Childhood Health and Lifecycle Human Capital Formation*

Hiroaki Mori†

December, 2016

Abstract

A growing body of literature emphasizes the role of childhood health in shaping labor market outcomes. Little is yet known whether poor health during childhood influences later outcomes by restricting skill formation, or by mainly affecting future health. To address this issue, this paper formulates and estimates a model of the joint dynamics of skills and health over the lifecycle. The estimated model is used to quantify the relative importance of the channels through which childhood health conditions affect labor market outcomes. In the model, individuals are endowed with a multi-dimensional human capital bundle that consists of skills and health. The human capital bundle evolves over time according to a production technology, with influences from endogenous decisions regarding schooling, labor supply, and occupations. The results indicate that the most important channel accounting for mental health-related earnings gaps is the skill channel. About 60-65% of the earnings gaps can be explained by the effects of childhood mental health conditions on skill formation. The effects of childhood health status on health formation are also found to play important roles.

Keywords: *childhood health, earnings inequality, dynamic factor analysis, skill-health complementarities, task-based approach*
JEL Classification: I14, I24, J24, J31

*I am deeply grateful to my advisors Chris Robinson and Todd Stinebrickner, and especially Audra Bowlus for their invaluable encouragement, guidance and support. An earlier version of this paper has been presented at the UM-MSU-UWO Annual Labor Day Conference at the University of Michigan and the 2015 Canadian Economic Association Annual Meeting. I thank the participants, especially Charles Brown, Todd Elder, Logan McLeod, and Jeffrey Smith, for helpful comments and discussions. All errors are mine.

†Department of Economics, Hitotsubashi University, Naka 2-1, Kunitachi, Tokyo, Japan. Email: h.mori@r.hit-u.ac.jp.

1 Introduction

Inequality in lifetime earnings depends critically on the dynamic process of human capital formation. A substantial share of lifetime earnings can be explained by skills developed before labor market entry (Keane and Wolpin, 1997). However, a growing body of literature also emphasizes the importance of childhood health status as a determinant of adult earnings.[1] The economic model of human capital formation suggests two main channels through which childhood health conditions may affect labor market outcomes.[2] First, childhood health may have a direct influence on adult health, which in turn may affect labor market outcomes. Second, past adverse health conditions may slow down skill formation due to the complementaries between skills and health in producing future skills. To the extent that the second channel operates, skill promoting policies may work as well as health interventions to alleviate the negative effects of childhood health conditions. Empirically, however, little is known about the magnitude of the two channels.[3]

Prior research has established the long-term effects of childhood health on various outcomes other than earnings such as adult health status, labor supply, and schooling outcomes.[4] As long as schooling and labor market experience increase skills, these results suggest that both channels contribute to the link between the childhood health conditions and adult earnings. Nonetheless, these results do not reveal the relative

[1]For example, Lundborg et al. (2014) show that major health conditions at age 18 have long-run effects on labor income using Danish administrative data. They find the strongest effects with mental health conditions. Smith and Smith (2010) estimate that childhood mental health conditions permanently lower individual labor earnings on average by $4,094 per year using retrospective childhood health data from the Panel Study of Income Dynamics. Fletcher (2014) reports using the Add Health data that childhood attention deficit/hyperactivity disorder (ADHD) reduces earnings at around age 30 by approximately 33%.

[2]Heckman (2007) provides a model of child development in which skills and health interact in producing future skills and health.

[3]A recent survey of the literature conclude that "while it is clear that shocks to health have long-term effects on domains such as education and earnings, it is not clear whether health shocks have direct effect on cognition or learning, or whether they act mainly by affecting future health (Almond and Currie, 2011a, p. 1468)."

[4]Empirical results on the lifecycle consequences of childhood health conditions are surveyed by Currie (2009), Case and Paxson (2010), and Almond and Currie (2011a,b).

importance of the two channels for two reasons. First, schooling and labor market choices are likely to affect not only skills but also health.[5] Separating these effects is necessary in order to quantify the sizes of each channel. Second, individuals may make schooling and labor market decisions based not only on their skills and health but also on other unobserved factors such as preferences. Childhood health conditions may affect both what individuals can do and what they want to do. To the extent that childhood health conditions affect preferences for schooling and work, the earnings gap associated with childhood health conditions may reflect taste-based compensating differentials. Ignoring the endogeneity of schooling and labor market decisions, therefore, may lead to biased estimates of the magnitude of the skill channel and the health channel.

In addition, accumulating evidence suggests that childhood mental disorders tend to have a substantially larger negative effect on schooling outcomes and adult earnings than physical disorders (Currie et al., 2010; Lundborg et al., 2014). Less is, however, known why specific childhood health conditions are more detrimental than others on those outcomes. This is potentially because health conditions are heterogeneous regarding how they limit individuals' ability to perform specific tasks. For example, mental health conditions may limit performing cognitive tasks such as reading documents and solving complex problems, while physical health conditions may limit performing manual tasks such as lifting heavy objects and using hands/fingers for production. The magnitude of the negative effects of specific childhood health conditions may differ depending on how the health conditions affect task-specific performance and how those tasks are related to the outcomes.

To examine the nature of specific childhood health conditions, this paper takes advantage of insights from the relatively new literature on multi-dimensional skills.

[5] Conti et al. (2010) among others estimate the causal effects of education on health outcomes. The effects of labor supply on health outcomes are studied for example by Sickles and Yazbeck (1998) and Gilleskie (1998). Fletcher et al. (2011) show that work experience in physically demanding occupations have negative effects on subjective health status among older male workers.

In particular, I apply a task-based approach to estimate how childhood health conditions affect the characteristics of tasks performed by the individuals. Past experience in specific tasks likely produces skills related to the tasks. The task-based approach is, therefore, useful for analyzing how childhood health conditions affect task-specific skills. For that purpose, I augment career histories obtained from National Child Development Study (NCDS) with task information provided by the UK Skills Survey. The NCDS follows all individuals born in the second week in March 1958 in Great Britain throughout their life courses. Most importantly, the NCDS contains the results of medical examinations conducted at ages 7 and 16, which are used to diagnose major health conditions during childhood. Thus, I do not need to rely on subjective reports of childhood health status. In Section 2, I show clear evidence that workers sort into different kinds of occupations depending on their childhood health conditions. In particular, individuals with childhood mental health conditions tend to select occupations that command less intensive cognitive tasks. In contrast, individuals with physical health conditions are less likely to choose occupations that require intensive manual tasks. Overall, the evidence from the task-based approach supports the view that different childhood health conditions affect occupational choice and, therefore, likely the accumulation of skills needed to perform tasks in those occupations. However, occupations are determined by individuals' choice like schooling and labor supply. Therefore as long as the choices are driven by unobserved factors other than skills, disregarding those factors may result in biased estimates of skills.[6]

To address all of these issues, Section 3 develops a lifecycle model of human capital formation, which features both the health channel and the skill channel through which childhood health conditions may operate to generate the long-term effects. The model builds on Yamaguchi (2012) which provides a framework within which one can

[6]Direct health measures are provided by medical examinations or by self-reports. Childhood skills can be measured through cognitive or psychological assessments. In contrast, such direct measures are not often available to measure adult skills so that researchers are forced to resort to inferring adult skills based on endogenous schooling choices and labor market choices.

estimate latent skills from observed task histories. I extend his framework to include health conditions as well as schooling choices and labor supply decisions. In my model, individuals are endowed with a bundle of human capital that consists of cognitive skill, manual skill, mental health, and physical health. The human capital bundle evolves according to a technology that captures two key aspects of the joint dynamics between skills and health: i) cross-productivity between skills and health in shaping future skills and ii) the influences of schooling and labor market choices on future skills and health. By modeling own-productivity and cross-productivity of the human capital bundle, it is possible to quantify how past health conditions affect both future skills and future health. To isolate the skill channel from the health channel, this paper estimates how schooling and labor market choices affect skills and health stocks separately. The model also allows childhood health conditions to affect preferences for schooling and working, which allows for inferring skills from endogenous schooling and labor market choices without relying on the assumption that those choices are driven only by skills. The likelihood function for the model is constructed by combining the Kalman filter algorithm and simulations. The model parameters are then estimated by maximizing the likelihood using the longitudinal cohort data from the NCDS.

The estimation results, including the model fit, are presented in Section 4. The model can account for the salient features of the data including the gaps in employment, occupation choices, and earnings across individuals with different types of childhood health conditions. The results display large and significant monetary returns to cognitive skills. Returns to manual skills, physical health and mental health are substantially smaller. I find that skills grow faster when individuals work longer and perform cognitive and manual tasks more intensively. These results are consistent with skill formation via "learning-by-doing". The parameter estimates suggest that individuals with childhood health conditions bring lower levels of skills into the labor market. The estimates also suggest that they experience slower skill growth and faster health depreciations. These results imply that both the skill channel and the health channel are operative in generating the observed health-related gaps in earnings. In addition, I find that performing intensive manual tasks leads to faster deterioration of physical health. This implies that working in an occupation that commands high levels of manual tasks is costly for maintaining physical health. Further, the estimates suggest that both physical and mental health tend to improve with the allocation of time for non-labor activities.

Section 5 quantifies the relative importance of the channels through which childhood health conditions affect earnings. To disentangle the alternative channels, the estimated model is simulated under the restrictions that individuals with different childhood health conditions are homogeneous in terms of (1) preferences, (2) skill formation, and (3) health formation. Outcomes from the counterfactual experiments reveal that the effect of childhood health on skill formation plays the greatest role in accounting for the observed earnings gaps between individuals with childhood mental health conditions and their healthy counterparts. The skill channel is also the main factor behind the observed earnings losses at younger ages among individuals with childhood physical health conditions. The role of the skill channel diminishes over time for childhood physical health conditions. The differences in tastes and health formation also play significant roles for both types of health conditions, especially at older ages. They account for about a quarter to one third of the earnings gaps at age 42. These results indicate the importance of accounting for complementarities between health and skills in shaping future skills and earnings. Section 6 provides some concluding remarks.

2 The Long Reach of Childhood Health

This section provides descriptive evidence regarding the link between childhood health and lifecycle skills among individuals who participated in the National Child Development Study (NCDS). The first subsection explains the data sources and sample selection criteria. The second subsection presents descriptive statistics and analyses using the NCDS.

2.1 Data Sources

The NCDS follows a cohort of individuals born in Great Britain between March 3rd and March 9th in 1958 until they die or permanently emigrate out of Great Britain.[7] The NCDS provides career histories up to age 50 with detailed occupation codes. Monthly earnings for first jobs and those for main jobs at ages 23, 33, 42, 46 and 50 are available. The NCDS conducted medical examinations when the cohort members were at ages 7 and 16. The NCDS is the data source for the influential analysis of Case et al. (2005) on the long-lasting effects of childhood health conditions on labor market outcomes. They used observations up to age 33. I extend their analysis by incorporating observations up to age 50. I focus on male individuals who took the medical examinations both at ages 7 and 16. To construct career histories, I eliminate individuals who did not respond to the survey at ages 23 and 33. These criteria yield a sample of 3,665 males.

I augment the occupation histories in the NCDS dataset with task measures that characterize how workers use their skills at various tasks conducted in their jobs. The task measures are obtained from the UK Skills Survey, which is a series of surveys that aim to investigate skills used by the employed workforce in Great Britain.[8] Using the 1997-2012 UK Skills Survey, I derive task measures using employee ratings of job-specific task characteristics. At each wave, respondents are asked how much a particular task is important for his/her job on a 5-point scale ranging from 1 ("not at all/does not apply") to 5 ("essential"). Following Yamaguchi (2012), I group tasks into two broad categories: the first group consists of cognitive skills/tasks and the

[7] More details of the NCDS can be found online (Last accessed: 05/22/15).

[8] See, e.g., Felstead et al. (2007) for details of the UK Skills Survey.

second comprises manual skills/tasks.[9] Examples of cognitive tasks include problem solving, analysing complex problems in depth, and doing calculations using advanced mathematical or statistical procedures. Examples of manual tasks include working for long periods on physical activities or carrying, pushing, and pulling heavy objects. For each type of task, a principal component analysis is performed to construct the coordinate-system to assign each four-digit occupation in the 2000 UK Standard Occupation Classification into the two dimensional task space (cognitive and manual task). Following Autor et al. (2003), the task indices are converted into percentile scores. Statistics from the joint distribution of the constructed task measures are given in Table 1. The cognitive skill requirements and the manual skill requirements of the jobs are highly negatively correlated.

Table 1: Distribution of Task Measures

	Mean	Std. Dev.
Cognitive	0.592	0.184
Manual	0.538	0.244
Corr.		-0.477

Note: The sample consists of all working individuals in the 1997-2012 Skills Surveys. The sample size is 17,424. The task measures are calculated as percentile scores divided by 100.

Health conditions are often grouped into two broad types: "mental" conditions and "physical" conditions.[10] To facilitate the analysis, I follow this convention and use the 10th revision of the International Statistical Classification of Diseases (ICD-10) to categorize health conditions into the two types. Through the medical examinations conducted for the NCDS, medical experts diagnose major childhood health conditions. Mental health conditions include emotional and behavioural disorders (EBD) and speech disorders. Physical health conditions cover a wider range of conditions, in-

[9] The subsets of task characteristics taken from the UK Skills Survey are presented in Appendix A.

[10] See, for example, Conti and Heckman (2013).

cluding vision defects, hearing defects, limb defects, nervous system disorders such as migraine and epilepsy, respiratory system problems such as asthma, heart conditions, and other physical abnormalities. A list of the subsets of health conditions taken from the NCDS is provided in Appendix B. Using the diagnoses, a particular health condition at ages 7 and 16 can be defined to be either "handicapping", "non-handicapping", or "non-existent". Following Goodman, Joyce and Smith (2011), I aggregate health conditions diagnosed at ages 7 and 16, and do not count non-handicapping physical health conditions.[11] Table 2 reports the fraction of individuals diagnosed with mental and physical conditions by age 16. About 24% of the sample has been diagnosed with either a mental or a physical condition. Physical health conditions appear to be relatively less prevalent than mental conditions partly because I do not count non-handicapping physical health conditions. It is noteworthy that the overlap between the two types of the health conditions is fairly small as only about 2% of the sample was diagnosed with both types of the health conditions. Accordingly, in what follows, I assume that individuals have physical conditions only when they have physical conditions but not mental conditions.

Table 2: Fraction of individuals ever diagnosed with mental and physical health conditions by age 16

	Physical	No physical	Total
Mental	0.022	0.124	0.147
No mental	0.091	0.762	
Total	0.114		

Note: The data source is the NCDS. The sample consists of 3,665 men. Appendix B provides a list of mental and physical health conditions.

[11] The non-handicapping physical conditions are highly common as about 41% of the male sample was diagnosed to have such conditions before age 16. Not surprisingly, those non-handicapping physical conditions during childhood do not have statistically significant correlations with labor earnings. In contrast, non-handicapping mental health conditions are correlated significantly and negatively with labor earnings. See Appendix B.

2.2 Descriptive Analysis

Earnings Table 3 demonstrates how the two types of health conditions are related to lifecycle earnings by regressing log-transformed annual labor earnings at each age on dummy variables that indicate the presence of each type of childhood health conditions. The estimation results suggest that both types of childhood health conditions have long-run negative effects on earnings. The negative effects appear to be greater with the physical conditions than the mental conditions in the early years after labor market entry. Interestingly, this pattern is reversed in later years. The health-related earnings gaps grow over the lifecycle with the mental conditions while they lessen with the physical conditions.

Table 3: Gaps in log annual earnings by childhood health conditions

	Age 23	Age 33	Age 42	Age 50
Mental	-0.089	-0.124	-0.133	-0.131
	(0.017)	(0.023)	(0.033)	(0.039)
Physical	-0.121	-0.064	-0.049	-0.043
	(0.026)	(0.031)	(0.042)	(0.048)

Note: Standard errors are in parentheses. The data source is the NCDS. The sample consists of 3,665 men.

Labor Supply Labor supply histories are often used as measures of worker skills. Figure 1 shows fraction of individuals working fulltime at each age.[12] Labor supply tends to fall as individuals get older. Throughout the lifecyle, individuals with childhood health conditions tend to work less than their healthy counterparts. During 20's, the fulltime employment rates are about 2%-4% points lower among those with childhood health conditions. These patterns becomes more evident in later years, especially for those with childhood mental conditions. The fulltime employment rates among indi-

[12] I define individuals work fulltime during a year if they work 40 hours per week for more than 43 weeks. In the data, I observe if an individual work either parttime or fulltime in a month. I regard fulltime work within a month as working 40 hours per week for each week in the month. Therefore, in the data, individuals work fulltime within a year if they work fulltime at least for 10 months. I count parttime work during a month as working 20 hours per week for each week in the month.

viduals with childhood health conditions are about 4%-8% points lower at age 50 than that of their healthy counter parts. The results suggest that individuals with childhood health conditions tend to experience slower accumulation of labor market experience. Nevertheless, most individuals (at least more than 80%) work fulltime regardless of their childhood health conditions.

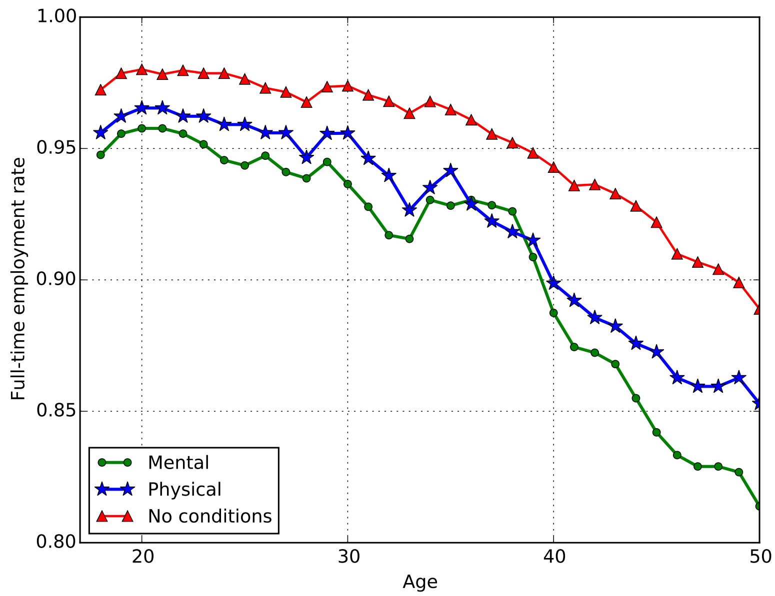


Figure 1: Fulltime employment rates at each age among individuals with different childhood health conditions. Source: the NCDS.

Task Selections Task measures characterize the portfolio of skills used to conduct the tasks in the workplace. Figure 2 plots the levels of cognitive tasks and manual tasks used in jobs at each age. The cognitive task profiles exhibit an increasing concave shape, which is similar to the shape of the lifecycle human capital profile found in Ben-Porath (1967).[13] The cognitive task profiles show a relatively fast increase initially, followed by a slowing down to a flat spot and possible decline thereafter. It is noteworthy that individuals with childhood mental health conditions select into occupations that command less intensive cognitive tasks throughout the lifecycle compared

[13] Bowlus and Robinson (2012) identify and estimate human capital prices and profiles from earnings data and find that empirical lifecycle human capital profiles exhibit the Ben-Porath concave shape.

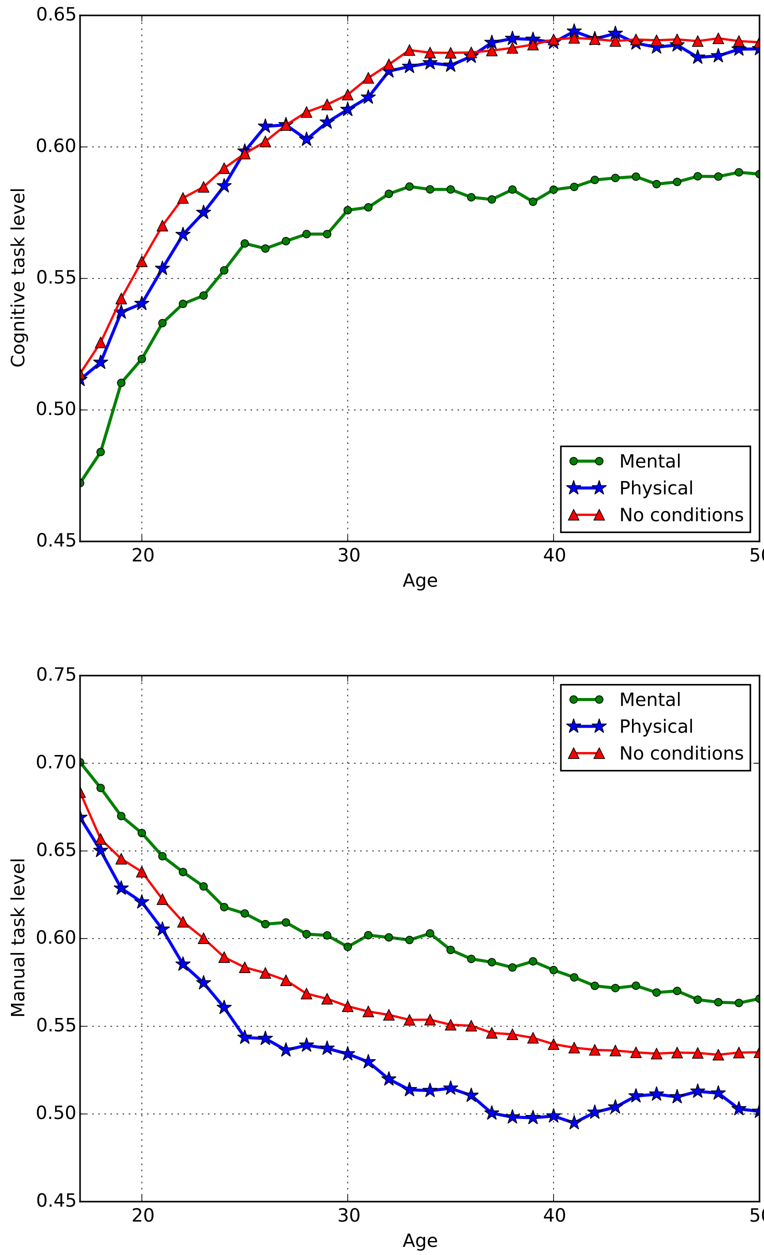


Figure 2: Cognitive and manual task levels at each age among individuals with different childhood health conditions. Source: the NCDS augmented with the UK Skills Survey.

to their healthy counterparts. The average cognitive task level of the occupations at age 35 for those with childhood mental health conditions only reach the average level of the occupations at age 22 for those without such conditions. While the individuals with childhood physical health conditions also tend to select less cognitive skill demanding occupations, the magnitude of the deviations from their healthy counterparts is relatively small.

Unlike the cognitive task profiles, the manual task profiles exhibit decreasing patterns. Individuals tend to move away from manual skill demanding occupations over the lifecycle. Individuals with childhood physical health conditions tend to have notably less manual skill demanding occupations compared to their healthy counterparts. In contrast, those with childhood mental conditions tend to have more manual skill demanding occupations.

Overall the task-based skill portfolio measures are able to capture differential labor market sorting patterns across individuals with heterogeneous childhood health conditions. Specific childhood health conditions appear to trigger sorting into particular skill directions. This implies that different types of health conditions may affect different components of skills. In particular, mental health conditions during childhood appear to have greater negative effects on cognitive skills than physical health conditions.

Educational Outcomes In parallel to the results from the task-based skill portfolio measures, childhood mental conditions appear to have greater negative effects on schooling decisions. As shown in Table 4 individuals with childhood mental conditions are notably less likely to proceed to higher education than their healthy counterparts. Such a pattern cannot be found among individuals with childhood physical conditions.

Table 4: Schooling probabilities by childhood health conditions

	Mental	Physical	No conditions
Compulsory	0.672	0.543	0.488
High-school	0.253	0.293	0.352
University	0.075	0.164	0.160

Note: The data source is the NCDS. The sample consists of 3,665 men.

Table 5 shows the associations between childhood health conditions and math test scores obtained at age 16. Both types of health conditions are negatively correlated with the test scores. Mental health conditions appear to have a stronger negative association with the test scores than physical health conditions. This implies that childhood health conditions may affect endowment of cognitive skills before labour market entry.

Table 5: Gaps in math test scores by childhood health conditions

	Mental	Physical
Math test scores at age 16	-0.491	-0.157
	(0.046)	(0.057)

Note: The math test scores are normalized to have a unit standard deviation. Standard errors are in parentheses. The data source is the NCDS. The sample consists of 3,665 men.

3 Model and Estimation Strategy

Health conditions during childhood may influence skill endowments, preferences, the technology of human capital formation, or all three. To juxtapose the alternative channels through which childhood health affects labor market outcomes, this section builds a lifecycle model of joint dynamics of skills and health.

3.1 Model Setup

Each individual has a finite decision horizon ending in an exogenous retirement age T. I start tracking individuals from age 16 with a one-shot schooling choice. Upon leaving school, individuals make annual choices over time allocation and job tasks.

Human Capital Bundle An individual at age t is endowed with a latent bundle of human capital (θ_t), which consists of skills (θ_t^S) and health (θ_t^H). Following Yamaguchi (2012), the skills are assumed to be task-specific: they are either cognitive $\left(\theta_t^{S_1}\right)$ or manual $\left(\theta_t^{S_2}\right)$. I consider two types of health capital; mental $\left(\theta_t^{H_1}\right)$ and physical $\left(\theta_t^{H_2}\right)$. The human capital bundle at age t is thus defined as a 4-dimensional vector: $\theta_t \equiv \left(\theta_t^S, \theta_t^H\right)'$ where $\theta_t^S \equiv \left(\theta_t^{S_1}, \theta_t^{S_2}\right)'$ and $\theta_t^H \equiv \left(\theta_t^{H_1}, \theta_t^{H_2}\right)'$. The human capital evolves according to a technology of human capital formation, as I discuss in a following section.

Post-schooling Choices During the post-schooling periods, the human capital bundle is affected by the choices regarding time allocation and job tasks. Individuals are endowed with a fixed amount of time at each age t and they split the time endowment between two types of activities: "labor" and "resting". Time allocated for labor may promote skills and is denoted by l_t.[14] The remaining time is used for a non-labor activity, called resting, which may promote health.[15] The labor activities are characterized by two kinds of tasks (τ_t) to be performed by the workers; cognitive (τ_t^1) and manual (τ_t^2). The labor market choices in a post-schooling period are thus defined as a vector (x_t) with three components:

$$x_t \equiv [l_t, \tau_t]'$$

where $\tau_t \equiv (\tau_t^1, \tau_t^2)'$.

Health conditions during post-schooling periods are measured with self-reports. Individuals are allowed to report their health status at the beginning of each post-schooling age t. The health reports are defined as a M-dimensional vector of reporting choices r_t.

Post-schooling Utilities During the post-schooling periods, instantaneous utilities from the labor market choices are derived from the earnings (e_t) and the tastes for work

[14] As in the framework of Heckman and MaCurdy (1980), individuals are allowed to desire negative working time in my model.

[15] My framework is closely related to the model of Sickles and Yazbeck (1998) in which leisure time is an input of health production. In the framework of Gilleskie (1998), individuals are allowed to allocate their time in a day for three activities: work, leisure, and medical care access. Like her model, I allow leisure activities to affect health. I do not explicitly model medical care access decisions as my dataset does not allow me to separate the amount of time spent for purely leisure activities and that used to access medical care services in each year.

(g_t). To model health reporting behaviour, I assume that individuals derive utilities (v_t) from their health reporting in addition to earnings and tastes for work. In sum, the instantaneous utilities during a post-schooling period are the sum of the three components described above:

$$u_t = \ln e_t + g_t + v_t \tag{1}$$

Individuals consume their earnings from labor and resting activities. I assume that non-labor income does not vary with the human capital bundle nor with the amount of resting time. labor is the only production factor in this economy and the labor activities offer heterogeneous monetary returns to the human capital bundles depending on the nature of the tasks performed by the worker, similarly to the task selection model of Heckman and Sedlacek (1985, 1990).

Total earnings are represented as a product of the output prices $p(\tau_t)$, the marginal output of the human capital bundle $q(x_t, \theta_t)$ and an unobserved idiosyncratic shock to earnings η_t:

$$e_t \equiv p(\tau_t) q(x_t, \theta_t) \exp(\eta_t) \tag{2}$$

The human capital price is parameterized as

$$p(\tau_t) = \exp(p_0 + p_1' \tau_t) \tag{3}$$

where the scaler component p_0 includes non-labor income and the inner product $p_1' \tau_t$ represents the price of labor output. The marginal output of the human capital bundle is defined as

$$q(x_t, \theta_t) = \exp(q_0 l_t) \exp\left[(q_1 + Q_2' \tau_t)' \theta_t\right] \tag{4}$$

where q_0 is a scaler, q_1 is a 4-dimensional vector, and Q_2 is a 2×4-dimensional matrix. The skills are productive only in a relevant task. The health capital components are coupled with the task-specific skills in determining labor output. In particular, I assume that the productivity at cognitive tasks may vary depending on the cognitive skill and the mental health, while the manual skill and the physical health affect worker productivity to perform manual tasks. On the other hand, the productivity of the human capital bundle does not depend on the amount of labor time. Besides the returns to the human capital bundles, the labor market choices are affected also by individual tastes for work. Tastes at age t depend on the observed individual characteristics ζ_1, the human capital θ_t, the past labor market choices x_{t-1} and choice-specific taste shocks ν_t as in the following quadratic function:

$$g_t \equiv (g_0' x_t + x_t' G_1 x_t) + (G_2 \zeta_1 + G_3 \theta_t)' x_t + (x_t - x_{t-1})' G_4 (x_t - x_{t-1}) + \nu_t' x_t \tag{5}$$

Here, g_0 is a 3-dimensional vector; G_1 is a 3×3 diagonal matrix; G_2 and G_3 are 3×4 matrices; and G_4 is a 3×3 diagonal matrix of taste parameters. The 4-dimensional vector ζ_1 includes observed characteristics at labor market entry, which I will specify with a human capital production technology. The first term imposes convexity of psychic costs from labor market choices. The second term specifies the influences of individual heterogeneity. The third term captures psychic costs from switching labor market choices over two periods. The final term reflects the influences of the choice-specific taste shocks.

I assume that the costs from health reports are instantaneous and only psychic. Further, the reporting costs do not affect any of the labor market choices. The utilities from health reports are defined as

$$v_t = \left(h_0 + H_1 \theta_t^H + H_2 x_{t-1} + \omega_t\right)' r_t + r_t' H_3 r_t \tag{6}$$

where h_0 is a M-dimensional vector; H_1 and H_3 are $2 \times M$ matrices; H_2 is a $M \times 3$ matrix; and ω_t is a M-dimensional vector of idiosyncratic preference shocks for health reporting behaviour, which I interpret also as measurement errors for subjective health reports. Notice that the utilities from health reports do not depend on worker skills (θ^S). Previous research demonstrate that subjective health reports are "state dependent". For example, Lindeboom and Kerkhofs (2009) find that non-working individuals tend to understate their health status. This may be because individuals have incentives to report health problems to justify their inactivity (Bound, 1991). In this light, I allow the utilities from reporting general health status to depend on past labour time allocation (l_{t-1}), which is a part of the state vector at age t. However, I assume that self-reports on specific health conditions do not depend on past labour time allocation (l_{t-1}).

Schooling Choices and Utilities Balancing expected returns and realized costs, individuals make a one-shot schooling choice at age 16 between three alternatives: secondary (the compulsory education), high school (A-level or similar) and university. The schooling options are defined as a vector of two indicator functions for each of the schooling levels above the compulsory education:

$$s \equiv (s_1, s_2)'$$

I assume that entrance to the labor force occurs at age 17 for secondary school graduates, age 19 for high school graduates, and age 22 for university graduates. During the schooling period, individuals consume the constant non-labor income. Besides the opportunity costs due to foregone earnings opportunities, the schooling choice is affected by the instantaneous psychic utility from schooling. Without loss of generality, I normalize the instantaneous utilities from the compulsory schooling level to be 1. The utilities from the other two schooling options are defined as:

$$u_0 = (k_0 + K_1\zeta_0 + \nu_0)'s \tag{7}$$

where K_0 is a 2-dimensional vector and K_1 is a 2×4 matrix of preference parameters; and ν_0 is a vector of choice-specific taste shocks. I specify the vector of initial observed characteristics (ζ_0) below.

Human Capital Formation Following Cunha and Heckman (2008) and Yamaguchi (2012), I assume that the human capital bundle evolves according to linear production technologies. The human capital bundle at labor market entry is affected by the observed characteristics (ζ_0), the schooling choice (s), and a vector of production shocks ϵ_1 that prevail after the schooling choice:

$$\theta_{t_s} = a_0 + A_1\zeta_0 + A_2 s + \epsilon_1 \tag{8}$$

where a_0 is a 4-dimensional vector; A_1 is a 4×4 matrix; A_2 is a 4×2 matrix; and ϵ_1 is a vector of idiosyncratic shocks on human capital production during the schooling period. The initial observed characteristics (ζ_0) include family income at age 16, arithmetic test scores obtained at age 7, as well as mental and physical health conditions that are recorded in the medical examinations.

During the post-schooling periods, the human capital bundle evolves according to the following technology:

$$\theta_{t+1} = b_0 + B_1\zeta_1 + B_2 x_t + B_3\theta_t + \epsilon_{t+1} \tag{9}$$

where b_0 is a 4-dimensional vector; B_1 and B_3 are 4×4 matrices; B_2 is a 4×3 matrix; and ϵ_{t+1} is a vector of idiosyncratic shocks on human capital production. The initial observed characteristics (ζ_1) include mental and physical health conditions that are recorded in the medical examinations and two indicator variables for schooling choices. Schooling choices, therefore, may affect not only human capital levels at labor market entry but also the speed of human capita formation in the labor market. The tasks performed in the labor market τ_t may affect future skills through "leaning-by-doing". Due to the task-specific nature of skills and health, cognitive tasks may affect only cognitive skills and mental health, while manual tasks may affect only manual tasks and physical health. Labor time (l_t) may affect all the components of the human capital bundle.

In my model, I allow skills and health to be cross-productive in shaping future skills. In particular, cognitive skills and mental health interact in producing future cognitive skills. Further, manual skills and physical health interact in producing future manual skills. However, I assume that skills do not directly affect health productions.

It is widely documented that health outcomes are highly correlated with socio-economic variables, such as education, income and wealth. Smith (2007) argues that those correlations are primarily driven by the effects of education on health outcomes and that financial resources do not have significant influences on health outcomes. My specification of the production technology is motivated by his findings. In particular, I allow education to affect both health endowments and the health formation technology. While I allow family income at age 16 to affect health endowments at labor market entry, I assume that earnings do not directly affect health formation. In my model, however, earnings and health can be correlated as a result of individuals' schooling and labor market choices.

3.2 Model Solution and Estimation

The model described above yields the following Bellman equation for a post-schooling age $t \in \{t_s, \cdots, T\}$:

$$V_t(\sigma_t, \eta_t) = \max_{x_t, r_t} \{u_t(x_t, r_t, \sigma_t, \eta_t) + \beta E V_{t+1}(\sigma_{t+1}, \eta_{t+1})\}$$

where $\sigma_t = (\theta_t', \zeta_1', x_{t-1}', \nu_t', \omega_t')'$ denotes the vector of state variables. The state transitions are constrained by the human capital formation technology. Since the dynamic programming problem has a quadratic objective function and linear constraints, the optimal post-schooling polities (x_t^*, r_t^*) are linear in the state vector.[16] This implies that the post-schooling dynamic programming problem permits a linear state space

[16] Hansen and Sargent (2013) prove this statement for a generic class of linear-quadratic dynamic programming models.

representation. The optimal choice of schooling is given by

$$s^* = \arg\max_s \{u_0(s, \sigma_0) + \beta EV_{t_s}(\sigma_{t_s}, \eta_{t_s})\} \tag{10}$$

where t_s denotes the age of entry into the labor force and $\sigma_0 = (\zeta_0', \nu_0')'$ is the initial state vector.

As discussed above, optimal post-schooling policies have a closed-form expression. In particular, optimal labor time policy (l_t^*) can be expressed as:

$$l_t^* = \Phi_t^l \sigma_t \tag{11}$$

where Φ_t^l is a matrix of composite model parameters that affect labor time decisions. This provides a threshold crossing rule to link the model solutions and the data on labor force participation, as in the framework of Heckman and MaCurdy (1980). In particular, I assume the following mapping rule:

$$\text{LFP}_t = \begin{cases} 1 & \text{if } l_t^* \geq 1 \\ 0 & \text{if } l_t^* < 1 \end{cases} \tag{12}$$

where LFP_t denotes an indicator variable for labor force participation. In the NCDS data, I observe how many months individuals worked full-time or part-time each year. Similarly to Keane and Wolpin (1997), an individual is considered to have participated in the labor force during the year if the individual was employed full-time or part-time in at least two-thirds of months in the year.

Similar to the post-schooling policies, optimal health reporting policies (r_t^*), which are specified as a M-dimensional vector, have the following linear relationship with the state vector (σ_t):

$$r_t^* = \Phi_t^r \sigma_t \tag{13}$$

where Φ_t^r is a matrix of composite model parameters that affect health reports. At ages $t \in \{23, 33, 46, 50\}$, I observe binary health reports (R_t) for mental and physical health conditions. The health indicators and latent health reports are linked by the following mapping rule: for each $m = 1, \cdots, M$,

$$R_t^m = \begin{cases} 1 & \text{if } r_{m,t}^* \leq c_m \\ 0 & \text{if } r_{m,t}^* > c_m \end{cases} \tag{14}$$

where c_m is a threshold parameter.

For each post-schooling period the econometrician observes error-driven measurements of labor income, time allocations, tasks and health status. The measurements in the schooling periods consist of a set of observed characteristics and schooling choices. I denote the vector of measurements obtained in the post-schooling age $t \in \{t_s, \cdots, T\}$ by y_t and measurements obtained in the schooling period by y_1. The data provide measurements up to age $T_d \leq T$.[17]

To estimate the model parameters, it is convenient to work with the following likelihood function:

$$\begin{aligned} f(y_1, y_{t_s}, \cdots, y_{T_d}) &= f(y_1) f(y_{t_s}, \cdots, y_{T_d} | y_1) \\ &= f(y_1) \prod_{t=t_s}^{T_d} f(y_t | y_{1:t-1}) \end{aligned} \tag{15}$$

where $y_{1:t-1} \equiv (y_1, y_{t_s}, \cdots, y_{t-1})$ is the history of measurements up to period $t-1$. The conditional distribution $f(y_t|y_{1:t-1})$ of measurements is derived from the conditional distribution of latent human capital bundles $f(\theta_t|y_{1:t-1})$. Provided that all the distributions of the idiosyncratic errors and the measurement errors are Gaussian, the conditional distribution of latent human capital bundle $f(\theta_t|y_{1:t-1})$ also follows a Gaussian distribution so that it is characterized solely by its mean $E(\theta_t|y_{1:t-1})$ and variance $\text{Var}(\theta_t|y_{1:t-1})$. The Kalman filter algorithm calculates these moments given the linear state representation of the model and the mapping rules to link discrete measurements and the latent factors of the model. I assume that labor earnings and tasks are ob-

[17] I set the exogenous retirement age as 60. The terminal values are set to be zero. The NCDS provides data up to age 50. Measurements after age 50 are assumed to be missing at random.

servable only when individuals work fulltime. When an other type of measurement is missing in the data, it is integrated out when constructing the likelihood. I compute the initial likelihood $f(y_1)$ by simulating the schooling choice probabilities with the model.[18] Notice that the rest of the likelihood $f(y_{t_s}, \cdots, y_{T_d}|y_1)$ can be computed without simulations, which substantially lessens computational costs. The model parameters are estimated by maximizing the constructed likelihood. Standard errors are obtained from an inverted Hessian matrix.

3.3 Identification

Both skills and health are latent in the model. They do not have natural units. High earnings can always be rationalized either by high returns to the human capital bundle or by high levels of the human capital components. Normalizing the units of the human capital bundle is, therefore, necessary to identify the model parameters from the data. Following Yamaguchi (2012), this paper normalizes the skill distributions at labour market entry to have zero means and unit variances. Similarly, I normalize the health distributions at labour market entry to have zero means and unit variances. Due to the discrete nature of measures for labour time and health, I need to further restrict the distributions of idiosyncratic taste shocks for labor time allocation and the distributions of health production shocks. I assume that those distributions follow a standard Gaussian distribution. That is, I impose probit specifications both for latent labor time allocation and health reports.

In the model, current tasks (τ_t) directly affect only the growth of task-specific skills (θ^S_{t+1}) and health (θ^H_{t+1}). The effects of current tasks on health production can be identified by observing how future health indicators (R_{t+1}) depends on the current tasks. Similarly, the effects of current tasks on skill production can be identified by

[18] Schooling choices are simulated 5,000 times for each individual in the sample. I do not need to simulate post-schooling choices for each simulation as the value functions at labour market entry V_{t_s} are known once I fix the model parameters up to idiosyncratic shocks drawn at labour market entry.

observing how future earnings (e_{t+1}) vary with current tasks conditional on the health reports. The own-productivity of health can be identified by the correlation between current or past health indicators and the future health indicators. If current or past health indicators affect future earnings conditional on future health indicators, this must be because health affected production of skills. Once the own-productivity and the cross-productivity of health are identified, the own-productivity of skills can be pinned down by observing how past tasks (τ_{t-1}) affect future earnings (conditional on future health indicators). In sum, the own-productivity and the cross-productivity of health as well as the own-productivity of skills can be identified by observing correlations between health indicators, earnings, and human capital shifters. By contrasting those correlations across individuals based on labor time (l_t), the model identifies the effects of the labor time on skill formation and health formation. The human capital production parameters during the schooling period can be identified by observing how schooling choices affect the levels and evolutions of earnings and health indicators.

Further, the variance of skill shocks ϵ_{t+1} are distinguished from the variance of earnings shocks η_{t+1} by observing how the variance of earnings vary depending on the human capital shifters τ_t.[19] The earnings equation parameters are identified from mean labor earnings. The variance of earnings then provides tells the variance of the measurement error of earnings. Finally, by observing sequential labor market choices x_t, the remaining preference parameters during the post-schooling periods can be identified. Observed schooling choices inform schooling preferences.

4 Estimation Results

4.1 Parameter Estimates

Skill Formation Technologies Parameter estimates for the skill formation technol-

[19]Recall that I assume that the distribution of health shocks to have a bivariate standard Gaussian distribution. The model, therefore, only identifies the relative size of skill shock variances.

ogy during post-schooling periods are reported in Table 6. The estimates for $B_2(1,1)$

Table 6: Parameter estimates: post-schooling skill formation

Parameter	Estimate	Standard error	Description
Cognitive skill growth			
$b_0(1)$	0.320	0.080	intercept
$B_1(1,1)$	-0.083	0.010	childhood mental health
$B_1(1,2)$	-0.009	0.011	childhood physical health
$B_1(1,3)$	0.013	0.002	high school education
$B_1(1,4)$	0.028	0.005	university education
$B_2(1,1)$	0.058	0.012	cognitive task
$B_2(1,3)$	0.031	0.013	labor supply
$B_3(1,1)$	0.928	0.030	retention rate
$B_3(1,3)$	0.048	0.025	mental health interaction
Manual skill growth			
$b_0(2)$	1.591	0.094	intercept
$B_1(2,1)$	-0.018	0.014	childhood mental health
$B_1(2,2)$	-0.049	0.016	childhood physical health
$B_1(2,3)$	-0.010	0.003	high school education
$B_1(2,4)$	-0.027	0.005	university education
$B_2(2,2)$	0.041	0.013	manual task
$B_2(2,3)$	0.021	0.011	labor supply
$B_3(2,2)$	0.876	0.027	retention rate
$B_3(2,4)$	0.056	0.020	physical health interaction
Skill shocks			
$\Sigma_\epsilon(1,1)$	0.230	0.089	cognitive skill shock variance
$\Sigma_\epsilon(1,2)$	-0.159	0.081	covariance of skill shocks
$\Sigma_\epsilon(2,2)$	0.168	0.087	manual skill shock variance

Source: NCDS augmented with UK Skills Survey. Sample consists of 3,665 men.
Note: Parameter estimates are for the skill components of the post-schooling human capital formation technology $\theta_{t+1} = b_0 + B_1\zeta_1 + B_2 x_t + B_3\theta_t + \epsilon_{t+1}$ where $\epsilon_{t+1} \sim N(0, \Sigma_\epsilon)$. Spending 1 unit of time for labor corresponds to working at least part time for 9 month in a year. The skill productivity shocks and the health productivity shocks are assumed to be independent.

and $B_2(2,2)$ are both positive and significant, indicating that skills grow faster when individuals perform more skill demanding tasks. These results are consistent with "learning-by-doing" skill formation and with the findings of Yamaguchi (2012). I find that labor supply increases both types of skills. The annual skill depreciation rates for cognitive and manual skills are about 8% and 12%, respectively, which implies that skills are highly persistent over time and that manual skills depreciate faster than cognitive skills. Skill shocks are negatively correlated with a correlation coefficient of -0.80. Mental health conditions during childhood are associated with slower growth of cognitive skills. Physical health conditions during childhood induce slower manual skill growth. Individuals with higher education experience faster cognitive skill growth, while they experience slower manual skill growth. The cross productivities between current skills and current health conditions are found to be positive and significant. These result imply that skills and health are complementary in producing skills.

Table 7 shows parameter estimates for the skills production technology in the schooling period. Childhood health conditions are again found to have negative effects on skills. Advanced schooling implies higher cognitive skills. Family income at age 16 is positively associated with cognitive skill level and negatively associated with manual skill level at labour market entry. Not surprisingly, math test scores at age 7 predicts higher cognitive skills and lower manual skills.

Health Formation Technologies Table 8 presents parameter estimates for the health components of the post-schooling human capital formation technology. Estimates suggest that childhood health conditions affect the technology of health formation. In particular, the estimates imply that individuals with childhood health conditions experience faster health deteriorations during the post-schooling periods. Higher educated individuals experience slower health deteriorations. These results are consistent with the findings of Conti et al. (2010). Working individuals experience faster health deteriorations than non-working individuals. The negative effect of labor supply is found to be larger for physical health than for mental health. These effects help me to explain deteriorating health patterns over the lifecycle. The estimates indicate that individuals performing high levels of manual tasks tend to depreciate their

Table 7: Parameter estimates: skills at labour market entry

Parameter	Estimate	Standard error	Description
Cognitive skill endowment			
$A_1(1,1)$	-0.120	0.029	childhood mental health
$A_1(1,2)$	-0.076	0.033	childhood physical health
$A_1(1,3)$	0.160	0.032	math test score
$A_1(1,4)$	0.075	0.020	family income
$A_2(1,1)$	0.120	0.039	high school
$A_2(1,2)$	0.223	0.082	university
Manual skill endowment			
$A_1(2,1)$	0.046	0.028	childhood mental health
$A_1(2,2)$	-0.115	0.031	childhood physical health
$A_1(2,3)$	-0.112	0.072	math test score
$A_1(2,4)$	-0.144	0.025	family income
$A_2(2,1)$	-0.104	0.040	high school
$A_2(2,2)$	-0.131	0.081	university
Initial skill shocks			
$\Sigma_{\epsilon_1}(1,1)$	0.635	0.225	variance, cognitive skill shock
$\Sigma_{\epsilon_1}(1,2)$	-0.570	0.222	skill shock covariance
$\Sigma_{\epsilon_1}(2,2)$	0.602	0.240	variance, manual skill shock

Source: NCDS augmented with UK Skills Survey. Sample consists of 3,665 men.
Note: Parameter estimates are for the skill components of the initial human capital formation $\theta_{t_s} = a_0 + A_1\zeta_0 + A_2 s + \epsilon_1$, where $\epsilon_{t+1} \sim N(0, \Sigma_{\epsilon_1})$. The skills shocks are independent of health shocks. I normalize skills at labor market entry to have zero unconditional means and unit variances.

physical health faster than others. This result is driven by the negative correlations between past experience in manual task and future physical health indicators.

Table 9 presents parameter estimates for the health formation technology during the schooling period. Childhood health conditions predicts lower levels of health endowments at labour market entry. Higher math test scores imply better mental health at labor market entry. This implies that cognitive skills produce better mental health. Conditional on the test scores, I do not find significant evidence that family income affects health endowments.[20] The estimates imply that education improves health,

[20]Empirical evidence regarding the relationship between family income and child health is mixed.

Table 8: Parameter estimates: post-schooling health formation

Parameter	Estimate	Standard error	Description
Mental health growth			
$B_1(3,1)$	-0.083	0.011	childhood mental health
$B_1(3,3)$	0.082	0.034	high school
$B_1(3,4)$	0.030	0.012	university
$B_2(3,1)$	0.031	0.012	cognitive task
$B_2(3,2)$	0.012	0.009	manual task
$B_2(3,3)$	-0.021	0.010	labor supply
$B_3(3,3)$	0.924	0.015	retention rate
Physical health growth			
$B_1(4,2)$	-0.049	0.012	childhood physical health
$B_1(4,3)$	0.076	0.055	high school
$B_1(4,4)$	0.042	0.014	university
$B_2(4,1)$	-0.021	0.011	cognitive task
$B_2(4,2)$	-0.031	0.013	manual task
$B_2(4,3)$	-0.042	0.017	labor supply
$B_3(4,4)$	0.913	0.022	retention rate

Source: NCDS augmented with UK Skills Survey. Sample consists of 3,665 men.
Note: Parameter estimates are for the health components of the post-schooling human capital formation technology $\theta_{t+1} = b_0 + B_1\zeta_1 + B_2 x_t + B_3\theta_t + \epsilon_{t+1}$ where $\epsilon_{t+1} \sim N(0, \Sigma_\epsilon)$. Spending 1 unit of time for labor corresponds to working at least part time for 9 month in a year. The health shocks are independent of skill shocks and drawn from a bivariate standard Gaussian distribution. The intercepts are normalized to be zero.

which are consistent with the findings of Conti et al. (2010).

Earnings Process Table 10 shows the parameter estimates for the earnings process. The prices of the labor output are given by $\tilde{p}_1 + p_2' x_t$. They significantly increase with the level of cognitive tasks. The results further suggest that the labor output rises with labor time, skills and health. The estimates imply that an increase in cognitive skills by 1 standard deviation raises the log annual earnings by 0.74 for the median job. An increase of manual skills by 1 standard deviation raises the log annual earnings by 0.27

Kuehnle (2014) estimates the causal effect of family income on various measures of child health using local labor market conditions as instruments. He argues that family income is not a major determinant of child health in UK.

Table 9: Parameter estimates: health at labor market entry

Parameter	Estimate	Standard error	Description
Mental health endowment			
$A_1(3,1)$	-0.280	0.048	childhood mental health
$A_1(3,3)$	0.663	0.065	math test scores
$A_1(3,4)$	-0.005	0.057	family income
$A_2(3,1)$	0.111	0.040	high school
$A_2(3,2)$	0.168	0.058	university
Physical health endowment			
$A_1(4,2)$	-0.264	0.057	childhood physical health
$A_1(4,3)$	0.228	0.064	math test scores
$A_1(4,4)$	-0.023	0.057	family income
$A_2(4,1)$	-0.055	0.040	high school
$A_2(4,2)$	0.095	0.057	university

Source: NCDS augmented with UK Skills Survey. Sample consists of 3,665 men.
Note: Parameter estimates are for the health components of the initial human capital $\theta_{t_s} = a_0 + A_1\zeta_0 + A_2 s + \epsilon_1$, where $\epsilon_{t+1} \sim N\left(0, \Sigma_{\epsilon_1}\right)$. The health shocks are independent of skill shocks and drawn from a bivariate standard Gaussian distribution. The intercepts are normalized to be zero. Both math test scores and family income are measured by quantile ranks.

for the median job. These estimates indicate that differences in returns to skills are sizeable. The estimates imply that an increase in mental health by 1 standard deviation raises the log annual earnings by 0.24 for the median job. An increase of manual skills by 1 standard deviation raises the log annual earnings by 0.27 for the median job. The corresponding number of physical health is 0.11. Thus, I find that returns to skills are far greater than returns to health. These results imply that younger individuals have stronger work incentives to accumulate skills. The model predicts that labor supply declines as individuals get older since the opportunity costs for non-working fall.

Preferences for Work and Schooling Table 11 reports the parameter estimates for work preferences. Overall, individuals tend to prefer to perform higher cognitive tasks and lower manual tasks. More educated individuals have stronger preferences to perform higher cognitive tasks and lower manual tasks. Mental health conditions are

Table 10: Parameter estimates: earnings process

Parameter	Estimate	Standard error	Description
Price			
$\tilde{p}_1$	0.213	0.098	intercept
$p_2(1)$	0.427	0.039	cognitive task price
$p_2(2)$	0.208	0.033	manual task price
Productivity			
q_0	8.766	0.121	labor supply
$q_1(1)$	0.170	0.038	cognitive skill
$q_1(2)$	0.060	0.032	manual skill
$q_1(3)$	0.080	0.033	mental health
$q_1(4)$	0.055	0.034	physical health
$Q_2(1,1)$	0.105	0.051	cognitive task interaction, cognitive skill
$Q_2(1,3)$	0.067	0.034	cognitive task interaction, mental health
$Q_2(2,2)$	0.041	0.028	manual task interaction, manual skill
$Q_2(2,4)$	0.032	0.021	manual task interaction, physical health
Measurement error			
σ^2_η	0.189	0.065	variance

Source: NCDS augmented with UK Skills Survey. Sample consists of 3,665 men.
Note: Parameter estimates are for the labor earnings process $\ln e^l_t = \tilde{p}_1 + p_2'\tau_t + q_0 l_t + (q_1 + Q_2'\tau_t)'\theta_t + \eta_t$, where $\eta_t \sim N\left(0, \sigma^2_\eta\right)$. Spending 1 unit of time for labor corresponds to work at least part time for 9 month in a year.

negatively associated with preferences for cognitive tasks. Physical health conditions lead to distastes for manual tasks. These results indicate that childhood health conditions may induce occupational sorting by affecting preferences for tasks. Individuals with higher cognitive skills and better mental health prefer to perform higher cognitive tasks while those with higher manual skills prefer to perform higher manual tasks. Individuals with better physical health also prefer to perform higher manual tasks, although not significantly. The estimates suggest that switching into occupations that command substantially different cognitive tasks incurs large psychic costs.

Individuals suffer from higher psychic costs when they work longer. Distastes for labor supply are stronger among lower educated individuals. Poor health conditions

Table 11: Parameter estimates: work preferences

Parameter	Estimate	Standard error	Description
Cognitive task			
$g_0(1)$	0.283	0.179	intercept
$G_2(1,1)$	-0.082	0.028	childhood mental health
$G_2(1,2)$	-0.032	0.021	childhood physical health
$G_2(1,3)$	0.153	0.004	high school
$G_2(1,4)$	0.323	0.011	university
$G_3(1,1)$	0.054	0.026	cognitive skill
$G_3(1,3)$	0.053	0.024	mental health
$G_4(1,1)$	-24.205	2.430	switching cost
Manual task			
$g_0(2)$	-0.543	0.206	intercept
$G_2(2,1)$	0.058	0.026	childhood mental health
$G_2(2,2)$	-0.078	0.023	childhood physical health
$G_2(2,3)$	-0.171	0.046	high school
$G_2(2,4)$	-0.239	0.028	university
$G_3(2,2)$	0.152	0.026	manual skill
$G_3(2,4)$	0.039	0.028	physical health
$G_4(2,2)$	-0.194	0.054	switching cost
Labor supply			
$g_0(3)$	-0.354	0.231	intercept
$G_2(3,1)$	-0.074	0.029	childhood mental health
$G_2(3,2)$	-0.055	0.026	childhood physical health
$G_2(3,3)$	0.125	0.046	high school
$G_2(3,4)$	0.139	0.068	university
$G_3(3,1)$	0.029	0.009	cognitive skill
$G_3(3,2)$	-0.012	0.008	manual skill
$G_3(3,3)$	0.171	0.066	mental health
$G_3(3,4)$	0.146	0.068	physical health
$G_4(3,3)$	-14.934	1.516	switching cost

Source: NCDS augmented with UK Skills Survey. Sample consists of 3,665 men.
Note: Parameter estimates are for the work preferences $g_t \equiv (g_0' x_t + x_t' G_1 x_t) + (G_2\zeta_1 + G_3\theta_t)' x_t + (x_t - x_{t-1})' G_4 (x_t - x_{t-1}) + \nu_t' x_t$ where $\nu_t \sim N(0, \Sigma_\nu)$. I normalize G_1 to be the negative of an identity matrix. Spending 1 unit of time for labor corresponds to work at least part time for 9 month in a year.

during childhood and adulthood are associated with distastes for labor supply. Individuals with higher cognitive skills prefer to work more while those with higher manual skills prefer to work less. The estimates suggest that changing time allocation over time also incurs large psychic costs.

Table 12 shows that both test scores at age 7 and family income matter for education choice. Thus family income affects human capital endowments at labor market entry both directly and indirectly through affecting educational attainment. Even after controlling those background factors, mental health conditions during childhood are still negatively associated with educational attainment. The unobserved costs of education also play an important role in determining education choices. I do not find evidence that education choices are driven significantly by childhood physical health conditions.

Table 12: Parameter estimates: schooling preferences

Parameter	Estimate	Standard error	Description
High school			
$k_0(1)$	-1.848	0.095	intercept
$K_1(1,1)$	-0.300	0.097	childhood mental health
$K_1(1,2)$	-0.279	0.080	childhood physical health
$K_1(1,3)$	2.485	0.113	math test score
$K_1(1,4)$	0.326	0.110	family income
University			
$k_0(2)$	-5.338	0.212	intercept
$K_1(2,1)$	-0.423	0.084	childhood mental health
$K_1(2,2)$	-0.174	0.086	childhood physical health
$K_1(2,3)$	5.673	0.237	math test score
$K_1(2,4)$	1.035	0.150	family income

Source: NCDS augmented with UK Skills Survey. Sample consists of 3,665 men.
Note: Parameter estimates are for the schooling preferences $u_0 = (k_0 + K_1\zeta_0 + \nu_0)'s$ where $\nu_0 \sim N(0, \Sigma_{\nu_0})$. The utility shocks for each schooling option are independent. The standard deviation of math test scores is normalized to be 1. Both math test scores and family income is measured by quantile ranks. The utility from compulsory education is normalized to be 0.

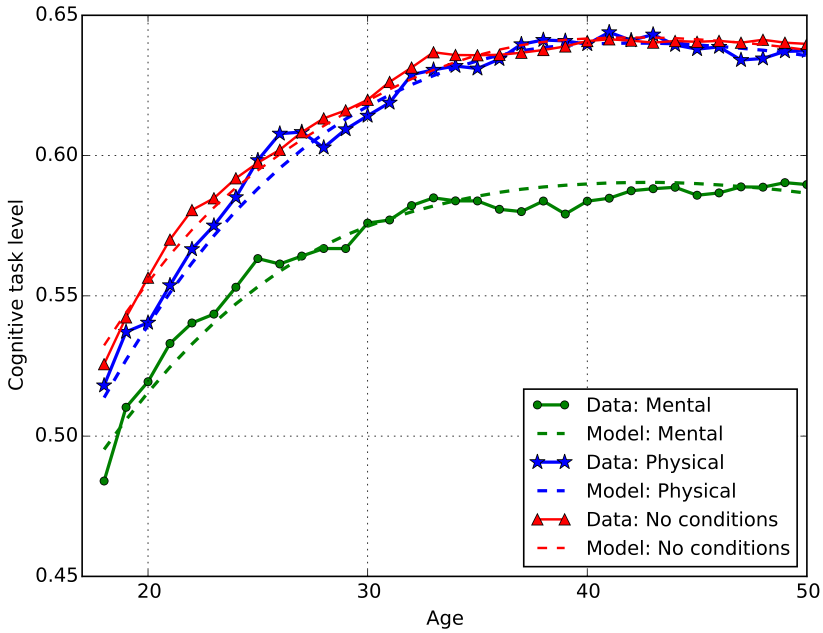
4.2 Model Fit

To assess the performance of the model, I first examine its ability to reproduce key empirical patterns observed in the sample. To predict lfiecycle outcomes using the estimated model, I simulate each individual in the NCDS sample 1,000 times. If observations are missing in a particular year, the corresponding simulation outcomes of the year are treated as missing.

Figure 3 compares the observed and predicted task profiles for each childhood health group. The model can replicate the occupation sorting patterns associated with childhood health conditions. Overall, the predicted profiles are reasonably close to the observed profiles from the data. The task selection patterns are driven both by returns to the human capital bundle and by tastes. In particular, individuals with childhood mental health conditions sort into lower cognitive tasks since they have lower cognitive skill endowment and stronger distastes for higher cognitive tasks.

The lifecycle profiles of fulltime employment are presented in Figure 4 for each health group. The declining profiles represent falling opportunity costs of non-labor activity. Monetary returns to skills are substantially higher than returns to health capitals. Therefore, individuals allocate more time for labor to accumulate their skills at younger ages while their health capitals depreciate as a result. The gaps in employment across the health groups are driven by the differences in tastes, health status, and opportunity costs of non-labor activity.

Table 13 presents the model predictions regarding annual labor earnings at ages 23, 33 and 42. The model can replicate the increasing earnings profiles for each health group. The earnings growth are driven mainly by skill accumulation in the model. The model slightly over-predicts earnings at age 23 and under-predicts earnings at later ages. The magnitude of the deviations amount to at most 600 pounds a year. Moreover, the model is successful in reproducing the increasing pattern over time for the mental health-related earnings gaps as well as the decreasing pattern for the



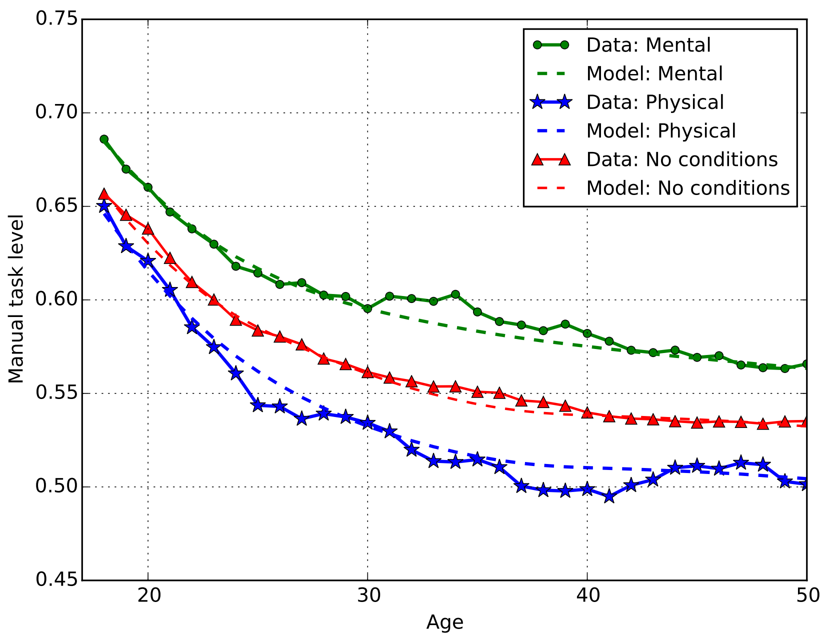


Figure 3: Task profiles by childhood health conditions: model vs. data.

physical health-related earnings gaps.

The model predictions on schooling choice probabilities are shown and contrasted with the data in Table 14. The model can replicate the fact that individuals with

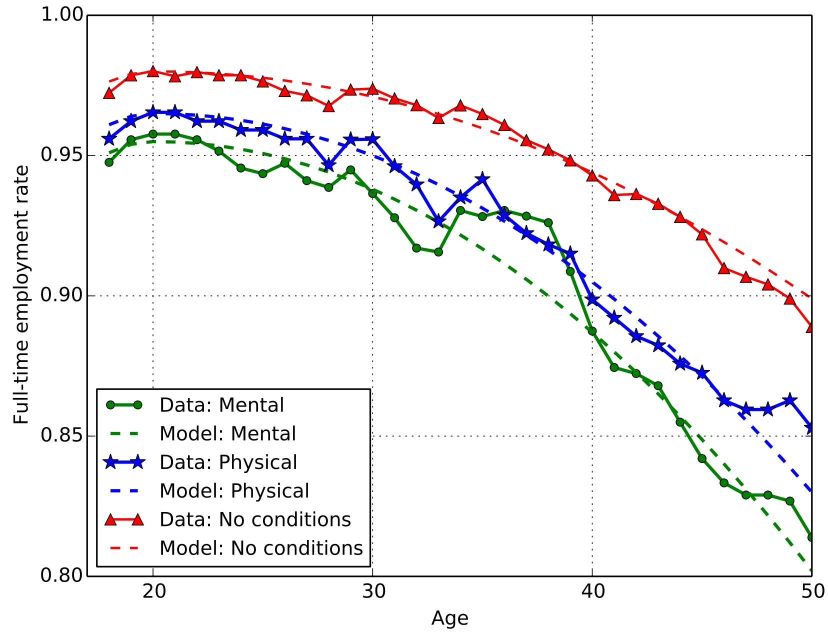


Figure 4: Fulltime employment rate by childhood health conditions: model vs. data.

Table 13: Model fit regading average log annual labor earnings

	Age 23		Age 33		Age 42	
Childhood health conditions	Data	Model	Data	Model	Data	Model
No conditions	9.402	9.423	9.841	9.815	10.033	9.994
Mental	9.313	9.352	9.717	9.701	9.900	9.869
	[-0.089]	[-0.071]	[-0.124]	[-0.114]	[-0.133]	[-0.125]
Physical	9.281	9.309	9.777	9.744	9.984	9.954
	[-0.121]	[-0.113]	[-0.064]	[-0.071]	[-0.049]	[-0.040]

Note: The numbers in brackets indicate log annual earnings gaps between individuals with childhood health conditions and their healthy counterparts.

childhood mental health conditions tend not to pursue advanced schooling options. This is because both of higher psychic costs for schooling and lower returns to schooling among them. Overall, the model can fit the schooling choice patterns fairly well. The model, however, slightly over-predict the probability to take the "high-school" option among individuals with childhood physical conditions.

Table 14: Fractions of individuals selecting high school or university: data vs. model

	High School		University	
Childhood health conditions	Data	Model	Data	Model
No conditions	0.352	0.361	0.160	0.169
Mental	0.251	0.252	0.075	0.078
Physical	0.293	0.314	0.164	0.161

Note: Author's estimates using the NCDS and the UK Skills Survey.

5 Counterfactual Experiments

Childhood health conditions may affect human capital endowments, speed of human capital formation, and tastes. What are the sources of the earnings gaps associated with childhood health conditions? Are they driven mainly by the gaps in skill endowments, or are they due to the differences in skill formation? Are they because childhood health conditions lead to poorer health conditions during the adulthood? Do they reflect taste-based earnings differentials? To evaluate the importance of alternative channels through which childhood health conditions affect earnings, the model is simulated under the restrictions that individuals with different childhood health conditions are homogeneous in terms of (1) preferences, (2) skill formation, and (3) health formation. When eliminating heterogeneity in preferences, I assume that individuals with childhood health conditions have the same preferences with their healthy counterparts regarding schooling choices, time allocation, and task selections. I eliminate heterogeneity in skill formation by imposing that (a) the distributions of test scores and family income are degenerate at their means and that (b) childhood health conditions do not directly affect skill formation both during the schooling period and during the post-schooling periods. I eliminate heterogeneity in health formation similarly.

The results from the counter-factual experiments including the baseline model predictions are summarized in Table 15. Those results indicate that the difference in skill formation is the most important factor to account for the mental health-related earn-

Table 15: Counterfactual experiments to eliminate channels through which childhood health affects earnings

Mental health-related earnings gaps					
Age	Data	Benchmark	Preferences	Skill formation	Health formation
23	-0.089	-0.071	-0.058 (17.7%)	-0.028 (60.0%)	-0.062 (12.7%)
33	-0.124	-0.114	-0.081 (28.9%)	-0.045 (60.5%)	-0.091 (20.1%)
42	-0.133	-0.125	-0.087 (30.1%)	-0.044 (65.1%)	-0.095 (24.4%)
Physical health-related earnings gaps					
Age	Data	Benchmark	Preferences	Skill formation	Health formation
23	-0.121	-0.113	-0.092 (18.8%)	-0.047 (58.5%)	-0.097 (14.5%)
33	-0.064	-0.071	-0.056 (20.5%)	-0.048 (31.8%)	-0.056 (20.7%)
42	-0.049	-0.040	-0.028 (31.0%)	-0.029 (28.0%)	-0.026 (34.3%)

Note: Author's estimates using the National Child Development Study with task data from UK Skills Survey. The numbers in parentheses stand for the fractions of health-related earnings gaps explained by each channel. Contributions of the alternative channels do not necessarily sum up to 100%.

ings gaps throughout the lifecycle. The skill channel accounts for about 60%-65% of the earnings gaps due to childhood mental health conditions. The health channel plays less significant role especially at younger ages. The contributions of the health channel increase as individuals get older. This is primarily because health capitals gradually depreciate over the lifecycle. At age 42, the health channel can account for about one quarter of the observed health-related earnings gaps. Differences in preferences play a significant role as well: they can explain about one third of the earnings gap at age 42.

The health channel and the taste channel are equally as important to explain the observed earnings gaps due to childhood physical health conditions. These two channels account for about one-third of the earnings gap at age 42, respectively. Both the data and the model show that the earnings gaps due to childhood physical health conditions lessen over the lifecycle. The experiments reveal that this pattern is driven mainly by the declining influences of the skill channel.

I conduct three additional counterfatual experiments to further decompose the skill formation channel into three components: (1) initial endowments, (2) skill formation during the schooling period, and (3) post-schooling skill formation. Table 16 summarize the results. The differences in endowments across the health groups, which are

Table 16: Decomposion of the skill formation channel

Mental health-related earnings gaps					
Age	Data	Benchmark	Endowment	Schooling	Post-schooling
23	-0.089	-0.071	-0.047 (33.8%)	-0.054 (23.9%)	-0.061 (14.1%)
33	-0.124	-0.114	-0.082 (28.1%)	-0.092 (19.2%)	-0.089 (21.9%)
42	-0.133	-0.125	-0.096 (23.2%)	-0.103 (17.6%)	-0.081 (35.2%)
Physical health-related earnings gaps					
Age	Data	Benchmark	Endowment	Schooling	Post-schooling
23	-0.121	-0.113	-0.061 (46.1%)	-0.106 (6.3%)	-0.107 (5.5%)
33	-0.064	-0.071	-0.056 (20.6%)	-0.067 (5.6%)	-0.066 (7.1%)
42	-0.049	-0.040	-0.034 (15.5%)	-0.038 (5.1%)	-0.037 (8.5%)

Note: Author's estimates using the National Child Development Study with task data from UK Skills Survey. The numbers in parentheses stand for the fractions of health-related earnings gaps explained by each channel. Contributions of the alternative channels do not necessarily sum up to 100%.

measured by test scores and family income, play the greatest role in accounting for earnings gaps at younger ages. The effect of the differences in endowments diminishes over time. Interestingly, the differences in endowments account for most of the skill effects for the group with childhood physical health conditions. This implies that the observed earnings gaps associated with childhood physical health conditions are driven mainly by the correlation between physical health status and human capital endowments. Skill formation during the schooling period is also an important factor especially for mental health. The differences in post-schooling skill formation play an increasingly important role as individual get older. The heterogeneity in cognitive skill formation accounts for about one third of of the earnings gap at age 42. Further, the experiments demonstrate that the differences in post-schooling skill formation are the main driving forces behind the increasing pattern of the mental-health related earnings gaps.

6 Conclusion

While previous research has emphasized the importance of childhood health conditions in shaping lifetime earnings, little is known about the channels through which childhood health conditions affect earnings. Childhood health conditions may affect earnings by restricting skill formation, or by causing poor health status in adulthood. Juxtaposing the alternative channels is an important step towards understanding effective policies to alleviate the negative effects of health adversity at earlier life stages.

This paper develops and estimates a lifecycle model that allows multiple channels through which childhood health conditions may affect future earnings. My framework embeds a multi-dimensional human capital formation technology into a dynamic model of schooling, labor supply and occupation choices. The model is estimated based on a longitudinal cohort panel survey that provides results of medical examinations during the childhood.

Many salient features of the data are closely reproduced by the model, including the occupation sorting patterns, employment rates, and earnings over the lifecycle. The parameter estimates indicate that childhood health conditions affect formation of skills and health as well as preferences for working and schooling. I then use the estimated model to study the relative importance of the alternative channels in accounting for the observed earnings gaps.

My results show that the effect of childhood health on skill formation plays the greatest role in accounting for the observed earnings losses among individuals who had childhood mental health conditions. About two-thirds of the earnings losses associated with childhood mental health conditions can be explained by the skill channel. The differences in skill endowments between the individuals with childhood mental health conditions and their healthy counterparts are the main driving forces behind the earnings gaps at younger ages while the differences in skill growth become more important as individuals get older. The skill channel is also the main factor behind the earnings losses at younger ages among those with childhood physical health conditions. However, this is primary because of the gaps in endowments and not because of the differences in skill growth. Further, I find that differences in tastes and health formation also play significant roles for both types of health conditions, especially at older ages.

These results imply that skills and good health are complementary in producing skills over the lifecycle. As the importance of cognitive skills grow in determining wages in the society, health conditions that restrict cognitive skill formation may become more detrimental for success in the labor market. This paper studied a sample of cohorts who experienced childhood in 1960s and 1970s. Investigating the skill-health complementarities among more recent cohorts is an important research agenda.

A Task Characteristics in the UK Skills Survey

A task-based approach requires the construction of interpretable factors as components of a task vector. Following Yamaguchi (2012), I assume a priori that there are two distinct types of tasks: "cognitive" and "manual" task. Each task is defined as the first principle factor in the factor analysis on two separate lists of skill/task characteristic ratings from the UK Skills Survey that are given in the following table with the estimated factor loadings.

Table 17: Task characteristics in the UK Skills Survey

	Factor loadings
Cognitive tasks	
[1] Using computers	0.795
[2] Adding, subtracting, multiplying and diving numbers	0.595
[3] Calculations using decimals, percentages, or fractions	0.714
[4] Calculations using advanced statistical procedure	0.695
[5] Reading written information	0.712
[6] Reading short documents	0.886
[7] Reading long documents	0.882
[8] Writing materials	0.789
[9] Writing short documents	0.884
[10] Writing long documents with correct spelling and grammar	0.827
[11] Specialist knowledge or understanding	0.776
[12] Organizing own time thinking ahead	0.717
[13] Spotting problems or faults	0.544
[14] Working out cause of problems/faults	0.627
[15] Thinking of solutions to problems	0.801
[16] Analyzing complex problems in depth	0.869
Manual tasks	
[1] Using physical strength	0.911
[2] Using physical stamina	0.889
[3] Accuracy in using hands/fingers	0.900
[4] Knowledge or use or operation or tools/equipment machinery	0.851

Note: The sample consists of all working individuals in the 1997-2012 Skills Surveys. The sample size is 17,424.

B Health Measures

B.1 Childhood Health Measures

The National Child Development Study (NCDS) conducts medical examinations at ages 7 and 16 to diagnose major health conditions during childhood.

Table 18: Prevalence of childhood health conditions

	Non-handicapping	Handicapping
Mental health conditions:		
EBD (Age 7)	0.035	0.011
EBD (Age 16)	0.025	0.014
Speech disorders (Age 7)	0.013	0.024
Speech disorders (Age 16)	0.042	0.006
Total (Age 7 or 16)	0.098	0.049
Physical health conditions:		
Nervous system disorders (Age 7)	0.050	0.002
Nervous system disorders (Age 16)	0.014	0.002
Heart problems (Age 7)	0.029	0.000
Heart problems (Age 16)	0.023	0.000
Respiratory system disorders (Age 7)	0.079	0.011
Respiratory system disorders (Age 16)	0.039	0.006
Limb defects (Age 7)	0.065	0.008
Limb defects (Age 16)	0.021	0.017
Hearing losses (Age 7)	0.061	0.004
Hearing losses (Age 16)	0.036	0.011
Vision losses (Age 7)	0.137	0.004
Vision losses (Age 16)	0.086	0.058
Other physical conditions (Age 7)	0.004	0.005
Other physical conditions (Age 16)	0.030	0.008
Total (Age 7 or 16)	0.477	0.114

Source: The NCDS. The sample consists of 3,665 men.

Following the 10th revision of the International Statistical Classification of Diseases (ICD-10), the health conditions are categorized either as "mental" or "physical". Mental health conditions include emotional and behavioural difficulties/disorders (EBD) and speech disorders.[21] EBDs refer to a wide range of disorders, including internalizing

[21] From 1930s through to early 1980s, "maladjustment" was the term in use to describe children who

disorders such as depression and autism; and externalizing disorders such as conduct disorders.

Physical health conditions cover a broad number of conditions, including vision defects, hearing defects, limb defects, nervous system disorders such as migraine and epilepsy, respiratory system problems such as asthma, heart conditions, and other physical abnormalities. Using the diagnoses, particular health condition can be defined to be either "handicapping", "non-handicapping", or "non-existent". Table 18 shows the fractions of individuals with specific childhood health conditions.

B.2 Adult Health Measures

The NCDS includes self-reported health conditions at ages 23, 33, 46, and 50. The specific names of the health conditions are coded according to the 9th revision of the International Statistical Classification of Diseases (ICD-9) at ages 23 and 33. The NCDS uses ICD-10 at ages 46 and 50. The ICD-9 and ICD-10 are largely compatible with each other. Using those self-reported health conditions, I determine whether each individual reported their mental of physical health conditions at each age. The NCDS also includes a battery of self-completion questions called the *Malaise Inventory* at ages 23, 33, and 42. The Malaise Inventory consists of 24 yes-no questions covering emotional disturbance and associated physical symptoms and individuals reporting 'yes' to at least 7 items as being at high risk of depression (Richman, 1978; Rutter et al. 1976). To separately measure mental health and physical health, I group the 24 items into two categories: i) psychological and ii) somatic as in Table 19. According to this categorization, I consider 'yes' to 5 psychological items and 3 somatic items as an indicator of adverse mental health conditions and physical health conditions, respectively.

---

would later be described as having EBD in Britain (Bilton and Cooper, 2013). The NCDS also uses the terms "maladjustment" or "emotional maladjustment" in the medical examinations. I interpret those terms as describing EBD.

Table 19: Malaise Inventory items

Psychological items
[1] Do you feel tired most of the time?
[2] Do you often feel miserable or depressed?
[3] Do you often get worried about things?
[4] Do you usually have great difficulty in falling or staying asleep?
[5] Do you usually wake unnecessarily early in the morning?
[6] Do you wear yourself out worrying about your health?
[7] Do you often get into a violent rage?
[8] Do people often annoy and irritate you?
[9] Do you often suddenly become scared for no good reason?
[10] Are you scared to be alone when there are no friends near you?
[11] Are you easily upset or irritated?
[12] Are you frightened of going out alone or of meeting people?
[13] Are you constantly keyed up and jittery?
[14] Is your appetite poor?
[15] Does every little thing get on your nerves and wear you out?
[16] Have you ever had a nervous breakdown?
Somatic items
[17] Do you often have back-ache?
[18] Do you often have bad headaches?
[19] Have you at times had a twitching of the face, head or shoulders?
[20] Do you suffer from indigestion?
[21] Do you suffer from an upset stomach?
[22] Does your heart often race like mad?
[23] Do you have bad pains in your eyes?
[24] Are you troubled with rheumatism or fibrosis?

Table 20 shows the fractions of individuals reporting mental or physical health conditions. It is evident that individuals are more likely to report physical health problems as they get older while mental health problems appear to decline after age 42. Interestingly, the prevalence of mental health problems appears to be higher with the Malaise Inventory indicator than with self-reports. In contrast, the prevalence of physical health problems appears to be lower with the Malaise Inventory indicator than with self-reports. This is probably because the Malaise Inventory covers only a limited number of somatic symptoms.

Table 20: Adult health indicators

	Age 23	Age 33	Age 42	Age 46	Age 50
Fraction reporting mental health conditions	0.033	0.024	0.064	0.044	0.039
	(0.179)	(0.156)	(0.245)	(0.204)	(0.194)
Fraction reporting physical health conditions	0.150	0.174	0.216	0.335	0.434
	(0.357)	(0.379)	(0.411)	(0.335)	(0.434)
Malaise Inventory psychological health risk indicator	0.060	0.063	0.153		
	(0.237)	(0.244)	(0.360)		
Malaise Inventory somatic health risk indicator	0.065	0.090	0.104		
	(0.247)	(0.286)	(0.306)		

Note: Standard errors are in parentheses. The data source is the NCDS. The sample consists of 3,665 men.

Table 21 presents the estimates of health reporting preference parameters. The estimates indicate that individuals with better mental health are less likely to report mental health problems. Likewise, individuals with better physical health are less likely to report physical health problems. However, I find that the Malaise Inventory somatic health indicator is not significantly associated with the physical health conditions. This suggests that the measurement of physical health in my model is driven mostly by the self-reported physical health indicators. I also find that past labor supply does not significantly affect mental health reports while past labor supply appears to have small but statistically significant effects on the Malaise Inventory somatic health indicators.

Table 21: Parameter estimates: health reports

Parameter	Estimate	Standard error	Description
Self-reported mental health			
$h_0(1)$	-1.693	0.071	intercept
$H_1(1,1)$	-0.088	0.038	mental health
$H_2(1,3)$	0.011	0.020	past labor supply
Malaise Inventory mental health			
$h_0(2)$	-1.400	0.060	intercept
$H_1(2,1)$	-0.096	0.032	mental health
$H_2(2,3)$	0.012	0.023	past labor supply
Self-reported physical health			
$h_0(3)$	-0.952	0.035	intercept
$H_1(3,1)$	-0.085	0.025	physical health
$H_2(3,3)$	0.022	0.013	past labor supply
Malaise Inventory somatic health			
$h_0(4)$	-1.040	0.046	intercept
$H_1(4,1)$	0.003	0.025	physical health
$H_2(4,3)$	0.044	0.021	past labor supply

Source: NCDS augmented with UK Skills Survey. Sample consists of 3,665 men.
Note: Parameter estimates are for the health reporting preferences: $v_t = (h_0 + H_1\theta_t^H + H_2 x_{t-1} + \omega_t)' r_t + r_t' H_3 r_t$ where $\omega_t \sim N(0,1)$. I assume that past task selections (τ_{t-1}) do not affect health reporting behavior. The parameter matrix H_3 is normalized to be an identity matrix.

References

Almond, Douglas and Janet Currie, "Human Capital Development before Age Five," *Handbook of Labor Economics*, 2011, *4*, 1315–1486.

_ **and** _ , "Killing Me Softly: The Fetal Origins Hypothesis," *Journal of Economic Perspectives*, 2011, *25* (3), 153.

Autor, David, Frank Levy, and Richard Murnane, "The Skill Content of Recent Technological Change: An Empirical Exploration," *The Quarterly Journal of Economics*, 2003, pp. 1279–1333.

Ben-Porath, Yoram, "The Production of Human Capital and the Life Cycle of Earnings," *Journal of Political Economy*, 1967, pp. 352–365.

Bilton, Katherine and Paul William Cooper, "ADHD and Children with Social, Emotional and Behavioural Difficulties," 2013.

Bound, John, "Self-Reported Versus Objective Measures of Health in Retirement Models," *Journal of Human Resources*, 1991, *26* (1), 106.

Bowlus, Audra and Chris Robinson, "Human Capital Prices, Productivity, and Growth," *American Economic Review*, 2012, *102* (7), 3483–3515.

Case, Anne and Christina Paxson, "Causes and Consequences of Early-life Health," *Demography*, 2010, *47* (1), S65–S85.

_ , Angela Fertig, and Christina Paxson, "The Lasting Impact of Childhood Health and Circumstance," *Journal of Health Economics*, 2005, *24* (2), 365–389.

Conti, Gabriella, James Heckman, and Sergio Urzua, "The Education-Health Gradient," *American Economic Review*, 2010, *100* (2), 234.

Cunha, Flavio and James Heckman, "Formulating, Identifying and Estimating the Technology of Cognitive and Noncognitive Skill Formation," *Journal of Human Resources*, 2008, *43* (4), 738–782.

Currie, Janet, "Healthy, Wealthy, and Wise: Socioeconomic Status, Poor Health in Childhood, and Human Capital Development," *Journal of Economic Literature*, 2009, *47* (1), 87–117.

_ , Mark Stabile, Phongsack Manivong, and Leslie Roos, "Child Health and Young Adult Outcomes," *Journal of Human Resources*, 2010, *45* (3), 517–548.

Felstead, Alan, Duncan Gallie, Francis Green, and Ying Zhou, "Skills at Work, 1986-2006," 2007.

Fletcher, Jason, "The Effects of Childhood ADHD on Adult Labor Market Outcomes," *Health Economics*, 2014, *23* (2), 159–181.

_ **, Jody Sindelar, and Shintaro Yamaguchi**, "Cumulative Effects of Job Characteristics on Health," *Health Economics*, 2011, *20* (5), 553–570.

Gilleskie, Donna, "A Dynamic Stochastic Model of Medical Care Use and Work Absence," *Econometrica*, 1998, pp. 1–45.

Hansen, Lars Peter and Thomas Sargent, *Recursive Models of Dynamic Linear Economies*, Princeton University Press, 2013.

Heckman, James, "The Economics, Technology, and Neuroscience of Human Capability Formation," *Proceedings of the National Academy of Sciences*, 2007, *104* (33), 13250–13255.

_ **and Guilherme Sedlacek**, "Heterogeneity, Aggregation, and Market Wage Functions: an Empirical Model of Self-selection in the Labor Market," *Journal of Political Economy*, 1985, pp. 1077–1125.

_ **and** _ , "Self-selection and the Distribution of Hourly Wages," *Journal of Labor Economics*, 1990, pp. S329–S363.

_ **and Thomas MaCurdy**, "A Life Cycle Model of Female Labour Supply," *Review of Economic Studies*, 1980, pp. 47–74.

Keane, Michael P and Kenneth Wolpin, "The Career Decisions of Young Men," *Journal of Political Economy*, 1997, *105* (3), 473–522.

Kuehnle, Daniel, "The Causal Effect of Family Income on Child Health in the UK," *Journal of Health Economics*, 2014, *36*, 137–150.

Lindeboom, Maarten and Marcel Kerkhofs, "Health and Work of the Elderly: Subjective Health Measures, Reporting Errors and Endogeneity in the Relationship between Health and Work," *Journal of Applied Econometrics*, 2009, *24* (6), 1024–1046.

Lundborg, Petter, Anton Nilsson, and Dan-Olof Rooth, "Adolescent Health and Adult Labor Market Outcomes," *Journal of Health Economics*, 2014, *37*, 25–40.

Sickles, Robim and Abdo Yazbeck, "On the Dynamics of Demand for Leisure and the Production of Health," *Journal of Business & Economic Statistics*, 1998, *16* (2), 187–197.

Smith, James, "The Impact of Socioeconomic Status on Health over the Life-course," *Journal of Human Resources*, 2007, *42* (4), 739–764.

_ **and Gillian Smith**, "Long-term Economic Costs of Psychological Problems during Childhood," *Social Science & Medicine*, 2010, *71* (1), 110–115.

Yamaguchi, Shintaro, "Tasks and Heterogeneous Human Capital," *Journal of Labor Economics*, 2012, *30* (1), 1–53.