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Essays on Human Capital Complementarities

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Abstract

The thesis consists of three chapters that study the interplay between skills and health in shaping labour market outcomes. I focus on two distinct but related issues: i) the wage losses among older workers due to work-limiting health conditions, and ii) the long lasting effects of childhood health conditions on human capital formation.

Chapter two studies how health conditions among older workers affect their wages depending on the characteristics of their occupations. The U.S. Social Security Act defines disability as the inability due to health conditions to perform physically or mentally demanding tasks. To examine the potentially task-specific nature of work-limiting health conditions, I estimate a wage equation that allows health conditions to have heterogeneous wage returns depending on what kinds of tasks the workers conduct within their occupations. The estimation results, based on a panel dataset of older workers in the U.S., indicate that the magnitude of health-induced wage losses differs substantially across occupations depending on their task characteristics, contrary to the commonly used assumption that health is uniformly valued across occupations. I also show that about 60% of the health-related wage gaps can be explained by the correlations between health and skills. This chapter further demonstrates that work-limiting health conditions are correlated with the time-varying components of multiple skills. This suggests that econometric models with single-dimensional, time-invariant unobserved heterogeneity may not be fully successful in isolating the influences of the correlations between health and skills.

The third chapter investigates the link between childhood health conditions and skill formation. While existing evidence suggests that certain childhood health conditions affect schooling outcomes, little is known as to whether and how such influences persist

into labour market skills beyond academic outcomes. By adopting a multidimensional skills/tasks approach, this chapter provides a set of new evidence regarding how childhood health conditions affect skills used in the labour market. To obtain objective measures of childhood health conditions, I exploit medical examinations conducted in the 1958 British National Child Development Study (NCDS). The results point to the importance of childhood health conditions in determining what kinds of occupations individuals pursue in the labour market. In particular, I find that those who had mental health conditions before age 16 tend to select into less cognitive skill demanding jobs while those who had physical health conditions sort into less manual skill demanding jobs. The observed variation in job selections are found as important predictors of the health-related earnings gaps.

An important question is whether poor health during childhood influences later outcomes by restricting skill formation, or by mainly affecting future health. To further examine the sources of the earnings gaps associated with childhood health conditions, the fourth chapter develops and estimates a lifecycle model where childhood health conditions can affect formation of skills and health over the life course. The estimated model is used to quantify the relative importance of the multiple channels through which childhood health conditions may affect labour earnings. 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 health conditions on skill formation. The effects of childhood health status on health formation are also found to play important roles.

keywords: health, skills, task-based approach, dynamic factor analysis

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Chapter 1

Introduction

My dissertation studies the interplay between health and skills in shaping labour market outcomes. In chapter two, I examine the wage losses among older workers due to work-limiting health conditions. In chapter three, I document descriptive evidence regarding the long lasting effects of childhood health conditions on skill formation. Chapter four develops and estimates a lifecycle model where childhood health conditions can affect labour earnings both through skill formation and health formation. Each of these chapters aims to facilitate our understanding regarding how the two kinds of human capitals, health and skills, interact and evolve over the life course.

Workers face a substantial lifetime risk of developing a work-limiting health condition: the U.S. Social Security Administration estimates that a 20-year-old U.S. worker has a three in ten chance of becoming disabled before reaching full retirement age.[1] It is not surprising, therefore, that there is a large body of literature that investigates work-limiting health conditions and the roles that they play in shaping labour market

[1]U.S. Social Security Administration, "Disability Benefits," SSA Publication No. 05-10029, July 2011.

outcomes. Understanding how such health conditions affect earnings is a central task for designing social insurance programs including the Social Security Disability Insurance (SSDI) and the Medicare.[2]

The second chapter studies wage returns to having a work-limiting health conditions. I focus in particular on estimating how the wage returns vary depending on the characteristics of workers' occupations. Wolfe (1984) argues that appropriate measures of disability for labour market analysis relates to the inability to carry out a specific task. This argument corresponds to the fact that the U.S. Social Security Act defines disability as the inability due to health conditions to perform physically or mentally demanding tasks. In practice, the U.S. Social Security Administration determines eligibility of disability insurance applicants by assessing how their health conditions affect their productivity in conducting various tasks. While the task-specific nature of work-limiting health conditions has been acknowledged in the literature, it has not been its main focus. Indeed, the existing literature estimates the effect of health on earnings assuming that health is uniformly valued across occupations, regardless of differences in the tasks workers conduct within the occupations. The main objective of this chapter is to address this gap by investigating the potentially task-specific nature of work-limiting health conditions.

I take advantage of insights from task-based approaches that allow me to observe what kinds of tasks workers conduct within their occupations. Following the previous research, especially Poletaev and Robinson (2008) and Bowlus et al. (2016), task measures are obtained from the Dictionary of Occupation Titles (DOT) and assigned to the

[2]French and Jones (2011) study the Medicare program and Low and Pistaferri (2015) examine the SSDI program in the U.S. As a part of their structural models, they estimate how health conditions affect wages among older workers.

sample of male workers in the National Longitudinal Survey of Older Men (NLSM). Motivated by the task selection model of Heckman and Sedlacek (1985, 1990), I then estimate a wage equation that allows health conditions to have heterogeneous wage returns depending on the task content of the occupations. Following Yamaguchi (2014), a multidimensional learning-by-doing skill formation technology is estimated together with the wage equation.

The estimates indicate that the magnitude of health-induced wage losses differs substantially across occupations depending on their task characteristics. The results do not support the assumption commonly used in the previous literature that health is uniformly valued across occupations. Further, I find that about 60% of the health-related wage gap can be explained by the correlations between health and skills. Existing empirical literature on wage returns to work-limiting health conditions commonly use fixed-effect approaches that model unobserved heterogeneity as a single-dimensional factor. I show that the existence of work-limiting health conditions is correlated with time-varying components of multiple skills. This suggests that the fixed-effect approaches may not fully isolate the influences of the skill-health nexus. While task-based approaches have been mainly applied to study wage dynamics among young workers, this chapter demonstrates that such approaches are also useful to investigate the task-specific nature of health-induced wage losses among older workers.

In chapter three, I investigate the relationship between childhood health conditions and skill formation. A growing body of literature emphasizes the importance of health conditions during childhood for shaping skills and earnings over the life course.[3] Existing evidence suggests that certain childhood health conditions negatively affect school-

[3]See, e.g., Almond and Currie (2011) for a survey of the recent literature on childhood health.

ing outcomes. Little is, however, known as to whether and how such influences persist into skills used in the labour market beyond academic outcomes. While academic outcomes may be useful to measure certain types of skills developed during schooling periods, it is not clear whether the gaps in such skills can fully account for the long reach of childhood health conditions on labour earnings.

The objective of the third chapter is to complement the previous research on childhood health by providing a set of new evidence regarding the link between childhood health conditions and various skills used in the labour market. To this end, this chapter also adopts a task-based approach that allows me to observe how skills of individuals are used in conducting various tasks within their occupations. Task measures are obtained based on workers' self-ratings of skills/tasks in the UK Skills Survey. The measures are then assigned to the individuals in the 1958 National Child Development Study (NCDS) and their age profiles are examined between individuals with childhood health conditions and those without. Following the previous research, I distinguish mental and physical health conditions during childhood and investigate how these two types of health conditions, observed before labour market entry, affect the age profiles of the multidimensional, task-based skill portfolios.

The results point to the importance of childhood health conditions in determining what kinds of occupations individuals pursue in the labour market. In particular, I find that those who had mental conditions before age 16 tend to select into less cognitive skill demanding occupations. In contrast, those who had physical conditions are more likely to sort into less manual skill demanding occupations. The evidence supports the view that childhood health conditions affect occupational choice and, therefore, likely the accumulation of skills needed to perform specific tasks conducted within the occupations. In chapter three, I further show that the observed variation in occupation choices is a significant predictor of the earnings gaps associated with childhood health conditions.

An important question that cannot be addressed with the descriptive analysis is the extent to which the earnings gaps are generated by the effect of childhood health conditions on skill formation. It is not clear whether poor health during childhood influences later outcomes mainly by restricting skill formation, or by affecting future health. Quantifying the roles of the "skill channel" and the "health channel" is, however, empirically challenging. Choices on schooling, labour supply, and tasks may be driven not only by the underlying skills but also by other unobserved factors such as psychic costs or tastes for those choices. Health conditions may affect not only what individuals can do but also what they prefer to do. To estimate the effect of childhood health on skill formation from the observed choices, it is necessary to distinguish the influence of childhood health on skills and tastes. An explicit model of schooling and labour market choices is useful for this particular purpose.

In chapter four, I formulate and estimate a lifecycle model where childhood health conditions affect the dynamics of both skills and health over the life course. My framework embeds a multidimensional technology of skill formation and health formation into a dynamic model of schooling, labour supply and occupation choices. The model is estimated based on the NCDS data that provides results of medical examinations during the childhood. The estimated model is used to quantify the relative importance of alternative channels through which childhood health conditions affect labour earnings.

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 schooling and labour market choices. The results indicate 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 skill channel is also the main factor behind the earnings losses at younger ages among those with childhood physical health conditions. Further, I find that differences in tastes and health formation also play significant roles for both types of health conditions, especially at older ages. Overall, these results suggest that skills and health during childhood are complementary in producing future skills and labour market outcomes over the life course.

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Chapter 2

Specificity of Health Capital

2.1 Introduction

Understanding how health affects workers' earnings is essential for designing social insurance programs against work-limiting health conditions.[1] The U.S. Social Security Act defines "disability" as the inability due to health conditions to perform physically or mentally demanding tasks.[2] In practice, the U.S. Social Security Administration assesses eligibility of disability insurance applicants by evaluating how the applicants' health conditions limit their productivity in conducting various tasks given their health conditions and their skill portfolio. The task-specific nature of work-limiting health conditions has been acknowledged in the literature at least since Wolfe (1984).[3]

A large body of literature, however, estimates the effect of health conditions on

[1] See, e.g., French (2005), French and Jones (2011), and Low and Pistaferri (2015). They all estimate the effect of health on wages as a part of their structural models.

[2] In this chapter I use interchangeably the term "disability" and "work-limiting health conditions".

[3] According to Wolfe (1984), "disability is not simply an impairment - persistent abnormality of physiological function; it is job related" so that "the appropriate measure of disability for labour market analysis relates to the inability to carry out a specific task or job" (p.189).

earnings by modelling health explicitly or implicitly as a form of general human capital, following the health capital model of Grossman (1972). The existing empirical models routinely assume that workers' health is uniformly valued across occupations and workers.[4] The potentially task-specific nature of health-induced wage losses has not been a major focus of the previous research. Moreover, the existing empirical models typically abstract from important interplay between health and skills in determining labour market outcomes.[5]

The objective of this chapter is to investigate how health conditions affect wages depending on workers' skills and the characteristics of tasks they perform in the labour market. To this end, I apply a multidimensional task-based approach that characterizes various occupations as a bundle of tasks performed within the occupations.[6] With this approach, I observe what kinds of tasks individuals conduct in the labour market through their occupation choices. While task-based approaches have been mainly used so far to study wage dynamics among young workers, this chapter argues that this approach is also well-suited to investigate the task-specific nature of health-related wage losses among older workers.

This chapter makes three main contributions. First, I investigate the nexus between health conditions and skills. Skills are defined to be task-specific, following the recent literature of multidimensional skills, and I estimate task-specific skills based on task-specific occupational experience. Following Poletaev and Robinson (2008) and Bowlus et al. (2016), the task measures are obtained from the Dictionary of Occupation

[4]See, e.g., Jäckle and Himmler (2010) for an empirical model of wage determination with workers' characteristics. Currie and Madrian (1999) provide a survey of the literature.

[5]See Heckman (2012) for further discussions of a framework in which skills and health jointly affect socio-economic outcomes.

[6]See Sanders and Taber (2012) for a recent survey of the literature on task-based approaches and multidimensional skills.

Titles (DOT) that provides analyst ratings of tasks conducted by workers in various occupations in the U.S. The task measures are then assigned to the sample of workers in the National Longitudinal Survey of Older Men (NLSM). While most of the previous research regards skill heterogeneity as a nuisance parameter, I explicitly model a multi-dimensional technology of skill formation and show how various health conditions are correlated with skills.

The second main contribution of this chapter is to examine how health conditions affect wages depending on the nature of tasks that workers conduct in the labour market. Motivated by the model of Heckman and Sedlacek (1985, 1990), I estimate a task-based wage equation in which returns to workers' attributes are allowed to be task-specific. In estimating the parameters of the wage equation, selection biases may arise if individuals sort into the labour force and specific occupations based on their unobserved skill endowments. To the extent that the unobserved skills are correlated with observed health indicators, due to genetic reasons and health investments, the estimates from a wage regression on the health status may also suffer from a simultaneity bias. To deal with the endogeneity issues, this chapter adopts a correlated random effect approach (Wooldridge, 2010), following Yamaguchi (2012), and characterizes workers' unobserved skill heterogeneity with career histories available from the NLSM.

Finally, based on the estimates of the task-based wage equation, this chapter conducts a wage decomposition to isolate the contributions of skills and health in generating the observed wage gap between individuals with different health conditions. To estimate the causal effect of health on wages, previous research has commonly used fixed effect approaches that model unobserved heterogeneity of individuals as a single-dimensional, time-invariant nuisance parameter. In contrast, this chapter explicitly models and estimates workers' multidimensional time-varying skills from observed choices and characteristics. This approach allows me to quantify the extent to which the observed wage gaps between two individuals with different health conditions is driven by their skill heterogeneity. This analysis features the interplay between multidimensional skills and health in determining wages.

The outline of the chapter and a preview of the results are as follows. Section 2.2 explains the data sources and presents descriptive evidence regarding the nexus between observed health conditions and skills. Skills are measured based on a learning-by-doing skill formation technology, combining educational outcomes, work experiences, and other observed characteristics. Measures of time-varying skills are shown to be correlated significantly with emergence of work-limiting health conditions among older individuals. This evidence suggests that conventional "fixed effect" approaches may not fully remove the correlations between skills and health conditions.

Section 2.3 develops a model of wage determination that allows task-specific returns to skills and health. By explicitly modelling how skills evolve and how skills and health affect wages, the framework allows me to disentangle the link between skills, health, and wages. This section also discusses approaches to deal with potential endogeneity issues in estimating the wage equation.

Section 2.4 first presents estimates of the task-specific returns to work-limiting health conditions. There is a sizeable difference between occupations in terms of their task characteristics. I show that health-induced wage losses are task-specific. Indeed, the results indicate that the magnitude of health-induced wage losses is not uniform across occupations. An explicit model of skill formation is used not only to isolate the partial effect of health on wages, but also to investigate the extent to which an observed wage gap between two health groups is driven by the differences in their skills. The average wage among individuals with work-limiting health conditions is about 25% less than that among individuals without such conditions. The wage decomposition analysis indicates that about 60% of this wage gap is attributable to differences in their skills. Importantly, I show that work-limiting health conditions are correlated with time-varying components of the multidimensional skills. This result suggests that conventional fixed effect approaches may not fully remove the influences of the skill-health nexus. Finally, Section 2.5 provides some discussion and conclusions.

2.2 The Skill-Health Nexus

2.2.1 Data Sources

I combine two datasets to conduct the descriptive analysis presented in this section. The National Longitudinal Survey of Older Men (NLSM), part of the NLS Original Cohort project, provides data on health conditions, lifespan, completed education, and labour market outcomes including detailed census occupations codes. The data on occupational task contents come from the 1977 edition of the Dictionary of Occupational Titles (DOT) compiled by the U.S. Department of Labor.

National Longitudinal Study of Older Men

The NLSM includes 5,020 men born in the years 1906-21 who are 45-59 in 1966. The original sample was designed to represent the civilian noninstitutionalized population of the United States at the time of the initial survey. The respondents were surveyed annually between 1966-1969. After that, they were interviewed three years out of every five until 1983. In 1990, a final interview was conducted with either living respondents, or widows/other family members of deceased respondents. To study the nexus between health, skills, and wages, I draw a sample from the 1966-1983 surveys, because there is a relatively long gap between the 1983 survey and the 1990 survey and all the respondents reach the early eligibility age for the Social Security retirement benefits (age 62) by 1983. I calculate lifespan of each respondent based on the mortality information obtained in 2008 from the National Death Index database and the Social Security database.

The entire sample was used to construct all relevant variables including health, education, and labour market outcomes. Sampling weights calculated at the initial survey are used. The NLSM uses the 3-digit 1960 census occupational classification system to record workers' occupations throughout the sampling period so there is no break in occupation coding unlike other panel surveys that are commonly used in the literature.[7] At the initial survey in 1966, all the respondents are asked to provide information regarding the occupation title and the job tenure of their post-schooling first job, the longest job, the previous job, and the current job. I use this career information to construct occupation histories up to the initial survey year. Hourly wages are calculated by dividing weekly labour income by weekly hours of work, and are deflated by the 1980 PCE Index.

[7]For instance, the Panel Study of Income Dynamics used initially a one-digit occupation code, and later a two-digit until 1981. Since 1981 the three-digit 1970 Census code became standard for the main jobs of employed Heads and Wives.

Dictionary of Occupational Titles

The DOT provides on-site analyst ratings of 12,741 jobs with respect to about 50 characteristics of five main types. The first type has characteristics that measure levels of interactions with "people", "data" and "things". The other four types measure (1) general educational development, broadly indicating the level of education required for the job, (2) aptitudes for various tasks, (3) temperaments for aspects of the job, and (4) physical requirements for the job.

Subsets of the DOT characteristics are chosen as the relevant characteristics for three predefined basic tasks. Task indices are constructed as the first principle component in a factor analysis using these subsets. The subsets are chosen to allow some comparability with the previous literature, especially Poletaev and Robinson (2008). The three pre-specified tasks are given the following shorthand labels: (1) "cognitive", (2) "motor", and (3) "manual". The subsets of DOT characteristics for each of these tasks are given in Table 2.1.

The data set for the factor analysis is the 1971 Current Population Survey (CPS) dual coded file that includes both 1960 census occupation codes and employment weights for DOT jobs. The analysis constructs each task index τ^k as a linear combination of the estimated scoring coefficients and standardized values of the relevant J_k DOT characteristics scores for each task k:

$$\tau^k = \sum_{j=1}^{J_k} \beta_j c_j, \quad k = 1, 2, 3, \tag{2.1}$$

where β_j is the scoring coefficient for the standardized value of the j-th DOT characteristic, c_j, in the subset for the k-th task. Given the estimate of the scoring coefficients

Table 2.1: Classification of DOT Characteristics

(1) **Cognitive**	(2) **Motor**	(3) **Manual**
(a) DOT code ratings		
data, people	things	
(b) General educational development		
reading, math, literacy		
(c) Aptitude		
intelligence, verbal	spacial	eye-hand-food coordination
	form perception	
	motor coordination	
	finger/manual dexterity	
	color discrimination	
(d) Temperaments		
direction-control-planning	tolerances	
dealing with people		
(e) Physical requirements		
		strength
		physical demand 2, 3, 5

vector from this factor analysis, and the means and standard deviations of the DOT characteristics for the individuals in the sample, the three task indices can be computed for any individuals in any data set with three digit occupation codes for which mean DOT characteristic values for each three digit census occupation code can be computed. Following Bowlus et al. (2016), I compute the three DOT task indices for each of the 3-digit 1960 census occupations.

The constructed task indices are not required to be orthogonal as in a standard factor analysis. The computed tasks are, in fact, correlated. The correlation matrix for the population used in the factor analysis is given in Table 2.2. There is a sizeable negative correlation between "cognitive tasks" and "manual tasks". Note that while "motor tasks" and "manual tasks" are positively correlated, there is a positive correlation between “cognitive tasks” and “motor tasks”.

Table 2.2: Correlation among Task Indices: CPS 1971

	(2) Motor	(3) Manual
(1) Cognitive	0.157	-0.361
(2) Motor		0.218

2.2.2 Measuring Multidimensional Skills

The past literature on heterogeneous human capital has made a distinction between tasks and skills, though often they have been treated interchangeably. Heckman and Sedlacek (1985, 1990) introduced the concept of a task-based production function through which labour output could be produced by workers conducting tasks with their endowed task-specific skills. A recent discussion of the distinction in the context of the DOT based measures used in this chapter is provided in Yamaguchi (2012). The basic concept is that workers, at any point in time, have a vector of skills that can grow or deteriorate over the lifecycle and are transferable across occupations. The occupations produce output through occupation specific bundling of tasks associated with these skills. Skills are measured based on the history of tasks chosen in the past, motivated by a learning-by-doing skill formation process.

As in Yamaguchi (2014), I assume that skills are accumulated through a learning-by-doing technology as in Equation (2.2), and that the endowment of the k-th skill ($k = 1, 2, 3$) at labour market entry is linear in observed characteristics z_i and unobserved heterogeneity $\tilde{\theta}_i^k$ as in Equation (2.3):

$$\begin{aligned}\ln s_{it+1}^k - \ln s_{it}^k &= d_{it}\left(\tilde{\beta}_1^k + \tilde{\beta}_2^k e_{it} + \tilde{\beta}_3^k \tau_{it}^k\right) &(2.2)\\ \ln s_{it_0}^k &= z_i'\tilde{\beta}_0^k + \tilde{\theta}_i^k, &(2.3)\end{aligned}$$

where s_{it}^k is the k-th skill of the individual i at period t, d_{it} is an indicator of labour force participation, e_{it} is general labour market experience, and τ_{it}^k is the k-th task characteristic. The observed individual characteristics z_i include years of completed education and cohort membership. Note that the skills stay constant over two periods if the individual does not work. The skill formation technology features diminishing returns to work experience if $\tilde{\beta}_1^k > 0$ and $\tilde{\beta}_2^k < 0$.

It is straightforward to show that, under the skill formation technology, skills in each period consist of observable components and unobservable permanent heterogeneity as in Equation (2.4) after rescaling the parameters:

$$\ln s_{it}^k = z_i'\beta_0^k + \beta_1^k e_{it} + \beta_2^k e_{it}^2 + \beta_3^k x_{it}^k + \theta_i^k, \quad k = 1, 2, 3, \tag{2.4}$$

where $x_{it}^k = \sum_{j=t_0}^{t-1} d_{ij}\tau_{ij}^k$ are referred to as task-specific work experience measures. Throughout this chapter I measure multidimensional task-specific skills based on Equation (2.4). Note that skills depend on the history of past tasks, but not directly on the tasks that workers currently choose in the labour market.

2.2.3 Health Measures

Work-limiting Health Conditions

The NLSM offers two distinct kinds of health measures. The first kind of health measure is obtained through asking whether individuals have any health condition that limit the kind or the amount of work they can perform.[8] The second kind of health measure is provided by a self-rating of one's health status compared with others of the same age on a discrete ordinal scale. Specifically, the respondents of the NLSM are asked the following question "Would you rate your health compared with other men of about your age as excellent, good, fair, or poor?"[9] I focus mainly on the measures of work-limiting health conditions in this chapter because they are likely more relevant to labour market outcomes and the responses are easily comparable between individuals of different ages.

The left panel of Figure 2.1 presents the age profiles of work-limiting health conditions. At age 45, around 17% of individuals report work-limiting health conditions. This fraction increases to around 24%-25% by age 55 and rises sharply afterwards to around 50%-55% by age 65. The age profiles are similar across cohorts with the earlier cohort somewhat less likely to report health conditions than the later cohort especially around age 60. The higher prevalence of work-limiting health conditions among the later cohort corresponds with lower labour force participation rates as shown in the

[8] The NLSM respondents are asked whether their health conditions prevent them from working if they are not employed during the survey week. If they are employed they are asked whether they have health conditions that limit either the kind of work or the amount of work they can do. These questions are asked first in 1966 and later in 1969, 1973, 1975, 1978, 1980, and 1983. In 1971, 1976, and 1981, the respondents are asked the following question regardless of their employment status: "Do you have any health problem or condition that limits in any way the amount or kind of work you can do?"

[9] The NLSM asks the same question to the respondents in 1969, 1978, 1980, 1981, 1983, and 1990 after asking the question in the initial survey in 1966.

right panel.

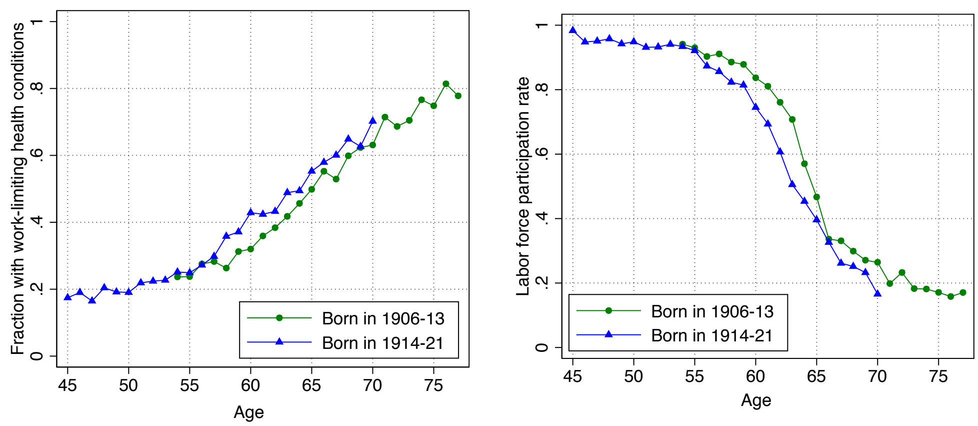

Figure 2.1: Age Profiles of Work-limiting Health Conditions and Labour Force Participation Rates by Cohort

Characterizing Work-limiting Health Conditions

The NLSM data provide additional information regarding the characteristics of the respondents' health conditions. In particular, the respondents report whether their health conditions limit various daily activities as well as the types of their health conditions. I categorize the daily activities into four broad groups: (1) physical, (2) social, (3) sensory, and (4) other. The health conditions are classified into three groups: (1) somatic, (2) mental, and (3) other. The specific daily activities and the health conditions in each category are given in Table 2.3.

Table 2.4 presents the fractions of individuals reporting each type of daily activity limitations and specific health conditions. I also tabulate the fractions of individuals reporting fair/poor health status compared to others in the age. In addition, this table also shows the length of remaining lifespans for each group defined by age and health reports.

Table 2.3: Classification of Daily Activities and Specific Health Conditions

A. Daily activities	
(1) Physical	walking, using stairs/inclines, standing for long time, stooping, kneeling, crouching, lifting, reaching, handling/fingering
(2) Social	dealing with people
(3) Sensory	seeing, hearing
(4) Other	any other activity
B. Specific conditions	
(1) Somatic	pain, weakness, lack of strength, aches, swelling. sick feeling, fainting spell, dizziness, troubled breathing, tiring easily
(2) Mental	nervousness, tension, anxiety, depression
(3) Other	any other condition

Table 2.4: Characteristics of Work-limiting Health Conditions

	Overall		Work-limiting health?			
			Yes		No	
Ages	46-55	56-65	46-55	56-65	46-55	56-65
Daily activity limitations						
(1) Physical	0.21	0.42	**0.75**	**0.82**	0.05	0.16
(2) Social	0.03	0.04	0.09	0.08	0.01	0.01
(3) Sensory	0.07	0.18	0.25	0.34	0.02	0.08
(4) Other	0.02	0.02	0.06	0.04	0.01	0.01
Specific health conditions						
(1) Somatic	0.16	0.32	**0.59**	**0.71**	0.03	0.06
(2) Mental	0.09	0.13	0.32	0.30	0.01	0.02
(3) Other	0.01	0.01	0.05	0.03	0.00	0.01
Fair/Poor health status	0.22	0.30	0.57	0.61	0.11	0.11
Remaining lifespan (years)	21.52	16.40	17.99	13.68	22.67	18.19

As individuals get older, the prevalence of physical or sensory activity limitations increases while the prevalence of social activity limitations declines slightly. Most of the reported work-limiting health conditions are somatic and limit physical activities, both at earlier and later ages. While about 34-35% of work-limiting health conditions are mental, less than 10% of the work-limiting health conditions affect social activities. It is clear that work-limiting health conditions are typically characterized as limitations on physical or sensory activities. Individuals who do not report work-limiting heath conditions typically have no daily activity limitations and no specific health conditions. Even among individuals without work-limiting health conditions, the most common health conditions are somatic and involve limitations in physical activities, if any.

While the proportion of individuals reporting relatively fair/poor health status increases with age, this trend is likely driven in part by the fact that more individuals report work-limiting health conditions at later ages. Indeed, the age pattern is substantially masked once work-limiting health conditions are controlled for. Note that the existence of work-limiting heath conditions is correlated with a shorter lifespan: individuals with work-limiting health conditions live about 4.3-4.5 years less than those without. The gaps in lifespan are statistically significant at the 1% level.

2.2.4 Descriptive Evidence of the Skill-Health Nexus

Estimating the causal effect of health on wages requires isolating health from other kinds of heterogeneity that correlates with wages such as skills and job characteristics. Most previous research has handled the skill-health nexus by modeling unobserved heterogeneity using a fixed effect approach. This approach may be justified if skills correlated with health are time-invariant. The correlations between health conditions and occupations are typically managed by using occupation dummies or task characteristics of the occupations.[10]

Table 2.5 presents how changes in health reports are correlated with work experience, employment status, and the task content of occupations. To measure changes in health reports, I select individuals who did not report any work-limiting health conditions in the initial survey. Then, I estimate how observed characteristics are correlated with health reports after 5 years, 10 years, and 15 years. To measure changes in observed skill characteristics, work experience measures are calculated based on additional experience in labour force and tasks since the initial survey. Task-specific work experience measures are normalized to have a unit standard deviation. All estimates in Table 2.5 show an average partial effect based on a probit model. Individuals with longer general work experience are less likely to report work-limiting health conditions. This may be driven partly by the negative effect of work-limiting health conditions on labour force participation. While individuals may over-report their work-limiting health conditions when out of the labour force, I do not find evidence that current labour force status is systematically correlated with current health reports conditional on past work experiences and past health reports.[11]

Individuals with more extensive experience in complex cognitive tasks are less likely to report work-limiting health conditions: a standard deviation higher experi-

[10]Haveman et al. (1994) include job characteristics based on DOT task measures in their wage equation, similar to this chapter. They, however, do not control the correlations between health conditions and task-specific work experience.

[11]Individuals may systematically change their subjective health reports depending on their labour force status. A person without a paid job might be inclined to exaggerate one's health conditions to justify inactivity since health may represent one of the few "legitimate" reasons for a working aged individual to be out of labour force (Bound, 1991). Using objective health measures as instruments, Lindeboom and Kerkhofs (2009) show that individuals report their health conditions differently depending on their labour force status.

Table 2.5: Correlation between Health Reports and Observed Skills Characteristics

	Outcome: work-limiting health		
Years since initial survey	(1) 5 yrs	(2) 10 yrs	(8) 15 yrs
Education	-0.0056**	-0.0094***	-0.0049
	(0.0024)	(0.0036)	(0.0043)
General exp	-0.0681***	-0.1507***	-0.1850***
	(0.0256)	(0.0325)	(0.0366)
Cognitive exp	-0.0454**	-0.0371	-0.0333
	(0.0200)	(0.0252)	(0.0290)
Motor exp	0.0198	-0.0208	-0.0084
	(0.0191)	(0.0210)	(0.0233)
Manual exp	0.0025	0.0635***	0.0721***
	(0.0169)	(0.0209)	(0.0234)
Current cognitive task	0.0257	-0.0155	-0.0186
	(0.0232)	(0.0309)	(0.0400)
Current motor task	-0.0572**	-0.0290	-0.0670*
	(0.0249)	(0.0294)	(0.0392)
Current manual task	-0.0030	-0.0533**	-0.0560*
	(0.0190)	(0.0264)	(0.0362)
Currently not employed	0.1245	-0.0387	-0.1323
	(0.1137)	(0.0889)	(0.1108)
Work-limiting health in initial survey?	No	No	No
Obs.	2972	2494	2016

Note: All estimates show an average partial effect based on a probit model. Standard errors in parentheses are clustered at the individual level. Ages are controlled in all specifications. The work-limiting health indicator takes the value 1 if individuals report work-limiting health conditions and 0 otherwise. Work experiences measure additional experiences since the initial survey in 1966. Task-specific work experiences are normalized to have a unit standard deviation. Task indices take the value 0 if individuals are not employed. *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.10$.

ence in cognitive tasks leads to about 4.5 percentage points lower reporting of work-limiting health conditions five years after the initial survey. In contrast, individuals with more extenive experience in manual tasks are more likely to report work-limiting health conditions: a standard deviation higher experience in manual tasks leads to about

6.4-7.2 percentage points higher reporting of work-limiting health conditions ten years after the initial survey.[12] This is not surprising given the fact that most of the reported work-limiting health conditions involve a somatic condition and limitations in physical activities. Note that the "complexity" of the current occupation in terms of manual tasks is negatively correlated with health reports after controlling for past work experience. This may be because those who stay in a manual-task complex occupation are relatively healthier than others.

Table 2.5 shows that changes in health reports are correlated with general and task-specific work experience even after controlling for current employment status and occupational characteristics. In particular, the emergence of work-limiting health conditions is associated with slower accumulation of work experience and more intensive exposure to manual tasks. This suggests that modelling individual heterogeneity as a single-dimensional time-invariant parameter may not completely remove the correlation between skills and health reports.

2.3 Estimating a Task-based Wage Equation

2.3.1 A Task-based Wage Equation

The descriptive evidence presented in the last section indicates that workers' health conditions are correlated both with their work experiences and task choices in the labour market. This section develops a framework to disentangle the link between health, skills, tasks, and wages.

[12]Fletcher et al. (2011) show that cumulative exposure to physically demanding or hazardous occupations negatively affects self-assessed health status among older workers. Cropper (1977) provides a model of occupation choices as health investments.

In estimating an occupational choice model, researchers often aggregate occupations arbitrarily into a small number of broad classes, such as blue collar and white collar, to reduce computational burdens. Task-based approaches instead characterize occupations as a set of tasks. This approach facilitates comparisons across occupations by their task contents. The task-based wage equation provides a clear interpretation as to how workers' attributes are rewarded depending on the nature of the tasks they conduct in the labour market. Consider a static economy in which labour is the only factor of production. Assume that workers, at any point in time, are endowed with a vector of attributes that consist of skills and health: $\theta = (\mathbf{s}, h)$ where $\mathbf{s} = (s^1, \cdots, s^K)$ is a K-dimensional vector of task-specific skills and h denotes an observed indicator of health. Occupations are characterized by specific bundling of tasks τ. Wages are paid in accordance with the value of the marginal product of labour:

$$w = P(\tau)Q(\tau, s, h). \tag{2.5}$$

Here, $P(\tau)$ denotes the price of the labour output that depends on the task characteristics τ of the occupation. The labour output Q is produced by a match between the task τ and the worker with productive attributes θ. Imposing a Cobb-Douglas functional form on the output function results in the following specification of the log-wage equation:

$$\ln \tilde{w}_{it} = \gamma_0(\tau_{it}) + \gamma_1(\tau_{it})h_{it} + \sum_{k=1}^{K} \left[\gamma_2^k\left(\tau_{it}^k\right) \ln s_{it}^k\right] + \eta_{it}, \tag{2.6}$$

where η_{it} is an i.i.d. wage measurement error. In the empirical model, the wage equation parameters are defined as follows:

$$\gamma_j(\tau_{it}) = \gamma_{j,0} + \gamma_{j,1}\tau^1_{it} + \gamma_{j,2}\tau^2_{it} + \gamma_{j,3}\tau^3_{it}, \quad j \in \{0, 1\} \tag{2.7}$$

$$\gamma^k_2\left(\tau^k_{it}\right) = \gamma^k_{2,0} + \gamma^k_{2,1}\tau^k_{it}, \quad k \in \{1, 2, 3\}. \tag{2.8}$$

The returns to task-specific skills s^k_{it} can vary depending on the characteristics of the corresponding tasks τ^k_{it}. As in a Roy model, workers' attributes have heterogeneous returns across different tasks. Workers therefore may sort into different tasks depending on their attributes. The task-based wage equation generalizes the previously estimated Mincerian health-wage equations by modeling the health-related wage losses to be potentially task-specific.

2.3.2 Dealing with Self Selection and Simultaneity

This chapter estimates the wage equation (2.6) with skills measured based on the equation (2.4). The parameter estimates may suffer from selection biases if individuals select into labour force and tasks/occupations according to their unobserved skills. We would not be able to estimate the returns to the workers' observed attributes if those attributes are corrlated with the unobserved skills and if the unobserved skills affect wages. Further, the health capital model of Grossman (1972) suggests that high earners invest more on health as the marginal benefits of health investment rises with earnings. Therefore, observed health status may also depend on the unobserved initial skills, thereby causing a simultaneity bias.[13]

[13] Lee (1982) and Haveman et al. (1994) use a simultaneous equation model to deal with the reverse causality problem. Another conventional approach is to model unobserved individual heterogeneity that correlates both with health and wages. See, e.g., Jäckle and Himmler (2010).

Yamaguchi (2014) argues that neither conventional first differencing nor demeaning do not necessarily alleviate those issues as the permanent unobserved skills are interacted with the time-varying observables in the wage equation (2.6). To handle the correlations between observed characteristics and the unobserved skill heterogeneity, this chapter also adopts a correlated random effects approach (Wooldridge, 2010) and models the permanent unobserved skills θ_i^k as a function of observed labour market histories and lifespans:

$$\theta_i^k = \beta_4^k \bar{\tau}_i^k + \beta_5^k \bar{d}_i + u_i^k, \quad k \in \{1, 2, 3\}. \tag{2.9}$$

To the extent that the observed career/life histories reflect unobserved skills heterogeneity, we can effectively "control" the influences of such heterogeneity by incorporating the observed histories into the wage equation (2.6). Individuals with a longer career or those conducting complex tasks in the labour market are likely to be high-skilled. Following Yamaguchi (2014), I include average task levels $\bar{\tau}_i$ and labour force participation $\bar{d}_i$ over the lifecycle. Inclusion of these factors likely captures unobserved skills that generate non-random selections into labour force and particular tasks/occupations in the labour market. Appendix A.1 tests the null hypothesis that the additionally included variables are uncorrelated with unobserved skills. The null hypothesis is soundly rejected, indicating that these variables are useful in controlling for unobserved skills of the individuals.

I assume that the residual unobserved skills (u_i^k) are uncorrelated with the wage measurement error and satisfy the following conditional mean independence restriction:

$$E\left(u_i^k | h_{it}, z_i, d_{it}, e_{it}, x_{it}, \tau_{it}, \bar{\tau}_i, \bar{d}_i\right) = 0. \tag{2.10}$$

This condition ensures that the health indicator (h_{it}) and the task choices (τ_{it}) are conditionally uncorrelated with unobserved skills, eliminating the endogeneity issues due to self-selection and simultaneity. The parameters in the skills equation (2.4) and the wage equation (2.6) can be jointly estimated by exploiting the moment restriction provided in Equation (2.10).

2.4 Estimation Results

This section presents the main empirical results of this chapter. The first subsection investigates and demonstrates the task-specific nature of health-related wage gaps. The following subsection proposes and implements a wage decomposition analysis to isolate the contributions of skills and health in generating the observed wage gaps associated with the indicator of work-limiting health conditions.

2.4.1 Task Specificity of Health-related Wage Gaps

Table 2.6 reports the estimates for the parameter γ_1 in Equation (2.6) that characterizes the effect of work-limiting health conditions on log-wages. Following the descriptive analysis in the previous section, I distinguish three types of pre-defined tasks: (1) cognitive tasks, (2) motor tasks, and (3) manual tasks. Note that the task-based wage equation allows the wage effect of health conditions to vary with the three tasks.

The estimates support the views of Wolfe (1984) that the labour market consequences of work-limiting health conditions are task-specific. In particular, the estimates indicate that the negative wage-effect of work-limiting health conditions is larger

Table 2.6: Wage Equation Parameters: Returns to Work-limiting Health Conditions

	Estimate	Std. Error
Intercept	-0.0931**	0.0461
Cognitive	0.0053	0.0194
Motor	0.0537***	0.0182
Manual	-0.0423**	0.0171

Note: This table shows the estimates for the parameter β_1 in Equation (2.6). Standard errors are clustered at the individual level. The sample consists of 3,804 men. The total number of observations is 15,145. *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.10$.

in occupations that command higher manual tasks.[14] This is not surprising given the fact that most work-limiting health conditions involve a limitation in physical activities. Interestingly, the estimates indicate also that the negative wage-effect of work-limiting health conditions is smaller in occupations that command higher motor tasks. While motor tasks and manual tasks are positively correlated, these results suggest the importance of distinguishing these two types of "physical" tasks. While previous research has commonly assumed that the wage returns to health conditions are uniform across workers in different occupations, the estimates presented in Table 2.6 do not support this assumption.

Researchers often rely on fixed-effect approaches to deal with correlations between health and other unobserved factors that may affect both health and wages. Such approaches may not work well with wage models in which health conditions are interacted with period-by-period choices. The estimates in Table 2.6 suggest the importance of modelling interactions between health and tasks in wage equations.

The estimates suggest that the wage effect of work-limiting health conditions differ across occupations as occupations are heterogeneous in bundling the tasks. Table 2.7

[14]See Table 2.1 for the DOT characteristics that define manual tasks.

reports the average task characteristics of each 1-digit census 1960 occupation along with estimated wage effect of having a work-limiting health condition. Note that the estimates are based only on the parameter estimates in Table 2.6 and the task characteristics of each occupation so that they do not reflect the differences in workers' skills in each occupation.

Table 2.7: The Partial Effect of Work-limiting Health on Wages at Each 1-digit Occupation

1960 Census 1-digit Occupation	Cognitive	Motor	Manual	Estimate	Std. Error
1. Professional/technical	2.9027	2.0262	0.5179	0.0091	0.0141
2. Farmers/farm managers	1.4307	1.5866	2.2038	-0.0935***	0.0154
3. Managers/officials/proprietors	2.3587	0.9123	0.5273	-0.0539***	0.0189
4. Clerical	1.6589	1.3432	0.3815	-0.0283**	0.0136
5. Sales	2.0694	0.6586	0.2847	-0.0588***	0.0145
6. Craftsman/foreman	1.4287	2.4893	1.5987	-0.0195*	0.0112
7. Operatives	1.1118	2.0857	1.4796	-0.0378***	0.0121
8. Private household workers	0.6577	1.1775	0.8892	-0.0640***	0.0165
9. Service	1.3568	1.3042	0.5997	-0.0846***	0.0115
10. Farm labourers	1.3906	1.6503	2.0635	-0.1125***	0.0195
11. labourers	0.8677	1.3816	2.3852	-0.1152***	0.0186

Note: Standard errors are clustered at the individual level. *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.10$.

The estimated wage effects of work-limiting health conditions are the largest among occupations that command relatively high manual tasks and low motor tasks such as farmers and labourers: the wage losses are around 9%-12%. The wage losses are substantially smaller in occupations that command relatively high motor tasks and low manual tasks. In particular, the estimated health-related wage loss is not statistically different from zero at the professional and technical occupations.

The results shown in Table 2.7 highlight the heterogeneity in health-related wage losses across occupations and provide an explanation behind the heterogeneous wage losses. While some of the previous research acknowledged the correlations between health and occupation choices, such correlations were often ignored or modelled as nuisance parameters.[15] Allowing rich interactions between occupation dummies and health indicators can be computationally demanding. Further, it is not clear how we can interpret the heterogeneity in health-related wage losses across occupations without knowing the characteristics of those occupations. The task-based wage equation provides a clear interpretation as to how health affects wages depending on the task contents of the occupations.

2.4.2 Decomposing the Health-related Wage Gap

Contributions of Skills/Tasks and Health

The estimates presented in the last section demonstrate significant correlations between the observed skill measures and the indicator of work-limiting health conditions. This suggests that a wage gap between individuals with work-limiting health conditions and those without may be in part due to the differences in their skills. Unlike fixed-effect approaches, the task-based wage equation explicitly takes into account the correlations between health and skills. This enables me to "partial out" the influences of the skill-health nexus in generating the wage gap between individuals with work-limiting health conditions and those without. In this section I estimate the contributions of skills and tasks in generating the health-related wage gap given the the estimates from the task-based wage equation and the skill formation equation.[16]

Table 2.8 decomposes the health-related wage gap into five components: the first

[15] See, e.g., the discussions in Jäckle and Himmler (2010).
[16] Appendix A.2 presents the estimates of the model parameters.

component arises due to the differences in task choices, the next three components reflect differences in task-specific skills, and the last component shows the partial effect of a work-limiting health condition. Note that both the wage structure and the skill formation technology are common for all the individuals. Individuals with work-limiting health conditions earn about 25% lower hourly wages than those without such conditions. The partial effect of a work-limiting health condition is found to be substantially smaller than their overall wage gap: the wage gap due to a work-limiting health condition is found to be about 7.9% after controlling for the skill gaps and task choices. The differences in cognitive skills explain about 44% ($\approx 0.1110/0.2502$) of the wage gap and the the differences in terms of manual skills/tasks explain additionally about 18% ($\approx 0.0451/0.2502$) of the wage gap. The wage decomposition demonstrates that about 60% of the overall health-related wage gap is attributable to the differences in the skill portfolios. These results point to the importance of the interplay between health and skills to account for health-related wage gaps. The differences in the observed characteristics, including the skill measures, work-limiting health conditions, and the task choices, can account for about 81% of the observed wage gap.

Disentangling the Skill-Health Nexus

The estimates presented in Table 2.8 indicates that the health-related wage gap is largely driven by the correlation between work-limiting health conditions and two types of skills: the cognitive skills and the manual skills. Table 2.9 further decomposes skills at each period of time into the following three components: the first component shows the effect of education on the skill, the second component is the effect of general and task-specific experiences on the skills, and the final component reflect the controlled

Table 2.8: Decomposition of Health-related Wage Gap

	Estimate	Std. Error
Tasks	0.0225	0.0167
Cognitive skills	-0.1110***	0.0320
Motor skills	0.0104	0.0112
Manual skills	-0.0451***	0.0201
Health	-0.0786**	0.0378
Unobs.	-0.0482***	0.0104
Overall	-0.2502**	0.0991

Note: The wage structure and the skill formation technology are common for all the individuals. Standard errors are clustered at the individual level. $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.10$.

factors defined in Equation (2.9). Again,both the wage structure and the skill formation technology are assumed to be common for all the individuals.

Table 2.9: Further Decomposition of the Skill Components

	Estimate	Std. Error
Cognitive skills:		
Intercept	-0.0034***	0.0014
Education	-0.0836***	0.0232
Experience	-0.0363***	0.0191
Other factors	0.0123	0.0112
Overall	-0.1110***	0.0320
Manual skills:		
Intercept	-0.0240***	0.0091
Education	-0.0028	0.0128
Experience	0.0454**	0.0211
Other factors	-0.0637***	0.0253
Overall	-0.0451***	0.0201

Note: The wage structure and the skill formation technology are common for all the individuals. Standard errors are clustered at the individual level. $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.10$.

Note that the wage gap due to the differences in cognitive skills/tasks is largely due to the fact that individuals with work-limiting health conditions have relatively low levels of education that lead to a lower level of cognitive skill endowment. The estimates suggest also that they accumulate such skills relatively slowly because they tend to work in occupations that command low levels of cognitive tasks.

In contrast, individuals with work-limiting health conditions have relatively higher manual skills as they tend to work in occupations that command high levels of manual tasks. However, the positive effect of higher manual skills on wages is offset by the wage losses from working in manual-task intensive occupations and by the effect of their relatively low endowment of manual skills.

The existence of health conditions is correlated with multiple skills, as shown in Table 2.9. While it is common to model unobserved heterogeneity as a single dimensional object, such an approach may not fully capture the skill differences between individuals with and without specific health conditions to the extent that different skills evolve differently over the lifecycle.[17] The multidimensional skills approach pursued in this chapter therefore provides a useful framework to disentangling the sources of health-related wage gaps.

2.5 Conclusion

Health capital models define health as a form of general human capital. Accordingly, previous research commonly assumes that health characteristics are uniformly priced across occupations. Adopting a multidimensional task-based approach, this chapter

[17] Bowlus et al. (2016) show that multidimensional skills do not have a homogeneous age profile.

estimates a wage equation that allows health conditions to have heterogeneous effects on wages depending on the nature of tasks that workers conduct in the labour market. The estimates indicate that workers performing complex manual tasks are likely to suffer from a larger wage loss given a work-limiting health condition. This suggests that the effects of certain health conditions on wages are task-specific. I show that the magnitude of health-induced wage losses differs substantially across occupations depending on their task characteristics.

This chapter also demonstrates that measured health and skills are highly correlated so that a wage gap between two individuals with and without work-limiting health conditions does not necessarily reflect the partial effect of such health conditions on wages. To deal with the influences of the skill-health nexus, this chapter estimates a wage equation that explicitly takes into account the correlations between skills and reported health conditions. In contrast to most of the health literature, this chapter models multidimensional skills. I find that about 60% of the overall wage gap between individuals with work-limiting health conditions and those without is due to the differences in their skill portfolios. I further show that work-limiting health conditions are correlated with the time-varying components of the multidimensional skill portfolio. The evidence suggests that econometric models with a univariate, time-invariant unobserved factor may not be fully successful in isolating the partial effect of health on wages.

Estimating how health affects earnings is a central task to designing social insurance programs for individuals with work-limiting health conditions. The evidence presented in this chapter suggests that simple wage regressions on health characteristics may overstate the magnitude of health-induced wage losses. This chapter demonstrates that multidimensional task-based approaches are useful to gain a deeper understanding of the task-specific nature of work-limiting health conditions.

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Chapter 3

The Long Reach of Childhood Health on Skills

3.1 Introduction

Growing evidence points to the importance of childhood health conditions in shaping skills and earnings over the life course (Currie, 2009, Almond and Currie, 2011a). Models of human capital formation suggest that health conditions may slow down skill growth due to the complementarities between health and skills in producing later skills (Heckman, 2007, Cunha and Heckman, 2009). Health conditions, therefore, may have a persistent effect on skill formation if they appear in a "sensitive period" of skill formation including childhood.[1]

To investigate the nexus between childhood health and skills, the existing literature

[1] Cunha and Heckman (2007) introduced the concept of sensitive periods for human capital formation. Cunha and Heckman (2008) and Cunha et al. (2010) estimate a multi-stage human capital formation technology and show that productivity of human capital investment varies substantially with development stages.

has focused primarily on academic outcomes such as test scores and years of schooling. Influential early research has shown that health conditions *in utero*, typically measured by birth weight, have long-lasting influences on various academic outcomes.[2] More recent studies have made similar observations regarding health conditions that tend to arise in later development stages, including various types of physical and mental health conditions (Case et al., 2005, Currie and Stabile, 2006, Oreopoulos et al., 2008, Currie et al., 2010). Despite these findings, little is currently known as to whether and how childhood health conditions affect skills beyond academic outcomes. While academic outcomes may be useful to measure certain academic skills developed during schooling periods, it is not clear whether differences in such skills can fully account for the long reach of childhood health conditions on labour market earnings.

The objective of this chapter is to complement the previous research by providing new evidence regarding the link between childhood health conditions and various skills used in the labour market. To this end, this chapter adopts a multidimensional skills/-tasks approach that characterizes various occupations as a bundle of skills/tasks used within the occupations. In this approach, I observe how the skills of individuals are used in the labour market through their occupation choices. Evidence from various disciplines suggests that different types of health conditions affect different kinds of skills. This chapter argues that the multidimensional skills/tasks framework is useful to investigate how specific kinds of childhood health conditions affect specific skills.

The main contributions of this chapter are two-fold. First, I construct multidimensional task measures that characterize how intensively workers conduct particular tasks in their occupations, folllowing the multidimenional skills/tasks literature, especially

[2] See, e.g., Almond and Currie (2011b) for a recent survey of the literature.

Poletaev and Robinson (2008) and Bowlus et al. (2016). I then use the task measures to contrast the evolution pattern of tasks between individuals with various health conditions. Task measures are obtained based on workers' self-ratings of skills/tasks in the UK Skills Survey. The measures are then assigned to the individuals in the 1958 National Child Development Study (NCDS) and their age profiles are compared between individuals with childhood health conditions and those without. Following the previous research, I distinguish mental and physical health conditions during childhood and investigate how these two types of health conditions, observed before labour market entry, affect the age profiles of the multidimensional tasks.

Self-reported health indicators are well-known to be susceptible to a number of problems such as justification bias and misclassification error. To circumvent the issues in health measurement, this chapter takes advantage of the medical examinations conducted in the NCDS. Unlike typical household surveys, medical experts visited each household in the NCDS to examine health conditions of survey respondents when they were at age 7 and age 16. Throughout this chapter, I use measures of childhood health conditions obtained from these medical examinations. The NCDS is also unique in offering remarkably long histories of schooling and labour market outcomes. I construct the age profiles of a multidimensional skill portfolio by exploiting the detailed occupation histories from 16 to 50.

Next, I show that both physical and mental health conditions during childhood are negatively correlated with labour earnings, confirming the findings of the previous research. Then, I decompose the sources of the observed earnings gaps using measures of academic outcomes, family background, and the lifecycle skill portfolio. The observed characteristics are clearly correlated. An important question is the extent to which each of these observed characteristics account for the health-related earnings gaps. The second main contribution of this chapter is to provide descriptive evidence regarding the sources of the earnings gaps associated with childhood health conditions. In particular, I investigate the roles of the gaps in the observed skill portfolio to explain the earnings gaps associated with childhood health conditions.

I organize the rest of the chapter as follows. Section 3.2 describes the essential features of the data from the NCDS and the UK Skills Survey that I use for my empirical analysis. Section 3.3 explains how I measure childhood health conditions and explores the associations between childhood health measures and various skill measures. In particular, I examine how childhood health conditions are correlated with multidimensional task measures that characterize the portfolio of skills used to conduct specific tasks in various occupations. I show that individuals select occupations depending on their childhood health conditions. Individuals with childhood mental health conditions tend to command less intensive cognitive tasks, while those with childhood physical health conditions command less intensive manual tasks. The evidence from the multidimensional skills/tasks approach supports the view that specific childhood health conditions affect occupational choice and, therefore, the accumulation of skills needed to perform tasks in those occupations. Section 3.3 also shows that childhood health conditions are associated with lower educational achievements and labour supply over the life course.

Section 3.4 examines how childhood health conditions affect earnings over the life course. The estimates indicate that both mental and physical health conditions during childhood negatively affect labour earnings. The negative effects appear to be greater with the physical conditions than the mental conditions at age 23 while this pattern is reversed in later ages. This chapter documents that health-related earnings gaps grow over the lifecycle with mental health conditions, while they lessen with the physical conditions.

While the descriptive evidence indicates that childhood health conditions are correlated negatively both with skill characteristics and earnings, it is not clear whether and how the skill gaps contribute to generating the earnings gaps. Section 3.4 also implements a simple earnings decomposition analysis to isolate the partial correlations between earnings and those observed skill characteristics. I show that the gaps in test scores and school attendance play a major role in accounting for the observed earnings gaps. Further, the differences in task-specific work experience (sum of task characteristics chosen in the past) significantly contribute to explaining the earnings gaps. I find that differences in general work experience and family income play a relatively minor role. Section 3.5 concludes.

3.2 Data Sources

This chapter combines two datasets to investigate the nexus between childhood health conditions and labour market skills. Information regarding health status, family background, academic outcomes, and labour market histories was obtained from the British National Child Development Study (NCDS). The UK Skills Surveys provide detailed information on various skills and tasks used in the British labour market.

3.2.1 National Child Development Study

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. 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 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 labour 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 23 and 33. These criteria yield a sample of 3,665 males.

3.2.2 UK Skills Survey

Task measures characterize how workers use their skills at various tasks conducted in their jobs/occupations. I augment the occupation histories in the NCDS data with the task measures obtained from the UK Skills Survey, a series of surveys that investigate skills used by the employed workforce in UK.[3] Using the 1997-2012 UK Skills Surveys, I derive task measures from employee ratings of job-specific task characteristics. At each wave, respondents are asked how important a particular task is for their 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

[3] I focus on the sample from Great Britain. See, e.g., Felstead et al. (2007) for details of the UK Skills Survey.

of cognitive skills/tasks and the second comprises manual skills/tasks.[4] 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. Appendix B.1 provides a list of task characteristics that I use to construct the two task indices.

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 3.1. The cognitive skill requirements and the manual skill requirements of the jobs are highly negatively correlated.

Table 3.1: 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.

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

3.3 Linking Childhood Health with Skill Characteristics

This section presents descriptive evidence regarding the nexus between childhood health and lifecycle skill formation. I first explain my strategy to measure childhood health conditions. I next proceed to examine the correlations between the childhood health measures and various observed skill-related characteristics.

3.3.1 Measuring Childhood Health Conditions

Health conditions are often grouped into two broad types: "mental" conditions and "physical" conditions.[5] 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 these 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.[6] Physical health conditions cover a wider range 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, a particular health condition at ages 7 and 16 can be defined to be either "handicapping", "non-handicapping", or "non-existent". Following Goodman et al. (2011), I aggregate health conditions diagnosed at

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

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

ages 7 and 16, and do not count non-handicapping physical health conditions.[7]

Table 3.2: Fractions Ever Diagnosed with Mental or 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 C.1 provides a list of mental and physical health conditions.

Table 3.2 reports the fraction of individuals diagnosed with mental or 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, I define three mutually exclusive groups of individuals based on their health conditions diagnosed by age 16: the first group consists of individuals diagnosed with mental health conditions, the second group includes those diagnosed with only physical health conditions, the third group comprises those without any diagnosed conditions.

[7]Non-handicapping physical conditions are highly common as about 41% of the male sample was diagnosed to have such conditions before age 16. The most conditions include minor injuries and a slight vision loss. Not surprisingly, those non-handicapping physical conditions during childhood do not have statistically significant correlations with labour earnings. In contrast, non-handicapping mental health conditions are correlated significantly and negatively with labour earnings.

3.3.2 General Work Experience

General work experience is often used as a measure of workers' skill. Figure 3.1 shows the fraction of individuals working full-time at each age by childhood health conditions.[8] labour supply tends to fall as individuals get older. Throughout the lifecycle, individuals with childhood health conditions tend to work less than their healthy counterparts. During their 20's, the full-time employment rates are about 2%-4% points lower among those with childhood health conditions. These patterns become more evident in later years, especially for those with childhood mental conditions. The full-time employment rates among individuals with childhood health conditions are about 4%-8% points lower at age 50 than that of their healthy counterparts. The results suggest that individuals with childhood health conditions tend to experience slower accumulation of labour market experience. Nevertheless, most individuals (at least more than 80%) work full-time regardless of their childhood health conditions.

3.3.3 Task-specific Work Experiences

Task measures characterize the portfolio of skills used to conduct the tasks in the workplace. Figure 3.2 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).[9] The cognitive task profiles show a relatively fast increase initially, followed by a slow-

[8] I define individuals work full-time 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 part-time or full-time in a month. I regard full-time work within a month as working 40 hours per week for each week in the month. Therefore, in the data, individuals work full-time within a year if they work full-time at least for 10 months. I count part-time work during a month as working 20 hours per week for each week in the month.

[9] 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.

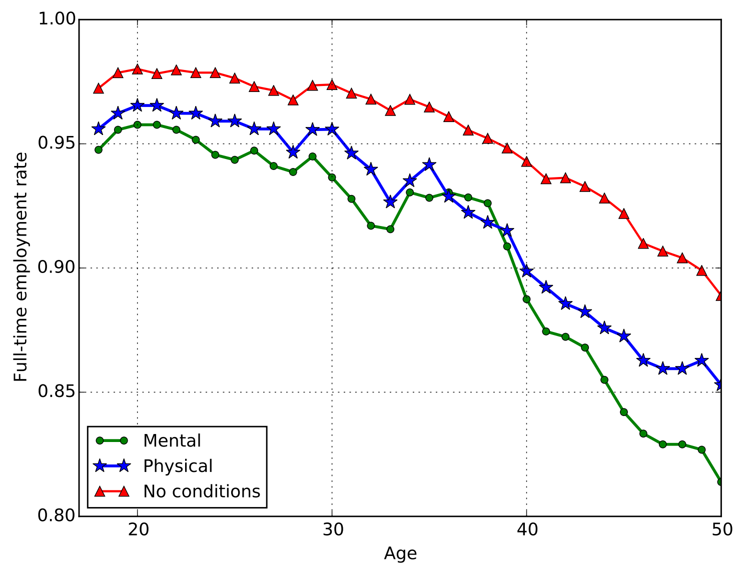

Figure 3.1: Full-time Employment Rates by Childhood Health Conditions.

ing 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 to their healthy counterparts. The average cognitive task level of the occupations at age 35 for those with childhood mental health conditions only reaches 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.

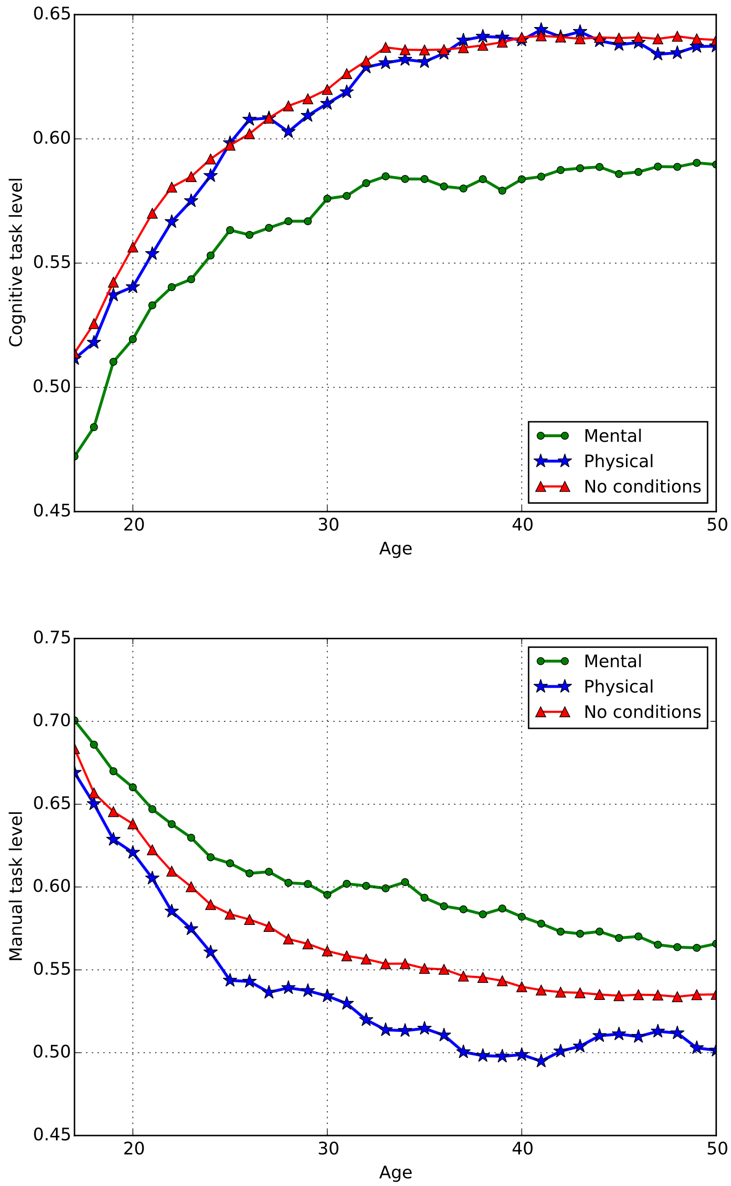

Figure 3.2: Task levels by Childhood Health Conditions

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 labour 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.

3.3.4 Educational Outcomes

In parallel to the results from the task-based skill portfolio measures, childhood mental health conditions appear to have greater negative effects on schooling decisions. As shown in Table 3.3 individuals with childhood mental health 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 health conditions.

Table 3.3: 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 3.4: 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.

Table 3.4 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 the endowment of cognitive skills before labour market entry.

3.4 Understanding the Health-related Earnings Gaps

The descriptive evidence presented in the last section demonstrates that individuals 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, the accumulation of skills needed to perform tasks in those occupations. The evidence also indicates that childhood health conditions are associated with lower educational achievements and lower lifecycle labour supply.

This section explores the contributions of the observed differences in the skill measures in accounting for the earnings gaps associated with childhood health conditions. First, I demonstrate the link between childhood health conditions and earnings over the lifecycle. Next, I implement simple decomposition analyses to investigate the extent to which the health-related earnings gaps are explained by the observed skill differences.

3.4.1 Earnings Gaps Associated with Childhood Health

Table 3.5 demonstrates the associations between mental and physical health conditions during childhood and lifecycle earnings. I regress log-transformed annual labour earnings at each age on dummy variables that indicate the presence of each type of childhood health conditions.

Table 3.5: Gaps in Annual Earnings by Childhood Health Conditions

	Age 23	Age 33	Age 42	Age 50
Mental	-0.089	-0.124	-0.133	-0.131
	(0.037)	(0.043)	(0.063)	(0.069)
Physical	-0.111	-0.064	-0.049	-0.043
	(0.036)	(0.041)	(0.042)	(0.048)

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

The estimates 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 at age 23. Interestingly, this pattern is reversed in later ages. The health-related earnings gaps grow over the lifecycle with the mental health conditions while they lessen with the physical health conditions.

3.4.2 Decomposition of Earnings Gaps Associated with Childhood Health Conditions

What are the sources of the long-lasting negative effect of childhood health conditions on earnings? While descriptive evidence suggests that childhood health conditions lead to gaps in observed skill characteristics, it is not clear whether and how each of the skill characteristics accounts for the observed earnings gaps. The observed skill characteristics are correlated with each other. In this section, I estimate partial correlations between earnings and the observed skill characteristics.

Table 3.6 examines the contributions of the observed skill characteristics in generating the earnings gaps associated with childhood health conditions. The decomposition is based on a regression of earnings at each age (age 23 and 50) on the observed skill characteristics and the childhood health indicators. Note that the wage structure is common across individuals regardless of their childhood health conditions. The gaps in test scores and education (years of schooling) play a major role in accounting for the observed earnings gaps. About 42%-44% of the earnings gaps associated with childhood mental health conditions can be explained by the differences in test scores at age 16 and school attendance. Educational outcomes also play a significant role for physical health conditions: they account for about 28%-39% of the earnings gaps.

Note that the differences in task-specific work experiences (sum of task characteristics chosen in the past) also play a significant role in explaining the earnings gaps. The differences in past experience in cognitive tasks contribute 16%-18% to the earnings gaps for the mental health conditions. At age 23, the difference in manual task experience accounts for about 30% of the earnings gap for the physical health conditions while it plays only a negligible role at age 50. Finally, I find that differences in general work experience and family income play only a relatively minor role in accounting for the health-related earnings gaps.

Table 3.6: Decomposing the Health-related Earnings Gaps

	Age 23		Age 50	
	Mental	Physical	Mental	Physical
Family income	-0.008	-0.013	-0.007	-0.004
	(0.008)	(0.009)	(0.008)	(0.005)
Test scores	-0.021**	-0.019*	-0.031**	-0.010
	(0.009)	(0.010)	(0.015)	(0.011)
Education	-0.017**	-0.012**	-0.026**	-0.007
	(0.008)	(0.006)	(0.011)	(0.009)
General work experience	0.009*	0.006	-0.014	-0.009
	(0.005)	(0.005)	(0.008)	(0.006)
Cognitive experience	-0.016*	-0.008	-0.021**	-0.001
	(0.010)	(0.015)	(0.010)	(0.013)
Manual experience	0.005	-0.030**	0.003	0.009
	(0.003)	(0.014)	(0.002)	(0.010)
Childhood health indicator	-0.041**	-0.067***	-0.035**	-0.012
	(0.018)	(0.025)	(0.018)	(0.020)
Total earnings gap	-0.089**	-0.111***	-0.131**	-0.043
	(0.037)	(0.036)	(0.069)	(0.048)

Note: The wage structure is assumed to be common across individuals. Robust standard errors are in parentheses. The data source is the NCDS. The sample consists of 3,665 men. *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.10$.

3.5 Conclusion

This chapter complements the literature on childhood health by providing a set of new evidence regarding the nexus between childhood health and lifecycle skill formation. The descriptive evidence indicates that childhood health conditions affect occupational sorting. In particular, I find that those who had mental health conditions before age 16 tend to select into less cognitive skill demanding occupations while those who had physical conditions sort into less manual skill demanding occupations. To the extent that occupation choices reflect workers' skills, the observed patterns suggest that specific health conditions may be affecting the formation of specific skills. This chapter also documents that the observed variations in task selections play an important role in accounting for the observed earnings gaps associated with childhood health conditions.

The evidence presented in this chapter is at most descriptive. The schooling outcomes, labour supply, and occupation choices are likely not driven only by the underlying skills of individuals, but also by other unobserved factors such as psychic costs or tastes for each choice. Isolating the determinants of choices remains an important step in quantifying the roles of skills in generating the earnings gaps associated with childhood health conditions.

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Chapter 4

Childhood Health and Lifecycle Human Capital Formation

4.1 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 labour market entry (Keane and Wolpin, 1997). 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 labour market

[1] For example, Lundborg et al. (2014) show that major health conditions at age 18 have long-run effects on labour 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 labour 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%.

outcomes.[2] First, childhood health may have a direct influence on adult health, which in turn may affect labour 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, labour supply, and schooling outcomes.[4] As long as schooling and labour 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 importance of the two channels for two reasons. First, schooling and labour market choices are likely to affect not only skills but also health in future.[5] Separating these effects is necessary in order to quantify the sizes of each channel. Second, individuals may make schooling and labour 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

[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).

[5]Conti et al. (2010) among others estimate the causal effects of education on health outcomes. The effects of labour 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.

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 labour 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 for 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 multidimensional skills. 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 lives. 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. The third chapter of this thesis documents that individuals 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 selected as a result of individuals' choices. Therefore, to the extent the task selections are driven by unobserved factors other than skills, the task-based skill portfolio measures may not fully reveal the dynamics of underlying skills.[6]

To address all of these issues, Section 4.2 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 estimate latent skills from observed task histories. I extend his framework to include health conditions as well as schooling choices and labour supply decisions. In my

[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 labour market choices.

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 labour market choices on future skills and health. By modelling 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 labour 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 labour 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 4.3. 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 labour market. The estimates also suggest that they experience slower skill growth and faster health depreciation. 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-labour activities.

Section 4.4 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 4.5 provides some concluding remarks.

4.2 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 labour market outcomes, this section builds a lifecycle model of joint dynamics of skills and health.

4.2.1 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: “labour” and “resting”. Time allocated for labour may promote skills and is denoted by l_t.[7] The remaining time is used for a non-labour activity, called resting, which may promote health.[8] The labour 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 labour 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 labour market choices are derived from the earnings (e_t) and the tastes for work (g_t). To model health reporting behavior, 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:

$$u_t = \ln e_t + g_t + v_t \tag{4.1}$$

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

[8]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.

Individuals consume their earnings from labour and resting activities. I assume that non-labour income does not vary with the human capital bundle nor with the amount of resting time. labour is the only production factor in this economy and the labour 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 output of the human capital bundle $q(x_t, \theta_t)$ and an unobserved idiosyncratic shock to earnings η_t:

$$e_t \equiv p(\tau_t) q(x_t, \theta_t) \exp(\eta_t) \tag{4.2}$$

The output price is parameterized as the following log-linear function:

$$p(\tau_t) = \exp(p_0 + p_1' \tau_t) \tag{4.3}$$

where the p_0 is a scalar and the inner product $p_1' \tau_t$ represents the component of the price that varies with tasks and labour supply. The output of the human capital bundle is defined as

$$q(x_t, \theta_t) = \exp(q_0 l_t) \exp\left[(q_1 + Q_2' \tau_t)' \, \theta_t\right] \tag{4.4}$$

where q_0 is a scalar, 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 labour 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. I further assume that the productivity of the human capital bundle does not vary with the amount of labour time supplied.

Not only by the returns to the human capital bundle, the labour market choices can also be affected by individual tastes for work. Work-related tastes at age t depend on the observed individual characteristics ζ_1, the human capital θ_t, the past labour market choices x_{t-1} and choice-specific taste shocks ν_t as in the following quadratic function:

$$g_t \equiv (g_0' x_t + x_t' G_1 x_t) + (G_2 \zeta_1 + G_3 \theta_t)' x_t + (x_t - x_{t-1})' G_4 (x_t - x_{t-1}) + \nu_t' x_t \tag{4.5}$$

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 labour market entry, which I will specify with a human capital production technology. The first term imposes convexity of psychic costs from labour market choices. The second term specifies the influences of individual heterogeneity. The third term captures psychic costs from switching labour 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 labour market choices. The utilities from health reports are defined as

$$v_t = \left(h_0 + H_1 \theta_t^H + H_2 x_{t-1} + \omega_t\right)' r_t + r_t' H_3 r_t \tag{4.6}$$

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 labour 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-labour 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:

$$u_0 = (k_0 + K_1\zeta_0 + \nu_0)' s \tag{4.7}$$

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 labour 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:

$$\theta_{t_s} = a_0 + A_1\zeta_0 + A_2 s + \epsilon_1 \tag{4.8}$$

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:

$$\theta_{t+1} = b_0 + B_1\zeta_1 + B_2 x_t + B_3\theta_t + \epsilon_{t+1} \tag{4.9}$$

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 labour market entry but also the speed of human capital formation in the labour market. The tasks performed in the labour 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. labour 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 labour 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 labour market choices.

4.2.2 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 policies (x_t^*, r_t^*) are linear in the state vector.[9] This implies that the post-schooling dynamic programming problem permits a linear state space representation. The optimal choice of schooling is given by

$$s^* = \arg\max_s \{u_0(s, \sigma_0) + \beta E V_{t_s}(\sigma_{t_s}, \eta_{t_s})\} \tag{4.10}$$

where t_s denotes the age of entry into the labour 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 labour time policy (l_t^*) can be expressed as:

$$l_t^* = \Phi_t^l \sigma_t \tag{4.11}$$

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

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

$$\mathrm{LFP}_t = \begin{cases} 1 & \text{if } l_t^* \geq 1 \\ 0 & \text{if } l_t^* < 1 \end{cases} \tag{4.12}$$

where LFP_t denotes an indicator variable for labour 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 labour 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):

$$r_t^* = \Phi_t^r \sigma_t \tag{4.13}$$

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 $m = 1, \cdots, M$,

$$R_t^m = \begin{cases} 1 & \text{if } r_{m,t}^* \leq c_m \\ 0 & \text{if } r_{m,t}^* > c_m \end{cases} \tag{4.14}$$

where c_m is a threshold parameter.

For each post-schooling period the econometrician observes error-driven measurements of labour 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 $T_d \leq T$.[10]

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

$$\begin{aligned} f(y_1, y_{t_s}, \cdots, y_{T_d}) &= f(y_1) f(y_{t_s}, \cdots, y_{T_d} | y_1) \\ &= f(y_1) \prod_{t=t_s}^{T_d} f(y_t | y_{1:t-1}) \end{aligned} \tag{4.15}$$

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 labour earnings and tasks are observable only when individuals work full-time. When an other type of measurement is missing in the data,

[10] 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.

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.[11] 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.

4.2.3 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 labour 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 labour 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 iden-

[11] 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.

tified 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 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 labour time (l_t), the model identifies the effects of the labour 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 evolution 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.[12] The earnings equation parameters are identified from mean labour earnings. The variance of earnings then provides tells the variance of the measurement error of earnings. Finally, by observing sequential labour market choices x_t, the remaining preference parameters during the post-schooling periods can be identified. Observed schooling choices inform schooling preferences.

[12]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.

4.3 Estimation Results

4.3.1 Parameter Estimates

Skill Formation Technologies Parameter estimates for the skill formation technology during post-schooling periods are reported in Table 4.1. The estimates for $B_2(1,1)$ 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 labour 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 productivity 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 4.2 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.

Table 4.1: 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	labour 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	labour 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 $\theta_{t+1} = b_0 + B_1\zeta_1 + B_2x_t + B_3\theta_t + \epsilon_{t+1}$ where $\epsilon_{t+1} \sim N(0, \Sigma_\epsilon)$. Spending 1 unit of time for labour 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.

Health Formation Technologies Table 4.3 presents parameter estimates for the health components of the post-schooling human capital formation technology. Estimates sug-

Table 4.2: 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 labour market entry to have zero unconditional means and unit variances.

gest that childhood health conditions affect the technology of health formation. In particular, the estimates imply that individuals with childhood health conditions experience faster health deterioration during the post-schooling periods. Higher educated individuals experience slower health deterioration. These results are consistent with the findings of Conti et al. (2010). Working individuals experience faster health deterioration than non-working individuals. The negative effect of labour supply is found

Table 4.3: 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	labour 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	labour 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 labour 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.

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 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 4.4 presents parameter estimates for the health formation technology during the schooling period. Childhood health conditions predicts lower levels of health en-

Table 4.4: Parameter Estimates: Health at Labour 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 $\epsilon_{t+1} \sim N(0, \Sigma_{\epsilon_1})$. 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.

dowments at labour market entry. Higher math test scores imply better mental health at labour 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.[13] The estimates imply that education improves health, which are consistent with the findings of Conti et al. (2010).

Earnings Process Table 4.5 shows the parameter estimates for the earnings process. The prices of the labour output are given by $\tilde{p}_1 + p_2' x_t$. They significantly increase with

[13]Empirical evidence regarding the relationship between family income and child health is mixed. Kuehnle (2014) estimates the causal effect of family income on various measures of child health using local labour market conditions as instruments. He argues that family income is not a major determinant of child health in UK.

Table 4.5: 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	labour 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_η^2	0.189	0.065	variance

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

the level of cognitive tasks. The results further suggest that the labour output rises with labour 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 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 labour supply declines as individuals get older since the opportunity costs for non-working fall.

Preferences for Work and Schooling Table 4.6 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 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 labour supply are stronger among lower educated individuals. Poor health conditions during childhood and adulthood are associated with distastes for labour 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 4.7 shows that both test scores at age 7 and family income matter for education choice. Thus family income affects human capital endowments at labour market

Table 4.6: 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
labour 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 labour corresponds to work at least part time for 9 month in a year.

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 4.7: 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.

4.3.2 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 lifecycle 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 4.1 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 full-time employment are presented in Figure 4.2 for each health group. The declining profiles represent falling opportunity costs of non-labour activity. Monetary returns to skills are substantially higher than returns to health capitals. Therefore, individuals allocate more time for labour 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-labour activity.

Table 4.8 presents the model predictions regarding annual labour 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 physical health-

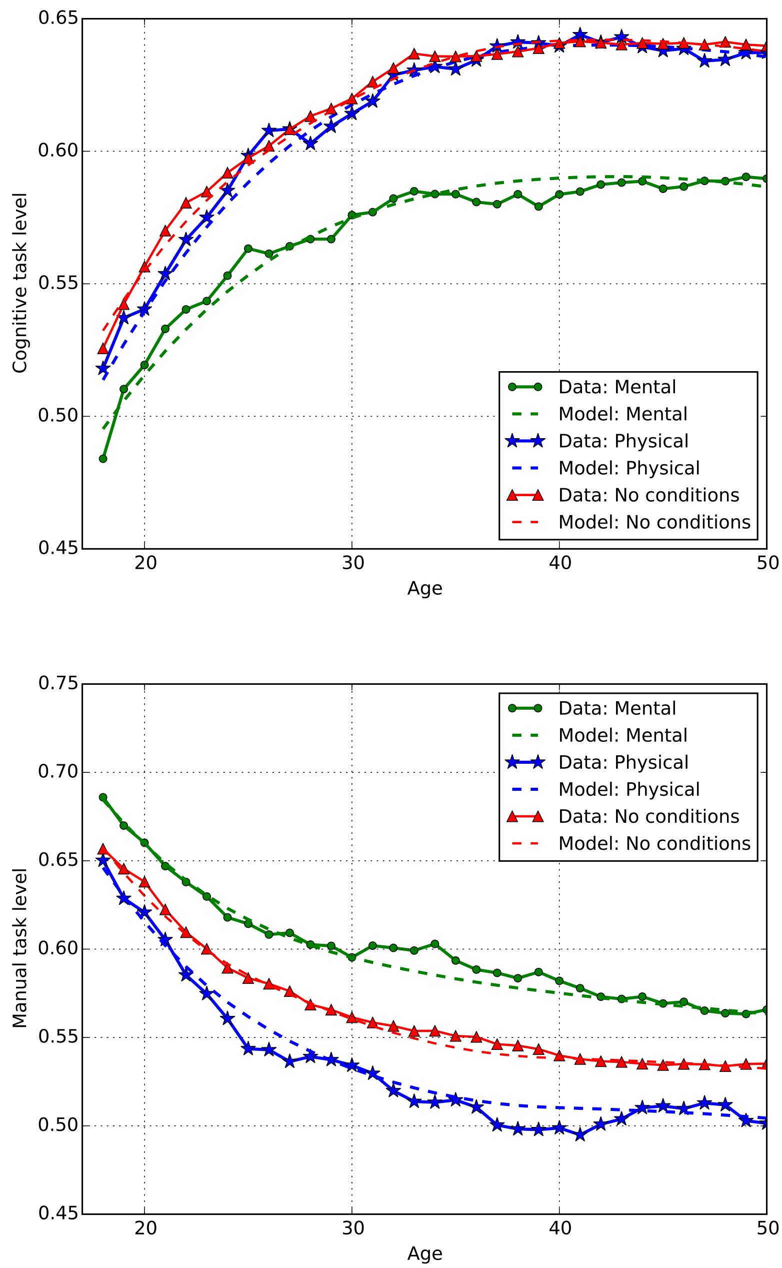

Figure 4.1: Task Profiles by Childhood Health Conditions: Model vs. Data.

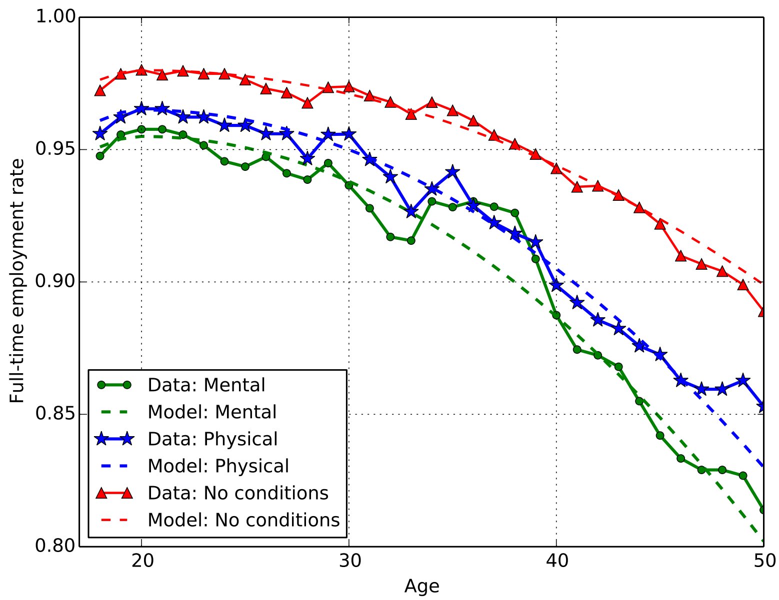

Figure 4.2: Full-time Employment Rates by Childhood Health Conditions: Model vs. Data.

related earnings gaps.

Table 4.8: Model Fit Regarding Average Annual Labour 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.

The model predictions on schooling choice probabilities are shown and contrasted with the data in Table 4.9. The model can replicate the fact that individuals with 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 4.9: Fractions 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.

4.4 Counterfactual Experiments

4.4.1 Quantifying the Sources of the Earnings Gaps Associated with Childhood Health Conditions

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 4.10. Those results indicate that the difference in skill formation is the most important factor to account for the mental health-related earnings gaps throughout the lifecycle. The skill channel accounts for about 60%-65% of

Table 4.10: Quantifying 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%.

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 4.11 summarize the results. The differences in endowments across the health groups, which

Table 4.11: Decompose of the Skill Formation Channels

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%.

are 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 individuals 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.

4.4.2 The Effects of Targeted Schooling Subsidy on Schooling Outcomes and Earnings

School attainment varies considerably between individuals who are diagnosed with childhood mental health conditions and those without such conditions as documented in chapter two. Table 4.12 explores further the schooling choices among individuals with childhood mental health conditions. Here I also consider the quantitative effect on schooling outcomes of a one-time tuition subsidy of £5,000 for those who are diagnosed with a mental health condition before age 16 and continue schooling beyond the compulsory education. The subsidy is designed to offset a part off the additional psychic costs to attend high school and university due to childhood mental health conditions. Overall, the tuition subsidy increases the percentage of high school graduates from 25.1% to 32.0%. The subsidy also increases the university graduation rates from 7.5% to 10.4%. Overall, the fraction with only compulsory education shrinks by about 9.8 percentage points.

Table 4.12: Effects of a Targeted Education Subsidy on Schooling Outcomes

	No subsidy	Subsidy	Diff.
% university graduates	7.5	10.4	2.9
% high school graduates	25.1	32.0	6.9
% only compulsory education	67.4	57.6	-9.8

Note: The subsidy offers a one-time payment of £5,000 for those diagnosed with a mental health condition by age 16 and attending either high school or university.

The subsidy, however, plays a limited role on alleviating the earnings losses associated with childhood medical health conditions. Among the treated group, the mean expected present value of lifetime earnings at age 16 increases from £544,490.30 to £550,634.38. This means that the gross lifetime earnings gap between the treated group and those untreated with no childhood health conditions shrinks from 7.04% to 5.94%. The relatively small effect on lifetime earnings is likely because those who are induced to go beyond the compulsory education by the subsidy tend to have low returns to education, having a comparative advantage in manual task intensive occupations.

Table 4.13: Effects of a Targeted Education Subsidy on the Present Value (PV) of Lifetime Earnings at Age 16

	No subsidy	Subsidy	Diff.
Expected PV of lifetime earnings at age 16			
Treated	544,490.30	550,634.38	6144.08
Untreated (w/ childhood mental health cond.)	458,554.39	458,243.25	-311.14
Untreated (w/ no childhood health cond.)	585,735.69	585,424.55	-311.14

Note: The sample consists for those diagnosed with a mental health condition before age 16. The per capita cost of the subsidy is £311.14.

4.5 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 multidimensional human capital formation technology into a dynamic model of schooling, labour 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 labour 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.

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Chapter 5

Conclusion

My dissertation studies the complementarities between skills and health in shaping labour market outcomes over the life course. The second chapter focuses on estimating the task-specific nature of wage returns to having a work-limiting health conditions at older ages. The third and the fourth chapter together examine how health conditions during childhood affect labour earnings through skill formation and health formation.

In my second chapter, I investigate the role of occupation characteristics in determining the magnitude of health-induced wage losses among older workers. To this end, I estimate a wage equation that allows health conditions to have heterogeneous wage returns depending on what kinds of tasks the workers conduct within their occupations. The estimates are obtained from a ample of workers in the National Longitudinal Survey of Older Men (NLSM). I found that the magnitude of health-induced wage losses varies substantially across occupations depending on their task characteristics, contrary to the assumption commonly used in the existing literature that health is uniformly valued across occupations. I show that the correlations between health and skills account for about 60% of the wage gap between individuals with and without work-limiting health conditions. Moreover, I demonstrate that work-limiting health conditions are closely related to the time-varying components of multiple skills. This evidence suggests that econometric models with single-dimensional, time-invariant unobserved heterogeneity may not fully isolate the influences of the correlations between health and skills.

In my third chapter, I document a set of new evidence regarding the link between childhood health conditions and human capital formation. Previous research has shown that certain childhood health conditions affect academic outcomes. It is, however, not well understood whether and how such influences persist into labour market skills beyond academic outcomes. By adopting a task-based approach, this chapter investigates the link between childhood health conditions and the workers' skill portfolios. I exploit medical examinations conducted in the 1958 British National Child Development Study (NCDS) to obtain objective measures of childhood health conditions. The results highlight the importance of childhood health conditions in determining what kinds of occupations individuals select in the labour market. In particular, I find that those who had mental health conditions before age 16 tend to select into less cognitive skill demanding jobs while those who had physical health conditions sort into less manual skill demanding jobs. The occupation sorting patterns are found to play an important role in predicting health-related earnings gaps.

The fourth chapter formulates and estimates a lifecycle model where childhood health conditions may affect earnings through their influences on skill formation and health formation. I use the estimated model assess the relative importance of the alternative channels through which childhood health conditions may affect labour earnings.

The results from a series of counterfactual experiments indicate that childhood health conditions affect labour earnings mainly through their effects on skill formation: about 60-65% of the earnings gaps associated with childhood health conditions can be explained by the effects of childhood health conditions on the evolution of skills. The effects of childhood health status on health formation are found to play important roles as well. Overall, these results highlight the complementarities between health and skills in shaping labor market outcomes.

Appendix A

Chapter 2 Appendix

A.1 Controlling for Unobserved Skills

This paper uses a correlated random effect approach to control for unobserved worker skills. As discussed in Equation (2.9), I include in the skill equations the average of task indices, labour force participation as well as lifespan and cohort information. I test the null hypothesis that these variables are uncorrelated with unobserved skills. Table A.1 presents the test statistic with its p-value. The null hypothesis is soundly rejected, indicating that these additional variables are useful in controlling for unobserved skills of the individuals.

Table A.1: Testing Correlated Random Effects

Wald Statistic	P-value
46.160	0.000

Note: The null hypothesis is that all of the parameters in Equation (2.9) are jointly zero.

A.2 Parameter Estimates

This section reports parameter estimates for the skill formation technology and the skill components of the wage equation.

A.2.1 Wage Equation

Table A.2: Parameter Estimates: Wage Equation

	Estimate	Std. Error
Intercepts:		
Constant	1.4887	0.0404
Cognitive task	-0.1216	0.1788
Motor task	0.1801	0.1937
Manual task	-0.0135	0.1484
Returns to skills:		
Cognitive		
Constant	0.0015	0.0013
Returns	1.0000	
Motor		
Constant	0.0079	0.0018
Returns	1.0000	
Manual		
Constant	-0.0041	0.0012
Returns	1.0000	

Note: The estimates are for the parameters in the first term in Equation (2.6). Standard errors are clustered at the individual level. The sample consists of 3,804 men. The total number of observations is 15,145.

A.2.2 Skill Formation Technology

Table A.3: Parameter Estimates: Skill Formation Technology

	Estimate	Std. Error
Cognitive		
Education	0.0160	0.0030
Exp	0.0032	0.0035
Exp^2	-0.0063	0.0051
Task exp	0.0261	0.0091
Avg. task	-0.0069	0.0193
Avg. lfp	-0.0296	0.0399
Lifespan	0.0007	0.0010
Cohort	-0.0013	0.0025
Motor		
Education	0.0019	0.0031
Exp	-0.0003	0.0042
Exp^2	-0.0050	0.0062
Task exp	0.0129	0.0084
Avg. task	-0.0336	0.0215
Avg. lfp	-0.0410	0.0437
Lifespan	-0.0009	0.0012
Cohort	0.0010	0.0026
Manual		
Education	0.0139	0.0022
Exp	0.0075	0.0037
Exp^2	-0.0024	0.0053
Task exp	-0.0315	0.0108
Avg. task	0.0452	0.0177
Avg. lfp	-0.0410	0.0437
Lifespan	0.0005	0.0008
Cohort	-0.0075	0.0195

Note: The estimates are for the parameters in Equation (2.4) and (2.9). Standard errors are clustered at the individual level. The sample consists of 3,804 men. The total number of observations is 15,145.

Appendix B

Chapter 3 Appendix

B.1 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 skills/tasks characteristic ratings from the UK Skills Survey that are given in the following table with the estimated factor loadings.

Table B.1: 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.

Appendix C

Chapter 4 Appendix

C.1 Health Measures

C.1.1 Childhood Health Measures

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

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 behavioral difficulties/disorders (EBD) and speech disorders. EBDs refer to a wide range of disorders, including internalizing 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 phys-

Table C.1: 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.

ical abnormalities. Using the diagnoses, particular health condition can be defined to be either “handicapping”, “non-handicapping”, or “non-existent”. Table C.1 shows the fractions of individuals with specific childhood health conditions.

C.1.2 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 C.2. 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.

Table C.3 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 C.4 presents the estimates of health reporting preference parameters. The

Table C.2: 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?

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

Table C.3: 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.

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 C.4: 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.

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