alternative is chosen (i.e., $Z_t^i = 1$). $V_{T+1}^*$ is the terminal function and will be discussed later. The $E\max_t$ function in (11), of which the notation is borrowed from Keane and Wolpin (1994), depends on whether attending school or not. In particular, if schooling is not chosen at period $t$, i.e., $d_{1,t} = 0$, then:

$$E \max_t = \Pr(sick|\Omega_t, Z_t^i = 1)E[V_{T+1}^*(\Omega_T, \Psi|\Omega_T, Z_T^i = 1, sick]$$

$$+ \Pr(healthy|\Omega_t, Z_t^i = 1)E[V_{T+1}^*(\Omega_T, \Psi|\Omega_T, Z_T^i = 1, healthy] \quad (13)$$

if schooling is chosen, i.e., $d_{2,t} = 1$, then:

$$E \max_t = \Pr(pass|\Omega_t, Z_t^i = 1)\Pr(sick|\Omega_t, Z_t^i = 1)E[V_{T+1}^*(\Omega_T, \Psi|\Omega_T, Z_T^i = 1, pass, sick]$$

$$+ \Pr(fail|\Omega_t, Z_t^i = 1)\Pr(sick|\Omega_t, Z_t^i = 1)E[V_{T+1}^*(\Omega_T, \Psi|\Omega_T, Z_T^i = 1, fail, sick]$$

$$+ \Pr(pass|\Omega_t, Z_t^i = 1)\Pr(healthy|\Omega_t, Z_t^i = 1)E[V_{T+1}^*(\Omega_T, \Psi|\Omega_T, Z_T^i = 1, pass, healthy]$$

$$+ \Pr(fail|\Omega_t, Z_t^i = 1)\Pr(healthy|\Omega_t, Z_t^i = 1)E[V_{T+1}^*(\Omega_T, \Psi|\Omega_T, Z_T^i = 1, fail, healthy] \quad (14)$$

Given the finite horizon, the solution method is conducted through backward recursion. The difficulty with this procedure is the well-known “curse of dimensionality” problem. When the dimension of the state space and the choice set are large, the solution of the model becomes computationally intractable. This is particularly true in the present structural model, since the choice set $d_1 \times d_2 \times d_3$ at each period contains 405 ($3 \times 15 \times 9$) elements.\(^\text{12}\) As the time horizon increases, the state space increases exponentially. To deal with this problem, we adopt an approximation method of simulation and interpolation in Keane and Wolpin (1994).

Specifically, we approximate the $E\max_t$ function by a polynomial of the state space.

\(^{12}\) Fifteen possible values for net asset savings are $\pm (7,500, 5,000, 3,000, 2,000, 1,000, 500)$ and 0, 10,000 and 15,000. Nine possible values for health expenditure are 0, 250, 500, 750, 1,000, 1,500, 3,000, 5,000, and 7,500.
elements. At each period $t$, we first compute the $E_{\text{max}}$ function at a randomly selected subset of the state space points. For each of these state space points, we use the Monte Carlo integration to simulate the required multivariate integrals to obtain its $E_{\text{max}}$ value. Next, we estimate a polynomial regression function using these state space points. The functional form of the polynomial as an approximation of $E_{\text{max}}$, denoted as $\hat{E}_{\text{max}}$, is given by:

$$\hat{E}_{\text{max}} = \lambda_{01}^t + \lambda_{02}^t I(\text{study type is high}) + \lambda_{03}^t I(\text{work type is high}) + D_t \left( \lambda_1^t + \lambda_2^t s_l \right)$$

$$+ \lambda_3^t \text{edu}_t + \lambda_4^t \text{edu}_t^3 + \lambda_5^t A_t + \lambda_6^t A_t^2 + \lambda_7^t e_p + \lambda_8^t e_p^2$$

$$+ \lambda_9^t \text{edu}_t I(\text{study type is high}) + \lambda_{10}^t \text{edu}_t I(\text{work type is high})$$

$$+ \lambda_{11}^t A_t I(\text{study type is high}) + \lambda_{12}^t A_t I(\text{work type is high})$$

$$+ \lambda_{13}^t e_p I(\text{study type is high}) + \lambda_{14}^t e_p I(\text{work type is high})$$

(15.1)

Finally, the $E_{\text{max}}$ values at other non-simulated state space points are interpolated by using the predicted values based on estimated coefficients from the regression in (15.1). The process is repeated for each period, and the coefficients in (15.1) are age-dependent.

Solving the maximum problem requires specifying the terminal condition. The terminal period, $T = 31$, is the maximum period of individuals in the sample. We use the polynomial form of the $E_{\text{max}}$ function in (15.1) at the terminal period $T$ as the terminal condition. Since a different set of parameters is necessary, we explicitly list the terminal condition in (15.2):

$$V_{T+1}^* = \tau_{01} + \tau_{02} I(\text{study type is high}) + \tau_{03} I(\text{work type is high}) + D_{T+1} (\tau_1 + \tau_2 s_l_{T+1})$$

$$+ \tau_3 \text{edu}_{T+1} + \tau_4 \text{edu}_{T+1}^2 + \tau_5 A_{T+1} + \tau_6 A_{T+1}^2 + \tau_7 e_p_{T+1} + \tau_8 e_p_{T+1}^2$$

$$+ \tau_9 \text{edu}_{T+1} I(\text{study type is high}) + \tau_{10} \text{edu}_{T+1} I(\text{work type is high})$$

$$+ \tau_{11} A_{T+1} I(\text{study type is high}) + \tau_{12} A_{T+1} I(\text{work type is high})$$

$$+ \tau_{13} e_p_{T+1} I(\text{study type is high}) + \tau_{14} e_p_{T+1} I(\text{work type is high})$$

(15.2)

The parameters of this terminal function are estimated along with the structural parameters of the model.

2.3. Estimation method

We apply the method of indirect inference (Gourieroux, Monfort, and Renault, 1993; 13 The number of selected state space points at each period is 400.
Keane and Smith, 2004) to estimate the model in (10). Typical estimation methods of either ML or MOM that requires calculating probability of a particular choice are extraordinarily computationally difficult in this case. This difficulty arises because the number of alternatives is extremely large (405 alternatives each year for sixteen years; the total number of outcomes is $405^{16}$). In addition, missing data and unobserved variables in the NLSY79 reinforce the computational difficulty to evaluate the choice probabilities. The simulation-based approach of indirect inference circumvents the requirement of calculating the choice probabilities. This approach chooses a descriptive statistical model that captures a substantial part of the characteristics of the observed data. The same descriptive statistical model is also used to summarize the simulated data at any given set of parameters. Instead of matching the observed outcomes with the predicted outcomes as in the case of ML or MOM, the indirect inference approach matches the coefficient estimates of the descriptive model from the simulated data with the ones from the observed data. This approach avoids the difficult numerical integrations required in both ML method and MOM method.

However, applying the indirect inference method to discrete choice models encounters another problem. The objective function of the discrete choice models is not smooth because a small change of structural parameters may cause a discrete change of simulated data. Keane and Smith (2004) suggest a practical method to smooth the objective function by using continuous functions with a smoothing parameter of the latent utilities instead of the discrete choice variables. The estimation is implemented in four stages.

2.3.1 Stage 1: Estimate the descriptive statistical model using the observed data.

The criteria for choosing an appropriate descriptive statistical model are computational tractability and statistical efficiency which can provide a good description of the data. The linear probability model, as suggested by Keane and Smith (2004), fits the criteria precisely.

Denote $\{y_{it}\}_{i=1}^{N}$, $t = 1, \ldots, T$ as the observed choices and outcomes for individual $i$ and period $t$. The observed choices include job participation, school attendance, or home. The outcomes include passing or failing a grade, healthy or sick status, wages, and assets.
Because of the missing data problem, the content of \( y_{it} \) may be different across both individuals and periods. The descriptive statistical model is given by:

\[
y_{it} = x_{it}\eta_t + \nu_t, \quad \nu_t \sim iid \ N(0, \Sigma_t),
\]  

where \( x_{it} \) is the vector of regressors for individual \( i \), and \( \theta_t = (\eta_t, \Sigma_t) \) is the set of parameters to be estimated. The details of selections of dependent variables \( y_{it} \) and independent variables \( x_{it} \) by age category are described in Appendix A. Note that the three activity choices of schooling, work and home are mutually exclusive, and one of the three choices has to be chosen. Therefore, \( y_{it} \) in equation (16) will only include two choices, such as schooling and work.

Denote the likelihood function of the descriptive statistical model as

\[
L(y; z, \Theta) = \prod_{i=1}^{N} \prod_{t=1}^{T} l(y_{it} ; x_{it}, \theta_t),
\]

where \( z \) is the observed exogenous initial variables, including health status, educational attainment, work experience, and assets. The initial values of both work experience and assets are zero. \( \Theta \) be the parameter set \( \{\theta_t\}_{t=1}^{T} \). The first step is to find the set of parameters that maximizes the likelihood function of the descriptive statistical model:

\[
\hat{\Theta} = \arg \max_{\Theta} L(y; z, \Theta).
\]

2.3.2 Stage 2: Simulate the outcomes from the structural model.

We simulate the choices made for each individual from age 16 to 31. Given the initial condition \( z \) and a set of structural parameters \( \Psi \), the structural model can be used to generate statistically independent simulated data sets \( \{\tilde{y}_{it} (\Psi)\}_{i=1}^{N} \), where \( f = 1, \ldots, F \), indicating simulated data set, \( t = 1, \ldots, T \), indicating time period, and \( N \) is the number of observations in each data set. The vectors of \( \tilde{y}_{it} \) and \( y_{it} \) consist of the same type of elements, such as activity choices (job participation, school enrollment, or staying at home), indicators for passing a grade, sickness dummy \( D_t \), wages \( w_t \), and assets \( A_t \). The data sets \( \{\tilde{y}_{it} (\Psi)\}_{i=1}^{N} \) are generated based on the above described solution method of the simulation and interpolation for computing \( E_{max} \). Each of the \( F \) simulated data sets is constructed using the same set of observed exogenous individuals’ initial variable \( z \). The difference of each simulated data set results solely from the different sequences of
random draws, which are held fixed for different values of the parameter $\Psi$.

2.3.3 Stage 3: Estimate the descriptive statistical model using the simulated data.

Each of the simulated data sets can then be applied to estimate the descriptive statistical model of (16). However, it is not computationally practical to simply plug the simulated discrete variables into the descriptive statistical model because of the non-smooth objective function (actually, its surface is a step function). We use functions of latent utilities to substitute the discrete choice variables as in Keane and Smith (2004). More specifically, we use the function:

$$
\tilde{d}_{1,t}(\Psi;\lambda) = \frac{\sum_{j \in \Xi_1} \exp(\frac{V_{1,t}(\Omega_j;\Psi)}{\lambda})}{\sum_{j \in \Gamma} \exp(\frac{V_{1,t}(\Omega_j;\Psi)}{\lambda})}
$$

in place of simulated $\tilde{d}_{1,t}$, where $\Xi_1$ is a subset of $\Gamma$ and consists of all the alternatives in which job participation is chosen, and $\lambda$ is the smoothing parameter. The functions $V_{1,t}(\Omega_j;\Psi)$ are defined in (11) and (12). As the latent utilities are smooth functions of the parameter set $\Psi$, $\tilde{d}_{1,t}(\Psi;\lambda)$ is also a smooth function of $\Psi$. Moreover, as the smoothing parameter $\lambda$ goes to zero, $\tilde{d}_{1,t}(\Psi;\lambda)$ goes to 1 if an alternative with job participation has the highest latent utility and to zero otherwise.

Similarly, we use the function:

$$
\tilde{d}_{2,t}(\Psi;\lambda) = \frac{\sum_{j \in \Xi_2} \exp(\frac{V_{2,t}(\Omega_j;\Psi)}{\lambda})}{\sum_{j \in \Gamma} \exp(\frac{V_{2,t}(\Omega_j;\Psi)}{\lambda})}
$$

in place of simulated $\tilde{d}_{2,t}$, where subset $\Xi_2$ consists of all the alternatives in which school attendance is chosen. As the smoothing parameter $\lambda$ goes to zero, $\tilde{d}_{2,t}(\Psi;\lambda)$ goes to 1 if an alternative with school attendance has the highest latent utility and to zero otherwise.

Wages are observed if and only if the individuals work during that period. To make the simulated wage match the observed wage, we apply the observed wage for any individual who work during that period, and set the wage to zero for those who don’t
work during that period. We use \( \tilde{d}_{t+1} (\psi; \lambda, \psi) \tilde{w}_t (\psi) \) in place of the simulated wage \( \tilde{w}_t (\psi) \).

Since both \( \tilde{d}_{t+1} (\psi; \lambda) \) and \( \tilde{w}_t (\psi) \) are smooth functions of \( \psi \), the estimated parameters of the descriptive statistical model using the simulated data are also smooth functions of \( \psi \). Moreover, as the smoothing parameter \( \lambda \) goes to 0, \( \tilde{d}_{t+1} (\psi; \lambda) \tilde{w}_t (\psi) \) goes to \( \tilde{w}_t (\psi) \) if an alternative with job participation choice has the highest latent utility and to zero otherwise.

Furthermore, as the sickness dummy is a discrete variable, it needs to be substituted by a continuous function. We use:

\[
\tilde{D}_{t+1} (\psi; \lambda) = \frac{\exp\left(H_{t+1}^* (\psi)/\lambda\right)}{1 + \exp\left(H_{t+1}^* (\psi)/\lambda\right)}
\]

(20)

in place of simulated \( \tilde{D}_{t+1} \). The latent variable \( H_{t+1}^* (\psi) \) in (20) is defined in equation (3). Thus, as the smoothing parameter \( \lambda \) goes to 0, \( \tilde{D}_{t+1} (\psi; \lambda) \) goes to 1 if \( H_{t+1}^* > 0 \) and to zero otherwise.

Finally, according to the same reason for the discrete variable of sickness, we use the continuous function \( \exp\left(\Phi_t^* (\psi)/\lambda\right) \) in place of the indicator for passing a grade, where the latent variable \( \Phi_t^* (\psi) \) is defined in equation (6).

Denote \( \{\tilde{\gamma}_f (\psi; \lambda)\}_{i=1}^{N} \), \( t = 1, \ldots, T \), and \( f = 1, \ldots, F \) as the simulated data, smoothed by using the continuous functions of the latent utilities. The descriptive statistical model then can be estimated using each of the smoothed simulated data to obtain the following parameters:

\[
\tilde{\Theta}_f (\psi; \lambda) = \arg \max_{\hat{\Theta}} L\left(\tilde{\gamma}_f (\psi; z), x, \Theta\right).
\]

(21)

Let the average of the estimated parameters be \( \tilde{\Theta}(\psi; \lambda) = \sum_{f=1}^{F} \tilde{\Theta}_f (\psi; \lambda) / F \). As the sample size \( N \) goes to large and the smoothing parameter \( \lambda \) goes to small (zero), \( \tilde{\Theta}(\psi; \lambda) \) converges to a nonstochastic “binding” function \( H(\psi) \) (Gourieroux, Monfort, and Renault, 1993, and Keane and Smith, 2004). The next step is to get an estimate \( \hat{\psi} \) of the
structural parameters so as to make \( \tilde{\Theta}(\Psi, \lambda) \) and \( \hat{\Theta} \) as close as possible.

### 2.3.3 Stage 4: Estimate the set of structural parameters \( \Psi \).

Estimates of the structural parameters \( \Psi \) can be obtained by minimizing a metric function that measures the distance between \( \hat{\Theta} \) and \( \tilde{\Theta}(\Psi) \). In the present context, we adopt the likelihood ratio as the metric function, which is used in Keane and Smith (2004). In particular,

\[
\hat{\Psi} = \arg \max_\Psi L \left( y; z, \tilde{\Theta}(\Psi, \lambda) \right)
\] (22)

In regards to the practical algorithm for the estimation of the structural parameters, we use the two-step approach proposed by Keane and Smith (2004). The details of choosing the number of simulated data sets \( F \) and the smoothing parameter \( \lambda \) at each step are described in the Appendix B.

### 3. Data

The data set used in this paper is from the 1979 youth cohort of the National Longitudinal Surveys of Youth (NLSY79). The NLSY79 contains extensive information about the individuals’ employment, education, health, income, and assets. An original 12,686 individuals were interviewed each year from 1979 to 1994. After 1994, the interviews switched to every other year. We use the information from 1979 to 1994. That gives us sixteen years of data to work with.

The analysis is based on the sample of the white males who aged 16 or younger as of October 1, 1977. Each individual in the sample is followed from the first year he reached age 16 as of October 1 of that year to September 30, 1993. The females are excluded in this paper, since the fertility choice that young females face calls for a model that is substantially different from the current model. Black males are also excluded to reduce heterogeneity. Finally, we exclude from our sample those who had any active military service. Modeling military service is not in the scope of this study.

#### 3.1. Health

In each survey year, the NLSY79 asked the respondents a standard set of health
questions. The focus of these questions was on the health problems that affected the respondent’s ability to work. In each year, if the respondents were not currently working, they were asked if their health would prevent them from working, and the rest of respondents who were currently working were asked if their health limited the type and the amount of work they could do. If a health limitation was reported, the NLSY79 then probed for the month and year that the health limitation began.  

Given the multi-dimensionality of a person’s health status, we use the answers to these questions to construct our health variables. An individual is classified as being sick \( (D_t = 1) \) in a given year if a health limitation was reported in that year. The construction of the sickness duration variable \( (sl_t) \) is based on the information of the individual’s reported date that the sickness began. The difficulty in constructing health variables is that a large portion, around thirty percent, of the self-reported sickness duration in the NLSY79 did not match the preceding self-reported sickness. For example, some respondents reported that the sickness began at some earlier point, for instance, two years ago, but no reported health limitation could be found during the last two years. This could be because that no surveys were conducted for these respondents at those years, or because that the respondents had not been aware of the sickness until the health limitations developed into a serious problem that affected their lives. To solve this problem of inconsistency, we check the subsequent self-reported answers to health questions, while also searching for references to the specific ailments. If the respondent kept reporting the same health problem and that the same date that the health limitation began, we then use this information to update the prior sickness variable. If the specific health problem was only reported once but the duration was longer than one year during the entire time of the survey, we simply classify the respondent as sick only during that reported year.

In the constructed health data, 21% of the respondents reported at least one sickness during the 16 years of surveys. The average duration is 2.28 years. Figure 2 shows the

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14 More details on health ailments were asked in the NLSY79 if the individuals gave affirmative answers that health limited either the kind or amount of work they could do.

15 Researchers usually use answers to these questions to generate severe sickness variables such as disability (Haveman and Wolfe, 2000).
percentage of respondents who reported sickness at each age from 16 to 29. At the early age of 16, 4.14% of respondents considered themselves sick. Over the subsequent 15 years, the percentage of the respondents reporting an illness increases steadily, peaking at the age of 29 with 5.17%. This number is slightly smaller than that from surveys on similar questions but with older population (Burkhauser and Daly, 1996).

3.2. Schooling, work, or home

At each interview date, the NLSY79 asked the respondents about their enrollment status, the highest grade attended and completed, the dates of leaving school, and the dates that diplomas and degrees were received. An individual is classified as attending school during the year if the individual reported enrollment in school at the time of the survey and did not report dropping out of school during that year in the subsequent surveys.

Employment data in the NLSY79 include the beginning and ending dates of all jobs, hours worked on each job, and salary paid on each job. An individual who did not attend school is classified as having worked during the year if the individual reported working at least 1,000 hours, i.e., at least 20 hours per week on average for 50 weeks.

Finally, an individual is classified as being at home during the year if the individual neither enrolled in school nor worked during the year. Note that some individuals would be classified as being at home if they worked during the year but did not work at least 1,000 hours.

Table 1 presents the choice distributions by age for the full sample and for the sickness subsample. The sickness subsample is cumulative, i.e., at each age $t$, it consists of the individuals who have reported sickness at least once up to age $t$. The initial sample size is 1,062 at age 16. From age 16 to age 29, the sample size declines slightly as a result of sample attrition such as deceases. The sample size falls from 1,045 to 776 at ages 29.

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16 The figure ends at age 29 instead of 31. The percentages of sickness reported at ages 30 and 31 are 4.81% and 5.18%, respectively. A dip at age 30 and the breaking of the increase trend may come from the shrinking of sample size. During the annual survey from 1979 to 1993, 98.4% of the original respondents reached age 28; however, only 73.0% and 43.6% of the respondents reached age 30 and 31, respectively.

17 Burkhauser and Daly (1996) find that the self-reported sickness percentage is roughly between 8% and 12% for working age people in 1989-1990. Our sample consists of people who are much younger and in earlier years.
and 30, and from 776 to 463 at ages 30 and 31. This is because some respondents have not yet reached age 31 during the survey periods. Overall, there are 15,972 person-periods in the full sample and 2,198 person-periods in the sickness subsample.

As table 1 shows, an individual’s decisions on school attendance, job participation, or staying at home are highly correlated with the individual’s health. Compared with the individuals in the full sample, individuals in the sickness subsample at each age have a smaller percentage of attending school and a larger percentage of staying at home. Moreover, although a slightly larger percentage of individuals in the sickness data worked from age 16 to age 18, a relatively smaller percentage of sick individuals worked after that. More specifically, 11.87% of the individuals in the sickness subsample attended school, 47.36% worked, and 40.77% stayed at home. The corresponding percentages for the individuals in the full sample are 25.34%, 54.46%, and 20.20%. Furthermore, the relative difference in the percentage of school attendance between the two data sets increases during the normal schooling ages. For example, at age 16, the percentage of individuals attending school while having been sick is 81.82% (i.e., 93.6% of the average 87.38%), but at the normal high school graduation age of 18, that percentage drops to 38.55% (i.e., 77.20% of the average 49.95%); at the normal college graduation age of 22, it drops to 11.51% (i.e., 60.01% of the average 19.18%). Additionally, the propensity to work increases monotonically over the first 11 years of both data sets, followed by slight fluctuations over the last five years.

Tables 2 and 3, which respectively show one-year transition rates for the full sample and for the sickness subsample, reveal substantial state persistence and substantial dependence on health status. The row percentages describe the transition percentages conditioned on the prior state, and the column percentages show transition percentages conditioned on the succeeding state. As shown, a large majority of the individuals who enrolled in school in the last year will enroll this year; while over 73% of the full sample and less than 60% of sickness subsample will make such a decision. Similarly, the majority of individuals who worked or stayed at home last year will work or stay at home this year. However, individuals in the sickness subsample are less likely to continue working and more likely to continue staying at home than those in the full sample.
3.3. Passing or failing grades
The NLSY79 collected the information from the high school transcripts during 1980, 1981, and 1983 for those respondents who were aged 17 or older, and who were expected to complete high school in the United States. For each person in the sample, the transcript data gathered up to 64 courses that include the grade level at which the course was taken, a code for high school courses, and a grade for each course based on a zero to 4.0 scale, corresponding to grade F to grade A. A course is classified as failure if the grade is F. An individual is assumed to fail a grade if and only if the individual failed over a half of the courses taken in that grade. This assumption implies that each course is equally important for assessing the progress in school.

Table 4 shows the percentages of failing in high school by grade for the full sample and for the sickness subsample. In both samples, the probability of failing a grade declines as the grade level becomes higher, from 13.90% in grade 9 to 3.63% in grade 12 for the full sample, and from 20.70% in grade 9 to 7.61% in grade 12 for the sickness subsample. The declining trend in grade failures may reflect the fact that some students dropped out of school before graduation because of bad grades, health problems, or both. More importantly, table 4 shows that an individual’s health status significantly influences his study outcomes. The possibility of failing a grade for the individuals who had been sick is more than twice as much as the average of the full sample, except for the grade 9 in which the failing probability is about 1.5 times higher.

3.4. Wages and assets
The real wages used in this analysis are based on the 1984 price level. The average wage in the full sample is $20,752, with a standard deviation of $47,535, while the average wage in the sickness subsample is $18,731, with a standard deviation of $11,367. Wages for people who have ever been sick are 9.73% lower than those who are healthy.

Beginning in 1985, the NLSY79 launched a much larger wealth section. Up to 20 questions about a variety of asset and debt holdings were asked at each subsequent interview, except for 1991. The asset items used in this analysis include (i) residential property, (ii) cash savings, stock and bond portfolio, etc., (iii) real estate, assets in the

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18 The wealth questions were eliminated in 1991 because of budgetary restrictions.
business, and farm operation, (iv) automobile, (v) mortgage debt, property debt, and other accumulated debt, (vi) other assets each individually worth more than $500, and (vii) other debts over $500. Together these variables are used to construct the net worth of the assets of each respondent. Since the asset data are collected at the household level, an individual’s assets are half of his household assets if he is currently married.

Tables 5 and 6 show the asset distributions by age for the full sample and for the sickness subsample. The youngest age with reported assets is 21, because the asset data were not collected until 1985. Outlier asset levels are deleted from the sample. In total, 107 observations with extremely large or small net asset values are deleted from the full sample, in which 34 observations are from the sickness subsample. As shown in the tables, both mean and median values of net assets in the sickness subsample are smaller than those in the full sample, reflecting the substantial influence of sickness on the accumulation of assets. The prevalent dependence of assets on health is also verified by the proportions of the negative net assets, which are higher in the sickness subsample from ages 22 to 31. In addition, tables 5 and 6 indicate that assets increase with age. Between the ages of 21 and 31, the mean value of net assets increase by 4.13 times for the full sample and 2.90 times for the sickness subsample, while the median value of net assets increase by 3.75 times for the full sample and 3.63 times for the sickness subsample. Moreover, the median values of net assets are, on average, less than half of the mean values, reflecting the positively skewed nature of the asset distribution.

3.5. Skill types

The model in section 2 introduces skill endowments for studying and for working. In particular, equation (6) introduces the unobserved study type that affects probability of passing a grade, and equation (7) introduces the unobserved work type that affects wages. The skill endowments at age 16 are assumed to be unobserved to the econometricians, however, the population proportions of skill types are known.\(^{19}\) Denote the type portions

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\(^{19}\) Some literatures use the Armed Forces Qualifying Test (AFQT) as a measure of IQ or endowment skill (Neal and Johnson, 1996; Cameron and Heckman, 1993, 2001). This analysis does not adopt AFQT for two reasons, as addressed in Keane and Wolpin (1994, 1997). First, AFQT reflects not only the innate endowment but also the parents and own investments in skills up to the time of the test. But, due to the age distribution of the samples in the NLSY79, small portion of the individuals took the test prior to age 16. Second, given that each individual is characterized by two skills (studying and
of high ability for studying and high skill for working as \( \rho_1 \) and \( \rho_2 \), respectively. An individual’s study or work type can be simulated by a random draw from the uniform distribution between 0 and 1. For example, if an individual’s drawn number of his study type is less than \( \rho_1 \), the individual is labeled as high study type; otherwise the individual is labeled as low study type. At each simulated data \( f \), the individual’s skill types are generated independently from the random draws.

Equations (6) and (7) with unobserved skills can be explained by regime switching model of Hamilton (1989). Consider equation (6) in which there are two regimes: a high-study-type regime and a low-study-type regime. For any individual, the probability that his latent academic performance variable \( \Phi_1^{*} \) is drawn from the high-study-type regime and from the low-study-type regime is \( \rho_1 \) and \( 1 - \rho_1 \), respectively. If the individual’s \( \Phi_1^{*} \) belongs to the high-study-type regime, the intercept term in the model is \( \zeta_{01} \). Otherwise, the intercept term is \( \zeta_{02} \). The two regimes thereby have two distributions that differ in their means. Identification of the skill type ratios requires two conditions. First, an individual’s unobserved skill endowments are assumed to be uncorrelated with any other observed factors that may affect his performances in school and at work. Second, no constants appear in both equations (6) and (7). It is important to point out that this model cannot identify if a particular individual is a high study or work type. The model can only tell the probability that any one of the individual is a high study or work type.

4. Estimation results

4.1. Parameter estimates

Table 7 reports the estimation results of all 53 parameters. The standard deviations are in parentheses. These parameters are estimated to fit the sequential choices of 15,972 person-period observations, out of which 2,198 had been sick at least once during the 16-year period. The choice set at each period consists of decisions on school attendance, job participation, or staying at home, as well as decisions on net asset savings and health expenditure.
The parameter estimates for $\beta_1$–$\beta_5$ of probability of being sick in equation (3), shown in the first panel in table 7, are all statistically significant at 5% level. They indicate that a person’s level of education ($\beta_3 = -0.0184$) and health expenditure ($\beta_2 = -2.5429$) is negatively related to the probability of being sick, whereas age ($\beta_2 = 0.0082$), current health status measured by sickness ($\beta_4 = 1.2126$) and previous health stock measured by the duration of prior sickness ($\beta_5 = 0.1083$) are positively related to the probability of being sick.

Table 8 and table 9 are created to showcase the effects of age, education, health expenditure, health status, and previous health stock on the probability of being sick. Table 8 reports the probabilities of being sick for an individual with 10 years of educational attainment by health expenditure and health status at ages 16, 25, and 30. As shown in the table, both health expenditure and health status have significant effects on the probability of sickness. If the health expenditure is zero, a healthy individual has 47.89% chance of getting sick, while a sick individual has 87.69% chance of getting sick. The elasticity of the probability of sickness with respect to health expenditure also differs between healthy people and sick people. For example, at age 16, a $500 spending on health reduces a healthy individual’s probability of sickness by 80.64%, from 47.89% to 9.27%. However, a $500 spending on health reduces a sick individual’s probability of being sick by 48.04% from 87.69% to 45.56% if his duration of prior sickness is zero, or by 30.26% from 95.56% to 66.64% if his duration of prior sickness is five years. These results indicate that health expenditures have a larger effect in reducing the probability of sickness for healthy people than for sick people. Table 8 also illustrates the effect of age on the probability of sickness. As people are older, the effect of health expenditure drops slightly. For example, at age 30, a healthy individual’s probability of sickness is 52.47% if he spends nothing on health, and 11.32% if he spends $500 on health. The probability of being sick is reduced by 78.43% at age 30, compared to 80.64% at age 16 with the same amount of health expenditure.

Table 9 reports the probability of being sick for a 20-year-old individual by health expenditure and health status at 8, 12, and 16 years of educational attainment, representing the education level of pre-high school, high school graduate, and four-year college graduate respectively. As shown in table 9, education has a positive effect on the
probability of sickness, especially for sick individuals, although the effect has a much smaller magnitude than that of health expenditure and health status as table 8 shows. For example, if there is no health expenditure, the probability of being sick for a 20-year-old healthy individual with 8 years of educational attainment is 50.67%. When his educational attainment is 12 and 16 years, the corresponding probabilities of sickness drop to 47.74% and 44.81%, respectively. Therefore, a 20-year-old individual with four more years of educational attainment would be about 6 percent less likely to be sick given that he is healthy and spends nothing on health. Table 9 also shows that a sick individual’s probability of being sick decreases with education at a lower rate. Overall, these results indicate that the marginal effect of education on the probability of being sick is thereby relatively small.

The second panel in table 7 reports the estimates for the parameters ($\alpha_0$, $\alpha_1$, and $\alpha_2$) in the mortality rate function as shown in equation (4). All parameters are statistically significantly estimated. The estimation results show that a healthy individual’s mortality is 3.26% ($\alpha_0 = -0.0326$) lower than that of the life table. Current sickness is associated with a very large increase in an individual’s mortality rate, while the duration of prior sickness seems to be associated with little additional increase on the mortality rate. The mortality rate for an individual who currently experience sickness is 20.5 times ($\exp(-0.0326+3.1018) - 1$) larger than the life-table mortality. However, being sick for 4 years is only associated with an additional increase of mortality rate by 9.28% ($= 4*0.0232$). As for the survival rate, being sick at age 16 with no prior sickness decreases the survival rate between age 16 and age 30 by 1.8%, from 98.4% to 96.6%.

The third panel of table 7 reports the parameter estimates ($\xi_{01}, \xi_{02}, \xi_1 - \xi_5$) of probability of passing a grade in equation (6). All parameters except the coefficient for the interaction between the sickness dummy and duration ($\xi_2$) are statistically significant at 5% level. We discuss the estimation results in the following four parts.

First, parameter estimates ($\xi_{01} = 1.1084$, $\xi_{02} = 0.1440$) suggest that endowed study skill has a significant effect on an individual’s academic success. The probabilities for a healthy individual of high study type to pass grade 9 to 12, given his school attendance in the last year, are respectively 91.6%, 95.4%, 95.7% and 96%. In comparison, the corresponding probabilities for a healthy individual of low study type to pass grade 9 to
12 are about 20 percentage points lower, at 66.1%, 76.4%, 77.3% and 78.2%, respectively. Among the sick population, the difference in probabilities of passing a grade between individuals of high study type and those of low study type is about 30%, which is larger than that among the healthy population.

Second, parameter estimates ($\xi_1$ and $\xi_2$) indicate that health has a substantial effect on an individual’s academic success, especially for those of low study type. Specifically, current sickness significantly reduces the individual’s school performance, while the duration of prior sickness introduces little additional effect. For example, given school attendance in the last year, an individual of high (low) study type with 10 years of educational attainment has a probability of 95.4% (76.4%) to pass a grade if he is healthy, and a probability of 88.1% (58.5%) if he is currently sick with zero duration of prior sickness. In this case, the passing probability for the individual of high study type decreases 7.3 percentage points as a consequence of sickness, whereas the passing probability for the individual of low study type decreases 17.9 percentage points. The effect of sickness duration, however, is very small. In fact, for both high and low study types, less than 1% decrease in the probability of passing a grade can be attributed to the four-year duration of prior sickness.

Third, parameter estimates ($\xi_3$ and $\xi_4$) imply the effect of education on academic performance. An additional year of educational attainment augments academic success at grade 9 by increasing the passing probability ranging from as low as 4 percentage points for healthy and high study type individuals to as high as 26 percentage points for sick and low study type individuals, given their school attendance last year. After that, each year of educational attainment increases passing probability, ranging from as low as around 0.3 percentage points for healthy and high study type individuals to as high as around 2 percentage points for sick and low study type individuals.

Finally, coefficient $\xi_5$, estimated at $-0.467$, indicates the significant effect of interruption of schooling. The passing probability in the year following an absence from school is lower by ranging from as low as 7% for a healthy individual of high study type with education beyond grade 9 to as high as 18% for a sick individual of low study type at grade 9.

The fourth panel in table 7 presents parameter estimates in the wage function. All
parameters except the coefficient for the interaction term between sickness dummy and duration are statistically significant. As revealed, the sickness reduces wages by 16.47% ($\gamma_5 = -0.1649$), consistent with some estimates in the literature.\textsuperscript{20} In addition, individuals of high work type earn 27.75% more than those of low work type if other characteristics are the same (difference between $\gamma_{01}$ and $\gamma_{02}$). Moreover, the estimates regarding the job adjustment cost, the returns for education and experience are quite reasonable: the absence of work in the last period reduces wages by 11.84% ($\gamma_7$); an additional year of educational attainment increases wages by 10.43% ($\gamma_1$); an additional year of experience increases wages by 9.74% ($\gamma_2$) in the first year, and 9% in the second year, and 8.2% in the third year.

With respect to the home production function, estimated parameters show that sickness reduces the home production by $2,685$ ($\phi_1$), and an additional year of sickness duration reduces the home production by $374$ ($\phi_2$). The average home production for a healthy individual is $9,716$ ($\varphi$). In addition, wage shock $\varepsilon_t^w$ and home production shock $\varepsilon_t^e$ are negatively correlated with the correlation coefficient $-0.48$ (i.e., $-2.1247/(0.5613*7.8657)$).

Finally, 84.62% of the population is high study type and 61.32% of population is high work type. The coefficient of relative risk aversion is 0.8165 and the preference discount factor is 0.965. The estimated cost of education beyond high school is $4,063 per year, and the net income boundary is -$557, below which the health expenditure is zero.

4.2. Within-sample fit

With the estimated parameters, the validation of the model can be tested by the within-sample fit. Based on a simulation of 8,000 individuals, table 10 compares the predicted and actual values of selected state variables by the full sample and the sickness subsample. As can be seen, the model accurately matches the average number of years of schooling completed in the full sample (13.20 predicted vs. 13.23 observed) and the

\textsuperscript{20} Empirical estimates on the effect of health on wages vary widely, in which Berkovec and Stern (1991) estimate that poor health status reduces wage by 16.7%. See Currie and Madrian (1999) for an extensive review.
sickness subsample (12.41 predicted vs. 12.36 observed). At a more disaggregate level, the predicted means match the observed means with reasonable accuracy. The model predicts that 74.64% of individuals will complete 12 years of schooling and 67.25% of individuals who have been sick at least once during the 16-year period will do. The comparable percentages in the actual data are 76.35% and 64.73%. The model also predicts the steep decline in the percentage of people completing 16 years of schooling (college). The predicted completion rates for the full sample and for the sickness subsample are 26.87% and 13.41%, respectively. The corresponding observed completion rates are 28.50% and 15.27%.

The model fits the proportions of people working, attending school, and staying at home well, except that it predicts a slightly smaller proportion of work alternative for the sickness subsample. A further comparison of the predicted and actual distributions of decisions on school attendance, work and home by age for the full sample and the sickness subsample is illustrated in figures 3a and 3b. As shown, the features in figures do not reveal large discrepancies between the predicted and observed distributions.

In terms of the probabilities of failing a grade, table 10 shows that the model correctly predicts the large health effect on the school performance. In addition, the model closely captures the decreasing pattern of grade failures, including the steep decline between grade 9 and grade 10 for the full sample. In comparison with the actual data, the only significant deviation arises with respect to failing the 12th grade for the sickness subsample. With respect to the asset fit, the model captures the broadly increasing pattern of age. Figures 4a and 4b display the predicted and actual mean assets by age. It is clear that the model does better in predicting asset values for the full sample than for the sickness subsample.

As predicted by the model, the mean health expenditure in the sickness subsample is 7.8% larger than in the full sample. This is because sick individuals have to spend more on health than healthy individuals to reduce the chance of being sick in succeeding years. Figure 5 illustrates the predicted and actual percentages of sick individuals in the full sample. The largest and smallest gaps between predicted and actual sick percentages are 0.29% at age 30 and 0.03% at age 24, respectively. Moreover, the age pattern of health expenditure and the percentage of zero health expenditure are portrayed in figure 6. It is
shown that the mean health expenditure increases by age, from $739 at age 16 to $872 at age 31 at an annual growth rate of 1.12%. Concurrently, the percentage of zero health expenditure increases from zero in the first four years (i.e., age 16 to 19) to 1.24% at age 31. Note that according to the model’s assumption, as the individual’s net income falls lower than the boundary of -$557, his health expenditure is zero. The increasing trend of the percentage of zero health expenditure implies the dispersion of assets and earnings.

4.3. Effects of initial health status and initial education

As has been illustrated, an individual’s initial characteristics have a significant effect on his future behavior of alternative choices, which will subsequently determine his health, educational attainment and wealth. This subsection investigates how the education, health and wellbeing are related to initial levels of completed education and health status at age 16.

Table 11 reports the simulation results of initial health status effect on selected variables. The simulated sample is divided into two groups: individuals with nine years or less educational attainment at age 16 and individuals with ten years or more educational attainment at age 16. Approximately 15% of individuals completed ten years or more educational attainment by age 16 in the actual data. As seen in the table, initial health status is an important determinant of education, survival probability, assets, health expenditure, and lifetime welfare. Moreover, the effects of initial health status are more substantial for individuals with low level of education than for individuals with high level of education. For instance, the average level of educational attainment at age 30 is reduced by 0.87 years as a consequence of sickness if the individual’s initial educational attainment is nine years or less, whereas it is reduced by 0.72 years if the individual’s initial educational attainment is ten years or more. In addition, the decrease in the probability of survival at age 30, resulting from the sickness at age 16, is 3.2% for those with low initial education, compared to 1.5% for those with high initial education. Finally, due to the health limitation at age 16, the mean present value of lifetime utility decreases by 20% for the individuals with low initial education and by 16% for those with high initial education, respectively.

Table 11 also illustrates the significant effect of initial level of education. If an
individual has ten or more years of educational attainment at age 16, on average he would have 0.4 more years of educational attainment, $3,562 more assets and about $160 more health expenditure when he reaches age 30 than individuals with initial educational attainment nine years or less. In addition, on average his lifetime utility is 8.5% larger than individuals with low initial level of education.

It is important to note that we cannot conclude whether the initial condition of health is more important than that of education because of different measures of education and health. Next we conduct a policy simulation to examine the relative importance of education and health by insuring the same cost of policy implementations.

4.4. Policy experiments

In this section, we conduct two policy experiments aiming to improve educational attainment. The first experiment is a direct college tuition subsidy, and the second is a health expenditure subsidy during high school. The two policy experiments will incur the same amount of per capita cost. Therefore, by comparing the outcomes of the two policy experiments, we are able to evaluate relative effectiveness between subsidizing health and subsidizing education. For each subsidy policy, we simulate a sample of 8,000 individuals. The results for both policy simulations are discussed below.

4.4.1. College tuition subsidy

Table 12 reports the distribution effect of a $2,000 per year college tuition subsidy, which is about 50% of the estimated cost of college education (estimated $ec = $4,063). Although the subsidy is limited to college students, it will also affect individuals’ decisions before entering college because they anticipate the subsidy and will behave accordingly. The simulated sample is divided into two subsamples: those who have been sick at least once before age 21 (11.03% of the population before the subsidy) and those who have remained healthy before age 21 (88.97% of the population before the subsidy). Also, individuals are classified by their skill endowments based on the estimated parameters of population type ratios: high study type and high work type (group 1), high study type and low work type (group 2), low study type and high work type (group 3), and low study type and low work type (group 4). For comparison convenience, the
baseline results without subsidy are listed.

As expected, the college tuition subsidy increases the levels of state variables, including schooling, years in college, assets, and present value of lifetime utility. Among the 8,000 simulated individuals, the average completed highest schooling year increases 0.53 years, from 13.20 to 13.73 years; and the average years in college increase 0.35 years from 1.48 to 1.93 years. It is important to note that although most (66.04%) improvements in schooling years happen in college, people who are motivated by the college tuition subsidy also increase their schooling years even in the end they may not make to the colleges. The mean value of assets at age 30 increases by 14%, from $19,626 to $22,327. The mean expected present value of lifetime utility at age 16 increases by 10.5%, from 204 to 225. Finally, the percentage of people who have ever been sick at least once before and up to age 20 decreases by 5.7%, from 11.03% to 10.4%.

As seen, the college tuition subsidy has a larger effect on healthy people than on sick people in terms of gains in schooling years and welfare. The average increase in schooling is 0.54 years for healthy people but only 0.37 years for sick people. More specifically, the largest difference in schooling between healthy people and sick people is among those of low study type. Healthy individuals in group 3 and group 4 (both with low study type) experience an average increase of 0.68 years and 0.72 years in schooling, respectively. In comparison, individuals who have experienced at least one bout of sickness before age 21 in the same group 3 and group 4 have only 0.04 and 0.12 years increase in schooling on average, respectively. In addition, the private gain of welfare from the subsidy is larger for the healthy individual than for the sick individual. The mean present value of lifetime utility increases by 5.4% for sick individuals, compared to 10.8% for healthy individuals. Although healthy individuals enjoy more gains in education and welfare, the percentage gains in asset values are roughly the same at age 30 (13.76% for healthy individuals vs. 13.78% sick individuals).

In this experiment, not all individuals in the simulated sample will attend college. For those who ever attend college, their average cost discounted at age 16 is $3,687, while for those who never attend college, their costs are zero. The per capita cost of the college tuition subsidy is $2,965, if shared by all of the individuals. As shown, the gains are very different across groups and health status. Overall, individuals in group 1 and group 2
experience greater pecuniary gains from the program because they have significantly large college attendance regardless of the subsidy. For the same reason, healthy people experience more pecuniary gains than sick people.

4.4.2. High school health expenditure subsidy

Table 13 explores the effect of a $812 per year health expenditure subsidy for high school students.\textsuperscript{21} The per capita cost of the program is $2,965 which is the same amount as the per capita college tuition subsidy. This amount is smaller than the cost of subsidizing everybody at $812 for four years starting at age 16 since some simulated individuals will choose to work or to stay at home and will not get the health expenditure subsidy.

As shown, the average highest year of schooling increases 0.61, from 13.20 years to 13.81 years. Compared with the college tuition subsidy, the high school health expenditure subsidy generates 0.08 more years of schooling. Furthermore, the mean years spent in college increases 0.52, from 1.48 years to 2.00 years. This amount of increase is also more than that due to the college tuition subsidy. The two subsidies, however, produce almost the same amounts of increase in both assets and welfare.

The high school health expenditure subsidy produces not only more gains in education, but also a very different distribution of gains compared with the college tuition subsidy. Rather than favoring healthy individuals, the high school health expenditure subsidy favors sick individuals, especially those who are sick and endowed with high academic ability have the largest increases in both education and welfare.

Gains of individuals who have experienced at least one bout of sickness before age 21 improve substantially. Their mean schooling years increase 1.21 years and mean lifetime utility increases by 28%, compared to 0.52 years and 10% for healthy individuals. More specifically, sick individuals of high study type experience the largest increase in schooling years and lifetime utility. Their average years of schooling increase 1.27 years and average lifetime utility increases by 31.2%.

\textsuperscript{21} Because the optimization model contains no individual behavior before age 16, we have assumed that the high-school health subsidy does not affect the sample initial state distributions, including that of educational attainment, work experience, and health at the age of 16. Providing subsidy effect before age 16 might yield a larger private gain.
The different outcomes from the two policy experiments could be explained by two reasons. First, health limitation decreases the possibility of passing a grade, and graduating from high school is the only path assumed in this paper to attend college. Hence, a college tuition subsidy is not as attractive to those who anticipate a small probability of passing a grade. However, a high school health expenditure provides a direct channel for this population to gain from the subsidy. Second, for those people who would go to college even without the tuition subsidy, the benefits are greatest because of the level effect of the subsidy. But, for those who are induced to attend college, the benefits come from the marginal effect, i.e., the marginal indifference between college attendance and other options.

5. Conclusion

In this paper we estimate a dynamic model of joint decisions of young men on schooling, work, or staying at home, on health expenditure, and on level of savings over the life cycle using 16 years of data from the NLSY79. The structural framework explicitly models two existing theoretical hypotheses on the correlation between health and education. The model is estimated using the method of indirect inference and the method of simulation and interpolation by Keane and Wolpin (1994).

The estimation results confirm that health and education are interdependent since all coefficients that correspond to the two alternative hypotheses are statistically significant. In particular, the estimation results imply that an individual’s education, health expenditure, and prior health status influence his health status. For example, a twenty-year-old individual with four more years of education would be about 6 percent less likely to be sick given that he is healthy and spends nothing on health. Meanwhile, the individual’s health has a substantial effect on his mortality rate, wage, home production, and academic success in school. Indeed, health plays an extremely important role in determining an individual’s educational attainment. On average, an individual who has been sick before age 21 has 1.08 less years of schooling compared with those who are healthy. Policy experiments based on the model’s estimates indicate that a high school health expenditure subsidy would have a larger impact on education and wellbeing than a direct college tuition subsidy at the same per capita cost. More specifically, a direct
college tuition subsidy will favor healthy individuals: those endowed with high academic ability will have the largest increase in their wellbeing and those endowed with low academic ability will have the largest increase in their schooling years. By contrast, the high school health expenditure subsidy favors sick individuals, especially those who are sick and endowed with high academic ability will have the largest increases in both education and wellbeing.
Appendix A: Forms of Descriptive Statistical Models

As discussed in Section 2.3.1, the descriptive statistical model at time $t$ is a linear model, given in (16). The construction of $\{y_t, x_t\}$ in (16) is described below.

(1) $t = 1$, i.e., age 16

The regressors include a constant term, schooling years, indicator of sickness, and duration of prior sickness:

$$x_1 = \left(1, sch_1, D_1, sl_1\right). \quad (A.1)$$

Note that because of the data limitation in calculating the effective schooling years $edu$, we use the observed schooling years $sch$. The indicator for success in school is chosen as a dependent variable.

The set of dependent variables consists of the dummies for working and schooling, wage, indicator of passing the grade, and the dummy for sickness at $t = 2$ (age 17). Some of the dependent variables are allowed to be missing. If for some individuals, one or more variables are missing or unobserved, then the corresponding dependent variables are accordingly missing from these individuals at this age. For example, if the transcript data are missing or unobserved for individual $i$ (an unobserved transcript may occur because he was in middle school or college during the time of survey), then the dependent variable of the indicator of passing the grade will not be included for this individual. The set of dependent variables for the observed data is:

$$y_1 = \left(d_{1,1}^1, w_1, d_{2,1}^1, passinciple of high school, D_2\right). \quad (A.2)$$

The simulated data consist of the same individuals as in the observed data, except that the simulated discrete variables are replaced by the smooth functions discussed in section 2. That is to say, the number of linear regression equations for simulated data and observed data is equal.

(2) $1 < t < 6$, i.e., from age 17 to 20

For $t = 3, 4, \text{ or } 5$, the regressors include a constant term, schooling years, work experiences, dummies for work and school attendance, indicator of sickness, and duration of sickness:

$$x_i = \left(1, sch_i, ep_i, d_{1,i}^1, d_{2,i}^1, D_i, sl_i\right). \quad (A.3.1)$$
The independent variables for \( t = 2 \) are different from those for \( t = 3, 4 \) or 5, in which work experience is not included because at this period \( ep_2 \) is equal to \( d_{i,1}^1 \) (remember that the initial work experience is set at zero):

\[
x_2 = (1, sch_2, d_{i,1}^1, d_{i,2}^1, D_2, sl_2).
\]  

(A.3.2)

The dependent variables are:

\[
y_i = (d_{i,1}^1, w_i, d_{i,2}^1, \text{pass(if in high school)}, D_i).
\]  

(A.4)

Similar to the case of \( t = 1 \), if some observed variables are missing or unobserved, the corresponding dependent variables are also missing.

(3) \( t = 6 \), i.e., age 21.

This is the earliest age that we start to observe asset data for some individuals. The set of independent variables are the same as in (A.3.1). The set of dependent variables is:

\[
y_6 = (d_{i,6}^1, w_6, d_{i,2,6}^1, \text{pass(if in high school)}, D_7, A_6).
\]  

(A.5)

(4) \( 6 < t < 16 \), i.e., from age 22 to 30

It is necessary to have two descriptive statistical models because of the asset data. Both models have the same set of dependent variables:

\[
y_i = (d_{i,t}^1, w_i, d_{i,2,t}^1, D_{t+1}, A_i).
\]  

(A.6)

Note that the indicator for passing the grade is not included in (A.6) because of the convenient assumption that individuals should have finished their high school by age 22. Actually, in the sample, only 5 individuals over 21 years old are still in high school.

The first descriptive statistical model includes all the individuals whose assets at \( t - 1 \) are missing or unobserved. In contrast, the second model includes all the individuals whose assets at \( t - 1 \) are observed. The set of independent variables for the first model is the same as in (A.3.1), while for the second one it is:

\[
x_t = (1, sch_t, ep_t, d_{i,t-1}^1, d_{i,2,t-1}^1, D_t, sl_t, A_{t-1}).
\]  

(A.7)

(5) \( t = 16 \), i.e., age 32

The descriptive statistical models are similar to the case of \( 6 < t < 16 \), in which the
models are distinguished by whether the assets at period 15 are observed. The set of
independent variables for the first model is:

\[ x_{16} = (1, sch_{16}, ep_{16}, d_{1,15}^1, d_{2,15}^1, D_{16}, sl_{16}), \]  

(A.8.1)

and for the second model is:

\[ x_{16} = (1, sch_{16}, ep_{16}, d_{1,15}^1, d_{2,15}^1, D_{16}, sl_{16}, A_{15}). \]  

(A.8.2)

Because the sample does not contain the information for health at \( t = 17 \), the set of
dependent variables is:

\[ y_{16} = (d_{1,16}^1, w_{16}, d_{2,16}^1, A_{16}). \]  

(A.9)

Appendix B: Two-Step Approach

For the sake of computational tractability, we use the two-step approach as proposed
by Keane and Smith (2004) to estimate the parameters of the structural model. The idea
of the first step is to obtain a consistent estimate \( \hat{\Psi}_1 \) of the structural parameters by
solving the optimization problem (22). In the first step, the number of simulated data sets
\( F \) is set to 1, which substantially reduces the computation time. In addition, a relatively
large value for the smoothing parameter \( \lambda \) is chosen (\( \lambda = 0.05 \)) to ensure that the objective
function is smooth.

In the second step, to reduce bias we choose \( \lambda \) to be 0.003 and \( F \) to be 100.
According to Proposition 2 in Keane and Smith (2004),

\[ \hat{\Psi}_2 = \hat{\Psi}_1 - \left( J_{\Theta \Theta} \left( y; z, \tilde{\Theta}(\hat{\Psi}_1) \right) J \right)^{-1} J_{\Theta \Theta} \left( y; z, \tilde{\Theta}(\hat{\Psi}_1) \right) \]

is a consistent and asymptotically normal estimate of \( \Psi \), where \( L_{\Theta \Theta} \) is the Hessian of
the likelihood function associated with the descriptive model, and \( \hat{J} \) is an estimate of
the Jacobian of the binding function \( H(\hat{\Psi}_1) \) (Gourieroux, Monfort, and Renault, 1993,
and Keane and Smith, 2004).
References


Economics of Education Review:

Table 1: Percentages of Choice Selections: White Males Aged 16-31

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<th>Age</th>
<th>Sickness Subsample</th>
<th>Full Sample</th>
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<td>(24)</td>
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<tr>
<td>19</td>
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<td>27.84</td>
</tr>
<tr>
<td></td>
<td>(31)</td>
<td>(27)</td>
</tr>
<tr>
<td>20</td>
<td>22.32</td>
<td>29.46</td>
</tr>
<tr>
<td></td>
<td>(25)</td>
<td>(33)</td>
</tr>
<tr>
<td>21</td>
<td>17.05</td>
<td>34.11</td>
</tr>
<tr>
<td></td>
<td>(22)</td>
<td>(44)</td>
</tr>
<tr>
<td>22</td>
<td>11.51</td>
<td>46.04</td>
</tr>
<tr>
<td></td>
<td>(16)</td>
<td>(64)</td>
</tr>
<tr>
<td>23</td>
<td>10.53</td>
<td>50.66</td>
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<tr>
<td></td>
<td>(16)</td>
<td>(77)</td>
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<td>6.06</td>
<td>52.73</td>
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<tr>
<td></td>
<td>(10)</td>
<td>(87)</td>
</tr>
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<td>3.98</td>
<td>56.82</td>
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<tr>
<td></td>
<td>(7)</td>
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</tr>
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<tr>
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<td>(6)</td>
<td>(110)</td>
</tr>
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<td>27</td>
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</tr>
<tr>
<td></td>
<td>(5)</td>
<td>(112)</td>
</tr>
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<td>52.45</td>
</tr>
<tr>
<td></td>
<td>(4)</td>
<td>(107)</td>
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<td>53.02</td>
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<tr>
<td></td>
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<td>(114)</td>
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<td>30</td>
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<tr>
<td></td>
<td>(2)</td>
<td>(85)</td>
</tr>
<tr>
<td>31</td>
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<td>51.16</td>
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<tr>
<td></td>
<td>(1)</td>
<td>(44)</td>
</tr>
<tr>
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<td>47.36</td>
</tr>
<tr>
<td></td>
<td>(261)</td>
<td>(1041)</td>
</tr>
</tbody>
</table>

Note: Number of observations is in parenthesis.
Sickness subsample at age $t$ consists of individuals who have been sick at least once up to and including age $t$. 

45
Table 2: Transition Matrix between Two States  
(Full Sample: White Males Aged 16-31 *)

<table>
<thead>
<tr>
<th>Choice (t - 1)</th>
<th>Choice (t)</th>
<th>School</th>
<th>Work</th>
<th>Home</th>
</tr>
</thead>
<tbody>
<tr>
<td>School:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Row %</td>
<td></td>
<td>73.49</td>
<td>12.98</td>
<td>13.52</td>
</tr>
<tr>
<td>Column %</td>
<td></td>
<td>92.59</td>
<td>9.25</td>
<td>17.61</td>
</tr>
<tr>
<td>Work:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Row %</td>
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<td>86.98</td>
<td>10.7</td>
</tr>
<tr>
<td>Column %</td>
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<td>3.71</td>
<td>78.97</td>
<td>17.77</td>
</tr>
<tr>
<td>Home:</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Row %</td>
<td></td>
<td>4.26</td>
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<tr>
<td>Column %</td>
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<td>3.7</td>
<td>11.78</td>
<td>64.62</td>
</tr>
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</table>

* Number of observations: 14,910

Table 3: Transition Matrix between Two States  
(Sickness Subsample: White Males Aged 16-31 *)

<table>
<thead>
<tr>
<th>Choice (t - 1)</th>
<th>Choice (t)</th>
<th>School</th>
<th>Work</th>
<th>Home</th>
</tr>
</thead>
<tbody>
<tr>
<td>School:</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Row %</td>
<td></td>
<td>58.7</td>
<td>15.38</td>
<td>25.97</td>
</tr>
<tr>
<td>Column %</td>
<td></td>
<td>83.09</td>
<td>6.25</td>
<td>10.66</td>
</tr>
<tr>
<td>Work:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Row %</td>
<td></td>
<td>1.81</td>
<td>82.3</td>
<td>15.89</td>
</tr>
<tr>
<td>Column %</td>
<td></td>
<td>5.95</td>
<td>77.9</td>
<td>16.15</td>
</tr>
<tr>
<td>Home:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Row %</td>
<td></td>
<td>3.49</td>
<td>19.25</td>
<td>77.26</td>
</tr>
<tr>
<td>Column %</td>
<td></td>
<td>11.22</td>
<td>16.72</td>
<td>72.05</td>
</tr>
</tbody>
</table>

* Number of observations: 2,154
Table 4: Percentage Failing Grades 9, 10, 11, and 12 *
White Males Aged 16-31

<table>
<thead>
<tr>
<th>Grade</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Full Sample</td>
<td>13.9</td>
<td>6.08</td>
<td>5.54</td>
<td>3.63</td>
</tr>
<tr>
<td></td>
<td>(374)</td>
<td>(954)</td>
<td>(903)</td>
<td>(799)</td>
</tr>
<tr>
<td>Sickness Subsample</td>
<td>20.69</td>
<td>20.93</td>
<td>19.57</td>
<td>7.61</td>
</tr>
<tr>
<td></td>
<td>(35)</td>
<td>(72)</td>
<td>(71)</td>
<td>(67)</td>
</tr>
</tbody>
</table>

* Number of observations with transcripts report are in parentheses.

Table 5: Asset Distribution
Full Sample: White Males Aged 21 - 31

<table>
<thead>
<tr>
<th>Age</th>
<th>Median</th>
<th>Mean</th>
<th>Std</th>
<th>Max</th>
<th>Min</th>
<th>No. Obs.</th>
<th>Percent Negative</th>
</tr>
</thead>
<tbody>
<tr>
<td>21</td>
<td>1,931</td>
<td>4,209</td>
<td>6,404</td>
<td>55,330</td>
<td>-15,296</td>
<td>230</td>
<td>9.8</td>
</tr>
<tr>
<td>22</td>
<td>2,248</td>
<td>5,019</td>
<td>8,262</td>
<td>80,524</td>
<td>-14,753</td>
<td>497</td>
<td>11.2</td>
</tr>
<tr>
<td>23</td>
<td>2,752</td>
<td>5,883</td>
<td>10,581</td>
<td>115,630</td>
<td>-12,703</td>
<td>921</td>
<td>16.4</td>
</tr>
<tr>
<td>24</td>
<td>2,863</td>
<td>6,263</td>
<td>12,507</td>
<td>176,972</td>
<td>-31,618</td>
<td>911</td>
<td>16.7</td>
</tr>
<tr>
<td>25</td>
<td>3,590</td>
<td>8,082</td>
<td>16,071</td>
<td>196,907</td>
<td>-36,624</td>
<td>907</td>
<td>15.3</td>
</tr>
<tr>
<td>26</td>
<td>4,003</td>
<td>9,833</td>
<td>20,235</td>
<td>209,874</td>
<td>-43,152</td>
<td>938</td>
<td>16.6</td>
</tr>
<tr>
<td>28</td>
<td>5,565</td>
<td>14,294</td>
<td>26,456</td>
<td>247,706</td>
<td>-33,388</td>
<td>607</td>
<td>15.0</td>
</tr>
<tr>
<td>29</td>
<td>7,443</td>
<td>15,424</td>
<td>27,621</td>
<td>262,705</td>
<td>-37,028</td>
<td>438</td>
<td>12.9</td>
</tr>
<tr>
<td>30</td>
<td>8,628</td>
<td>18,501</td>
<td>35,369</td>
<td>298,728</td>
<td>-21,211</td>
<td>589</td>
<td>11.6</td>
</tr>
<tr>
<td>31</td>
<td>9,168</td>
<td>21,599</td>
<td>48,360</td>
<td>338,994</td>
<td>-24,756</td>
<td>351</td>
<td>10.7</td>
</tr>
</tbody>
</table>

Note: In 1984 dollars.
Table 6: Asset Distribution*
Sickness Data: White Males Aged 21 - 31**

<table>
<thead>
<tr>
<th>Age</th>
<th>Median</th>
<th>Mean</th>
<th>Std</th>
<th>Max</th>
<th>Min</th>
<th>No. Obs.</th>
<th>Percent Negative</th>
</tr>
</thead>
<tbody>
<tr>
<td>21</td>
<td>1,333</td>
<td>3,389</td>
<td>6,306</td>
<td>16,927</td>
<td>-8,035</td>
<td>29</td>
<td>6.7</td>
</tr>
<tr>
<td>22</td>
<td>2,058</td>
<td>2,737</td>
<td>4,091</td>
<td>19,434</td>
<td>-7,402</td>
<td>67</td>
<td>20.9</td>
</tr>
<tr>
<td>23</td>
<td>2,566</td>
<td>5,064</td>
<td>8,042</td>
<td>36,585</td>
<td>-8,714</td>
<td>130</td>
<td>17.7</td>
</tr>
<tr>
<td>24</td>
<td>2,654</td>
<td>5,257</td>
<td>10,030</td>
<td>61,999</td>
<td>-13,719</td>
<td>141</td>
<td>17.0</td>
</tr>
<tr>
<td>25</td>
<td>3,000</td>
<td>6,289</td>
<td>9,488</td>
<td>52,133</td>
<td>-10,518</td>
<td>148</td>
<td>17.6</td>
</tr>
<tr>
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<td>3,545</td>
<td>7,054</td>
<td>12,002</td>
<td>62,358</td>
<td>-11,312</td>
<td>160</td>
<td>20.0</td>
</tr>
<tr>
<td>27</td>
<td>4,886</td>
<td>10,454</td>
<td>17,390</td>
<td>93,206</td>
<td>-6,415</td>
<td>114</td>
<td>18.2</td>
</tr>
<tr>
<td>28</td>
<td>3,481</td>
<td>8,470</td>
<td>14,398</td>
<td>69,612</td>
<td>-12,197</td>
<td>103</td>
<td>18.5</td>
</tr>
<tr>
<td>29</td>
<td>3,703</td>
<td>9,898</td>
<td>15,695</td>
<td>84,883</td>
<td>-12,583</td>
<td>97</td>
<td>17.5</td>
</tr>
<tr>
<td>30</td>
<td>5,036</td>
<td>11,823</td>
<td>18,375</td>
<td>77,389</td>
<td>-9,347</td>
<td>118</td>
<td>16.1</td>
</tr>
<tr>
<td>31</td>
<td>6,169</td>
<td>13,203</td>
<td>23,483</td>
<td>96,098</td>
<td>-8,479</td>
<td>65</td>
<td>12.3</td>
</tr>
</tbody>
</table>

* In 1984 dollars.

** Sickness data at age $t$ consist of individuals who reported health limitation at least once up to and including age $t$. 
Table 7: Estimates of the Model

<table>
<thead>
<tr>
<th>Probability of being Sick:</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>age $\beta_1$:</td>
<td>0.0082 (0.0025)</td>
<td></td>
</tr>
<tr>
<td>health expenditure/1000 $\beta_2$:</td>
<td>-2.5429 (0.0373)</td>
<td></td>
</tr>
<tr>
<td>educational attainment $\beta_3$:</td>
<td>-0.0184 (0.0057)</td>
<td></td>
</tr>
<tr>
<td>sickness $\beta_4$:</td>
<td>1.2126 (0.4730)</td>
<td></td>
</tr>
<tr>
<td>Interaction between sickness and duration $\beta_5$:</td>
<td>0.1083 (0.0368)</td>
<td></td>
</tr>
</tbody>
</table>

| Mortality Rate:            |          |          |
| constant $\alpha_0$:       | -0.0326 (0.00217) |
| sickness $\alpha_1$:       | 3.1018 (0.2165) |
| interaction between sickness and duration $\alpha_2$: | 0.0232 (0.00317) |

| Probability of Passing a Grade: |          |          |
| high study type $\xi_{01}$:     | 1.1084 (0.3782) |
| low study type $\xi_{02}$:      | 0.1440 (0.0583) |
| sickness $\xi_1$:               | -0.5042 (0.1485) |
| interaction between sickness and duration $\xi_2$: | -0.0063 (0.0037) |
| educational attainment $\xi_3$: | 0.0302 (0.0082) |
| educational attainment no less than ten $\xi_4$: | 0.2738 (0.0878) |
| absence from school in the last period $\xi_5$: | -0.467 (0.0782) |

| Wage:                      |          |          |
| high work type $\gamma_{01}$: | 1.5023 (0.183) |
| low work type $\gamma_{02}$:  | 1.2248 (0.487) |
| educational attainment $\gamma_1$: | 0.1043 (0.0169) |
| experience $\gamma_2$:       | 0.09735 (0.0352) |
| experience squared/100 $\gamma_3$: | -0.3885 (0.0581) |
| age $\gamma_4$:              | -0.0064 (0.0026) |
| sickness $\gamma_5$:         | -0.1649 (0.0653) |
| interaction between sickness and duration $\gamma_6$: | -0.0042 (0.0037) |
| absence from work in the last period $\gamma_7$: | -0.1184 (0.0613) |

| Home Production:            |          |          |
| constant $\bar{e}$:         | 9715.7 (3728.2) |
| sickness $\phi_1$:          | -2684.5 (569.4) |
| interaction between sickness and duration $\phi_2$: | -374.4 (128.36) |
Table 7 Estimates of the Model (Cont.)

Terminal Value Function:
- constant $\tau_{01}$: 4.4952 (1.4701)
- high study type $\tau_{02}$: 0.6201 (0.0351)
- high work type $\tau_{03}$: 0.5102 (0.0496)
- sickness $\tau_1$: -0.4375 (0.1478)
- interaction between sickness and duration $\tau_2$: -0.0383 (0.0567)
- educational attainment $\tau_3$: 4.6915 (1.538)
- educational attainment squared /100 $\tau_4$: 3.5393 (0.7539)
- assets $\tau_5$: 0.5428 (0.4242)
- assets squared / 10^5 $\tau_6$: -0.000216 (0.00054)
- experience $\tau_7$: 1.7538 (0.4783)
- experience squared /100 $\tau_8$: 0.4775 (0.4792)
- interaction between education and high study type $\tau_9$: 0.5904 (0.8931)
- interaction between education and high work type $\tau_{10}$: 0.6428 (0.0537)
- interaction between assets and high study type $\tau_{11}$: 0.00425 (0.0753)
- interaction between assets and high work type $\tau_{12}$: 0.000436 (0.00032)
- interaction between experience and high study type $\tau_{13}$: 0.00438 (0.00852)
- interaction between experience and high work type $\tau_{14}$: 0.00753 (0.00073)

Error:
- standard deviation of wage $\sigma_w$: 0.5613 (0.2436)
- standard deviation of home production $\sigma_e$: 7.8657 (5.538)
- correlation $\sigma_{we}$: -2.1247 (0.4349)

Type Ratio:
- high study type $r_01$: 0.8462 (0.2463)
- high work type $r_02$: 0.6132 (0.1305)

Preference Discount Factor $\delta$: 0.9645 (0.3541)

Coefficient of Relative Risk Aversion $\sigma$: 0.8165 (0.3202)

Education Cost $ec$: $4063 (1673.2)

Net Income Boundary $NIB$: -$557.4 (148.42)

Note: Standard errors are in parentheses.
<table>
<thead>
<tr>
<th>Age</th>
<th>Health Expenditure**</th>
<th>Healthy</th>
<th>Sick 0-year duration</th>
<th>Sick 1-year duration</th>
<th>Sick 3-year duration</th>
<th>Sick 5-year duration</th>
</tr>
</thead>
<tbody>
<tr>
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<td>87.69</td>
<td>89.76</td>
<td>93.12</td>
<td>95.56</td>
</tr>
<tr>
<td></td>
<td>$250</td>
<td>24.56</td>
<td>69.99</td>
<td>73.64</td>
<td>80.21</td>
<td>85.67</td>
</tr>
<tr>
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<td>9.27</td>
<td>45.56</td>
<td>49.87</td>
<td>58.44</td>
<td>66.64</td>
</tr>
<tr>
<td></td>
<td>$750</td>
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<td>22.74</td>
<td>26.14</td>
<td>33.63</td>
<td>41.84</td>
</tr>
<tr>
<td></td>
<td>$1,000</td>
<td>0.47</td>
<td>8.33</td>
<td>10.12</td>
<td>14.5</td>
<td>20</td>
</tr>
<tr>
<td></td>
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<td>0.05</td>
<td>0.07</td>
<td>0.15</td>
<td>0.3</td>
</tr>
<tr>
<td>25</td>
<td>0</td>
<td>50.84</td>
<td>89.13</td>
<td>91.02</td>
<td>94.04</td>
<td>96.21</td>
</tr>
<tr>
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<td>$250</td>
<td>26.94</td>
<td>72.50</td>
<td>76.00</td>
<td>82.19</td>
<td>87.27</td>
</tr>
<tr>
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<td>52.81</td>
<td>61.3</td>
<td>69.27</td>
</tr>
<tr>
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<td>28.59</td>
<td>36.37</td>
<td>44.75</td>
</tr>
<tr>
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<td>11.49</td>
<td>16.25</td>
<td>22.13</td>
</tr>
<tr>
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<td>0.09</td>
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<td>0.37</td>
</tr>
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<td>0</td>
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<td>91.67</td>
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</tr>
<tr>
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<td>77.25</td>
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</tr>
<tr>
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<td>50.13</td>
<td>54.44</td>
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<tr>
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<td>26.35</td>
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<td>37.92</td>
<td>46.37</td>
</tr>
<tr>
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<td>12.30</td>
<td>17.27</td>
<td>23.37</td>
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<tr>
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<td>0.07</td>
<td>0.11</td>
<td>0.22</td>
<td>0.42</td>
</tr>
</tbody>
</table>

* Educational attainment is 10 years.

** In 1984 dollars.
Table 9: Estimated Sickness Probabilities in Percentage* by Grade, Health Expenditure, and Health Status

<table>
<thead>
<tr>
<th>Grade</th>
<th>Health Expenditure**</th>
<th>Sick</th>
<th>0-year duration</th>
<th>3-year duration</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Healthy</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>0</td>
<td>50.67</td>
<td>89.05</td>
<td>93.99</td>
</tr>
<tr>
<td></td>
<td>$500</td>
<td>10.48</td>
<td>48.32</td>
<td>61.14</td>
</tr>
<tr>
<td></td>
<td>$1,000</td>
<td>0.58</td>
<td>9.45</td>
<td>16.14</td>
</tr>
<tr>
<td>12</td>
<td>0</td>
<td>47.74</td>
<td>87.61</td>
<td>93.07</td>
</tr>
<tr>
<td></td>
<td>$500</td>
<td>9.20</td>
<td>45.40</td>
<td>58.29</td>
</tr>
<tr>
<td></td>
<td>$1,000</td>
<td>0.47</td>
<td>8.27</td>
<td>14.41</td>
</tr>
<tr>
<td>16</td>
<td>0</td>
<td>44.81</td>
<td>86.04</td>
<td>92.03</td>
</tr>
<tr>
<td></td>
<td>$500</td>
<td>8.05</td>
<td>42.50</td>
<td>55.4</td>
</tr>
<tr>
<td></td>
<td>$1,000</td>
<td>0.38</td>
<td>7.21</td>
<td>12.8</td>
</tr>
</tbody>
</table>

* Age is 20.

** In 1984 dollars.
Table 10: Predicted and Actual State Variables

<table>
<thead>
<tr>
<th></th>
<th>Sickness Subsample</th>
<th>Full Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Predicted</td>
<td>Actual</td>
</tr>
<tr>
<td>Years of schooling:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Completed schooling years</td>
<td>12.41</td>
<td>12.36</td>
</tr>
<tr>
<td>Percent completing 12 years</td>
<td>67.25</td>
<td>64.73</td>
</tr>
<tr>
<td>Percent completing 16 years</td>
<td>13.41</td>
<td>15.27</td>
</tr>
<tr>
<td>Mean percentage of employment</td>
<td>43.30</td>
<td>47.36</td>
</tr>
<tr>
<td>Mean percentage of school attendance</td>
<td>12.76</td>
<td>11.87</td>
</tr>
<tr>
<td>Mean percentage of staying at home</td>
<td>43.94</td>
<td>40.77</td>
</tr>
<tr>
<td>Percent grade failing *:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Grade 9</td>
<td>22.13</td>
<td>20.69</td>
</tr>
<tr>
<td>Grade 10</td>
<td>19.49</td>
<td>20.93</td>
</tr>
<tr>
<td>Grade 11</td>
<td>18.37</td>
<td>19.57</td>
</tr>
<tr>
<td>Grade 12</td>
<td>11.05</td>
<td>7.61</td>
</tr>
<tr>
<td>Mean assets at age ($) **:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>21</td>
<td>2,784</td>
<td>3,389</td>
</tr>
<tr>
<td>24</td>
<td>4,692</td>
<td>5,257</td>
</tr>
<tr>
<td>27</td>
<td>9,836</td>
<td>10,452</td>
</tr>
<tr>
<td>30</td>
<td>13,140</td>
<td>11,823</td>
</tr>
<tr>
<td>Mean health expenditure ($)</td>
<td>883.7</td>
<td>--</td>
</tr>
</tbody>
</table>

Note:
1. Predicted values are based on 8,000 simulated individuals.
2. Except in the following two cases, the sickness data include all the individuals who have been sick during the 16-year period.
   * In this case, the sickness data consist of cumulative individuals who reported sickness by the specified grade.
   ** In this case, the sickness data consist of cumulative individuals who have been sick up to age $t$. 
Table 11: Initial Health Status Effects by Initial Education

<table>
<thead>
<tr>
<th>Initial Educational Attainment 9 Years or Less</th>
<th>Healthy at Age 16</th>
<th>Sick at Age 16</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean educational attainment at age 30 (years)</td>
<td>13.17</td>
<td>12.30</td>
</tr>
<tr>
<td>Mean percent survival probability at age 30 (%)</td>
<td>97.43</td>
<td>94.32</td>
</tr>
<tr>
<td>Mean assets at age 30</td>
<td>$19,407</td>
<td>$12,073</td>
</tr>
<tr>
<td>Mean health expenditure by age 30</td>
<td>$794</td>
<td>$844</td>
</tr>
<tr>
<td>Expected present value of lifetime utility at 16</td>
<td>203.4</td>
<td>162.3</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Initial Educational Attainment 10 Years or More</th>
<th>Healthy at Age 16</th>
<th>Sick at Age 16</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean educational attainment at age 30 (years)</td>
<td>13.56</td>
<td>12.84</td>
</tr>
<tr>
<td>Mean percent survival probability at age 30 (%)</td>
<td>98.62</td>
<td>97.14</td>
</tr>
<tr>
<td>Mean assets at age 30</td>
<td>$22,843</td>
<td>$18,508</td>
</tr>
<tr>
<td>Mean health expenditure by age 30</td>
<td>$953</td>
<td>$1,012</td>
</tr>
<tr>
<td>Expected present value of lifetime utility at 16</td>
<td>220.3</td>
<td>184.5</td>
</tr>
</tbody>
</table>

Note: Based on a simulation of 8,000 individuals.
<table>
<thead>
<tr>
<th>Characteristics</th>
<th>All</th>
<th>Sick up to and including Age 20**</th>
<th>Healthy up to and including Age 20</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average highest schooling years completed:</td>
<td></td>
<td>All Groups</td>
<td>Group 1</td>
</tr>
<tr>
<td>Mean years in college:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No subsidy</td>
<td>1.48</td>
<td>0.80</td>
<td>0.82</td>
</tr>
<tr>
<td>Subsidy</td>
<td>1.93</td>
<td>1.11</td>
<td>1.17</td>
</tr>
<tr>
<td>Mean Assets at age 30 ($)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No subsidy</td>
<td>19,626</td>
<td>12,044</td>
<td>12,940</td>
</tr>
<tr>
<td>Subsidy</td>
<td>22,327</td>
<td>13,704</td>
<td>14,854</td>
</tr>
<tr>
<td>Mean expected present value of lifetime utility at age 16:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No subsidy</td>
<td>203.9</td>
<td>160.1</td>
<td>168.4</td>
</tr>
<tr>
<td>Subsidy</td>
<td>225.4</td>
<td>168.8</td>
<td>177.8</td>
</tr>
</tbody>
</table>

Note: * The per capita cost of the subsidy is $2,965.
** The percentage of people who were sick at least once before age 20 (including age 20): without subsidy, 11.03%; with subsidy, 10.4%.
1. Based on a simulation of 8,000 individuals.
2. Group 1: high ability in school and work; Group 2: high ability in school and low ability in work;
   Group 3: low ability in school and high ability in work; Group 4: low ability in school and work.
3. The study and work skill endowments are randomly drawn according to the estimated population ratios of types.
4. The initial sickness and duration are drawn from the health limitation distribution at age 16.
Table 13: Effect of a $812 Health Expenditure Subsidy for High School Students on Selected State Variables*

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>All</th>
<th>Sick up to and including Age 20**</th>
<th>Healthy up to and including Age 20</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All Groups</td>
<td>Group 1</td>
<td>Group 2</td>
<td>Group 3</td>
</tr>
<tr>
<td>Average highest schooling years completed:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean years in college</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No subsidy</td>
<td>1.48</td>
<td>0.80</td>
<td>0.82</td>
<td>1.13</td>
</tr>
<tr>
<td>Subsidy</td>
<td>2.00</td>
<td>1.70</td>
<td>1.86</td>
<td>2.21</td>
</tr>
<tr>
<td>Mean Assets at age 30 ($)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No subsidy</td>
<td>19,626</td>
<td>12,044</td>
<td>12,940</td>
<td>13,754</td>
</tr>
<tr>
<td>Subsidy</td>
<td>22,401</td>
<td>19,798</td>
<td>21,059</td>
<td>23,743</td>
</tr>
<tr>
<td>Mean expected present value</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>of lifetime utility at age 16:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No subsidy</td>
<td>203.9</td>
<td>160.1</td>
<td>168.4</td>
<td>155.7</td>
</tr>
<tr>
<td>Subsidy</td>
<td>228.7</td>
<td>204.9</td>
<td>215.4</td>
<td>209.3</td>
</tr>
</tbody>
</table>

Note: * The per capita cost of the subsidy is $2965, same amount as the per capita college tuition subsidy.
** The percentage of people who were sick at least once before age 20 (including age 20): without subsidy, 11.03%; with subsidy, 7.4%.
1. Based on a simulation of 8,000 individuals.
2. Group 1: high ability in school and work; Group 2: high ability in school and low ability in work;
   Group 3: low ability in school and high ability in work; Group 4: low ability in school and work.
3. The skill endowments are drawn according to the population ratio of types.
4. The initial sickness and duration are randomly drawn from the health limitation distribution at age 16.
Figure 1: Stochastic Shocks and Decisions

- Wage and home production shocks
- Health status (sick/healthy)
- Choices on work, school, home, savings, and health expenditure
- Grade shock given school attendance
- Health shock
- Pass/fail the grade

Figure 2: White Male Sickness Reports

Age

Sick Percentage

4 4.25 4.5 4.75 5 5.25

16 17 18 19 20 21 22 23 24 25 26 27 28 29
Figure 3a: Predicted and Actual Choice Selections by Age
(Full Sample)
Employment

Home

Percent

Age

Age

Actual
Predicted

Actual
Predicted
Figure 3b: Predicted and Actual Choice Selections by Age
(Sickness Subsample)
Figure 4a: Predicted and Actual Mean Assets by Age (Full Sample)

Figure 4b: Predicted and Actual Mean Assets by Age (Sickness Subsample)
Figure 5: Predicted and Actual Sickness Percentage

Figure 6: Predicted Mean Health Expenditure and Percentage of Zero Health Expenditure