A Dynamic Model of Health, Education, and Wealth with Credit Constraints and Rational Addiction*

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Abstract

This paper develops and structurally estimates a life-cycle model where health, education, and wealth are endogenous accumulated processes depending on the history of an individual's optimal behaviors, on parental factors, and on cognitive and noncognitive abilities. The model investigates many different pathways between education, health, and wealth by introducing endogenous health capital production and addictive preferences of unhealthy behavior in the presence of credit constraints. Using data from National Longitudinal Survey of Youth 97, we estimate the model using a two-step estimation procedure based on factor analysis and simulated method of moments. The estimated model decomposes the causal effects of education on health into the direct benefits of improving health production efficiency and the indirect benefits of reducing unhealthy behavior and raising earnings. We show that rational addiction has important quantitative implication on predicted patterns of unhealthy behavior by socioeconomic status and over the life-cycle. We find sizable impacts of both health and parental transfers on individuals' college decisions. We find that relaxing credit constraints increases college attainment and 4-year college completion rate while its effects on healthy behavior and health evolves nonlinearly over the life cycle. Finally, we show that both cognitive and noncognitive factors are important determinants of health, education, and wealth.

JEL codes: I1, I2, J2

Keywords: Health Capital, Education, Wealth, Human Capital, Rational Addiction, Credit Constraints, Unhealthy Behavior

1 Introduction

This paper develops and structurally estimates a life-cycle model where health, education, and wealth are endogenous accumulated processes depending on the history of individuals' optimal behaviors, on parental factors, and on individual' s cognitive and noncognitive abilities. This paper is motivated by the following two well-known facts (Currie (2009), Cutler and Lleras-Muney (2010), Conti, Heckman, and Urzua (2010), and Heckman, Humphries, Veramendi, and Urzua (2014)). First, there is large and persistent heterogeneity in individuals' adult outcomes in health, education, and wealth. Such heterogeneity in adult outcomes is strongly correlated with the parental socioeconomic status and individuals' early cognitive, noncognitive, and health endowments. Second, better health early in life is associated with higher educational attainment; more educated individuals, in turn, have better health later in life, better labor market prospects, and higher wealth level. The objective of this paper is to establish an estimable modeling framework that can jointly explain these empirical facts. To the best of our knowledge, this is the first paper that quantitatively evaluates the pathways through which health, education, and wealth are jointly determined and how do they interact with each other over the life cycle.

The model introduces two key features. The first feature is the introduction of endogenous formation of addictive preference regarding unhealthy behavior. In the U.S. and many other developed countries, cross-sectional differences in health outcomes can mainly be contributed to differences in unhealthy behavior (such as smoking and heavy drinking). Introducing rational addiction can better characterize the determinants and dynamics of unhealthy behavior in order to evaluate its effects on health. The second feature is the endogenous production of human capital in terms of education, health, and labor market experience, in the presence of credit constraints and parental influence. Such features are important to characterize the dynamic relationship between education, health, and wealth as well as to explain the positive correlation between a child's adult outcomes and his parental background.

In the model, individuals make decisions on unhealthy behavior, schooling, working, and savings at every age in order to maximize his expected discounted remaining lifetime utility. Health can affect an individual's choices on education and wealth in four ways. First, health affects an individual's labor market productivity and thus wages. Second, health affects an individual's preferences towards schooling and leisure. Third, it enters an individual's subjective discount rate, which effectively alters the individual's decision horizon, and thus affects the individual's investment decisions on human capital and wealth. Fourth, current health impacts future health as health production is a persistent process. The effects of education come from three channels: eduction directly impacts future health by entering a health production function; education affects the flow utility of unhealthy behavior; education improves human capital and thus labor market wages. Wealth impacts education and health indirectly by affecting the available resources through the budget constraint. In the presence of credit constraint, individuals with low current wealth may underinvest in their human capital such as enrolling in college and can not smooth their consumption over the life cycle.

Our model has several sources of heterogeneity among its agents: (1) Individuals differ in their initial endowments including cognitive and noncognitive abilities and health. These initial endowments not only directly impact individuals' later life outcomes such as earnings and health, but also affect individuals' investment behavior in schooling, working, and unhealthy behavior. (2) Individuals' parents are different in terms of education and wealth. Both parental education and wealth affect college transfers the individual receives. In addition, parents' education can also shift the individual's preference towards schooling. (3) The model uses an life cycle model to produce heterogeneity in health, education, wealth, past history of unhealthy behavior, and accumulated labor market skills across individuals over time as a result of rational investment behavior in the presence of financial market imperfections. Individuals also face an endogenous borrowing limit which depends on their ages and human capital levels. All three sources of heterogeneity are important in explaining the cross-sectional and life cycle inequality in health, education, and wealth.

The model is estimated in two steps using data from the National Longitudinal Survey of Youth 1997 (NLSY97). The first step applies factor analysis and estimates a measurement system on unobserved cognitive and noncognitive abilities and health using Simulated Maximum Likelihood.

In the second step, we structurally estimate the model using simulated method of moments (SMM).

Our results show that cognitive and noncognitive ability are important determinants of education, health, and wealth. Individuals with higher cognitive and noncognitive ability invest more heavily in their human capital, and therefore the initial disparity in health, education, and wealth by ability reinforces over time. We show that rational addiction has important quantitative implication on predicted patterns of unhealthy behavior by socioeconomic status and over the life-cycle. In particular, we simulate individuals' optimal decisions imposing myopic considerations for unhealthy behavior; we find the predicted probability of unhealthy behavior is much higher and the predicted probability of unhealthy behavior stays relatively stable over the life cycle.

We find a sizable effect of health on education. In particular, if we remove the health benefit on the psychic cost of schooling, the average years of schooling is reduced by 0.29 year at age 30. To evaluate the importance of parental transfers, we shut down the parental transfers and find a 0.33 year reduction in the predicted average years of schooling. Moreover, compared to the benchmark model, removing parental transfers reduces the average probability of 4-year college graduation by 7.6 percentage points and such a negative effect is especially pronounced among the second and third cognitive ability quartile individuals.

To evaluate the importance of credit constraints on education and health, we simulate the model by relaxing the credit constraint and find a large increase in the 4-year college graduation rate when compared with the benchmark model. Furthermore, compared with the benchmark model, once the credit constraint is relaxed, the predicted fraction of individuals who conduct unhealthy behavior first increases at the initial age and then gradually decreases over time as the average education level increases; consequently, the predicted changes in median health stock first decrease and then increase over time. We also conduct a counterfactual experiment of providing college tuition subsidy and find a small increase in average years of schooling as well as the 4-year college graduation rate. Lastly, we conduct a counterfactual analysis of imposing an excise tax of 50% on unhealthy goods consumption while keeping government revenue unchanged. Our model predicts sizable reduction in unhealthy behavior and large welfare gains in terms of increases in health capital.

Our paper contributes to three threads of literature. First, our model contributes to the literature of health capital proposed by Mushkin (1962), Becker (1964), and Fuchs (1966)) and Grossman (1972). In particular, Grossman (1972) models health as a durable capital stock and shows that the demand for health increases with education if more educated people are more efficient producers of health.[1] Since then, a large growing body of research has been developed to document and empirically investigate the relationship between health and other socioeconomic factors including education, income, wealth, and family background (see Deaton (2003) and Currie (2009) for a literature review). Kenkel (1991) shows that part of the relationship between schooling and the consumption of cigarettes, alcohol, and exercise is explained by differences in health knowledge; however, most of schooling's effects on health behavior remain after differences in knowledge are controlled for. Cutler and Lleras-Muney (2006) show that the better educated have healthy behaviors. Case, Lubotsky, and Paxson (2002) show that the relationship between household income and children's health becomes more pronounced as children age due to the accumulation of adverse health effects such as chronic conditions. Currie (2009) presents evidence both regarding the link between parental socioeconomic status and child health and link between child health to future educational and labor market outcomes. Conti, Heckman, and Urzua (2010) show that family background characteristics, and cognitive, noncognitive, and health endowments developed at an earlier age are important determinants of labor market and health disparities in later years. Heckman, Humphries, Veramendi, and Urzua (2014) show that education at most levels causally produces gains in health and that early cognitive and socio-emotional ability have important effects on health outcomes and schooling choices. Savelyev and Tan (2014) find strong effects of education and personality skills on health and health-related outcomes.

Second, our paper contributes to the rational addiction literature proposed in the seminal work of Becker and Murphy (1988). A large amount of empirical research has dedicated itself to test the empirical implications of the rational addiction model. Becker, Grossman, and Murphy (1991),

[1] Galama (2011) and Galama and van Kippersluis (2010) provide theoretic framework through with education and wealth may impact the disparity in health.

and Becker, Grossman, and Murphy (1994) find that cross price effects for cigarette consumption are negative and that long-run responses exceed short-run responses. Chaloupka (1991) and Gruber and Köszegi (2001) provide evidence that cigarette smoking is an addictive behavior and smokers are forward-looking in their smoking decisions. Adda and Cornaglia (2006) apply the rational addiction model to study smoking intensity and show smokers compensate for tax hikes by extracting more nicotine per cigarette. Grossman, Chaloupka, and Sirtalan (1998) show that alcohol consumption is addictive and there is a positive and significant future consumption effect. Research also shows that the rational addiction model can be applied to empirically investigate individuals' demand for caffeine consumption (Olekalns and Bardsley (1996)) and cocaine consumption (Grossman and Chaloupka (1998)). Sundmacher (2012) finds that health shocks had a significant positive impact on the probability that smokers quit during the same year in which they experienced the health shock, providing evidence that smokers are aware of the risks associated with tobacco consumption and are willing to quit for health-related reasons.

Finally, our paper contributes to the literature on schooling and credit constraints (see Heckman and Mosso (2014) for an overview). The evidence on the existence of credit constraints and their effect on schooling decisions is mixed. Using the National Longitudinal Survey of Youth 1979 (NLSY79) data, Keane and Wolpin (2001) show that borrowing constraints, though exist, have no impact quantitatively on youths' schooling decisions by structurally estimating a life cycle model.[2] Cameron and Taber (2004) reject the hypothesis that there are binding credit constraints in NLSY79 data. Using NLSY79 and NLSY79 Children (CNLSY79), Carneiro and Heckman (2002) find that the role of family income in determining college enrollment decisions is minimal once ability is controlled. By linking the information between children and parents (CNLSY79 and NSLY79), Caucutt and Lochner (2012) find strong evidence of credit constraints among young and highly skilled parents. More recent studies suggest that borrowing constraints may play a bigger role in individuals' college enrollment in the National Longitudinal Survey of Youth 1997 (NLSY97) cohorts (see Belley and Lochner (2007), Bailey and Dynarski (2011), and Lochner and

[2]Keane and Wolpin (2001) assume parental transfers to be a function of parents schooling, the current school attendance status of the youth, and the amount of the youth's assets. However Keane and Wolpin (2001) do not actually observe parental transfers in their data.

Monge-Naranjo (2012)).[3] Navarro (2011) finds that there are sizable effects of relaxing borrowing constraint on schooling decisions whereas the effects of reducing tuition are very small. Our model extends the schooling choices models of Keane and Wolpin (2001), Caucutt and Lochner (2012), and Navarro (2011), which emphasizes the importance of the borrowing constraints and parental transfers, in three ways: (i) by allowing cognitive and noncognitive abilities and health to affect youths' decisions; (ii) by allowing consumption to affect the endogenous evolution of health capital which in turn exacerbates the importance of credit constraint; and (iii) by allowing for student loans and by introducing both parental wealth and education which affect individuals' decision differently.

The rest of the paper is organized as follows. Section 2 provides data description and basic regression analysis. Section 3 presents the model. Section 4 discusses empirical strategy of estimating the model and Section 5 discuss model estimation results. Finally, Section 7 conducts counterfactual simulation analysis and Section 8 concludes.

2 Data and Regression Analysis

We use data from the National Longitudinal Survey of Youth 1997 (NLSY97). The NLSY97 consists of a nationally representative sample of approximately 9,000 youths who were born during the years 1980 through 1984. Over the sample period 1997 to 2011, NLSY97 provides extensive information every year on the respondents' health, health behaviors, schooling, employment, earnings, and monetary transfers from parents and government. It also provides individuals' information on cognitive skills measures, earlier-life adverse behaviors, and parental education and wealth. One of the advantages of using NLSY97 is that we can trace the complete path of each individual's health behaviors, health outcomes, labor supply, and schooling decisions from an early age (age 17). The disadvantage of this data is that so far the sampled individuals are still young (up to 31 years old). However, by age 30, most of the education choice is complete, many of the unhealthy behaviors

[3] The presence of credit constraints in these studies is captured by the estimated effects of quantities of family income on college attendance.

already formed, and health disparity has opened up. NLSY97 is the ideal data set to analyze the formation of human capital investment and health behavior at an early age.

We restrict our sample to white males, so the estimation results on inequality is isolated from discrimination by race or gender. Our final sample contains 2,103 individuals, with 27,213 individual-year observations. Section 2.1 provides detailed variable descriptions and Section 2.2 describes summary statistics of the data. In Section 2.3, we conduct reduced form analysis and estimate (1) the effect of the youth's initial health, and cognitive and noncognitive ability on adult outcomes including health, education, and wealth; (2) a myopic model of unhealthy behavior as a function of the accumulated years of past unhealthy behaviors, education, health, and cognitive and noncognitive skill measures.

2.1 Variable Description

Unhealthy Behavior

Unhealthy behavior in this paper refers to smoking behavior. Every year, the NLSY97 asks respondents the following two questions on smoking behavior: "During the past 30 days, on how many days did you smoke a cigarette," and "When you smoked a cigarette during the past 30 days, how many cigarettes did you usually smoke per day." Figure A2 plots the frequency distribution of days smoking and average number of cigarettes per day. We create an indicator variable of unhealthy behavior that equals 1 if an individual smokes every day and at least 10 cigarettes per day.[4]

Measures of Health

We use three sets of measures on health for each individual every year. The first measure is self-reported health status, where the respondent is asked "in general, how is your health," on a holistic 1 to 5 scale, from "excellent" to "poor". The second measure is based on Body Mass Index (BMI).[5] We construct a dummy variable of healthy weight for those who are neither underweight nor obese,

[4] Centers for Disease Control and Prevention define: light smoker: <10 cigarettes per day; moderate smoker: 10-25 cigarettes per day; heavy smoker: >25 cigarettes per day.

[5] $\text{BMI} = 703 \cdot \text{Weight in pounds}/\text{Height in inches}^2$.

i.e., BMI is between 18.5 and 30. The third set of measures is on various health conditions. In 2002, 2007, 2008, 2009, the NLSY97 asks respondents about various chronic conditions and mental/emotional/eating disorders, as well as the age at which the condition was first diagnosed. We construct an indicator for health conditions, including cardiovascular condition, heart condition, asthma, anemia, diabetes, cancer, epilepsy, mental/emotional problems and eating disorders, for these selected years. We also construct an indicator variable on whether the respondent had any of these health conditions when aged 17 or younger using information on the first age the individual was diagnosed with each of these conditions.

Education and Labor Market Outcomes

Education is measured by the highest grade completed. We manually recode this variable by cross-checking the highest grade completed with data on enrollment and the highest degree received, in order to correct for missing data, data coding errors, and GEDs. In particular, a high school dropout with a GED is recoded to his highest grade of school actually completed.

The NLSY97 records the number of hours worked in each week, number of weeks worked in a year, and total income earned in a year. We define full-time working to be working no less than 40 hours a week and more than 26 weeks a year, and part-time working to be working less than 40 hours a week but more than or equal to 20 hours a week and more than 26 weeks a year. Frequency distribution of weeks and hours worked is provided in the data appendix Figure A2. For employed workers, hourly wages rate is the ratio between total earned income and total hours worked (in 2010 dollars).

The youth's net worth is measured as all financial assets and vehicles minus financial debts and money owned in respect to vehicle owned. Financial assets include business, pension and retirement accounts, savings accounts, checking accounts, stocks, and bonds. The changes associated with home market value and mortgages is not reflected in the youth's net worth measure.

Measures of Cognitive Ability and Noncognitive Ability

The set of cognitive measures we use includes the Armed Services Vocational Aptitude Battery (ASVAB), a subset of which are utilized to generate the Armed Forces Qualification Test (AFQT) score.[6] Specifically, we consider the scores from Mathematical Knowledge (MK), Arithmetic Reasoning (AR), Word Knowledge (WK), and Paragraph Comprehension (PC). These four scores have been used by NLSY staff to create a summary percentile score (AFQT), which has been used commonly in the literature as a measure of IQ or cognitive ability.

Our measure for noncognitive ability includes three variables that indicate respondents' adverse behaviors at very early ages. Specifically, we consider: violent behavior in 1997 (ever attack anyone with the intention of hurting or fighting), any sexual intercourse before age 15, and theft behavior in 1997 (ever steal something worth $50 or more). Individuals with high noncognitive ability are less likely to display adverse behaviors.

Parental Education, Net Worth, and Transfers

NLSY97 asks each respondent about their parents' schooling and net worth information only in round 1 (1997). We define parents' education as the average years of schooling of father and mother if both the father's and mother's schooling are available.[7] For single-parent families where only one parent's schooling level is available, we define the parents' schooling only using the single parent's schooling level. Parents' net worth is defined as all assets (including housing assets and all financial assets) minus all debt (including mortgages and all other debts). Parental transfer data is constructed as total monetary transfers received from parents in each year, including allowance, non-allowance income, college financial aid gift, and inheritance.[8]

[6] The CAT-ASVAB is an automated computerized test developed by the United States Military which measures overall aptitude. The test is composed of 12 subsections and has been well researched for its ability to accurately capture a test-takers aptitude.

[7] We top code parents years of schooling to be 16 years (4-year college graduate) and bottom code parents schooling to be 8 years (high school dropouts).

[8] College financial aid gift includes loans from parents and family members which the youth does not expect to pay back.

2.2 Summary Statistics

Education is generally positively correlated with good health and more wealth, however we know very little so far about the quantitative importance of economic mechanisms through which education affects health. As shown in Table 1, on average, individuals with higher education have better health and health behaviors and have higher wages and wealth. On the other hand, better health enables an individual to obtain higher education and wealth in the future ("reverse causality"). As seen in Figure 1, individuals' outcomes in education and wealth measured at age 25 to 30 are increasing functions with initial health (measured by health status) at age 17.

There is a positive impact of parental education and wealth on young men's education and health. As seen in Figure 2, adults' education and health measured at age 25 to 30 are increasing with their parental wealth, suggesting a potential role of parental wealth in the presence of credit constraints. Similarly, Figure A4 in the appendix documents a positive impact of parental education level on the youths' education and health outcome. Furthermore, even after controlling measures of the youths' own cognitive ability, there is still a strong positive influence of parents' education and net worth on individuals' college attendance and 4-year college completion (see Figures 3 and 4).

The distribution of parental transfers is skewed.[9] The amount of parental transfer to the youth is either positive or zero. On average, 29% youths receive zero monetary transfers from their parents. Among those who received positive parental transfers, the average amount of transfers received is \$3,172, and the median amount is \$1,047. As seen in Figure 5, on average, the amount of parental transfers depends crucially on parental education and net worth and varies over the youth's life cycle.

Table 5 reports the statistics of key variables over age groups. We also report summary statistics for the entire sample in appendix Table A1. The average health, measured by self-reported health status and whether BMI is within healthy range, is deteriorating over age. Individuals' education level and wealth level, on the other hand, increase from age 17 to age 30. At age 17, only 14% of

[9]Conditional on parental transfers being positive, the top 1 percentile of the parental transfers amount is about \$28,000. I top code the maximum amount of positive parental transfers to be \$30,000 per year.

Table 1: Education Gradient in Health, Smoking, Wages, and Wealth (Age 25 to 30)

	Health Status	Health Condition	Smoking	Wage Rate	Net Worth
HS Dropouts	2.47	0.24	0.50	14.14	17.86
4-Yr College	3.15	0.18	0.05	22.76	34.76

Data source: NLSY97 white males. Health status is measured on the scale of 1 (poor/fair) to 4 (excellent). Health condition is a dummy variable for having at least a chronic condition.

(a) Education & Initial Health

(b) Net Worth & Initial Health

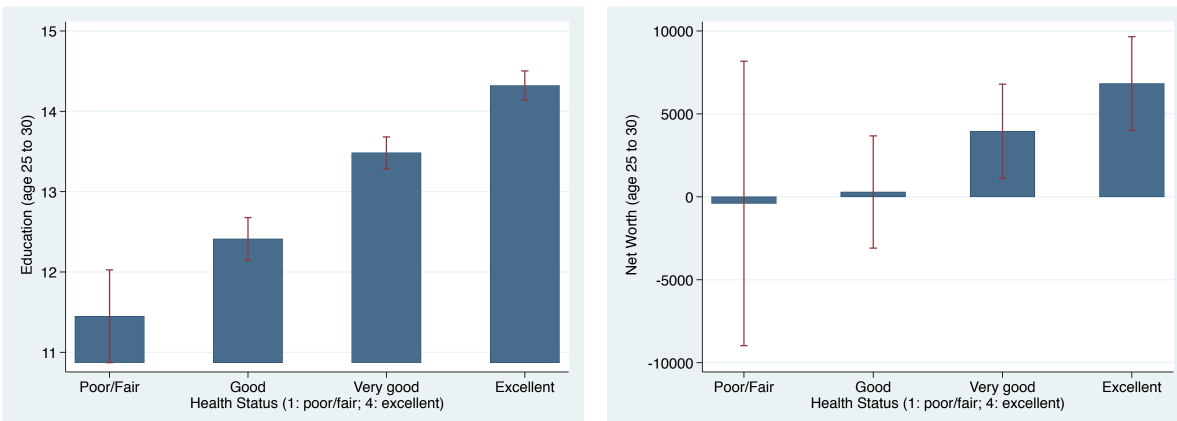
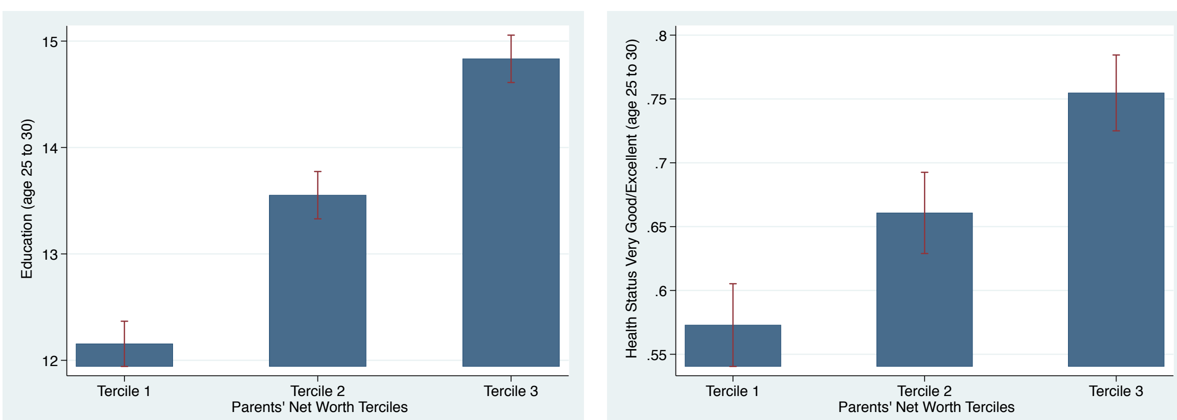


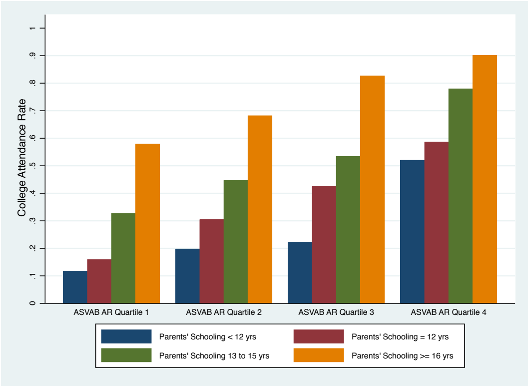
Figure 1: Reverse Causality of Health: Initial Health and Adult Outcomes



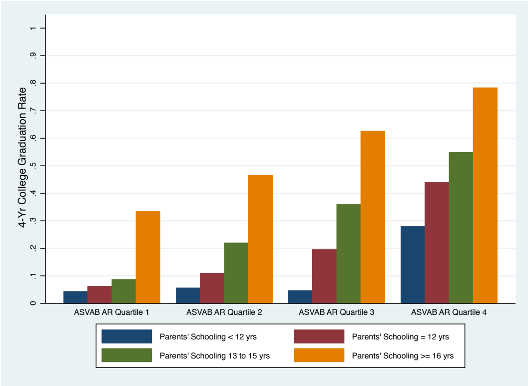
(a) Education

(b) Health Status

Figure 2: Average Adult Outcomes by Parents' Net Worth Terciles

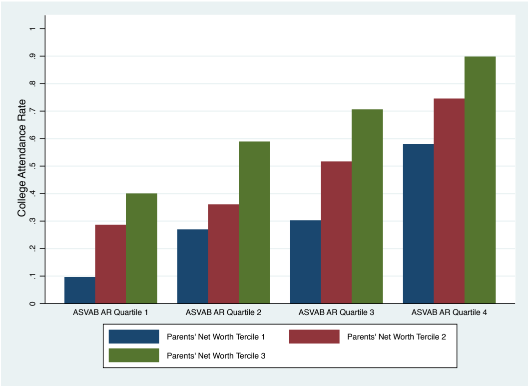


(a) College Attendance Rate at Age 21

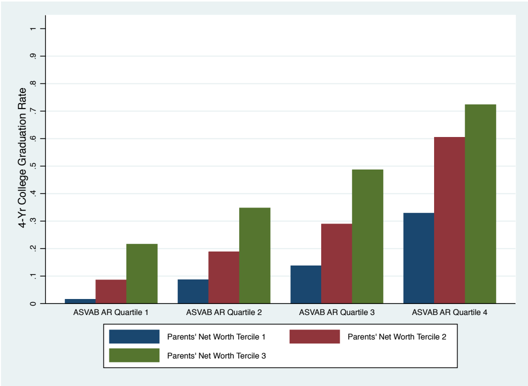


(b) 4-Year College Graduation Rate at Age 25

Figure 3: Parental Education & Youth Education Outcomes

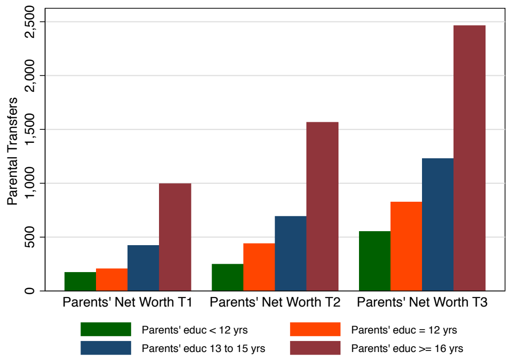


(a) College Attendance Rate at Age 21

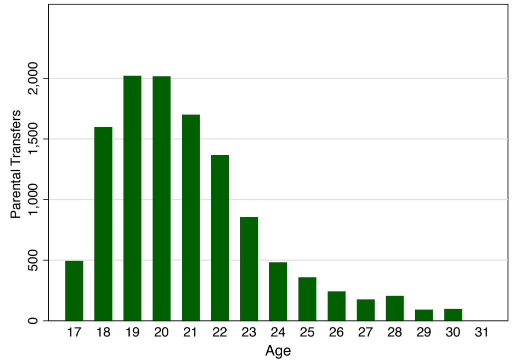


(b) 4-Year College Graduation Rate at Age 25

Figure 4: Parental Net Worth, & Youth Education Outcomes



(a) By Parents' Net Worth & Education



(b) By Youth's Age

Figure 5: Parental Transfers By Parental Characteristics

the youth engages in unhealthy behavior (measured by regular smoking); this ratio first increases and peaks at age 23, then steadily decreases to 22% at age 30. By age 30, the average years of unhealthy behavior is about 3 years across all individuals. In age 17, 87% of the youth enrolled in school and the fraction of the youth in school at age 30 decreases at 3%. The fraction of the youths who work full time steadily increases from 28% in age 20 to 56% in age 30; the fraction of part-time employment first increases from 27% in age 17 to 31% in age 20 and then gradually decreases to 10% in age 30. The average hourly wages (both part-time job and full-time job) increase between age 17 and age 30, ranging from \$5 to \$23. On average, the youths' parents completed 13 years of schooling and have roughly \$190,000 net worth. All the nominal variables are in 2010 dollars. Furthermore, an individuals' educational achievement is positively associated with his adult outcomes including health, unhealthy behavior, employment, wages, and net worth (see Table 6).[10] Measures of health, cognitive and noncognitive skills at age 17 are presented in Table 7.

2.3 Regression Analysis

2.3.1 Unhealthy Behavior and Addiction

Let $d_{q,t}$ be an indicator variable of an individual engaging unhealthy behavior at age t. We consider a myopic regression model of unhealthy behavior as follows:

$$d_{q,t} = \beta_0 + \beta_1 d_{q,t-1} + \beta_2 \sum_{\tau=t_0}^{t-1} d_{q,\tau} + X_t' \gamma_x + Z_{h,t}' \gamma_h + Z_c' \gamma_c + Z_n' \gamma_n + \varepsilon_{q,t} \tag{1}$$

where $\sum_{\tau=t_0}^{t-1} d_{q,\tau}$ is the accumulated years of past unhealthy behaviors from age $t_0 = 17$ to $t-1$, X_t is a vector of individual characteristics including education and age, $Z_{h,t}$ is a vector of health measures at age t, and Z_c and Z_n are measures of the individual's cognitive and noncognitive skills, respectively. Equation 1 allows for rich dynamics of $d_{q,t}$ depending on the youth's past history of unhealthy behaviors.

[10] Figure A5 in the appendix reports educational gradient in health status, smoking behavior, wages, and wages for individuals aged 25 to 30.

Table A2 reports the regression results of Equation 1. As we can see, education is negatively correlated with unhealthy behavior and such correlation is statistically significant. The negative correlation becomes smaller in magnitude once we control for measures of cognitive and noncognitive ability (Column 2). Moreover, after controlling previous unhealthy behavior, the magnitude of the education coefficient becomes much smaller (still significant). Furthermore, after controlling for previous unhealthy behavior and its stock, the age slope turns from positive to negative. The age slope of unhealthy behavior is positive without controlling for previous unhealthy behavior and turns to negative. This is suggestive evidence that addiction is important for characterizing age-pattern of unhealthy behavior. Current unhealthy behavior is positively correlated with previous period's unhealthy behavior and previously accumulated unhealthy behavior stock. Finally, individuals' unhealthy behavior also correlates with various measures of health, and both the magnitude and sign can be different for different measures of health.

This reduced-form regression does not imply causal relationship and may be subject to reverse causality and selection. Furthermore, this reduced-form, myopic model estimation does not take into account the rationally anticipation effect of future unhealthy behavior and health on current unhealthy behavior decision. It serves as a motivation evidence for the dynamic structure model presented in Section 3.

2.3.2 Adult Outcomes and Initial Health, Cognitive and Noncognitive Ability

Table A3 reports the OLS regression results of adult outcomes at age 25 to 30 as a function of individuals' initial conditions. As we can see, measured initial health level has a positive and significant coefficient on individuals' health, education, and net worth at age 25 to 30. Measures of cognitive ability are positively correlated with adult health and education. Early adverse behaviors are negatively correlated with adult education and health, which suggests a positive correlation between these adult outcomes and noncognitive ability, because noncognitive ability are measured by the absence of adverse behaviors. Parental education and wealth have a significant and positive correlation on individuals' health and education.

3 Model

In this section, we develop a life cycle model with three forms of human capital investment: health, education, and labor market experience. Furthermore, the production of health capital not only depends on current health, education, and consumption (thus monetary wealth) but is also affected by individuals' current health behavior and decisions on labor supply and school enrollment. Every year, forward-looking individuals maximize their expected discounted remaining lifetime utility by making decisions on schooling, working, unhealthy behavior, and savings, in the presence of financial market frictions, taking into consideration that their current unhealthy behavior can impact their future unhealthy behaviors (i.e., unhealthy behavior is rationally addictive). The model abstracts from choices on health insurance and medical expenditure and focuses more on individuals' behavior aspects due to both the computational tractability and data availability. The framework developed here is useful in investigating the mechanism through which health, education, and wealth affect each other. It also provides a more careful treatment of cognitive and noncognitive skills, parental education, wealth and transfers, government transfers, and a borrowing limit that is a function of an individuals' human capital and choices.

3.1 Setup

3.1.1 Choice Set

At each age $t = t_0, \ldots T$, an individual makes decisions on the following four dimensions: (i) decisions on consumption c_t and savings s_{t+1}, (ii) whether engage in unhealthy behavior, indexed by $d_{q,t} \in \{0,1\}$, (iii) whether go to school $d_{e,t} \in \{0,1\}$, and (iv) employment decisions $d_{k,t} \in \{0,0.5,1\}$, where $d_{k,t} = 0$, $d_{k,t} = 0.5$ and $d_{k,t} = 1$ indicate not working, part-time working, and full-time working, respectively.[11] An individual cannot go to school and work full-time at the same time, i.e. $d_{e,t} + d_{k,t} < 2$.

[11] Education choice $d_{e,t} = 1$ is available up to age 27.

3.1.2 State Variables

At each age t, an individual is characterized by a vector of predetermined state variables that shape the individual's preferences, production technology, and outcomes:

$$\overline{\Omega}_t \equiv (t, h_t, \theta_c, \theta_n, k_t, e_t, s_t, q_t, d_{e,t-1}, e_p, s_p) \tag{2}$$

where h_t is the individual's age-t health stock, θ_c (θ_n) is the individual's cognitive (noncognitive) ability, e_t is the years of schooling, k_t is the stock of accumulated labor market experience, q_t is the stock of addiction capital accumulated from past unhealthy behavior, $d_{e,t-1}$ is the previous schooling status, e_p is the youth's parents' education, and s_p is parents' net worth. Therefore, an individual's information set, that includes all the predetermined state variables and realized idiosyncratic shocks at age t (ε_t), can be written as $\Omega_t \equiv \{\overline{\Omega}_t, \varepsilon_t\}$.

3.1.3 Preferences

The accumulation of the addiction capital stock (or "habit"), q_{t+1}, is determined by the agent's past history of accumulated unhealthy behaviors:

$$q_{t+1} = (1-\delta_q)q_t + d_{q,t} \tag{3}$$

where $\delta_q \in [0,1]$ is the depreciation rate of previous stock of unhealthy behavior. If $\delta_q = 1$, $q_{t+1} = d_{q,t}$, only the previous decisions of unhealthy behavior matter for this period's unhealthy behavior; if $\delta_q = 0$, the total number of years of unhealthy behavior matters for an individual's current decision.

An individual has well-defined preferences over his consumption c_t, unhealthy behavior $d_{q,t}$, and choices on schooling and working($d_{e,t}, d_{k,t}$):

$$U(c_t, d_{q,t}, d_{e,t}, d_{k,t}; \Omega_t) = u_c(c_t; \Omega_t) + d_{q,t} \cdot u_q(q_t, h_t, e_t, \theta_c, \theta_n, \varepsilon_{q,t}) + u_{ek}(d_e, d_k; h_t, \theta_c, \theta_n, d_{e,t-1}, e_p, \varepsilon_{e,t}, \varepsilon_{k,t})$$

where $(\varepsilon_{q,t}\varepsilon_{e,t},\varepsilon_{k,t})$ represent preference shocks to unhealthy behavior, schooling, and working decisions respectively.

The flow utility associated with unhealthy behavior $d_{q,t}=1$ is $u_q(q_t,h_t,e_t,\theta_c,\theta_n,\varepsilon_{q,t})$. By explicitly allowing for both time-dependent preferences in unhealthy behavior and forward-looking maximization behavior, our model can generate rational addiction behavior patterns. We say that the unhealthy behavior is "addictive" in its past consumption, if the utility of engaging unhealthy behavior increases with the past history of accumulated experience of unhealthy behaviors (q_t), i.e. $\partial u_q(q_t,h_t,e_t,\theta_c,\theta_n,\varepsilon_{q,t})/\partial q_t>0$. Furthermore, if $\partial(-u_q(q_t,e_t,h_t,\theta_c,\theta_n,\varepsilon_{q,t}))/\partial h_t>0$, the cost of engaging in unhealthy behavior is increasing in his health, the model can generate addiction patterns in (un)healthy behavior through health capital. In such a case, an individual with high health capital stock has a high cost of engaging in unhealthy behavior and will be "addictive" in maintaining good health, whereas an individual with low health incurs low psychic cost of conducting unhealthy behavior and will exhibit "addiction" in keeping low health. Here we also allow education level to affect an individual's preferences towards unhealthy behavior, which could be due to both health knowledge and peer groups associated with education level. We do not differentiate among exact channels through which education affects unhealthy behavior. Lastly, we allow an individual's preferences of unhealthy behavior to be directly affected by his cognitive ability and noncgontive ability.

The individual's flow utility (or disutility) on schooling and working is characterized by the function $u_{ek}(d_e,d_k;h_t,\theta_c,\theta_n,d_{e,t-1},e_p,\varepsilon_{e,t},\varepsilon_{k,t})$. Allowing the flow utility of schooling and working to depend on health captures the idea that health as a form of human capital affects an individual's capacity of seeking higher education and participating in labor market. Similarly, individuals with different cognitive and noncogntive ability may also have different psychic cost associated with schooling and working. Furthermore, based on the individual's previous schooling status, $d_{e,t-1}$, he may face different cost of attending schooling in the current period. Finally, we also allow for preference heterogeneity in schooling depending on agents' parents' education level e_p.

An individual discount future returns with a subjective discount factor $\exp(-\rho(\theta_c,\theta_n,h_t))$, where $\rho(\theta_c, \theta_n, h_t) > 0$ is the subjective discount rate that depends on the individual's cognitive ability, noncognitive ability, and health. The dependence of discount rate on both cognitive ability and noncognitive ability aims to capture heterogeneity in patience level based on the latent ability distribution. Furthermore, by allowing the discount rate to depend on health, we implicitly allow for the impact of life expectancy on the individual's decisions in our current framework without explicitly modeling mortality. This is because healthy individuals have a longer life expectancy and a longer decision horizon, thus they effectively have a relatively lower discount rate.[12]

3.1.4 Health Capital Production

Health capital h_{t+1} is a form of human capital and is produced through a health production function based on an individual's current state and choices. First, health is self-productive and current health affects next period health directly in the health production function. Second, an individual's unhealthy behavior, $d_{q,t}$, has a direct impact on the individual's next period's health. Third, an individual's decisions of schooling and working can also potentially directly affect future health, via their effects on time allocation. Fourth, consumption also affects health proaction directly, and thus everything else being equal, an individual with rich assets can affect their health level next period by changing their consumption levels.[13] Lastly, individuals' education and latent abilities can also directly impact an individual's health by affecting the allocation efficiency in the health production. In particular, the production function of next period's health is given as follows:

$$h_{t+1} = H(h_t, d_{q,t}, d_{e,t}, d_{k,t}, c_t, e_t, \theta_c, \theta_n, t, \varepsilon_{h,t}) \tag{4}$$

where $\varepsilon_{h,t}$ is an idiosyncratic shock to health capital production. We say engaging unhealthy behavior reduces the next period's health capital if $H(h_t, d_{q,t} = 1, d_{e,t}, d_{k,t}, c_t, e_t, \theta_c, \theta_n, t, \varepsilon_{h,t}) < H(h_t, d_{q,t} = 0, d_{e,t}, d_{k,t}, c_t, e_t, \theta_c, \theta_n, t, \varepsilon_{h,t})$.

[12] In our model, we do not explicitly model mortality.

[13] We do not explicitly distinguish the role of medical care from other consumption expenditure, because we do not observe medical care expenditure in our data.

3.1.5 Human Capital Production and Wage Equations

An individual's human capital level at age t is produced according to the following function:

$$\psi_t = F^{\psi}(h_t, e_t, k_t, \theta_c, \theta_n). \tag{5}$$

This function allows an agent's productivity in the labor market to depend on his health capital, education, experience, and his cognitive and noncognitive abilities.

At each time t, an individual receives a part-time and a full-time hourly wage offer ($w_{1,t}$ and $w_{2,t}$). The wage offers of an agent depends on the agent's human capital and school enrollment status (if works part-time), and are given as follows:

$$w_{1,t} = F_1^w(\psi_t, d_{e,t}, \varepsilon_{w,1,t}) \tag{6}$$

$$w_{2,t} = F_2^w(\psi_t, \varepsilon_{w,2,t}) \tag{7}$$

where $\varepsilon_{w,1,t}$ and $\varepsilon_{w,2,t}$ are idiosyncratic shock to part-time and full-time wage offers, respectively. The dependence of school enrollment status is meant to capture the fact that part-time jobs held while enrolled in school may pay different wages than those paid when an agent is fully attached to the labor market (see Johnson (2013)).

Accumulation of work experience evolves as follows:

$$k_{t+1} = k_t + d_{k,t} - \delta_k k_t \mathbf{1}(d_{k,t} = 0). \tag{8}$$

where δ_k is the depreciation rate of work experience when the individual does not work.

Finally, next period education level, measured by years of schooling, is given by:

$$e_{t+1} = e_t + d_{e,t}. \tag{9}$$

3.1.6 Budget Constraint and Transfer Functions

Parents are allowed to provide nonnegative monetary transfers to the youth, $\mathrm{tr}_{p,t} \geq 0$. The amount of parental transfers depend on the parents' characteristics including education and net worth (e_p, e_s) and the youth's own schooling and working decisions $(d_{e,t}, d_{k,t})$ as well as the youth's own education level and age:[14]

$$\mathrm{tr}_{p,t} = \mathrm{tr}_p(e_p, s_p, d_{e,t}, d_{k,t}, e_t, t). \tag{10}$$

Examples of monetary parental transfer includes college financial aid gift if the youth chooses to attend college. Parents can also provide direct consumption subsidy to the youth when the youth is attending high school, such as shared housing and meals, denoted by $\mathrm{tr}_{c,t}$. The parental transfer rule is taken by the youth as given. The amount of government transfers, $\mathrm{tr}_{g,t}$, consist of unemployment benefits and means-tested transfers that guarantees a minimum consumption floor $c_{\min}$. Compared to the monetary parental transfers, parental consumption subsidy and government transfers can not be used to finance one's education.

Denoting an individual's wage income to be $y_t = w_{1,t}\bar{L}/2$ if the individual works part-time and $y_t = w_{2,t}\bar{L}$ if the individual works full-time, where $\bar{L}$ is the total hours worked if working full-time. Therefore, an individual's budget constraint is given as follows:

$$c_t + p_q d_{q,t} + \mathrm{tc}(e_t + d_{e,t}, s_p)d_{e,t} + s_{t+1} = (1 + r_l \mathbf{1}(s_t > 0) + r_b \mathbf{1}(s_t < 0)) \cdot s_t + y_t + \mathrm{tr}_{p,t} + \mathrm{tr}_{c,t} + \mathrm{tr}_{g,t} \tag{11}$$

where p_q is the monetary cost of unhealthy behavior, $\mathrm{tc}(e_t + d_{e,t}, s_p)$ is the total direct expenditure (including tuition and fees) net of grants and scholarships associated with parental wealth s_p, r_l is the lending interest rate, and r_b is the borrowing interest rate. We require that the choice of attending college is available only if the direct cost of college $\mathrm{tc}(e_t + d_{e,t}, s_p)$ can be financed. Furthermore, we require that the choice of attending college is available only if the consumption

[14]This is an extension of the parental transfer function in Keane and Wolpin (2001).

c_t is higher than the cost of college room and boards $\text{rc}(e_t + d_{e,t})$ and the minimum consumption level c_{min} , i.e., $c_t \geq \{\text{rc}(e_t + d_{e,t}), c_{min}\}$

3.1.7 Credit Constraints and Borrowing Limits

The presence of financial market frictions in this model is manifested not only as the gap between lending rate and borrowing rate but also as the existence of a borrowing limit. Specifically, the young agent faces a borrowing limit, that not only evolves as a function of the youth's own human capital capacity (captured by ψ_t), but also depends on his own college enrollment decisions due to the existence of government student loan program. Following Lochner and Monge-Naranjo (2011, 2012), we specify the borrowing limit as follows,

$$s_{t+1} \geq -l_g \cdot d_{e,t} \mathbf{1}(d_{e,t} + e_t > 12) - F^s(t, \psi_t) \tag{12}$$

where $l_g \geq 0$ is the government student loan (GSL) borrowing limit and $F^s \geq 0$ is a private borrowing limit. GSL borrowing limit l_g is characterized by a flow limit $\bar{l}^g$ and a total limit $\bar{L}^g$, and is directly tied to the student's college attendance decision ($d_{e,t}\mathbf{1}(d_{e,t} + e_t > 12)$). In contrast, private borrowing limit F^s depends on the individual's age and labor market human capital level. This is because private lenders link credit to projected borrower's earnings (characterized by his human capital level ψ_t) and face limited repayment incentives due to the inalienability of human capital and lack of collateral. Lochner and Monge-Naranjo (2011) show that allowing private borrowing limit to depend on labor market skills can explain a number of patterns observed in higher education as the equilibrium responses to the increased returns to and costs of college observed since the early 1980s, given stable GSL limits.

3.2 Model Solution

An individual's value function $V_t(\cdot)$ for $t = 1, \dots T$ is characterized by the following Bellman equation:

$$V_t(\Omega_t) = \max_{d_{q,t}, d_{e,t}, d_{k,t}, s_{t+1}} \{u_c(c_t;\Omega_t) + d_{q,t} \cdot u_q(h_t, e_t, q_t, \theta_c, \theta_n, \varepsilon_{q,t}) \tag{13}$$
$$+ u_{ek}(d_e, d_k; h_t, \theta_c, \theta_n, d_{e,t-1}, e_p, \varepsilon_{e,t}, \varepsilon_{k,t})$$
$$+ \exp(-\rho(\theta_c, \theta_n, h_t))\mathbb{E}(V_{t+1}(\Omega_{t+1})|\Omega_t, d_{q,t}, d_{e,t}, h_{t+1}, s_{t+1}, k_{t+1}, e_{t+1})\}$$

subject to Equations 4 to 12. The individual's value function at age $T+1$ is a function of wealth and health at $T+1$, specifically:

$$V_{T+1}(\Omega_{T+1}) = \bar{V}(h_{T+1}, s_{T+1}). \tag{14}$$

The decision of unhealthy behavior today depends on both current health (via time-dependence in the preference) and the anticipated damage to the next period's health (via the health production and Bellman Equation). Furthermore, unhealthy behavior can be affected by the accumulated wealth level as individuals with a higher wealth level can afford higher levels of both harmful addictive goods consumption and normal goods consumption. Lastly, unhealthy behavior can be affected an individual's education and cognitive/noncognitive ability, because all these factors not only directly shift one's preference towards unhealthy behavior but also affect the next period health production.

First-order conditions with respect to c_t and s_{t+1} are respectively:

$$\frac{\partial u_c(c_t;\Omega_t)}{\partial c_t} + \exp(-\rho(\theta_c, \theta_n, h_t)) \left(\frac{\partial \mathbb{E}(V_{t+1}(\Omega_{t+1}))}{\partial h_{t+1}} \frac{\partial h_{t+1}}{\partial c_t} \right) = \lambda_{1,t} \tag{15}$$

$$\exp(-\rho(\theta_c, \theta_n, h_t)) \left(\frac{\partial \mathbb{E} V_{t+1}}{\partial s_{t+1}} \right) + \lambda_{2,t} = \lambda_{1,t} \tag{16}$$

where $\lambda_{1,t}$ and $\lambda_{2,t}$ is the Lagrangian multiplier of the budget constraint and borrowing constraint, respectively. Envelop condition implies

$$\frac{\partial \mathbb{E}(V_t)}{\partial s_t} = \lambda_{1,t}(1 + r(s_t)) \tag{17}$$

where $r(s_t) = r_l \mathbf{1}(s_t > 0) + r_b \mathbf{1}(s_t < 0)$ and λ_t is the Lagrangian multiplier of the borrowing constraint.

3.3 Initial Conditions and Dedicated Measurement System

The model is completed by defining the initial conditions and a set of measurement equations that relate the unobserved skill endowment and latent health level to a set of observables. Individuals start to make decisions at age 17 ($t_0 = 17$). The deterministic components of age 17 information set, $\overline{\Omega}_{17}$ is given by:

$$\overline{\Omega}_{17} \equiv (17, h_{17}, \theta_c, \theta_n, k_{17}, e_{17}, s_{17}, d_{q,16}, d_{e,16}, e_p, s_p).$$

The observed initial condition at age 17 from the data is as follows,

$$\overline{\Omega}_{17}^{\text{observed}} \equiv (17, k_{17}, e_{17}, s_{17}, d_{q,16}, d_{e,16}, e_p, s_p).$$

The initial distribution of the youth's education, lagged school attendance, lagged unhealthy behavior, parental education, and parental wealth ($e_{17}, d_{q,16}, d_{e,16}, e_p, s_p$) are directly obtained from data. We also set the accumulated years of working experience and net worth to be zero ($k_{17} = 0$, $s_{17} = 0$).

In our model, we focus on the evolution of health factor, while holding the cognitive and noncognitive levels constant at their initial level (age 17). The joint distribution of the unobserved ability at initial age 17 is given by the following:

$$\left.\begin{pmatrix}\theta_c\\ \theta_n\\ \log h_{17}\end{pmatrix}\right| X_{17} \sim N\left(\begin{pmatrix}\mu_c(e_p,s_p)\\ \mu_n(e_p,s_p)\\ \mu_h(e_p,s_p)\end{pmatrix}, \begin{pmatrix}\sigma_c^2 & & \\ \sigma_{c,n} & \sigma_n^2 & \\ \sigma_{c,h} & \sigma_{n,h} & \sigma_h^2\end{pmatrix}\right)$$

where $\mu_j(e_p,s_p) = \mu_{j,e,1}\mathbf{1}(e_p = 12) + \mu_{j,e,2}\mathbf{1}(e_p > 12 \,\&\, e_p < 16) + \mu_{j,e,3}\mathbf{1}(e_p \geq 16) + \mu_{j,s,1}\mathbf{1}(s_p = 2) + \mu_{j,s,2}\mathbf{1}(s_p = 3)$, for $j = c,n,h$. Thus we allow the initial distribution to differ by parents' wealth and education, to capture early parental investment due to parents' financial resources, knowledge, or preferences.

However, as econometricians, we observe neither individuals' skill endowment nor health. We observe instead, a set of measurement equations for $\theta_c, \theta_n, h_{17}$. Specifically, we assume that at age 17 there exist two sets of dedicated measurement equations for (θ_c, θ_n) given by Equations 18 and 19, respectively; and there is a set of dedicated measurement equations for unobserved health level h_t at each time period t given by Equation 20 as follows:

$$Z^*_{c,j} = \mu_{z,c,j} + \alpha_{z,c,j}\theta_c + \varepsilon_{z,c,j}, \qquad j = 1,\ldots,J_c \tag{18}$$

$$Z^*_{n,j} = \mu_{z,n,j} + \alpha_{z,n,j}\theta_n + \varepsilon_{z,n,j}, \qquad j = 1,\ldots,J_n \tag{19}$$

$$Z^*_{h_t,j} = \mu_{z,h,j} + \alpha_{z,h,j}\log h_t + \varepsilon_{z,h_t,j}, \qquad j = 1,\ldots,J_h \tag{20}$$

where individuals' control variables, including parental education and wealth, initial education level, and lagged schooling are omitted from the measurement equations. The measurement errors $\varepsilon_{z,c}, \varepsilon_{z,n}, \varepsilon_{z,h_t}$ are independently distributed. The unconditional distribution of $(\theta_c, \theta_n, \log h_{17})$ is assumed to be jointly normal.

Moreover, to incorporate both continuous and binary measurements, we assume that the following relationship holds for each measurement at every point of time:[15]

$$Z_{k,j} = \begin{cases} Z^*_{k,j} & \text{if } Z_{k,j} \text{ is continuous} \\ \mathbf{1}(Z^*_{k,j} > 0) & \text{if } Z_{k,j} \text{ is binary} \end{cases}, \quad k \in \{c, n, h_t\} \tag{21}$$

Furthermore, we use an ordered Probit model for measures that are categorical discrete variables (such as health status).

4 Empirical Strategy

Our model is full parameterized. The detailed parameterization is reported in Appendix section B. In the next subsection we discuss external calibration of parameters that can be easily identified without the structure model. After that, we turn to a description of our model identification (Section 4.2), and estimation (Section 4.3).

4.1 External Calibration

For parameters that can be easily identified without the structure model, such as monetary cost of unhealthy behavior and government transfers, we calibrate them outside the model. Table 8 summarizes all the parameters that are calibrated or estimated outside the structure model. Below we discuss these calibration in detail. In our sample, a youth with $d_{q,t} = 1$ smokes 18 cigarettes per day on average. In 1997, the average retail price of a pack of cigarettes in the United States was about \$2 (including federal, state, and municipal excise taxes).[16] We set the monetary direct cost of unhealthy behavior to be \$2 $\times \frac{18}{20} \times$ 365=\$657. We calculate the cost of college tuition and fees and grants and scholarships from the following two sources: (i) Total direct expenditures (including tuition and fees) of higher education level e_t are calculated as the average expenditures per student using data from The Integrated Postsecondary Education Data System (IPEDS); (ii) We also

[15] Here I omit the time subscript t for health measurements for notation abbreviation.

[16] On April 1, 2009, the federal cigarette tax increased by 62 cents to \$1.01 per pack, the average price of a pack of cigarettes increased above \$5.

calculate the average amount of the grant for each education level associated with every parental net worth tercile using our NLSY97 sample. We also obtain the average cost of college room and board from IPEDS for two year college and 4 year college, respectively. The lending interest rate r_l is set equal to 1 percent annually, and the borrowing interest rate is 4 percent annually.

We estimate the parental monetary transfer function using a Tobit model (see Section B) and estimate it using our NLSY97 sample; the parameter estimates are reported in Table 9. In the sample, 94% of youth who are attending high school live with their parents.[17] Following Kaplan (2012) and Johnson (2013), we set the consumption subsidy provided by parents for those who are living with their parents, χ, to be \$650 monthly (\$7800 annually); χ includes both the direct and indirect costs of housing. The unemployment benefits function are estimated outside the model through an OLS regression using our NLSY97 sample. Specifically, we regress the logarithm of unemployment benefits on the respondent's education, experience, and squared experience. In the model, we assume individuals who are not working or in school receive unemployment benefits, which are substantially more generous than the actual unemployment benefits. We thus reduce the predicted unemployment benefits amount by one-third (for the same practice, please also refer to Kaplan (2012)).[18] In our sample, the average amount of means-tested transfers among recipients is about $\$2,800$, we therefore set $c_{min} = 2800$. We set the relative risk aversion parameter to be $\gamma = 1.5$; previous literature generally estimates a risk aversion value between one and three. The data from Consumer Survey of Finance shows that over the period 1997 to 2013, the median value of net financial asset for an household head age 50 is about \$70,000 in 2010 dollars. Therefore, we set the terminal value on wealth to be $\phi_{T+1,s} = 4$ to match up with the mean financial net worth level.[19] We also experiment on using different values of the terminal function parameters and find that individuals' decisions made in their 20s are insensitive to the terminal value function parameters at age 50 in our model.

[17]This ratio is 42% for those who are not attending high school.

[18]Conditional on receiving unemployment benefits, the mean and median annual benefits are \$4387.513 and \$2614.302. Conditional on receiving means-tested government transfers, the mean and median amount in the data are \$2861.741 and \$1696.451 annually in 2010 dollars.

[19]

4.2 Identification

4.2.1 Factor Model and Measurement System

The identification of factor models requires normalizations that set the location and scale of the factors (see Anderson and Rubin (1956)). For each factor $(\theta_c, \theta_n, \log h_{17})$, we normalize its unconditional mean to be zero, i.e., $\mathbb{E}_{e_p,s_p}(\mu_c(e_p,s_p)) = \mathbb{E}_{e_p,s_p}(\mu_c(e_p,s_p)) = \mathbb{E}_{e_p,s_p}(\mu_c(e_p,s_p)) = 0$, and standard deviation to be one, i.e., $\sigma_c = \sigma_n = \sigma_h = 1$.[20]

4.2.2 Dynamic Model and Structure Parameters

This section provides an overview of the identification. Discussion about the identification of specific parameters will be discussed along with the estimation results in Section 5.1.

The identification of our model parameter relies on conditional independence assumptions and exclusion restrictions. Conditional on an individual's initial endowment (including cognitive and noncognitive abilities and health), parents' wealth only impacts an individual's decisions through its effect on parental transfer and thus budget constraint. Thus, the correlation between final schooling level and parental wealth aids the identification of the preference parameters on schooling; among individuals who have entered the labor market after completing the highest degree of schooling, the correlation between parental wealth and employment helps to identify the preference parameter on labor supply.[21] Similarly, government transfer function of unemployment benefits also provides exogenous variation to an individual's decisions through its effect on the individual's budget constraint.

The parameters on the subjective discount rate are identified by asset distribution. To illustrate, let us consider the Euler equation under CRRA utility specification for those who are far away

[20]Therefore, $\mathbb{E}(h_{17}) = \exp(0.5) = 1.6487$ and $SD(h_{17}) = \sqrt{(\exp(1)-1)\cdot\exp(0.5)} = 2.1612$.

[21]On the other hand, parental education impacts a youth's decisions either through its effects on parental transfer (and thus budget constraint) or though shifting the youth's preference towards schooling. Conditional on received parental transfers, which is directly observed in the data, parental education provides an exogenous preference shifter to schooling choices.

from borrowing constraints (abstracting away from uncertainty and health production):[22]

$$\gamma \cdot (\log c_{t+1} - \log c_t) = -\rho(\theta_c, \theta_n, h_t) + \log(1+r).$$

The identification of subjective discount rate parameters relies on variations in consumption growth and thus savings. Under the parameterization $\rho(\theta_c, \theta_n, h_t) = \rho_0 - \rho_c \theta_c - \rho_n \theta_n - \rho_h h_t$, the average net worth level identifies the constant term of the subjective discount rate, ρ_0. The correlation between wealth and cognitive skills helps to identify the effect of cognitive ability on the subjective discount rate ρ_c. Similarly, the correlation between wealth and noncognitive ability and the correlation between wealth and health identify ρ_n and ρ_h, respectively.[23]

Under our functional form and distribution assumptions, the choice probabilities on unhealthy behavior, school enrollment, and employment identify the preference parameters towards unhealthy behavior, schooling, and working. Parameters on production technology and outcome equations are identified through control function approach. We have repeated observations on an individual's health status, which provides information on an individual's underlying health given parameters on measurement equations. Health production parameters are identified by the dynamics of measured health status. Moreover, the conditional correlation between the next period's health status and current health production inputs such as unhealthy behavior. The impact of log consumption on next period's health is identified by the coefficient of log earnings in the health status regression. Lastly, the effect of cognitive/noncognitive ability is identified by the conditional correlation between measures of cognitive/noncognitive ability and the next period's health.

4.3 Estimation Method

We use a two-step estimation procedure to estimate the structural model parameters. In the first step, we estimate the parameters on the measurement system and the joint distribution of health, and cognitive and noncognitive ability at age 17.

[22]For illustrative purposes, here we assume $u_c(c_t;\Omega_t) = c_t^{1-\gamma}/1-\gamma$ and r is the borrowing/lending interest rate.

[23]To identify (ρ_c, ρ_n, ρ_h), we assume marginal utility of consumption, $\partial u_c(c_t;\Omega)/\partial c_t$, does not depend on cognitive ability, noncognitive ability, or health. This is our exclusion restriction.

In the second step, we use the method of simulated moments to estimate parameters on individuals' preferences, production function on health and labor market skills, and budget constraint.[24] The initial conditions for health and cognitive and noncognitive ability in the second step are obtained by simulation using the parameter estimates from the first step.

5 Estimation Results

In this section, we discuss estimation results. Specifically, in Section 5.1 we discuss the estimate results of the measurement system in the first-stage estimation using a simulated maximum likelihood method. Section 5.2 discusses the estimation results of the structural model in the second-stage estimation using simulated method of moments. Finally, Section 5.3 evaluates the quantitative importance of cognitive and noncognitive abilities on adult outcomes and the direct benefit of health on education.

5.1 Measurement System

The initial distribution of $(\theta_c, \theta_n, \log(h_{17}))$ is reported in Table C4. The parameter estimates of the measurement equations are reported in Table C5. These three initial endowments are positively correlated with each other.[25] The correlation between cognitive ability and noncognitive ability is moderate (0.280), the correlation between cognitive ability and log health is much smaller (0.143), and the correlation between noncognitive ability and log health is relatively high (0.369).

To interpret the parameter estimation on the distribution of factors and measurement equations, we decompose the variance of each measurements into three components: variance explained by unobserved factors, variance explained by the observed controls, and variance explained by measurement errors. Table C6 reports variance decomposition based on the measurement equations. As we can see, a significant portion of variation in these variances are due to measurement errors.

[24]The choice variables in the model include not only discrete controls such as schooling and working decisions but also continuous controls such as asset level. As a result, we use Simulated Method of Moments (SMM) to estimate the model.

[25]The variance of each factor is normalized to one for identification.

In particular, the measurement errors account for 20 to 30 percent of the variance in cognitive ability measures, 50 to 60 percent of variance in noncognitive measures, and 30 to 80 percent of the variance in health measures.

5.2 Structural Parameter Estimates and Model Fit

5.2.1 Preference Parameters on Unhealthy Behavior

Table 10 panel A reports estimated value of preferences parameters on unhealthy behavior. The estimated positive and statistically significant coefficient $\phi_{q,q} > 0$ implies that current unhealthy behavior is addictive to its past history of accumulated addiction stock (q_t). Higher health capital stock increases the psychic cost of unhealthy behavior ($\phi_{q,h} < 0$). Education reduces individuals' preferences towards smoking downwards ($\phi_{q,e} < 0$), which can be contributed to better knowledge as well as peer effects, etc. Individuals who have higher cognitive and noncogntive abilities also dislike smoking more. As seen in Figure D7, the model can match the average probabilities of unhealthy behavior as well as accumulated years of unhealthy behavior both over time and over different education groups.

5.2.2 Preference Parameters on Schooling and Working

Table 10 panels B and C report preference parameter estimates on schooling and working. The psychic benefit of schooling is higher for individuals with higher cognitive and noncognitive abilities and better health; individuals whose parents have higher education also have higher flow utility of schooling. Figures D8 plots the model fit on schooling and education. Overall, the model can replicate the schooling decision patterns over time. The model can also match the average employment probability both over time and over health status categories (see Figure D9).

5.2.3 Subjective Discount Rate and Debt Limit

Parameter estimates of discount rate are reported in Table 2. Figure C6 in the appendix plots the discount factor as a function of cognitive and noncognitive abilities and health. Parameter estimates

Table 2: Subjective Discount Rate: $\rho(\theta_c, \theta_n, h_t) = \rho_0 - \rho_c\theta_c - \rho_n\theta_n - \rho_h h_t$.

Description	Parameter	Estimate	S.E.
Cognitive Ability	ρ_c	0.0056	0.0005
Noncognitive Ability	ρ_n	0.0030	0.0002
Health	ρ_h	0.0052	0.0004
Constant	ρ_0	0.0920	0.0003

Note: We evaluate the marginal effects of latent factors at their unconditional means in the initial distribution, which implies a discount rate of value $\rho(\theta_c = 0, \theta_n = 0, h_t = \exp(0.5)) = 0.0912$ and the associated discount factor is 0.9129.

of discount factor and borrowing limit are reported in Table 11.

The discount rate parameter ρ_0 is identified from the average level of assets; parameters ρ_c, ρ_n, and ρ_h are identified from the covariance between asset level and cognitive ability, noncognitive ability, and health, respectively. The credit constraints parameter $\beta_{\underline{s},0}$ is identified by the mean debt level, and $\beta_{\underline{s},1}$ is identified by the covariance between debt level and education level because education level is a key determinant of labor market human capital level. Figure D10 plots our model fits of average net worth and average debt at ages 20, 25, and 30. Table D10 shows model fit on conditional correlation between asset level and measures on cognitive ability, noncognitive ability, and health.

5.2.4 Health Production Parameters and Moments

The estimated health production function characterizes the direct causal impact of each input on the next period's health. Using education as an example, the direct causal impact of education on health is the estimated coefficient of education in the health production function. Reasons for such direct causal impact include better knowledge and higher allocation efficiency in the health production.[26] Such direct effect is disentangled from education's indirect benefits of reducing unhealthy behavior and increasing available financial resources. It is also isolated from the effects of other confounding factors such as latent abilities.

[26] Other inputs (such as exercise), that are not explicitly controlled in the model, can also contribute to the estimated effects of education on health, because individuals' decisions on these inputs can be affected by their education levels.

Figure 14 plots the estimated parameters of the health capital production function, where the error bars indicate the range of 95% confidence interval. The y-axis is the changes of next period health capital relative to current health capital: $(\log h_{t+1} - \log h_t)$ and can be interpreted as the rate of change in health capital. The estimated value of intercept is -0.0551, implying the average rate of change in health capital is -0.0551. The estimated coefficient to current health is $-0.0200 \in (-1, 0)$, reflecting the fact that health is highly persistent and that the next period's health production exhibits diminishing marginal productivity with respect to current health. Compared to high school dropouts, *ceteris paribus*, the growth rate of health increases by 0.0198 for 4-year college graduates. Higher consumption promotes better health. Engaging in unhealthy behavior changes the growth rate of health by -0.0299. The effects of schooling is small and statistically insignificant from zero. Working has a small negative effects on health production. Finally, both cognitive ability and noncognitive ability have positive impact on health production.

Under estimated parameter values, our model can replicate the dynamics of measured health status as well as its conditional correlation with different health production inputs in the observed data. In particular, ae seen in Figure D11, our estimated model can replicate changes in health status both over time and across education group. Table D11 also shows that our model can match the coefficients of various inputs in the health status regression.

5.2.5 Labor Market Skill Production and Wages

Table 12 reports parameter estimates for the human capital production function and Table 13 reports parameter estimates for the wage equation. A one standard deviation increase in cognitive ability increases an individual's human capital level by $\alpha_{\psi,c} = 0.0701$ log points; equivalently, if an individual's cognitive ability increases by one standard deviation, the logarithm of his offered full-time hourly wage increases by 0.0701. The effects of noncognitive ability on human capital level and thus wages is small and not statistically different from zero. Health also contributes to an individual's human capital level and thus offered wages.

Figure D12 in the appendix plots the model fit of wages by age, education, and health status. Our estimated model can replicate the observed accepted wage patterns over time and across education groups for both full-time wages and part-time wages.

5.2.6 Sorting into Education

Using simulated data based on estimated model parameters, we now illustrate the magnitude of sorting into education at age 30 based on unobserved ability and initial health capital stock.[27] Figure 6 is the density plot of three unobservables by education groups in the simulated data. As we can see, based on cognitive and noncognitive ability and initial health capital stock, individuals sort into higher education levels and better health status in adulthood.

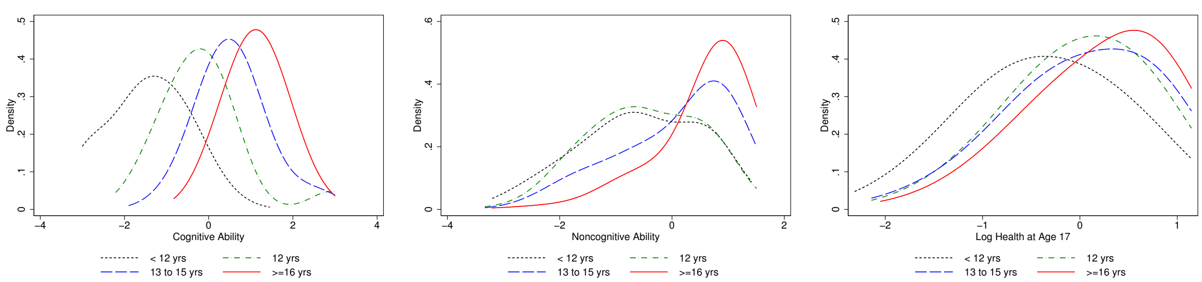


Figure 6: Density of Initial Factors Conditional on Age-30 Education

5.3 Economic Implications of Model Estimates

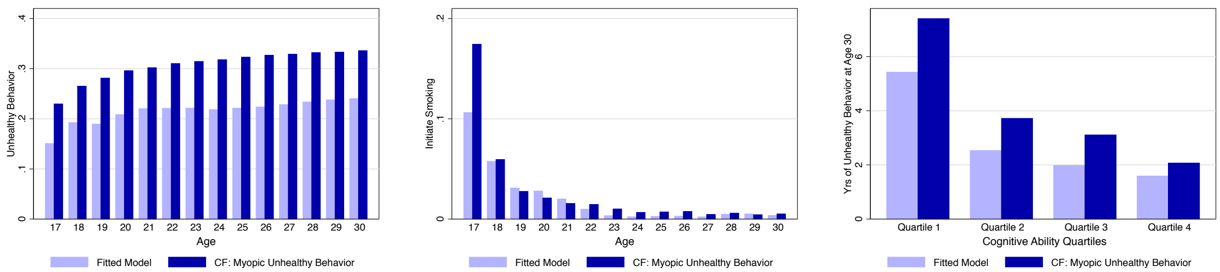
5.3.1 Effects of Removing Forward-looking Consideration in Unhealthy Behavior

In this section we compare our model to a counterfactual model where individuals make myopic decisions on their unhealthy behavior. Recall individuals' optimal decisions in our dynamic benchmark model. A forward-looking individual optimally chooses $d^*_{q,t} = 1$ if and only if :

$$\frac{U^*(d_{q,t}=1;\Omega_t)-U^*(d_{q,t}=0;\Omega_t)}{\exp(-\rho(\theta_c,\theta_n,h_t))} > \underbrace{\mathbb{E}(V_{t+1}|d_{q,t}=0,h^*_{t+1}(d_{q,t}=0))-\mathbb{E}(V_{t+1}|d_{q,t}=1,h^*_{t+1}(d_{q,t}=1))}_{\text{cost of } d_{q,t}=1 \text{ in terms of changes in remaining lifetime utility}}$$

[27] In Appendix E.1, we also investigate the distribution of initial health and abilities conditional on age 30 health measures.

where $U^*(d_{q,t};\Omega_t)$ is the flow utility associated with $d_{q,t}$, $h^*_{t+1}(d_{q,t})$ is the endogenous health capital associated with $d_{q,t}$, and $\mathbb{E}(V_{t+1}|d_{q,t}, h^*_{t+1}(d_{q,t}))$ is the remaining lifetime utility at age $t+1$ associated with $d_{q,t}$.[28]



(a) Unhealthy Behavior Probability (b) Initiating Unhealthy Behavior (c) Yrs of Unhealthy Behavior (Age 30)

Figure 7: Forward-looking Unhealthy Behavior vs Myopic Unhealthy Behavior

The cost of $d_{q,t} = 1$ in terms of changes in remaining life time utility consists of two effects: a negative "human capital effect" and a positive "addictive preference effect". On one hand, engaging unhealthy behavior reduces the health capital level in the next period, *ceteris paribus*, and thus reduces the remaining life-time utility because of loss in human capital. On the other hand, because of the addictive nature of unhealthy behavior, conducting unhealthy behavior at period t may lead to future gains in terms of flow utility at $t+1$. Finally, as an individual ages and health deteriorates, both the remaining lifetime utility and the discount factor becomes smaller, thus the forward-looking consideration becomes less and less important.

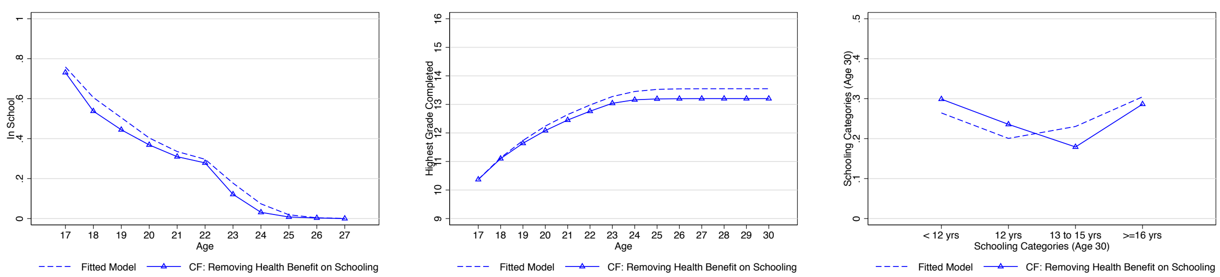
To evaluate the effects of rational expectation on the decisions of unhealthy behavior, we remove the future value consideration for individuals' choices on unhealthy behavior. In this model with myopic unhealthy behavior, an individual chooses $d_{q,t} = 1$ if and only if $U^*(d_{q,t} = 1;\Omega_t) > U^*(d_{q,t} = 0;\Omega_t)$. Note that in this counterfactual model, only the unhealthy behavior decision is myopic, individuals' decisions on education, savings, and working are still forward-looking. Figure 7 plots the predicted unhealthy behavior in the myopic model against our fitted model. As we can see, in the model with myopic unhealthy behavior, the predicted probability of unhealthy be-

[28] More precisely, $U^*(d_{q,t};\Omega_t) \equiv U(c^*_t(d_{q,t}), d_{q,t}, d^*_{e,t}(d_{q,t}), d^*_{k,t}(d_{q,t});\Omega_t)$ and $\mathbb{E}(V_{t+1}|d_{q,t}, h^*_{t+1}(d_{q,t})) \equiv \mathbb{E}(V_{t+1}(\Omega_{t+1})|\Omega_t, d_{q,t}, d^*_{e,t}(d_{q,t}), h^*_{t+1}(d_{q,t}), s^*_{t+1}(d_{q,t}), k^*_{t+1}(d_{q,t}), e^*_{t+1}(d_{q,t}))$ where $c^*_t(d_{q,t}), d^*_{e,t}(d_{q,t}), d^*_{k,t}(d_{q,t})$ are the optimal choices on consumption, schooling, and working associated for a given $d_{q,t} \in \{0,1\}$.

havior is much higher when individuals do not take into account the negative human capital impact and the probably of initiating unhealthy behavior at age 17 increases by more than 60%.

5.3.2 Direct Benefits of Health on Schooling

In our model, health can directly affect an individual's educational decision by reducing his psychic cost associated with schooling ($\phi_{e,h} = 0.0773 > 0$). Health can also indirectly impact educational choices through its effects on subjective discount factor and wage equation, as well as complex interactions between different inputs (including health itself) in the health production function. Here we evaluate the direct benefit of health on education by shutting down the preference parameter on schooling associated with health, i.e., we set $\phi_{e,h} = 0$. The result is reported in Figure 8. As we can see in Figure 8, removing the direct benefits of health on schooling reduces a sizable fraction of schooling enrollment.[29]



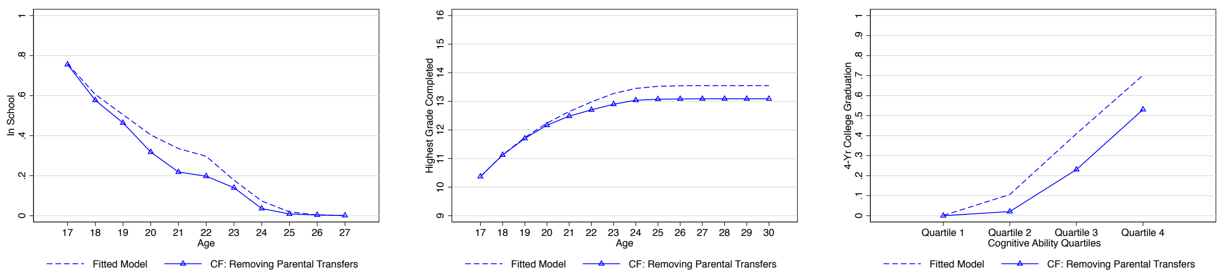
(a) In School (b) Education (c) Education Category (Age 30)

Figure 8: Economic Implications: Removing Direct Benefits of Health on Schooling ($\phi_{e,h} = 0$)

5.3.3 Economic Importance of Parental Transfer

In this section, we aim to evaluate the quantitative importance of parental transfers on youths' choices over school, work, and unhealthy behavior. To do this, we conduct the counterfactual simulation by setting the parental transfer function to be zero, i.e., $\mathrm{tr}_{p,t} = 0$ and compare individuals' choices with the fitted model to evaluate the importance of empirically estimated parental transfers.

[29] The quantified importance of health on schooling in our model provides a lower bound for the direct benefit of health on schooling. This is because, in our model, the avenue of health on education is through its effects on whether to attend school next year, i.e., when to stop investing in education. Health can also affect one's education outcome by



(a) In School

(b) Education

(c) 4-Year College Graduation (Age 25)

Figure 9: Economic Implications: Removing Parental Transfer ($\mathrm{tr}_{p,t} = 0$)

As seen in Figure 9, compared to the fitted model, there is a sizable reduction in the average level of highest grade completed; the fraction of 4-year college graduation is also reduced among the second and third cognitive ability quartile individuals. This indicates that parental transfers are important in determinants in individuals' 4-year college graduation decisions.

6 Accounting for Human Capital Inequality

6.1 Inequality Decomposition in Health and Labor Market Skills

In this section, we use the model to analyze the determinants of the inequality in labor market skills and health capital. In particular, we are interested in the following question: To what extend do differences in cognitive ability, noncognitive ability, initial health, and parental factor account for the observed cross-section inequality in health and labor market skills? To address this question, we perform four counterfactual experiments that equalizing the initial conditions regarding to (i) cognitive ability, (ii) noncognitive ability, (iii) initial health, and (iv) parental factors (including both schooling and net worth).

The results are reported in Table 3. The cross-sectional inequality in health and labor market skills during individuals' adulthoods are measured by the standard deviation of log health and the standard deviation of log skills at age 30, respectively. Here, we focus on labor market skills

affecting one's academic test score and college major choices.

instead of wages, because an individual's labor market skills provide a complete description of the individual's labor market opportunity in terms of *offered* wages, which is independent from the individual's employment decisions. The first row of Table 3 reports the baseline prediction from the fitted model, and the following rows show the counterfactual experiments.

Difference in cognitive ability accounts for a large portion of variation in adulthood labor market skills. Equalizing cognitive ability reduces the age-30 inequality in labor market skills by 48.03%. Equalizing cognitive ability also leads to a sizable reduction (9.14%) of the youths' health inequality at age 30. Equalizing noncognitive ability has a sizable impact (12.58%) on individuals' health inequality at age 30, but its effect on labor market skills is relatively small (2.74%). Initial difference in health capital accounts for majority of the health disparity at adulthood. Equalizing initial health reduces the age-30 health inequality by 52.46%. However, the Initial health heterogeneity only explains a small fraction of labor market skills heterogeneity at age 30. Finally, after controlling for the differences in individuals' early cognitive, noncognitive, and health endowment, difference in parental factors in terms of schooling and wealth accounts for 0.39% of the measured inequality in health and 3.09% of the measured inequality in labor market skills at age 30.

Table 3: Accounting for Inequality in Health and Labor Market Skills (Age 30)

	Inequality		Inequality Reduction (%)	
	Health	Skill	Health	Skill
Baseline	0.8218	0.3843	N/A	N/A
Equalizing Cognitive Ability	0.7467	0.1997	9.14	48.03
Equalizing Noncognitive Ability	0.7185	0.3737	12.58	2.74
Equalizing Initial Health	0.3907	0.3722	52.46	3.15
Equalizing Parental Factors	0.8186	0.3724	0.39	3.09

Note: Inequality in health and labor market skills are measured using standard deviation of log health and log skills at age 30, respectively. Reduction in inequality is calculated as the percentage reduction in inequality compared to the benchmark case.

6.1.1 The Importance of Ability Cognitive and Noncognitive Ability over the Lifecycle

As shown in the model, both cognitive and noncognitive factors affect a youth's optimal decisions and adult outcomes through their effects in preferences, technologies (in terms of both labor market skill production and health production), and discount factors. To evaluate the economic impact of cognitive and noncognitive ability on adult outcomes, we simulate the model by varying the cognitive ability and noncognitive ability for a large sample of artificial individuals.[30]

Figures E14 to E16 plot the importance of cognitive and noncognitive ability on individuals' health, education, and wealth at age 20 and age 30. Individuals in each cell only differ in their initial cognitive ability and noncognitive ability. As we can see from Figure E14, the average health level increases with both cognitive ability and noncognitive ability, and this positive relationship strengthens over time not only because these abilities improves the efficiency of health production but also because higher ability individuals invest more in health as these inputs are complementary to ability. Similarly, there is a positive impact of cognitive and noncognitive abilities on education, years of accumulated healthy behavior, labor market experience, and accepted wages, and these positive impact also strengthens over time (Figure E15, and Figures E17 to E19). However, the difference in wealth by cognitive ability and noncognitive ability remains relatively small by age 30 (Figure E16).

7 Counterfactual Policy Experiments

7.1 Policy Experiment: Subsidizing College Tuition

In this section, we evaluate the effects of tuition subsidy policy on individuals' schooling choices. In particular, we provide each individual a college tuition subsidy of $1000.[31] As seen from Figure 10, the predicted average years of schooling slightly increases under this experiment when compared to the fitted model. The increase in the fraction of fraction of youths who complete 4-year college is also small. The effect of subsidizing college tuition on Unhealthy Behavior is quantitatively negligible (see Figure E21 in appendix).

Due to the small increase in education, individuals' health is also improved over time (Table

[30]Except cognitive and noncognitive abilities, the rest initial conditions of these artificial individuals such as parental wealth and education are drawn from the NLSY97 data.

[31]In the simulation, we do not allow the amount of student loan that an individual can borrow if he decides to attend college to be directly affected by such college tuition subsidy.

4). The effects of such college tuition subsidy on unhealthy behavior is also small (see Figure E20 in the appendix).

7.2 Policy Experiment: Relaxing Credit Constraints

In this section, we relax credit constraints for each individual to evaluate the importance of credit constraint on individuals' decisions. In particular, individuals are allowed to borrow up to their nature borrowing limit based on their age and earnings' capacity.[32] Figure 11 shows that removing credit constraints leads to a sizable increase in highest grade completed; and the fraction of individuals who graduate from a 4-year college also increases, especially among high ability ones. In particular, model simulation shows that when an youth's credit constraint is relaxed and makes decisions to attend college, the youth also receives a larger amount of parental transfers which they would not receive had they not chosen to attend college (see Figure 22(d)). Therefore parental transfers amplify the effects of relaxing borrowing constraint to the youth's college attendance decision.

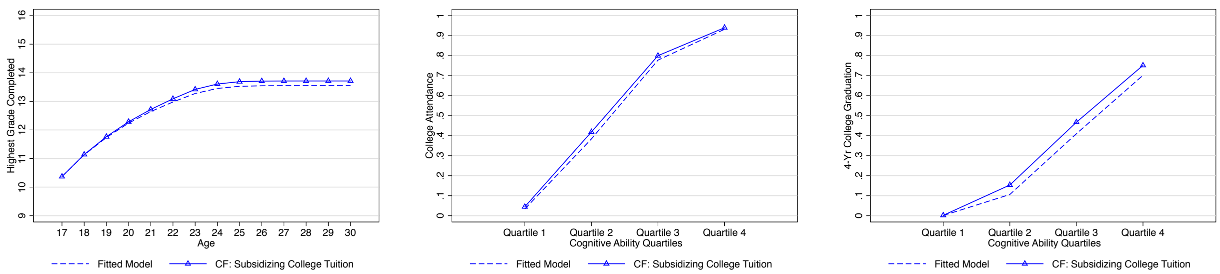
Figure 12 shows that the fraction of individuals who conduct unhealthy behavior will increase once the credit constraint is relaxed, and such increase is mainly due to an increase in initiating smoking at age 17. However, as individuals' acquire more education, over time, the fraction of individuals who conduct unhealthy behavior slowly decline and reaches the same level as the baseline model by age 30.

As seen in Table 4, the median health stock first decrease and then increase over time under this experiment. The time path of other endogenous variables under this experiment is reported in Figure E22 in the appendix.

[32] Let $F^{s*}(t,\Psi_t)$ be the maximum amount of money that an individual of age t and human capital level Ψ can repay back in the future:

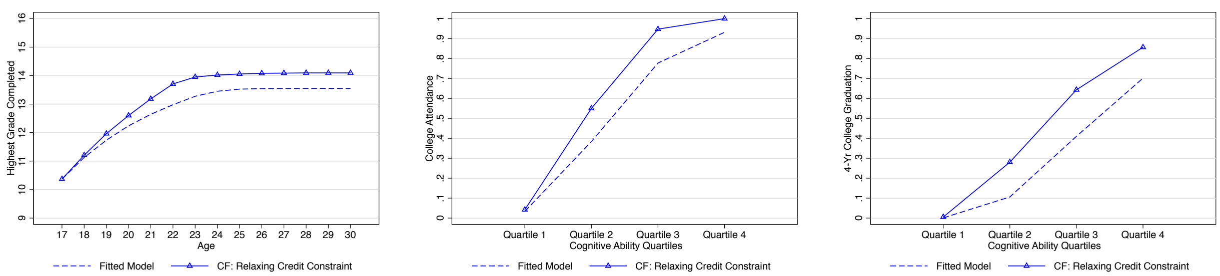
$$F^{s*}(t,\Psi_t) = \sum_{\tau=t+1}^{T} (\Psi_t\overline{L} - c_{min})/(1+r_b)^{\tau-t}$$

where $\Psi_t\overline{L}$ is the predicted earnings if the individual works full-time and c_{min} is the sustainable consumption level.



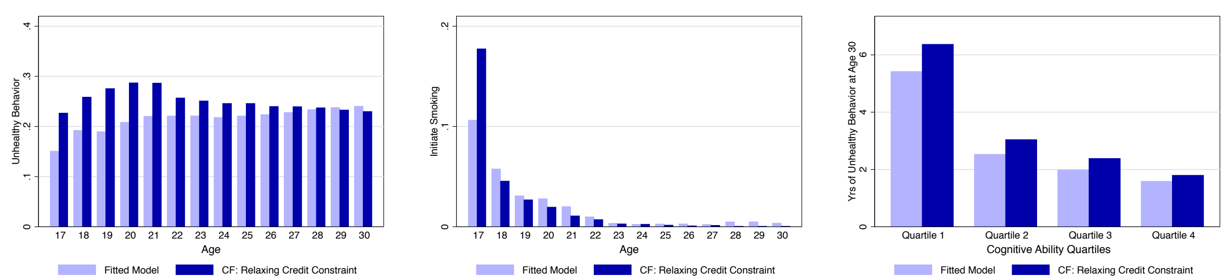
(a) Education (b) College Attendance (Age 21) (c) 4-Year College Graduation (Age 25)

Figure 10: Effects of College Tuition Subsidy on Education



(a) Education (b) College Attendance (Age 21) (c) 4-Year College Graduation (Age 25)

Figure 11: Effects of Relaxing Credit Constraints on Education



(a) Unhealthy Behavior Probability (b) Initiating Unhealthy Behavior (c) Yrs of Unhealthy Behavior (Age 30)

Figure 12: Effects of Relaxing Credit Constraints on Unhealthy Behavior

Table 4: Predicted Percentage Change in Health Under Policy Experiments 1-2

	Age 18 to 24		Age 25 to 30		Age 18 to 30	
	p50	mean	p50	mean	p50	mean
Tuition Subsidy	0.08	0.04	0.28	0.23	0.10	0.12
Relaxing Credit Constraints	-0.19	0.02	1.02	0.91	0.21	0.38

7.3 Discussion: Experiments on College Tuition and Credit Constraint

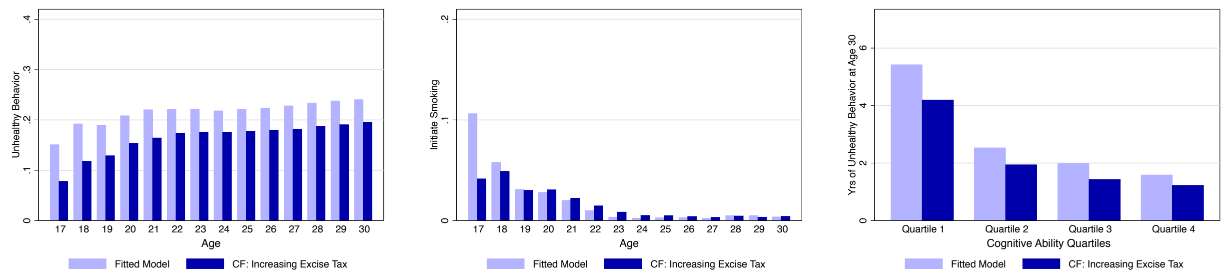
Our findings suggest that credit constraints are important for education decisions, which is consistent with Navarro (2011), Belley and Lochner (2007), and Lochner and Monge-Naranjo (2012). However, our results are different from the findings of Keane and Wolpin (2001), which conclude that credit constraint, though exits, does not matter for individuals' college decisions.

There are four possible reasons that may contribute to the importance of credit constraints in our model (compared to Keane and Wolpin (2001)). First, our study is based on a more recent cohort, NLSY97, in comparison to NLSY79. Studies suggest that borrowing constraints may play a bigger role in individuals' college enrollment in NLSY97 cohorts, possibly due to the rising college tuition cost. Second, we allow consumption as an input to health capital production, and thus the importance of credit constraint is higher in our model compared to models without consumption-health relationship. In the presence of borrowing constraint, an individual who pursues higher education endures low consumption when he is young. Once credit constraint is removed, such an individual can borrow against his higher future income and does not need to experience low consumption while in college. Third, when implementing the experiment of relaxing borrowing constraint, we allow individuals to borrow up to their nature borrowing limit, instead of a fixed amount.[33] Fourth, we directly extract individuals' unobserved ability using various cognitive and noncognitive measures without utilizing information on agents' endogenous choices. We therefore identify individuals with high (unobserved) ability but low parental net worth, and compare their decisions with individuals of high ability level and high parental net worth.[34] Fourth, we directly utilize parental transfer data to estimate parental transfer function.[35]

[33] In their counterfactual experiment of relaxing borrowing constraint, Keane and Wolpin (2001) allows students to borrow $3000 per semester.

[34] In contrast, Keane and Wolpin (2001) does not use information on measures of unobserved ability or parental wealth; instead they introduce discrete unobserved types that are correlated with agents' initial conditions such as parents' schooling. Their specification of unobserved heterogeneity is a version of a factor model in which all factor loadings are implicitly determined (through Bellman iterations) by structural model parameterization and the distribution function of unobserved variables and sample distribution of observables. Their results on credit constraints strictly rely on the assumption that the estimated "types" are invariant to the experiment of relaxing credit constraints.

[35] Keane and Wolpin (2001) do not observe the parental transfer data directly.



(a) Unhealthy Behavior Probability

(b) Initiating Unhealthy Behavior

(c) Yrs of Unhealthy Behavior (Age 30)

Figure 13: Predicted Percentage Change in Health Under Increased Excise Tax

	Age 18 to 24		Age 25 to 30		Age 18 to 30	
	p50	mean	p50	mean	p50	mean
Tax Exp	0.41	0.29	0.38	0.33	0.26	0.31

7.4 Policy Experiments: Increasing Revenue-Neutral Excise Tax

In this section, we experiment on imposing an excise tax schedule τ and a lump-sum subsidy $b(t)$ on age-t individuals and evaluate individuals' optimal response and associated health outcomes. An individual's budget constraint is given as follows:

$$c_t + (1+\tau)p_q d_{q,t} = b(t) + \Delta s_{t+1} + y_t + \text{tr}_{p,t} + \text{tr}_{c,t} + \text{tr}_{g,t} - \text{tc}(e_t + d_{e,t}, s_p)d_{e,t}$$

where $\Delta s_{t+1} = (1 + r_l \mathbf{1}(s_t > 0) + r_b \mathbf{1}(s_t < 0)) \cdot s_t - s_{t+1}$. To ensure that the exercise tax together with the subsidy is revenue-neutral, we require the lump-sum subsidy $b(t)$ satisfies $b(t) = \tau \cdot p_q \cdot \mathbb{E}(d_{q,t} = 1)$ for given tax schedule τ.[36] The equilibrium subsidy for given tax schedule is solved numerically through iteration.

We consider a flat tax schedule $\tau = 0.5$ for all t. In our estimated model, we set the monetary cost of a pack of cigarettes to be \$2, which implies the monetary cost of unhealthy behavior (regular smoking) to be \$657, a tax rate of 0.5 implies a \$1 increase in tax rate on each pack of cigarettes.[37] The fraction of individuals with unhealthy behavior over time is plotted in Figure 13 (solid line), the dash line is the age pattern using estimated model. As we can see, an 50% increase in cigarette price

[36] The expectation is taken with respect to the entire age-t population.

[37] The tax effects on the onset of smoking for adolescents between eighth and twelfth grades is found to be weak (see DeCicca, Kenkel, and Mathios (2002)).

reduces a sizable fraction of individuals with unhealthy behavior. Furthermore, such reduction mainly occurs by reducing the probability of initiating smoking at age 17.

8 Conclusion

We develop and structurally estimate a life cycle model with endogenous decisions on health, education, and wealth. Using this estimated model, we evaluate the dynamic economic mechanisms through which health, education, and wealth impact each other. We also use the estimated model to assess the economic importance of parental factors and unobserved cognitive and noncognitive ability, on the determinants of both health and education.

With the development of our model we hope to lay down a framework to investigate other applied questions on the origins of inequality in human capital development and their dynamic relationships over the life cycle. For example, in our current application, we only focus on a sample of white males. This model can be directly extended to study life cycle inequality in health, education, and wealth by race. In particular, we can investigate the racial disparity in education, health, and wealth by evaluating the different impacts resulting from the racial differences in offered wages, subjective discount rates, preferences over schooling, employment, and unhealthy behavior, and heath production functions. This model can also be extended to study questions on intergenerational mobility. The current model has already introduced the effects of parents' education and wealth on youth outcomes through parental transfers and preferences towards schooling, and the youth forms rational expectations and takes parental decisions as exogenous rules. In future work, we can investigate the substitutability/complementarity between public education subsidies and parental investment by introducing endogenous parental decisions and by allowing the interaction between parental decisions and the youth's choices.

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Table 5: Key Variables over Age

	Age 17	Age 20	Age 25	Age 30
Health Status (1: poor/fair; 4: excellent)	3.19	3.06	2.91	2.76
BMI [18.5, 30)	0.86	0.85	0.79	0.68
Education	10.30	12.23	13.41	13.78
Net Worth	0.00	-155.47	2024.37	11454.56
Unhealthy Behavior (Regular Smoking)	0.14	0.23	0.23	0.22
Yrs of Unhealthy Behavior as of t-1	0.11	0.62	1.73	2.63
In School	0.87	0.37	0.10	0.03
Work Full Time	0.02	0.28	0.53	0.56
Work Part Time	0.27	0.31	0.18	0.10
Working Experience	0.00	0.80	3.42	6.65
Full-Time Hourly Wage	5.60	11.06	16.81	23.42
Part-Time Hourly Wage	5.95	9.20	15.35	16.80
Receive Parental Transfers	0.36	0.46	0.18	0.06
Receive Govern. Transfers	0.02	0.08	0.14	0.19
Receive Govern. Unemployment Benefits	0.00	0.03	0.05	0.08
Receive Govern. Means-tested Transfers	0.02	0.05	0.11	0.12
Total Parental Transfers	492.21	2015.33	357.22	96.40
Total Government Transfers	87.70	204.90	524.99	959.48
Govern. Unemployment Benefits	1.21	74.34	292.98	460.02
Govern. Means-tested Transfers	86.78	133.45	275.06	500.86
Parents Education	13.19	13.19	13.19	13.13
Parents Net Worth	187932.29	187932.29	187932.29	195707.12

Table 6: Health, Smoking, Wages, and Wealth By Education Categories (Age 25 to 30)

	HS Dropouts	High School	Some College	4-Yr College
Health Status (1: poor/fair; 4: excellent)	2.47	2.71	2.91	3.15
BMI [18.5, 30)	0.75	0.70	0.71	0.82
Has Health Condition	0.24	0.20	0.22	0.18
Unhealthy Behavior (Regular Smoking)	0.51	0.27	0.18	0.05
Work Full Time	0.52	0.62	0.57	0.64
Full-Time Hourly Wage	13.71	17.48	18.37	22.55
Net Worth (in Thousands)	-1.19	4.02	2.36	9.00

Table 7: Measures of Initial Health, Cognitive and Noncognitive Ability

	mean	sd	N
Health status (1: poor/fair; 4: excellent) at age 17	3.19	0.85	2,047
Had health condition before age 17	0.15	0.36	1,939
BMI [18.5, 30) at age 17	0.86	0.34	2,039
ASVAB arithmetic reasoning (1997)	-0.08	0.95	1,787
ASVAB mathematics knowledge (1997)	0.06	0.99	1,782
ASVAB paragraph comprehension (1997)	-0.16	0.93	1,785
ASVAB word knowledge (1997)	-0.28	0.89	1,786
Violent behavior (1997)	0.22	0.42	2,098
Had sex before Age 15	0.18	0.38	2,101
Theft behavior (1997)	0.10	0.29	2,099

Table 8: Parameters Calibrated Outside the Structural Model

Description	Parameter	Value	Source
Direct Cost of Unhealthy Behavior	p_q	\$657	a pack of cigarettes \$2.0
Cost of College Tuition & Fees Net Grants and Scholarship	$tc(e=13,14,s_p=T1)$ $tc(e=13,14,s_p=T2)$ $tc(e=13,14,s_p=T3)$ $tc(e\geq 15,s_p=T1)$ $tc(e\geq 15,s_p=T2)$ $tc(e\geq 15,s_p=T3)$	1655.11 1994.61 1775.62 9004.47 10207.02 10011.79	IPEDS data on average tuition and fees 1999-2006 for 2- year college and 4-year college from 1999-2006; NLSY97 data on average grants and scholarship by parental wealth terciles.
College Room and Board	2-year college 4-year college	4580.85 7648.11	IPEDS data on average room and board for 2-year college and 4-year college 1999-2006.
GSL Borrowing Limit	$\bar{l}^g$ $\bar{L}^g$	\$11000 \$35000	Federal Student Aid
Borrowing Interest Rate Lending Interest Rate	r_b r_l	4% 1%	Federal Student Aid and WSJ bankrate.com savings rate $[0.05\%, 1.05\%]$
Parental Transfer Function	$\text{tr}_p(e_p,s_p,d_{e,t},d_{k,t},e_t,t)$	Table 9	NLSY97 sample
Parents Housing Subsidy	χ	\$7800	Kaplan (2012) & Johnson (2013)
Unemployment Benefit	$b_{g,0}$ $b_{g,e}$ $b_{g,k}$ $b_{g,kk}$	6.36 0.07 0.17 -0.01	NLSY97 sample
Minimum Consumption Floor	$c_{\min}$	2800	NLSY sample average means-tested transfers among recipients
Risk Aversion Coefficient	γ	1.5	Previous literature: $\gamma \in [1,3]$
Terminal Value function	$\phi_{T+1,s}$	4	SCF age-50 financial net worth \$70K

IPEDS = Integrated Postsecondary Education Data System. Average tuition and fees are weighted by full-time enrollment and are deflated in 2010 dollars. Because expenditures are higher at four-year institutions than at two-year institutions, there is a noticeable jump in cost between two and three years of college.
Federal Student Aid current annual limit is \$5,500 for Perkins Loans and \$5,500 for Stafford Loans. https://studentaid.ed.gov/
The Interest rate ranges from 3.34 to 8.25% for Stafford Loans over the time period 1997 to 2011, and remains 5% for Perkins Loans. WSJ prime rate is 3.25% and 30 year fixed rate is 4.08% in 2014.

Table 9: Estimation of Parental Transfer Function (Tobit Model)

	(1)		(2)	
	Parental Transfers/1000		Parental Transfers/1000	
model				
Parents' Net Worth T2	0.559**	(0.150)	0.570**	(0.149)
Parents' Net Worth T3	1.382**	(0.171)	1.382**	(0.171)
Parents' Education	0.447**	(0.047)	0.442**	(0.047)
In First/Second Yr College	17.123**	(1.581)	16.853**	(1.577)
In Third/Fourth Yr College	19.743**	(1.729)	19.465**	(1.725)
In Graduate School	1.717**	(0.348)	2.246**	(0.368)
Work Part Time	-0.816**	(0.139)	-0.194	(0.196)
Work Full Time	-1.700**	(0.163)	-1.460**	(0.172)
Age	-0.447**	(0.047)	-0.453**	(0.047)
Age * In College	-0.698**	(0.080)	-0.663**	(0.080)
Age 17	-2.514**	(0.277)	-2.204**	(0.286)
Age 18	-0.397*	(0.223)	-0.227	(0.226)
$>$ Age 23	-0.636**	(0.263)	-0.605**	(0.263)
Parents' Education $\geq$ 16	0.758**	(0.258)	0.764**	(0.258)
Parents' Education $\geq$ 16 * Parents' Net Worth T3	0.559**	(0.279)	0.540*	(0.279)
Work Part Time while in School			-1.164**	(0.261)
Constant	0.103	(1.113)	0.069	(1.112)
sigma				
Constant	5.613**	(0.059)	5.607**	(0.059)
Observations	16422		16422	
Pseudo R^2	0.088		0.088	

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$

Table 10: Parameter Estimates of Flow Utility Function

Description	Parameter	Estimate	S.E.
Panel A			
Unhealthy Behavior Intercept	$\phi_{q,0}$	-0.0516	0.0007
Unhealthy Behavior $\times$ Addiction Stock	$\phi_{q,q}$	0.0360	0.0002
Unhealthy Behavior $\times$ Health Stock	$\phi_{q,h}$	-0.0020	0.0004
Unhealthy Behavior $\times$ Yrs of Schooling	$\phi_{q,e}$	-0.0040	0.0004
Unhealthy Behavior $\times$ Cognitive Ability	$\alpha_{q,c}$	-0.0100	0.0006
Unhealthy Behavior $\times$ Noncognitive Ability	$\alpha_{q,n}$	-0.0400	0.0010
S.D. of Preference Shock to Unhealthy Behavior	σ_q	0.0218	0.0008
Depreciation Rate of Addiction Stock	δ_q	0.4300	0.0005
Panel B			
Flow Utility of Attending High School	$\phi_{e,0}$	-0.1121	0.0220
Flow Utility of Attending College	$\phi_{e,1}$	-0.1798	0.0143
Flow Utility of Attending Graduate School	$\phi_{e,2}$	-0.4039	0.0086
Psychic Cost of Returning to School	$\phi_{e,e}$	1.5073	0.0158
Schooling $\times$ Health	$\phi_{e,h}$	0.0773	0.0068
Schooling $\times$ Cognitive Ability	$\alpha_{e,c}$	0.4001	0.0111
Schooling $\times$ Noncognitive Ability	$\alpha_{e,n}$	0.1307	0.0101
Schooling $\times$ Parents Education	$\phi_{e,p}$	0.0408	0.0065
Flow Utility of Attending College after Age 22	$\phi_{e,a}$	-1.1225	0.0183
S.D. of Preference Shock to Schooling	σ_e	0.0753	0.0152
Panel C			
Flow Utility of Part-Time Working	$\phi_{k,0}$	-0.4837	0.0003
Flow Utility of Full-Time Working	$\phi_{k,1}$	-0.8381	0.0000
Working $\times$ Health	$\phi_{k,h}$	0.0207	0.0001
Working $\times$ Cognitive Ability	$\alpha_{k,c}$	0.0022	0.0007
Working $\times$ Noncognitive Ability	$\alpha_{k,n}$	0.0200	0.0012
Working while in High School	$\phi_{k,e,1}$	-0.0783	0.0121
Working while in College or Graduate School	$\phi_{k,e,2}$	-0.0549	0.0087

Table 11: Parameter Estimates on Private Debt Limit

Description	Parameter	Estimate	S.E.
Borrowing Limit			
Intercept	$\beta_{\underline{s},0}$	7.5076	0.0023
Slope of Labor Market Human Capital	$\beta_{\underline{s},1}$	0.1499	0.0004
Slope of Labor Market Human Capital Squared	$\beta_{\underline{s},2}$	-0.1211	0.0006
Shifter for Age $\geq$ 18	$\beta_{\underline{s},3}$	0.5800	0.0002
Shifter for Age $\geq$ 23	$\beta_{\underline{s},4}$	0.4167	0.0031

Table 12: Parameter Estimates on Human Capital Production Function

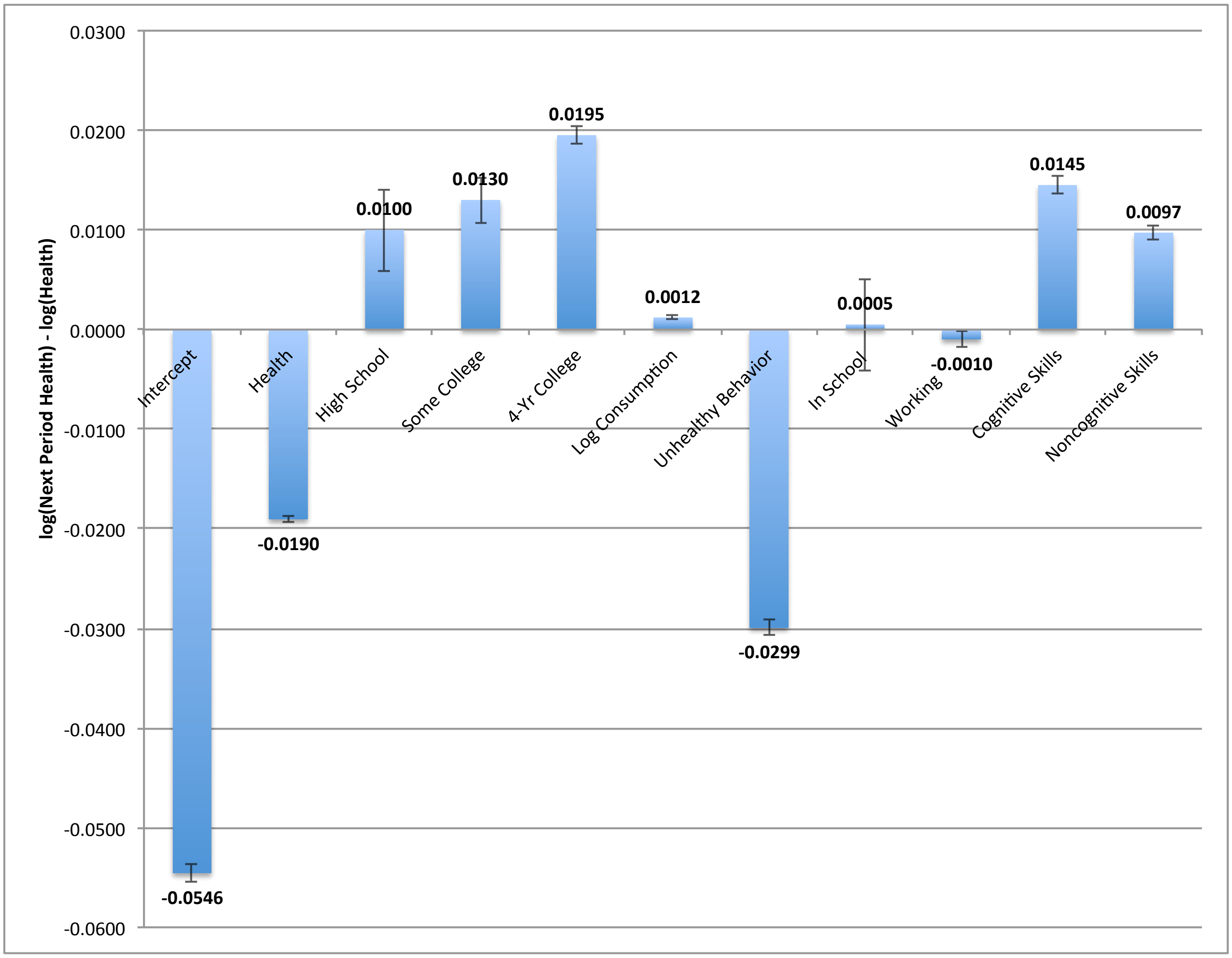
Description	Parameter	Estimate	S.E.
Cognitive Ability	$\alpha_{\psi,c}$	0.0701	0.0011
Noncognitive Ability	$\alpha_{\psi,n}$	0.0012	0.0008
Health	$\beta_{\psi,h}$	0.0501	0.0002
Yrs of Schooling-12	$\beta_{\psi,e,0}$	0.0205	0.0001
Yrs of Schooling ≥ 12	$\beta_{\psi,e,1}$	0.1813	0.0005
Yrs of Schooling ≥ 16	$\beta_{\psi,e,2}$	0.2083	0.0005
Experience	$\beta_{\psi,k}$	0.1121	0.0001
Experience Squared	$\beta_{\psi,kk}$	-0.4534	0.0001
Intercept	$\beta_{\psi,0}$	1.9422	0.0005
Age < 18	$\beta_{\psi,1}$	0.0000	0.0001
Depreciation Rate of Experience	δ_k	0.1265	0.0001

Table 13: Parameter Estimates on Wage Equation

Description	Parameter	Estimate	S.E.
Part-Time	$\beta_{w,0}$	-0.0161	0.0004
Part-time * Enroll	$\beta_{w,1}$	-0.2921	0.0086
S.D. Part-time Wage Shock	$\sigma_{w,1}$	0.2278	0.0007
S.D. Full-time Wage Shock	$\sigma_{w,2}$	0.2907	0.0001

Figure 14: Estimated Health Capital Dynamics:

$$\log h_{t+1} - \log h_t = \beta_{h,0} + \beta_{h,h} h_t + \beta_{h,e,1}\mathbf{1}(e_t = 12) + \beta_{h,e,2}\mathbf{1}(e_t > 12 \ \& \ e_t < 16) + \beta_{h,e,3}\mathbf{1}(e_t \geq 16) + \beta_{h,c}\log c_t + \beta_{h,1} d_{q,t} + \beta_{h,2} d_{e,t} + \beta_{h,3} d_{k,t} + \alpha_{h,c}\theta_c + \alpha_{h,n}\theta_n + \varepsilon_{h,t}$$



Online Appendix Not for Publication

Appendix A Data and Basic Analysis

Table A1: Descriptive Statistics of NLSY97 Sample

	mean	sd	min	max	N
Age	23.05	3.85	17.00	31.00	27,213
Education	12.64	2.33	8.00	20.00	24,542
Work Full Time	0.38	0.49	0.00	1.00	26,806
Work Part Time	0.23	0.42	0.00	1.00	26,806
Working Experience	2.49	2.69	0.00	13.50	25,405
Full-Time Hourly Wage	16.00	10.13	2.00	128.21	7,482
Part-Time Hourly Wage	11.46	9.70	2.00	149.66	4,724
Net Worth	1607.51	25346.12	-50000.00	200000.00	6,246
Unhealthy Behavior (Regular Smoking)	0.22	0.41	0.00	1.00	24,335
Yrs of Unhealthy Behavior as of t-1	1.20	2.45	0.00	15.00	22,845
Parents Education	13.18	1.95	8.00	16.00	26,339
Parents Net Worth	188218.60	215636.10	-13586.04	815162.62	20,854
Total Parental Transfers	918.46	3142.02	0.00	30000.00	24,884
Total Government Transfers	414.27	1801.72	0.00	30918.01	26,663
Health Status (1: poor/fair; 4: excellent)	2.99	0.89	1.00	4.00	23,962
Had Health Conditions before Age 18	0.15	0.36	0.00	1.00	24,991
BMI [18.5, 30)	0.81	0.40	0.00	1.00	23,481
ASVAB: Arithmetic Reasoning	-0.06	0.95	-3.14	2.37	23,069
ASVAB: Mathematics Knowledge	0.10	0.99	-2.80	2.68	23,006
ASVAB: Paragraph Comprehension	-0.13	0.93	-2.36	1.83	23,041
ASVAB: Word Knowledge	-0.24	0.89	-3.15	2.35	23,055
Noncognitive: Violent Behavior (1997)	0.23	0.42	0.00	1.00	27,157
Noncognitive: Had sex before Age 15	0.18	0.38	0.00	1.00	27,185
Noncognitive: Theft Behavior (1997)	0.10	0.30	0.00	1.00	27,168

Table A2: OLS Regression of Unhealthy Behavior (Myopic Model)

	(1)	(2)	(3)	(4)	(5)
Education	-0.062**	-0.045**	-0.005**	-0.004**	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Age	0.019**	0.015**	-0.008**	-0.009**	-0.007**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Unhealthy Behavior in t-1			0.524**	0.513**	0.485**
			(0.007)	(0.007)	(0.013)
Yrs of Unhealthy Behavior as of t-1			0.041**	0.041**	0.043**
			(0.001)	(0.001)	(0.002)
Health Status (1: poor/fair; 4: excellent)				-0.019**	-0.020**
				(0.002)	(0.004)
Having Health Conditions					0.002
					(0.008)
BMI [18.5, 25]					0.019**
					(0.007)
Constant	0.563**	0.405**	0.287**	0.356**	0.280**
	(0.017)	(0.019)	(0.015)	(0.017)	(0.026)
Cog and Noncog Measures	No	Yes	Yes	Yes	Yes
Observations	23763	20280	18962	18703	6964
Adjusted R^2	0.103	0.123	0.522	0.519	0.515

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$

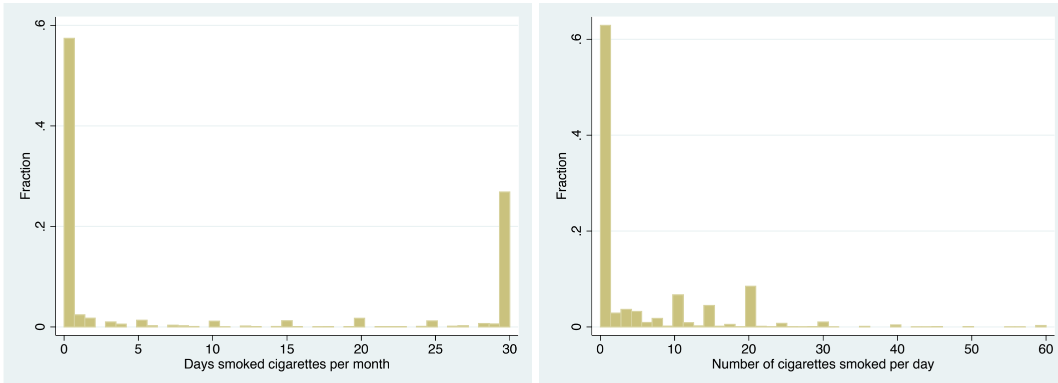
Table A3: OLS Regression of Adult Outcomes on Initial Health, Cognitive and Noncognitive Skills

	Educ		Health Status		Log Wage		$\frac{\text{Wealth}}{100{,}000}$	
Health Status Good at Age 17	0.57**	(0.16)	0.07	(0.07)	0.01	(0.07)	0.02	(0.06)
Health Status Very Good at Age 17	0.96**	(0.15)	0.29**	(0.06)	0.10	(0.06)	0.03	(0.06)
Health Status Excellent at Age 17	1.47**	(0.15)	0.67**	(0.06)	0.14**	(0.06)	0.03	(0.06)
Had Health Conditions before Age 18	0.10	(0.08)	-0.08**	(0.03)	-0.06*	(0.03)	-0.01	(0.03)
BMI [18.5, 30) at Age 17	0.39**	(0.08)	0.04	(0.03)	0.05	(0.03)	-0.01	(0.03)
ASVAB: Arithmetic Reasoning	0.15**	(0.05)	0.05**	(0.02)	0.11**	(0.02)	0.02	(0.02)
ASVAB: Mathematics Knowledge	0.42**	(0.05)	0.02	(0.02)	0.09**	(0.02)	0.00	(0.02)
ASVAB: Paragraph Comprehension	0.42**	(0.05)	0.05**	(0.02)	-0.03	(0.02)	-0.00	(0.02)
ASVAB: Word Knowledge	0.02	(0.05)	-0.02	(0.02)	-0.08**	(0.02)	-0.03	(0.02)
Noncognitive: Violent Behavior (1997)	-0.53**	(0.07)	-0.12**	(0.03)	-0.03	(0.03)	-0.01	(0.03)
Noncognitive: Had sex before Age 15	-0.95**	(0.08)	-0.05	(0.03)	-0.02	(0.03)	-0.01	(0.03)
Noncognitive: Theft Behavior (1997)	-0.39**	(0.10)	0.01	(0.04)	0.03	(0.04)	-0.07**	(0.04)
Parents' Education	0.31**	(0.02)	0.02**	(0.01)	0.02**	(0.01)	-0.00	(0.01)
Parental Net Worth/100,000	0.16**	(0.01)	0.02**	(0.01)	0.03**	(0.01)	0.03**	(0.01)
Age	0.03*	(0.02)	-0.03**	(0.01)	0.04**	(0.01)	0.02**	(0.00)
R^2	0.46		0.14		0.10		0.05	
Observations	5065		5211		3099		1399	

Standard errors in parentheses

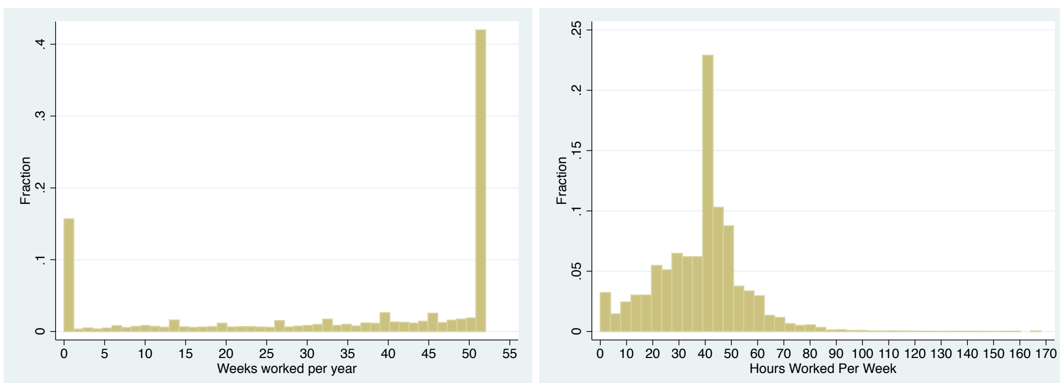
* $p < 0.10$, ** $p < 0.05$

Figure A1: Smoking



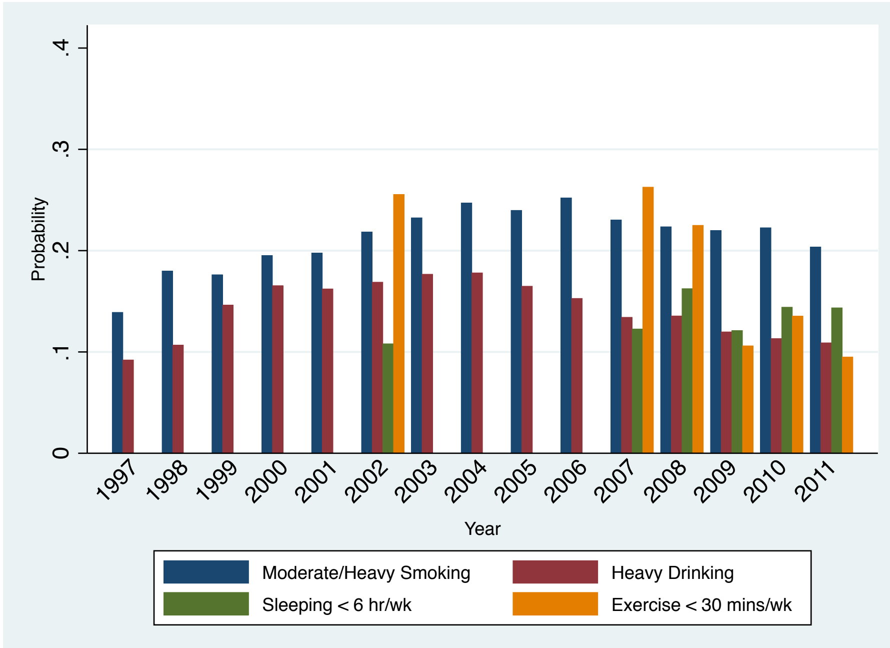
Source: NLSY97 white males.

Figure A2: Weeks and Hours Worked

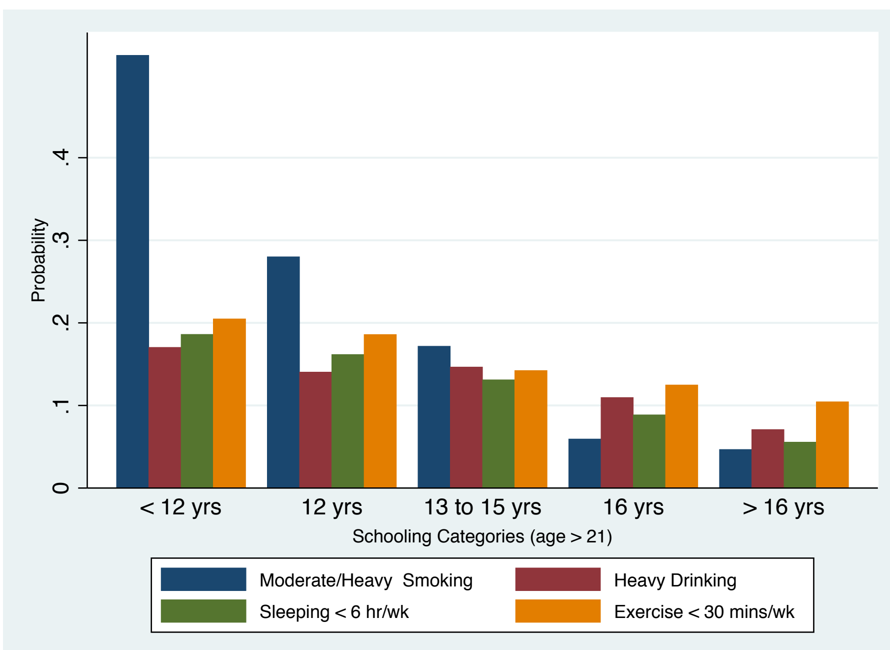


Source: NLSY97 white males.

Figure A3: Various Unhealthy Behaviors

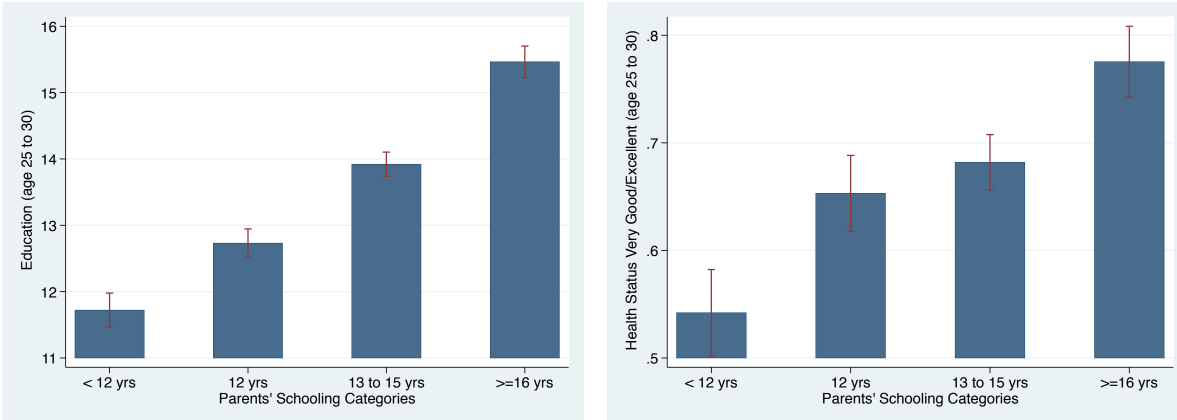


(a) Evolution over Age



(b) Education Gradient

Source: NLSY97 white males age 22 and above. We create a dummy variable for heavy drinking based on commonly used measures, including the Center for Disease Control and Prevention (CDC) which defines heavy drinking as more than 2 drinks per day for men, and 1 drink per day for women. We modified this to be an average of 3 drinks or more per day, or 90 drinks per month.



(c) Education (d) Health Status

Figure A4: Average Adult Outcomes by Parental Education Groups

Data source: NLSY97 white males aged 17 to 31.

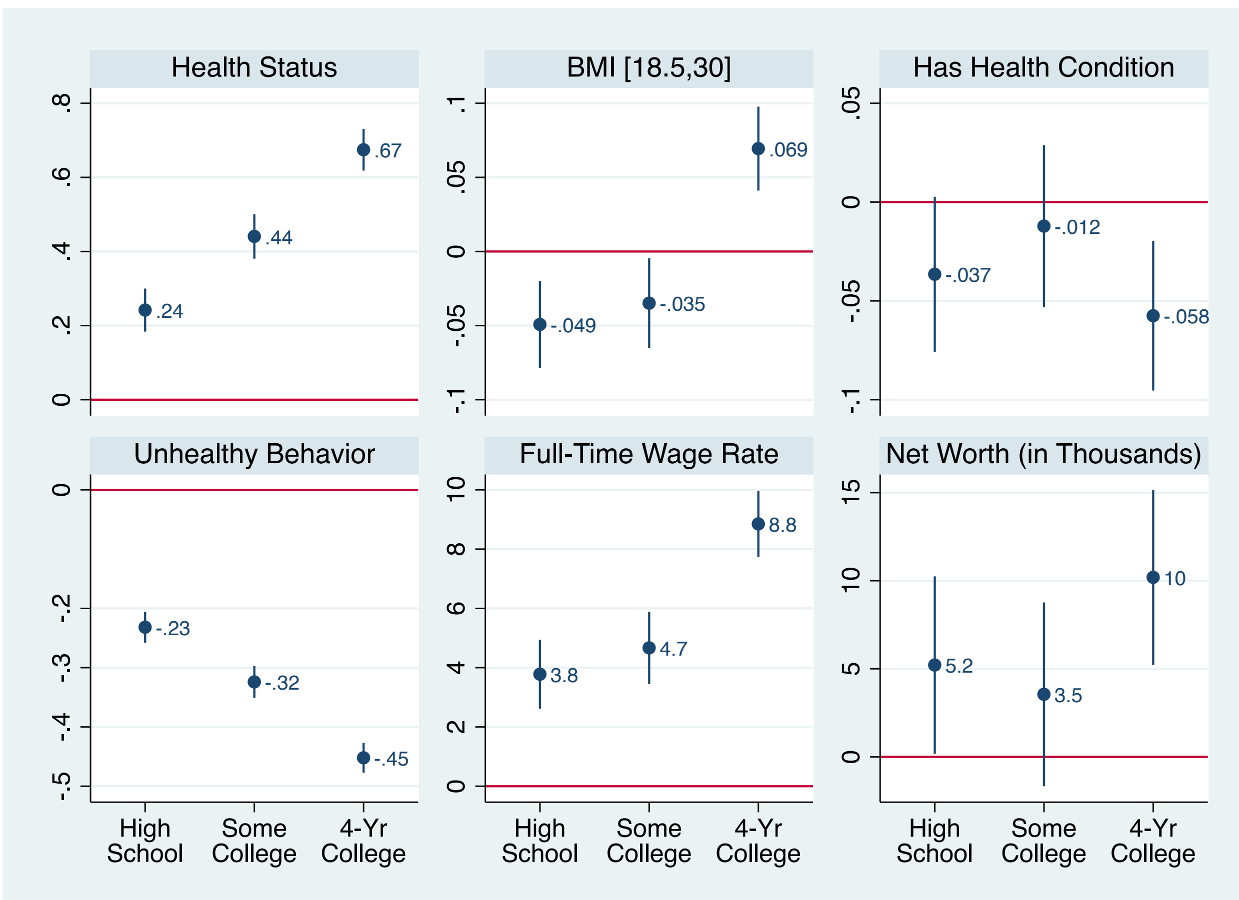


Figure A5: Educational Gradient in Health, Smoking, Wages, and Wealth (Age 25 to 30)

Appendix B Model Parameterization

We use a semi-separable utility function

$$U(c_t, d_{q,t}, d_{e,t}, d_{k,t}; \Omega_t) = \frac{1}{1-\gamma}\left(\frac{c_t}{\mathrm{es}_{t,e}}\right)^{1-\gamma} + u_q(q_t, h_t, e_t, \theta_c, \theta_n, \varepsilon_{q,t})d_{q,t} + u_e(\theta_c, \theta_n, h_t, d^e_{t-1}, e_p, \varepsilon_{e,t})d_{e,t}$$
$$+ u_k(\theta_c, \theta_n, h_t)) \cdot [\phi_{k,0}\mathbf{1}(d_{k,t} = 0.5) + \phi_{k,1}\mathbf{1}(d_{k,t} = 1)] + \phi_{k,e}d_{e,t}\mathbf{1}(d_{k,t} = 0.5) \tag{22}$$

where $\mathrm{es}_{t,e}$ is the equivalence scales of family size,[38] and

$$u_q(q_t, h_t, e_t, \theta_c, \theta_n, \varepsilon_{q,t}) = \alpha_{q,c}\theta_c + \alpha_{q,n}\theta_n + \phi_{q,q}q_t + \phi_{q,h}h_t + \phi_{q,e}(e_t - 12) + \phi_{q,0} + \sigma_q\varepsilon_{q,t} \tag{23}$$

$$u_e(\theta_c, \theta_n, h_t, d^e_{t-1}, e_p, \varepsilon_{e,t}) = \alpha_{e,c}\theta_c + \alpha_{e,n}\theta_n + \phi_{e,h}h_t + \phi_{e,p}(e_p - 12)\mathbf{1}(e_p > 12) - \phi_{e,e}(1 - d^e_{t-1}) + \sigma_e\varepsilon_{e,t} \tag{24}$$
$$+ \phi_{e,0}\mathbf{1}(d_{e,t} + e_t \le 12) + (\phi_{e,1} + \phi_{e,a}\mathbf{1}(t > 22)) \cdot \mathbf{1}(d_{e,t} + e_t > 12 \ \&\ d_{e,t} + e_t \le 16) + \phi_{e,2}\mathbf{1}(d_{e,t} + e_t > 16)$$

$$u_k(\theta_c, \theta_n, h_t) = 1 + (\alpha_{k,c}\theta_c + \alpha_{k,n}\theta_n + \phi_{k,h}h_t)/\phi_{k,0} \tag{25}$$

$$\phi_{k,e} = \phi_{k,e,1}\mathbf{1}(e_t < 12) + \phi_{k,e,2}\mathbf{1}(e_t \ge 12) \tag{26}$$

where $\phi_{e,0}$, $\phi_{e,1}$, and $\phi_{e,2}$ controls the level of psychic costs for attending high school, college, and graduate school respectively, $\phi_{e,e}$ is the psychic cost of re-entering school. $\phi_{k,e,1}$ and $\phi_{k,e,2}$ are preference parameters associated with part-time working while in high school and college respectively. The preference shocks $(\varepsilon_{q,t}, \varepsilon_{e,t})$ are pair-wise independent and are i.i.d. standard normal distributed.

We allow the subjective discount rate $\rho(\theta_c, \theta_n, h_t)$ to depend on individuals' cognitive and noncognitive skills and their health,

$$\rho(\theta_c, \theta_n, h_t) = \rho_0 - \rho_c\theta_c - \rho_n\theta_n - \rho_h h_t \tag{27}$$

Therefore the associated subjective discount factor is $\exp(-\rho_0 + \rho_c\theta_c + \rho_n\theta_n + \rho_h h_t))$.

The health production function is give by

$$\log h_{t+1} - \log h_t = \beta_{h,0} + \beta_{h,h}h_t + \alpha_{h,c}\theta_c + \alpha_{h,n}\theta_n \tag{28}$$
$$+ \beta_{h,e,1}\mathbf{1}(e_t = 12) + \beta_{h,e,2}\mathbf{1}(e_t > 12 \ \&\ e_t < 16) + \beta_{h,e,3}\mathbf{1}(e_t \ge 16)$$
$$+ \beta_{h,c}\log c_t + \beta_{h,1}d_{q,t} + \beta_{h,2}d_{e,t} + \beta_{h,3}d_{k,t} + \varepsilon_{h,t}$$

[38] Household equivalence scales measure the change in consumption expenditures needed to keep the welfare of a family constant when its size varies. We calculate the equivalence scales of different household sizes following Fernández-Villaverde and Krueger (2007). For example, this scale implies that a household of two needs 1.34 times the consumption expenditure of a single household. We do not model endogenous changes in family size; instead we allow family size to vary exogenously depending on education level e and age t. The average family size for each education group at every age is obtained from CPS data 1997 to 2012.

where $\varepsilon_{h,t} \sim N(0,\sigma_h^2)$. The productivity improvement of 4-year college education, compared to less than high school, is given by $\beta_{h,e,3}$.

An individual's human capital level ψ_t at age t is produced according to the following function:

$$\begin{aligned}\log \psi_t =& \alpha_{\psi,c}\theta_c + \alpha_{\psi,n}\theta_n + \beta_{\psi,h}h_t + \beta_{\psi,e,0}(e_t - 12) + \beta_{w,e,1}\mathbf{1}(e_t \geq 12) + \beta_{w,e,2}\mathbf{1}(e_t \geq 16) \\ &+ \beta_{\psi,k}k_t + \beta_{\psi,kk}k_t^2 + \beta_{\psi,0} + \beta_{\psi,1}\mathbf{1}(t < 18) \end{aligned} \tag{29}$$

This function allows agent's productivity in the labor market to depend on his health capital, education, experience, and his cognitive and noncognitive abilities.

Wage equations for full-time job ($m = 2$) and part-time job ($m = 1$) are given by:

$$\log w_{2,t} = \log \psi_t + \sigma_{w,2}\varepsilon_{w,t} \tag{30}$$

$$\log w_{1,t} = \log \psi_t + \beta_{w,0} + \beta_{w,1}d_{e,t} + \sigma_{w,1}\varepsilon_{w,1} \tag{31}$$

where $\varepsilon_{w,t} \sim N(0,1)$ is idiosyncratic transitory wage shock at age t.[39]

We estimate the following Tobit model as a function not only of parents' education and net worth terciles but also of individuals' decisions on schooling and employment:

$$\mathrm{tr}_{p,t} = \mathrm{tr}^*_{p,t} \cdot \mathbf{1}(\mathrm{tr}^*_{p,t} > 0) \tag{32}$$

where

$$\begin{aligned}\mathrm{tr}^*_{p,t} =& \mathbf{1}(s_p = T2) + \mathbf{1}(s_p = T3) + \beta_{\mathrm{tr},p,1}e_p + \beta_{\mathrm{tr},p,3}d_{e,t}\mathbf{1}(d_{e,t} + e_t \geq 13 \; \& \; d_{e,t} + e_t \leq 14) \\ &+ \beta_{\mathrm{tr},p,3}d_{e,t}\mathbf{1}(d_{e,t} + e_t \geq 15 \; \& \; d_{e,t} + e_t \leq 16) + \beta_{\mathrm{tr},p,3}d_{e,t}\mathbf{1}(d_{e,t} + e_t > 16) \\ &+ \beta_{\mathrm{tr},p,4}\mathbf{1}(d_{k,t} = 0.5) + \beta_{\mathrm{tr},p,5}\mathbf{1}(d_{k,t} = 1) \\ &+ \beta_{\mathrm{tr},p,6}t + \beta_{\mathrm{tr},p,6}td_{e,t}\mathbf{1}(d_{e,t} + e_t \geq 13 \; \& \; d_{e,t} + e_t \leq 16) + \beta_{\mathrm{tr},p,7}\mathbf{1}(t < 18) + \beta_{\mathrm{tr},p,8}\mathbf{1}(t > 23) \\ &+ \beta_{\mathrm{tr},p,1}\mathbf{1}(e_p \geq 16) + \beta_{\mathrm{tr},p,1}\mathbf{1}(e_p \geq 16 \; \& \; s_p = T3) + \beta_{\mathrm{tr},p,0} + \varepsilon_{p,t}.\end{aligned}$$

In our data, we do not observe parental transfers beyond age 30, however given we are focusing on parental transfer targeting the youth's college education, it is reasonable to assume that parental transfers are zero for a youth after age 30, i.e. $\mathrm{tr}_{p,t} = 0$ for $t \geq 30$.[40]

[39] Here, we assume the wage shock of full-time job and the wage shock of part-time job are perfectly correlated.

[40] This assumption is appropriate as we focus on the role of parental transfer on young adults' college attainment and the majority of individuals obtain their college degree before age 30. For the same reason, here we only focus on non-negative parental transfers. Negative parental transfers may be important for older adults and their parents for a

Parental consumption subsidy is given as follows:

$$\text{tr}_{c,t} = \chi \cdot d_{e,t} \cdot \mathbf{1}(e_t < 12)$$

where χ is the value of direct consumption subsidy provided by the parents such as shared housing and meals when the youth attends high school.

Government transfers, $\text{tr}_{g,t}$, are comprised of two components: an unemployment benefit component $\text{tr}^b_{g,t}$ that is offered for individuals who are currently unemployed ($\mathbf{1}(d_k = 0 \ \& \ d_e = 0)$), and a means-tested component $\text{tr}^c_{g,t}$ that supports a minimum consumption floor c_{min}. Specifically,

$$\text{tr}_{g,t} = \text{tr}^b_{g,t}\mathbf{1}(d_k = 0 \ \& \ d_e = 0) + \text{tr}^c_{g,t} \tag{33}$$

where

$$\text{tr}^c_{g,t} = \max\{0, c_{min} - ((1 + r(s_t))s_t + y_t + \text{tr}^b_{g,t}\mathbf{1}(d_k = 0 \ \& \ d_e = 0)) - \text{tr}_{p,t} - \text{tr}_{c,t}\}.$$

where $r(s_t) = r_l\mathbf{1}(s_t > 0) + r_b\mathbf{1}(s_t > 0)$. Government means-tested transfers bridge the gap between an individual's available financial resources and the consumption floor. Hubbard, Skinner, and Zeldes (1995), Keane and Wolpin (2001), and French and Jones (2011) show that allowing for the effects of means-tested benefits is important in understanding savings behavior of poor households. Treating c_{min} as a sustenance consumption level, we require $c_t \geq c_{min}$ and that government means-tested consumption transfer cannot be used to finance individuals' schooling ($d_{e,t} = 1$) or increase private savings ($s_{t+1} - s_t > 0$).

GSL borrowing limit l_g is characterized by a flow upper limit $\bar{l}^g$ and a total upper limit $\bar{L}^g$. Furthermore, under GSL, students can only borrow up to the total cost of college (including tuition, room, board, and other expenses directly related to schooling) less any other financial aid that they receive in the form of grant or scholarship. Specifically, we assume that:

$$l_g = \begin{cases} 0 & \text{if} \quad s_t \leq -\bar{L}^g \ \ \& \ \ \sum_{\tau=17}^{t-1}(\text{tc}_t + \text{rc}_t)d_{e,\tau} \geq \bar{L}^g \\ \min\{\bar{l}^g, \ (\text{tc}_t + \text{rc}_t)\} & \text{otherwise} \end{cases} \tag{34}$$

where $\text{tc}_t = \text{tc}(e_t + d_{e,t}, s_p)$ is the tuition and fees net grants and scholarships and $\text{rc}_t = \text{rc}(e_t + d_{e,t})$ is the cost of room and board. When imposing the total available credit under GSL in our model, we set $l_g = 0$ if both the current accumulated debt level and the accumulated total cost of college exceed the GSL upper limit $\bar{L}^g$.[41] If the GSL upper

different purpose, but it is outside the scope of this paper.

[41] Due to heavy computation burden, we do not separately keep track of GSL loans and private borrowing in our model.

borrowing limits $(\bar{L}^g, \bar{l}^g)$ never bind, a youth can borrow to finance the direct total cost of college expenses $(\text{tc}(e_t + d_{e,t}, s_p) + \text{rc}(e_t + d_{e,t}))$, but they cannot borrow to raise their consumption; however, if either $\bar{l}^g = 0$ or $\bar{L}^g = 0$, only private lender is available in the economy.

The private borrowing limit is given by:

$$F^s(t, \psi_t, k_t) = \exp\left(\beta_{s,0} + \beta_{s,1}\psi + \beta_{s,2}\psi^2 + \beta_{s,3}\mathbf{1}(t \geq 18) + \beta_{s,4}\left(\mathbf{1}(t \geq 23) + \mathbf{1}(t < 23)\frac{t-17}{23-17}\right)\right) \tag{35}$$

where ψ is the human capital level. We allow the borrowing constraint to change over ages until age 23, by when majority of youths have completed their college decisions; after age 23, the changes in borrowing constraint depends the agent's labor market human capital level.

The terminal value function at age $T+1$ is given by

$$V_{T+1}(\Omega_{T+1}) = \phi_{T+1,s}\frac{\left(s_{T+1} - \underline{S}_{T+1}\right)^{1-\gamma}}{1-\gamma} \tag{36}$$

where $\underline{S}_{T+1}$ is the the maximum private borrowing limit in the population at age T, i.e., $s_{T+1} \geq \underline{S}$ holds for all individuals when making decisions at age T. Notice the terminal value function does not depend on health, this is because we treat health as a human capital and it affects individuals' decisions on savings, schooling, and working through its impact on discount rate, labor market wages as well as direct preferences. At the final decision period $t = T$, the effect of health only comes from its effects on discount rate $\rho(\theta_c, \theta_n, h_{T+1})$ and thus affects how much the individual values $T+1$ wealth. Because our data only tracks individuals' choices from age 17 up to 31, we calibrate the parameter values of the terminal value function, which is discussed the calibration in detail in Section 4.1. We also experiment on using different values of the terminal function parameters and find that individuals' decisions made in their 20s are insensitive to the terminal value function parameters at age 50 in our model; this assures that our structural model parameter estimates are not sensitive to the calibrated values of terminal value function.

For health status measures, we use a ordered Probit model:

$$Z_{h,t,1} = \begin{cases} 1 & \text{if} \quad Z^*_{h,t,1} \leq 0 \\ 2 & \text{if} \quad 0 < Z^*_{h,t,1} \leq \mu_{z,1} \\ 3 & \text{if} \quad \mu_{z,1} < Z^*_{h,t,1} \leq \mu_{z,2} \\ 4 & \text{if} \quad \mu_{z,2} < Z^*_{h,t,1} \end{cases}$$

where $\mu_{z,2} > \mu_{z,1} > 0$.

Appendix C Parameter Estimates

Table C4: Parameter Estimates of Joint Initial Distribution of $(\theta_c, \theta_c, \log h_{17})$

	θ_c: Cognitive	θ_n: Noncognitive	$\log h_{17}$: Log Health
		Mean	
Parents Wealth 3rd Tercile	0.304	1.507	1.257
	(0.050)	(0.093)	(0.068)
Parents Wealth 2nd Tercile	0.000	1.027	0.430
	(0.050)	(0.085)	(0.065)
Parents 4-Yr College	0.354	1.378	0.180
	(0.069)	(0.141)	(0.090)
Parents Some College	0.314	0.782	0.172
	(0.043)	(0.077)	(0.062)
Parents High School	0.241	0.570	0.108
	(0.055)	(0.107)	(0.080)
Constant	-0.541	-1.545	-0.621
	(N.A.)	(N.A.)	(N.A.)
		Variance Matrix	
	1.000		
	(N.A.)		
	0.280	1.000	
	(0.050)	(N.A.)	
	0.143	0.369	1.000
	(0.039)	(0.059)	(N.A.)

Constant terms are normalized such that $\mathbb{E}(\theta_c) = \mathbb{E}(\theta_n) = \mathbb{E}(\log(h_{17})) = 0$.

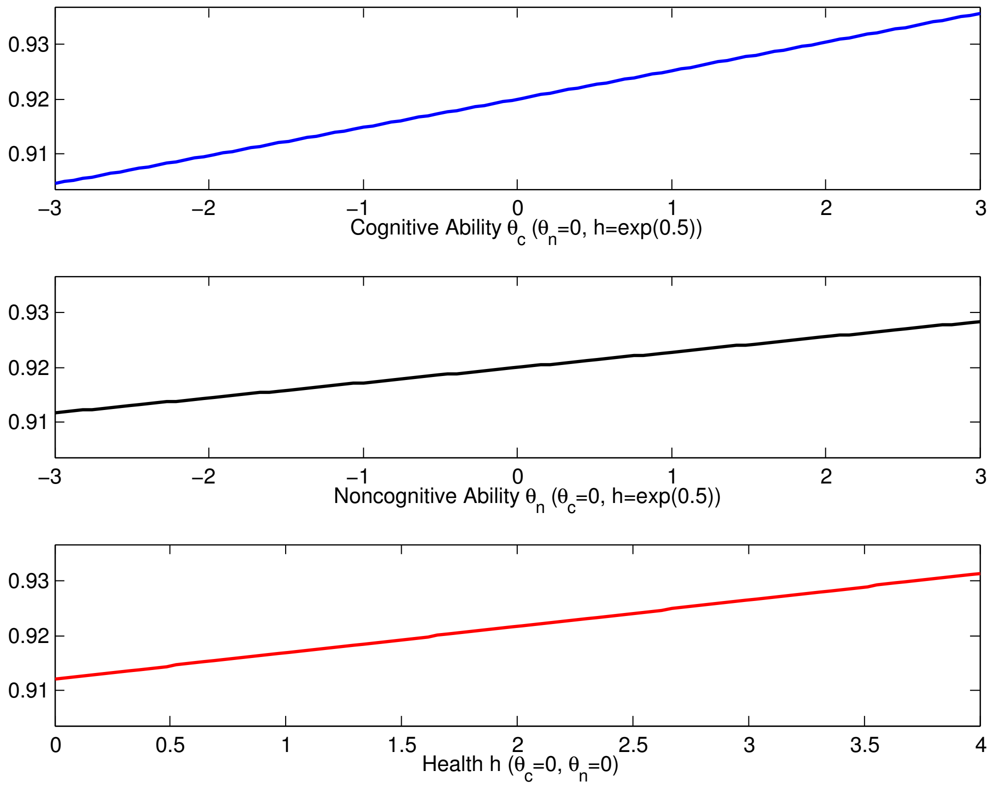
Table C5: Parameter Estimates of Measurement Equations

	ASVAB: Arithmetic Reasoning	ASVAB: Mathematics Knowledge	ASVAB: Paragraph Comprehen-sion	ASVAB: Word Knowledge	Noncognitive: Violent Behavior	Noncognitive: Had Sex bef. Age 15	Noncognitive: Theft Behavior	Health Status at Age 17	Had Health Condition Age $\leq$ 17	BMI [18.5, 30) at Age 17
θ_c	0.743	0.696	0.654	0.569						
	(0.013)	(0.015)	(0.017)	(0.015)						
θ_n					-0.661	-1.181	-0.369			
					(0.035)	(0.079)	(0.029)			
$\log h_{17}$								1.891	-0.729	0.674
								(0.078)	(0.098)	(0.112)
Age in 1997	0.151	0.255	0.152	0.192	0.103	0.104	0.097	0.001	-0.057	0.043
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.005)	(0.002)	(0.005)	(0.006)	(0.007)
Parents Wealth 3rd Tercile	(0.069)	0.134	0.084	0.017	0.567	1.012	0.448	-1.416	0.090	-0.343
	0.024	0.026	0.026	0.028	0.088	0.170	0.055	0.128	0.168	0.182
Parents Wealth 2nd Tercile	0.193	0.203	0.242	0.179	0.435	0.814	0.236	-0.478	-0.074	-0.108
	(0.027)	(0.025)	(0.028)	(0.029)	(0.081)	(0.134)	(0.057)	(0.128)	(0.164)	(0.169)
Parents Yrs of Schooling	0.106	0.110	0.108	0.115	0.030	-0.014	0.018	0.058	0.141	0.068
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.006)	(0.002)	(0.006)	(0.007)	(0.007)
$\mu_{z,1}$								2.457		
								(0.084)		
$\mu_{z,2}$								4.934		
								(0.078)		
Constant	-4.114	-5.600	-4.228	-4.932	-2.218	-2.094	-2.190	3.000	-2.767	0.593
	(0.015)	(0.015)	(0.015)	(0.016)	(0.047)	(0.080)	(0.030)	(0.074)	(0.095)	(0.099)
Measurement Error SD	0.426	0.448	0.492	0.518	0.978	1.452	0.463	1.632	2.149	2.131
	(0.012)	(0.011)	(0.011)	(0.010)	(0.059)	(0.096)	(0.026)	(0.099)	(0.097)	(0.092)

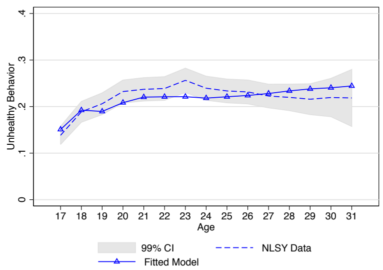
Table C6: Percent of Total Variance in Measurements

		Variance			Percent of Total Variance		
		Signal	Obs	Noise	Signal	Obs	Noise
Cognitive	ASVAB: Arithmetic Reasoning (1997)	0.556	0.097	0.181	66.649	11.660	21.690
	ASVAB: Mathematics Knowledge (1997)	0.488	0.183	0.201	55.980	20.939	23.082
	ASVAB: Paragraph Comprehension (1997)	0.432	0.104	0.242	55.513	13.401	31.085
	ASVAB: Word Knowledge (1997)	0.326	0.140	0.268	44.434	19.069	36.496
Noncognitive	Noncognitive: Violent Behavior (1997)	0.304	0.164	0.678	26.568	14.293	59.138
	Noncognitive: Had Sex bef. Age 15	0.714	0.382	1.082	32.792	17.519	49.689
	Noncognitive: Theft Behavior (1997)	0.093	0.071	0.144	30.120	23.142	46.738
Health	Health Status at Age 17	2.158	0.244	1.355	57.429	6.497	36.074
	Had Health Condition when Age $\leq$ 17	0.346	0.058	3.196	9.623	1.624	88.753
	BMI [18.5,30) at Age 17	0.605	0.083	6.286	8.681	1.188	90.131

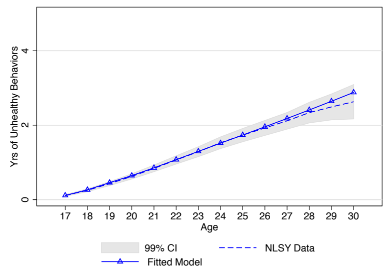
Figure C6: Estimated Discount Factor



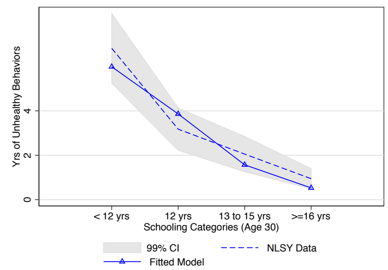
Appendix D Goodness of Model Fit



(a) Unhealthy Behavior

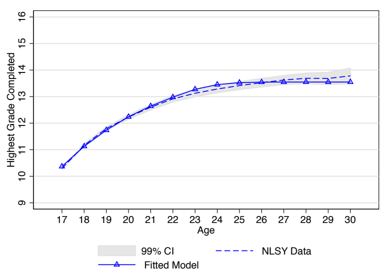


(b) Yrs of Unhealthy Behavior

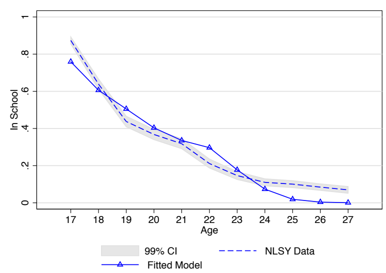


(c) Yrs of Unhealthy Behavior by Education (Age 30)

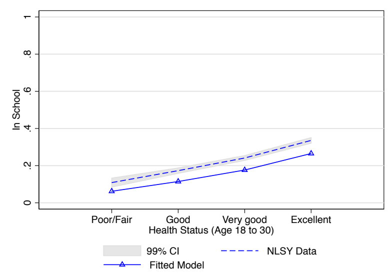
Figure D7: Model Fit on Unhealthy Behavior



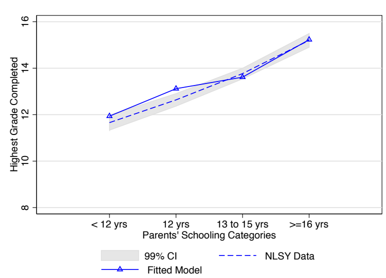
(a) Education



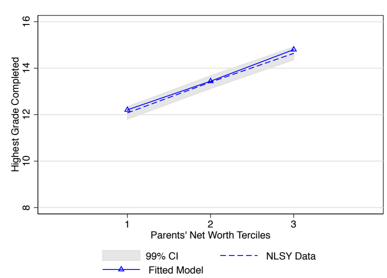
(b) In School



(c) In School

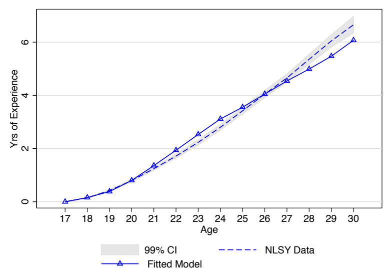


(d) Education By Parental Education

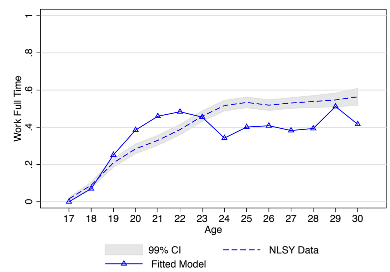


(e) Education By Parental Wealth

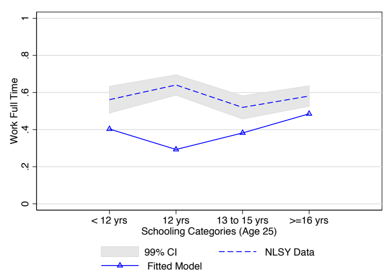
Figure D8: Model Fit on Schooling and Education



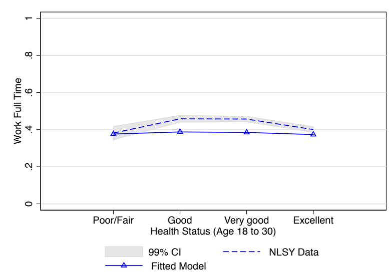
(a) Yrs of Working



(b) Working (Full-time)

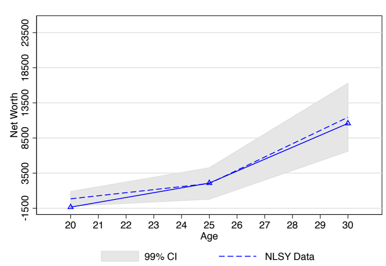


(c) Working (Full-time)

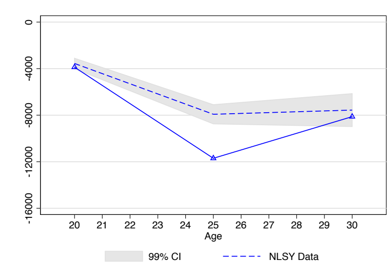


(d) Working (Full-time)

Figure D9: Model Fit on Working

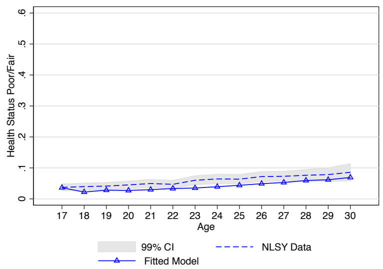


(a) Net Worth

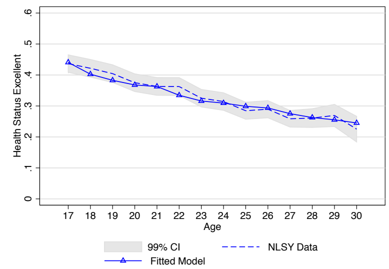


(b) Net Worth if Net Worth is Negative $s_t \mathbf{1}(s_t < 0)$

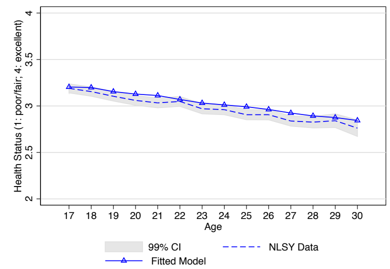
Figure D10: Model Fit on Net Worth



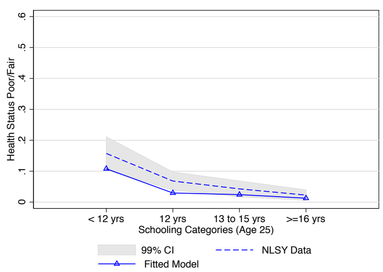
(a) Poor Health Status by Age



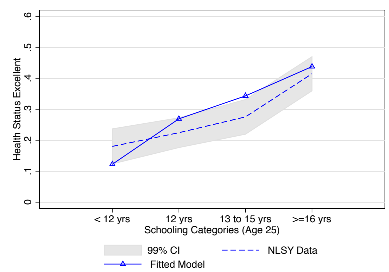
(b) Excellent Health Status by Age



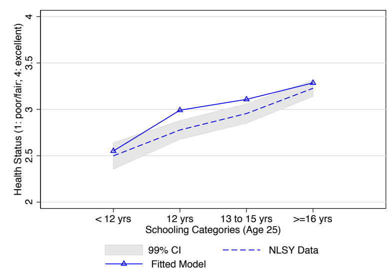
(c) Health Status (1: Poor/Fair, 4: Excellent) by Age



(d) Poor Health Status by Education

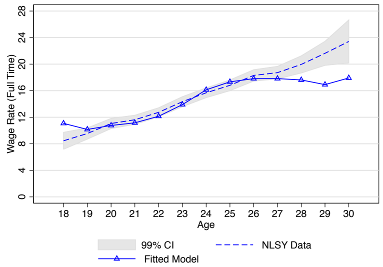


(e) Excellent Health Status by Education

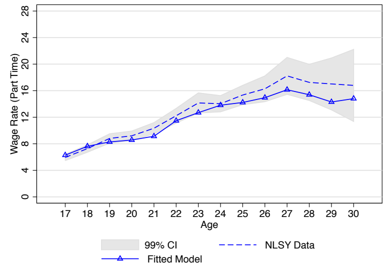


(f) Health Status (1: Poor/Fair, 4: Excellent) by Education

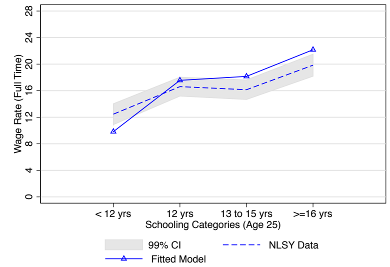
Figure D11: Model Fit on Measured Health Status



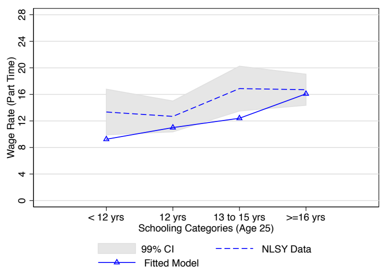
(a) Full Time Wages over Age



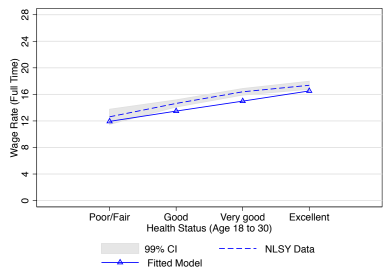
(b) Part-Times Wages over Age



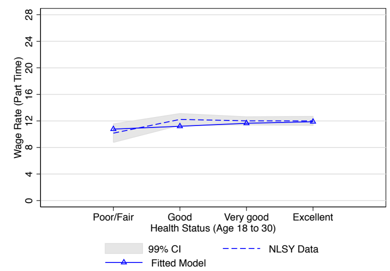
(c) Full Time Wages by Education (age 25 to 30)



(d) Part-Time Wages by Education (age 25 to 30)



(e) Full Time Wages by Health Status (age 18 to 30)



(f) Part-Time Wages by Health Status (age 18 to 30)

Figure D12: Model Fit on Hourly Wages

Table D7: Model Fit: Linear Regression on Unhealthy Behavior

	Data	Data S.E.	Model Simulation
Unhealthy behavior (t-1)	0.4799	0.0109	0.6987
Unhealthy behavior (t-2)	0.2724	0.0117	0.2000
Education	-0.0184	0.0023	−0.0061
ASVAB AR	-0.0024	0.0037	−0.0119
# Early Adverse Behaviors	0.0221	0.0047	0.0217

Note: ASVAB AR and number of early adverse behaviors are measures of cognitive and noncognitive abilities respectively.

Table D8: Model Fit: Linear Regression on Enrollment

	Data	Data S.E.	Model Simulation
Parents' Education	0.0368	0.0026	0.0133
ASVAB AR	0.0453	0.0043	0.0620
# Early Adverse Behaviors	-0.0503	0.0053	−0.0216
Health Status	0.0272	0.0045	0.0125

Note: ASVAB AR and number of early adverse behaviors are measures of cognitive and noncognitive abilities respectively. Regression also controls for previous period's enrollment status, and age.

Table D9: Model Fit: Linear Regression on Full-Time Employment

	Data	Data S.E.	Model Simulation
ASVAB AR	0.0135	0.0050	0.0459
# Early Adverse Behaviors	-0.0032	0.0058	−0.0098
Health Status	0.0169	0.0049	0.0172

Note: ASVAB AR and number of early adverse behaviors are measures of cognitive and noncognitive abilities respectively. Regression also controls for age and years of schooling.

Table D10: Model Fit: Net Worth Regression

	Data	Data S.E.	Model Simulation
ASVAB AR	1374.055	618.127	514.905
# Early Adverse Behaviors	-909.416	754.815	−158.760
Health Status	1759.910	629.766	−267.378

Note: ASVAB AR and number of early adverse behaviors are measures of cognitive and noncognitive abilities respectively. Estimates on other control variables (including age, experience, education, and a constant term) are not reported here.

Table D11: Model Fit: Next Period's Health Status Regression

	Data	Data S.E.	Model Simulation
Unhealthy Behavior	-0.1344	0.0168	-0.3277
Schooling	0.1037	0.0169	0.1063
Full-time Working	0.0096	0.0185	-0.0135
Log (Earnings)	0.0037	0.0018	0.0076
ASVAB AR	0.0404	0.0074	0.0166
# Early Adverse Behaviors	-0.0409	0.0090	-0.0381

Note: ASVAB AR and number of early adverse behaviors are measures of cognitive and noncognitive abilities respectively. Estimates on the constant term is not reported here. The regression also controls for health status and education category dummies.

Table D12: Model Fit: Log Hourly Wage Regression

	Data	Data S.E.	Model Simulation
Yrs Worked	0.1348	0.0129	0.1184
Yrs Worked Squared	-0.5544	0.1545	-0.1694
Yrs of Schooling	0.0393	0.0077	0.0451
Yrs of Schooling $\geq$ 12	0.0914	0.0309	0.0341
Yrs of Schooling $\geq$ 16	0.1433	0.0321	0.2060
ASVAB AR	0.0723	0.0088	0.0143
# Early Adverse Behaviors	0.0345	0.0103	0.0174
Health Status	0.0625	0.0087	0.0150
Part-time Working	-0.0937	0.0189	-0.2831
Part-time Working while in School	-0.1596	0.0260	-0.0177
Previously Not Working	-0.0518	0.0232	0.0024

Note: ASVAB AR and number of early adverse behaviors are measures of cognitive and noncognitive abilities respectively. Estimates on the constant term is not reported here.

Appendix E Results

E.1 Sorting into Adult Health

As seen in figure E13, initial health status measured at age 17 is highly persistent with health status measured at age 30. There is also strong evidence of selection in terms of noncognitive ability, while the selection based on cognitive ability is relatively small.

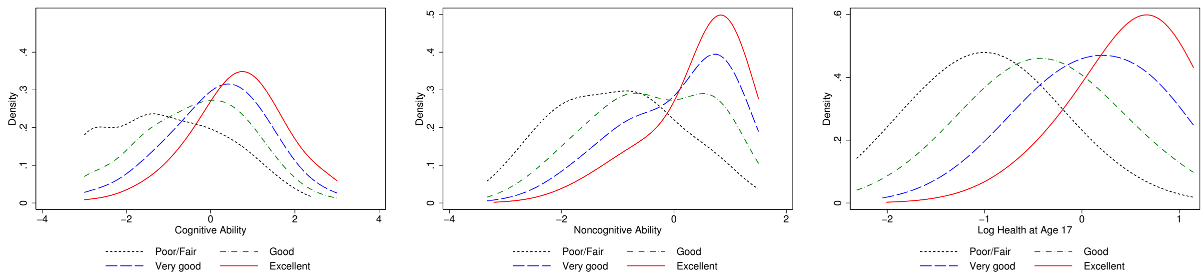
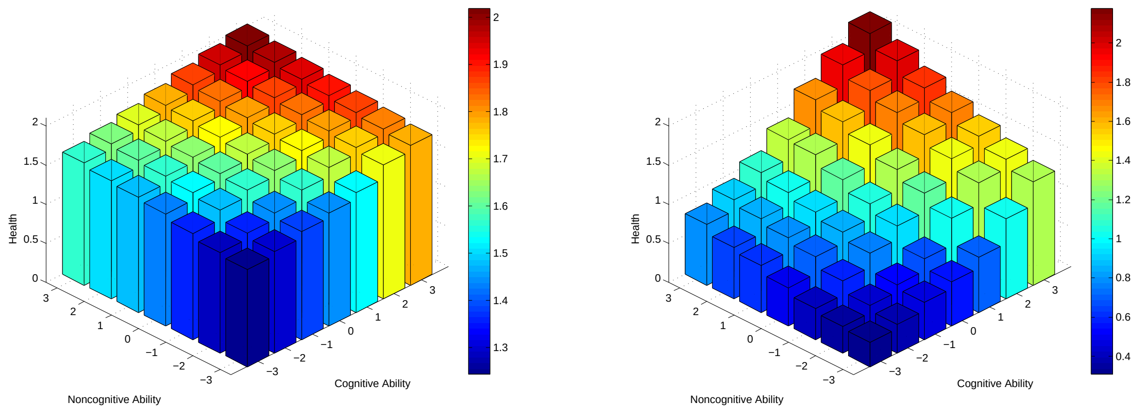


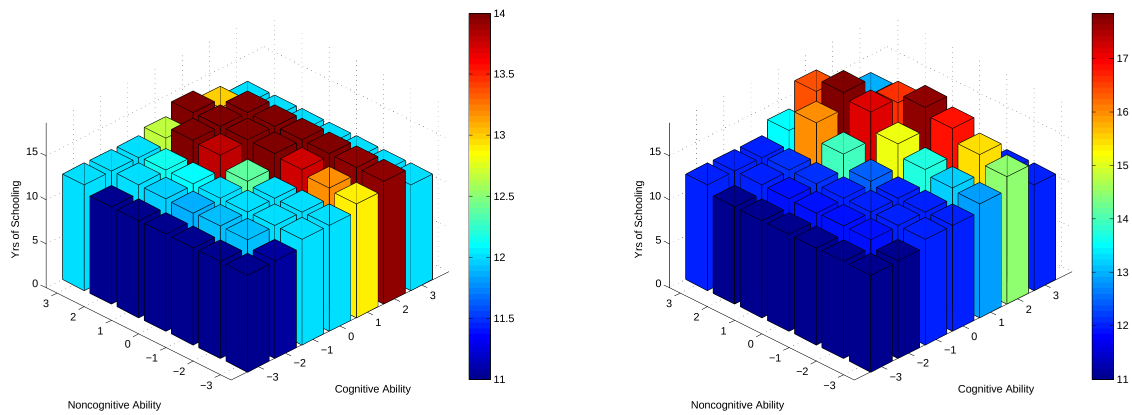
Figure E13: Density of Initial Factors Conditional on Age-30 Health Status

E.2 The Importance of Ability Cognitive and Noncognitive Ability



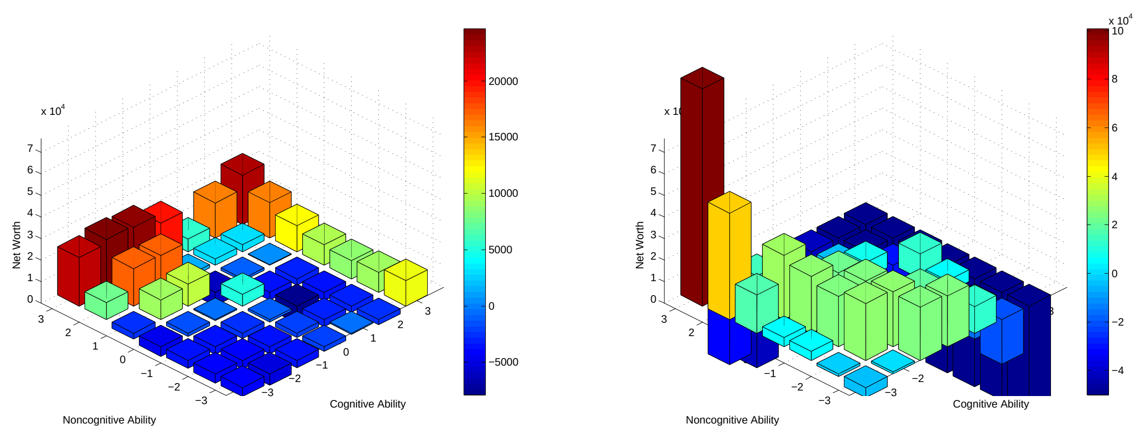
(a) Age 20 (b) Age 30

Figure E14: Health By Cognitive and Noncognitive Ability: h_t



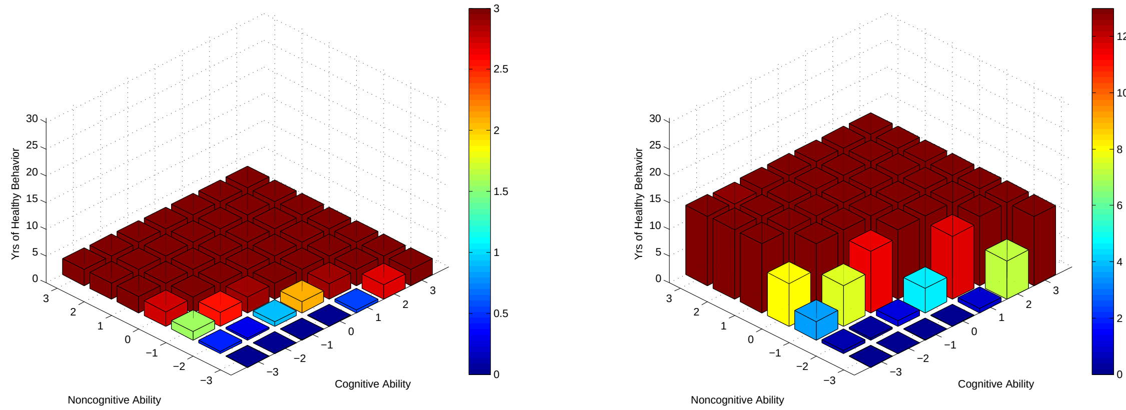
(a) Age 20 (b) Age 30

Figure E15: Education By Cognitive and Noncognitive Ability: e_t



(a) Age 20 (b) Age 30

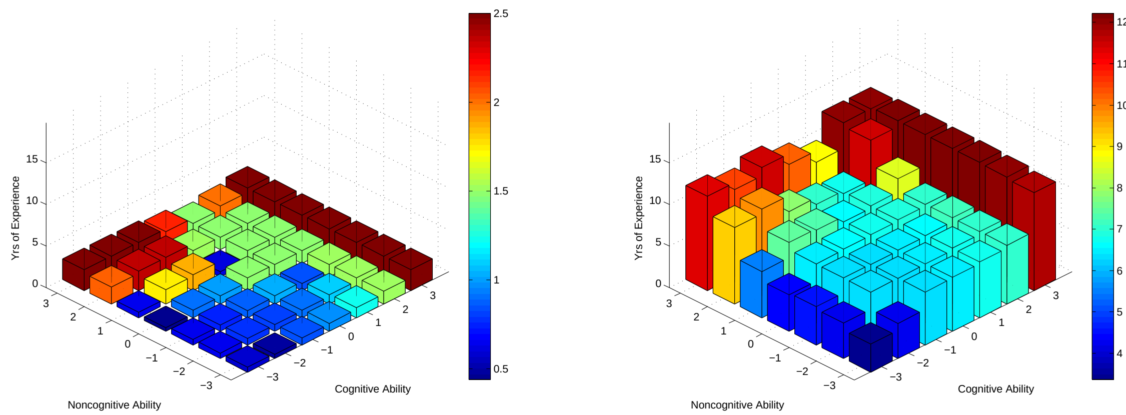
Figure E16: Wealth By Cognitive and Noncognitive Ability: s_t



(a) Age 20

(b) Age 30

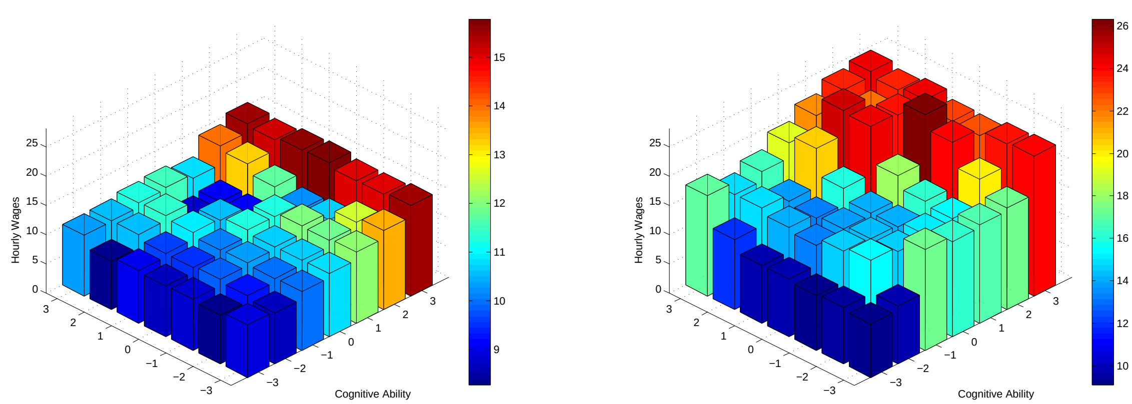
Figure E17: Years of Healthy Behavior By Cognitive and Noncognitive Ability: $t - q_t = \sum_t (1 - d_{q,t})$



(a) Age 20

(b) Age 30

Figure E18: Years of Working Experience By Cognitive and Noncognitive Ability: k_t

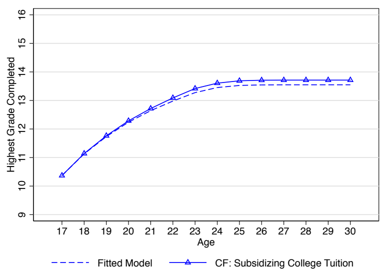


(a) Age 20

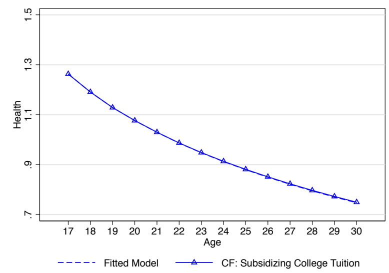
(b) Age 30

Figure E19: Accepted Hourly Wages By Individual Cognitive and Noncognitive Ability: w_t

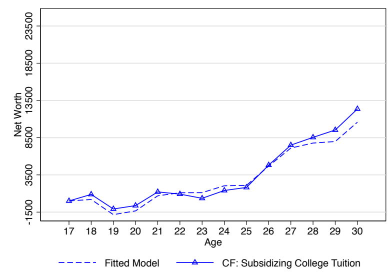
E.3 Counterfactual Simulation: Effects of College Tuition Subsidy



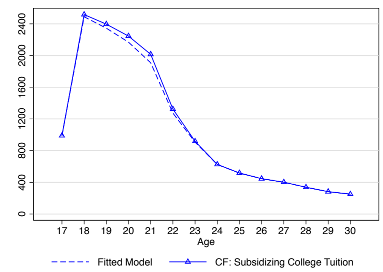
(a) Education



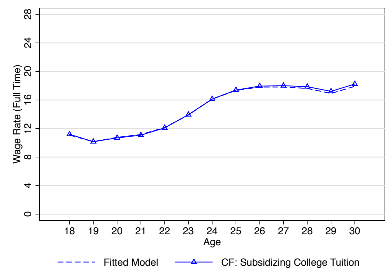
(b) Health (Latent Factor)



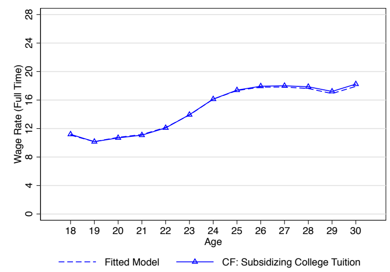
(c) Net Worth



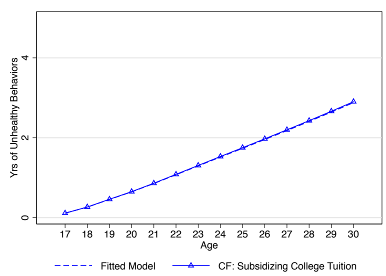
(d) Parental Transfers



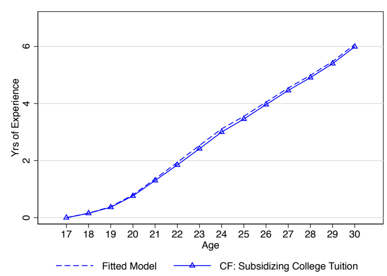
(e) Accepted Wage (Full-time)



(f) Accepted Wage (Part-time)

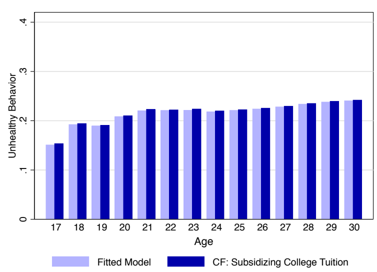


(g) Yrs of Unhealthy Behavior

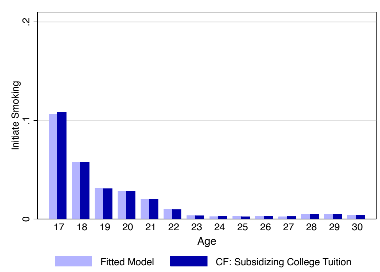


(h) Yrs of Working

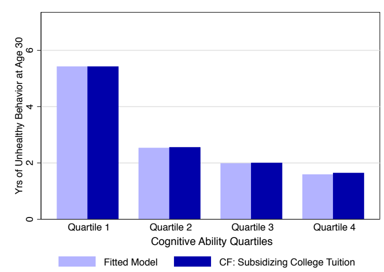
Figure E20: Counterfactual Simulation of Subsidizing College Tuition



(a) Unhealthy Behavior Probability



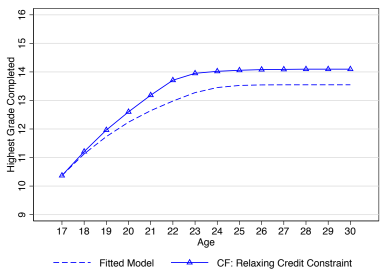
(b) Initiating Unhealthy Behavior



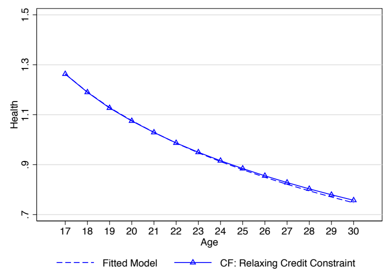
(c) Yrs of Unhealthy Behavior (Age 30)

Figure E21: Effects of Subsidizing College Tuition on Unhealthy Behavior

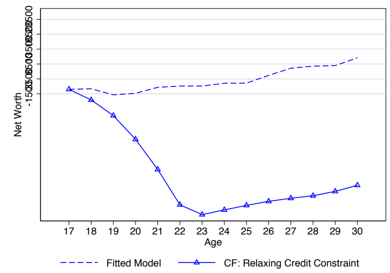
E.4 Counterfactual Simulation: Removing Credit Constraint



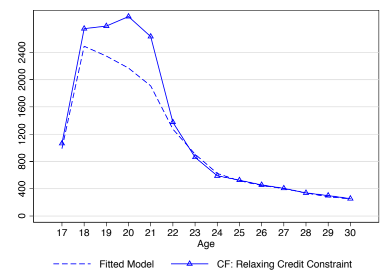
(a) Education



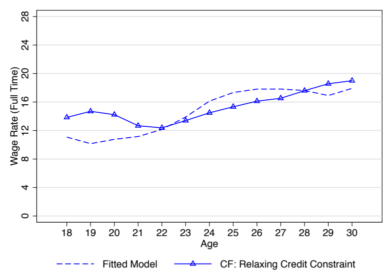
(b) Health (Latent Factor)



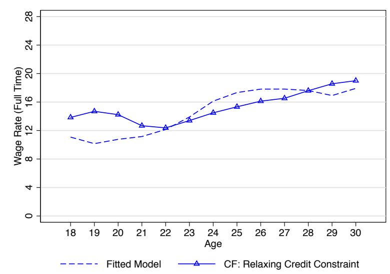
(c) Net Worth



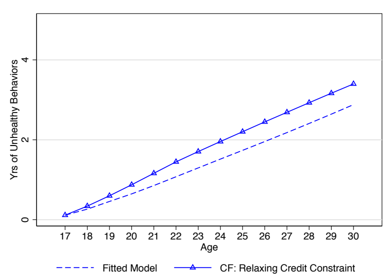
(d) Parental Transfers



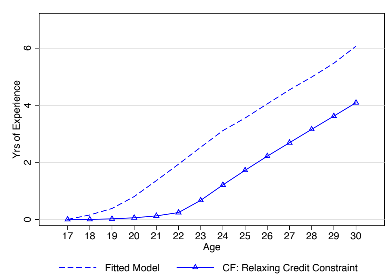
(e) Accepted Wage (Full-time)



(f) Accepted Wage (Part-time)



(g) Yrs of Unhealthy Behavior



(h) Yrs of Working

Figure E22: Counterfactual Simulation of Relaxing Credit Constraint