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Three essays on health and labour market participation

Health determinants, health detriments, and resilience

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Contents

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List of papers

1. Berthung E, Gutacker N, Abelsen B, Olsen JA. Inequality of opportunity in a land of equal opportunities: The impact of parents' health and wealth on their offspring's quality of life in Norway. BMC public health. 2022;22(1):1-10.

2. Berthung E, Gutacker N, Olsen JA, Abelsen B. The heterogeneous impact of health shocks on labour market participation: Evidence from Norway. [Under review in Health Economics]

3. Berthung E, Gutacker N, Friborg O, Abelsen B, Olsen JA. Who keeps on working? The importance of resilience for labour market participation. Plos one. 2021;16(10):e0258444.

Abbreviations

LMP – Labour Market Participation

HRQoL – Health-Related Quality of Life

SEP – Socioeconomic Position (SEP),

IOp – Inequality of Opportunity

Psycap – Psychological capital theory

RSA – Resilience Scale for Adults

LOC – Locus of Control

NAV – Norwegian Labour and Welfare Administration

NPR – Norwegian Patient Registry

SSB – Statistic Norway (norwegian: statistisk sentralbyrå)

FE – Fixed effects

CRE – Correlated random effects

MM2+ – Multi-morbidity

CFC – Childhood Financial Conditions

ISCED – International Standard Classification of Education

OLS – Ordinary Least Square

ICD-10 codes – International Classification of Diseases, 10th version

EQ-5D – EuroQoL five-dimension questionnaire (3L = three levels; 5L = five levels)

Summary

'Good health for all' and 'employment for all' are two widely agreed-upon goals in Norwegian politics. Nevertheless, considerable inequalities in health exist, and the economic sustainability of public pensions is pressured by a substantial increase in life expectancy. Improving our understanding of inequalities in health and the relationship between health detriments and labour market participation (LMP) can help policymakers identify where and how policy strategies should be implemented. Subsequently, this can improve individuals' health and make society more economically sustainable in transitioning to longer working life. This thesis aims to improve our knowledge of inequalities in health and the relationship between health detriments and individuals' LMP. More specifically, this thesis investigates the effects of parental health, childhood financial conditions, and own education on individuals' adult health. Moreover, the thesis investigates the relative importance of these three sets of variables for individuals' health. Furthermore, this thesis compares the impact of three different health detriments on individuals' LMP. Proxies for health detriments are stroke, heart attack, and three cancer severity levels. In addition, it investigates if there exists heterogeneity in the impacts by education. Finally, this thesis investigates if individuals' resilience moderates the effect of health shocks on individuals' LMP. I find that parental health, childhood financial circumstances (CFC), and individuals' education creates lasting inequalities in health. Furthermore, individuals' education and CFC have similar magnitudes, i.e., the gaps between the top and bottom levels in the CFC variable and individuals' education are approximately the same. In addition, I find that parental health and CFC are each as important for their health as own education. Moreover, I find that cancer with a poor survival prognosis leads to the greatest reduction in LMP, followed by stroke, cancer with an intermediate survival prognosis, acute heart attack, and cancer with a good survival prognosis. In addition, the negative impact of cancer is greater among lower-educated individuals. However, I did not find that individuals' resilience moderated the impact created by health shocks.

Oppsummering (summary in Norwegian)

Et sentralt mål for den norske regjeringen er å begrense *ulikheter i helse* og holde så mange som mulig i arbeid. Likevel er det store ulikheter i helse mellom ulike sosiale lag og en aldrende befolkning øker presset på velferdssystemet. Mer kunnskap om ulikheter i helse og sammenhengen mellom redusert helsetilstand og arbeidsdeltagelse er nødvendig for å kunne minimere forskjeller og holde folk lengre i arbeid. Hovedformålet med denne avhandlingen er å øke kunnskapsgrunnlaget om ulikheter i helse og sammenhengen mellom helsereduksjon og arbeidsdeltakelse. Mer spesifikt er målsetningen først å undersøke sammenhengen mellom foreldrenes helse, økonomiske forhold i barndommen og egen utdanning for helse i voksen alder. Deretter å sammenligne effekten av ulike helsesjokk på folks arbeidsdeltagelse. Variablene for helsesjokk var slag, hjerteinfarkt og kreft. Kreftdiagnosene ble delt inn i tre alvorlighetsgrader basert på deres fem-års overlevelsesrate. Jeg undersøkte også om det er utdanningsforskjeller i hvordan et helsesjokk påvirker individers arbeidsdeltagelse. Helt til slutt undersøkte jeg om individers motstandsdyktighet (målt som et personlighetstrekk) modererer effekten av et helsesjokk for arbeidsdeltagelsen. Data fra Tromsøundersøkelsen, Statistisk Sentralbyrå (SSB) og Norsk Pasientregister (NPR) ble brukt. Først tyder funnene individers utdanning og økonomiske forhold i barndommen bidrar til like mye ulikhet i helse i voksen alder. Med andre ord, gapet mellom topp og bunn nivåene i disse variablene er cirka lik. Jeg finner også at foreldrenes helse, økonomiske forhold i barndommen og egen utdanning forklarer like mye av helsen i voksen alder. Videre viser funnene at de alvorligste kreftdiagnosene reduserer arbeidsdeltagelsen mest, etterfulgt av slag, de nest alvorligste kreftdiagnosene, hjerteinfarkt og de minst alvorligste kreftdiagnosene. Funnene viser også at kreft reduserer arbeidsdeltagelsen mer for lavt utdannede. Avslutningsvis fant jeg ikke noe bevis for at individers motstandsdyktighet moderer effekten av et helsesjokk.

1. Introduction

'Good health for all' and 'employment for all' are two widely agreed-upon goals in Norwegian politics. The reasons are obvious; health is crucial for individuals' general wellbeing, while individuals' labour market participation (LMP) is vital for the economic sustainability of a society. Nevertheless, considerable inequalities in health exist, and the economic sustainability of public pensions is pressured by a substantial increase in life expectancy. Individuals are expected to prolong their work life to alleviate this pressure. However, as workers age they tend to accumulate health impairments that limit their ability to work.

Presently, we observe inequalities in health where individuals with a university degree are expected to live 5-6 years longer than individuals with primary education (1). In addition, if those with a university degree are married, they are expected to live 8-9 years longer than unmarried individuals with primary education (1). Similarly, low-income individuals systematically report poorer health-related quality of life (HRQoL) than high-income individuals (2).

Health is also essential for individuals' LMP (3). Moreover, a substantial increase in life expectancy puts pressure on public pension systems, which must support retirees for longer. Increasing the upper retirement limit to alleviate this pressure is one possible solution. However, with age comes age-related *health detriments* that limit individuals' LMP. For example, individuals who experience a health detriment as a result of a stroke (4) or cancer(5) are less likely to work.

The societal impact of inequalities in health and health detriments causes several problems. First, it is a public health problem because the full health potential of the population is underutilised. Furthermore, it is a fairness issue; in addition to having a lower income, poor health gives people from lower social classes fewer opportunities and freedom to live the life they want. Finally, health detriments will have severe consequences for economic sustainability in a transition to higher retirement age, thus eroding a welfare system (6). There has been a political focus on reducing *inequalities* in health; nevertheless, inequalities in health have been increasing (7). This strongly suggests that our understanding of what causes inequalities in health is inadequate. As for LMP, in the transition to a higher retirement age, it is necessary to improve our understanding of the relationship between health detriments and LMP.

This PhD thesis is part of the project "Tracing causes of inequalities in health and well-being". It aims to improve our knowledge of inequalities in health and individuals' LMP by focusing on determinants of health, health detriments, and individuals' resilience. Improving our understanding can help policymakers identify where and how policy strategies should be implemented. Subsequently, this can improve individuals' health and make society more economically sustainable in transitioning to longer working life.

2. Background

2.1 Determinants of Health

The World Health Organization defines health as "*a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity*"(8). This broad definition allows for several proxies of health. Examples of proxies for health are longevity (9, 10), birth weight (11, 12), BMI (13), mortality (14-16), individuals' self-assessed health (SAH) (17-24), and depression indexes (16, 25), just to mention a few.

Factors that affect our health are commonly referred to as the *determinants of health*. Childhood conditions, education, income, access to health-care, and health-related behaviour are all determinants. The determinants can be categorised into *genetics*, the *environment*, and *health-related behaviour* (26). Genetics refers to endowments from parents to their descendants, such as height, IQ, and other aspects of human biology. The environment is further differentiated into *physical factors* such as pollution, climate, etc., and *social factors* such as social networks, culture, and individuals' socioeconomic position (SEP), whereas health-related behaviour refers to smoking, exercise, drinking, diet and obesity (27, 28). The determinants of interest in this thesis are parental health, childhood circumstances, and individuals' SEP.

A genetic endowment is generally referred to as *intergenerational transmission of health* (ITH). ITH is defined as the degree to which health from parents is passed down from one generation to the next (29). Literature reports positive correlations between parents' and descendants' height (30), BMI (31), birthweight (11, 32), IQ (33) and SAH (34, 35). Even when the health measures for parents and children are mixed, there is still a significant association between them, such as those between parents' longevity and children's SAH (9), parental SAH and children's birthweight (34), and parental height and children's mortality risk (36).

Childhood circumstance (CC) is an environmental factor that has been given extensive attention (37-39). Commonly used indicators for CC are parental education and occupation. It is well established that CC is associated with inequalities in health. Children born into poorer households experience worse childhood health (40) and worse health as they age (41). Similar research reports that children of fathers who had a blue-collar job report poorer SAH in adulthood compared to children of fathers with a white-collar job (42). Deprived childhood circumstances are also associated with higher mortality (43), risk of cancer (44), and increased risk for depression (45) in adulthood. More specific measures of childhood economic disadvantage are also found to be associated with inequalities in health. For example, mothers' financial problems are negatively associated with the descendants' cognitive abilities as young adults (46), while childhood economic stress is negatively associated with the descendants' SAH in adulthood (47).

The mechanisms behind these associations are mainly explained through parents' SEP. SEP indicates individuals', or families', access to resources. Well-established proxies for SEP are individuals' education, occupation, and income. Education indicates job security (39) and the capability to understand and use health information (48). It also leads to an *occupation* that indicates an individual's position in a social hierarchy (49). Moreover, occupation leads to *income*, which provides money and security to buy healthier food and better medical care (50). In fact, in all countries, health and illness follow a social gradient: the lower the SEP, the worse the health (51).

However, these determinants of health differ in whether they are *within* or *outside* an individual’s control. The childhood environment individuals are born in, and the health they have received from their parents, suggests a *social* and *biological* ‘lottery’. Such *circumstances* are further addressed in the next section.

2.2 Fair and unfair inequalities in health

For most individuals, the word *inequality* in a social context is associated with something bad. When social scientists observe that a variation is characterised with systematic differences, it is referred to as an *inequality*. For example, assume that the overall life expectancy in a population varies between 70 to 90 years but that the life expectancy for highly-educated individuals varies between 80-90 years compared to 70-80 years for the low-educated. In that case, the discrepancy is referred to as *inequality*.

The focus on inequalities in health implicitly indicates a distinction between *fair* and *unfair* inequalities. That is, are individuals in control of the health state they have ended up with? The determinants of health differs to the degree individuals exercise control over them. We have little control over our genetic inheritance and the childhood conditions in which we are born. At the same time, we exercise considerable control over our health-related behaviour. Hence, one central challenge with health inequalities is knowing whether they are *fair* or *unfair.* According to Whitehead, for an inequality to be considered unfair “the *cause* has to be examined and *judged* to be unfair” (52).

The theoretical framework of Inequality of Opportunity (IOp) (or Equality of Opportunity (EOp) is a theory that addresses *fair* and *unfair* causes of inequalities in health. Shaped by Roemer, this theory differentiates between *circumstances* and *effort* variables (53, 54). Circumstances are defined as factors that lie *outside* individuals' control, something they cannot be held responsible for. On the contrary, efforts are factors *within* individuals' control, and any resulting inequalities are *not* judged to be unfair. To achieve Equality of Opportunity, Roemer argued that an "*individual's final condition will be, as far as possible, only a function of the effort he makes*" and that the government should "level the playing field" by compensating individuals for the unfortunate circumstances they face (53).

Literature has shown that determinants that are defined as circumstances contribute to inequalities in health. However, we would expect the *contribution* of each particular determinant to differ, i.e., some determinants are relatively more important than others in contributing to inequalities in health. So far, papers have investigated the relative importance of the two categories *effort* vs. *circumstances* for individuals' health (55, 56). A Colombian study reported that effort variables (individuals' educational level *and* smoking status) accounted for 25% of the variation in individuals' health. In comparison, circumstances (parental education and economic situation during childhood) accounted for 27%. The remaining 48% were attributed to demographics (sex, age, ethnicity, and place of birth)(55). Similarly, a study from Luxembourg reported that circumstances (parental education, financial circumstance during childhood, place of birth, parents' place of birth, and year of immigration) accounted for 28% of those variables that explain inequalities in health, with effort (smoking, physical activity, and education) variables accounting for another 20%; the last 52% were associated with demographics (sex and age) (56). However, when comparing the relative importance of the *categories* (effort vs. circumstances) it is impossible to distinguish the relative importance of any particular determinant itself.

2.3 Health Detriments

Health is an essential input factor for individuals' labour market participation (LMP)(3). Hence, any health detriment will affect individuals' LMP. LMP refers to how much an individual is working. Standard proxies for measuring LMP are binary categories of *working vs. not working* (4, 5, 57-63), continuous measures that refer to *hours worked per week* (62-64) or *weeks worked per year* (64).

In several countries, there is a policy concern that increasing life expectancy means that people must work longer to finance general welfare. Subsequently, with age comes age-related *health detriments (65)* affecting LMP, which are in turn particularly threatening to the sustainability of welfare arrangements.

Since health detriments are challenging to measure, previous literature generally refers to *health shocks*. The literature has defined a health shock as an unexpected, sharp health reduction (64) or the onset of a chronic condition (66). Some have used accidents and injuries (67-69) and a decline in self-assessed health (66, 68, 70) as health shock indicators. Others have used specific diseases that come with age, such as stroke (4, 63, 64), heart attacks (63), and cancer (5, 58-63).

Different types of health shocks are likely to affect LMP differently, although this has received little empirical attention in the literature so far (64). After a review, I find only one study (63) that has compared the impact of different types of health shocks on LMP and found these to differ in magnitude, with stroke having the greatest effect on LMP, followed by cancer and acute heart attacks.

There is also considerable uncertainty about the modifying influence of education. Previous literature has argued for the protective role of education when it comes to understanding and using health information (71). This logic is akin to the Grossman model[1], which states that individuals' level of education influences the efficiency of the production of health (3).

For stroke, one paper (4) found that highly educated individuals were more likely to work, whereas another (64) reported no modifying effect. Still another(63) reported that highly educated women showed a larger reduction in LMP than less educated women. For cancer, studies have reported a modifying effect of education where highly educated individuals are more likely to work after diagnosis (5, 59, 62). This supports the protective effect of education. However, these studies differ in their institutional setting, which calls for further research in other countries.

Not only is it likely that different types of health shocks affect LMP differently, it is also likely that the effect depends on the severity level of the disease itself. Previous cancer studies have relied on either one or two cancer diagnoses or a collective term of several diagnoses. When collapsing several cancer diagnoses into one term, one assumes a homogenous shock. It is

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[1] The Grossman model also state that higher education makes individuals demand more health. Their health is then used as an investment commodity. This commodity determines the total amount of time available for market and non-market activities.

unlikely that a wide range of cancer diagnoses provides a homogenous reduction in LMP. In addition, it is difficult for policymakers to know which diagnoses cause more reduction in LMP. What is unexplored is if different severity levels of cancer diagnoses lead to different reductions in individuals' LMP, and investigating the impact of different severity levels can help policymakers determine which diagnoses should be prioritised to reduce their negative impact on LMP.

2.4 Resilience

People differ in their ability to cope with adversities. For example, some are more able to handle a job dismissal, the loss of a family member, or severe disease better than others—while some who fail a challenge never try again. In contrast, others keep trying. This demonstrates how individuals differ in their *resilience*. Resilience is a phenomenon that has been given more focus in recent years, especially after the Covid-19 pandemic, as it is considered valuable for crisis management (72).

The resilience concept is used to explain why people exposed to adversity or serious risks continue to function relatively well and maintain their health and well-being (73, 74). Numerous definitions of resilience exist, but a prominent one provided by psychological capital theory (Psycap) describes resilience as '*the positive psychological capacity to rebound, to 'bounce back' from adversity, uncertainty, conflict, failure or even positive change, progress and increased responsibility*'(75). In Psycap theory, resilience is one of four psychological capital components (the others are hope, optimism, and self-efficacy). It is used to explain why people exposed to adversity or serious risks continue to function relatively well and maintain their health and well-being (73, 74). The literature further emphasises two aspects of resilience: i) recovery, which is how well individuals bounce back and recover from adversity (76); and ii) sustainability, which is the capacity to continue forward after adverse events (77).

Existing psychological studies suggest that protective factors cluster around three broad domains: personal resources, family cohesion and extra-personal social resources. A validated resilience measure that captures these domains is the Resilience Scale for Adults (RSA) (78).

However, other variables also considered representative of resilience are locus-of-control (79-81) and optimism (80, 82, 83).

Psychosomatic studies show that higher resilience may counteract ischemic pain and stressful experiences (73) as well as hopelessness and depressive symptoms (84). Economic research has found that PsyCap and resilience are positively associated with work engagement (85), job performance (86), and job satisfaction (87). Conversely, resilience is negatively associated with voluntary absenteeism (88) and burnout (89, 90). Moreover, research that used resilience as a moderator has found that it mitigates the adverse effects of job insecurity, such as emotional exhaustion and counterproductive work behaviour (91). These studies indicate that resilient individuals could counteract reductions in individuals' human capital as caused by a health shock.

After a review, I found that only one paper had examined the role of resilience as a moderator for health shocks in the context of LMP. To help fill this gap, this paper (79) investigates how *Locus of Control* (LOC) relates to LMP among men who experienced health shocks. The results show that men with negative control beliefs were twice as likely as those with positive control beliefs to drop out of the labour market a year after the health shock. However, as the study did not include women, the research cannot be generalised. Moreover, unexplored resilience indicators still exist, and since different institutional settings can affect how individuals employ their resilience, the effects can therefore differ. There is thus, overall, a huge knowledge gap.

2.5 The Norwegian context

This PhD thesis occurred in the Norwegian institutional setting. Norway is widely considered to be one of the most egalitarian countries in the world, with excellent access to public education, health care, and social security systems. In 2015, Norway was ranked 1st on the human development index compiled by the United Nations Development (92).

However, despite the egalitarian system, there are considerable inequalities in health in Norway, particularly between socioeconomic groups. A study that examined income-related health inequalities among European countries found that Norway only holds an intermediate position (93) compared to other countries. Moreover, general income inequalities have increased over time (94).

The Norwegian labour market has a high employment rate compared to other European countries, and Norway is among the countries with the highest employment rate for women. However, the employment rate has declined since 2008. Some of this decline is due to an ageing population. In addition, Norway has the highest proportion of people on permanent and temporary health-related benefits and the highest sickness absence among the countries in the OECD (95).

Socioeconomic differences are also present in the Norwegian labour market. One paper reported a difference in sickness absence based on social class (blue collar vs. white collar), where blue collar workers were more likely to be absent from work due to sickness (96). Other researchers have reported similar findings, where those with lower education tend to be sick for longer periods of time (97). Another paper found that chronic musculoskeletal complaints were associated with SEP, where individuals with lower SEP tend to have more musculoskeletal complaints (98).

3. Aim

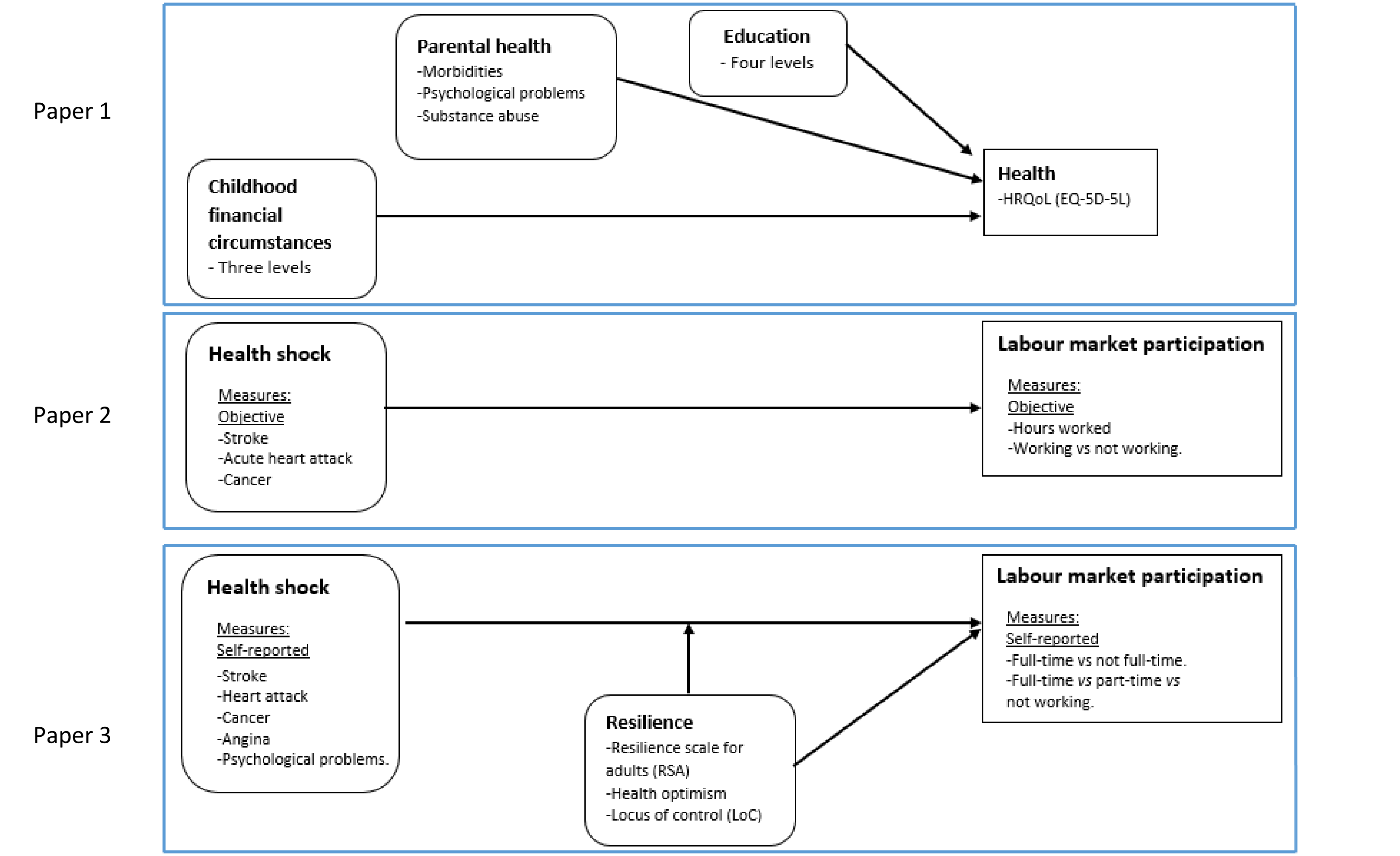
The general aim of this thesis is to improve our current understanding of inequalities in health and individuals' labour market participation. The centre of attention is health determinants, health detriments, and resilience. Figure 1 provides a graphical overview of the three papers.

Paper 1 investigates inequalities in health by focusing on three determinants of health: parental health, parental wealth (both outside individuals' control) and own education. Moreover, it investigates the relative importance of the three sets of determinants.

Paper 2 investigates the impact of three different health detriments on individuals' LMP. It focuses on stroke, heart attack, and three cancer severity levels. Moreover, it investigates if education operates as a protective effect that moderates the impact from the health shocks.

Paper 3 investigates if individuals' resilience moderates the effect of health shocks on individuals' LMP. Specifically, the paper uses individuals' Locus of Control (LoC), health optimism, and the resilience scale for adults (RSA) as proxies for resilience, as well as three sets of health shocks (cardiovascular diseases, psychological problems, and cancer).

Figure 1


Paper 1
Paper 2
Paper 3
Parental health
-Morbidities
-Psychological problems
-Substance abuse
Education
- Four levels
Childhood financial circumstances
- Three levels
Health
-HRQoL (EQ-5D-5L)
Health shock
Measures:
Objective
-Stroke
-Acute heart attack
-Cancer
Labour market participation
Measures:
Objective
-Hours worked
-Working vs not working.
Health shock
Measures:
Self-reported
-Stroke
-Heart attack
-Cancer
-Angina
-Psychological problems.
Resilience
-Resilience scale for adults (RSA)
-Health optimism
-Locus of control (LoC)
Labour market participation
Measures:
Self-reported
-Full-time vs not full-time.
-Full-time vs part-time vs not working.

4. Data sources, materials, and methods

4.1 Data sources

I have used data from The Tromsø Study, the Norwegian Labour and Welfare Administration (NAV), and the Norwegian Patient Registry (NPR). The Tromsø Study is a prospective cohort study of the adult population residing in the municipality of Tromsø in Northern Norway. The study population is considered representative of the Norwegian adult population; however, people with a university degree are slightly overrepresented. The study design is described elsewhere (99). Presently, the Tromsø Study consists of seven waves between the years 1974 and 2016. This thesis uses data from the sixth (2007-08) and seventh (2015-16) waves. Statistic Norway (Statistisk sentralbyrå; SSB) provided data from the State Register of Employers and Employees (Aa-register), which is owned and managed by NAV. The Aa-register was established in 1978 when the sick pay scheme was introduced and lists all employment relationships in Norway (100). This register is a digital coordinated service where employers report information about income and employees. Public authorities such NAV, the Norwegian Tax Administration, and SSB use this register. SSB also provided data of individuals' income and 'taxable and non-taxable transfers'. Income includes salary from work, capital income, sickness benefits, and parental benefits, while 'taxable and non-taxable transfers' includes retirement pension, disability benefits, and unemployment benefits among others. This information is from individuals' tax returns. This thesis uses employment and income data for the period 2007 to 2018. NPR is one of Norway's central registers for health; it collects and manages medical information (hospitalisation records, ICD-10 codes (International Classification of Diseases, 10th version), injury, time of injury, time of death, etc.).

All papers in this thesis were approved by the regional committee for Medical and Health Research Ethics (ID 2016/607). Table 1 shows which survey and waves are used in the respective papers. Data in the three papers were analysed using R version 1.4.1106.

Table 1. Overview of data source, data structure, number of participants, type of outcome, and statistical method used in the respective papers. Fixed effects (FE) and correlated random effects (CRE)			
	Paper 1	Paper 2	Paper 3
Data source:	The seventh wave of the Tromsø Study.	The sixth and seventh waves of the Tromsø Study, SSB and NPR.	The sixth and seventh wave of the Tromsø Study.
Data structure:	Cross sectional.	Panel data (11 panels).	Longitudinal (two cross sectional waves)
Participants analysed:	20,150.	10,367.	3,840.
Outcome variable:	HRQoL (self-assessed) EQ-5D-5L.	Hours worked, and working vs. not working.	Full-time vs (part-time and not working)
Statistical models	Ordinary least square regression and logistic regression.	Linear and linear probability models with FE and CRE estimators.	Ordinary least square regression, binary and multinomial logistic regression.

4.2. Paper 1

4.2.1 Materials

Paper 1 is a cross-sectional study that uses data from the seventh wave, N=21,083, aged 40 and above (40-104 years). The 20,150 participants who answered the HRQoL questionnaire completely were selected. No other exclusion criteria were imposed on the sample.

The outcome variable is individuals' health-related quality of life (HRQoL), which is measured through the EQ-5D-5L generic descriptive system. Participants were asked to describe the level of problems they experience (none, slight, moderate, severe, or extreme) along the five dimensions of mobility, self-care, usual activities, pain & discomfort and anxiety & depression (101). Participants' responses are then converted into utility scores using an amalgam value set of four Western countries (102). These utility scores are the outcome variable.

Parents' health was not a part of the survey. Instead, participants answered seven questions about their parents' morbidity profiles on the day of the survey. Five questions (whether parents had been diagnosed with chest pain, stroke, asthma, diabetes, or had a heart attack before age 60) were used to calculate the total burden of somatic diseases. Since few participants reported more than two chronic conditions I chose a widely used measure of multi-morbidity (MM2 +)(65). I grouped parents' morbidity burdens into three levels: 0 morbidities, 1 morbidity, 2 or more morbidities (coded as 0, 1, or $\geq$ 2). Participants were also asked whether their parents had known psychological problems and whether their parents had had a history of alcohol and/or substance abuse. Their response was dichotomised into yes-no groups.

Participants' childhood financial conditions (CFC) were used as a proxy for their parent's wealth. The question participants answered was, 'How was your family's financial situation during your childhood?' The response categories were the following: very good, good, difficult, and very difficult. The latter two categories were collapsed due to low frequency (difficult N=4730, very difficult N=354).

Participants' education was obtained with the question, 'what is the highest level of education you have completed?' The response categories followed the International Standard Classification of Education (ISCED) of four levels: primary and lower secondary school; upper secondary school; lower university degree (< 4 years); and higher university degree (≥ 4 years). Age was coded in the three bands 40-69, 70-79, and 80+. The unusual age band 40-69 was chosen because previous analysis reported that individuals' HRQoL is stable until their late sixties before it declines (2).

The IOp theory is used to organise the variables in Paper 1. However, one central challenge with the IOp framework is that circumstances and effort variables are often correlated (or *dependent* on each other) (103). Some argue that if an effort variable is correlated with a circumstance variable, then both are circumstances. However, others have argued that effort should be entirely rewarded (104). Nevertheless, I create partial models for each set of determinants to investigate multicollinearity.

4.2.2 Methods

The following cross-sectional regression model was used:

$$y_i = f(\alpha + X_i{}'\beta) + \varepsilon_i \qquad (1)$$

Here, y_i is a measure of HRQoL for individual $i = 1, \ldots, N$, X_i is a matrix of explanatory variables, f is a link function, while ε_i is the error term. Two regression specifications are estimated, without and with education. Model 1 contains the sets of circumstance variables (parental health and wealth), while education is added in Model 2 (full model). Three partial regression models for each set of explanatory variables are also provided. This makes it easy to compare the coefficients' standard errors and magnitude in the partial models with the full model such that multicollinearity can be detected. All models include age and sex as covariates, and the Shapley decomposition method is used on the full model for quantifying the relative importance of all explanatory variables. The Shapley method quantifies the relative importance of *each* explanatory variable for the overall R^2(105, 106). To account for heterogeneity across the sexes (107), the full model was also estimated separately for men and women. As a sensitivity analysis, potential cohort effects were explored. Moreover, I estimated separated regression models for the age cohorts 40-49; 50-59; 60-69, and 70+, and ordinary least square regression (OLS) was used for analysing the utility scores.

4.3. Paper 2

4.3.1 Materials

This study sample is based on the 25,158 individuals who participated in at least one of the sixth and seventh wave of the Tromsø Study (conducted in 2007/8 and 2015/16, respectively). The study period was from 2007 to 2018. SSB provided yearly labour market participation data (LMP), NPR provided the healthcare data, while the demographics were derived from the Tromsø Study. I rearranged the cross-sectional LMP data into a panel structure and then added the healthcare and demographic data. The study period was from 2007 to 2018. I selected all non-hospitalised individuals who suffered a stroke, acute heart attack or cancer during the study period. To identify the impact of the health shocks on LMP, first I restricted the sample to working-age individuals. I excluded those who reached the age of 67 (the upper retirement age in Norway) before the end of the study period. Next, I excluded individuals who were either not working or had had a health shock in the first year of the study (2007). To further identify the impact of the health shocks, I excluded people who were not working one year before a shock *and* not working in the year of the shock. Moreover, I assumed that individuals had died in a given year if they were not working and otherwise not financially active (e.g., no income, no taxable and non-taxable transfers) in that or any subsequent years. I removed all observations (years) after death but retained those prior to death. Figure 1 in Paper 2 presents the sampling procedure, leading to a sample of 10,367 unique individuals, and an unbalanced panel data of 124,053 individual-period observations.

Yearly LMP data refer to participants' *contractual working time (denoted as 'hours worked').* Hours worked are the *agreed working hours the* employee is expected to work *each week* in a particular year. It does not include sick leave, vacation, or overtime work. The 'hours worked' variable only has values for years when individuals are working. Years where individuals are not working are recorded as missing values. I imputed missing values as zero. Based on this, I also created a new binary variable indicating whether people were working (at least one hour per week) or not working (zero hours per week).

Stroke (ICD-10 code I63), acute heart attack (I21), and cancer (C01-C92) are treated as separate health shocks. Cancer was further categorised into three severity levels by their five-year survival rate prognosis provided by the Cancer Registry of Norway (108). Cancer diagnoses with a five-year survival prognosis equal to and above 85% were categorised as *good*; those from 85% to 60% were considered *intermediate* and those below 60% *poor*. These cut-off points were motivated by the frequency distribution of the five-year survival rates. The frequency distribution is found in the Supplementary file for Paper 2 as Figure A1 in the. Table A1 in the Supplementary file for Paper 2 shows the categorisation of the prognoses into good, intermediate and poor by type of cancer.

Age was obtained by recalculating participants' age when they participated in the Tromsø Study, and further split into two-year bins for the analyses. Individuals' self-reported educational attainment was grouped into four levels based on the International Standard Classification of Education: primary and lower secondary school, upper secondary school, lower university degree (< 4 years), and higher university degree (≥ 4 years). I further dichotomised the four educational groups into ‘no university degree’ and ‘university degree’.

4.3.2 Methods

First, I estimated a linear model with fixed effects (FE) to quantify the within-effect of a health shock on hours worked. We then replaced the FE with correlated random effects (CRE), which enabled time-invariant individual characteristics to be included (109). CRE is also known as the Mundlak estimator and is further discussed and explained by Antonakis, Bastardoz (110). The FE model is specified as follows:

$$y_{it} = \lambda + \sum_{a=1}^{A} \delta_a Age_{it,a} + \sum_{k=1}^{5} \beta_k Shock_{it,k} + \alpha_i + e_{it} \tag{2}$$

The outcome y_{it} is hours worked for individual i=1,..,N at time t=1,..T; λ is a constant term, and $Age_{it,a}$ is a=1,…, A binary variables denoting two year bins. $Shock_{it,k}$ refers to indicator variables that take the value of 1 following the health shock k at $t = t^*$ and 0 before it. The parameters of interest are β_k, which captures the within-effect for each health shock *k* over the post-shock periods, α_i, which captures individual heterogeneity (individual-specific and time-invariant characteristics) , while e_{it} is the random error term. The CRE model is specified as follows:

$$y_{it} = \lambda + \sum_{a=1}^{A} \delta_a Age_{it,a} + \sum_{k=1}^{5} \beta_k Shock_{it,k} + \gamma X'_{it} + \sum_{a=1}^{A} \delta_a \overline{Age_{it,a}} + \sum_{k=1}^{5} \beta_k \overline{Shock_{it,k}} + u_i + e_{it} \tag{3}$$

y_{it}, λ, $Age_{it,a}$, $Shock_{it,k}$, and e_{it} are the same as in the previous specification. X' is a vector of time-invariant independent variables while $\overline{Age_{it,a}}$ and $\overline{Shock_{it,k}}$ are the cluster means for the age bins and the health shocks. The term u_i also captures individual heterogeneity. The main difference between these two models is that, in the first (FE) cluster, specific values were estimated for α_i , while in the second (CRE), the variance of u_i was estimated. I also investigated heterogeneity by including interaction terms in the two model specifications. I used the same estimators and regression specifications in linear probability (LP) models with a binary indicator of working (no/yes) as a dependent variable.

I assume that individuals do not anticipate such health shocks and do not adjust their LMP in advance, i.e., health shocks are exogenous and lead to a sudden and unexpected change in health at $t = t^*$. In addition, I am interested in dynamic effects that follow a health shock, i.e., the incremental change in LMP over time. I estimated the following event study model with a fixed effects estimator to test for anticipatory behaviour and dynamic effects:

$$y_{it} = \lambda + \sum_{a=1}^{A} \delta_a \mathrm{Age}_{it,a} + \sum_{l=2}^{5} \beta_l \mathrm{Shock}_{i,t^*-l} + \beta_0 \mathrm{Shock}_{i,t^*} + \sum_{l=1}^{4} \beta_l \mathrm{Shock}_{i,t^*+l} + \alpha_{it} + e_{it} \tag{4}$$

$Shock_{i,t^*-l}$ is a set of binary variables that indicates whether worker i will experience a shock in a lead period of time. It takes the value of 1 if the individual experiences a shock at time t* and 0 otherwise. The full term $\sum_{s=2}^{5} \beta_l Shock_{i,t^*-l}$ captures the anticipatory effects. $Shock_{i,t^*}$ is a binary variable that takes the value of 1 if worker i experiences a shock at time t*. $Shock_{i,t^*+l}$ is a set of binary variables that indicates whether worker i had a shock at time t*. These variables also take the value of 1 if the individual experiences a shock at time t*. The full term $\sum_{l=1}^{4} \beta_l Shock_{i,t^*+l}$ captures the dynamic effects. I set the reference point to one year prior to the health shock ($t^* - 1$) and performed an F-test of the lead and lagged terms to test for anticipation and dynamic effects. In this analysis, I only included those who experienced a health shock. The shocks were modelled separately to investigate the exogeneity assumption for each shock.

4.4 Paper 3

4.4.1 Materials

Paper 3 uses data from the sixth and seventh waves of the Tromsø Study. Again, to identify the impact of health shocks on individuals' LMP, the sample must consist of working individuals below retirement age who have never experienced a health shock before baseline. A total of 5,685 individuals participated in both waves and were below the upper retirement age in Norway (70 years) at follow-up. I excluded 1,253 individuals who did not work full-time at baseline; 546 who reported one or more health shocks prior to baseline; 42 who, at baseline, had reported severe problems on at least one of the five health dimensions in the EQ-5D-3L descriptive system; and 4 individuals who were reported to be studying or in military service. Based on these criteria, I analysed a sample of 3,840 healthy individuals who were working full time at baseline.

The LMP outcome at follow-up is a self-assessed measure with three categories: full-time, part-time, and not working. The not-working category included a variety of sub-categories: unemployment, early retirement, disability recipient, work assessment allowance, family income supplement and unpaid domestic work. In the main analysis, the part-time and not-working categories are combined, both of which reflect *reductions* in LMP from full-time work at baseline.

The modifier is individuals' resilience. In the seventh wave of the Tromsø Study, an abbreviated version of the resilience scale for adults (RSA) was included. The original RSA consists of 33 items, but only 6 items were included, of which three items represent the *personal domain* of the RSA, which could be satisfactorily summed together in a single index score.

Individuals were asked to rate on a Likert scale (from 1= 'disagree completely' to 5 = 'agree completely') how well the following statements describe them: "confidence in personal judgements", "Aptitude to thrive/prosper despite adversity", and "Able to overcome difficulties due to positive self-beliefs". The resilience index score represented the average of these three item scores. Data completeness was high, with only 2% (64) missing values. In the case of one missing value, it was replaced by the average of the individual's two other item scores, that is, average imputations.

Individuals' *locus-of-control* (LoC) and *optimism* with regard to one's future health (health optimism) measured at baseline were included. Both variables were measured on a 7-point scale (1 disagree completely, 7 agree completely). For LoC the item asked about was: 'I have sufficient influence on when and how my work should be done'. For health optimism, the statement was: 'I have a positive view of my future health'.

Participants reported whether they have, or have had, any of the following health conditions: heart attack, angina, stroke, cancer and psychological problems. Due to their limited numbers, I combined the first three conditions into cardiovascular diseases (CVD). The health shocks are treated as binary variables in the analysis. Given that I only included subjects that had *not* reported any of these adversities at baseline, all reported health shocks are assumed to have occurred *between* baseline and follow-up.

In addition to the effect of health shocks occurring *after* baseline, participants' health *at* baseline is likely to affect LMP at follow-up. Study participants reported their health-related quality of life (HRQoL) by use of the EQ-5D-3L generic descriptive system, which consists of five dimensions (mobility, self-care, usual activities, pain & discomfort and anxiety & depression), each described along three severity levels (no problem, moderate, severe). I distinguish subjects who reported full health (N = 2436), i.e., no problems on all 5 dimensions (EQ-5D profile 11111), from those reporting a moderate health problem (level 2) along at least one dimension (N= 1404). Within this latter group, the majority reported a health profile with moderate pain/discomfort, and no problems on any of the other dimensions (EQ-5D profile 11121) (N =871).

Individuals' age, sex, and educational attainment level are controlled for at follow-up. The age variable was split into three groups: 40–49; 50–61; 62–69 years. I chose these age bands because Norwegians can combine part-time work while receiving partial pension payments after the age of 62. Educational attainment was again categorised into the abovementioned four levels, which is in line with the International Standard Classification of Education (ISCED).

4.4.2 Methods

The data are analysed by using binary logistic regression with several specifications. Model 1 specification includes age, sex, education, health at baseline, and the presence of health shocks (each entered as indicator variables). Specification 2 adds RSA, specification 3 adds LOC, and specification 4 adds health optimism. To test for any moderation effects, I estimated three models that allowed for interactions between the resilience variables and the health shocks. Calculating marginal effects in nonlinear models can be complicated because a coefficient can be statistically indistinguishable from zero, although the cross-partial derivative is different from zero. The delta method suggested by Ai and Norton (111) for exploring interaction terms in nonlinear models was applied. The sensitivity analysis consists of a multinomial logistic model that distinguishes these two non-fulltime outcomes to further investigate any differences between those working part-time and not-working. All results are presented as odds ratios (OR).

5. Summary of results

5.1 Paper 1

Paper 1 investigates inequalities in individuals' HRQoL by focusing on three sets of determinants of health and estimating their relative importance for individuals' HRQoL. Two determinants are sets of variables that lie outside an individual's control: Parents' *health* is measured by their somatic diseases, psychological problems and substance abuse, while parents' *wealth* is indicated by childhood financial conditions (CFC). The last determinant is individuals' own educational attainment.

The first model specification suggests that all sets of determinants *outside* individuals' control contribute to explaining individuals' HRQoL. Individuals' education enters the second model specification and also contributes to inequalities in individuals' HRQoL.

The difference in HRQoL between having had Very Good vs. Difficult CFC (0.008 – (-0.024) = 0.032) is approximately equal to the education gap (=0.030). In other words, the inequality between the top and bottom levels in the CFC variable and that of individuals' education is approximately the same. All three measures of parental health are still associated with inequalities in individuals' adult HRQoL. In addition, once education is adjusted for, there is no notable change in the the size of the coefficients for parental psychological problems and substance abuse.

Having a mother with psychological problems or substance abuse issues is associated with more reductions in individuals' HRQoL than having a father with the same problems. Moreover, mothers with 2 or more somatic diseases are associated with a greater reduction in individuals HRQoL compared to fathers with the same amount of somatic multi morbidities. This suggests that mothers' ill health reduce individuals HRQoL more than fathers' ill health..

There are also some noteworthy differences between men and women. For example, difficult CFC and mothers' ill health lead to greater reductions in women's HRQoL than men's.

The stable coefficients on parents' health and wealth in Model specification 1 vs. 2 suggests non-collinearity with education. Results from the three partial models suggest that multicollinearity is not a problem, i.e. each of the three sets of predictors is independent of each other.

Figure 1 at page 8 in paper 1, provides the results from the Shapley decomposition from Model 2. In the full sample, parental health (3.8% +14.6% +8.5%) and CFC (22.5%) account for nearly 50% of the explained variance (R^2), while educational attainment account for 22.4%. For both sexes, the relative importance of the three determinants appears similar. The parental health variables together explain around 31%, with CFC slightly less (29%).

In the sensitivity analysis, I find stable results across the age cohorts for CFC. Having experienced difficult CFC seems to create inequalities in health for all age cohorts. Moreover, the inequality from education diminishes and loses significance for the two oldest age cohorts – reflecting a completely different distribution across educational attainment. In Table A4 in the supplementary file for paper 1, we see that only 9% had primary education among the youngest cohort, while it was 44.7% for the oldest cohort.

5.2 Paper 2

The aim of Paper 2 is to investigate the impact of three health shocks (stroke, heart attack, and cancer) on individuals' LMP. Moreover, it investigates if education operates as a protective effect that moderates the effects from the health shocks.

Table 1 in Paper 2 (page six) provides the sample characteristics from the first year of the study period. The sample includes more men than women, and more than half the sample had a university degree (57.2%). During the study period, 690 individuals suffered their first health shock that led to hospitalisation: 71 had a stroke, 137 had an acute heart attack, and 482 were diagnosed with cancer. Table 4 (page nine) provides the results. The first two linear models analyse hours worked using the FE and CRE estimators, respectively. The next two linear probability models analyse the binary outcome of working (yes/no) with FE and CRE estimators, respectively. The average within-effects from the FE model are not exactly replicated using the CRE estimator due to missing values in the education variable. I find that all health shocks reduce individuals' LMP. Following a stroke, individuals worked on average 3.7 hours less, whereas individuals who suffered an acute heart attack reduced their weekly hours by 1.5. For cancer, the average reduction was 1.4 hours for a good survival prognosis, 3.65 hours for an intermediate survival prognosis and 4.9 hours for a poor survival prognosis. The results from the linear probability models are remarkably similar. Except for cancer with a good survival prognosis, all health shocks reduced the probability of working. On average, stroke reduced the probability of working by 8%, while the reduction was 4% for acute heart attack. Again, the effect of cancer on LMP increased with severity; however, only the intermediate and poor cancer prognoses had significant effects of -7% and -10%, respectively.

Table 6 in Paper 2 (page 11) provides the analysis of the protective effect of education. In these models, the reference category is individuals without a university degree, and thus the health shocks that do not interact are the average within-effects for individuals with a university degree. All health shocks except stroke reduce hours worked for individuals without a university degree. By contrast, individuals with a university degree show a larger reduction in hours worked following a stroke and a smaller reduction in hours worked following all cancer severities. In the linear probability models, the results are similar, but the heterogeneity by cancer is less pronounced. Individuals with a university degree are more likely to work following acute heart attack and cancer with a poor survival prognosis.

The results from Tables A2 and A3 in the Supplementary file for Paper 2 suggests that the exogenous assumption holds for all health shocks. No anticipatory effects are found prior to the health shocks. This indicates that shocks are unforeseen and that any subsequent adjustments in LMP are probably due to the health shock itself. I also see dynamic effects that are intuitive. Table A2 in the Supplementary file for Paper 2 shows a general trend of incremental reduction in hours worked over time, and the significance levels of the lag coefficients for cancer with a poor prognosis decrease over time. This is not surprising since fewer individuals with a poor survival prognosis are expected to remain working at those time points. In Table A3 in the Supplementary file for Paper 2, the first three lag coefficients for stroke are barely significant, while the last two lag coefficients for cancer with a poor survival prognosis are not significant at all. The latter is again not surprising since fewer individuals remained in employment at these time points.

5.3 Paper 3

Paper 3 investigates if individuals' *resilience* can moderate the impact of health shocks on individuals' LMP. The paper uses heart attack, angina, stroke, psychological problems, and cancer as health shocks. The paper uses the resilience scale for adults (RSA), individuals' Locus of Control (LoC), and *health optimism* as proxies for individuals' resilience.

Table 1 at page five in Paper 3 provides the sample characteristics by LMP at follow-up. Pearson's chi-square tests indicate unadjusted associations between the explanatory variables and LMP. As expected, health shocks after baseline are associated with a reduced LMP at follow-up. The same applies to lower educational attainment and reduced health-related quality of life (HRQoL) at baseline.

In the first model, in Table 2 in Paper 3 (page six), the results of health shocks are similar to those in Paper 2, i.e., all health shocks reduce individuals' LMP. In this analysis, individuals are less likely to work full-time after experiencing a health shock. Men and workers with a university degree are more likely to work full-time. At the same time, individuals with moderate health at baseline are less likely to work full-time at follow-up. In Model 2, the RSA enters and is significantly associated with full-time work. In Model 3, the LoC is added and is also significantly associated with full-time work. In Model 4, *health optimism* is added to the specification and is associated with working full-time. However, the LoC variable is no longer significant, and the RSA is less significant. However, these results suggest that the concept of resilience, as measured in different ways, significantly influences individuals' propensity to work full-time.

Table 3, at page seven in Paper 3, provides the interaction results. None of the resilience indicators modifies the effect of any health shock. In the sensitivity analysis the LMP outcome is split into three categories (working, part-time working, and not working). I observe a similar pattern for the health shocks, age, sex, education and health at baseline. Interestingly, the resilience indicators are only significant in the not-working category. Thus, the multinomial models indicate that lower resilience explains why individuals opt not to work at all, but *not* why they reduce their LMP from full-time to part-time. The results from the sensitivity analysis are found in Table S3-S5 in the supporting information for Paper 3.

6. Discussion

6.1. Paper 1

6.1.1 Results

Paper 1 investigated inequalities in individuals' HRQoL by focusing on three sets of determinants of health and estimating their relative importance for individuals' HRQoL. Two determinants are sets of variables that lie outside of individuals' control: Parents' *health* is measured by their somatic diseases, psychological problems and substance abuse, while parents' *wealth* is indicated by childhood financial conditions (CFC). The last determinant is the individuals' own educational attainment.

In short, all determinants are significantly associated with individuals' HRQoL. The determinants outside of individuals' control, parental health and CFC, seem to create lasting reductions in adults' HRQoL. Although education slightly mitigated the effect from CFC for adult health, these two determinants have similar magnitudes, i.e., the gap (inequality) between the top and bottom levels in the CFC variable and education is approximately the same. Lastly, the Shapley analysis showed that parental health and wealth are each as important for HRQoL as individuals' education.

Previous research has also shown that CFC creates lasting inequalities in adult health (40, 41, 112) and that individuals' education can modify the inequality (39, 112-114). Similarly, studies report that intergenerational transmission of health (ITH) creates inequalities in descendants' health (11, 32, 115), and that the inequality created by ITH was mitigated after controlling for the place of residence (11), parental income(32), and descendants' educational level (115). The authors of the latter study argued that the ITH could be weakened by investing in descendants' education. However, when adjusting for education, there are no notable differences in the coefficients for parents' health. This suggests that the determinants are independent of each other and can be seen as complementary explanations for reductions in individuals' HRQoL.

The categorisation of parents' health as *outside* individuals' control is suggestive of inherited genetics. Nevertheless, the parental health variables do not directly state which pathway the ITH has taken (i.e., the genetic or the environmental way). For example, parents' health-related behaviour could partly cause their morbidities, which they have passed on to their descendants (116). I am therefore cautious in pointing to which pathway the intergenerational transmission of health has taken. Nevertheless, the results from the parental health variables suggest that some *unfair* inequalities are not easy to alter. According to the IOp theory, this indicates that there is an upper limit to how much a welfare state can help in achieving equal opportunities for individuals' health.

Of the explained variance (R^2), the circumstances variables (parental health and wealth) accounted for nearly 50%, whereas effort (own education) accounted for 22.4%. However, one cannot directly compare these numbers to previous studies since the types of determinants differ and other sets of variables were used.

Nevertheless, the magnitudes of the relative importance of the determinants in Paper 1 are noteworthy. It suggests that CFC is as important as education in explaining inequalities in health. However, if the CFC variable is a good proxy for relative deprivation, then this suggests that inequalities in health can, to a degree, be reduced but will not vanish.

Proponents of the IOp theory suggest therefore that societies should 'level the playing field' such that inequalities are only a result of determinants *within* individuals' control. However, the results from Paper 1 suggest that if an egalitarian country like Norway cannot eradicate unfair inequalities in health, then other countries will also struggle, suggesting that there is an upper limit to how much a welfare state can contribute to equal opportunities.

The novelty of Paper 1 is the combination of *three* well-known sets of determinants of health and the calculation of their relative importance for individuals' health. This combination advances current knowledge by providing a broader picture of the determinants' relative importance and some of the dynamics between them. However, other determinants, such as individuals' health-related behaviour, are also likely to affect individuals' health and mitigate some of the associations. Several papers have shown the positive association between, for example, physical activity and health (117-119). For future research, such health-related determinants should be included with determinants *outside* of individuals control. This will provide an even broader picture of their relative impact and relationship with other determinants.

6.1.2 Material and methods

Paper 1 analysed cross-sectional data that have some potential biases. The first is *recall* bias. The seventh wave of the Tromsø Study included individuals aged 40 and above, and all participants were asked to recall their childhood financial circumstances. Obviously, this task involves participants who do not remember their CFC accurately, and hence results in *recall bias*.

Moreover, regarding parental health, the distribution in the responses is different for older participants. There is a downward trend where older participants report fewer psychological problems and substance abuse from their parents. There are several potential explanations for this. First, psychological problems and substance abuse were less pronounced in earlier generations. Second, there is a *recall bias*, where the descendants do not remember. Third, in earlier generations, substance abuse and psychological problems were not given any attention and were viewed as 'normal'. Hence, these variables can have some measurement errors. Another challenge with cross-sectional data is that the explanatory and the outcome variables are measured simultaneously. Thus, knowing the direction of the association is difficult. For example, it could be that children's poor health requires parents to take on care duties, with negative consequences for parental health.

These data do, however, have several strengths as the outcome variable, health-related quality of life (HRQoL), is unique compared to other research. Previous studies mostly relied on ordinal, single-item measures of self-assessed health(17-24) or have focused on narrowly defined aspects of health, such as the presence of psychiatric disorders (16, 25). These approaches do not capture the multidimensional nature of health and how it affects different aspects of HRQoL.

The parental health variables are also unique when compared to other research. Paper 1 uses parents' multimorbidities, psychological problems, and substance abuse as proxies for parental health. Off-course, these measures of parental health are incomplete proxies since health is multidimensional. Still, the categorisation of the parental health variables appears to be an estimate of 'severity'. The results are highly intuitive, where more diseases are associated with greater reductions in descendants' health. Some of the parents' morbidities burdens have occurred after the descendants have left the nest. I am therefore cautious in interpreting which pathway the intergenerational transmission of health has taken (i.e., via genetics or (un)healthy behaviour).

Regarding the childhood financial circumstance variable, most papers in the literature have used parental education as an indicator for childhood conditions. However, in this sample, relatively few participants above 60 years old reported their parents as having a university degree. The childhood financial circumstance (CFC) variable was therefore preferred. As mentioned in this thesis (and the paper as well), the distributions of respondents on the three CFC levels are remarkably similar across age cohorts (See Table A4 in the supplementary file for Paper 1), whose *absolute* standard of living during childhood increased tremendously over time (approximately 3% p.a. GDP/capita growth between 1950 and 1990). This indicates that our measure of CFC represents a proxy for *relative* deprivation, which makes it a good representation of the CFC across the age cohorts.

Investigating the independence between the determinants is important for at least two reasons. From a statistical perspective, independence makes our results less biased from collinearity; hence they are more reliable. From a more theoretical perspective, it suggests that the variables are a good proxy for their respective dimensions. It is possible that this independence between the variables is a coincidence. However, it is not surprising that education is independent of CFC. Education in Norway is free, which makes individuals less dependent on their parents' financial resources.

6.2. Paper 2

6.2.1. Results

Paper 2 investigated the impact of three health shocks (stroke, heart attack, and cancer with three severity levels) on individuals' labour market participation (LMP). Moreover, it investigated if education operates as a protective effect that moderates the impact from health shocks.

I found that all health shocks causes a reduction in individuals' LMP. Stroke causes a larger reduction in individuals' LMP than acute heart attack. For cancer, the higher the severity, the larger the reductions in LMP. Among all health shocks, cancer with a poor survival prognosis caused the greatest LMP-reduction, followed by stroke, cancer with an intermediate survival prognosis, acute heart attack, and cancer with a good survival prognosis. In addition, I found that education operates as a protective effect for cancer, where having a university degree reduces its impact. From Paper 3 I find that higher levels of resilience are associated with a higher propensity to work. However, resilience did not moderate the effect of health shocks.

A previous study (63) also reported that a stroke caused greater reduction in LMP than an acute heart attack. Moreover, this paper also found that strokes cause a greater reduction in LMP than cancer, which is broadly in line with results from Paper 2. One important difference is that they collapsed all cancer diagnoses into one term, thus assuming a homogeneous shock across potentially quite different types of cancer diseases with different survival prognoses. Their result may be driven by a large proportion of cancer diagnoses in their sample with a good or intermediate survival prognosis. Furthermore, Paper 2 adjusts for different severity levels among the cancer diseases. This adjustment maintains the disease specific impact caused by different diagnoses and enriches the analysis. The cancer results from Paper 2 indicate that one can identify which diagnoses should be given more attention when it comes to preventive strategies for reducing its effect on individuals' LMP.

The protective effect of education on health has been emphasised in the literature (71). The modification results for cancer support this theory; workers with a university degree display a smaller reduction in LMP compared to workers without a university degree. This result is also in line with previous research (5, 59), which found that highly-educated workers are more likely to work in the years after being diagnosed with cancer.

This result is intuitive; cancer is a disease that slowly develops with symptoms. Therefore, higher educated individuals may detect signs of cancer earlier, which leads to a better prognosis and, thus, reduces its impact on LMP. This logic is akin to the Grossmann model, which assumes that educated individuals exploit health information more efficiently in the production of health.

For strokes, I find that higher educated individuals had a larger reduction in LMP compared to those lower educated. This finding is as inconsistent as previous results in the literature. One paper did not find heterogeneity by education (64), while another paper did (4). The main result suggests that stroke is more severe for LMP than acute heart attack, which indicates that stroke survivors could need more recovery time. This notwithstanding, a university degree could provide an occupation with a higher job security. This security can allow stroke survivors to substitute LMP with recovery without the fear of losing their job.

The novelty of Paper 2 is that it estimated and compared the differential effect of health shocks caused by three different diseases (stroke, acute heart attack, and cancer), thereby adding to the limited literature on differential effects caused by different health shocks (63). Moreover, inspired by Aaskoven, Kjær, and Gyrd-Hansen (120), Paper 2 explored different severity levels in cancer and implemented it in the context of LMP. This method has not been implemented in the context of LMP before. Lastly, the paper contributes to the small contradictory literature (4, 59, 64) that investigates the protective effect of educational attainment.

6.2.2. Materials and methods

Paper 2 investigated the impact of several health shocks on individuals' LMP. This paper used GLS and linear probability (LP) models with fixed effects (FE) and correlated random effects (CRE) estimators. First, several attempts were made with a Probit model with FE and CRE estimators. However, the model failed to converge due to little variation in the outcome variable (working yes/no). The LP model was therefore used. The reason for using the FE estimator is that the random effects assumption did not hold. Hence, the effects of the health shocks would be biased. However, the FE estimator does not allow time-invariant variables to be modelled. To account for this, the CRE estimator was integrated into the analyses.I acknowledge that only having data for individuals first onset of disease is a limitation. If individuals experience another similar health shock during the study period, it may affect the estimates of the initial health shock and bias the results.

There are several factors that affect individuals' LMP. However, one acknowledged factor in the literature is wealth. Hence, there is a high probability that the analysis has *omitted variable bias*. It is likely that wealth is an important factor in the decision to continue working after a health shock, especially as individuals approach retirement age.

The major strength of this analysis is the use of objective measurements of both the health shocks and the labour market participation variables. This minimises justification bias. Another strength is that the exogenous assumption holds for each health shock, which suggests that *simultaneous equation bias* is not a challenge. In other words, individuals' health can affect how much they work, but the work can also affect individuals' health. When two equations are jointly determined within a system, there is an endogeneity problem. Since the exogeneity assumption holds, it suggest that the health shocks cause the decline in individuals' LMP.

6.3. Paper 3

6.3.1. Results

Paper 3 investigated if individuals' *resilience* could moderate the effect of health shocks on individuals' LMP. It used individuals *Locus of Control* (LoC), *health optimism* and the resilience scale for adults (RSA) as proxies for resilience, in addition to three sets of health shocks (cardiovascular diseases, psychological problems, and cancer).

Resilience itself is positively associated with working full time. This indicates that higher levels of resilience help individuals in sustaining their LMP. This result is coherent with the definition of resilience in Psycap theory, since adversity is not required for resilience to be meaningful. This finding supports previous studies, which finds that resilience is positively associated with work engagement (85), job performance (86) and job satisfaction (87). Although these studies do not directly confirm each other, still, they point in the same direction in terms of job sustainability.

Psychosomatic research has shown that higher resilience may counteract ischemic pain and stressful experiences (73) as well as hopelessness and depressive symptoms (84). However, none of the resilience indicators moderated the effect from health shocks. This deviates from a previous study that used LoC as a proxy for resilience (79). There could be several reasons for the deviating result. However, one obvious distinction is the different institutional setting. Norway provides financial support through social insurance systems with generous sickness benefits. The general rule is full financial cover for the first year of sickness absence, which is then reduced to 66% for the second year. This financial protection can incentivise individuals not to work full time after experiencing a health shock. Thus, individuals' resilience becomes less important for explaining why people keep on working after experiencing a health shock.

The novelty of Paper 3 is the examination of the role of individuals' resilience for mitigating the impact of health shocks on LMP, thereby adding to a limited literature (79). Moreover, the paper explored three proxies for resilience in the labour market context, which has not been done before. Finally, this is the first study analysing the mitigating effect of resilience on health shocks for LMP in Norway, a country widely known for its generous social insurance schemes that support individuals who are unable to work. Hence, Norway offers a useful 'best-case' benchmark against which other countries can be compared.

6.3.2 Material and methods

Paper 3 investigated if individuals' resilience would moderate the effect of a health shock on individuals' LMP. The paper used self-reported data for individuals' health shocks and their LMP. Self-reported health shocks open up for *justification bias*, and justification bias occurs when individuals report a worse state of health to justify their LMP level (121).

The main focus, however, is individuals' resilience. In the seventh wave of the Tromsø Study, six of the original 33 items of the resilience scale for adults (RSA) were included. Three items represented the *personal domain* while the remaining represented the *family domain*. For the purpose of this paper, I was interested in the *individual* who are working. I chose the three items that represented the individual through the personal domain. One could argue that this selection makes the RSA more incomplete. However, a confirmatory one-factor analysis confirmed a good fit [$x^2_{df=1}$ = 0.10, P = 0.76; RMSEA = 0 (95% CI 0-0.013)]. Higher scores on these three items indicated a better adaptation response to life stresses.

A potential weakness is that the RSA items are measured at follow-up. The resilience literature argues that the RSA is of a highly stable character. RSA correlates strongly with the stable *Big Five* personality traits, which are seen as stable, especially neuroticism (122). In a Norwegian general population study, the four-month test-retest stability correlation of the RSA dimension used in the current study was very high (*r* = .79)(123). However, a health shock can affect individuals' level of resilience. To adjust for this, individuals' *Locus-of-control* and *optimism* with regard to one's future health (Health optimism) measured at baseline were included. A Pearson correlation test was performed to investigate any connection between the resilience indicators. The positive correlation suggests that they all represent a resilience resource (see Table S2 in the Supporting file for Paper 3). *Locus of Control* and being *optimistic* are traits that are related to resilience; while *health optimism* is a concept that has not been used before. However, *health optimism* appears particularly meaningful since it is used in the context of health *detriments*.

8. Conclusions

The aim of this thesis was to investigate inequalities in health-related quality of life (HRQoL) and individuals’ labour market participation (LMP). This thesis used data from the sixth and seventh waves of the Tromsø Study, Statistics Norway, and the Norwegian Patient Registry.

I have shown that determinants outside of individuals' control, such as parental health and childhood financial conditions (CFC), have lasting impacts on HRQoL. Furthermore, individuals’ education and CFC have similar magnitudes, i.e., the gaps between the top and bottom levels in the CFC variable and individuals’ education is approximately the same. Lastly, the Shapley analysis showed that parental health and CFC are each as important for HRQoL as own education.

All health shocks reduce individuals LMP. Stroke causes a greater reduction in individuals’ LMP than acute heart attack, whereas for cancer, the higher the severity, the larger the reduction in LMP. Cancer with a poor survival prognosis leads to the greatest reduction, followed by stroke, cancer with an intermediate survival prognosis, acute heart attack, and cancer with a good survival prognosis. Higher education seems to have a protective effect for cancer. However, individuals’ resilience (with three proxies) did not mitigate the impact created by health shocks.

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Paper 1

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Inequality of opportunity in a land of equal opportunities: The impact of parents' health and wealth on their offspring's quality of life in Norway

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Abstract

Background: The literature on Inequality of opportunity (IOp) in health distinguishes between *circumstances* that lie outside of own control vs. *efforts* that – to varying extents – are within one's control. From the perspective of IOp, this paper aims to explain variations in individuals' health-related quality of life (HRQoL) by focusing on two separate sets of variables that clearly lie outside of own control: Parents' *health* is measured by their experience of somatic diseases, psychological problems and any substance abuse, while parents' *wealth* is indicated by childhood financial conditions (CFC).

We further include own educational attainment which may represent a circumstance, *or* an effort, and examine associations of IOp for different health outcomes. HRQoL are measured by EQ-5D-5L utility scores, as well as the probability of reporting limitations on specific HRQoL-dimensions (mobility, self-care, usual-activities, pain & discomfort, and anxiety and depression).

Method: We use unique survey data ($N = 20{,}150$) from the egalitarian country of Norway to investigate if differences in circumstances produce unfair inequalities in health. We estimate cross-sectional regression models which include age and sex as covariates. We estimate two model specifications. The first represents a narrow IOp by estimating the contributions of parents' health and wealth on HRQoL, while the second includes own education and thus represents a broader IOp, alternatively it provides a comparison of the relative contributions of an effort variable and the two sets of circumstance variables.

Results: We find strong associations between the circumstance variables and HRQoL. A more detailed examination showed particularly strong associations between parental psychological problems and respondents' anxiety and depression. Our Shapley decomposition analysis suggests that parents' health and wealth are each as important as own educational attainment for explaining inequalities in adult HRQoL.

Conclusion: We provide evidence for the presence of the lasting effect of early life circumstances on adult health that persists even in one of the most egalitarian countries in the world. This suggests that there may be an upper limit to how much a generous welfare state can contribute to equal opportunities.

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Keywords: Inequality of opportunity, Childhood circumstances, Intergenerational transmission of health, EQ-5D, Abbrevations, IOp: Inequality of Opportunity, HRQoL: Health-Related Quality of Life, CFC: Childhood Financial Conditions, ITH: Intergenerational Transmission of Health, MO: Mobility, SC: Self-Care, UA: Usual Activities, PD: Pain & Discomfort, AX: Anxiety & Depression, GDP: Gross Domestic Product

Background

Inequalities in health among socioeconomic groups are well documented in many countries and constitute a major policy concern. In her seminal paper, Whitehead held that for an inequality to be considered unfair "the *cause* has to be examined and *judged* to be unfair" [1]. Inspired by the conceptual dichotomy of *circumstances vs. efforts* [2, 3] an expanding literature in economics investigates the extent to which observed inequalities in health are caused by inequalities of opportunity (IOp) [4–8]. Circumstances are factors that lie *outside* of individuals' control and, thus, something they cannot be held responsible for. If health inequalities are caused by systematic differences in circumstances, i.e. unequal opportunities, they are judged to be unfair. Efforts, on the other hand, reflect factors that are *within* individuals' control and resulting inequalities are, therefore, not judged to be unfair [2, 9, 10]. The IOp literature distinguishes between *two* approaches: the *ex-ante* approach analyses IOp without considering effort, while *ex-post* analyses IOp when both circumstances and effort variables are considered [11, 12]. In the current paper, we adopt an *ex-ante* approach, followed by a model specification that includes a variable that can either be considered an additional circumstance, alternatively an effort.

This paper makes several contributions to the literature on IOp in health: First, except for Rivera [13], previous studies have either relied on ordinal, single-item measures of self-assessed health or have focused on narrowly defined aspects of health such as the presence of psychiatric disorders. These approaches fail to capture the multidimensional nature of health and how it affects different aspects of health-related quality of life (HRQoL). In this paper, health is measured by preference-based values obtained via the EQ-5D-5L instrument. Furthermore, we examine inequalities on opportunity with respect to different HRQoL dimensions (mobility, self-care, usual-activities, pain & discomfort, and anxiety & depression), which previous work has not explored. Second, we investigate the extent to which two different types of circumstances that both lie outside of individuals' own control contribute to explaining inequalities in adult health. By considering childhood financial conditions, we contribute to a growing literature on the importance of childhood circumstances in determining adult health [14–17], particularly the financial environment in which children grow up [18–20]. Aside from the financial conditions during childhood, parents are likely to contribute to their offspring's adult health by passing on some of their health stock (e.g. through genetics) and health-related behaviors [4, 21]. The existence of such *intergenerational transmission of health* (ITH) is well established. However, we extend this literature by the use of a comprehensive measure of parental health, i.e. the somatic *and* mental health of fathers *and* mothers. Beyond parents' wealth and health, we consider the influence of own educational attainment. We take no position as to whether own education should be considered a circumstance [22] or effort [5]. Following on from this, we contribute to the literature by comparing the relative importance of childhood financial conditions (CFC), parental health and own education for explaining health inequalities. Our institutional context for studying inequality of opportunity in health is a country widely considered to be one of the most egalitarian in the world, with excellent access to public education, health care, and social security systems. At data collection, Norway was ranked 1st on the human development index compiled by the United Nations Development [23]. In addition, compared to other European countries, Norway have one of the lowest IOp for disposable income [24, 25]. Hence, Norway offers a useful 'best-case' benchmark against which other countries can be compared.

Methods

Data sources

We used data from a large general population survey (conducted in 2015/16) of 21,083 individuals aged 40–97 years living in Tromsø, Norway. The study population is considered broadly representative of the Norwegian population aged 40 and above, however, with individuals holding a university degree being slightly overrepresented. The design of this Tromsø Study is described elsewhere [26].

Health outcome

HRQoL was measured through the EQ-5D-5L instrument, in which respondents were asked to describe the level of problems they experience (either *no*, *slight*, *moderate*, *severe* or *extreme*) along five dimensions (mobility (denoted as MO), self-care (SC), usual activities (UA), pain and discomfort (PD), anxiety and depression (AD)) [27]. In the absence of a Norwegian value set, EQ-5D-5L responses were converted into utility scores using an amalgam value set of four Western countries [28]. To examine inequalities in the specific HRQoL domains, we dichotomize responses into *no problems* vs *any problems*, because in four of the five dimensions there were relatively few individuals reporting problems of any degree (see Table A1).

Explanatory variables

Parental health

Parents' HRQoL was not assessed as part of the survey. Instead, respondents answered seven questions about their parents' morbidity profiles on the day of the survey. Five questions (whether parents had been diagnosed with chest pain, stroke, asthma, diabetes, or had a heart attack before age 60) were used to calculate the total burden of somatic diseases (coded as 0, 1, or ≥ 2). As few respondents reported more than two chronic conditions, we chose a widely used measure of multimorbidity (MM2 +) as the top category [29]. Respondents were also asked whether their parents' had known psychological problems and whether parents had had a history of alcohol and/or substance abuse.

Childhood financial conditions

Childhood financial conditions (CFC) was measured by the question: 'How was your family's financial situation during your childhood?' The response categories were: very good, good, difficult, and very difficult. The latter two categories were collapsed due to low frequency.

Education level

Respondents' level of educational attainment is categorized in line with the International Standard Classification of Education (ISCED): primary school (10 years); upper secondary school; lower university degree (< 4 years), and; higher university degree (≥ 4 years).

Econometric specifications

We estimate the following cross-sectional regression model: $y_i = f(\alpha + X_i^{'}\beta) + \varepsilon_i$. Here, y_i is a measure of HRQoL for individual $i = 1, \ldots, N$, X_i is a matrix of explanatory variables, f is a link function and ε_i is the error term. We estimate two specifications, with and without the inclusion of own education. We also provide three partial regression models for each set of the explanatory variables. Thereby, we can compare the coefficients' standard errors and magnitude in the partial models with those in the full model, and thus identify the extent of multicollinearity. All models include age and sex as covariates. Age was coded in three bands: 40–69, 70–79, and 80 +. The larger age band 40–69 was chosen because previous analysis showed that HRQoL is approximately stable until the late sixties before it declines [30].

Table 1 Descriptive statistics of study sample

			EQ-5D-5L utility score	
	N	%	Mean	(SD)
Total	20,150	100%	0.890	(0.109)
Sex				
Women	10,558	52.4%	0.879	(0.114)
Men	9,592	47.6%	0.902	(0.102)
Age				
40–69 years	16,984	84.3%	0.892	(0.106)
70–79 years	2,508	12.4%	0.891	(0.113)
80 + years	658	3.3%	0.849	(0.146)
Educational attainment				
Primary school (10 years)	4,481	22.6%	0.873	(0.120)
Upper secondary school	5,509	27.8%	0.885	(0.108)
Lower university degree < 4 years	3,880	19.6%	0.895	(0.104)
Higher university degree ≥ 4 years	5,951	30.0%	0.906	(0.100)
Childhood financial conditions (CFC)				
Difficult	5,084	25.5%	0.869	(0.120)
Good	13,720	68.8%	0.897	(0.103)
Very Good	1,138	5.7%	0.907	(0.107)
Parental health Number of somatic diseases				
Father				
0	12,017	59.6%	0.894	(0.107)
1	5,656	28.1%	0.888	(0.109)
2 +	2,477	12.3%	0.879	(0.114)
Mother				
0	13,742	68.2%	0.894	(0.108)
1	4,812	23.9%	0.886	(0.109)
2 +	1,596	7.9%	0.870	(0.117)
Psychological problem				
Father				
No	19,396	96.3%	0.891	(0.108)
Yes	754	3.7%	0.862	(0.117)
Mother				
No	18,521	91.9%	0.893	(0.107)
Yes	1,629	8.1%	0.860	(0.127)
Substance abuse				
Father				
No	18,954	94.1%	0.891	(0.108)
Yes	1,196	5.9%	0.873	(0.119)
Mother				
No	19,814	98.3%	0.891	(0.108)
Yes	336	1.7%	0.857	(0.131)

Model specification 1 includes CFC and parental health, both of which reflect circumstances outside of own control. Model 2 further includes respondents' highest educational attainment. To account for heterogeneity across sexes [31], this main model was also estimated separately for men (Model 2M) and women (Model 2W). We quantify the relative importance of *each* explanatory variable for the overall R^2 by using the Shapley decomposition method. This decomposition derives the marginal effect of the explanatory variables on the R^2 by eliminating each variable in sequence, and then assigns to each variable the average of its marginal contributions in all possible elimination sequences [32, 33].

Finally, by comparing the magnitude of the education coefficients in the partial Model Edu (Table A2) with those in the full Model 2, we get an indication of the extent to which the associations between own education and HRQoL operates through parent's health and wealth.

All models were estimated by OLS (utility scores) or logit regressions (dimension responses). We do not model responses on the EQ-dimensions as ordered outcomes, because few individuals report worse levels than *slight* problems (see Table A1), and because the proportional odds assumption was found to be violated in our data. To explore potential cohort effects, we also estimated separated regressions (based on Model 2) for individuals aged 40–49; 50–59; 60–69, and 70 +.

In the sensitivity analyses, we first wanted to assess the appropriateness of the main model specification. For this, we apply the least absolute shrinkage and selection operator (LASSO) method. The LASSO method standardizes predictors and utilizes a regularization factor, the L1-norm or lambda (λ), to maximize the out-of-sample model fit by applying a penalty to predictor coefficients. This removes predictors that do not contribute to the out-of-sample performance of the model [34]. In the next sensitivity analysis, we split the sample into four based on the age bands (40–49; 50–59; 60–69, and 70 +.) and rerun the main specification on these subsamples.

All analyses were conducted using R version 1.4.1106; packages used were stats, relaimpo, margins, glmnet, and caret.

Results

Main results

Table 1 provides descriptive statistics of the sample and mean utility scores by level of respondent characteristic. Table 2 presents the main regression results by use of two model specifications, and with EQ-5D-5L utility scores as dependent variable. The stable standard errors and coefficients across the two models indicate that the key sets of predictors are independent of each other. Furthermore, by comparing the standard errors and coefficients in the three partial model specifications (Table A2) with those in the full Model 2, there is further evidence that multicollinearity is not a problem; i.e. each of our three sets of predictors are independent of each other. Note in particular that the education coefficients and their standard errors in Model 2 are remarkably similar to those in the partial model (Table A2).

Now, we focus on results from Model 2. The difference in adult HRQoL between having had Very good vs. Difficult CFC (0.008 – (-0.024) = 0.032) is approximately equal to the education gap (= 0.030). All three measures of parental health have statistically significant effects on respondents' adult HRQoL. In Model 2M and 2W, there are some noteworthy differences between men and women: difficult CFC and mothers' somatic diseases and psychological problem affect women more than men.

Table 3 provides the coefficient estimates from the logit regression models and the average marginal effect of variables on the probability of reporting *no problems*, for each EQ-dimension. There is considerable heterogeneity across dimensions. For example, having experienced difficult CFC reduces the probability of reporting no problems with Pain/discomfort by -6.9 percentage points (pp) compared to -1.7 pp for Self-care. Parental psychological problems affect own Anxiety/depression most, whereas parental somatic problems are most closely associated with Pain/discomfort, Mobility and Usual activities.

The Shapley decomposition analyses in Fig. 1 illustrate the relative importance of CFC, parental health, and own educational attainment for respondents' HRQoL for the pooled sample and separately for each sex. In the pooled sample analysis, CFC and parental health account for nearly 50% of the explained variance, while educational attainment account for 22.4%. For both sexes, the relative importance of the three main predictors appear broadly similar: parental health variables together explain around 31%; CFC slightly less (29%), while own education is relatively more important in explaining men's HRQoL.

Sensitivity analysis

For the LASSO method, we choose the optimal parameterization of lambda by means of 10-fold cross validation. After regularizing the model, all parameters were nonzero, thus supporting the appropriateness of the model specification.

Table A3 shows results by age groups. The effects of parents' psychological problems and substance abuse are more pronounced in younger respondents, which may reflect cohort differences in the awareness of mental health and substance abuse. For example, the oldest cohort reported much lower frequencies of parents' mental health problems (Table A4). The HRQoL-gap due to CFC is larger in the oldest age group, suggesting life-long effects of CFC. The educational gradient is more pronounced in younger respondents but diminishes around retirement age.

Table 2 Linear regression on the EQ-5D-5L utility score

	Full sample		**Men**	**Women**
Variables	Model 1	Model 2	Model 2M	Model 2W
Intercept	0.896***	0.879***	0.898***	0.884***
	(0.001)	(0.002)	(0.003)	(0.003)
Men	0.021***	0.022***		
	(0.002)	(0.002)		
Age groups (Ref. 40–69)				
70–79	0.000	0.005**	0.012***	-0.002
	(0.002)	(0.002)	(0.003)	(0.004)
80+	-0.045***	-0.036***	-0.022***	-0.048***
	(0.004)	(0.005)	(0.006)	(0.007)
Childhood financial conditions (Ref. Good)				
Difficult	-0.026***	-0.024***	-0.020***	-0.027***
	(0.002)	(0.002)	(0.002)	(0.003)
Very good	0.010***	0.008**	0.006	0.010**
	(0.003)	(0.003)	(0.005)	(0.005)
Number of somatic diseases (Ref. 0)				
Father 1	-0.004**	-0.004**	-0.004*	-0.004
	(0.002)	(0.002)	(0.002)	(0.002)
Father 2+	-0.012***	-0.012***	-0.012***	-0.012***
	(0.002)	(0.002)	(0.003)	(0.003)
Mother 1	-0.004**	-0.003	-0.002	-0.003
	(0.002)	(0.002)	(0.003)	(0.003)
Mother 2+	-0.016***	-0.014***	-0.009**	-0.017***
	(0.003)	(0.003)	(0.004)	(0.004)
Psychological problem (Ref. No)				
Father: Yes	-0.020***	-0.022***	-0.024***	-0.020***
	(0.004)	(0.004)	(0.006)	(0.005)
Mother: Yes	-0.025***	-0.027***	-0.020***	-0.032***
	(0.003)	(0.003)	(0.004)	(0.004)
Substance abuse (Ref. No)				
Father: Yes	-0.009***	-0.010***	-0.010**	-0.010**
	(0.003)	(0.003)	(0.004)	(0.005)
Mother: Yes	-0.016***	-0.018***	-0.021**	-0.015*
	(0.006)	(0.006)	(0.009)	(0.008)
Educational attainment (Ref. Primary school 10 years)				
Upper secondary school		0.008***	0.011***	0.004
		(0.002)	(0.003)	(0.003)
Lower university degree < 4 years		0.019***	0.020***	0.015***
		(0.002)	(0.003)	(0.004)
Higher university degree ≥ 4 years		0.030***	0.027***	0.030***
		(0.002)	(0.003)	(0.003)
R^2	0.041	0.051	0.031	0.050

Note: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Discussion

This study contributes to the growing literature on inequalities in opportunity by providing new evidence from one of the wealthiest and most equal countries in the world on the extent that circumstances such as parental health and CFC have lasting impacts on adult HRQoL. Earlier Norwegian studies on IOp have focused on childcare [35], education [36] and income [37]. However, we have not identified Norwegian IOp-studies on health that have included parental health. Our results show parents'

Table 3 Logistic regression results of the probability of reporting no problems on the EQ-5D-5L dimensions

	Mobility		Self-care		Usual activities		Pain discomfort		Anxiety/depression		
	Est(SE)	AME(SE)	Est(SE)	AME(SE)	Est(SE)	AME(SE)	Est(SE)	AME(SE)	Est(SE)	AME(SE)	
Intercept	1.462***		3.323***		1.327***		-0.908***		1.186***		
	(0.052)		(0.102)		(0.052)		(0.045)		(0.049)		
Men	0.337***	0.046***	0.155**	0.006**	0.638***	0.085***	0.384***	0.083***	0.288***	0.048***	
	(0.039)	(0.005)	(0.074)	(0.003)	(0.041)	(0.005)	(0.031)	(0.007)	(0.036)	(0.006)	
Age groups (ref. 40–69)											
70–79	-0.357***	-0.052***	-0.198*	-0.008*	0.098	0.013	0.187***	0.041***	0.495***	0.074***	
	(0.056)	(0.009)	(0.108)	(0.005)	(0.062)	(0.008)	(0.048)	(0.011)	(0.062)	(0.008)	
80 +	-1.371***	-0.258***	-0.954***	-0.054***	-0.552***	-0.087***	0.198**	0.044**	0.229**	0.037**	
	(0.090)	(0.021)	(0.153)	(0.012)	(0.100)	(0.018)	(0.092)	(0.021)	(0.111)	(0.017)	
Childhood financial conditions (Ref = Good)											
Difficult	-0.340***	-0.049***	-0.405***	-0.017***	-0.374***	-0.053***	-0.330***	-0.069***	-0.350***	-0.061***	
	(0.043)	(0.006)	(0.079)	(0.004)	(0.043)	(0.006)	(0.038)	(0.008)	(0.039)	(0.007)	
Very Good	-0.065	-0.009	0.056	0.002	0.154	0.019*	0.250***	0.057***	0.401***	0.057***	
	(0.087)	(0.012)	(0.176)	(0.006)	(0.093)	(0.011)	(0.064)	(0.015)	(0.088)	(0.011)	
Number of somatic diseases (Ref. 0)											
Father 1	-0.048	-0.006	-0.097	-0.004	-0.086*	-0.011*	-0.090**	-0.020**	-0.031		-0.005
	(0.044)	(0.006)	(0.083)	(0.003)	(0.044)	(0.006)	(0.035)	(0.008)	(0.040)		(0.007)
Father 2 +	-0.192***	-0.027***	-0.251**	-0.010**	-0.193***	-0.027***	-0.281***	-0.059***	-0.103*		-0.017*
	(0.058)	(0.009)	(0.107)	(0.005)	(0.059)	(0.008)	(0.050)	(0.010)	(0.054)		(0.009)
Mother 1	-0.150***	-0.021***	-0.084	-0.003	-0.062	-0.008	-0.075**	-0.016**	0.030		0.005
	(0.045)	(0.006)	(0.086)	(0.003)	(0.046)	(0.006)	(0.037)	(0.008)	(0.042)		(0.007)
Mother 2 +	-0.378***	-0.056***	-0.228*	-0.009*	-0.315***	-0.045***	-0.344***	-0.071***	0.012		0.002
	(0.066)	(0.011)	(0.125)	(0.006)	(0.066)	(0.010)	(0.063)	(0.012)	(0.065)		(0.011)
Psychological problem (Ref. No)											
Father: Yes	0.023	0.003	-0.192	-0.008	-0.232**	-0.033**	-0.145*	-0.031*	-0.885***		-0.177***
	(0.103)	(0.014)	(0.179)	(0.008)	(0.096)	(0.015)	(0.085)	(0.018)	(0.079)		(0.018)
Mother: Yes	-0.106	-0.015	-0.199	-0.008	-0.311***	-0.045***	-0.222***	-0.046***	-0.754***		-0.146***
Substance abuse (Ref. No)	(0.070)	(0.010)	(0.126)	(0.006)	(0.067)	(0.010)	(0.061)	(0.012)	(0.057)		(0.012)
Father: Yes	-0.146*	-0.021*	0.024	0.001	0.022	0.003	-0.065	-0.014	-0.231***		-0.040***
	(0.080)	(0.012)	(0.155)	(0.006)	(0.083)	(0.011)	(0.068)	(0.014)	(0.069)		(0.013)
Mother: Yes	-0.421***	-0.065***	-0.123	-0.005	-0.208	-0.030	-0.164	-0.034	-0.099		-0.017
	(0.136)	(0.023)	(0.268)	(0.011)	(0.140)	(0.021)	(0.131)	(0.027)	(0.125)		(0.022)

Table 3 (continued)

	Mobility		Self-care		Usual activities		Pain discomfort		Anxiety/depression	
Educational attainment (Ref. Primary school 10 years)										
Upper secondary school	0.159***	0.025***	-0.075	-0.003	0.069	0.011	-0.002	0.000	0.092*	0.016*
	(0.051)	(0.008)	(0.098)	(0.004)	(0.052)	(0.008)	(0.046)	(0.009)	(0.050)	(0.009)
Lower university degree < 4 years	0.374***	0.055***	0.093	0.004	0.304***	0.044***	0.234***	0.050***	0.097*	0.017*
	(0.059)	(0.009)	(0.112)	(0.004)	(0.060)	(0.009)	(0.049)	(0.010)	(0.055)	(0.009)
Higher university degree ≥ 4 years	0.643***	0.088***	0.382***	0.013***	0.634***	0.083***	0.455***	0.100***	0.217***	0.036***
	(0.056)	(0.008)	(0.109)	(0.004)	(0.057)	(0.008)	(0.045)	(0.010)	(0.051)	(0.008)
Pseudo R2: McFadden	0.041		0.018		0.037		0.023		0.033	

Note: *$p<0.1$, **$p<0.05$, ***$p<0.01$. *Est* Estimated coefficient on logit scale, *AME* Average marginal effect on probability scale, *SE* Standard error

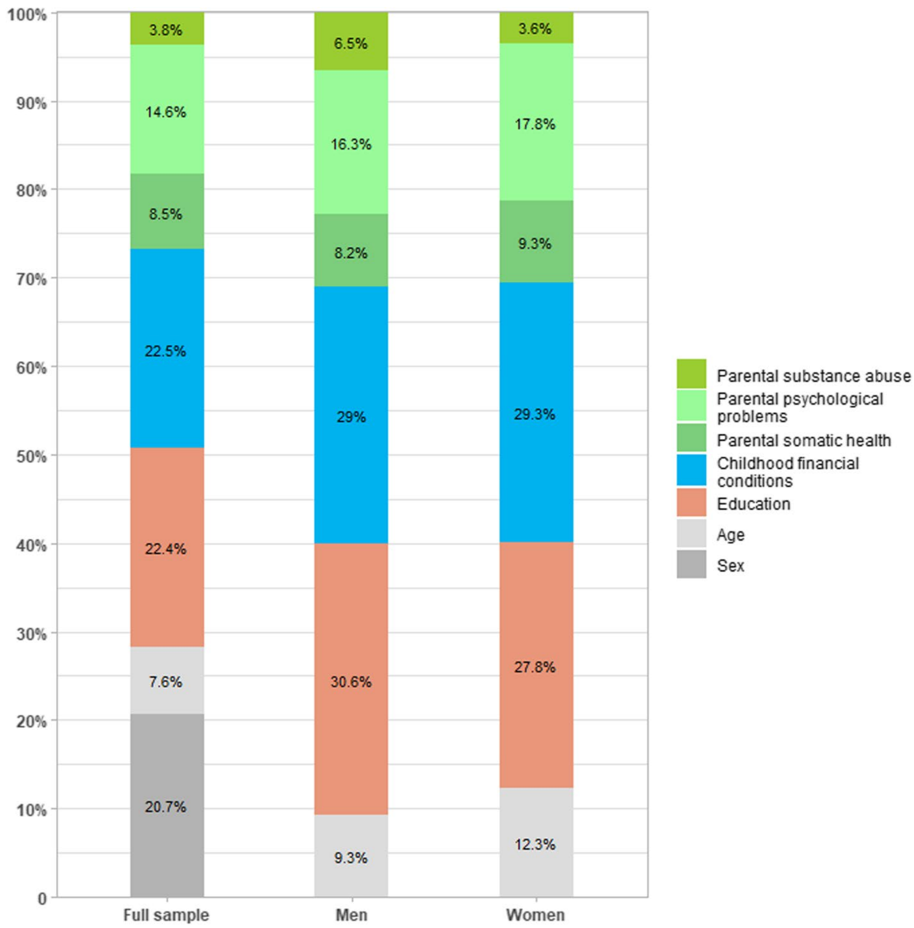

Fig. 1 Shapley decomposition of explained variance (R^2 for utility score) based on model specification 2, 2M, and 2W

somatic health affect their offspring's pain and functional ability, while parents' psychological problems and substance abuse have substantial effects on their children's self-reported levels of anxiety/depression.

Furthermore, our findings support previous studies from other countries which show lasting impacts of CFC on adult health [19], and we find these to have similar magnitude to the impact of educational attainment. Interestingly, the distributions of respondents on the three CFC-levels are remarkably similar across age-cohorts (Table A4), whose *absolute* standard of living during childhood increased tremendously over time (approximately 3% p.a. GDP/capita growth between 1950 and 1990). This suggest that our measure of CFC represents a good proxy for *relative* deprivation. Finally, the Shapley analysis showed that CFC and parental health are each as important for HRQoL as own educational attainment.

We found evidence of heterogeneity by sex in how much circumstances affect descendants' health. As for parental health, the general pattern is that fathers' ill health have similar effects on sons and daughters, while mothers' ill health have stronger effects on daughters. However, sons appear to be relatively more negatively affected than daughters by their fathers' substance abuse and psychological problems. As for the 'social lottery' of early life, childhood financial conditions appear to be more important for women's than men's adult health.

While CFC and parental health are assumed to reflect circumstances, own educational attainment is arguably *partly* outside of one's control and therefore more difficult to locate on the circumstances-efforts continuum. Previous work has considered education either as circumstance [22] or effort [5]. This disagreement in the literature emphasizes the importance of defining an *age of consent* to delineate circumstances from effort as suggested by Arneson [38] and empirically investigated by Hufe [39]. In this paper, we prefer to take no firm position on this issue. However, we do observe that the estimated effect of educational attainment on HRQoL is remarkably stable across econometric specifications, indicating that it is largely independent of assumed circumstances (i.e. CFC and parental health).

We acknowledge that our categorization of parental health as *circumstances* might be suggestive of inherited genetics that are outside of children's control. However, parents' ill health may have been caused in part by their health-related behaviors or unhealthy habits, which they can pass on to their children (e.g. Balasooriya [40]). While it certainly takes efforts to quit inherited bad habits, they may be easier to alter than bad genes. Thus, focusing on unhealthy habits may appeal to policymakers who seek to tackle health inequalities in their communities.

Our study has some limitations. First, we approximate parents' health through their morbidities burden sometime *after* their offspring are likely to have left the nest. We are therefore cautious in interpreting these results to reflect any particular pathway of intergenerational transmission of health (i.e. genetics, habits). Second, parents' morbidity patterns and health-related behaviors are likely to be incomplete proxies of the parental health stock and its determinants. Finally, we cannot rule out reverse causality in which children's poor health requires parents to take on care duties, with negative consequences for parental health.

In this paper, we have focused on two sets of circumstance variables that are clearly outside of own control, and further included one variable, education, that lies somewhere in between the end points on the *circumstances-effort continuum*. Certainly, there is a need for research that includes more variables that lie towards the effort-end on this continuum, i.e. indicators of health related behaviour, e.g. physical activity. Such research would provide important knowledge on the difficult question: how much of observed health inequalities reflect inequalities in opportunity, and hence considered *unfair*, as compared to how much that reflect own choices, and hence considered *acceptable*?

We have shown that even in a land of equal opportunities, large inequalities in HRQoL are caused by circumstances beyond individuals' control. If Norway cannot eradicate unfair inequalities in health, other countries will also struggle. This suggests that there may be an upper limit to how much a generous welfare state can contribute to equal opportunities.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12889-022-14084-x.

Additional file 1: Table A1. Distributions of EQ-5D-5L responses by dimension (N, %). **Table A2.** Linear regressions on the EQ-5D-5L utility score. Partial effects: parents' wealth (Model PW); parents' health (Model PH); own education (Model Edu). **Table A3.** Analysis of utility scores by age-groups (Model 2 specification). **Table A4.** Descriptive statistics (N, %) by age groups.

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Authors' contributions
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Availability of data and materials
Since the data contains potentially identifying or sensitive information about the participants in the Tromsø study, we are not allowed to share a data set. Contact information for the Tromsø study can be found by the following link: https://uit.no/research/ tromsostudy/project?pid = 709,148.

Declarations

Ethics approval and consent to participate
All methods were carried out in accordance with relevant guidelines and regulations. The study was approved by the regional committee for Medical and Health Research Ethics (ID 2016/607). All participants gave written informed consent before admission.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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Publisher's Note

Paper 2

Berthung, E., Gutacker, N., Olsen, J.A., & Abelsen, B.

The heterogeneous impact of health shocks on labour market participation: Evidence from Norway.

(Submitted manuscript).

The heterogeneous impact of health shocks on labour market participation: Evidence from Norway

1 Introduction

Substantial increases in life expectancy in many OECD countries are putting pressure on public pension systems. Governments are considering increases in the retirement age to alleviate this pressure by prolonging the time people work. However, as people age, they tend to accumulate health problems that limit their ability to work. In order to design effective policies that support labour market participation (LMP), more knowledge is needed on how individuals with different demographic characteristics adjust to health shocks.

A large body of literature has studied the causal effect of unforeseen health shocks on individuals' LMP. As a proxy for health shocks, some papers have used accidents (1-3), some have used decreases in self-assessed health (2, 4-6), but most papers have relied on the incidence of particular diseases such as stroke (7, 8), heart attacks (Tanaka 2021) or cancer (9-15).

Different types of health shocks are likely to affect LMP differently, although this has received little empirical attention in the literature to date (Tanaka 2021). To our knowledge, only Trevisan and Zantomio (14) have compared the impact of different types of health shocks on LMP and found these to differ in magnitude, with stroke having the greatest effect on LMP, followed by cancer and acute heart attacks. There is also considerable uncertainty about the modifying influence of education. For stroke, Trevisan and Zantomio (14) found that highly educated women showed a larger reduction in LMP than less educated women, whereas Hackett, Glozier (8) reported the opposite, and Tanaka (2021) found no modifying effect of educational attainment. These studies differ in institutional setting (England, the USA and Australia), which calls for further research in other countries.

In this paper, we investigate the impact of three different health shocks (stroke, acute heart attack, and three cancer severity levels) on individuals' LMP in Norway, and how the effects are modified by educational attainment. We combine rich data from the State Register of Employers and Employees, the Norwegian Patient Registry, and the prospective Tromsø Study. This combination provides detailed panel data with annual observations. We apply linear models with fixed effects (FE) and correlated random effects (CRE) estimators. The FE estimator controls for individual unobserved heterogeneity, e.g. ability, income and preferences for leisure, and estimates the within-effect of the health shocks. The CRE estimator allows us to include variables that only vary between individuals while retaining the interpretation of the within-effect of health shocks. Our identification strategy follows previous work in this field (e.g. Tanaka (7), Heinesen and Kolodziejczyk (12), Heinesen, Imai (13)) and rests on the assumption that the health shocks are sudden and unexpected. Thus, individuals do not adjust their LMP in anticipation of the shock.

Our paper makes several contributions to the literature. First, we estimate and compare the differential effect of health shocks caused by three different diseases (stroke, acute heart attack, and cancer), thereby adding to the limited literature on heterogeneous effects by type of health shock (14). Second, inspired by (16), we explore heterogeneity by severity of the health shock, particularly for cancer, measured by differences in predicted five-year survival rates. Third, there is little and contradictory evidence of heterogeneity in health shocks by educational level in different institutional settings. We contribute to previous research (7, 8, 12) by investigating heterogeneity by educational attainment. Finally, this is the first study of the effect of health shocks on LMP in Norway, a country widely known for its generous social insurance schemes that support individuals who are unable to work.

We find that stroke reduces individuals' LMP more than acute heart attack, and the reduction increases with the severity levels for cancer. Among all health shocks, cancer with a poor survival prognosis leads to the greatest reduction in LMP, followed by stroke, cancer with an intermediate survival prognosis, acute heart attack, and cancer with a good survival prognosis. We also found evidence that education modifies the effect of cancer.

2 Method

2.1 Data sources and material

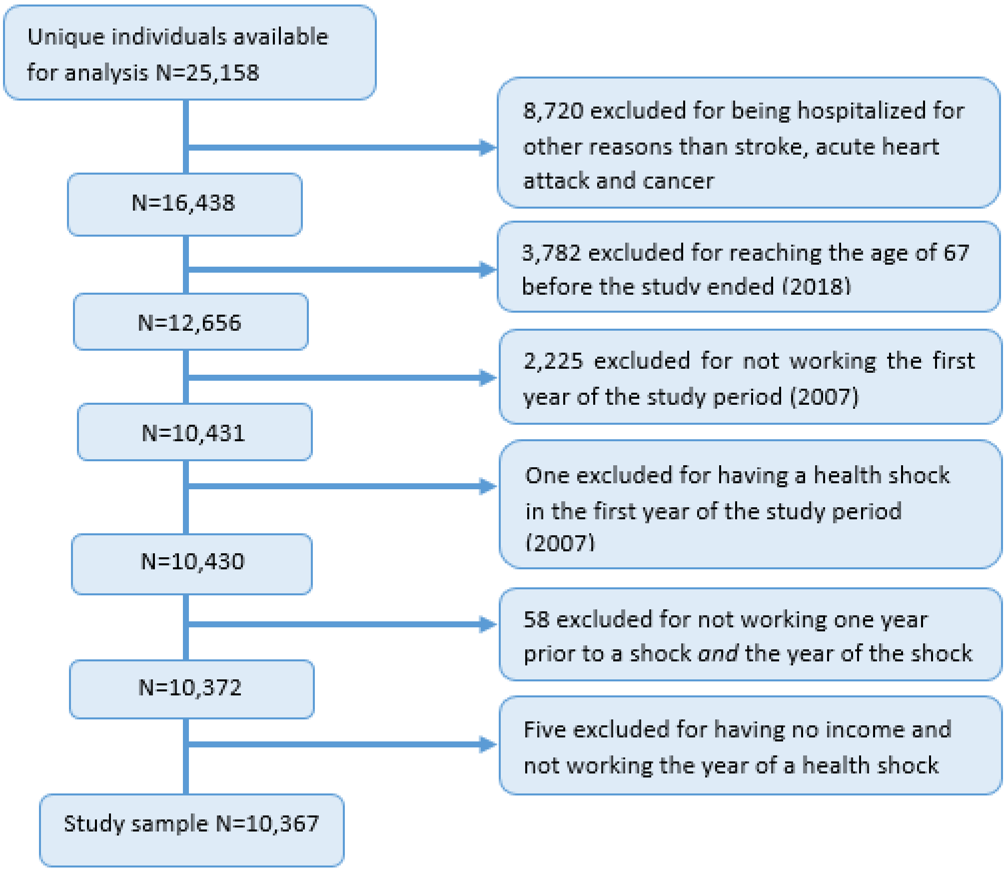
The study sample is based on participants in at least one of the sixth and seventh waves of the Tromsø Study (conducted in 2007/8 and 2015/16, respectively). This is a prospective cohort study of the adult population living in the municipality of Tromsø in Northern Norway. The study population is considered broadly representative of the Norwegian adult population, although people with a university degree are slightly overrepresented. The study design is described in detail elsewhere (17). All participants gave written informed consent before admission. Statistics Norway provided the participants' yearly LMP data from 2007 to 2018. The LMP data are obtained from the State Register of Employers and Employees. This register was established in 1978 when the sick pay scheme was introduced and lists all current employment in Norway (18). This register is a coordinated digital service where employers report information about income and employees. Public authorities such as the Norwegian Labour and Welfare Administration (NAV), the Norwegian Tax Administration, and Statistics Norway use this register. Statistics Norway also provides data on individuals' income and 'taxable and non-taxable transfers' for the same period. Income includes salary from work, capital income, sickness benefits, and parental benefits, while 'taxable and non-taxable transfers' includes retirement pension, disability benefits, and unemployment benefits. This information is obtained from individuals' tax returns.
The Norwegian Patient Registry provided healthcare data, including the first onset of any hospital admission during the study period. The data include ICD-10 (International Classification of Diseases, 10th version) codes and the date of occurrence (between 2006 and 2018). No information on subsequent admissions or unrelated care is provided. We rearranged the cross-sectional LMP data into a panel structure and then merged healthcare and demographic data from the Norwegian Patient Registry and the Tromsø Study.

This study was approved by the Regional Committee for Medical and Health Research Ethics (ID 2016/607).

2.2 Sample selection

A total of 25,158 individuals participated in at least one of the sixth and seventh waves of the Tromsø Study. The study period was from 2007 to 2018. We selected all non-hospitalized individuals who suffered a stroke, acute heart attack or cancer during the study period. To identify the impact of the health shocks on LMP, we first restricted our sample to working-age individuals. We excluded those who reached the age of 67 (the upper retirement age in Norway) before the end of the study period. Next, we excluded individuals who were either not working or who had a health shock in the first year of the study (2007). To further identify the impact of the health shocks, we excluded people who were not working one year before a shock *and* not working in the year of the shock. Moreover, we assumed that individuals had died in a given year if they were not working and not otherwise financially active (e.g. no income, no taxable and non-taxable transfers) in that or any subsequent years. We removed all observations (years) after death but retained those prior to death. Figure 1 presents the sampling procedure, leading to a sample of 10,367 unique individuals, and an unbalanced panel data of 124,053 individual-period observations.

Figure 1. Sampling procedure



2.3 Variables

2.3.1 Labour market participation variables

Yearly LMP data refer to participants' *contractual working time (denoted as 'hours worked').* Hours worked are the *agreed working hours the* employee is expected to work *each week* in a particular year. It does not include sick leave, vacation, or overtime work. The 'hours worked' variable only has values for years when individuals are working. Years where individuals are not working are recorded as missing values. We imputed missing values as zero. Based on this, we also created a new binary variable indicating whether people were working (at least one hour per week) or not working (zero hours per week).

2.3.2 Health shocks

We treated stroke (ICD-10 code I63), acute heart attack (I21), and cancer (C01-C92) as separate health shocks. Cancer was further categorized into three severity levels by their five-year survival rate prognosis provided by the Cancer Registry of Norway (19). Cancer diagnoses with a five-year survival prognosis equal to and above 85% were categorized as *good*, those from 85% to 60% as *intermediate*, and those below 60% as *poor*. These cut-off points were motivated by the frequency distribution of the five-year survival rates in Figure A1 in the Supporting Information File. Table A1 in the Supporting Information File shows the categorization of the prognoses into good, intermediate and poor by type of cancer.

2.3.3 Age and education

Age was obtained by recalculating participants' age when they participated in the Tromsø Study, and further split into two-year bins for the analyses. Individuals' self-reported educational attainment was grouped into four levels based on the International Standard Classification of Education: primary and lower secondary school, upper secondary school, lower university degree (< 4 years), and higher university degree (≥ 4 years). We further dichotomized the four educational groups into 'no university degree' and 'university degree'.

3 Econometric model specification

First, we estimated a linear model with fixed effects (FE) to quantify the within-effect of a health shock on hours worked. We then replaced the FE with correlated random effects (CRE), which enabled time-invariant individual characteristics to be included (20).

The FE model was specified as follows:

$$y_{it} = \lambda + \sum_{a=1}^{A} \delta_a Age_{it,a} + \sum_{k=1}^{5} \beta_k Shock_{it,k} + \alpha_i + e_{it} \tag{1}$$

The outcome y_{it} is hours worked for individual i=1,..,N at time t=1,..T, λ is a constant term, and $Age_{it,a}$ is a=1,…, A binary variables denoting two year bins. $Shock_{it,k}$ is indicator variables that take the value of 1 following the health shock k at $t = t^*$ and 0 before it. The parameters of interest are β_k, which captures the within-effect for each health shock *k* over the post-shock periods, α_i, which captures individual heterogeneity (individual-specific and time-invariant characteristics), while e_{it} is the random error term.

The CRE model was specified as follows:

$$y_{it} = \lambda + \sum_{a=1}^{A} \delta_a Age_{it,a} + \sum_{k=1}^{5} \beta_k Shock_{it,k} + \gamma X'_{it} + \sum_{a=1}^{A} \delta_a \overline{Age_{it,a}} + \sum_{k=1}^{5} \beta_k \overline{Shock_{it,k}} + \mathrm{u}_i + e_{it} \tag{2}$$

y_{it}, λ, $Age_{it,a}$, $Shock_{it,k}$, and e_{it} are the same as in the previous specification. X' is a vector of time-invariant independent variables while $\overline{Age_{it,a}}$ and $\overline{Shock_{it,k}}$ are the cluster means for the age bins and the health shocks. The term u_i also captures individual heterogeneity. The main difference between these two models is that in the first (FE) cluster specific values were estimated for α_i while in the second (CRE) the variance of u_i was estimated. We also investigated heterogeneity by including interaction terms in the two model specifications. We used the same estimators and regression specifications in linear probability (LP) models with a binary indicator of working (no/yes) as dependent variable.

We assume that individuals do not anticipate such health shocks and do not adjust their LMP in advance, i.e. health shocks are exogenous and lead to a sudden and unexpected change in health at $t = t^*$. In addition, we are interested in dynamic effects that follow a health shock, i.e. the incremental change in LMP over time. We estimated the following event study model with a fixed effects estimator to test for anticipatory behaviour and dynamic effects:

$$y_{it} = \lambda + \sum_{a=1}^{A} \delta_a Age_{it,a} + \sum_{l=2}^{5} \beta_l Shock_{i,t^*-l} + \beta_0 Shock_{i,t^*} + \sum_{l=1}^{4} \beta_l Shock_{i,t^*+l} + \alpha_{it} + e_{it} \tag{3}$$

$Shock_{i,t^*-l}$ is a set of binary variables that indicates whether worker i will experience a shock in a lead period of time. It takes the value of 1 if the individual experiences a shock at time t* and 0 otherwise. The full term $\sum_{s=2}^{5} \beta_l Shock_{i,t^*-l}$ captures the anticipatory effects. $Shock_{i,t^*}$ is a binary variable that takes the value of 1 if worker i experiences a shock at time t*. $Shock_{i,t^*+l}$ is a set of binary variables that indicates whether worker i had a shock at time t*. These variables also take the value of 1 if the individual experiences a shock at time t*. The full term $\sum_{l=1}^{4} \beta_l Shock_{i,t^*+l}$ captures the dynamic effects. We set the reference point to one year prior to the health shock ($t^* - 1$). We performed an F-test of the lead and lagged terms to test for anticipation and dynamic effects. In this analysis, we only included those who experienced a health shock. The shocks were modelled separately to investigate the exogeneity assumption for each shock.

4 Results

4.1 Descriptive statistics

Table 1 provides descriptive statistics from the first year of the study period when all individuals were healthy and working. The sample includes more men than women, and more than half the sample had a university degree (57.2%). During the study period, 690 individuals suffered their first health shock that led to hospitalization: 71 had a stroke, 137 had an acute heart attack, and 482 were diagnosed with cancer.

Table 1. Characteristics of the sample

At baseline 2007			
Sex	N=10,367	%	Hours worked (SD)
Women	5,008	48.3	33.9 (7.20)
Men	5,359	51.7	36.2 (5.37)
Age groups			
29-34 years	1,693	16.3	35.0 (6.87)
35-39 years	2,214	21.4	35.4 (6.21)
40-44 years	2,333	22.5	35.1 (6.30)
45-49 years	1,923	18.5	35.3 (5.95)
50-54 years	1,689	16.3	34.9 (6.69)
55-56 years	515	5.0	34.3 (6.96)
Education			
Primary/lower secondary school	1,421	13.8	34.3 (7.11)
Upper secondary school	3,000	29.1	34.8 (6.71)
Lower university degree <4 years	2,193	21.3	35.6 (5.80)
Higher university degree >4 years	3,698	35.9	35.4 (6.12)
Missing values	55		
Health shocks, and hours worked at baseline 2007			
		N	
Stroke		71	35.5 (5.75)
Acute heart attack		137	35.1 (6.96)
Cancer, survival prognosis[1]			
Good		282	35.5 (5.69)
Intermediate		157	35.1 (6.33)
Poor		43	36.0 (5.21)
Total shocks		690	

[1] See Table A1 in the Supplementary file for a complete description of cancers and their survival rates.

Table 2. Sample characteristics in the year of a health shock

	Stroke			Acute heart attack		
	N	%	Mean age (SD)	N	%	Mean age (SD)
Total	71	100.0	51.5 (7.4)	137	100.0	53.3 (6.2)
Sex						
Women	22	31.0	49.4 (8.4)	24	17.5	53.5 (6.7)
Men	49	69.0	52.5 (6.8)	113	82.5	53.2 (6.1)
Education[1]						
No university degree	38	53.5	52.6 (6.5)	79	58.5	53.4 (5.7)
University degree	33	46.4	50.3 (8.2)	56	41.5	53.2 (6.6)

	Cancer, five-year survival prognosis								
	Good survival prognosis			Intermediate survival prognosis			Poor survival prognosis		
	N	%	Mean age (SD)	N	%	Mean age (SD)	N	%	Mean age(SD)
Total	282	100.0	52.8 (7.9)	157	100.0	52.2 (7.4)	43	100.0	52.3 (5.8)
Sex									
Women	149	52.8	51.0 (7.2)	77	49.0	51.5 (8.3)	19	44.2	53.3 (4.7)
Men	133	47.2	54.9 (8.2)	80	51.0	53.0 (6.5)	24	55.8	51.5 (6.6)
Education[1]									
No university degree	122	43.7	53.2 (6.9)	75	47.8	52.8 (7.2)	18	41.9	53.8 (4.8)
University degree	157	56.3	52.5 (8.6)	82	52.2	51.7 (7.7)	25	58.1	51.2 (6.4)

[1]In the educational variable there are two missing values for acute heart attacks and three missing values for cancer with a good survival prognosis.

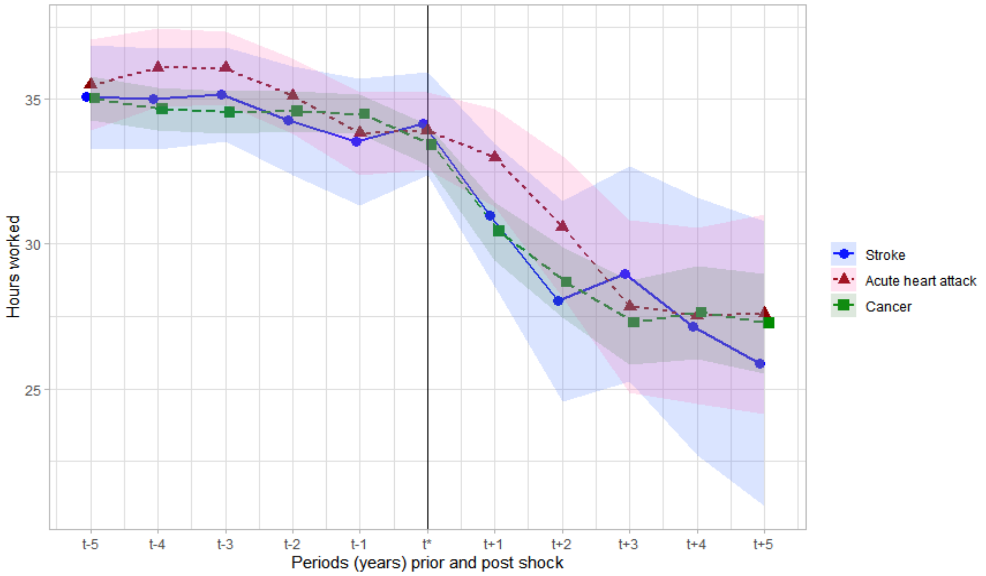
Table 3. Descriptive statistics of the short-term effect of the shocks on labour market participation

	One year before shock (t-1)		One year after shock(t+1)	
	Mean hours worked (SD)	% working[1]	Mean hours worked (SD)	% working
Stroke	34.5 (7.9)	98.6	28.3 (14.2)	85.3
Acute heart attack	33.9 (8.7)	97.1	31.8 (12.1)	89.6
Cancer, five-year survival prognosis				
Good	34.6 (6.5)	99.3	30.2 (12.7)	90.0
Intermediate	34.4 (6.8)	100.0	28.0 (13.8)	88.6
Poor	34.7 (8.0)	97.7	28.1 (15.5)	81.8

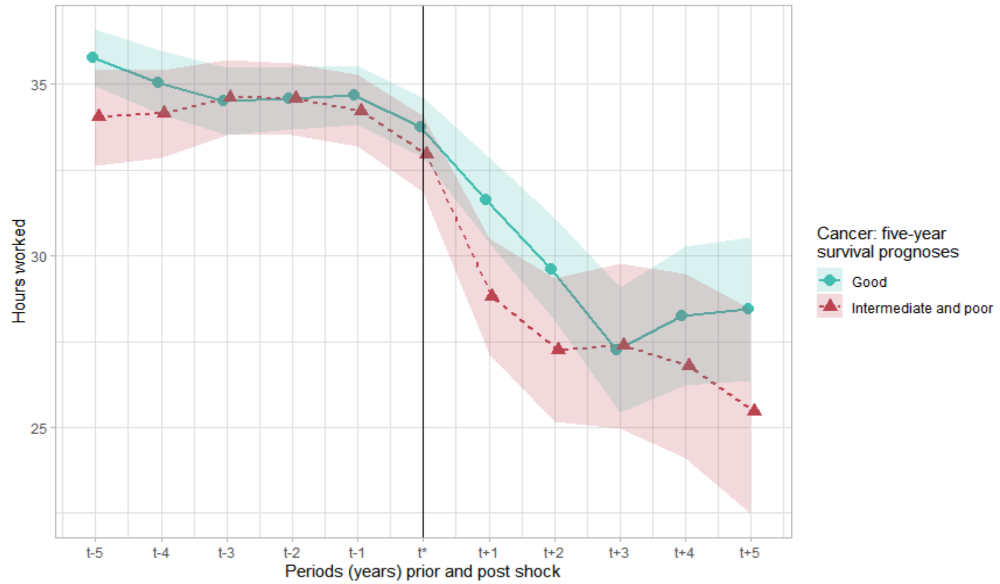
[1]Individuals who were not working one year before the shock are working in the year of the shock.

Figure 2. Trajectories in hours worked for stroke, acute heart attack and cancer severity levels.

Panel A. All health shocks



Panel B. Cancer prognoses



The 95 % confidence intervals increase with the years of the post-shock period. This increase is due to fewer observations and variation in individuals' adjustments to a health shock. In Panel B, cancer diagnoses with a poor survival prognosis are merged with intermediate prognoses due to fewer observations at later time points.

Table 2 provides sample characteristics and mean age at the time of the health shocks. The three health shocks typically occur at different times in people's lives. Individuals who had an acute heart attack were on average older than the other groups. Interestingly, individuals without a university degree were diagnosed with cancer at a later age. Figure 2 shows the trajectories in hours worked among those who had a health shock. Because health shocks occurred randomly during the study period, we centred the time series around the health shocks at t^*. Figure 2 provides support for our identification assumption: mean working hours are stable until a health shock occurs and decrease rapidly afterwards. In Figure 2, panel B, cancer diagnoses with a poor survival prognosis are merged with intermediate prognoses due to fewer observations at later time points.

Table 3 provides descriptive statistics for short-term changes in LMP one year prior to and one year after the health shock. These statistics suggest that stroke has a greater short-term effect on LMP than acute heart attack and that the effect of cancer increases with severity. These effects are observed both as hours worked and as the percentage of individuals still working.

4.2 Main analysis

Table 4 provides the results of the main analysis. Linear models 1 and 2 analyse hours worked using the FE and CRE estimators, respectively. The linear probability models 3 and 4 analyse the binary outcome of working (yes/no) with FE and CRE estimators, respectively. The average within-effects from the FE model are not exactly replicated using the CRE estimator due to missing values in the education variable.

Table 4. The effects of stroke, acute heart attacks and cancer on hours worked and the probability of working (no/yes). Linear model (LM), linear probability model (LP), fixed effects (FE) and correlated random effects (CRE).

	Hours worked		Working(yes)	
	LM FE	LM CRE	LP FE	LP CRE
Stroke	-3.67***	-3.67***	-0.08***	-0.08***
	(0.61)	(0.61)	(0.02)	(0.02)
Acute heart attack	-1.52***	-1.34***	-0.04***	-0.04***
	(0.44)	(0.44)	(0.01)	(0.01)
Cancer, five-year survival prognosis				
Good survival prognosis	-1.41***	-1.43***	-0.01	-0.01*
	(0.31)	(0.31)	(0.01)	(0.01)
Intermediate survival prognosis	-3.65***	-3.64***	-0.07***	-0.07***
	(0.42)	(0.42)	(0.01)	(0.01)
Poor survival prognosis	-4.88***	-4.88***	-0.11***	-0.11***
	(0.87)	(0.87)	(0.02)	(0.02)
Men (ref: women)		2.39***		0.01***
		(0.13)		(0.003)
Education (ref: no university)				
University degree		2.18***		0.03***
		(0.14)		(0.003)
Other control variables				
Age groups with two-year bins	V	V	V	V
Mean age groups, two-year bins		V		V
Mean health shocks		V		V
Constant		-182.62*		-3.55
		(104.88)		(2.28)
Observations	124,053	123,398	124,053	123,398
R^2	0.12	0.13	0.12	0.13

Note: *p<0.1, **p<0.05, ***p<0.01

All health shocks significantly reduced hours worked per week. Following a stroke, individuals worked on average 3.7 hours less, whereas individuals who suffered an acute heart attack reduced their weekly hours by 1.5. For cancer, the average reduction was 1.4 hours for a good survival prognosis, 3.65 hours for an intermediate survival prognosis and 4.9 hours for a poor survival prognosis. The results from the linear probability models are remarkably similar. Except for cancer with a good survival prognosis, all health shocks reduced the probability of working. On average, stroke reduced the probability of working by 8%, while the reduction was 4% for acute heart attack. Again, the effect of cancer on LMP increased with severity; however, only the intermediate and poor cancer prognoses had significant effects of -7% and -10% respectively.

Tables 5 and 6 provide the results from the heterogeneity analysis by sex and education, respectively. The models are organized as in Table 4, with additional interaction terms.
In Table 5, the reference category is women, and thus the health shocks that do not interact are the average within-effects for women. All health shocks reduced women's hours worked per week. In contrast, the reduction was smaller for men with an acute heart attack and cancer with a good survival prognosis. In the linear probability models, all shocks except stroke reduced women's probability of working. Meanwhile, stroke reduced the probability of working for men, and men were more likely to work following cancer with a good and poor survival prognosis.

In Table 6, individuals without a university degree is the reference category. All health shocks except stroke reduced hours worked for individuals without a university degree. By contrast, individuals with a university degree show a larger reduction in hours worked following stroke and a smaller reduction in hours worked following all cancer severities. In the linear probability models, the results are similar, but the heterogeneity by cancer is less pronounced. Individuals with a university degree are more likely to work following acute heart attack and cancer with a poor survival prognosis.

The validity of our analyses relies on the exogeneity assumption of health shocks. Tables A2 and A3 in the Supporting Information File provide the event study analysis for hours worked per week and the probability of working, respectively. In both tables, the reference point is t*-1. We do not detect any anticipatory effects. This indicates that shocks are unforeseen and that any subsequent adjustments in LMP are probably due to the health shock itself. We also see dynamic effects. Table A2 shows a general trend of incremental reduction in hours worked over time. The significance levels of the lag coefficients for cancer with a poor prognosis decrease over time. This is not surprising since fewer individuals with a poor survival prognosis are expected to remain working at those time points. In Table A3, the first three lag coefficients for stroke are barely significant, while the last two lag coefficients for cancer with a poor survival prognosis are not significant at all. The latter is again not surprising since fewer individuals remained in employment at these time points.

Table 5. Heterogeneity analyses by sex. Linear model (LM), linear probability model (LP), fixed effects (FE) and correlated random effects (CRE).

	Hours worked		Working(yes)	
	LM FE	LM CRE	LP FE	LP CRE
Stroke	-2.26**	-2.26**	-0.01	-0.01
	(1.08)	(1.08)	(0.03)	(0.03)
Acute heart attack	-4.13***	-3.22***	-0.13***	-0.11***
	(1.09)	(1.16)	(0.03)	(0.03)
Cancer, five-year survival prognosis				
Good survival prognosis	-2.52***	-2.54***	-0.04***	-0.04***
	(0.42)	(0.43)	(0.01)	(0.01)
Intermediate survival prognosis	-4.06***	-4.05***	-0.08***	-0.08***
	(0.61)	(0.61)	(0.02)	(0.02)
Poor survival prognosis	-6.31***	-6.31***	-0.17***	-0.17***
	(1.27)	(1.27)	(0.03)	(0.03)
Interaction terms				
Men * **stroke**	-2.07	-2.07	-0.10***	-0.10***
	(1.31)	(1.31)	(0.03)	(0.03)
Men * **acute heart attack**	3.10***	2.20*	0.10***	0.08**
	(1.19)	(1.26)	(0.03)	(0.03)
Cancer, five-year survival rate				
Men * good survival prognosis	2.36***	2.38***	0.05***	0.05***
	(0.62)	(0.62)	(0.02)	(0.02)
Men * intermediate survival prognosis	0.80	0.79	0.03	0.03
	(0.84)	(0.84)	(0.02)	(0.02)
Men * poor survival prognosis	2.67	2.67	0.11**	0.11**
	(1.74)	(1.74)	(0.04)	(0.04)
Men (ref: women)		4.52		0.18
		(6.96)		(0.15)
University degree (ref: no university)		2.18***		0.03***
		(0.14)		(0.003)
Other control variables				
Age with two-year bins	V	V	V	V
Mean age groups with two-year bins		V		V
Mean health shocks		V		V
Mean interaction terms		V		V
Constant		-184.15*		-3.58
		(105.14)		(2.28)
Observations	124,053	123,398	124,053	123,398
R2	0.12	0.13	0.12	0.13

Note: *p<0.1, **p<0.05, ***p<0.01

Table 6. Heterogeneity analyses by education. Linear model (LM), linear probability model (LP), fixed effects (FE), and correlated random effects (CRE).				
	Hours worked		Working(yes)	
	LM FE	LM CRE	LP FE	LP CRE
Stroke	-1.07	-1.07	-0.03*	-0.03*
	(0.81)	(0.81)	(0.02)	(0.02)
Acute heart attack	-1.90***	-1.90***	-0.06***	-0.06***
	(0.58)	(0.58)	(0.01)	(0.01)
Cancer, five-year survival prognosis				
Good survival prognosis	-2.37***	-2.37***	-0.02*	-0.02*
	(0.46)	(0.46)	(0.01)	(0.01)
Intermediate survival prognosis	-4.38***	-4.38***	-0.06***	-0.06***
	(0.60)	(0.60)	(0.02)	(0.02)
Poor survival prognosis	-8.78***	-8.78***	-0.21***	-0.21***
	(1.33)	(1.33)	(0.03)	(0.03)
Interaction terms				
University degree * **stroke**	-6.10***	-6.10***	-0.11***	-0.11***
	(1.23)	(1.23)	(0.03)	(0.03)
University degree * **acute heart attack**	1.33	1.33	0.06***	0.06***
	(0.89)	(0.89)	(0.02)	(0.02)
Cancer, five-year survival rate				
University degree * good survival prognosis	1.71***	1.71***	0.01	0.01
	(0.62)	(0.62)	(0.02)	(0.02)
University degree * intermediate survival prognosis	1.45*	1.45*	-0.01	-0.01
	(0.84)	(0.84)	(0.02)	(0.02)
University degree * poor survival prognosis	6.82***	6.82***	0.18***	0.18***
	(1.75)	(1.75)	(0.04)	(0.04)
Men (ref: women)		2.39***		0.01***
		(0.13)		(0.003)
University degree (ref: no university)		9.57		0.18
		(6.53)		(0.14)
Other control variables				
Age with two-year bins	V	V	V	V
Mean age groups with two-year bins		V		V
Mean health shocks		V		V
Mean interaction terms		V		V
Constant		-189.72*		-3.70
		(104.92)		(2.28)
Observations	123,398	123,398	123,398	123,398
R2	0.12	0.13	0.12	0.13
Note: *p<0.1, **p<0.05, ***p<0.01				

5 Discussion

The aim of this paper was to estimate and compare the impact of stroke, acute heart attack, and three levels of cancer severity on individuals' LMP in Norway. We used hours worked per week and the binary variable of working (no/yes) as measures of LMP and controlled for time-invariant unobserved fixed effects.

We found that stroke caused a larger reduction in hours worked than acute heart attack, and the reduction increased along the severity gradient for cancer. Among all health shocks, cancer with a poor survival prognosis reduced LMP the most, followed by stroke, cancer with an intermediate survival prognosis, acute heart attack, and cancer with a good survival prognosis. We found evidence that education modified the effect of cancer. Moreover, we found heterogeneity by sex, where cancer caused a larger reduction in LMP for women.

Trevisan and Zantomio (14) found that stroke reduced LMP more than acute heart attack and cancer, which is broadly in line with our results. However, they collapsed all cancer diagnoses into one term, thus assuming a homogeneous shock across potentially quite different types of cancer with different survival prognoses. It follows that their results may be driven by a large proportion of cancer diagnoses in their sample with good or intermediate survival prognosis.

For women, acute heart attack reduced LMP more than stroke, which contrasts with the findings of Trevisan and Zantomio (14). However, women with an acute heart attack were older than women who suffered a stroke. They were therefore closer to retirement, which can explain this inconsistency from the main results. Such age differences were not reported by Trevisan and Zantomio (14).

Cancer reduced LMP for women more than for men, which contrasts with previous literature (11, 13, 15, 21). This heterogeneity is more pronounced when the outcome is whether individuals are working (no/yes).

Previous literature argues for the protective role of education in understanding and using health information (22). One could hypothesize that highly educated individuals are more focused on their health and detect signs of cancer earlier, which leads to a better prognosis and thus reduces its impact on LMP. Our heterogeneity results for cancer support this theory; individuals with a university degree reduced LMP less than those without. These results are also consistent with the research of Heinesen and Kolodziejczyk (12) and Heinesen, Imai (13), who found that highly educated individuals are more likely to work in the years following a cancer diagnosis. The age difference between the educational groups for the various cancers (Table 2) supports the protective role of education, i.e. highly educated individuals discover cancer earlier in its development, which reduces its impact.

Only individuals with a university degree reduced their LMP after a stroke. Although one might assume that a university degree leads to an occupation that is easier to adjust to after a stroke, this result is expected. Previous research reports mixed results: Tanaka (7) did not find heterogeneity by education, while Hackett, Glozier (8) reported that individuals with higher education are more likely to work after a stroke. Our main result suggests that stroke is more severe for LMP than acute heart attack, which indicates that stroke survivors could need more recovery time. However, a university degree could provide an occupation with greater job security. This security could allow stroke survivors a longer recovery period without fear of losing their job.

This paper makes several contributions to the literature. First, we analyse an objective measure of health shocks at onset, which avoids justification bias based on self-report, which has been a concern in several previous studies (23, 24). Second, our categorization of different cancer severities is based on objective measures of the five-year survival rate from the Cancer Registry of Norway. This differentiation is unique in this context and offers new insight into individuals' adjustments to cancer based on sex and education. In particular, we find new evidence of heterogeneity by sex within the cancer severities. Third, panel data with FE and CRE estimators allow us to control for individual unobserved heterogeneity, study dynamic adjustments, and measure the effects of shocks more accurately. Finally, this is the first study from Norway which offers unique insight into how individuals adjust to health shocks in a country with very generous social insurance and sickness benefit schemes. We acknowledge that only having data for individuals' *first* health shock is a limitation. If individuals experience a similar or different health shock during the study period, this may affect the estimates of the initial health shock and bias our results. Another limitation is that we only observe individuals' incomes but not their wealth. It is likely that wealth is an important factor in the decision to continue working after a health shock, especially as individuals approach retirement age.

6 Conclusions

All health shocks studied (stroke, acute heart attack and cancer) reduce individuals' LMP. Individuals adjust differently to different types of health shocks. The impact of cancer is modified by education.

Policymakers who seek to raise the retirement age should focus on measures to decrease health shocks, especially cancer with a poor survival prognosis and stroke.

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Paper 3

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Who keeps on working? The importance of resilience for labour market participation.

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RESEARCH ARTICLE

Who keeps on working? The importance of resilience for labour market participation

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Abstract

Background

It is widely recognized that individuals' health and educational attainments, commonly referred to as their human capital, are important determinants for their labour market participation (LMP). What is less recognised is the influence of individuals' latent resilience traits on their ability to sustain LMP after experiencing an adversity such as a health shock.

Aim

We investigate the extent to which resilience is independently associated with LMP and moderates the effect of health shocks on LMP.

Method

We analysed data from two consecutive waves of a Norwegian prospective cohort study. We followed 3,840 adults who, at baseline, were healthy and worked full time. Binary logistic regression models were applied to explain their employment status eight years later, controlling for age, sex, educational attainment, health status at baseline, as well as the occurrences of three types of health shocks (cardiovascular diseases, cancer, psychological problems). Individuals' resilience, measured by the Resilience Scale for Adults (RSA), entered as an independent variable and as an interaction with the indicators of health shocks. In separate models, we explore the role of two further indicators of resilience; locus of control, and health optimism.

Results

As expected, health shocks reduce the probability to keep on working full-time. While both the RSA and the two related indicators all suggest that resilience increases the probability to keep on working, we did not find evidence that resilience moderates the association between health shocks and LMP.

Competing interests: The authors declare no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Conclusion

Higher levels of resilience is associated with full-time work as individuals age.

1. Introduction

Health is a crucial determinant of labour market participation (LMP) [1]. Individuals who experience health adversities are less likely to work [2–4], and, if they do work, they are more likely to work fewer hours [5, 6]. However, the heterogeneity in how people respond to health shocks is noteworthy. Studies report that educational attainment is independently associated with a higher probability of returning to work after suffering health shocks [7]. Thus, analyses of LMP would often start by considering variations in individuals' health and education, i.e. their human capital.

The knowledge of how personality traits influence LMP is less clear. A relevant factor for improving our understanding of the LMP dynamics may be individuals' resilience. In psychological capital (PsyCap) theory resilience is defined as '*the capacity to rebound or bounce back from adversity*, *conflict*, *failure or even positive events*, *progress and increased responsibility*' [8]. It is used to explain why people exposed to adversity or serious risks continue to function relatively well and maintain their health and well-being [9, 10]. The literature emphasizes two aspects of resilience: i) recovery, which is how well individuals bounce back and recover from adversity [8], and; ii) sustainability, which is the capacity to continue forward after adverse events [11]. Few studies have examined the role of potential resilience indicators for LMP. However, one study by Schurer [12] investigated how *Locus of Control* (LOC) relates with LMP among men who experienced health shocks. The results showed that men with negative control beliefs were 100% more likely to drop out of the labour market a year after the health shock than those with positive control beliefs.

In PsyCap theory, resilience is considered an important component of psychological capital. It therefore may contribute–beyond human capital, to explain variations in LMP. Economic research has found that PsyCap and resilience are positively associated with work engagement [13], job performance [14] and job satisfaction [15]. Conversely, resilience is negatively associated with voluntary absenteeism [16] and burnout [17, 18]. Moreover, research that used resilience as a moderator has found that resilience mitigates the negative effects of job insecurity, such as emotional exhaustion and counterproductive work behaviour [19]. Hence, resilient individuals would better counteract reductions in their *human capital* as caused by a health shock.

In the current study, we expand prior research by testing the hypothesis that higher personal resilience helps individuals sustain their level of LMP as they age. For this purpose, we employ an abbreviated version of a validated resilience measure, i.e. the Resilience Scale for Adults (RSA). In addition, for improving measurement reliability, we also add two variables that is considered as representatives of resilience, i.e., locus-of-control [12, 20, 21] and optimism [20, 22, 23]. In the current study, the two variables emerge as particularly meaningful, in that they were specifically referring to locus of control *at work*, and optimism with regard to one's future *health*. Furthermore, we examine the hypothesis that resilience operates as a protective factor, i.e. whether it moderates the presumed negative association between health shock and LMP. We provide new evidence about LMP in an institutional setting characterised by generous welfare arrangements for people who may have limited capacity to work.

2. Method

2.1 Material

We used data from the Tromsø Study, which is a prospective cohort study of the adult population residing in the municipality of Tromsø. With around 78,000 inhabitants, Tromsø is the largest city in Northern Norway. The study population is considered broadly representative of the Norwegian adult population, with individuals holding a university degree being slightly overrepresented. The analysis presented in this paper is based on a balanced sub-sample drawn from the sixth wave conducted in 2007/08 (n = 12,981, aged 30 and above), and the seventh wave conducted in 2015/16 (n = 21,083, aged 40 and above). The design of the Tromsø Study is described in detail elsewhere [24]. The study was approved by the regional committee for Medical and Health Research Ethics (ID 2016/607). All participants gave written informed consent before admission.

2.2 Participants

Out of 5,685 individuals who participated in both waves and were below the upper retirement age in Norway (70 years) at follow-up, we excluded: 1,253 individuals who did not work full-time at baseline; 546 who reported one or more health shocks prior to baseline; 42 who, at baseline, had reported severe problems on at least one of the five health dimensions in the EQ-5D-3L descriptive system [25], and; 4 individuals who reported to be studying or in military service. Based on these criteria, we analysed a sample of 3,840 healthy individuals who were working full time at baseline.

2.3 Variables

2.3.1 Outcome. The outcome variable is LMP at follow-up, with three categories: full time, part time and not working. The not-working category included a variety of sub-categories: unemployment, early retirement, disability recipient, work assessment allowance, family income supplement and unpaid domestic work. In our main analysis, we combined the part-time and not-working categories, both of which reflect *reductions* in LMP from full-time work at baseline.

2.3.2 Resilience. An abbreviated version of the RSA was included in wave 7 of the survey (referred to as the follow-up). We chose three items that represented the personal domain of the RSA, which could be satisfactorily summed together in a single index score. A confirmatory one-factor analysis confirmed a good fit [$x^2_{df=1} = 0.10$, P = 0.76; RMSEA = 0 (95% CI 0–0.013)]. Higher scores on these three items indicated a better adaptation response to life stresses. The items asked about: confidence in personal judgements, the ability to thrive/prosper despite difficulties and the use of personal beliefs to overcome difficult times. Items were rated on a Likert scale (1 = 'disagree completely' to 5 = 'agree completely'). The resilience index score represented the average of these three item scores. Data completeness was high, with only 2% (64) missing values. In the case of one missing value, it was replaced by the average of the individual's two other item scores, that is average imputations.

Since the RSA variable is measured at follow-up, we included *Locus-of-control* and *optimism* with regard to one's future health (Health optimism) measured at baseline. Both variables were measured on a 7-point scale (1 disagree completely, 7 agree completely). For LOC the item asked about were: 'I have sufficient influence on when and how my work should be done'. For health optimism the item asked about were: 'I have a positive view of my future health'.

2.3.3 Health shocks. Participants were asked to report whether they have, or have had, any of the following health conditions: heart attack, angina, stroke, cancer and psychological problems. Due to their limited numbers, we combined the first three conditions into cardiovascular diseases (CVD). We treat health shocks as binary variables in the analysis. Given that we only included subjects that had *not* reported any of these adversities at baseline, all reported health shocks are assumed to have occurred at some point *between* baseline and follow-up.

2.3.4 Health at baseline. In addition to the effect of health shocks occurring *after* baseline, we expect participants' health *at* baseline to influence LMP at follow-up. Study participants reported their health-related quality of life (HRQoL) by use of the EQ-5D-3L generic descriptive system, which consists of five dimensions (mobility, self-care, usual activities, pain & discomfort and anxiety & depression), each described along three severity levels (no problem, moderate, severe). We distinguish subjects who reported full health (N = 2436), i.e. no problems on all 5 dimensions (EQ-5D profile 11111), from those reporting a moderate health problem (level 2) along at least one dimension (N = 1404). Within this latter group, the majority reported a health profile with moderate pain and discomfort, and no problems on any of the other dimensions (EQ-5D profile 11121) (N = 871).

2.3.5 General covariates. We controlled for age at follow-up, sex and educational attainment level. The age variable was split into three groups: 40–49; 50–61; 62–69 years. We chose these age bands because Norwegians can combine part-time work while receiving partial pension payments after the age of 62. Educational attainment was categorised into four levels in line with the International Standard Classification of Education (ISCED): primary and secondary school (10 years); upper secondary school (3 years); lower college or university degree (< 4 years); higher college, and; university degree (≥ 4 years).

2.4 Statistical analysis

We analyzed the data by using binary logistic regression with several specifications. Model 1 specification includes age, sex, education, health at baseline, and presence of health shocks (each entered as indicator variables). Specification 2 adds RSA, specification 3 adds LOC, and specification 4 adds health optimism.

In addition, to test for possible moderations effects, we estimated three models that allowed interactions between the resilience variables and the health shocks. Calculating marginal effects in nonlinear models can be complicated, because a coefficient can be statistically indistinguishable from zero, although the cross-partial derivative is different from zero. We therefore applied the delta method, suggested by Ai and Norton(2003) [13] for exploring interaction terms in nonlinear models.

To further investigate any differences between those working part-time and not-working, our sensitivity analysis consists of a multinomial logistic model that distinguishes these two non-fulltime outcomes. All results are presented as odds ratios (OR).

3. Results

Table 1 shows the sample characteristics by LMP at follow-up. Pearson's chi-square tests indicate unadjusted associations between the explanatory variables and LMP at follow-up. As expected, reductions in LMP is associated with lower education levels, reduced HRQoL at baseline, and health shocks after baseline, i.e. lower human capital.

S1 Table in S1 File provides the precise wording of the resilience variables as used in the survey, and their mean values by LMP at follow-up. The low p-values support the expected associations between the mean values in the resilience measures and level of LMP. In S2 Table in S1 File, the correlation matrix for the three resilience measures support that they are all representative of a resilience resource.

Table 1. Sample characteristics by labour market participation at follow-up, N = 3840.

	Full-time (N = 2885)		Part-time (N = 243)		Not-working (N = 712)		P-value from Chi.Sq tests
Sex	N	%	N	%	N	%	< 0.001
Men	1550	53.7	78	32.1	354	49.7	
Women	1335	46.3	165	67.9	358	50.3	
Age							< 0.001
40–49	804	27.9	28	1.5	31	4.4	
50–61	1677	58.1	84	34.6	103	14.5	
62–69	404	14.0	131	53.9	578	81.2	
Educational level[a]							< 0.001
Primary School (10 years)	340	11.8	38	15.6	160	22.6	
Upper Secondary (3 years)	925	32.1	101	41.6	263	37.2	
University < 4 years	679	23.6	49	20.2	146	20.7	
University ≥ 4 years	936	32.5	55	22.6	138	19.5	
EQ-5D-3L at baseline[b]							< 0.001
Full health (11111)	1749	64.3	107	46.7	351	52.9	
Moderate health	969	35.7	122	53.3	313	47.1	
Individuals with health shock after baseline							< 0.001
No	2609	90.4	187	77.0	545	76.5	
Yes	276	9.6	56	23.0	167	23.5	
Diagnosis[c]**. % by LMP. Ref: No**							
Heart attack	34	1.2	6	2.5	19	2.7	0.007
Angina	15	0.5	0	0.0	8	1.1	0.080
Stroke	13	0.5	8	3.3	26	3.7	< 0.001
Psychological problems	116	4.0	27	11.1	35	4.9	< 0.001
Cancer	119	4.1	19	7.8	91	12.8	< 0.001

[a]10 missing values on education.

[b]229 missing observations on EQ-5D. Moderate health = all EQ-5D-3L profiles with at least one dimension at level 2. Respondents with at least one dimension at level 3 were excluded.

[c]The number of health shock diagnosis (536) are larger than total number of individuals who have experienced health shocks (499): 465 individuals have experienced 1 shock, 33 have experienced 2 shocks, and 1 reported 5 shocks.

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Table 2 presents the results of the four specifications of the binary logistic models. To ease the comparing between the models they are introduced stepwise from simplest (Model 1) to full model (Model 4). All four model specifications suggest a similar pattern regarding the impacts of sex, age, education, and health. Women are more likely to leave full time work than men. The much higher odds ratios in the oldest age groups (62–69) is attributed to the entitlements to early retirement in the Norwegian social security system. Higher education is strongly associated with a propensity to continue working full-time. Moderate health problems at baseline, or having experienced a health shock after baseline, are associated with reduced LMP at follow-up.

Model 2 shows that individuals with higher levels of RSA is more likely to work full-time at follow-up (OR = 0.81, $p < 0.01$), After including RSA, we note a slight reduction in health shocks coefficients. This reduction could, potentially, indicate that RSA moderate health shocks. Model specification 3 shows that higher levels of LOC also makes individuals more likely to work full-time (OR = 0.94, $p < 0.10$). Finally, Model 4 includes *health optimism*, which also shows that higher levels of *health optimism* increases the likelihood of working full-time at

Table 2. Binary models.

Reference: Full-time work	Part time and Not-working											
	Model 1			Model 2			Model 3			Model 4		
	OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI	
Variables		Lower	Upper		Lower	Upper		Lower	Upper		Lower	Upper
Intercept	0.05***	0.03	0.07	0.12***	0.06	0.24	0.15***	0.07	0.32	0.21***	0.09	0.49
Women	2.01***	1.64	2.47	2.04***	1.66	2.52	1.98***	1.61	2.45	2.00***	1.61	2.48
Age: reference 40–49												
Age 50–61	1.50**	1.07	2.14	1.54**	1.10	2.21	1.51**	1.07	2.17	1.57**	1.11	2.27
Age 62–69	30.18***	21.76	42.78	30.96***	22.24	44.05	31.05***	22.23	44.33	33.34***	23.7	48.02
Education: ref: Primary 10 years												
Upper secondary 3 years	0.89	0.66	1.20	0.87	0.65	1.18	0.89	0.66	1.21	0.87	0.64	1.19
University <4 years	0.62***	0.45	0.85	0.60***	0.43	0.83	0.62***	0.45	0.86	0.62***	0.44	0.86
University ≥4 years	0.36***	0.26	0.50	0.35***	0.25	0.48	0.37***	0.26	0.51	0.36***	0.26	0.51
Health at baseline. Ref: Full health; EQ-5D (11111)												
Moderate health	1.58***	1.29	1.93	1.54***	1.25	1.89	1.58***	1.28	1.94	1.48***	1.19	1.84
Health shocks after baseline. Ref: no health shock												
CVD	2.99***	1.85	4.85	2.89***	1.78	4.72	2.91***	1.79	4.76	2.83***	1.73	4.67
Psychological prob.	3.30***	2.16	4.98	3.16***	2.06	4.81	3.18***	2.05	4.87	3.16***	2.02	4.87
Cancer	2.15***	1.50	3.08	2.12***	1.48	3.05	2.10***	1.46	3.04	2.07***	1.42	3.00
Resilience												
RSA, at follow-up				0.81***	0.70	0.92	0.82***	0.71	0.95	0.85**	0.73	0.98
Locus of control, at baseline							0.94*	0.88	1.01	0.95	0.89	1.02
Health optimism, at baseline										0.90**	0.83	0.99
AIC	2578.0			2549.6			2499.9			2428.6		

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follow-up (OR = 0.90, p <0.05). This association is smaller than RSA but larger than LOC and still persists after adjusting for both. These results suggest that the concept of resilience, as measured in different ways, plays a significant role for individuals' propensity to continue working.

Table 3 provides the three models that includes interactions between each of the resilience measures and the health shocks. Although not statistically significant, all interactions in Model 2-RSA point in the same consistent direction, i.e. a higher propensity to continue working full-time, particularly in the case of CVD (OR = 0.75) and cancer shocks (OR = 0.78). As for the other two resilience measures, interaction results are mixed.

3.1 Sensitivity analysis

Our results demonstrate that RSA (at follow-up) and health optimism (at baseline) is positively associated with a propensity to work full-time at follow-up. To further investigate these effects we split those who are not working full-time into part-time (n = 243), and not-working (n = 712). The S3-S5 Tables in S1 File presents the multinomial logit models, which has the same specifications as Model 2, 3 and 4.

We observe a similar pattern across these three multinomial models for sex, age, education, health at baseline and health shocks. S3 Table in S1 File Model 2 contains the first specification where only RSA is included of the resilience measures. Note the much stronger RSA association in the not-working group (OR = 0.76, p <0.01), as compared with the part-time group (OR = 0.91). S4 Table in S1 File Model 3 further includes LOC. Again, the direction of the associations are similar to the binary model, but only significant for the not-working category: RSA (OR = 0.78, p<0.05) and LOC (OR = 0.93, p<0.10). Finally, S5 Table in S1 File Model 4

Table 3. Binary models including interactions. Reference: Full-time working.

	Model 2-RSA			Model 3-LOC			Model 4-Hopt		
	Odds ratio	95% CI		Odds ratio	95% CI		Odds ratio	95% CI	
Intercept	0.10 ***	0.05	0.22	0.06 ***	0.04	0.11	0.10 ***	0.05	0.19
Women	2.05 ***	1.66	2.52	1.94 ***	1.57	2.39	2.02 ***	1.63	2.50
Age: reference 40–49 years									
Age 50–61	1.54 **	1.10	2.20	1.47 **	1.04	2.10	1.53 **	1.09	2.20
Age 62–69	30.95 ***	22.21	44.08	30.47 ***	21.88	43.39	32.35 ***	23.12	46.30
Education: ref. Primary 10 years									
Upper secondary 3 years	0.87	0.64	1.18	0.90	0.67	1.22	0.86	0.63	1.17
University <4 years	0.60 ***	0.43	0.83	0.63 ***	0.45	0.88	0.60 ***	0.43	0.83
University ≥4 years	0.35 ***	0.25	0.48	0.38 ***	0.27	0.52	0.35 ***	0.25	0.49
Health at baseline. Ref: Full health; EQ-5D (11111)									
Moderate health	1.53 ***	1.25	1.88	1.60 ***	1.30	1.97	1.46 ***	1.18	1.82
Health shocks after baseline. Ref: no health shock									
CVD	9.96	0.42	244.0	3.06	0.41	23.07	11.67 **	1.21	135.09
Psychological prob.	4.16	0.45	35.28	2.76	0.49	14.23	2.06	0.28	13.83
Cancer	5.89	0.64	62.35	4.02 **	1.03	16.43	2.08	0.42	10.32
Resilience									
RSA, at follow-up	0.83 **	0.72	0.97						
Locus of control at baseline				0.94 *	0.88	1.01			
Health optimism at baseline							0.88 ***	0.80	0.97
Interactions									
CVD*RSA	0.75	0.36	1.56						
Psych.Prob*RSA	0.93	0.54	1.63						
Cancer*RSA	0.78	0.45	1.32						
CVD*Locus of control				1.00	0.70	1.42			
Psych.Prob*Locus of control				1.04	0.77	1.42			
Cancer*Locus of control				0.89	0.69	1.13			
CVD*Health optimism							0.77	0.49	1.17
Psych.Prob*Health optimism							1.10	0.76	1.61
Cancer*Health optimism							1.00	0.74	1.34
AIC	2554.1			2527.3			2470.3		

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includes health optimism. This indicator is only statistically significant in the not-working category (OR = 0.89, $p < 0.05$). Thus, the multinomial models indicate that lower resilience contributes to explain why individuals opt not to work at all, but *not* why individuals reduce their LMP from full-time to part-time.

4. Discussion

The purpose of this longitudinal study was to investigate the hypotheses that resilience helps individuals in sustaining their level of labour market participation (LMP) and if resilience operates as a protective factor against a health shock. We used a validated resilience measure as well as two related measures; locus of control, and health optimism, to investigate these hypotheses.

We find that more personal resilience resources are positively associated with maintaining full-time work. The results were consistent after controlling for sex, age, educational attainment and health. In other words, this indicate that higher level of resilience helps individuals in sustaining their level of LMP, independent of their human capital. The results converge with the PsyCap theory, which does not require any adversity for resilience to be meaningful. This finding lends support to earlier studies, that suggest resilience is positively associated with work engagement, [14] job performance [15] and job satisfaction [16]. Although these earlier studies do not directly confirm each other, they point in the same direction in terms of job sustainability.

Psychosomatic studies have shown that higher resilience may counteract ischemic pain and stressful experiences [9], as well as hopelessness and depressive symptoms [17]. However, our results did not support the hypothesis that higher resilience score operates as a protective factor against health shocks. As such, our result deviate from Schurer's study [12] which used LOC as a proxy for resilience, showing that non-resilient individuals are more likely to reduce their labour supply after experiencing a health shock. The following reasons may explain the deviating results. First, while economists do not emphasise the difference between LOC and resilience, psychologists argue that these two concepts are different and subsequently claim that studies measure different concepts. Second, the previous study was conducted in different institutional setting. Norway has an extensive social insurance system including generous sickness benefit schemes. Such financial protection affords people not to work full time after experiencing a health shock, i.e. they do not have the same financial incentive to utilize their psychological capital. In other words, the more an attractive universal financial protection scheme make people decide *not* to work when their health deteriorates, the less important becomes individual variations in their resilience for explaining why people keep on working despite experiencing a health shock.

Our study have several strengths. First, it is a longitudinal study with an eight year interval. Second, we use comprehensive measures of respondents' health; at baseline measured by the most widely applied generic preference based descriptive system for health-related quality of life (EQ-5D-3L), and after baseline; self-reported experiences of three sets of health shocks (cardiovascular, cancer, mental health). Third, we adjust for socio-economic differences measured by four levels of educational attainment.

A potential weakness is that our key measure of resilience (RSA) was collected at follow-up, while health shocks occurred between the baseline and the follow-up. Thus, survey participants' resilience levels might have been affected by experiencing a health shock. However, as some individuals might strengthen rather than weakening their resilience resources after an adversity, this need not be a major limitation. Also, the RSA seems to capture personal resources of the individual that are of a highly stable character, and it also correlates strongly with stable Big Five personality traits, in particular neuroticism [18]. In a Norwegian general population study the four month test-retest stability correlation of the RSA dimension used in the current study was very high ($r = .79$) [19]. Still, acknowledging bias in measuring resilience at follow-up, we included two additional indicators measured at baseline as representatives of resilience. The correlation tests between our resilience measures show that these measures points in the same direction and provide support to the hypothesis that having more rather than less resilience resources heightens the likelihood to keep on working.

5. Conclusions

Higher levels of resilience is associated with full-time work as individuals age. However, our results did not provide evidence to support the hypothesis that resilience moderates the effect of health shocks on LMP. This might be explained by an institutional context whereby people are fortunate to rely on universal sickness benefit schemes rather than having to activate a key attribute of their individual psychological capital.

Supporting information

S1 File.
(DOCX)

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