Social Inequalities in Mental Health: Evidence on Global Patterns, Life-Course Dynamics, and Policy Solutions

Christoph Henking

Trinity term 2025

Department of Social Policy and Intervention

Wolfson College

A thesis submitted for the degree of Doctor of Philosophy (DPhil) in

Social Intervention and Policy Evaluation

Table of content

Thesis abstract 4

Acknowledgements 7

List of figures and tables 10

Abbreviations 12

Introduction 14

Background 14

Theoretical and empirical foundations 17

Research puzzles and empirical contributions 31

Methodology 44

Statements of authorship 50

References 52

Paper 1: Global inequalities in mental health problems: understanding the predictors of lifetime prevalence, treatment utilisation and perceived helpfulness across 111 countries 76

Paper 2: What predicts the decline in mental health during mid-life? A Machine Learning analysis of the 1970 British Cohort Study 101

Paper 3: Benefit conditionality, sanctions and the self-rated health of the unemployed: a longitudinal analysis of European countries 127

Paper 4: What shapes trust in healthcare? Socio-economic and structural determinants of trust in formal and traditional health providers across 111 countries 163

General Discussion 196

Summary of main findings 196

Wider academic contributions 198

Policy recommendations...208

Limitations 213

Avenues for future research 215

References 218

Appendices 231

Appendix Paper 1 231

Appendix paper 2..249

Appendix paper 3..260

Appendix paper 4..269

Thesis abstract

The growing burden of mental health problems is a major global challenge. Importantly, this burden is not evenly distributed, but is socially stratified within and between countries. Individuals with lower socio-economic status are more likely to experience mental health problems. Less affluent countries tend to have a higher burden of mental health problems. Various theories have been posed to explain why health inequalities exist based on the social determinants of health framework such as working conditions, unemployment or education. Based on this work, individual-level and structural pathways have been identified to link socio-economic circumstances with mental health outcomes.

Despite growing knowledge and efforts to address the social determinants of mental health, social inequalities in mental health remain persistent – even in advanced welfare states. This has sparked a debate between scholars questioning what can be done to better understand and address mental health inequalities – and, in doing so, improve the health of the most vulnerable in society. To advance this debate, more evidence is essential. In particular, comparative studies that span across countries, use longitudinal analyses, and examine the effects of social policies are needed to deepen our understanding and inform better policy design and implementation.

This DPhil identifies three research perspectives and puzzles within the problem of mental health inequalities to help improve our understanding of (1) how mental health inequalities differ globally between countries (global perspective), (2) how they evolve over the life-course (life-course perspective), and (3) how labour market policies can address health inequalities (labour market perspective). Each of these perspectives will be explored in a separate paper, with an additional follow-up analysis in study 4 that further explores the global dimension.

Study 1 adopts a global perspective on mental health to investigate the socio-economic and country-level determinants of lifetime prevalence, treatment utilisation and helpfulness for depression symptomology. The study uses a nationally representative individual-level survey

dataset (Wellcome Global Monitor 2020) in 111 countries (N=117,088) and employs multilevel regression models with both individual and country-level predictors. The analysis reveals a global 'triple inequality in mental health', whereby disadvantages of individuals with lower socio-economic status persist in three outcomes (lifetime prevalence, treatment utilisation and helpfulness). Treatment utilisation and helpfulness also vary by trust in healthcare professionals and treatment type.

Study 2 adopts a life-course perspective to investigate the mid-life decline in mental health, a phenomenon well-documented across countries and datasets, from a social determinants of health perspective. The study uses data from a prospective birth cohort study (1970 British Cohort Study) with measures at birth, as well as the ages of 10, 26, 34 and 42 – to explore the predictors of mental health decline between the ages 34 and 42. Through a combination of machine learning algorithms and logistic regression analyses, the study identifies four key predictors of experiencing a mid-life decline: low social class at birth, sex (being female), low income at the start of the midlife period, and experiencing physical multimorbidity in early adulthood. Taken together, these social determinants could reduce the risk of mental health decline from 18% (observed) to 11%, and up to 28% if risk constellation changes in the population.

Study 3 adopts a labour market policy perspective to examine the impact of benefit conditionality and sanctions on the health of job seekers in Europe. The study combines longitudinal panel data from the European Union Statistics on Income and Living Conditions (EU-SILC, 2014 – 2019) with OECD indicators on activation policy strictness in 30 countries (898,598 observations in total; n = 4992 per country and year). Using first-difference regression models with country-level clustering, I estimated the effect of becoming unemployed on changes in self-rated health (5-point scale) and tested whether this effect was moderated by policy strictness. Becoming unemployed had a small but significant association with self-rated health. This association varied

depending on the strictness of the sanction regime, with the predicted decline being strongest in low-sanction countries (e.g. Hungary, Cyprus) compared to higher sanction countries (e.g. Croatia and Poland). The findings indicate that stricter sanction rules are associated with worse self-rated health among job seekers.

Study 4 extends the global perspective on mental health inequalities. Study 1 identified trust in healthcare professionals as a crucial psycho-social factor linked to mental health treatment use, but no global study has examined its determinants. This study examines global variations in trust in healthcare professionals and traditional healers, utilising data from the Wellcome Global Monitor 2020 in 111 countries. Multilevel models estimate individual and country-level predictors of trust. The results show that trust in healthcare professionals increases with national income, but only after countries reach a medium income level. In contrast, there is no clear relationship between GDP and trust in traditional medicine practitioners. On the individual level, people with higher income have higher trust in healthcare professionals and lower trust in traditional healers than individuals with lower incomes. Finally, higher levels of perceived corruption are associated with lower levels of trust in healthcare professionals. This global distribution of trust should be considered in the political economy of health and in policy efforts to strengthen healthcare systems.

Acknowledgements

It was an uncertain time when I came to Oxford to start my DPhil journey. In autumn of 2021, the world was just starting to recover from a global pandemic. Before starting this thesis, I had spent several years working outside of the academia. I wrote my PhD proposal perhaps more out of curiosity, coming from an academic background in psychology, rather than deep knowledge of ongoing academic debates in health and social policy. When I arrived in Oxford, my research ideas and interests had somewhat shifted from my original proposal – and I was extremely grateful to be met by my supervisors and a research community who were so welcoming and helped me develop my ideas. The support of many people around me carried me throughout my DPhil journey.

I am very thankful to my two supervisors, Aaron Reeves and Ben Chrisinger, for their guidance in shaping my research interests and helping me grow as a researcher. Thank you, Ben, for your exceptional intellectual guidance and empathy. Your input was essential in shaping my ideas and my focus on health inequalities, through countless meetings, discussions and extremely thoughtful feedback. I am also very grateful to Aaron for his supervision throughout my DPhil. Thank you, Aaron, for being a rare combination of academic excellence, clear guidance, and personal kindness. You not only guided my work, but also built a research community for us all. Our research group meetings, where we met every second Tuesday, were one of the highlights of my DPhil and gave us the chance to present our ideas in a non-judgmental environment. In an academic world that can often be harsh, competitive, and unfair, both of you were a great support.

My doctoral experience was most enjoyable because of our community at the Department of Social Policy and Intervention and the friendship of my fellow DPhil students. The Department became my academic and personal home, where all struggles, successes and challenges could be shared with the community. I would like to highlight a few people who have made my journey special for their friendship and support: Adrienne McManus, Alex Blackwell, Ben Goodair, Ben Scher, Bridgit Steele, Cherise Regier, Clara Weißenfels, François Schoenberger, Francisco Calderon, Kathleen Murphy, Kun Lee, Lukas Lehner, Madison Little, Maria Ambrosio, Marianne Joy Vital, Michael Ganslmeier, Nhat An Trinh, Nontokozo Langwenya, Sophia Backhaus, Solhee Han, Steffen Redeker, Stephanie Eagling-Peche, Susie Swingler, Victoria Tan. I am also very grateful to Dave Humphreys, Mark Fransham, and Jane Barlow for their guidance and feedback during my DPhil milestones and to Dave for the examination of my DPhil. A special thank you

also to all staff at DSPI, who make the Department run and create a special atmosphere of being welcomed and supported.

I am very grateful to my funders and their staff – the ESRC Grand Union Doctoral Training Programme and the Scatchard European Scholarships – without whom this research project would not have been possible.

There are a few more people at Oxford University to whom I would like to express my gratitude. I thank Wolfson College for offering me a community and home away from the Department and I am thankful for the friends I made at Wolfson. I am also grateful to Prabin Dahal and Sînziana Oncioiu for fun research talks and their kind guidance around statistics and research methods. Furthermore, it was a pleasure to work with Flavia Galvani at the Blavatnik School of Government, where I taught in the MPP programme and the AIG Public Leaders Programme with civil servants from Nigeria. You have been an exceptionally kind and supportive supervisor. I am also very grateful to the colleagues and staff at the Blavatnik School, as well as the Nigerian public leaders I had the privilege to work with.

In the autumn of 2023, I had the fantastic opportunity to pursue an academic visit at the University of Lausanne and the LIVES research centre. This experience opened a new academic environment for me and provided me with space for reflection (as well as running, hiking, swimming and cycling) by the beautiful Lake Geneva. I thank Dawid Gondek for inviting me for the visit, hosting me, and discussing research ideas. I also thank Laura Bernardi and Daniel Oesch for welcoming me at LIVES, and Claire Mariano for our many research chats and collaboration. A special mention goes to François Schoenberger, who, having become a friend during his prior academic visit at Oxford University, organised for us to have a shared office in Lausanne. Our friendship will carry on long beyond this dissertation (and hopefully, my French will be better one day!).

There are many others who supported and inspired me along the way. I would like to thank Jan Paul Heisig at the WZB in Berlin for kindly hosting me as a visiting researcher, Michaela Kreyenfeld for welcoming me into her research group at the Hertie School, and Ulrich Reininghaus for encouraging me to pursue my research in public mental health and for examining this dissertation. I am also grateful to Graham Thornicroft, Laura Sochas and Tessa Roberts for their inspiration in research, Xavier Romero Vidal and Dennis Grube at Cambridge University for their encouragement, as well as to Daina Kosīte and Felipe Brescancini for their friendship and sharing the ups and downs of this PhD at different institutions. I thank Julia Reisach for

welcoming me to Paris and kindly offering me a space to work in her PhD office at Dauphine University during the final phase of this journey.

I am very grateful to my family – my parents, Katharina and Arwed, and my brother, Jan Bernhard – for their unwavering support. You supported me throughout my whole educational journey and gave me the courage to move to the UK and take up this DPhil. I will always cherish the memory of your visit to Oxford. I am also deeply thankful to my friends from different phases of life, who have stood by me through visits, countless phone calls, and offered very welcome distractions from my DPhil life. I would particularly like to thank Adrian, Chris, Greta, Justin, Lina, Sophia, Tani, and Yannik.

Finally, I thank my partner, Stella, for being my biggest supporter on this DPhil journey that I could have wished for. Your love and kindness made this time joyful and light-hearted and your incredible support kept me going forward, even when things got difficult. I will always be grateful for our experience of living in the UK together as a team.

List of figures and tables

List of Figures

Figure 1.1 Concept of mental health and well-being, adapted from World Health Organization (2022)……………………………………………………………………………………………….....18

Figure 1.2. Conceptual Framework: Pathways from Structural and Social Determinants to Mental Health Outcomes and Treatment Utilisation……………………………………...22

Figure 1.3. Illustration of the treatment gap for major depressive disorder, adapted from Thornicroft et al. (2017) and Evans-Lacko et al. (2018)………………………………………………………….........31

Figure 2.1. Predicted probabilities for the lifetime prevalence of mental health problems, treatment utilisation and perceived helpfulness by household income quintiles (95% CIs)………………………86

Figure 3.1. Variable importance (mean decrease in accuracy when permuted) based on Random Forest to predict the mid-life decline in mental health…..………………..………………..…..………………..111

Figure 3.2. Predicted probabilities based on the logistic regression models shown in Table 3.3… ...………….……………………………………………...…………..….…….115

Figure 4.1. Effect of unemployment on self-rated health, years 2014 – 2019……….………...…..…..142

Figure 4.2. Predicted health change depending on the overall strictness of behavioural conditionality. 95% CIs clustered at the country level…………………………………….………………….........146

Figure 4.3. Predicted health change depending on sanction rules. 95% CIs clustered at the country level……………………………………………………………………..…..……….....147

Figure 5.1. Mean trust in healthcare professionals by country………… ……………..………….......171

Figure 5.2. Mean trust in traditional health practitioners by country………………………….....…….172

Figure 5.3. Predicted probabilities of trust in health professionals and traditional healers as a function of GDP and within country income quintile (95% CIs)………………………………………….......….177

Figure 5.4. Predicted probabilities of within country household income quintiles, country groups and trust (95% CIs). Income Quintile 1 is used as reference category…………………………………...178

List of Tables

Table 1.1. Overview of empirical papers……………………………………………….………………41

Table 2.1. Descriptive statistics…………………………………………………….……….................84

Table 2.2. Associations between socio-economic, psycho-social, and country-level predictors with mental health outcomes…………………………….…………………………………….………………87

Table 3.1. Descriptive statistics by survey wave (before imputation of missing values)………………..107

Table 3.2. Description of the groups of stable mental health and mental health decline………………109

Table 3.3. Logistic regression; outcome: the likelihood of experiencing a mid-life decline in mental health from age 34 to 42 (Odds Ratios)…………………………………………………..113

Table 4.1. Descriptive statistics of the analytical sample (pooled 2014 – 2019 across countries)……………………………………………………………………..……………….134

Table 4.2. Descriptive statistics, country level. Country sample sizes aggregated for the years 2014 – 2019…………………………………………………………………...……………135

Table 4.3. Indicators on the strictness of behavioural conditionality and sanctions…………….……...139

Table 4.4. First difference model for the transition of unemployment. Dependent variable: Change in self-rated health…………………………………………………...…………...……….144

Table 5.1. Descriptive statistics………………………………………………………….……...…...173

Table 5.2. Multi-level regression model………………………………………...…….…………..176

Abbreviations

ALMP	Active Labour Market Policy/Policies
CI	Confidence Interval
CMDs	Common Mental Disorders
COVID-19	Coronavirus Disease 2019
DSM	Diagnostic and Statistical Manual of Mental Disorders
DPhil	Doctor of Philosophy
DSPI	Department of Social Policy and Intervention
EU	European Union
EU-SILC	European Union Statistics on Income and Living Conditions
FD	First Difference
FE	Fixed Effects
GDP	Gross Domestic Product
HIC	High-Income Country
ICD	International Classification of Diseases
IAPT	Improving Access to Psychological Therapies
LMIC	Low- and Middle-Income Country
ML	Machine Learning
N	Sample Size
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
RCT	Randomised Controlled Trial
RF	Random Forest
RQ	Research Question
SDH	Social Determinants of Health
SD	Standard Deviation
SE	Standard Error
SES	Socio-Economic Status

UN United Nations

VI Variable Importance

WHO World Health Organization

WMH World Mental Health (Survey Initiative)

Introduction

Background

Mental health is a global and urgent public health challenge (Vigo et al., 2016). Around one in three individuals experience a mental health condition during their lifetime, and 970 million people globally are affected at any given time (Kessler et al., 2009; World Health Organization, 2022). Depression and anxiety are the most common mental health conditions, with the global burden steadily increasing over recent decades (Prince et al., 2007; World Health Organization, 2022).

This growing burden has been accompanied by a rise in public attention. Discussions about mental health are everywhere: on social media, television, in businesses, universities, or in everyday family conversations. Mental health has become a central theme in debates about the youth crisis following COVID-19, the impact of digital technologies, the cost of living and affordability crisis, as well as growing concerns around political polarisation and climate change (Broadbent et al., 2023; Charlson et al., 2021; De Witte et al., 2021; Nettle et al., 2023; Orben et al., 2024; Van Bavel et al., 2024; Zolopa et al., 2022).

Rarely has a public health topic been discussed so widely and with so many different policy approaches. These include improving mental healthcare, banning smartphones in schools, introducing digital health interventions, and implementing income and employment protection policies (Campbell et al., 2024; De Witte et al., 2021; Heshmati et al., 2023; Renahy et al., 2018; Thomson et al., 2022; Wakefield et al., 2021). While the policy solutions to mental health are plentiful, they are often fragmented and lack coordination.

Amid this complexity, one thing becomes increasingly clear: Mental health is highly political. It is not merely about individual well-being or suffering, but a societal problem rooted in social inequalities. In Europe, individuals with low socio-economic status (such as income and education) are more than three times more likely to experience depression (McNamara et al., 2017). Socio-

economic inequalities are also present in low-and middle income countries, while the overall prevalence of mental health conditions tends to be higher, and resources for healthcare are particularly sparse (Thornicroft & Tansella, 2013; World Health Organization, 2022). Any meaningful contribution to the mental health discussion needs to confront the reality of these social and structural inequalities. Addressing these inequalities and improving the health of the most vulnerable is not only a matter of fairness – ensuring that everyone has an equal opportunity for well-being – but also a prerequisite for economic productivity, social cohesion, and the long-term stability of our health systems (Burns, 2015; Fone et al., 2007; Knapp & Wong, 2020; Macintyre et al., 2018). This requires robust evidence on the social and structural determinants of mental health: evidence that can support analysis and action beyond the context of any single crisis or social phenomenon.

The World Health Organization (WHO) Commission on the Social Determinants of Health has identified key factors, such as early life experiences, financial insecurity, housing, precarious work conditions and unemployment, as significant social determinants of health (Marmot et al., 2012; Motrico et al., 2021; World Health Organization, 2010). Moreover, different theoretical approaches explain the mechanisms by which the social determinants affect mental health, such as material deprivation or psycho-social stress (Allen et al., 2014; Marmot et al., 2012; Phelan et al., 2010). Despite our growing knowledge, social inequalities of mental health conditions remain a persistent societal problem – even in countries with advanced welfare states that offer solid social protection and universal healthcare services (Bambra, 2011a; Mackenbach, 2012). Debates in research and policymaking are therefore ongoing on how to best reduce health inequalities and improve the health of vulnerable populations, while others doubt that it might not be possible to effectively reduce these inequalities (Bambra et al., 2023; Kelly-Irving et al., 2022; Mackenbach, 2020).

More evidence is needed to advance this debate and design better policies. In particular, studies with a cross-national scope, longitudinal analyses and policy evaluations are essential to improving

our understanding of how to address mental health inequalities (Bambra et al., 2023; Kelly-Irving et al., 2022; Thomson et al., 2022). This paper-based DPhil dissertation adopts a problem-based approach (Prasad, 2018), addressing pressing challenges in the field of mental health inequalities through three distinct research perspectives: a global perspective, a life-course perspective, and a labour market perspective.

1. **Global perspective:** This DPhil examines how mental health inequalities are distributed globally and across health outcomes such as depression/anxiety prevalence, treatment utilisation and perceived treatment helpfulness. It aims to unveil the socio-economic, psychological and country-level drivers of these health outcomes. Previous research has shown socioeconomic inequalities in each health outcome separately, but the global pattern and country-level factors associated with treatment use and helpfulness are largely unknown (Harris et al., 2020; Lewer et al., 2015). My first analysis identifies *trust in healthcare professionals* as an important driver of treatment utilisation and helpfulness of treatment for mental health conditions. Based on this finding, I further expand the global perspective to examine how trust in healthcare providers is distributed worldwide and to identify the socio-economic and country-level drivers of trust in healthcare professionals.
2. **Life-course perspective:** This DPhil investigates the social determinants of mental health during midlife. Previous research on life-course trajectories has found that average mental health levels decline during midlife (Blanchflower, 2021; Gondek, Bann, et al., 2021) – and I aim to investigate whether this shift could be understood through the distributions of social determinants of health.
3. **A labour market perspective:** This DPhil explores whether country-level active labour market policies, such as behavioural conditionality and sanctions for unemployment, affect the health of the unemployed. Although prior research has shown that the health impact of unemployment varies across countries (Picchio & Ubaldi, 2024; Tøge & Blekesaune, 2015), it remains unclear whether differences in policy design explain these disparities.

The dissertation is structured as follows: Chapter 2 provides the theoretical and empirical foundations for my research. Chapter 3 outlines Research puzzles and empirical contributions. Chapter 4 provides an overview of the research methodology. Chapters 5 to 8 present the empirical chapters of this DPhil. Finally, Chapter 9 provides the general discussion for the findings of this DPhil.

Theoretical and empirical foundations

This section outlines the key elements of theory and literature that underpin the empirical studies presented in this dissertation. My work addresses various facets of social inequalities in mental health, drawing on a range of academic fields. These include psychology, public health, social epidemiology and social policy.

a. Mental Health: Definitions, Prevalence, and Social Inequalities

Definitions and concepts

The World Health Organization (2022, p. 8) defines mental health as a "*state of mental well-being that enables people to cope with the stresses of life, to realize their abilities, to learn well and work well, and to contribute to their communities. Mental health is an integral component of health and well-being and is more than the absence of mental disorder*". This definition focuses on *positive mental health* and is closely related to the idea of s*ubjective well-being,* which has become widely used as a metric in population-based surveys and used as a public policy objective (Diener & Ryan, 2009; Dolan et al., 2011; Kahneman & Deaton, 2010). In contrast, in the medical context, the WHO's International Classification of Diseases (ICD) and the Diagnostic and Statistical Manual (DSM) by the American Psychiatric Association are focused on mental disorders and define them as "*a syndrome characterized by clinically significant disturbance in an individual's cognition, emotion regulation, or behavior that reflects a dysfunction in the psychological, biological, or development processes underlying mental functioning.*" (Hunsley & Lee, 2017; Stein et al., 2021).

Among these disorders, the different types of depression and anxiety disorders, and somatoform disorders are often referred to as *Common Mental Disorders (CMDs)* (Prince et al., 2007; Vigo et al.,

2016; Whiteford et al., 2013). Different terminology is used throughout academic fields and language norms. In my work, I will mostly use the term *mental health problems* when referring to general psychological distress measured at the population level and *mental health conditions* when referring to a specific type of symptomology, such as anxiety or depression.

Given the two-sided definition of mental well-being on the one hand, and mental health problems/conditions on the other, how do they relate to one another? The World Health Organization (2022, p. 8) conceptualizes *symptoms of mental health conditions and mental well-being* as two dimensions that are related to each other and show a clear correlation (Fujiwara & Dolan, 2014, World Health Organization, 2022) but do not form one single continuum. This relationship is displayed in Figure 1.1. Importantly, even individuals affected by severe mental health conditions can – with the right support – achieve a high level of well-being (e.g., through positive emotions, meaningful experiences and decent life satisfaction).

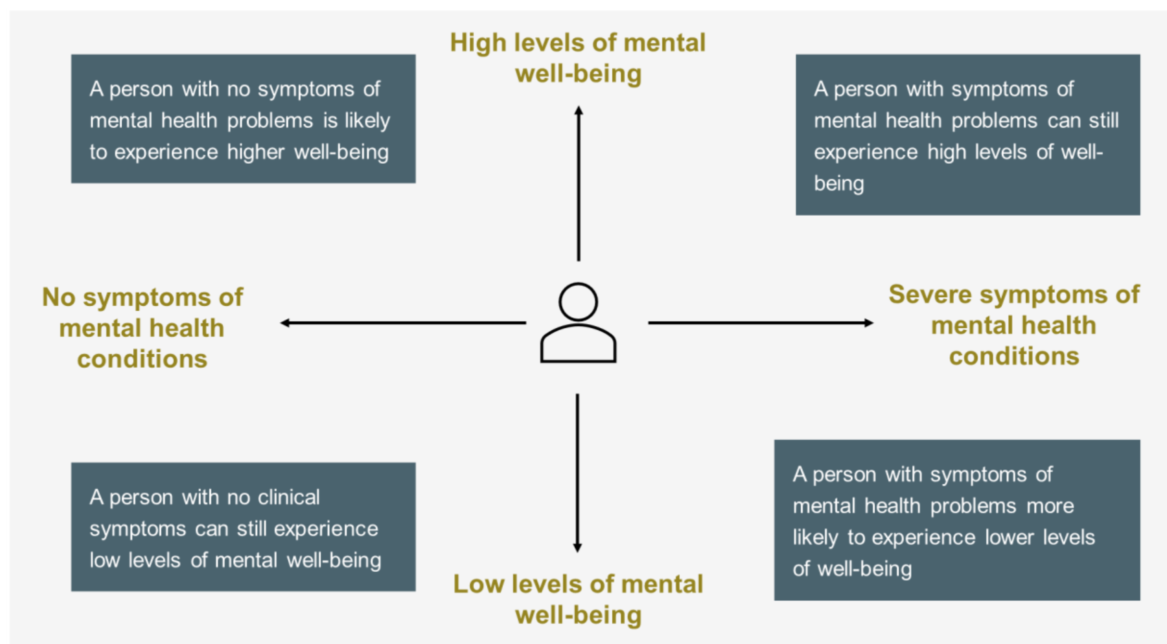


Figure 1.1 Concept of mental health and well-being, adapted from World Health Organization (2022)

While positive mental well-being is an important policy goal, my dissertation primarily focuses on social determinants and changes in the symptomology of mental health problems (e.g., depression

or anxiety). This enables me to effectively address both the public health and social policy literature and motivate the need for political action to support health.

Prevalence, global burden and social inequalities

Mental health problems, alongside cardiovascular diseases, constitute the largest share of the global disease burden (Vigo et al., 2016). Globally, approximately one in three people experience a mental health condition in their lifetime, and about 20% do so in any given year (Kessler et al., 2009). The most common mental health conditions are anxiety and depression, with a lifetime prevalence of up to 25% in the general population in European countries (Torre et al., 2021). According to the World Health Organization (2022) and its global mental health report, anxiety disorders make up 31% and depressive disorders make up 29% of the worldwide burden.

Social inequalities are closely reflected in mental health outcomes. Socio-economic factors are associated with mental health conditions through so-called "social gradients" (Marmot, 2005, 2015). That is, individuals with higher socio-economic status (SES) (e.g., income, education or occupational status) have, on average, better physical and mental health. In Europe, depression has the steepest socio-economic inequalities among all chronic health conditions, with low SES individuals being 3.12 times more likely to be affected (McNamara et al., 2017). In addition, women are more frequently affected by mental health problems than men (Buffel et al., 2014; World Health Organization, 2022). Between countries, low- and middle-income countries (LMICs) on average have a higher prevalence of mental health problems (World Health Organization, 2022). Among high-income countries (HICs), studies suggest that countries with higher income inequality have higher rates of mental health problems and a variety of social problems (Wilkinson & Pickett, 2010). In my research, my primary focus is on the relationship between social inequalities and the symptomology of mental health problems.

b. Theoretical framework

My research is based on the Framework on the Social Determinants of Health (SDH), as established by the commission on the Social Determinants of health by the World Health Organization (2010), which seeks to explain why and how societal factors affect health outcomes for both physical and mental health. In addition, several theoretical papers lay down the pathways between social and socio-economic factors and mental health outcomes, which are synthesised in my research model (Bambra, 2011b, 2011a; Fisher & Baum, 2010; Mackenbach, 2012). I visualise my theoretical understanding in Figure 1.2. The model distinguishes between three major levels of analysis.

At the top of the graph, the *structural determinants* sit in the economic and political sphere and are directly influenced by policy making at the country level. They form the political economy of health inequalities – and determine how vulnerabilities and health risks are distributed throughout society (Bambra, 2011b).

Below this sit the typical *social determinants* – the living and working conditions – that influence mental health and produce mental health outcomes and inequalities between population groups through specific intermediary mechanisms (Allen et al., 2014; Marmot et al., 2012).

Lastly, I include mental health *outcomes and treatment* use in my framework. Treatment plays a major role in responding to mental health problems, and its accessibility is influenced by the structural and social determinants as well, and not simply determined by the need of an individual (Andersen, 1995; Knesebeck, 2015). These different layers of analysis also provide different layers for intervention, from upstream public policies on the structural mechanisms through more downstream interventions and treatment roll-out. Each of these policy and intervention efforts has the potential to reduce mental health inequalities (Chrisinger, 2022; Marteau et al., 2021; Reininghaus et al., 2024; Shah et al., 2021).

Notably, there are many elements beyond the social sphere that affect mental health. Following the bio-psycho-social model of health, both genetic factors and psychological dynamics, such as individual cognition and emotions, play a crucial role (Hunsley & Lee, 2017, p. 58; Kendler, 2008). However, this line is generally out of scope for this DPhil. Furthermore, when it comes to mental health and inequalities in mental health across populations, social factors and dynamics play a crucial role – and can be directly addressed by social and health policies (Keyes & Galea, 2016; Shah et al., 2021).

Finally, I would like to outline the overarching goals and strategies in population-based approaches to mental health. These approaches typically pursue two main goals (McAllister et al., 2018): first, to reduce the overall burden of disease (or improve an average level of health in a population); and second, to improve equity by reducing health disparities between certain groups or populations. My DPhil is primarily focused on the latter. Health disparities can be reduced through two key strategies (Rose et al., 2008). The first involves targeted approaches, which aim to improve the health of specific vulnerable groups (e.g., unemployed people, those with the lowest incomes) through interventions and policies that address their social determinants. The second involves universal population approaches, which seek to improve overall health across groups (e.g., scaling up psychotherapy in a country), while specifically ensuring that groups with high vulnerability have a clear benefit (Frohlich & Potvin, 2008; Reininghaus et al., 2024; Rose et al., 2008). Comprehensive public mental health approaches ideally do both – improving average levels of population health while being particularly helpful to the most vulnerable, thereby improving health equity (World Health Organization, 2025).

This DPhil covers both strategies: For example, my investigation into inequalities in access and helpfulness in mental healthcare is more focused on population-wide efforts (paper 1). Similarly, my investigation of mental health in midlife (paper 2) and the social determinants of trust in healthcare providers deals with broad, population-wide phenomena across all social groups. In contrast, my investigation into unemployment protection (paper 3) is focused on policies

surrounding the vulnerable group of job seekers and how policy design affects their health compared to those who stay in employment. To gain a deeper understanding of the extent of social inequalities and their underlying causes, the Social Determinants of Health serve as the central framework and will be outlined in the following section.

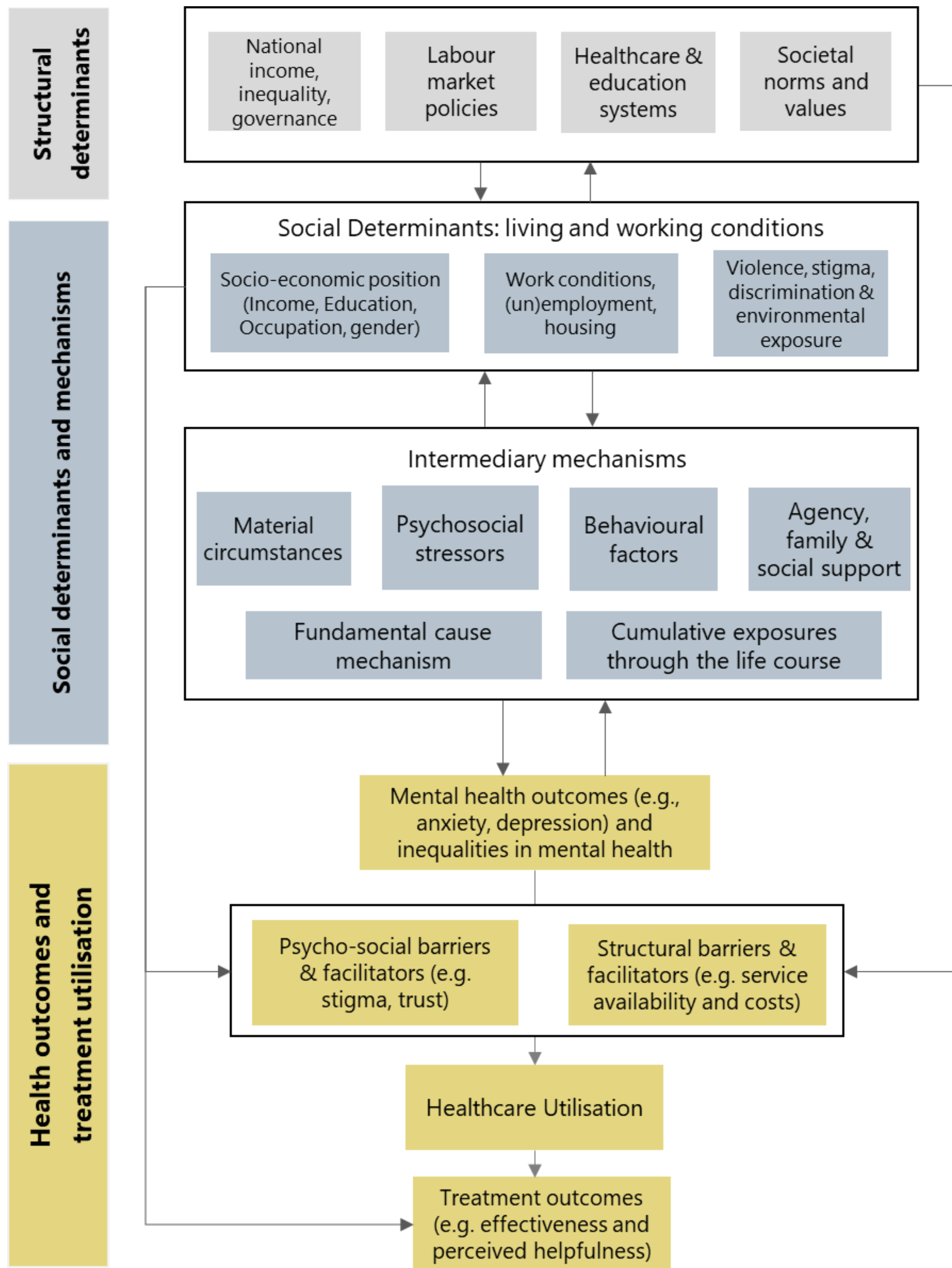


Figure 1.2. Conceptual Framework: Pathways from Structural and Social Determinants to Mental Health Outcomes and Treatment Utilisation

c. Social Determinants of Mental Health

Social determinants of health are *the conditions in which people are born, grow, live, work and age* (Marmot et al., 2012). They are the central part of my theoretical model (see Figure 1.2) and underpin all investigations on inequalities in mental health.

Here, socio-economic position (i.e., income, education and occupation) relates to the so-called *social gradient of health* (Allen et al., 2014), as the health of individuals is (on average) better the higher their socio-economic position. The socio-economic position is closely related to work (e.g., experience of demand and control), (un)employment and housing conditions (and many more) which were all identified to influence mental health (Alegría et al., 2018; S. B. Harvey et al., 2017; Shah et al., 2021). For example, both experiencing unemployment or precarious working conditions are established causes of mental health problems (Demiral et al., 2022; Knabe & Rätzel, 2011; Murphy & Athanasou, 1999). Similarly, social exclusion, stigma, discrimination and violence are adverse exposures and increase the risk of experiencing depression or anxiety, while decent education, high-quality work and social connectedness are considered protective factors (Alegría et al., 2018; Henseke, 2018; Herrick & Bell, 2020; Steele et al., 2024). Notably, mental health stigma operates both as a determinant of mental health problems by creating minority stress and social exclusion and as a psychosocial barrier to treatment utilisation (Link & Phelan, 2014) (as shown in the lower part of Figure 1.2).

Across individuals and communities, the social determinants come together in an intersectoral way, shaping the exposure to risk and protective factors (Rojas-García et al., 2022).

The social determinants not only shape the distribution of health outcomes across society, but also influence how mental healthcare is utilised. Most health inequality frameworks do not include this aspect; however, it is important because very similar social determinants not only affect mental health status but might also affect treatment utilisation (Dey & Jorm, 2016; Harris et al., 2020; Packness et al., 2017). This is because social determinants affect attitudinal and structural barriers

to treatment (Andersen, 1995; Tomczyk et al., 2020). Therefore, access to treatment is also an important health equity issue and can add to the social gradient in health outcomes.

d. Intermediary mechanisms

Why do the living and working conditions – known as social determinants of health – contribute to mental health? Different theoretical mechanisms and perspectives are proposed and illustrated in Figure 1.2. For this dissertation, three perspectives are of particular interest and will be discussed in further detail: the fundamental cause theory, psychosocial mechanisms, and the life-course perspective.

Fundamental cause mechanism

Different theoretical approaches aim to explain the intermediary mechanisms of how social determinants affect health (see Figure 1.2). The *fundamental cause theory* situates high socio-economic status as a fundamental cause of better health outcomes. The theory states that socio-economic status (the "fundamental cause") is linked to various health "enhancing resources" such as money, power, prestige, knowledge of health risks (Phelan et al., 2010). These health enhancing resources – which remain stable – are then connected to flexible (often behavioural) linking mechanisms which directly affect health outcomes. For example, high SES individuals with more money and health knowledge (health-enhancing resources) may have better cardiovascular health through their diet, lower rates of smoking or exercise (linking mechanisms). If one of these linking mechanisms is addressed (e.g., smoking rates are drastically reduced through legislation), other linking mechanisms remain and new ones come into play (e.g., new treatments first accessible by well informed and affluent individuals) so that health inequalities remain persistent (Phelan & Link, 2005). The more preventable a health outcome is, the stronger the expected association with socio-economic status (McCartney et al., 2021).

Psychosocial stress mechanism

The psychosocial stress mechanism is more focused on a specific pathway connecting the social determinants (e.g., income, working conditions or housing) and health outcomes. In this perspective, the key pathway operates through exposure to chronic stress and adverse life events, which then affect health outcomes (Allen et al., 2014; Marmot, 2015). For example, experiencing long-term unemployment induces chronic stress and social isolation, which causes both mental and physical health to deteriorate over time (Bambra & Eikemo, 2018; Jahoda, 1982; Selenko et al., 2011). Individuals living in poverty are also more likely and more vulnerable to experiencing adverse life events (Turner, 2013).

Lifecourse perspective

Exposures to the social determinants of health and their intermediating mechanisms are not a steady state, but differ across the life-course. Lifecourse approaches investigate how health risks and exposures produce health outcomes throughout life and how health risks in earlier life stages influence health outcomes later in life (Keyes & Galea, 2016; Koenen et al., 2013). In life-course approaches, researchers investigate both critical time periods or risks and health effects, as well as the accumulation of risks (Keyes & Galea, 2016). Given the importance of early life experience in all life-course models, research has focused on preventing adverse childhood events, improving parenting, and early adulthood to prevent mental health conditions (Ellsberg et al., 2015; Guyer et al., 2009). Adolescence and emerging adulthood (e.g., between 14 and 25 years of age) is also seen as a critical period where many mental health conditions have their onset and manifestation (Allen et al., 2014; Arnett et al., 2014). Data from UK cohort studies show substantial variability in the life trajectories of individuals affected by anxiety or depression in their 20s, with some experiencing significant improvements over time – but many others start experiencing more severe symptoms during mid-life (Gondek, Bann, et al., 2021; Gondek et al., 2022; Lang et al., 2011). The mid-life period has consequently been identified as a critical time point for poor mental health, but has received little policy attention.

Additional theoretical perspectives

While my work mostly draws on fundamental cause theory, psychosocial stress and the life-course perspective, further mechanisms complement the theoretical picture. First, in the materialist mechanism, the deprivation of material circumstances (e.g., living in poverty, experiencing a lack of necessary resources and food insecurity) directly harms mental health (Marmot & Wilkinson, 2001; Thomson et al., 2022). Second, the behavioural mechanism suggests that social determinants also influence health behaviours (e.g., alcohol consumption, smoking, physical inactivity or economic decision-making) which cause adverse mental health outcomes (Bambra, 2011a; Prättälä & Puska, 2012). Third, mental health links back to the social determinants of health ("*social selection"*) as suggested by the arrow between mental health outcomes and intermediary mechanisms in Figure 1.2 (Hudson, 2006). For example, individuals who experience severe mental health problems have impaired chances to maintain an occupation and generate income. Empirically, both causal directions have been confirmed and reinforce each other (Mossakowski, 2014). Finally, the theoretical mechanisms introduced in this section do not operate automatically, they are not mutually exclusive, nor do they represent a fully deterministic account of individual health: individuals and communities can improve living and working conditions, or lessen the impact of adverse conditions through personal resilience, agency and social support (Anaf et al., 2013; Sen, 2014; Yanos et al., 2007).

Limitations of theory and the Scandinavian paradox

Despite our growing knowledge of the social determinants of health and their theoretical mechanisms on health, many crucial theoretical gaps remain. A central one is the Scandinavian paradox. That is, within-country social inequalities of mental health conditions remain persistent, even in the most advanced welfare states (Bambra, 2011a; Mackenbach, 2012). That is, while these countries offer generous social protection, universal healthcare and lower income inequality, they continue to exhibit relatively high relative inequalities in both physical and mental health. Existing

theoretical mechanisms – as listed above – fall short of explaining the so paradox (Bambra, 2011a; Mackenbach, 2012). As a consequence, scholars even argue that researchers and policymakers have misdirected our efforts as health inequalities cannot be effectively reduced through policy (Mackenbach, 2020). Other scholars demonstrate cases of successful reduction of both health inequalities and population health improvements of people living in poverty (e.g., through increases in income and social assistance) (Kelly-Irving et al., 2022; Thomson et al., 2022). Better knowledge on specific structural and economic determinants of health, especially through longitudinal evidence and policy evaluations, is needed to advance this debate.

e. Structural Determinants and the Political Economy of Health Inequalities

One way we could make progress in closing health inequalities is to focus on the structural determinants of mental health – the most "upstream" angle on Figure 1.2.

Mental health inequalities are shaped by political and structural dynamics above the individual and community levels of analysis. These include democratic and welfare state systems, economic inequality, labour market institutions, consumer markets and healthcare systems. Conceptually, these political and economic factors, shaped in the context of nation states, are situated on top of Figure 1.2. Notably, health outcomes are not merely produced by a combination of personal vulnerabilities and risk exposures, but a result of complex dynamics within political and economic systems (Bambra, 2011b; M. Harvey, 2021). While this may sound abstract, the impact of political and economic decisions is omnipresent and can often be immediate. For example, when the UK and several EU governments decided to cut public services to save money and introduce austerity measures, this led to mental health problems and higher suicide rates (Cherrie et al., 2021; Stuckler et al., 2017). More recently, projections suggest that if the United States stops funding for development cooperation and makes drastic cuts to the United States Agency for International Development, this will cause more than a million additional HIV deaths by the year 2030 (Ten

Brink et al., 2025). While many structural determinants are essential in shaping population health, labour market policies and healthcare systems are of particular importance for this dissertation.

Labour market and labour market policies are key structural determinants of mental health and considered in this research project. They shape access to work, provide support for those out of work and set standards for working conditions and safety – all of which are crucial to mental health (Bambra, 2011b; Henseke, 2018; Immervoll & Knotz, 2018). One example of the impact of labour market policy on mental health is the minimum wage, which has been shown to protect mental health at the population level (Gülal & Ayaita, 2020; Reeves et al., 2016). A further example is unemployment protection, which also impacts mental health (Reeves et al., 2014; Sochas & Reeves, 2023). Since the 1990s, European countries have increasingly structured their unemployment protection systems around Active Labour Market Policies (ALMP), which aim to both qualify and incentivise unemployed individuals to re-enter the workforce swiftly by combining supportive measures such as training with more punitive elements like monitoring and sanctions (de Beer & Schils, 2009; Immervoll & Knotz, 2018; Pattaro et al., 2022; Raffass, 2017; Reeve, 2017; Williams, 2021). Evidence shows that countries with stronger labour protection policies and more generous unemployment insurance tend to have better health outcomes for job seekers and precariously employed individuals (Huijts et al., 2015; MacEachen et al., 2022; Tøge, 2016).

Moreover, the design and funding of the healthcare system are a key structural determinant of mental health and central to this research project (Langheim, 2014; Reeves et al., 2015; Shah et al., 2021). How mental healthcare systems are organised, financed and delivered shapes both access and quality of care. Yet globally, mental health systems remain under-resourced to meet growing demand (Evans-Lacko et al., 2018; Thornicroft & Tansella, 2013), with only 2% of the world's governmental health expenditure allocated to mental health (~ 3% in HICs) (Ridley et al., 2020; WHO Mental Health ATLAS, 2017). Furthermore, many countries still primarily rely on psychiatric hospitals rather than community-based care, particularly in poorer countries

(Thornicroft & Tansella, 2013). In response, researchers have called for "psychological therapies as a universal first-line treatment step" instead of directly prescribing medication (Ormel et al., 2020). While several European countries have expanded community-based care and coverage of psychological treatments, gaps still remain (Lewer et al., 2015). Moreover, scaling up healthcare does not guarantee improved outcomes. For instance, the UK's "Improving Access to Psychological Therapies (IAPT) initiative increased treatment uptake but was criticised for being a "get back to work" effort rather than a long-term treatment plan(Scott, 2018; Wakefield et al., 2021). This has resulted in the paradoxical finding that treatment struggles to improve population health and reduce inequalities (Ormel et al., 2020, 2022).

f. Summary

The existing literature offers a range of theoretical perspectives to explain the drivers of social inequalities in mental health and the societal processes that maintain them. Research also gives us a variety of options where to intervene, may it be on the "downstream" level by improving access to quality mental healthcare, or interventions and prevention efforts that aim to improve behavioural or stress-related mechanisms of the existing stratification (Holman et al., 2018; Marteau et al., 2021; Reininghaus et al., 2024). It is also possible to address health inequalities more "upstream", by shaping the political economy in a way that working and living conditions of disadvantaged groups in society are improved (e.g., through better labour legislation, minimum wages, etc.) (Chrisinger, 2022; Humphreys et al., 2016; Marmot, 2015; Reeves et al., 2017; Thomson et al., 2022). However, there are also significant gaps in our theoretical and empirical knowledge on why mental health inequalities persist and how they could be reduced. These include the "Scandinavian Paradox" (persistent health inequalities in advanced welfare states), insufficient and unequal access to mental healthcare (the "treatment gap"), and challenges in scaling up interventions to effectively improve population mental health (Bambra, 2011a; Mackenbach, 2012; Ormel et al., 2020, 2022; Roberts et al., 2022; Thornicroft et al., 2017). Further, there is a lack of evidence on health inequalities through the midlife phase of the life-course, cross-country investigations that span over different

global regions and the effects of unemployment protection as a structural determinant of mental health (Bambra & Eikemo, 2018; Gondek et al., 2022).

In the next section, I will draw on these theoretical and empirical shortcomings to introduce four specific research puzzles in the study of social inequalities in mental health and define the empirical contributions of my DPhil papers.

Research puzzles and empirical contributions

This chapter introduces my research puzzles and contributions. Building on the theoretical framework and broader theoretical challenges discussed in the preceding chapter, I identify and address three major research perspectives (global, life-course, and labour market perspectives) and four specific research puzzles in the study of public mental health. I then address these puzzles using four research papers. Each research puzzle engages with a body of literature that builds on, but is more specific than, the broader theoretical framework introduced in Chapter 2. A summary of all research papers is displayed in Table 1.1 at the end of this section.

1. **Global perspective: How do inequalities in mental healthcare use and treatment helpfulness vary between countries?**

The first research puzzle in this DPhil is situated in a global perspective on social inequalities in mental health. It focuses on understanding social inequalities in the prevalence of mental health problems, treatment use, and perceived treatment helpfulness across countries worldwide. Cross-country variations in mental health prevalence, treatment access as well as social inequalities within countries are an essential challenge in public mental health (Harris et al., 2020; Thornicroft et al., 2017; World Health Organization, 2022). Researchers attempt to estimate the prevalence of mental health problems across countries (such as anxiety and depression) and understand inequalities in treatment access and treatment effectiveness (Harris et al., 2020; Knesebeck, 2015; Thomson et al., 2022).

As discussed in the previous chapter, one key observation in public mental health are disparities in the access and utilisation of mental health problems. According to the WHO, minimally adequate treatment for anxiety and depression is defined as either pharmaceutical treatment (e.g., through antidepressants) with at least four visits to a medical doctor or at least eight sessions of psychotherapy (Thornicroft et al., 2017; Wang et al., 2007). However, it is well documented that there is a "treatment gap" for mental health problems, whereby only a proportion of those affected by depression or anxiety receive adequate care (Alonso et al., 2018). The size of this treatment gap strongly differs by country. Only 30% of people affected by mental health conditions receive any professional treatment (i.e., medication or talking therapy), and under 10% in middle- and low-income countries (Alonso et al., 2018; Thornicroft et al., 2017). Figure 1.3 illustrates this treatment gap of depression by using data from 21 countries based on the representative World Mental Health Survey. Of the individuals who meet the criteria of a major depressive disorder (an average of 4.6% of the population in the surveyed countries), only 15% receive treatment in line with the minimum quality standards.

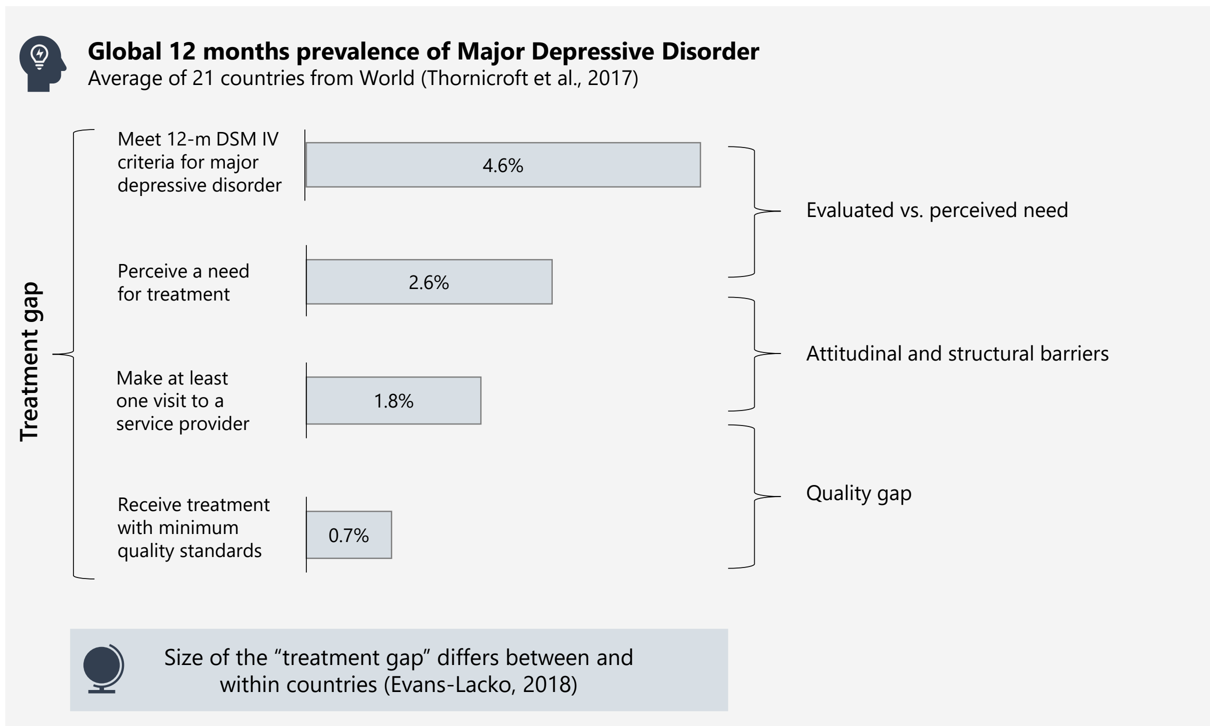


Figure 1.3. Illustration of the treatment gap for major depressive disorder, adapted from Thornicroft et al. (2017) and Evans-Lacko et al. (2018)

The size of the treatment gap differs between countries, but also between socio-economic groups within countries. Those with lower socio-economic status (SES) have particularly low access to treatment, and there is also first evidence that psychotherapy and medication might be less effective for those from lower SES groups (Dey & Jorm, 2016; Elwadhi & Cohen, 2020). However, there is little evidence to suggest whether these socio-economic inequalities exist globally across country contexts or whether their magnitude might differ depending on a country's investment in healthcare systems and the type of treatments offered.

Thirdly, besides treatment utilisation, another important indicator in mental health is treatment effectiveness and perceived helpfulness of treatment. Two systematic reviews showed that treatment effectiveness of both psychological therapies (Finegan et al., 2018) and antidepressant treatments (Elwadhi & Cohen, 2020) might be lower for low SES individuals. This suggests that individuals with lower SES might face more socio-economic stressors, which cannot be relieved by either type of treatment (Pathare et al., 2021; Roberts et al., 2022), and talking therapies might

generally be less suitable for such groups (Holman, 2014). Besides treatment effectiveness, perceived helpfulness can be used as a patient-centred way to measure treatment outcomes (also called perceived effectiveness) (Morgan et al., 2020). While more subjective, such measures can yield a high external validity and generalisability (Edlund et al., 2015). Research found that higher educational levels made it more likely to perceive treatment as helpful (Harris et al., 2020). Country-level variation in treatment helpfulness is not well-documented. The only two studies on this topic using the WMH Survey Initiative involved too few countries to include specific country-level predictors (Harris et al., 2020; Kazdin et al., 2021).

While we have a fundamental understanding about inequalities in prevalence, healthcare use and helpfulness, cross-country evidence is very limited. Evidence on inequalities stems almost exclusively from high-income countries, and the majority of studies focused on prevalence rather than treatment access and treatment helpfulness (Harris et al., 2020; Whiteford et al., 2013). No investigation has yet used a sample of over 100 countries to estimate global variation and differences by country-level factors such as national income, healthcare investments, and out-of-pocket health spending.

Paper 1: Research questions and contributions

This research gap is addressed by paper 1, where I investigate the predictors of these three health outcomes (prevalence, treatment utilisation and helpfulness) using a global survey across 111 countries. By bringing these different health outcomes together, the study attempts to comprehensively show how social inequalities cut through different mental health outcomes in a global context. The study addresses the following research questions:

- Do social inequalities in prevalence, treatment utilisation and helpfulness exist globally?
- Which county-level factors influence these three health outcomes?

To answer these questions, my study uses a nationally representative individual-level survey dataset (Wellcome Global Monitor 2020) in 111 countries. The study uses a multilevel regression model and includes both individual and country-level predictors of mental health outcomes. The analysis reveals a global 'triple inequality in mental health': disadvantages of lower SES individuals persist in three outcomes (lifetime prevalence, treatment utilisation and helpfulness). Besides its empirical contribution, this research contributes to our knowledge of the fundamental cause theory (Phelan et al., 2010) which states that socio-economic inequalities exist regardless of the specific health outcomes. I show to what extent this aspect of the fundamental cause theory also applies to treatment use and treatment helpfulness across the cascade of care. Further, the work toads to the evidence base on healthcare and country wealth as structural determinants of mental health inequalities. That is, the study measures differences in mental healthcare usage between countries and examines if they are associated with structural factors such as GDP, healthcare expenditure or out-of-pocket payments.

2. **Life-course perspective: How do mental health inequalities evolve in midlife?**

The paper adopts a life-course perspective, and investigates mental health inequalities in the midlife period. Mental health inequalities – as well as the social determinants of health – are not stable over people's lifetime (Koenen et al., 2013). Therefore, the life-course perspective has become crucial tool for researchers and health policy makers to address population mental health.

Because social determinants and early life events have a strong influence on trajectories in later life, much policy impetus has been put on early phases (Cohen & Galea, 2011; Guyer et al., 2009). However, the mid-phase of life, with its crucial aspects, has received less attention as a developmental phase for mental health. In fact, there is a lot of crucial variation happening in the life stage around 35 – 55 years of age that sets up crucial mental health trajectories for older adulthood and retirement age (Gondek et al., 2022). Due to the density of life events in personal and professional life (e.g., family foundation, marriage or divorce, peak career achievements), and

increasing inequalities in socio-economic trajectories, midlife is now considered a pivotal period for lifecourse researchers (Lachman et al., 2015).

One important phenomenon of the development of mental health in midlife is the U-shape in well-being (Blanchflower, 2021; Ploubidis et al., 2017). Documented across many countries and periods, individuals' mental health typically declines in mid-life before improving again towards later adulthood (Blanchflower, 2021; Gondek et al., 2022). While this pattern has been criticised for relying heavily on cross-sectional data and limited methodological diversity (Galambos et al., 2020), the U-shape was found in various indicators of subjective well-being (e.g., life satisfaction) and depressive symptoms (Dijk & Mierau, 2023; Lang et al., 2011) and deaths of despair (Blair & Siddiqi, 2022). However, we do not know why it happens, who is most likely to experience it and what interventions could prevent the mid-life decline in mental health

While the reasons for this pattern remain unclear (Blanchflower, 2021; Weiss et al., 2012), there are plausible biological and psychological explanations. A similar U-shaped curve in well-being is observable in other primates suggesting the biological effects may drive this trend (Weiss et al., 2012). Psychological explanations suggest that people experience more negative emotions and regret in mid-life, and then become more content towards later adulthood (Brassen et al., 2012; Demiral et al., 2022). Studies focusing on the social determinants have focused on social-demographic characteristics and found that people with lower education and women are more likely to experience a mid-life decline trajectory in mid-life (Gondek et al., 2022). However, most research has focused on modelling the u-shape pattern in various contexts and has merely treated factors like gender and socio-economic status as control variables (Blanchflower, 2021; Ploubidis et al., 2017), rather than investigating how these specific social determinants contribute to the mid-life decline. Therefore, the social drivers of mental health in mid-life and the contributing factors are not known.

Paper 2: Research questions and contributions

Paper 2 of this DPhil fills this gap by investigating the mid-life decline in mental health from a social determinants of health perspective. The study describes the socio-economic characteristics of individuals who experience a mid-life decline in mental health, identifies which of the social determinants of mental health (World Health Organization, 2010) best predict the subsequent mid-life decline, and estimate the overall contribution of these predictors to the mid-life decline on the population level.

The paper addresses the following **research questions**:

- Which of the social determinants of health (before mid-life) are the best predictors of the subsequent decline in mental health?
- What is the overall contribution of the most relevant predictors to the mid-life decline in mental health?

To address these research questions, the study uses data from a prospective 1970 British Birth Cohort Study with measures at birth, as well as at the ages 10, 26, 34 and 42 – to explore the strongest predictors of mental health decline in midlife. The study uses a combination of exploratory machine learning to identify the most important predictors and confirmatory analysis to estimate population-wide effect sizes. As social determinants, I include socio-economic position such as social class at birth, gender, education and occupational group, as well as work-related social determinants (e.g., job insecurity, low job satisfaction and working multiple jobs to make ends meet), demographic factors (marital status and number of children) and behavioural factors included exercise and smoking.

The study makes a main contribution to the study of life-course mental health by bringing us new evidence on the midlife period. Additionally, the study makes a significant contribution to the question of different types of social determinants, some stable and others changing in frequency, and provides some new theoretical insights. That is, some of the social determinants (e.g., social

class at birth, gender, education) are not novel to mid-life and remain relatively stable over the observed period, while others start to appear in much higher frequency as critical life events (e.g., marital status, having children, work transitions). If the more stable ones are associated with midlife changes a *effect heterogeneity* is critical for understanding mid-life decline, where existing things (such as social class or education differences) might loom particularly large (Lachman et al., 2015). On the other hand, the greater concentration of life events in mid-life, such as changes in family foundation, taking up care responsibilities, experiencing peak career, or the onset of physical health deterioration. adds to increased stress and mental health problems (Ballas & Dorling, 2007; Gondek, Moltrecht, et al., 2021). In distinguishing between these factors, this study can make a crucial theoretical contribution to the life-course study of mental health.

3. **Labour market perspective: Does behavioural conditionality of unemployment protection affect the health of job seekers?**

The third DPhil paper delves into the social policy literature and adopts a labour market perspective on health inequalities. From this perspective, there is a major academic and policy debate regarding the support and activation of job seekers – and how unemployment policies affect their mental health. Unemployment is a major determinant of bad mental health (Knabe & Rätzel, 2011; Picchio & Ubaldi, 2024). The negative consequences on unemployment on health stem from both psychosocial stress associated with unemployment as well as material deprivation when work-related income is discontinued (Bambra & Eikemo, 2018; Jahoda, 1982). However, the magnitude of the negative health consequences varies between European countries. Tøge and Blekesaune (2015) examined the impact of unemployment on self-rated health in European countries between 2008 and 2011, with varying results depending on the country. However, it is unclear on why country-level differences exist and how employment protection policies can be effectively designed to mitigate the mental health impacts of job losses.

One possible explanation is that countries with more generous financial support of job seekers are more successful in protecting their health following job loss. Indeed, studies found that indeed the generosity of unemployment benefits is associated with better health of those who become unemployed (Huijts et al., 2015; Tøge, 2016). However, this does not present the full picture, as it neglects important aspects of the delivery of active labour market policy. That is, a key feature of ALMPs is that unemployment benefits are conditional upon behavioural requirements from job seekers (Asenjo & Pignatti, 2019; Immervoll & Knotz, 2018; Immervoll & Scarpetta, 2012) in order to incentivise job search (Liepmann & Pignatti, 2024). These include job search and availability requirements as well as monetary sanctions and cuts to the financial support if requirements are not met. In studies in the UK, punitive sanctions have been linked to an increased number of antidepressant prescriptions (Williams, 2021), but research has not investigated this aspect using a cross-country and comparative angle. Could the differences in activation requirements be a reason for these different consequences of becoming unemployed, beyond benefit generosity? And could an adaptation of activation requirements therefore help protect the health of those who lose their employment?

Paper 3: research questions and contributions

To address this research gap, paper 3 investigates whether the negative health consequences of experiencing unemployment depend on the strictness of activation requirements and sanctions. I hypothesise that in countries with particularly restrictive access to unemployment benefits, the negative effects of becoming unemployed are stronger.

The study addresses the following **research questions**:

- Does the strength of welfare conditionality and sanction regimes help explain the variation in health effects of unemployment across European countries?
- Which dimensions of conditionality matter most?

The study combines individual-level panel data from the EU statistics on income and living conditions (EU-SILC) and country-level data from the OECD's database of activation requirements from 29 countries, which quantify the strictness of requirements and the strengths of sanctions (Immervoll & Knotz, 2021; Tøge & Blekesaune, 2015). The study uses first difference regression to measure the effect of unemployment transitions across countries for the years after the recession between 2014 and 2019, and adds country-level activation requirements as a moderator for the effect of unemployment transitions on self-perceived health. Hereby, I contrast the people who stay in employment with those who become unemployed.

The study aims to directly contribute to the literature on the political economy of health inequalities and labour market policy as a structural determinant of mental health (Bambra, 2011b). Improving the policy design of unemployment protection could improve the health and well-being of millions of job seekers in Europe (Asenjo & Pignatti, 2019; Tøge, 2016). Moreover, by disentangling the effects of different behavioural requirements (i.e., activation measures, job search obligations, and sanctions) the study can offer a theoretical contribution to understanding how specific policy elements shape the social determinants of unemployment and contribute to health inequalities between employed and unemployed individuals.

4. **Extension of the global perspective: What are the determinants of trust in healthcare providers?**

Finally, the fourth research puzzle builds directly on research paper 1 and adds a further study to the global perspective. Research paper 1 finds that trust in health professionals is associated with mental health treatment utilisation and helpfulness. That is, across the 111 countries in this study, people who have experienced mental health problems and have higher trust in healthcare professionals (such as doctors or nurses) are more likely to speak to a mental health professional and perceive this as useful compared to those with lower levels of trust. This finding aligns with the idea that trust in healthcare professionals is an essential part of a healthcare system and a

requirement for investments in health to produce positive health outcomes (Birkhäuer et al. 2017; Douglliass and Calnan 2016). The evidence on the determinants of trust in healthcare providers is sparse, especially on a global level. For example, while there is some evidence on socio-economic gradients (Antinyan et al., 2021; Brown et al., 2009), it is unclear if greater affluence at the country or individual level are consistently associated with higher trust. I examine whether national income (GDP per capita) and individual-level socio-economic status (SES) are systematically associated with trust in healthcare professionals across different country contexts.

Further, the role of trust in traditional and complementary medical providers is underexplored. Across many countries and cultures, traditional and alternative medicine are used to replace or supplement biomedically trained healthcare professionals (Puckree et al., 2002; Van der Schee & Groenewegen, 2010; Xu & Yang, 2009). Yet, the socio-economic determinants of trust in these alternative healthcare providers are not well understood in a global, cross-national context and in contrast to conventional biomedical providers.

And finally, beyond personal and national economic prosperity, healthcare system and political factors such as quality of care, healthcare investment, and corruption may determine trust (Naher et al., 2020; Radin, 2013). These factors could help explain why higher national income does not uniformly translate into higher trust. Answering these questions would provide us with a clearer understanding of how trust is shaped in healthcare systems worldwide, and also help examine a possible lever to improve access to mental healthcare by strengthening trust in healthcare providers.

Paper 4: research questions and contributions

My fourth research paper investigates the social determinants of trust in healthcare professionals and traditional medicine practitioners across 111 countries. It complements the other three papers by focussing on a specific finding made before.

The study addresses the following **research questions**:

- What is the global relationship between personal SES, national income (GDP) and (a) trust in healthcare professionals and (b) trust in non-Western/traditional health practitioners?
- Beyond national income, what political and healthcare-related country characteristics are associated with trust in health professionals and traditional health practitioners?

I considered household income and national income (GDP) as main socio-economic predictors and also examined political and healthcare-specific determinants at the country level. Notably, the contribution of this paper is somewhat distinct from the other three papers. It investigates trust in healthcare providers, rather than directly focusing on the determinants of mental health. However, this paper 4 provides more depth to the findings provided by the first paper, and provides an important research and policy lever to improve inequalities in healthcare utilisation and helpfulness. By identifying the key factors that contribute to building trust, these can be addressed within the healthcare system. Further, it established trust in health providers as an important – but previously understudied – structural determinant of mental health, thereby complementing my theoretical framework.

All four papers, research questions, methods and results are summarised in Table 1.1. The next chapter will discuss the overarching methodology of this DPhil, followed by the empirical chapters.

Table 1.1. Overview of empirical papers

	Title	Research questions	Data and methods	Findings
Paper 1: Global perspective	Global inequalities in mental health problems: understanding the predictors of lifetime prevalence, treatment utilisation and perceived helpfulness across 111 countries	• Do social inequalities in prevalence, treatment utilisation and helpfulness exist globally? • What county-level factors influence these three health outcomes?	• Cross-sectional multi-level analysis of survey data in 111 countries from the Wellcome Global Monitor 2020 • Key outcomes: lifetime prevalence of depression/anxiety, treatment utilisation (talking therapy and medication), perceived treatment helpfulness	• Low SES in adults is linked to more mental health problems, lower treatment utilisation and helpfulness. • Exception: SES is not linked to the utilisation of medication across all countries. • Trust in health professionals is also associated with treatment use and helpfulness
Paper 2: Life-course perspective	What predicts the decline in mental health during mid-life? A Machine Learning analysis of the 1970 British Cohort Study	• Which of the social determinants are the most important predictors of the midlife decline in mental health? • What is the overall contribution of the social determinants on the midlife decline in mental health?	• 1970 British Cohort Study – with measures at birth, as well as the ages 10, 26, 34 and 42 – to explore the predictors of mental health decline between the ages of 34 to 42. • Analyses combined exploratory Machine Learning (Random Forest) algorithms to identify the strongest predictors of midlife decline; followed by logistic regression analyses to estimate effects	• Four key predictors of a mid-life decline identified: low social class at birth; sex; low income at the start of the midlife period; and physical multimorbidity in early adulthood • Overall, these social determinants could reduce the risk of mental health decline from 18% (observed) to 11%, and up to 28% if risk constellation changes in the population
Paper 3: Labour market perspective	Behavioural benefit conditionality, sanctions and the self-rated health of the unemployed: a longitudinal analysis of European countries	• Does the strength of behavioural requirements and sanction regimes explain the variation in health effects of unemployment across European countries? • Which of the behavioural requirements (job search &	• National-level activation requirements (OECD database) • Individual-level panel data from EU-SILC in 30 countries for years 2014 – 2019 • First difference regression analysis: effect of transitioning to unemployment on	• Stricter sanction rules are associated with worse self-rated health among job seekers in Europe • The predicted decline in self-rated health ranged from −0.047 in low-sanction countries (e.g., Hungary, Cyprus) to −0.109 in high sanction countries

		availability requirements and sanctions) matters most for health?	self-perceived health, moderated by country-level behavioural requirements	• Job-search and availability requirements did not significantly moderate the association.
Paper 4: Global perspective II	What shapes trust in healthcare? Socio-economic and structural determinants of trust in formal and traditional health providers across 111 countries	• What are the socio-economic and country-level determinants of trust in health professionals and traditional medicine practitioners?	• Cross-sectional multi-level analysis of survey data in 111 countries from the Wellcome Global Monitor 2020 • Key outcomes: Trust in healthcare professionals; trust in traditional healers	• Trust in healthcare professionals is highest among the wealthiest individuals in high-income countries, with a positive link to GDP and a positive association with corruption levels • Trust in traditional medicine practitioners follows a reversed pattern, being higher among individuals in lower within-country income quintiles

Methodology

This section provides an overview of the methodological choices of this dissertation. All four empirical papers approach different research questions and use different types of data to do so. Here, I aim to convey the underlying rationale for these analyses, their similarities and key differences and why I made methodological choices. The technical and statistical details of each paper can then be read in the empirical papers below and will not be restated here.

a. Use of population-based survey data

All individual-level data presented in this dissertation are based on secondary, representative population-based surveys. This representativeness is important when studying mental health inequalities to cover societal dynamics on the societal level (Keyes & Galea, 2016; Momen et al., 2022; Skapinakis et al., 2013). All these data sources measure mental health via survey questions posed to individual respondents, as typically seen in the population mental health literature

(Gondek, Bann, et al., 2021; McCabe et al., 1996). I made the choice of using secondary data because the collection of cross-national, representative data would be highly costly and time-consuming, while adequate data sources were newly available from the Wellcome Trust (papers 1 and 4), the UK Data Service (paper 2), and Eurostat (paper 3). All of the data sources were either open access (Wellcome Trust and UK Data Service for the British Cohort Study 1970) or were obtained via a project proposal (via Eurostat for paper 3) as detailed in each individual chapter.

Notably, the Wellcome Trust Global Monitor dataset (used in papers 1 and 4) is based on cross-sectional data, while the British Cohort Study 1970 (paper 2) and the EU-SILC household panel (paper 3) are longitudinal data sources. This variation allowed me to cover different perspectives of public mental health research. In the case of the Wellcome Trust (2020) dataset, the cross-sectional nature allows the survey to span across 111 countries and cover all global regions without having to re-trace participants. In the case of the British Cohort Study 1970, this dataset allowed for a unique life-course perspective, as all participants were born in the same week and followed throughout their lives, allowing a connection between factors at birth and mid-life mental health in the British context (Elliott & Shepherd, 2006; Sullivan et al., 2023). The EU statistics on income and living conditions (EU-SILC) provide answers from its participants for up to four years, which is ideal for covering changes in employment status in this investigation (Arora et al., 2015).

Papers 1, 3, and 4 include cross-national elements in their research questions and datasets. This provides a unique, comparative angle – particularly helping to draw conclusions on the structural determinants of mental health at the country level. These papers therefore merge national-level data into the individual-level data sources. This data is obtained from trusted international organisations such as the World Bank, OECD, or the European Union. My statistical analyses then take such country-level data into account by using multilevel models (papers 1 and 4) or clustering standard errors at the country level (paper 3).

Finally, part of this methodological variety – from using cross-sectional data across 111 countries to birth cohort data in one country – reflects my own training and education in using different types of data. As a DPhil researcher, it was my intention to learn about the possibilities offered by secondary data in mental health research – from merging and cleaning longitudinal, cross-national data to making methodological choices that suit each individual dataset. Each analysis posed its specific challenges, and I hope this DPhil helps to showcase some of the methodological variety in this field of research. The specific approaches, as well as the strengths and limitations of each data source, are discussed in the individual paper sections below.

b. Measuring mental health

In a dissertation focused on social inequalities in mental health, the measurement of mental health problems is critical. Unlike clinical practitioners, whose main goal is to diagnose and treat specific mental disorders using specific tools for different conditions (Hunsley & Lee, 2017), this DPhil investigates population-wide mental health inequalities and changes in population mental health across different country contexts and life stages. Importantly, the survey datasets used in my dissertation are not specifically about mental health – and contain only limited items on health, such as single items of composite scales of mental distress, rather than full diagnostic scales for specific mental health conditions (Gondek, Bann, et al., 2021; McCabe et al., 1996).

The Wellcome Global Monitor dataset used in papers 1 and 4 used a single item to measure lifetime experience of anxiety and depression, and then employed follow-up questions on treatment utilisation and helpfulness (Wellcome Trust, 2020). The item was specifically designed for this survey with the international applicability of 111 countries in mind, rather than epidemiological precision. As I explain in the papers, despite its limitations, the item effectively captures participants' lifetime experiences of typical symptoms and allows us to subsequently ask those who reported symptoms about their use of healthcare services.

Paper 2 uses the Malaise Inventory to capture life-course changes in mental health problems. It uses binary "yes or no" questions to test for different symptoms of psychological distress (e.g., depression, anxiety, lack of sleep), forming a sum score for each individual from 0 – 9, where 0 represents no symptoms (Rodgers et al., 1999). This scale is not one of the most modern ways to measure population mental health, especially due to its binary question style. However, it was posed to participants throughout their lives, which is a major strength to measure life-course changes in mental health. It has also shown good validity compared to other scales and is frequently used by researchers (Rodgers et al., 1999; Torre et al., 2021).

Paper 3 uses a measure of general, self-perceived health instead of a pure mental health measure. It is one of the most widely used scales in population health and has been available for many decades ("*How is your health in general?*"). In the case of my research, this was a compromise due to the lack of a specific mental health measure in the dataset. Although this pragmatism is a downside, it also has some advantages: it extends beyond mental health, capturing a combination with physical health, and has a strong association with both mortality and mental health outcomes (Jylhä, 2009). In fact, the single-item self-appraisal, while simplistic, captures a lot of health outcomes of concern to public mental health (DeSalvo et al., 2006). The use of this measurement item also makes my research comparable across many studies that have used it to measure the impact of unemployment on health (Huijts et al., 2015; Tøge & Blekesaune, 2015). Further, as unemployment is likely to affect mental health first and more directly than physical health, our general health measures (which capture both) are likely to provide a conservative estimation (Pharr et al., 2012). The advantages of each of these measurement approaches are described for each individual paper below as well as in the general discussion of this dissertation.

c. *Analytical approaches: description, prediction and causal inference*

Quantitative social and health sciences typically follow one out of three analytical goals: description, prediction or causal inference (Ito et al., 2025; Leist et al., 2022; Pearl, 2010). While

research should be transparent about the goals and limitations, in reality, studies often assume causal inference or use causal language without adequate methodology (Haber et al., 2022). My DPhil addresses all three analytical goals in different ways across the research papers, and I seek to use the elements of them in a transparent way. For example, throughout my papers, I communicate transparently about the choice of control variables in regression analyses. In this way, I aim to avoid the so-called 'Table 2 fallacy,' where models include all available control variables indiscriminately and without theoretical justification (Westreich & Greenland, 2013). Instead, I attempt to make my choices of control variables in regression analyses transparent, theory-driven, and conduct sensitivity tests to assess the robustness of findings. In addition, I set a focus on portraying confidence intervals over p-values, and on visualising effect sizes.

Papers 1 and 4, using a global cross-national dataset, are primarily of descriptive nature. They seek to demonstrate the socio-economic correlates of mental health problems, treatment utilisation and helpfulness, while not directly investigating the causal pathways. Yet, while I do not attempt to identify causal effects in strict sense, the theoretical foundation does include causal explanations, and my main analyses chooses control variables in a strategic way following concepts form the causal inference literature (e.g., avoiding to control for mediators) which could offer the grounding for future longitudinal work.

Paper 2 is primarily of a predictive nature, attempting to identify the social determinants of mental health in midlife. For the purpose of exploring which of the social determinants of mental health are the most relevant, the study uses a Machine Learning algorithm, and then follows up the exploratory efforts with a more confirmatory regression analysis (Fife & D'Onofrio, 2023). This combination of analysis approaches helps overcome issues of regression models with a large number of predictors, such as multicollinearity and overfitting (Wiemken & Kelley, 2020). This reduced emphasis on theory might draw criticism from social scientists. However, this can

become a strength in this particular context and research question, as I do so deliberately and with transparency, avoiding table 2 fallacy and post-hoc theoretical explanations.

Paper 3 contains the clearest causal inference approaches by capturing within-person changes of employment and their effects on health using panel data. At the same time, the analysis includes country-level moderators, which are more of an associative character.

d. Notes on statistics and use of tools

Finally, I would like to report some conventions used in this DPhil. Statistical analyses typically included inferential statistics, drawing conclusions from a representative sample to the population. This includes the construction of confidence intervals and p-values as a sign of statistical significance. Confidence intervals are always reported and are the focus of analysis, to allow the reader to assess the precision of estimates. This aims to ensure more accurate estimates of statistical associations, rather than placing excessive focus on p-values. I still report levels of statistical significance (* for $p < 0.05$ and ** for $p < 0.01$) in many places across this DPhil to help guide the readers' attention, but only in combination with Confidence Intervals. Further, I placed an emphasis on computing effect sizes by visualising what effects and outcomes would mean in different countries or different socio-economic groups. Each paper includes a range of robustness tests, presented in the appendices, to demonstrate whether results are sensitive to different methodological choices.

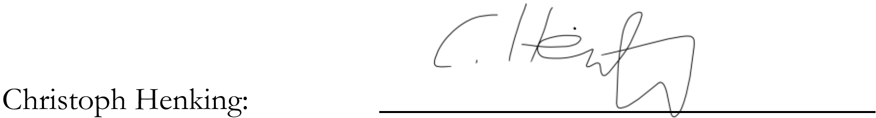
All analyses reported in this dissertation were done using the R statistical software and RStudio. As a non-native English speaker, I used AI-based tools like Grammarly and ChatGPT as writing aids to correct grammatical errors and improve sentence structure and readability. All intellectual work is my own, unless otherwise stated. The following chapters will include the individual research articles. Table 1.1 provides an orientation of the papers and their order in this dissertation.

Statements of authorship

DPhil paper 1: Global inequalities in mental health problems: understanding the predictors of lifetime prevalence, treatment utilisation and perceived helpfulness across 111 countries

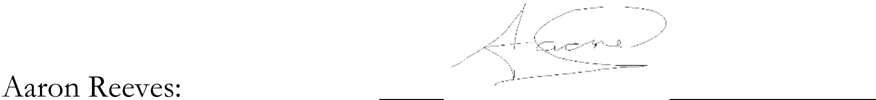
Full published reference: Henking, C., Reeves, A., & Chrisinger, B. (2023). Global inequalities in mental health problems: understanding the predictors of lifetime prevalence, treatment utilisation and perceived helpfulness across 111 countries. *Preventive Medicine*, *177*, 107769.

We the co-authors certify that the majority (at least 70%) of this study represents the work of the DPhil candidate Christoph Henking.



Christoph Henking: ______________________________

Benjamin Chrisinger: ______________________________

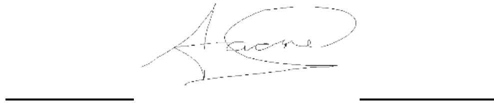


Aaron Reeves: ______________________________

DPhil paper 2: What predicts the decline in mental health during mid-life? A life-course analysis of the 1970 British Cohort Study

We the co-authors certify that the majority (at least 70%) of this study represents the work of the DPhil candidate Christoph Henking.

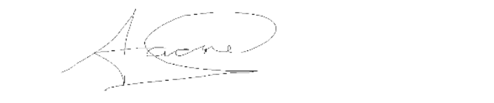
Christoph Henking:

Aaron Reeves: 

DPhil paper 3: Behavioural benefit conditionality, sanctions and the self-rated health of the unemployed: a longitudinal analysis of European countries

We the co-authors certify that the majority (at least 70%) of this study represents the work of the DPhil candidate Christoph Henking.

Christoph Henking:

Aaron Reeves: 

DPhil paper 4: Trust in healthcare professionals and traditional medicine practitioners: Socio-economic and country-level determinants across 111 countries

This work is a single author paper by the DPhil candidate Christoph Henking.

References

Alegría, M., NeMoyer, A., Bagué, I. F., Wang, Y., & Alvarez, K. (2018). Social determinants of mental health: where we are and where we need to go. *Current Psychiatry Reports, 20*(11), 95. https://doi.org/10.1007/S11920-018-0969-9

Allen, J., Balfour, R., Bell, R., & Marmot, M. (2014). Social determinants of mental health. *International Review of Psychiatry*, *26*(4), 392–407. https://doi.org/10.3109/09540261.2014.928270

Alonso, J., Liu, Z., Evans-Lacko, S., MPH, E. S., Sampson, N. B., Chatterji, S., Abdulmalik, J., Aguilar-Gaxiola, S., Al-Hamzawi, A., Andrade, L. H., Bruffaerts, R., Cardoso, G., Cia, A., Florescu, S., Girolamo, G. de, Gureje, O., Haro, J. M., Levinson, D., Medina-Mora, M. E., … Wojtyniak, B. (2018). Treatment gap for anxiety disorders is global: Results of the World Mental Health Surveys in 21 countries. *Depression and Anxiety*, *35*(3), 195–208. https://doi.org/10.1002/DA.22711

Anaf, J., Baum, F., Newman, L., Ziersch, A., & Jolley, G. (2013). The interplay between structure and agency in shaping the mental health consequences of job loss. *BMC Public Health*, *13*, 1–12. https://doi.org/10.1186/1471-2458-13-110

Andersen, R. M. (1995). Revisiting the behavioral model and access to medical care: Does it matter? *Journal of Health and Social Behavior*, *36*(1), 1–10. https://doi.org/10.2307/2137284

Antinyan, A., Bassetti, T., Corazzini, L., & Pavesi, F. (2021). Trust in the health system and COVID-19 treatment. *Frontiers in Psychology*, *12*, 643758. https://doi.org/10.3389/fpsyg.2021.643758

Arnett, J. J., Žukauskienė, R., & Sugimura, K. (2014). The new life stage of emerging adulthood at ages 18–29 years: Implications for mental health. *The Lancet Psychiatry*, *1*(7), 569–576. https://doi.org/10.1016/S2215-0366(14)00080-7

Arora, V. S., Karanikolos, M., Clair, A., Reeves, A., Stuckler, D., & McKee, M. (2015). Data resource profile: The European Union statistics on income and living conditions (EU-SILC). *International Journal of Epidemiology*, *44*(2), 451–461. https://doi.org/10.1093/ije/dyv069

Asenjo, A., & Pignatti, C. (2019). *Unemployment insurance schemes around the world: Evidence and policy options*. International Labour Office Geneva, Switzerland.

Ballas, D., & Dorling, D. (2007). Measuring the impact of major life events upon happiness. *International Journal of Epidemiology*, *36*(6), 1244–1252. https://doi.org/10.1093/ije/dym182

Bambra, C. (2011a). Health inequalities and welfare state regimes: Theoretical insights on a public health 'puzzle'. *Journal of Epidemiology & Community Health*, *65*(9), 740–745. https://doi.org/10.1136/JECH.2011.136333

Bambra, C. (2011b). Work, worklessness and the political economy of health inequalities. *Journal of Epidemiology & Community Health*, *65*(9), 746–750.

Bambra, C., & Eikemo, T. A. (2018). Insecurity, unemployment, and health: A social epidemiological perspective. *The Oxford Handbook of Job Loss and Job Search*, 111–125.

Bambra, C., Smith, K., Nwaru, C., Bennett, N., Albani, V., Kingston, A., Todd, A., & Matthews, F. (2023). *Targeting Health Inequalities: Realising the Potential of Targets in Reducing Health Inequalities*. Health Equity North, Northern Health Science Alliance, Newcastle. https://www.health.org.uk/sites/default/files/upload/publications/2023/Targeting%20Health%20Inequalities%20Report_Health%20Equity%20North_0.pdf

Birkhäuer, J., Gaab, J., Kossowsky, J., Hasler, S., Krummenacher, P., Werner, C., & Gerger, H. (2017). Trust in the health care professional and health outcome: A meta-analysis. *PloS One*, *12*(2), e0170988. https://doi.org/10.1371/journal.pone.0170988

Blair, A., & Siddiqi, A. (2022). The social determinants of substance use associated with deaths of despair: Individual risks and population impacts. *Preventive Medicine*, *164*, 107327. https://doi.org/10.1016/j.ypmed.2022.107327

Blanchflower, D. G. (2021). Is happiness U-shaped everywhere? Age and subjective well-being in 145 countries. *Journal of Population Economics*, *34*(2), 575–624. https://doi.org/10.1007/S00148-020-00797-Z/FIGURES/15

Brassen, S., Gamer, M., Peters, J., Gluth, S., & Büchel, C. (2012). Don't look back in anger! Responsiveness to missed chances in successful and nonsuccessful aging. *Science*, *336*(6081), 612–614. DOI: 10.1126/science.1217516

Broadbent, P., Thomson, R., Kopasker, D., McCartney, G., Meier, P., Richiardi, M., McKee, M., & Katikireddi, S. V. (2023). The public health implications of the cost-of-living crisis: Outlining mechanisms and modelling consequences. *The Lancet Regional Health–Europe*, *27*. https://doi.org/10.1016/j.lanepe.2023.100585

Brown, P., Calnan, M., Scrivener, A., & Szmukler, G. (2009). Trust in Mental Health Services: A neglected concept. *Http://Dx.Doi.Org/10.3109/09638230903111122*, *18*(5), 449–458. https://doi.org/10.3109/09638230903111122

Buffel, V., Velde, S. V. de, & Bracke, P. (2014). Professional care seeking for mental health problems among women and men in Europe: The role of socioeconomic, family-related and mental health status factors in explaining gender differences. *Social Psychiatry and Psychiatric Epidemiology*, *49*(10), 1641–1653. https://doi.org/10.1007/S00127-014-0879-Z/TABLES/4

Burns, J. K. (2015). Poverty, inequality and a political economy of mental health. *Epidemiology and Psychiatric Sciences*, *24*(2), 107–113. https://doi.org/10.1017/S2045796015000086

Campbell, M., Edwards, E. J., Pennell, D., Poed, S., Lister, V., Gillett-Swan, J., Kelly, A., Zec, D., & Nguyen, T.-A. (2024). Evidence for and against banning mobile phones in schools: A scoping review. *Journal of Psychologists and Counsellors in Schools*, *34*(3), 242–265. https://doi.org/10.1177/20556365241270394

Charlson, F., Ali, S., Benmarhnia, T., Pearl, M., Massazza, A., Augustinavicius, J., & Scott, J. G. (2021). Climate change and mental health: A scoping review. *International Journal of Environmental Research and Public Health*, *18*(9), 4486. https://doi.org/10.3390/ijerph18094486

Cherrie, M., Curtis, S., Baranyi, G., Cunningham, N., Dibben, C., Bambra, C., & Pearce, J. (2021). A data linkage study of the effects of the Great Recession and austerity on antidepressant prescription usage. *European Journal of Public Health*, *31*(2), 297–303. https://doi.org/10.1093/EURPUB/CKAA253

Chrisinger, B. W. (2022). Getting to Root Causes: Why equity must be at the center of planning and public health collaboration. *Journal of the American Planning Association*, *89*(2), 160-166. https://doi.org/10.1080/01944363.2022.2041466

Cohen, N., & Galea, S. (2011). Twenty-first century public health practice: Preventing mental illness and promoting mental health. In *Population Mental Health* (pp. 341–357). Routledge.

de Beer, P., & Schils, T. (2009). Introduction: Achieving an optimal social policy mix. In *The Labour Market Triangle*. Edward Elgar Publishing.

De Witte, N. A., Joris, S., Van Assche, E., & Van Daele, T. (2021). Technological and digital interventions for mental health and wellbeing: An overview of systematic reviews. *Frontiers in Digital Health*, *3*, 754337. https://doi.org/10.3389/fdgth.2021.754337

Demiral, Y., Ihle, T., Rose, U., Conway, P. M., & Burr, H. (2022). Precarious Work as Risk Factor for 5-Year Increase in Depressive Symptoms. *International Journal of Environmental Research and Public Health 2022*, *19*(6), 3175. https://doi.org/10.3390/IJERPH19063175

DeSalvo, K. B., Fisher, W. P., Tran, K., Bloser, N., Merrill, W., & Peabody, J. (2006). Assessing measurement properties of two single-item general health measures. *Quality of Life Research*, *15*(2), 191–201. https://doi.org/10.1007/s11136-005-0887-2

Dey, M., & Jorm, A. F. (2016). Social determinants of mental health service utilization in Switzerland. *International Journal of Public Health*, *62*(1), 85–93. https://doi.org/10.1007/S00038-016-0898-5

Diener, E., & Ryan, K. (2009). Subjective well-being: A general overview. *South African Journal of Psychology*, *39*(4), 391–406.

Dijk, H., & Mierau, J. (2023). Mental health over the life course: Evidence for a U-shape? *Health Economics*, *32*(1), 155–174. https://doi.org/10.1002/HEC.4614

Dolan, P., Layard, R., & Metcalfe, R. (2011). *Measuring subjective well-being for public policy*. Office for National Statistics. https://eprints.lse.ac.uk/35420/1/measuring-subjective-wellbeing-for-public-policy.pdf

Douglass, T., & Calnan, M. (2016). Trust matters for doctors? Towards an agenda for research. *Social Theory & Health*, *14*(4), 393-413. https://doi.org/10.1057/s41285-016-0010-5

Edlund, M. J., Pettiford, A. G., Hampton, J., Forman-Hoffman, V. L., Ault, K. L., Colpe, L. J., & Hedden, S. L. (2015). Adolescents' assessments of the helpfulness of treatment for major depression: Results from a national survey. *Psychiatric Services*, *66*(10), 1064–1073. https://doi.org/10.1176/APPI.PS.201400018

Elliott, J., & Shepherd, P. (2006). Cohort profile: 1970 British birth cohort (BCS70). *International Journal of Epidemiology*, *35*(4), 836–843. https://doi.org/10.1093/ije/dyl174

Ellsberg, M., Arango, D. J., Morton, M., Gennari, F., Kiplesund, S., Contreras, M., & Watts, C. (2015). Prevention of violence against women and girls: What does the evidence say? *The Lancet*, *385*(9977), 1555–1566. https://doi.org/10.1016/S0140-6736(14)61703-7

Elwadhi, D., & Cohen, A. (2020). Social inequalities in antidepressant treatment outcomes: A systematic review. *Social Psychiatry and Psychiatric Epidemiology*, *55*(10), 1241–1259. https://doi.org/10.1007/S00127-020-01918-5

Evans-Lacko, S., Aguilar-Gaxiola, S., Al-Hamzawi, A., Alonso, J., Benjet, C., Bruffaerts, R., Chiu, W.-T., Florescu, S., de Girolamo, G., & Gureje, O. (2018). Socio-economic variations in the mental health treatment gap for people with anxiety, mood, and substance use disorders: Results from the WHO World Mental Health (WMH) surveys. *Psychological Medicine*, *48*(9), 1560–1571. https://doi.org/10.1017/S0033291717003336

Fife, D. A., & D'Onofrio, J. (2023). Common, uncommon, and novel applications of random forest in psychological research. *Behavior Research Methods*, *55*(5), 2447–2466. https://doi.org/10.3758/s13428-022-01901-9

Finegan, M., Firth, N., Wojnarowski, C., & Delgadillo, J. (2018). Associations between socioeconomic status and psychological therapy outcomes: A systematic review and meta-analysis. *Depression and Anxiety*, *35*(6), 560–573. https://doi.org/10.1002/DA.22765

Fisher, M., & Baum, F. (2010). The social determinants of mental health: Implications for research and health promotion. *Australian and New Zealand Journal of Psychiatry*, *44*(12), 1057–1063. https://doi.org/10.3109/00048674.2010.509311/ASSET/IMAGES/LARGE/10.3109_00048674.2010.509311-FIG1.JPEG

Fone, D., Dunstan, F., Lloyd, K., Williams, G., Watkins, J., & Palmer, S. (2007). Does social cohesion modify the association between area income deprivation and mental health? A

multilevel analysis. *International Journal of Epidemiology*, *36*(2), 338–345. https://doi.org/10.1093/ije/dym004

Frohlich, K. L., & Potvin, L. (2008). Transcending the known in public health practice: The inequality paradox: The population approach and vulnerable populations. *American Journal of Public Health*, *98*(2), 216–221. https://doi.org/10.2105/AJPH.2007.114777

Fujiwara, D., & Dolan, P. (2014). *Valuing mental health: How a subjective wellbeing approach can show just how much it matters*. http://www.psychotherapy.org.uk/UKCP_Documents/Reports/ValuingMentalHealth_web.pdf

Galambos, N. L., Krahn, H. J., Johnson, M. D., & Lachman, M. E. (2020). The U Shape of Happiness Across the Life Course: Expanding the Discussion. *Perspectives on Psychological Science*, *15*(4), 898–912. https://doi.org/10.1177/1745691620902428/ASSET/IMAGES/LARGE/10.1177_1745691620902428-FIG1.JPEG

Gondek, D., Bann, D., Patalay, P., Goodman, A., McElroy, E., Richards, M., & Ploubidis, G. B. (2021). Psychological distress from early adulthood to early old age: Evidence from the 1946, 1958 and 1970 British birth cohorts. *Psychological Medicine, 52*(8)*,* 1471-1480. https://doi.org/10.1017/S003329172000327X

Gondek, D., Lacey, R. E., Blanchflower, D. G., & Patalay, P. (2022). How is the distribution of psychological distress changing over time? Who is driving these changes? Analysis of the 1958 and 1970 British birth cohorts. *Social Psychiatry and Psychiatric Epidemiology*, *57*(5), 1007–1016. https://doi.org/10.1007/S00127-021-02206-6/FIGURES/4

Gondek, D., Moltrecht, B., & Ploubidis, G. (2021). Mental health crisis in midlife – a proposed research agenda. *Research Ideas and Outcomes*, *7*. https://doi.org/10.3897/RIO.7.E62024

Gülal, F., & Ayaita, A. (2020). The Impact of Minimum Wages on Well-Being: Evidence from a Quasi-experiment in Germany. *Journal of Happiness Studies*, *21*(7), 2669–2692. https://doi.org/10.1007/S10902-019-00189-5/TABLES/5

Guyer, B., Ma, S., Grason, H., Frick, K. D., Perry, D. F., Sharkey, A., & McIntosh, J. (2009). Early Childhood Health Promotion and Its Life Course Health Consequences. *Academic Pediatrics*, *9*(3), 142-149.e71. https://doi.org/10.1016/J.ACAP.2008.12.007

Haber, N. A., Wieten, S. E., Rohrer, J. M., Arah, O. A., Tennant, P. W., Stuart, E. A., Murray, E. J., Pilleron, S., Lam, S. T., & Riederer, E. (2022). Causal and associational language in observational health research: A systematic evaluation. *American Journal of Epidemiology*, *191*(12), 2084–2097. https://doi.org/10.1093/aje/kwac137

Harris, M. G., Kazdin, A. E., Chiu, W. T., Sampson, N. A., Aguilar-Gaxiola, S., Al-Hamzawi, A., Alonso, J., Altwaijri, Y., Andrade, L. H., Cardoso, G., Cía, A., Florescu, S., Gureje, O., Hu, C., Karam, E. G., Karam, G., Mneimneh, Z., Navarro-Mateu, F., Oladeji, B. D., … Kessler, R. C. (2020). Findings From World Mental Health Surveys of the Perceived Helpfulness of Treatment for Patients With Major Depressive Disorder. *JAMA Psychiatry*, *77*(8), 830–841. https://doi.org/10.1001/JAMAPSYCHIATRY.2020.1107

Harvey, M. (2021). The political economy of health: Revisiting its Marxian origins to address 21st-century health inequalities. *American Journal of Public Health*, *111*(2), 293–300. https://doi.org/10.2105/AJPH.2020.305996

Harvey, S. B., Modini, M., Joyce, S., Milligan-Saville, J. S., Tan, L., Mykletun, A., Bryant, R. A., Christensen, H., & Mitchell, P. B. (2017). Can work make you mentally ill? A systematic meta-review of work-related risk factors for common mental health problems. *Occupational and Environmental Medicine*, *74*(4), 301–310. https://doi.org/10.1136/OEMED-2016-104015

Henseke, G. (2018). Good jobs, good pay, better health? The effects of job quality on health among older European workers. *The European Journal of Health Economics*, *19*(1), 59–73. https://doi.org/10.1007/s10198-017-0867-9

Herrick, C., & Bell, K. (2020). Concepts, disciplines and politics: On 'structural violence' and the 'social determinants of health'. *Https://Doi.Org/10.1080/09581596.2020.1810637*, *32*(3), 295–308. https://doi.org/10.1080/09581596.2020.1810637

Heshmati, A., Honkaniemi, H., & Juárez, S. P. (2023). The effect of parental leave on parents' mental health: A systematic review. *The Lancet Public Health*, *8*(1), e57–e75. https://doi.org/10.1016/S2468-2667(22)00311-5

Holman, D. (2014). 'What help can you get talking to somebody?' Explaining class differences in the use of talking treatments. *Sociology of Health & Illness*, *36*(4), 531–548. https://doi.org/10.1111/1467-9566.12082

Holman, D., Lynch, R., & Reeves, A. (2018). How do health behaviour interventions take account of social context? A literature trend and co-citation analysis. *Health*, *22*(4), 389–410. https://doi.org/10.1177/1363459317695630

Hudson, J. (2006). Institutional trust and subjective well-being across the EU. *Kyklos*, *59*(1), 43–62. https://doi-org.ezproxy-prd.bodleian.ox.ac.uk/10.1111/j.1467-6435.2006.00319.x

Huijts, T., Reeves, A., McKee, M., & Stuckler, D. (2015). The impacts of job loss and job recovery on self-rated health: Testing the mediating role of financial strain and income. *The European Journal of Public Health*, *25*(5), 801–806.

Humphreys, D. K., Panter, J., Sahlqvist, S., Goodman, A., & Ogilvie, D. (2016). Changing the environment to improve population health: A framework for considering exposure in natural experimental studies. *J Epidemiol Community Health*, *70*(9), 941–946. https://doi.org/10.1136/jech-2015-206381

Hunsley, J., & Lee, C. M. (2017). *Introduction to clinical psychology*. John Wiley & Sons.

Immervoll, H., & Knotz, C. (2018). *How demanding are activation requirements for jobseekers?* [OECD Policy Report]. IZA Discussion Paper. https://www.oecd-ilibrary.org/docserver/2bdfecca-en.pdf?expires=1725485200&id=id&accname=guest&checksum=6F8D0351F88D95007416F20C3F217811

Immervoll, H., & Knotz, C. (2021). How Demanding are Activation Requirements for Jobseekers? *SSRN Electronic Journal*. https://doi.org/10.2139/SSRN.3234227

Immervoll, H., & Scarpetta, S. (2012). Activation and employment support policies in OECD countries. An overview of current approaches. *IZA Journal of Labor Policy*, *1*, 1–20.

Ito, C., Al-Hassany, L., Kurth, T., & Glatz, T. (2025). Distinguishing description, prediction, and causal inference: A primer on improving congruence between research questions and methods. *Neurology*, *104*(4), e210171. https://doi.org/10.1212/WNL.0000000000210171

Jahoda, M. (1982). Employment and unemployment. *Cambridge Books*.

Jylhä, M. (2009). What is self-rated health and why does it predict mortality? Towards a unified conceptual model. *Social Science & Medicine*, *69*(3), 307–316. https://doi.org/10.1016/j.socscimed.2009.05.013

Kahneman, D., & Deaton, A. (2010). High income improves evaluation of life but not emotional well-being. *Proceedings of the National Academy of Sciences*, *107*(38), 16489–16493. https://doi.org/10.1073/pnas.1011492107

Kazdin, A. E., Wu, C. S., Hwang, I., Puac-Polanco, V., Sampson, N. A., Al-Hamzawi, A., Alonso, J., Andrade, L. H., Benjet, C., Caldas-De-Almeida, J. M., Girolamo, G. D., Jonge, P. D., Florescu, S., Gureje, O., Haro, J. M., Harris, M. G., Karam, E. G., Karam, G., Kovess-Masfety, V., … Have, M. T. (2021). Antidepressant use in low- middle- and high-income

countries: A World Mental Health Surveys report. *Psychological Medicine, 53*(4), 1583-1591. https://doi.org/10.1017/S0033291721003160

Kelly-Irving, M., Ball, W. P., Bambra, C., Delpierre, C., Dundas, R., Lynch, J., McCartney, G., & Smith, K. (2022). Falling down the rabbit hole? Methodological, conceptual and policy issues in current health inequalities research. *Critical Public Health*, *33*(1), 37-47. https://doi.org/10.1080/09581596.2022.2036701

Kendler, K. S. (2008). Explanatory models for psychiatric illness. *American Journal of Psychiatry*, *165*(6), 695–702. https://doi.org/10.1176/appi.ajp.2008.07071061

Kessler, R. C., Aguilar-Gaxiola, S., Alonso, J., Chatterji, S., Lee, S., Ormel, J., Üstün, T. B., & Wang, P. S. (2009). The global burden of mental disorders: An update from the WHO World Mental Health (WMH) Surveys*. *Epidemiology and Psychiatric Sciences*, *18*(1), 23–33. https://doi.org/10.1017/S1121189X00001421

Keyes, K. M., & Galea, S. (2016). Population Health Across Levels, Systems, and the Life Course. *Population Health Science*, 45–66. https://doi.org/10.1093/MED/9780190459376.003.0004

Knabe, A., & Rätzel, S. (2011). Scarring or Scaring? The Psychological Impact of Past Unemployment and Future Unemployment Risk. *Economica*, *78*(310), 283–293. https://doi.org/10.1111/J.1468-0335.2009.00816.X

Knapp, M., & Wong, G. (2020). Economics and mental health: The current scenario. *World Psychiatry*, *19*(1), 3–14. https://doi-org.ezproxy-prd.bodleian.ox.ac.uk/10.1002/wps.20692

Knesebeck, O. V. D. (2015). Concepts of social epidemiology in health services research. *BMC Health Services Research*, *15*(1), 1–4. https://doi.org/10.1186/S12913-015-1020-Z/PEER-REVIEW

Koenen, K. C., Rudenstine, S., Susser, E., & Galea, S. (2013). *A life course approach to mental disorders*. Oxford University Press.

Lachman, M. E., Teshale, S., & Agrigoroaei, S. (2015). Midlife as a pivotal period in the life course: Balancing growth and decline at the crossroads of youth and old age. *International Journal of Behavioral Development*, *39*(1), 20–31. https://doi.org/10.1177/0165025414533223

Lang, I., Llewellyn, D., Hubbard, R., Langa, K., & Melzer, D. (2011). Income and the midlife peak in common mental disorder prevalence. *Psychological Medicine*, *41*(7), 1365–1372. *Psychological medicine, 41*(7), 1365-1372. https://doi.org/10.1017/S0033291710002060

Langheim, F. J. (2014). Poor access to health care as a social determinant of mental health. *Psychiatric Annals*, *44*(1), 52–57. https://doi.org/10.3928/00485713-20140108-09

Leist, A. K., Klee, M., Kim, J. H., Rehkopf, D. H., Bordas, S. P., Muniz-Terrera, G., & Wade, S. (2022). Mapping of machine learning approaches for description, prediction, and causal inference in the social and health sciences. *Science Advances*, *8*(42), eabk1942. https://doi.org/10.1126/sciadv.abk1942

Lewer, D., O'Reilly, C., Mojtabai, R., & Evans-Lacko, S. (2015). Antidepressant use in 27 European countries: Associations with sociodemographic, cultural and economic factors. *The British Journal of Psychiatry*, *207*(3), 221–226. https://doi.org/10.1192/BJP.BP.114.156786

Liepmann, H., & Pignatti, C. (2024). Welfare effects of unemployment benefits when informality is high. *Journal of Public Economics*, *229*, 105032. https://doi.org/10.1016/j.jpubeco.2023.105032

Link, B. G., & Phelan, J. (2014). Stigma power. *Social science & medicine*, *103*, 24-32. http://dx.doi.org/10.1016/j.socscimed.2013.07.035

MacEachen, E., Rijk, A. de, Dyreborg, J., Fassier, J. B., Fletcher, M., Hopwood, P., Koivusalo, M., Majowicz, S., Meyer, S., Ståhl, C., & Welti, F. (2022). Laws, Policies, and Collective Agreements Protecting Low-wage and Digital Platform Workers During the COVID-19

Pandemic. *New Solutions: A Journal of Environmental and Occupational Health Policy*, *32*(3), 201-212. https://doi.org/10.1177/10482911221133796

Macintyre, A., Ferris, D., Gonçalves, B., & Quinn, N. (2018). What has economics got to do with it? The impact of socioeconomic factors on mental health and the case for collective action. *Palgrave Communications*, *4*(1), 1–5. https://doi.org/10.1057/s41599-018-0063-2

Mackenbach, J. P. (2012). The persistence of health inequalities in modern welfare states: The explanation of a paradox. *Social Science & Medicine*, *75*(4), 761–769. https://doi.org/10.1016/J.SOCSCIMED.2012.02.031

Mackenbach, J. P. (2020). Re-thinking health inequalities. *European Journal of Public Health*, *30*(4), 615–615. https://doi.org/10.1093/EURPUB/CKAA001

Marmot, M. (2005). Social determinants of health inequalities. *The Lancet*, *365*(9464), 1099–1104.

Marmot, M. (2015). The health gap: The challenge of an unequal world. *The Lancet*, *386*(10011), 2442–2444. https://doi.org/10.1016/S0140-6736(15)00150-6

Marmot, M., Allen, J., Bell, R., Bloomer, E., & Goldblatt, P. (2012). WHO European review of social determinants of health and the health divide. *The Lancet*, *380*(9846), 1011–1029.

Marmot, M., & Wilkinson, R. G. (2001). Psychosocial and material pathways in the relation between income and health: A response to Lynch et al. *BMJ : British Medical Journal*, *322*(7296), 1233. https://doi.org/10.1136/BMJ.322.7296.1233

Marteau, T. M., Rutter, H., & Marmot, M. (2021). Changing behaviour: An essential component of tackling health inequalities. *BMJ*, *372*. https://doi.org/10.1136/BMJ.N332

McAllister, A., Fritzell, S., Almroth, M., Harber-Aschan, L., Larsson, S., & Burström, B. (2018). How do macro-level structural determinants affect inequalities in mental health? - A systematic review of the literature. *International Journal for Equity in Health*, *17*(1), 1–14. https://doi.org/10.1186/S12939-018-0879-9/TABLES/4

McCabe, C. J., Thomas, K. J., Brazier, J. E., & Coleman, P. (1996). Measuring the Mental Health Status of a Population: A Comparison of the GHQ–12 and the SF–36 (MHI–5). *The British Journal of Psychiatry*, *169*(4), 517–521. https://doi.org/10.1192/BJP.169.4.516

McCartney, G., Dickie, E., Escobar, O., & Collins, C. (2021). Health inequalities, fundamental causes and power: Towards the practice of good theory. *Sociology of Health & Illness*, *43*(1), 20–39.

McNamara, C. L., Balaj, M., Thomson, K. H., Eikemo, T. A., Solheim, E. F., & Bambra, C. (2017). The socioeconomic distribution of non-communicable diseases in Europe: Findings from the European Social Survey (2014) special module on the social determinants of health. *European Journal of Public Health*, *27*(suppl_1), 22–26. https://doi.org/10.1093/EURPUB/CKW222

Momen, N. C., Lasgaard, M., Weye, N., Edwards, J., McGrath, J. J., & Plana-Ripoll, O. (2022). Representativeness of survey participants in relation to mental disorders: A linkage between national registers and a population-representative survey. *International Journal of Population Data Science*, *7*(4), 1759. https://doi.org/10.23889/ijpds.v7i4.1759

Morgan, A. J., Ross, A. M., Yap, M. B. H., Reavley, N. J., Parker, A., Simmons, M. B., Scanlan, | Faye, & Jorm, A. F. (2020). What works for mental health problems in youth? Survey of real-world experiences of treatments and side effects. *Wiley Online Library*, *15*(6), 1502–1512. https://doi.org/10.1111/eip.13087

Mossakowski, K. N. (2014). Social Causation and Social Selection. *The Wiley Blackwell Encyclopedia of Health, Illness, Behavior, and Society*, 2154–2160. https://doi.org/10.1002/9781118410868.WBEHIBS262

Motrico, E., Salinas-Perez, J. A., Rodero-Cosano, M. L., & Conejo-Cerón, S. (2021). Editors' Comments on the Special Issue "Social Determinants of Mental Health". *International*

Journal of Environmental Research and Public Health, 18(8), 3957. https://doi.org/10.3390/IJERPH18083957

Murphy, G. C., & Athanasou, J. A. (1999). The effect of unemployment on mental health. *Journal of Occupational and Organizational Psychology*, *72*(1), 83–99. https://doi.org/10.1348/096317999166518

Naher, N., Hoque, R., Hassan, M. S., Balabanova, D., Adams, A. M., & Ahmed, S. M. (2020). The influence of corruption and governance in the delivery of frontline health care services in the public sector: A scoping review of current and future prospects in low and middle-income countries of south and south-east Asia. *BMC public health, 20(1), 880.* https://doi.org/10.1186/s12889-020-08975-0

Nettle, D., Chevallier, C., de Courson, B., Johnson, E. A., Johnson, M. T., & Pickett, K. (2023). Short-term changes in financial situation have immediate mental health consequences: The Changing Cost of Living Study. *OSF.* https://researchportal.northumbria.ac.uk/ws/portalfiles/portal/148832825/preprint_v1.pdf

Orben, A., Meier, A., Dalgleish, T., & Blakemore, S.-J. (2024). Mechanisms linking social media use to adolescent mental health vulnerability. *Nature Reviews Psychology*, *3*(6), 407–423. https://doi.org/10.1038/s44159-024-00307-y

Ormel, J., Cuijpers, P., Jorm, A., & Schoevers, R. A. (2020). What is needed to eradicate the depression epidemic, and why. *Mental Health & Prevention*, *17*, 200177. https://doi.org/10.1016/j.mhp.2019.200177

Ormel, J., Hollon, S. D., Kessler, R. C., Cuijpers, P., & Monroe, S. M. (2022). More treatment but no less depression: The treatment-prevalence paradox. *Clinical Psychology Review*, *91*, 102111. https://doi.org/10.1016/j.cpr.2021.102111

Packness, A., Waldorff, F. B., Christensen, R. de P., Hastrup, L. H., Simonsen, E., Vestergaard, M., & Halling, A. (2017). Impact of socioeconomic position and distance on mental health care utilization: A nationwide Danish follow-up study. *Social Psychiatry and Psychiatric Epidemiology*, *52*(11), 1405–1413. https://doi.org/10.1007/S00127-017-1437-2/TABLES/4

Pathare, S., Burgess, R. A., & Collins, P. Y. (2021). World Mental Health Day: Prioritise social justice, not only access to care. *The Lancet*, *398*(10314), 1859–1860. https://doi.org/10.1016/S0140-6736(21)02232-7

Pattaro, S., Bailey, N., Williams, E., Gibson, M., Wells, V., Tranmer, M., & Dibben, C. (2022). The impacts of benefit sanctions: A scoping review of the quantitative research evidence. *Journal of Social Policy*, *51*(3), 611–653. https://doi.org/10.1017/S0047279421001069

Pearl, J. (2010). An introduction to causal inference. *The International Journal of Biostatistics*, *6*(2). https://doi.org/10.2202/1557-4679.1203

Pharr, J. R., Moonie, S., & Bungum, T. J. (2012). The impact of unemployment on mental and physical health, access to health care and health risk behaviors. *International Scholarly Research Notices*, *2012*(1), 483432. https://doi-org.ezproxy-prd.bodleian.ox.ac.uk/10.5402/2012/483432

Phelan, J. C., & Link, B. G. (2005). Controlling Disease and Creating Disparities: A Fundamental Cause Perspective. *The Journals of Gerontology: Series B*, *60*(Special_Issue_2), S27–S33. https://doi.org/10.1093/GERONB/60.SPECIAL_ISSUE_2.S27

Phelan, J. C., Link, B. G., & Tehranifar, P. (2010). Social Conditions as Fundamental Causes of Health Inequalities: Theory, Evidence, and Policy Implications. *Journal of health and social behavior*, *51*(1_suppl), S28-S40. https://doi.org/10.1177/0022146510383498

Picchio, M., & Ubaldi, M. (2024). Unemployment and health: A meta-analysis. *Journal of Economic Surveys*, *38*(4), 1437–1472. https://doi-org.ezproxy-prd.bodleian.ox.ac.uk/10.1111/joes.12588

Ploubidis, G. B., Sullivan, A., Brown, M., & Goodman, A. (2017). Psychological distress in mid-life: Evidence from the 1958 and 1970 British birth cohorts. *Psychological Medicine*, *47*(2), 291–303. https://doi.org/10.1017/S0033291716002464

Prasad, M. (2018). Problem-Solving Sociology. *Contemporary Sociology*, *47*(4), 393-398. https://doi.org/10.1177/0094306118779810

Prättälä, R. S., & Puska, P. (2012). Social determinants of health behaviours and social change. *The European Journal of Public Health*, *22*(2), 166–166. https://doi.org/10.1093/eurpub/ckr211

Prince, M., Patel, V., Saxena, S., Maj, M., Maselko, J., Phillips, M. R., & Rahman, A. (2007). No health without mental health. *The Lancet*, *370*(9590), 859–877. https://doi.org/10.1016/S0140-6736(07)61238-0

Puckree, T., Mkhize, M., Mgobhozi, Z., & Lin, J. (2002). African traditional healers: What health care professionals need to know. *International Journal of Rehabilitation Research*, *25*(4), 247–251.

Radin, D. (2013). Does corruption undermine trust in health care? Results from public opinion polls in Croatia. *Social Science & Medicine*, *98*, 46–53. https://doi.org/10.1016/j.socscimed.2013.08.033

Raffass, T. (2017). Demanding activation. *Journal of Social Policy*, *46*(2), 349–365. https://doi.org/10.1017/S004727941600057X

Reeve, K. (2017). Welfare conditionality, benefit sanctions and homelessness in the UK: ending the 'something for nothing culture' or punishing the poor? *Journal of Poverty and Social Justice*, *25*(1), 65–78. https://doi.org/10.1332/175982717X14842281240539

Reeves, A., Gourtsoyannis, Y., Basu, S., McCoy, D., McKee, M., & Stuckler, D. (2015). Financing universal health coverage—Effects of alternative tax structures on public health systems: Cross-national modelling in 89 low-income and middle-income countries. *The Lancet*, *386*(9990), 274–280. https://doi.org/10.1016/S0140-6736(15)60574-8

Reeves, A., Karanikolos, M., Mackenbach, J., McKee, M., & Stuckler, D. (2014). Do employment protection policies reduce the relative disadvantage in the labour market experienced by unhealthy people? A natural experiment created by the Great Recession in Europe. *Social Science & Medicine*, *121*, 98–108. https://doi.org/10.1016/j.socscimed.2014.09.034

Reeves, A., Mckee, M., Mackenbach, J., Whitehead, M., & Stuckler, D. (2017). Introduction of a national minimum wage reduced depressive symptoms in low-wage workers: a quasi-natural experiment in the UK. *Health economics*, *26*(5), 639-655. https://doi-org.ezproxy-prd.bodleian.ox.ac.uk/10.1002/hec.3336

Reininghaus, U., Reinhold, A. S., Priebe, S., Rauschenberg, C., Fleck, L., Schick, A., Schirmbeck, F., Myin-Germeys, I., Morgan, C., & Hartmann, J. A. (2024). Toward equitable interventions in public mental health: A review. *JAMA Psychiatry*, *81*(12), 1270–1275. https://doi.org/10.1001/jamapsychiatry.2024.3206

Renahy, E., Mitchell, C., Molnar, A., Muntaner, C., Ng, E., Ali, F., & O'Campo, P. (2018). Connections between unemployment insurance, poverty and health: A systematic review. *European Journal of Public Health*, *28*(2), 269–275. https://doi.org/10.1093/EURPUB/CKX235

Ridley, M., Rao, G., Schilbach, F., & Patel, V. (2020). Poverty, depression, and anxiety: Causal evidence and mechanisms. *Science*, *370*(6522). https://doi.org/10.1126/science.aay0214

Roberts, T., Esponda, G. M., Torre, C., Pillai, P., Cohen, A., & Burgess, R. A. (2022). Reconceptualising the treatment gap for common mental disorders: A fork in the road for global mental health? *The British Journal of Psychiatry*, 1–5. https://doi.org/10.1192/BJP.2021.221

Rodgers, B., Pickles, A., Power, C., Collishaw, S., & Maughan, B. (1999). Validity of the Malaise Inventory in general population samples. *Social Psychiatry and Psychiatric Epidemiology*, *34*, 333–341. https://doi.org/10.1007/s001270050153

Rojas-García, A., Holman, D., Tinner, L., Ejegi-Memeh, S., Ben-Shlomo, Y., & Laverty, A. A. (2022). Use of intersectionality theories in interventional health research in high-income countries: A systematic scoping review. *The Lancet*, *400*, S58. https://doi.org/10.1016/S0140-6736(22)02268-1

Rose, G. A., Khaw, K.-T., & Marmot, M. (2008). *Rose's strategy of preventive medicine: The complete original text*. Oxford University Press.

Scott, M. J. (2018). Improving Access to Psychological Therapies (IAPT)—The Need for Radical Reform. *Journal of Health Psychology*, *23*(9), 1136–1147. https://doi.org/10.1177/1359105318755264

Selenko, E., Batinic, B., & Paul, K. (2011). Does latent deprivation lead to psychological distress? Investigating Jahoda's model in a four-wave study. *Journal of Occupational and Organizational Psychology*, *84*(4), 723–740. https://doi.org/10.1348/096317910X519360

Sen, A. (2014). Development as freedom (1999). *The Globalization and Development Reader: Perspectives on Development and Global Change*, *525*.

Shah, N., Walker, I. F., Naik, Y., Rajan, S., O'Hagan, K., Black, M., Cartwright, C., Tillmann, T., Pearce-Smith, N., & Stansfield, J. (2021). National or population level interventions addressing the social determinants of mental health – an umbrella review. *BMC Public Health*, *21*(1), 1–14. https://doi.org/10.1186/S12889-021-12145-1/FIGURES/2

Skapinakis, P., Bellos, S., Koupidis, S., Grammatikopoulos, I., Theodorakis, P. N., & Mavreas, V. (2013). Prevalence and sociodemographic associations of common mental disorders in a nationally representative sample of the general population of Greece. *BMC Psychiatry*, *13*, 1–14. https://doi.org/10.1186/1471-244X-13-163

Sochas, L., & Reeves, A. (2023). Does collective bargaining reduce health inequalities between labour market insiders and outsiders? *Socio-Economic Review*, *21*(2), 827–862. https://doi.org/10.1093/ser/mwac052

Steele, B., Martin, M., Sciarra, A., Melendez-Torres, G., Degli Esposti, M., & Humphreys, D. K. (2024). The prevalence of sexual assault among higher education students: A systematic review with meta-analyses. *Trauma, Violence, & Abuse*, *25*(3), 1885–1898. https://doi.org/10.1177/15248380231196119

Stein, D. J., Palk, A. C., & Kendler, K. S. (2021). What is a mental disorder? An exemplar-focused approach. *Psychological Medicine*, *51*(6), 894. https://doi.org/10.1017/S0033291721001185

Stuckler, D., Reeves, A., Loopstra, R., Karanikolos, M., & McKee, M. (2017). Austerity and health: The impact in the UK and Europe. *European Journal of Public Health*, *27*(suppl_4), 18–21. https://doi.org/10.1093/EURPUB/CKX167

Sullivan, A., Brown, M., Hamer, M., & Ploubidis, G. B. (2023). Cohort profile update: The 1970 British cohort study (BCS70). *International Journal of Epidemiology*, *52*(3), e179. https://doi.org/10.1093/ije/dyac148

Ten Brink, D., Martin-Hughes, R., Bowring, A. L., Wulan, N., Burke, K., Tidhar, T., Dalal, S., & Scott, N. (2025). Impact of an international HIV funding crisis on HIV infections and mortality in low-income and middle-income countries: A modelling study. *The Lancet HIV*, *12*(5), e346–e354. https://doi.org/10.1016/S2352-3018(25)00074-8

Thomson, R. M., Igelström, E., Purba, A. K., Shimonovich, M., Thomson, H., McCartney, G., Reeves, A., Leyland, A., Pearce, A., & Katikireddi, S. V. (2022). How do income changes impact on mental health and wellbeing for working-age adults? A systematic review and meta-analysis. *The Lancet Public Health*, *7*(6), e515–e528. https://doi.org/10.1016/S2468-2667(22)00058-5

Thornicroft, G., Chatterji, S., Evans-Lacko, S., Gruber, M., Sampson, N., Aguilar-Gaxiola, S., Al-Hamzawi, A., Alonso, J., Andrade, L., Borges, G., Bruffaerts, R., Bunting, B., Almeida, J. M. C. D., Florescu, S., Girolamo, G. D., Gureje, O., Haro, J. M., He, Y., Hinkov, H., … Kessler, R. C. (2017). Undertreatment of people with major depressive disorder in 21 countries. *The British Journal of Psychiatry*, *210*(2), 119–124. https://doi.org/10.1192/BJP.BP.116.188078

Thornicroft, G., & Tansella, M. (2013). The balanced care model: The case for both hospital- and community-based mental healthcare. *The British Journal of Psychiatry*, *202*(4), 246–248. https://doi.org/10.1192/BJP.BP.112.111377

Tøge, A. G. (2016). Health effects of unemployment in Europe during the great recession: The impact of unemployment generosity. *International Journal of Health Services*, *46*(4), 614–641. https://doi.org/10.1177/0020731416664688

Tøge, A. G., & Blekesaune, M. (2015). Unemployment transitions and self-rated health in Europe: A longitudinal analysis of EU-SILC from 2008 to 2011. *Social Science & Medicine*, *143*, 171–178. https://doi.org/10.1016/j.socscimed.2015.08.040

Tomczyk, S., Schmidt, S., Muehlan, H., Stolzenburg, S., & Schomerus, G. (2020). A Prospective Study on Structural and Attitudinal Barriers to Professional Help-Seeking for Currently Untreated Mental Health Problems in the Community. *Journal of Behavioral Health Services and Research*, *47*(1), 54–69. https://doi.org/10.1007/S11414-019-09662-8/TABLES/5

Torre, J. A. la, Vilagut, G., Ronaldson, A., Serrano-Blanco, A., Martín, V., Peters, M., Valderas, J. M., Dregan, A., & Alonso, J. (2021). Prevalence and variability of current depressive disorder in 27 European countries: A population-based study. *The Lancet Public Health*, *6*(10), e729–e738. https://doi.org/10.1016/S2468-2667(21)00047-5

Turner, R. J. (2013). Understanding Health Disparities: The Relevance of the Stress Process Model. *Society and Mental Health*, *3*(3), 170–186. https://doi.org/10.1177/2156869313488121/ASSET/IMAGES/LARGE/10.1177_2156869313488121-FIG2.JPEG

Van Bavel, J. J., Gadarian, S. K., Knowles, E., & Ruggeri, K. (2024). Political polarization and health. *Nature Medicine*, 1–9. https://doi.org/10.1038/s41591-024-03307-w

Van der Schee, E., & Groenewegen, P. P. (2010). Determinants of public trust in complementary and alternative medicine. *BMC Public Health*, *10*, 1–12. https://doi.org/10.1186/1471-2458-10-128

Vigo, D., Thornicroft, G., & Atun, R. (2016). Estimating the true global burden of mental illness. *The Lancet. Psychiatry*, *3*(2), 171–178. https://doi.org/10.1016/S2215-0366(15)00505-2

Wakefield, S., Kellett, S., Simmonds-Buckley, M., Stockton, D., Bradbury, A., & Delgadillo, J. (2021). Improving Access to Psychological Therapies (IAPT) in the United Kingdom: A systematic review and meta-analysis of 10-years of practice-based evidence. *British Journal of Clinical Psychology*, *60*(1), e12259. https://doi.org/10.1111/bjc.12259

Wang, P. S., Aguilar-Gaxiola, S., Alonso, J., Angermeyer, M. C., Borges, G., Bromet, E. J., Bruffaerts, R., Girolamo, G. de, Graaf, R. de, Gureje, O., Haro, J. M., Karam, E. G., Kessler, R. C., Kovess, V., Lane, M. C., Lee, S., Levinson, D., Ono, Y., Petukhova, M., … Wells, J. E. (2007). Use of mental health services for anxiety, mood, and substance disorders in 17 countries in the WHO world mental health surveys. *The Lancet*, *370*(9590), 841–850. https://doi.org/10.1016/S0140-6736(07)61414-7

Weiss, A., King, J. E., Inoue-Murayama, M., Matsuzawa, T., & Oswald, A. J. (2012). Evidence for a midlife crisis in great apes consistent with the U-shape in human well-being. *Proceedings of the National Academy of Sciences*, *109*(49), 19949–19952. https://doi.org/10.1073/pnas.1212592109

Wellcome Trust. (2020). *Wellcome Global Monitor 2020* [Dataset]. https://wellcome.org/reports/wellcome-global-monitor-mental-health/2020

Westreich, D., & Greenland, S. (2013). The table 2 fallacy: Presenting and interpreting confounder and modifier coefficients. *American Journal of Epidemiology*, *177*(4), 292–298. https://doi.org/10.1093/aje/kws412

Whiteford, H. A., Degenhardt, L., Rehm, J., Baxter, A. J., Ferrari, A. J., Erskine, H. E., Charlson, F. J., Norman, R. E., Flaxman, A. D., Johns, N., Burstein, R., Murray, C. J. L., & Vos, T. (2013). Global burden of disease attributable to mental and substance use disorders: Findings from the Global Burden of Disease Study 2010. *The Lancet*, *382*(9904), 1575–1586. https://doi.org/10.1016/S0140-6736(13)61611-6

WHO Mental Health ATLAS. (2017). Geneva: World Health Organization; 2018. Licence: CC BY-NC-SA 3.0 IGO. https://www.who.int/publications/i/item/9789241514019

Wiemken, T. L., & Kelley, R. R. (2020). Machine learning in epidemiology and health outcomes research. *Annu Rev Public Health*, *41*(1), 21–36. https://doi.org/10.1146/annurev-publhealth-040119-094437

Wilkinson, R., & Pickett, K. (2010). *The spirit level: Why equality is better for everyone*. Penguin UK.

Williams, E. (2021). Unemployment, sanctions and mental health: The relationship between benefit sanctions and antidepressant prescribing. *Journal of Social Policy*, *50*(1), 1–20. https://doi.org/10.1017/S0047279419000783

World Health Organization. (2010). *A conceptual framework for action on the social determinants of health*. WHO IRIS. https://iris.who.int/handle/10665/44489

World Health Organization. (2022). *World mental health report: Transforming mental health for all*. World Health Organization. https://www.who.int/publications/i/item/9789240049338

World Health Organization. (2025). *World report on social determinants of health equity*. World Helath Organiuhttps://www.who.int/publications/i/item/9789240107588

Xu, J., & Yang, Y. (2009). Traditional Chinese medicine in the Chinese health care system. *Health Policy*, *90*(2–3), 133–139. https://doi.org/10.1016/j.healthpol.2008.09.003

Yanos, P. T., Knight, E. L., & Roe, D. (2007). Recognizing a role for structure and agency: Integrating sociological perspectives into the study of recovery from severe mental illness. In *Mental health, social mirror* (pp. 407–433). Springer.

Zolopa, C., Burack, J. A., O'Connor, R. M., Corran, C., Lai, J., Bomfim, E., DeGrace, S., Dumont, J., Larney, S., & Wendt, D. C. (2022). Changes in youth mental health, psychological wellbeing, and substance use during the COVID-19 pandemic: A rapid review. *Adolescent Research Review*, *7*(2), 161–177. https://doi.org/10.1007/s40894-022-00185-6

Paper 1: Global inequalities in mental health problems: understanding the predictors of lifetime prevalence, treatment utilisation and perceived helpfulness across 111 countries

Authors: Christoph Henking, Aaron Reeves, Benjamin Chrisinger

Manuscript was published using the following reference:
Henking, C., Reeves, A., & Chrisinger, B. (2023). Global inequalities in mental health problems: understanding the predictors of lifetime prevalence, treatment utilisation and perceived helpfulness across 111 countries. *Preventive Medicine*, *177*, 107769.
https://www.sciencedirect.com/science/article/pii/S0091743523003547

Abstract

Background

Socio-economic inequalities in mental health problems are found in measures covering prevalence, treatment utilisation, and treatment helpfulness. However, whether these inequalities exist globally and what factors explain between-country variation is unclear.

Methods

We use a nationally representative individual-level survey dataset (Wellcome Global Monitor 2020) in 111 countries (N=117,088) to test if socio-economic factors (household income, education), psycho-social factors (stigma perception, trust in health professionals) and country-level factors (GDP, Gini, health expenditure) predict (1) self-reported lifetime prevalence of anxiety and depression symptomology, (2) treatment utilisation and (3) perceived treatment helpfulness of talking to a mental health professional and taking prescribed medication. Multi-level logistic regression models were used.

Results

Across both HICs and LMICs, being in the richest income quintile within each country is associated with a lower probability of experiencing symptoms of anxiety and depression compared to the poorest quintile (OR=0.67 CI[0.64–0.70]), as well as a higher probability of

talking to a mental health professional (OR=1.25[1.14–1.36]), and of perceiving this treatment as very helpful (OR=1.23[1.07–1.40]). However, being among the richest income quintile is not associated with taking prescribed medication (OR=0.97[0.89–1.06]) and its perceived helpfulness (OR=1.06[0.94–1.21]) across all countries. Trust in health practitioners is associated with higher mental health professional utilisation (OR=1.10[1.06–1.14]) and helpfulness (OR=1.32[1.25–1.40]).

Interpretation

This analysis reveals a global ‘triple inequality in mental health’, whereby disadvantages of lower SES individuals persist in three outcomes (lifetime prevalence, treatment utilisation and helpfulness). Treatment utilisation and helpfulness also vary by trust in healthcare professionals and treatment type. Policymakers must address all three inequalities and their fundamental causes.

Keywords

common mental disorders; depression; global mental health; health inequalities; help-seeking mental healthcare; mental health stigma; social determinants of health

Highlights

- Low SES in adults is linked to more mental health problems, lower treatment utilisation and helpfulness.
- This ‘triple inequality’ in mental health occurs in both HICs and LMICs.
- Exception: SES is not linked to the utilisation of medication across all countries.
- Trust in health practitioners is linked to higher treatment use and helpfulness.
- Policy should address each of the three inequalities and its root causes.

1. Introduction

Common mental health problems, such as depression and anxiety, are a primary cause of global disease burden (Whiteford et al., 2013) and they are socially stratified. This becomes clear in the association between socio-economic status (SES) and three related health outcomes: Individuals with lower SES (1) have a higher lifetime prevalence of anxiety and depression, (2) are less likely to utilise professional treatment and (3) are less likely to perceive treatment as helpful when they do receive it (Harris et al., 2020; Knesebeck, 2015; Thomson et al., 2022).

This sequence of socio-economic inequalities suggests that inequalities persist as individuals move from being affected to experiencing treatment outcomes. Besides socio-economic inequalities, psycho-social factors (e.g., stigma) and country-level factors (e.g., economic conditions and healthcare spending) may play a role in determining who receives and who benefits from treatment (Harris et al., 2020; Lewer et al., 2015). This is true for high-income countries (HICs) at least, where most of this work has been carried out (Bracke et al., 2019; Schomerus et al., 2015). What we do not know is whether socio-economic and psycho-social patterns in lifetime prevalence, treatment utilisation and perceived helpfulness exist universally, and what factors explain between-country variations. This study addresses this gap by investigating the socio-economic, psycho-social and country-level correlates of these three health outcomes in a global survey across 111 countries.

Socio-economic factors

Out of the different health outcomes in this study, the link between SES and prevalence of mental health problems is the most thoroughly documented across countries (McNamara et al., 2017) and the mechanisms that generate this association are commonly thought to be material circumstances, psycho-social stress, and behavioural differences (Thomson et al., 2022). Further, SES affects treatment utilisation for psychiatric problems (Knesebeck, 2015), even though only a minority of affected individuals receives minimally adequate treatment (Alonso et al., 2018).

Evidence from Europe suggests that those utilising treatment have higher educational attainment and income (Dey & Jorm, 2016; Lewer et al., 2015).

Lastly, SES is associated with treatment effectiveness. Two systematic reviews using studies from the US and Europe showed that low SES individuals benefit less from psychological therapies (Finegan et al., 2018) and antidepressant treatments (Elwadhi & Cohen, 2020), potentially because lower SES individuals face more socio-economic stressors which cannot be relieved by treatment (Roberts et al., 2022). Besides treatment effectiveness, perceived helpfulness is a patient-centred way to measure treatment outcomes (Morgan et al., 2020) that yields high levels of external validity (Edlund et al., 2015). Using data from WHO's World Mental Health (WMH) Survey Initiative across 16 countries, researchers found that individuals with higher education perceive depression treatment as more helpful (Harris et al., 2020). In summary, evidence suggests that SES stratifies lifetime prevalence, treatment utilisation and helpfulness in HICs but we do not know if these associations are stable across all country contexts. We hypothesise that SES is associated with these three outcomes in both HICs and LMICs (H1).

Psycho-social factors

Mental health stigma and negative help-seeking attitudes are well-documented barriers for utilising mental health treatment (Tomczyk et al., 2020). Stigma is a well-documented barrier to treatment-seeking across Europe (Bracke et al., 2019) while other psycho-social factors have been given less attention. Trust in mental health practitioners and services could be an important determinant of help-seeking (Brown et al., 2009; Majumder et al., 2015) but this has not been examined in quantitative, cross-national studies. These psycho-social factors might also be associated with perceived helpfulness in part because outcome expectations and associated placebo effects influence the effectiveness of pharmacological treatments and talking therapies (Kirsch, 2019). However, again, these associations have not been investigated beyond HIC contexts. We

hypothesise that stigma and trust in healthcare professionals are associated with treatment utilisation and helpfulness across a sample of 111 countries (H2).

Country-level factors

The Global Burden of Diseases study shows us that lifetime prevalence of mental health problems varies across country contexts but these need to be evaluated further (Whiteford et al., 2013). Regarding treatment utilisation, the size of mental health treatment gaps varies depending on country-level economic and healthcare capabilities. The WMH Survey Initiative shows that 36% of people affected by anxiety disorders utilise treatment in HICs, and only 13% in lower-middle-income countries (Alonso et al., 2018). Evidence on country-level variations in healthcare utilisation is based on the Eurobarometer surveys 2006 and 2010. In Europe, healthcare spending and the available mental healthcare workforce explain cross-national variation in antidepressant use (Lewer et al., 2015). Country-level variation in treatment helpfulness is not well-documented. The only two studies on this topic using the WMH Survey Initiative involved too few countries to include specific country-level predictors (Harris et al., 2020; Kazdin et al., 2021). Surprisingly, patients in LMICs reported a higher treatment helpfulness for antidepressants than in HICs (Kazdin et al., 2021). However, it is unclear if national-level differences in healthcare spending or quality-of-care influence treatment helpfulness. We hypothesise that GDP, health expenditure and lower out-of-pocket health expenditure are associated with higher treatment utilisation and helpfulness (H3).

Study rationale and hypotheses

Using an individual-level survey dataset in 111 countries, we investigate if socio-economic and psycho-social inequalities in the three health outcomes (lifetime prevalence, treatment utilisation and treatment helpfulness) exist universally, and what factors explain between-country variation.

There are two main reasons for studying the three health outcomes together. First, we cannot fully understand the mechanisms behind inequalities in the burden of disease by studying single health outcomes in isolation. Research on infectious diseases and depression (Knoblauch et al., 2020; Pence et al., 2012) has used *cascades of care* approaches to examine where in the treatment journey patients drop out. Here, we apply this thinking to mental health problems and examine three major health outcomes (who is affected, who receives treatment and who perceives treatment as helpful), while our interest is in understanding inequalities at each step. Notably, we focus on three key health outcomes in many countries, instead of a larger healthcare cascade in one specific context. Second, differences in the determinants of the three health outcomes might have differential implications on what policies are needed to reduce health inequalities. Studying the outcomes together in one study can make such differences explicit.

Hypotheses

In summary, existing work suggests three hypotheses relevant to our main research objective.

H1 (SES). Lower SES individuals have a higher lifetime prevalence of mental health problems, are less likely to utilise professional treatment and perceive this treatment as helpful, irrespective of HIC/LMIC country context.

H2 (Psycho-social). Lower levels of stigma perceptions and higher levels of trust in health practitioners are associated with higher treatment utilisation and helpfulness.

H3 (Country-level/Macroeconomic). Higher GDP and health expenditure, and lower out-of-pocket health expenditure are associated with higher treatment utilisation and helpfulness.

2. Methods

Sample

The data was collected via telephone between August 2020 and January 2021 by Gallup commissioned by the Wellcome Trust. The dataset is publicly available online, alongside research

and methodology reports (Wellcome Trust, 2020). The dataset included representative population-based surveys in 113 countries. Two countries were excluded because of missing data on either the mental health items (Tajikistan) or the income data (Venezuala). Therefore, the final sample included 111 counties and 117,088 participants (see Table S3 in Appnedix A). Data collection occurred during the context of the Covid-19 pandemic but our conclusions are relevant beyond the pandemic's context: the survey was developed before the pandemic and all outcome variables used in this study refer to *lifetime experiences* rather than pandemic-related events. Furthermore, in supplementary analyses (see Appendix 1B), we show that our findings remain stable when including Covid-19 related indicators (death rates and lockdown stringency).

Variables

Dependent variables

Lifetime prevalence of anxiety or depression symptomology was measured using a single item *"Have you ever been so anxious or depressed that you could not continue your regular daily activities as you normally would for two weeks or longer"* with "Yes" or "No". The item was designed by Wellcome Trust researchers considering the general diagnostic criteria for anxiety and depression with the goal to elicit analytical comparisons across countries and cultures (rather than epidemiological precision) (Wellcome Trust, 2020). The item underwent cognitive testing to fulfil this purpose of cross-country comparability. Respondents who reported lifetime experience with anxiety or depression symptomology were asked about two types of treatment utilisation: *"When you were feeling so anxious or depressed, did you ever do any of the following to make yourself feel better?* Talk to a mental health professional" and "Take medication prescribed by a healthcare professional" ("Yes" / "No"). Both items underwent cognitive testing in 10 countries to confirm interpretability across countries. This showed that "talking to a mental health professional" was interpreted by the participants in a variety of ways such as *"talking to a therapist, doing talk therapy, or talking to a mental*

health professional". Similarly, for "taking prescribed medication", the type of medication was intentionally left open.

Those who answered treatment utilisation questions with "Yes" were questioned on their perceived treatment helpfulness *"Did you find the following very helpful, somewhat helpful, or not helpful in making you feel better?"* regarding both treatment types (3=*Very helpful*, 2=*Somewhat helpful*, 1=*not helpful*). To ensure consistency of interpretation and effect sizes across all statistical models (Figure 2.1 and Table 2.2), we categorised "*not helpful*" and "*somewhat helpful*" together as "*not entirely helpful*" (contrasted with the category "*very helpful*"). As sensitivity tests, we re-run main analyses with the alternative coding of the helpfulness variables (e.g., "somewhat helpful" and "very helpful" grouped together) and our results remain stable (see Appendix 1B and Table S6).

Individual-level socio-economic factors

Household income was measured using per capita income quintiles, defined for each specific country, with the poorest coded as 1. Education was categorised as 1=*Elementary or less* (8 years or less), 2=*Secondary* (8–15 years) and 3=*Tertiary* (16+ years).

Psycho-social factors

Local stigma perceptions were measured using the item "*In general, if someone in your local community was experiencing extreme anxiety or depression, how comfortable do you think they would feel speaking about it with someone they know?"* (1 =*Very comfortable*, 2 = *Somewhat comfortable*, 3 = *Not at all comfortable*). Belief in science to treat mental health conditions was measured using the item "*In general, how much do you think science helps us treat the following health problems? Extreme anxiety or depression"* and Trust in healthcare professionals using *"How much do you trust each of the following? Doctors and nurses in this country"* (scale for both items: 1=*not at all,* 2=*not much,* 3=*some,* 4=*a lot).*

Country-level factors

Most recent data on gross domestic product per capita (GDP), Gini coefficient, health expenditure as percentage of GDP, and percentage of out-of-pocket healthcare expenditure were extracted from the World Bank (World Bank, 2022). In four countries, some World Bank data were missing and substituted by national statistics. Table S3 in Appendix 1A shows this in detail. Covid-19 deaths rates were derived from (Our World in Data, 2023) and lockdown stringency from the (Oxford Covid-19 Government Response Tracker, 2023). Details are provided in table S4.

Analyses

First, we compute predicted probability of our mental health outcomes (prevalence, utilisation and helpfulness) as a function of income quintiles. This analysis is segregated by HICs and LMICs to provide a first overview of country-level variation. We then performed multilevel-logistic regression analyses with individuals (*i*) nested in countries (*j*). First, a random intercept model without fixed effects established that the probability of lifetime prevalence and treatment utilisation vary as a function of countries (see Appendix 1A). Next, fixed effects for both individual and country-level predictors were added to the random intercept model:

$$logit(ExperiencedAnxietyorDeprression_{ij)} = \gamma_{00} + \gamma_{01} \times Gini_j + \gamma_{02} \times \log(GDP)_j + \mu_{0j} + \gamma_{10} \times Income_{ij} + \gamma_{20} \times Education_{ij} + \gamma_{30} \times Gender_{ij} + \gamma_{40} \times Age_{ij} + \varepsilon_{ij}$$

The model was adjusted using variables from Table 2.2. We categorized our models as "simple" and "full" (see Table 2.2). "Simple models" focus on interpreting the relationship between our primary SES indicator, household income, and various mental health outcomes (while controlling for age, gender and education as factors temporarily prior to income). These models exclude psycho-social predictors, as they might mediate and suppress the relationship between SES and mental health. In contrast, "full models" include all psycho-social predictors.

For each outcome variable, we condition on the answer "Yes" in the previous question. Therefore, sample sizes of the different regression models vary as shown in Table 2.2. For the multi-level models, survey weights were applied to yield representative samples within each country. We ran supplementary analyses (Appendix 1B) to triangulate all SES effects for education as predictor, and to show that varying "treatment helpfulness" coding and including Covid-19 variables had no impact on the results.

3. Results

Table 2.1 summarises descriptive statistics for both individual and country-level variables. Overall, 20.4% of participants reported lifetime experience with anxiety or depression symptomology. 43.1% of participants report talking to a mental health professional and 47% report taking prescribed medication. The mean helpfulness of both forms of treatment was high (M = 2.56 for mental health professional utilisation and M = 2.47 for prescribed medication). Most participants rated both treatment types as “very helpful”.

Table 2.1. Descriptive statistics

Variable		All countries	High income countries	Low- & middle-income countries
Countries and sample characteristics	Countries, N,	111, N= 117,088	43, N= 43,201	70, N= 73,887
	Gender	F = 50.9%, M = 49.1%	F = 50.7%, M = 49.3%	F = 48.1%, M = 51.9%
	Age (mean)	40.2 years	49.1 years	35.0 years
	Age (SD)	17.3	18.1	12.8
Country-level indicators (N= 111 countries)	GDP per capita in USD (mean, SD)	15,862 (18,908)	35,340 (18,750)	2,165 (1,034)
	Gini coefficient (mean, SD)	36.8 (7.3)	33.1 (5.7)	37.9 (6.7)
	Health expenditure as % of GDP (mean, SD)	6.6 (2.6)	8.5 (2.3)	4.6 (1.6)
	% Out of pocket healthcare expenditure	32.3 (15.5)	21.2 (8.9)	44.9 (15.2)
Education (individual level)	Elementary or less	13.3%	7.5%	16.7%
	Secondary	55.1%	53.2%	56.3%
	Tertiary	31.5%	39.3%	27.0%
	Number of responses	116,352	42,980	73,372
Local stigma perception	mean (SD)	2.08 (0.75)	2.17 (0.72)	2.03 (0.76)
Belief in science to treat anxiety or depression	mean (SD)	3.03 (0.88)	3.06 (0.81)	3.01 (0.93)
Trust in health practitioners (doctors and nurses)	mean (SD)	3.27 (0.80)	3.51 (0.66)	3.12 (0.84)
Lifetime experience of depression or anxiety	Yes	20.4 %	17.8%	21.9%
	No	79.6%	82.2%	78.1%
	Number of responses	115,813	42,773	73,040
Talked to mental health professional if experienced anxiety or depression	Yes	43.1%	62.1%	34.1%
	No	56.9%	37.9%	65.9%
	Number of responses	23,526	7,586	15,940
Took prescribed medication prescribed by healthcare professional if experienced anxiety or depression	Yes	47.0%	56.9%	42.3%
	No	53.0%	43.1%	57.7%
	Number of responses	23,543	7,590	15,953
Helpfulness of talking to a mental health professional	Mean (SD)	2.56 (0.63)	2.53 (0.64)	2.59 (0.62)
	Very helpful	63.4%	60.7%	65.8%
	Not entirely helpful ("somewhat" or "not helpful")	36.6%	39.3%	34.2%
	Number of responses	10,001	4,644	5,357
Helpfulness of taking medication prescribed by a healthcare professional	Mean (SD)	2.47 (0.67)	2.41 (0.69)	2.51 (0.65)
	Very helpful	56.7%	52.8%	59.1%
	Not entirely helpful ("somewhat" or "not helpful")	43.3%	47.2%	40.9%
	Number of responses	10,893	4,246	6,647

Socio-economic factors (H1)

H1 states that individual-level SES is associated with higher lifetime prevalence, lower treatment utilisation and lower helpfulness. We used *household income quintiles* as main SES outcome to test H1.

Figure 2.1 shows the predicted probability of the mental health outcomes as a function of within-country income quintiles (based on simple general linear models). The top three graphs illustrate that higher income levels are associated with gradually lower lifetime prevalence, higher mental health professional utilisation and higher perceived helpfulness of talking to a mental health professional in both HICs and LMICs. The lower two graphs show that this social gradient is not found for taking prescribed medication and perceived helpfulness of this treatment. Figure S2 in Appendix 1B shows the exact predicted probabilities and CIs displayed in Figure 2.1. For example, in HICs, the predicted probabilities of talking to a mental health professional is 0.58 (95% CI:[0.55–0.60]) in the lowest income quintile to 0.67 (CI:[0.58–0.67]) in the highest quintile.

The findings are confirmed by the models displayed in Table 2.2 across all countries (see "simple models" to interpret income effects). As main SES associations, we report the difference of being highest income quintile (5) compared to the poorest quintile (1). As shown in Table 2.2 ("simple models"), being in the richest within-country income quintile (5) is linked to a lower probability of experiencing symptoms of anxiety and depression compared to the poorest quintile (OR=0.67, CI [0.64–0.70]), as well as a higher probability of talking to a mental health professional (OR=1.25, CI:[1.14–1.36]), and of perceiving this treatment as helpful (OR=1.23, CI:[1.07–1.40]) compared to the poorest individuals.

However, being among the richest income quintile is not significantly linked to utilisation (OR=0.97, CI:[0.89–1.06]) and helpfulness (OR=1.06, CI:[0.94–1.21]) of prescribed medication across all countries. In LMICs, Figure 2.1 and Figure S2 show that that the poorest individuals even have a higher probability (0.46, CI:[0.44–0.48]) than the richest individuals (0.40, CI:[0.39–

0.42]) to take prescribed medication when affected by mental health symptoms. The associations for education as SES predictor follow the same pattern as outlined in Appendix 1B (Table S5).

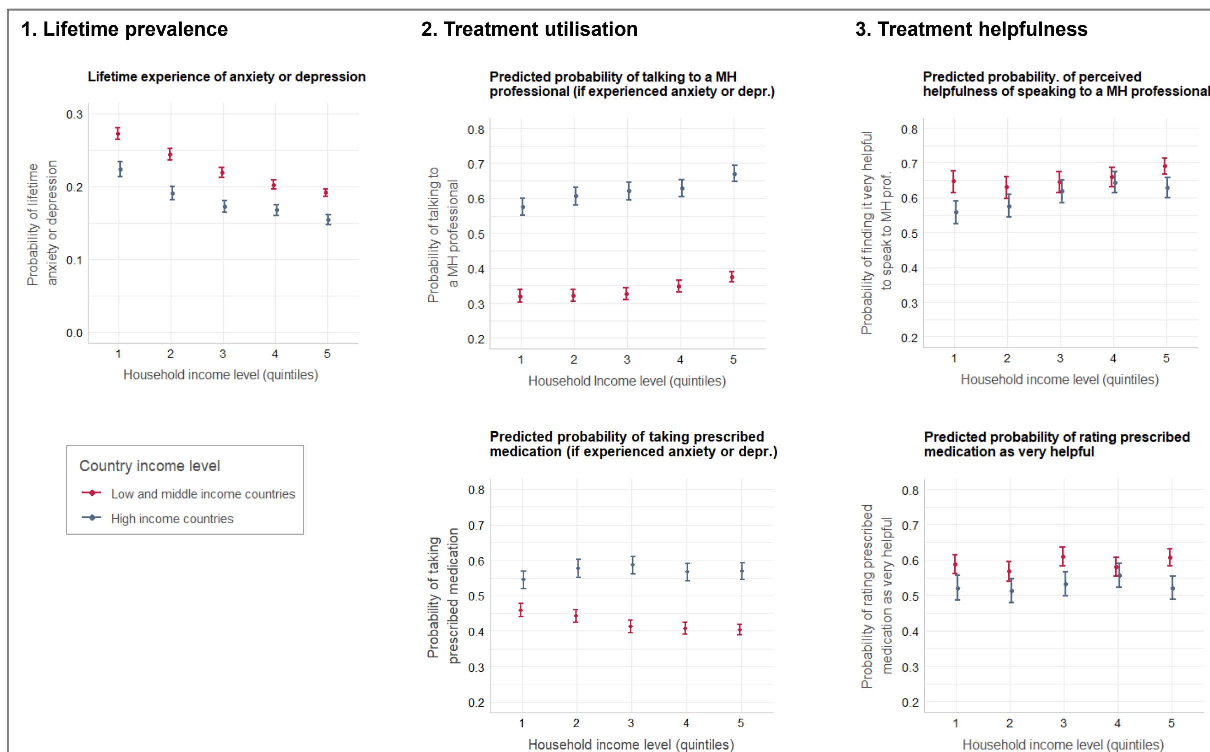


Figure 2.1. Predicted probabilities for the lifetime prevalence of mental health problems, treatment utilisation and perceived helpfulness by household income quintiles (95% CIs).

Table 2.2. Associations between socio-economic, psycho-social, and country-level predictors with mental health outcomes

Predictors	**Dependent variable 1:** Lifetime experience of anxiety or depression (= Yes)	**Dependent variable 2a:** 'Talking to a mental health professional' (= Yes)		**Dependent variable 2b:** 'Taking medication prescribed by a healthcare professional' (=Yes)		**Dependent variable 3a:** Rating 'talking to mental health professional' as very helpful (=Yes)		**Dependent variable 3b:** Rating 'taking medication prescribed by a healthcare professional' as very helpful (=Yes)	
Individual-level socio-economic factors	**Full model**	**Simple model**	**Full model**	**Simple model**	**Full model**	**Simple model**	**Full model**	**Simple model**	**Full model**
Household income quintile 2 (ref= quintile 1)	0.83** [0.79–0.86]	1.00 [0.93–1.09]	1.00 [0.92–1.09]	0.99 [0.92–1.08]	1.02 [0.94–1.11]	0.88 [0.78–0.99]	0.84* [0.74–0.95]	0.89* [0.80–1.00]	0.86* [0.76–0.97]
Household income quintile 3 (ref= quintile 1)	0.73** [0.70–0.76]	1.02 [0.94–1.12]	1.02 [0.93–1.11]	0.93 [0.86–1.01]	0.95 [0.87–1.03]	1.01 [0.89–1.15]	0.97 [0.85–1.11]	1.10 [0.98–1.23]	1.11 [0.98–1.26]
Household income quintile 4 (ref= quintile 1)	0.69** [0.66–0.72]	1.10* [1.01–1.20]	1.10* [1.00–1.23]	0.90* [0.83–0.98]	0.91* [0.83–0.99]	1.19* [1.04–1.35]	1.12 [0.98–1.29]	1.02 [0.90–1.15]	1.01 [0.89–1.14]
Household income quintile 5 (ref= quintile 1)	0.67** [0.64–0.70]	1.25** [1.14–1.36]	1.23** [1.12–1.35]	0.97 [0.89–1.06]	0.99 [0.90–1.08]	1.23** [1.07–1.40]	1.16* [1.01–1.34]	1.06 [0.94–1.21]	1.01 [0.89–1.16]
Psycho-social factors									
Perception of local mental health stigma			0.93** [0.90–0.97]		0.93** [0.89–0.96]		0.76** [0.72–0.81]		0.80** [0.76 – 0.85]
Belief in science to treat mental health conditions			1.08** [1.05–1.12]		1.08** [1.05–1.11]		1.32** [1.26–1.38]		1.33** [1.27–1.39]
Trust in health practitioners (doctors & nurses)			1.10** [1.06–1.14]		1.07** [1.04–1.11]		1.32** [1.25–1.40]		1.27** [1.21–1.34]
Country-level factors									
GDP per capita (log)	1.01 [0.93–1.11]	1.24** [1.06–1.45]	1.26** [1.08–1.47]	0.95 [0.84–1.08]	0.98 [0.86–1.11]	0.76** [0.66–0.88]	0.78** [0.68–0.90]	0.78** [0.68–0.90]	0.80** [0.70–0.93]
GINI coefficient	1.02* [1.00–1.03]	0.99 [0.98–1.01]	1.00 [0.98–1.01]	0.99 [0.98–1.01]	0.99 [0.98–1.01]	1.01 [1.00–1.03]	1.02 [1.00–1.03]	1.01 [0.99–1.02]	1.01 [1.00–1.03]
Health expenditure as % of GDP		1.12** [1.05–1.20]	1.11** [1.04–1.19]	1.07* [1.01–1.13]	1.05 [1.00–1.11]	1.03 [0.97–1.10]	1.02 [0.97–1.09]	0.96 [0.91–1.02]	0.95 [0.89–1.00]
% Out of Pocket healthcare expenditure		0.99 [0.98–1.00]	0.99 [0.98–1.00]	0.99 [0.99–1.00]	1.00 [0.99–1.00]	0.99 [0.98–1.00]	0.99 [0.98–1.00]	0.99* [0.98–1.00]	0.99* [0.98–1.00]
All models above also control for individual-level education, age and gender									
Observations (n)	115,121	23,340	21,677	23,359	21,692	9,929	9,387	10,809	10,154

Notes: Values reflect unstandardised regression coefficients as odds ratios (OR); * $p < 0.05$; ** $p < 0.01$. Country sample consists of 111 countries for all analyses. "Simple models" are for the optimal interpretation of the association of income levels and mental health outcomes.

Psycho-social factors (H2)

H2, which states that psycho-social factors are associated with treatment utilisation and helpfulness, is confirmed by the results shown in Table 2.2 ("full models"). Perceived stigma (OR=0.93, CI:[0.90–0.97]), belief in science to treat mental health conditions (OR=1.08, CI:[1.05–1.12]) and trust in health professionals (OR=1.10, CI:[1.06–1.14]) are all associated with mental health professional utilisation. They also predict the utilisation of prescribed medication in the same direction. Similarly, perceived stigma (OR=0.76, CI:[0.72–0.81]) and trust in health professionals (OR=1.32, CI:[1.24–1.40]) are also associated with the perceived helpfulness of both treatment types in the hypothesised direction. Again, the effects are also stable for the utilisation of medication (Table 2.2). Thus, these results did not yield the same differentiation between treatment types as shown for socio-economic factors.

Country-level factors (H3)

H3 states that country-level economic and healthcare factors explain between-country variation in the health outcomes. Table 2.2 ("full models") highlights several country-level effects. Higher income inequality (Gini) is associated with a higher prevalence of anxiety or depression (OR=1.02, CI:[1.004–1.03]). GDP (OR=1.26, CI:[1.08–1.47]) and health expenditure (OR=1.11, CI:[1.04–1.19]) are related to higher mental health professional utilisation. In contrast, for utilisation of prescribed medication, such country level effects were small and not significant. Unexpectedly, higher GDP is related to lower perceived helpfulness of both types of treatment (OR=0.78, CI:[0.68–0.91] for mental health professional utilisation and OR=0.81, CI:[0.70–0.93] for medication). The association of out-of-pocket health and the outcome variables was not substantive.

4. Discussion

This study used a survey dataset in 111 countries to investigate the predictors of the three health outcomes lifetime prevalence of mental health problems, treatment utilisation and perceived treatment helpfulness.

This study demonstrates that socio-economic inequalities cut across the three health outcomes of prevalence, mental health professional utilisation, and perceived helpfulness in both HICs and LMICs. Firstly, in line with previous research individuals with lower SES (income and education) have a higher lifetime experience of anxiety and depression symptomology (McNamara et al., 2017; Thomson et al., 2022).

It is crucial to recognise that our single-item measure for anxiety and depression symptomology is not a psychiatric diagnosis, nor should it be interpreted as an epidemiological prevalence estimate. Instead, it captures participants' lifetime experiences of typical symptoms, influenced by their interpretation of the survey item and memory accuracy.

Secondly, individuals with higher SES are more likely to talk to a mental health professional when they are affected by anxiety or depression. These results indicate that higher SES individuals are more likely to engage in talking therapy and specialist mental health care. This is in line with Europe-based research on treatment utilisation for mental health service (Dey & Jorm, 2016; Knesebeck, 2015). Thirdly, talking to a mental health professional was perceived as more helpful by higher SES individuals. As potential explanations, talking therapy might be better tailored to the needs of those with higher education (Holman, 2014) and might more readily provide perceivable progress for individuals without poverty related pressures (Roberts et al., 2022). Lower SES individuals may also experience higher treatment dropout rates due to time and financial constraints, and insufficient health insurance coverage (Dijk et al., 2022).

In conclusion, these findings reveal a global 'triple inequality in mental health', whereby disadvantages of lower SES individuals deepen along each of the three health outcomes.

However, this 'triple inequality' was only shown for the utilisation of mental health professionals, and not regarding utilisation and perceived helpfulness for pharmacological treatments. SES had no significant association with utilisation with taking prescribed medication in HICs, while in LMICs, the reversed social gradient was shown for utilisation. In LMICs, richer and more educated individuals were less likely to take prescribed medication when affected by anxiety or depression. Different explanations for these effects can be considered. First, antidepressant medication tends to be cheaper and easier to access for both healthcare providers than specialist care and talking therapy (Lewer et al., 2015; Vos et al., 2016).

Therefore, income might not be an important determinant for medication. Relatedly, medication is often prescribed by primary health care professionals (Buffel et al., 2014) which is – opposed to specialist care – is more frequently used by lower SES individuals (Fjaer et al., 2017). As a second potential explanation, the survey item did not refer to a specific type of pharmacological treatment, and these types might differ between HICs and LMICs. As in LMICs, depression and anxiety are particularly strongly underdiagnosed, people reporting mental health symptoms might be treated for their somatic symptoms (Fekadu et al., 2022). In such cases, higher SES individuals might be less likely to take such potentially unsuitable medication. Future research needs to differentiate between the specific types of treatment and find explanations for the different socio-economic effects.

Besides stigma perceptions, trust in healthcare professionals was identified as predictors for treatment utilisation, stressing the importance of trust to reduce inequalities in mental health (Majumder et al., 2015). Interestingly, stigma and trust were also associated with perceived helpfulness of both treatment types. Thus, treatment helpfulness might be influenced by psychological factors that shape expectations and interactions during the treatment. Conversely,

a successful therapy might influence perceptions of stigma and trust. Future research should attempt to disentangle these alternative causal pathways.

This paper extends previous findings on national-level treatment variation in Europe (Bracke et al., 2019; Lewer et al., 2015) and shows that GDP and health expenditure are predictors of treatment utilisation globally. The richer a country, the more likely citizens are to access mental health specialists. However, health expenditure and GDP do not explain cross-national variations in the use of medication in this study. As highlighted earlier, this might be because providing and using medication requires fewer country-level financial resources than providing specialist mental healthcare. Surprisingly, higher GDP is negatively associated with perceived treatment helpfulness of both types of treatment. Based on H3, we expected that higher country-level economic resources would entail higher service availability and quality of care, and relate to higher treatment satisfaction. Previous findings also indicate that antidepressant treatments were perceived as more helpful in LMICs than HICs (Kazdin et al., 2021). Possibly, richer countries might have higher expectations of treatment helpfulness which are harder to fulfil.

Our findings suggest that two complementary approaches should be used to address the triple inequality in mental health (Rose et al., 2008). First, policy should aim to reduce population-wide socioeconomic inequalities to tackle all three mental health disparities simultaneously. And secondly, policy should enhance the accessibility and patient experience of psychological therapies for low SES individuals.

This study has several limitations. First, the study uses cross-sectional data and memory recall for lifetime events, which might have been influenced by the Covid-19 pandemic. Second, the item to measure lifetime experience of anxiety or depression symptomology is not clinically precise and involves subjective interpretation by the participants. Therefore, the item entails a risk of measurement bias if its interpretation differs systematically across different groups of participants (e.g., nationalities or socio-economic groups). Third, differences in the meaning of

"talking to mental health professional" and "taking medication prescribed by a healthcare professional" create some ambiguity in how we interpret the results which will hopefully be resolved in future work. Fourth, the direction of the association between psycho-social variables and healthcare utilisation remains unclear and might be bi-directional as service use could influence trust and stigma perceptions. Future research should use longitudinal designs and distinctive measures for anxiety, depression, and treatment types to extend our findings.

Conflict of interest

All authors declare no conflict of interest.

References

Alonso, J., Liu, Z., Evans-Lacko, S., MPH, E. S., Sampson, N. B., Chatterji, S., Abdulmalik, J., Aguilar-Gaxiola, S., Al-Hamzawi, A., Andrade, L. H., Bruffaerts, R., Cardoso, G., Cia, A., Florescu, S., Girolamo, G. de, Gureje, O., Haro, J. M., Levinson, D., Medina-Mora, M. E., … Wojtyniak, B. (2018). Treatment gap for anxiety disorders is global: Results of the World Mental Health Surveys in 21 countries. *Depression and Anxiety*, *35*(3), 195–208. https://doi.org/10.1002/DA.22711

Blair, A., & Siddiqi, A. (2022). The social determinants of substance use associated with deaths of despair: Individual risks and population impacts. *Preventive Medicine*, *164*, 107327. https://doi.org/10.1016/j.ypmed.2022.107327

Bracke, P., Delaruelle, K., & Verhaeghe, M. (2019). Dominant Cultural and Personal Stigma Beliefs and the Utilization of Mental Health Services: A Cross-National Comparison. *Frontiers in Sociology*, *4*, 40. https://doi.org/10.3389/FSOC.2019.00040/BIBTEX

Brown, P., Calnan, M., Scrivener, A., & Szmukler, G. (2009). Trust in Mental Health Services: A neglected concept. *Journal of Mental Health, 18(5), 449-458.* https://doi.org/10.3109/09638230903111122

Buffel, V., Velde, S. V. de, & Bracke, P. (2014). Professional care seeking for mental health problems among women and men in Europe: The role of socioeconomic, family-related and mental health status factors in explaining gender differences. *Social Psychiatry and Psychiatric Epidemiology*, *49*(10), 1641–1653. https://doi.org/10.1007/S00127-014-0879-Z/TABLES/4

Dey, M., & Jorm, A. F. (2016). Social determinants of mental health service utilization in Switzerland. *International Journal of Public Health 2016 62:1*, *62*(1), 85–93. https://doi.org/10.1007/S00038-016-0898-5

Dijk, D. A. van, Deen, M. L., Boogaard, T. M. van den, Ruhé, H. G., Spijker, J., & Peeters, F. (2022). Prevalence and prediction of dropout during depression treatment in routine outpatient care: An observational study. *European Archives of Psychiatry and Clinical Neuroscience*, 1–11. https://doi.org/10.1007/s00406-022-01499-1

Edlund, M. J., Pettiford, A. G., Hampton, J., Forman-Hoffman, V. L., Ault, K. L., Colpe, L. J., & Hedden, S. L. (2015). Adolescents' assessments of the helpfulness of treatment for major depression: Results from a national survey. *Psychiatric Services*, *66*(10), 1064–1073. https://doi.org/10.1176/APPI.PS.201400018

Elwadhi, D., & Cohen, A. (2020). Social inequalities in antidepressant treatment outcomes: A systematic review. *Social Psychiatry and Psychiatric Epidemiology 2020 55:10*, *55*(10), 1241–1259. https://doi.org/10.1007/S00127-020-01918-5

Fekadu, A., Demissie, M., Birhane, R., Medhin, G., Bitew, T., Hailemariam, M., Minaye, A., Habtamu, K., Milkias, B., & Petersen, I. (2022). Under detection of depression in primary care settings in low and middle-income countries: A systematic review and meta-analysis. *Systematic Reviews*, *11*(1), 1–10. https://doi.org/10.1186/s13643-022-01893-9

Finegan, M., Firth, N., Wojnarowski, C., & Delgadillo, J. (2018). Associations between socioeconomic status and psychological therapy outcomes: A systematic review and meta-analysis. *Depression and Anxiety*, *35*(6), 560–573. https://doi.org/10.1002/DA.22765

Fjaer, E. L., Balaj, M., Stornes, P., Todd, A., McNamara, C. L., & Eikemo, T. A. (2017). Exploring the differences in general practitioner and health care specialist utilization according to education, occupation, income and social networks across Europe: Findings from the European social survey (2014) special module on the social determinants of health. *European Journal of Public Health*, *27*(suppl_1), 73–81. https://doi.org/10.1093/EURPUB/CKW255

Harris, M. G., Kazdin, A. E., Chiu, W. T., Sampson, N. A., Aguilar-Gaxiola, S., Al-Hamzawi, A., Alonso, J., Altwaijri, Y., Andrade, L. H., Cardoso, G., Cía, A., Florescu, S., Gureje, O., Hu, C., Karam, E. G., Karam, G., Mneimneh, Z., Navarro-Mateu, F., Oladeji, B. D., … Kessler, R. C. (2020). Findings From World Mental Health Surveys of the Perceived Helpfulness of Treatment for Patients With Major Depressive Disorder. *JAMA Psychiatry*, *77*(8), 830–841. https://doi.org/10.1001/JAMAPSYCHIATRY.2020.1107

Holman, D. (2014). 'What help can you get talking to somebody?' Explaining class differences in the use of talking treatments. *Sociology of Health & Illness*, *36*(4), 531–548. https://doi.org/10.1111/1467-9566.12082

Kazdin, A. E., Wu, C. S., Hwang, I., Puac-Polanco, V., Sampson, N. A., Al-Hamzawi, A., Alonso, J., Andrade, L. H., Benjet, C., Caldas-De-Almeida, J. M., Girolamo, G. D., Jonge, P. D., Florescu, S., Gureje, O., Haro, J. M., Harris, M. G., Karam, E. G., Karam, G., Kovess-Masfety, V., … Have, M. T. (2021). Antidepressant use in low- middle- and high-income countries: A World Mental Health Surveys report. *Psychological Medicine*, *53*(4), 1583-1591. https://doi.org/10.1017/S0033291721003160

Kirsch, I. (2019). Placebo effect in the treatment of depression and anxiety. *Frontiers in Psychiatry*, *10, 464277*, https://doi.org/10.3389/FPSYT.2019.00407/BIBTEX

Knesebeck, O. V. D. (2015). Concepts of social epidemiology in health services research. *BMC Health Services Research*, *15*(1), 1–4. https://doi.org/10.3389/fpsyt.2019.00407

Knoblauch, A. M., Lapierre, S. G., Randriamanana, D., Raherison, M. S., Rakotoson, A., Raholijaona, B. S., Ravaoarimanga, M., Ravololonandriana, P. E., Rabodoarivelo, M. S., Ratsirahonana, O., Rakotomanana, F., Razafindranaivo, T., Rasolofo, V., & Rakotosamimanana, N. (2020). Multidrug-resistant tuberculosis surveillance and cascade of care in Madagascar: A five-year (2012-2017) retrospective study. *BMC Medicine*, *18*(1), 1–14. https://doi.org/10.1186/s12916-020-01626-6

Lewer, D., O'Reilly, C., Mojtabai, R., & Evans-Lacko, S. (2015). Antidepressant use in 27 European countries: Associations with sociodemographic, cultural and economic factors. *The British Journal of Psychiatry*, *207*(3), 221–226. https://doi.org/10.1192/BJP.BP.114.156786

Majumder, P., O'Reilly, M., Karim, K., & Vostanis, P. (2015). 'This doctor, i not trust him, I'm not safe': The perceptions of mental health and services by unaccompanied refugee adolescents. *International Journal of Social Psychiatry*, *61*(2), 129–136. https://doi.org/10.1177/0020764014537236

McNamara, C. L., Balaj, M., Thomson, K. H., Eikemo, T. A., Solheim, E. F., & Bambra, C. (2017). The socioeconomic distribution of non-communicable diseases in Europe: Findings from the European Social Survey (2014) special module on the social determinants of health. *European Journal of Public Health*, *27*(suppl_1), 22–26. https://doi.org/10.1093/EURPUB/CKW222

Morgan, A. J., Ross, A. M., Yap, M. B. H., Reavley, N. J., Parker, A., Simmons, M. B., Scanlan, | Faye, & Jorm, A. F. (2020). What works for mental health problems in youth? Survey of real-world experiences of treatments and side effects. *Wiley Online Library*, *15*(6), 1502–1512. https://doi.org/10.1111/eip.13087

Our World in Data. (2023). *Our World in Data—Coronavirus.* [Dataset]. https://github.com/owid/covid-19-data/tree/master/public/data.

Oxford Covid-19 Government Response Tracker. (2023). *Oxford Covid-19 Government Response Tracker (OxCGRT)* [Dataset]. https://github.com/OxCGRT/covid-policy-dataset

Parsons, S. (2014). Childhood cognition in the 1970 British cohort study. *CLS Data Note*.

Pence, B. W., O'Donnell, J. K., & Gaynes, B. N. (2012). The depression treatment cascade in primary care: A public health perspective. *Current Psychiatry Reports*, *14*(4), 328–335. https://doi.org/10.1007/S11920-012-0274-Y/FIGURES/5

Roberts, T., Esponda, G. M., Torre, C., Pillai, P., Cohen, A., & Burgess, R. A. (2022). Reconceptualising the treatment gap for common mental disorders: A fork in the road for global mental health? *The British Journal of Psychiatry, 221(3), 553-557*. https://doi.org/10.1192/BJP.2021.221

Rose, G. A., Khaw, K.-T., & Marmot, M. (2008). *Rose's strategy of preventive medicine: The complete original text*. Oxford University Press.

Schomerus, G., Evans-Lacko, S., Rüsch, N., Mojtabai, R., Angermeyer, M. C., & Thornicroft, G. (2015). Collective levels of stigma and national suicide rates in 25 European countries. *Epidemiology and Psychiatric Sciences*, *24*(2), 166–171. https://doi.org/10.1017/S2045796014000109

Thomson, R. M., Igelström, E., Purba, A. K., Shimonovich, M., Thomson, H., McCartney, G., Reeves, A., Leyland, A., Pearce, A., & Katikireddi, S. V. (2022). How do income changes impact on mental health and wellbeing for working-age adults? A systematic review and meta-analysis. *The Lancet Public Health*, *7*(6), e515–e528. https://doi.org/10.1016/S2468-2667(22)00058-5

Tomczyk, S., Schmidt, S., Muehlan, H., Stolzenburg, S., & Schomerus, G. (2020). A Prospective Study on Structural and Attitudinal Barriers to Professional Help-Seeking for Currently Untreated Mental Health Problems in the Community. *Journal of Behavioral Health Services and Research*, *47*(1), 54–69. https://doi.org/10.1007/s11414-019-09662-8

Torre, J. A. la, Ronaldson, A., Prina, M., Matcham, F., Hatch, S. L., Pickles, A., Hotopf, M., Dregan, A., London, S., Nhs, M., Torre, J. A. la, Ronaldson, A., Prina, M., Matcham, F., Pereira, S. M. P., Hatch, S. L., Armstrong, D., Pickles, A., Hotopf, M., & Dregan, A. (2021). *Depressive symptoms during early adulthood and the development of physical multimorbidity in the UK: an observational cohort study. The Lancet Healthy Longevity, 2(12), e801-e810.* https://doi.org/10.1016/S2666-7568(21)00259-2

Vos, T., Corry, J., Haby, M. M., Carter, R., & Andrews, G. (2016). Cost-Effectiveness of Cognitive–Behavioural Therapy and Drug Interventions for Major Depression. *Http://Dx.Doi.Org/10.1080/j.1440-1614.2005.01652.x*, *39*(8), 683–692. https://doi.org/10.1080/J.1440-1614.2005.01652.X

Wellcome Trust. (2020). *Wellcome Global Monitor 2020* [Dataset]. https://wellcome.org/reports/wellcome-global-monitor-mental-health/2020

Whiteford, H. A., Degenhardt, L., Rehm, J., Baxter, A. J., Ferrari, A. J., Erskine, H. E., Charlson, F. J., Norman, R. E., Flaxman, A. D., Johns, N., Burstein, R., Murray, C. J. L., & Vos, T. (2013). Global burden of disease attributable to mental and substance use disorders: Findings from the Global Burden of Disease Study 2010. *The Lancet*, *382*(9904), 1575–1586. https://doi.org/10.1016/S0140-6736(13)61611-6

World Bank. (2022). *World Bank Open Data* [Dataset]. https://data.worldbank.org/

Paper 2: What predicts the decline in mental health during mid-life? A Machine Learning analysis of the 1970 British Cohort Study

Authors: Christoph Henking and Aaron Reeves

Abstract

Background

Mental well-being generally follows a U-shaped pattern across the life course, with psychological distress worsening as people enter their forties. The reasons for this decline remain a puzzle. This study seeks to identify the social determinants that might be driving this phenomenon as well as assess the overall contribution of social determinants to mid-life mental health.

Methods

We use data from the 1970 British Cohort Study, from the ages 26, 34, and 42 (N=6992, 51.5% female). Mental distress was measured using the 9-score Malaise Inventory. We contrasted a group of those whose mental health declines with those exhibiting stable mental health. We combined Random Forest and logistic regression models to explore whether mental health decline is predicted by socio-economic and family predictors, as well as physical health and health behaviours (at ages 26, 34, or at birth).

Results

Social class at birth (VI=0.027) and income quintile at age 34 (VI=0.022) emerge as the most important predictors of the mental health decline in mid-life from our Random Forest analysis. Multivariate regression analyses confirmed that coming from a working class background (OR=1.51 [1.25–1.83]) and being in the highest-income quintile at age 34 (OR=0.68 [0.53–0.88]) are strong predictors of the mental health decline. People with an unfavourable combination of social determinants are almost three times more likely to experience a mental health decline

(0.277 vs 0.109). Crucially, however, coming from a working class background does not predict changes in mental health before mid-life.

Interpretation

Being born into a working class background and having low earnings at age 34 both strongly predict the mid-life decline in mental health. The contribution of social class appears specific to mid-life and suggests that disadvantage in early life has a lingering impact on mental which only manifests in mid-life.

1. Introduction

There is strong evidence that mental well-being declines for many people in the middle of their lives before increasing again towards older ages, producing a U-shaped pattern (Furnham & Cheng, 2015; Gondek, Bann, et al., 2021). While the reasons for this remain unclear (Blanchflower, 2021; Weiss et al., 2012), there are plausible biological and psychological explanations. A similar U-shaped pattern in well-being is observable in other primates suggesting this trend may be driven by the biological effects(Weiss et al., 2012). Psychological explanations suggest people experience more negative emotions and regret in mid-life and then become more content towards later adulthood (Brassen et al., 2012; Demiral et al., 2022).

Alongside these explanations, there might be social determinants of this mid-life decline (World Health Organization, 2010). We know that mental health is correlated with various dimensions of "socio-economic position", such as social class, gender, and occupational group, as well as "intermediary determinants" such as working conditions, family support and social relationships (Alegría et al., 2018; Blair & Siddiqi, 2022). These social determinants affect mental health throughout the life course by altering material circumstances, exposure to stress and health behaviours (Bambra, 2011; Mackenbach, 2012). Given their importance throughout the life course, could the distribution of social determinants of health help explain the "U-shape" pattern, and particularly the mid-life decline in mental well-being?

We argue that these social determinants may affect mental health decline because of effect heterogeneity which varies throughout the life course. In other words, the impact of particular social determinants may become stronger as people approach mid-life (Lang et al., 2011; Weiss et al., 2012). For example, individuals experiencing low income and financial hardship are more likely to experience a mid-life decline (Lang et al., 2011) as well as those with lower education (Gondek, Moltrecht, et al., 2021). It could be that income and education loom particularly large in this period as socio-economic situations become more fixed and upward social mobility

becomes less likely than in early adulthood (Gondek, Moltrecht, et al., 2021; Manzoni & Mooi-Reci, 2020). Therefore, health inequalities based on these socio-economics factors might widen and contribute to the mid-life decline. However, despite the potential importance of social determinants, most research focused on modelling the U-shape pattern in various contexts and merely treated factors like gender and socioeconomic status as control variables (Blanchflower, 2021; Ploubidis et al., 2017), rather than directly investigating how specific social determinants contribute to the mid-life decline. Therefore, the social drivers of mid-life decline and potential mechanisms of how they might affect mid-life mental health remain poorly understood.

In this study, we investigate the mid-life decline in mental health from a social determinants of health perspective. We aim to (1) describe the socio-economic characteristics of individuals who experience a mid-life decline in mental health, (2) identify which of the social determinants of mental health are the best predictors of the subsequent mid-life decline and (3) estimate the overall contribution of these predictors on the mid-life decline on the population level. To do so, this study will focus on health decline in mid-life which is typically observed between the ages of 30 and 45, which has been found to be the main period of increases in depressive symptoms in the 1958 and 1970 British Cohort Studies (Furnham & Cheng, 2015; Gondek, Bann, et al., 2021; Gondek et al., 2022; Ploubidis et al., 2017).

2. Methodology

Sample

The data for this prospective observational study is derived from the 1970 British Cohort Study (BCS 1970). The data is provided by the University College London and was downloaded from the UK data service platform (University College London, 2024). The BCS started with a representative sample of 17,196 individuals born in the UK in one week in 1970 (Elliott & Shepherd, 2006; Sullivan et al., 2023). Participants are the same age at every survey wave, with waves happening every four to eight years. Following previous research, we select the waves that

include the Malaise Inventory to measure psychological distress (ages 26, 34, and 42). Our primary focus is on the change in mental health between the ages of 34 and 42 where the mid-life increase in depressive symptoms occurs in the BCS 1970 cohort while the prevalence of mental health problems stabilises between the ages of 42 and 46 (Furnham & Cheng, 2015; Gondek, Bann, et al., 2021; Gondek et al., 2022). We therefore focus our analysis on the specific mental health decline between ages 34 and 42. We included all participants who provided a valid response to the mental health items at ages 34 and 42 (N=6992 participants; 51.5% female, 48.5% male).

Dependent variable

The dependent variable of the study is "decline in mental health". Firstly, to measure it, we started by assessing mental health using the short version of the Malaise Inventory, which was used at the ages of 26, 34 and 42 to measure psychological distress (Furnham & Cheng, 2015; Rodgers et al., 1999; Sullivan et al., 2023). The scale uses binary questions to test for different symptoms of psychological distress, forming a sum score for each individual from 0–9. Lower values on the scale indicate lower psychological distress, while values over 3 indicate high distress and risk of depression (Gondek et al., 2022; Torre et al., 2021). The Malaise Inventory has shown good validity compared to other scales and has been frequently used in similar studies concerning population mental health (Rodgers et al., 1999; Torre et al., 2021). Secondly, we defined the decline in mental health as an increase in psychological distress on the Malaise scale by at least two points (one standard deviation) between the ages of 34 to 42. All other individuals are included in the "stable mental health" group (see Table 3.1 and Table 3.2). Following this definition, 17.8% of individuals (*n* = 1247) were identified as decliners in mental health. To verify the robustness of results, we also include different definitions of mental health decline in our supplementary analysis (see Appendix Paper 2; section B1).

Predictors

Predictors in this study were selected from survey waves at birth, age 10, age 26 and 34 to be prognostic of the change in psychological distress from age 34 to 42. Some variables were only available at age 34 (see Table 3.1). Variable selection was based on the framework of the Social Determinants of Health by the World Health Organization (WHO) (World Health Organization, 2010). Here, the social determinants are grouped into *Socio-Economic Position* (social class, education, income, employment status, sex) and *Intermediary Determinants* (living and working conditions, family and behavioural factors). This also corresponds to similar public health research based on the WHO framework (Blair & Siddiqi, 2022; Yusuf et al., 2023).

As indicators of Socio-Economic Position, we used sex assigned at birth as well as Social Class at birth. Social class at birth was measured through the father's occupation following the Register General's classification (Gondek et al., 2022) with a categorisation as "low" (IV partly skilled/V unskilled), "medium" (III skilled nonmanual/manual), and "high" (I professional/II intermediate). Education at age 34 was categorised into "high" (university/higher education), "medium" (completing A-levels), and "low" (GCSE and below). Self-reported income is the total take-home pay in British Pounds and is categorised into 1=lowest; 5=highest income quintiles. Employment status was categorised into "full-time", "part-time", "unemployed", "looking after home/family", and "sickness/disability". We could not include a substantive indicator of ethnic group due to the low diversity in terms of ethnic background in the BCS 1970 (94.2% British white participants and 96.2% white overall (Elliott & Shepherd, 2006)).

As Intermediary Social Determinants, working conditions were measured as job insecurity, low job satisfaction and working multiple jobs to make ends meet (Demiral et al., 2022; Henseke, 2018). Marital status and number of children were included as family factors. Behavioural factors included exercise and smoking (while dangerous alcohol consumption was not measured).

Furthermore, we also included a measure of physical multimorbidity (having at least 2 medical conditions) as it was shown to be strongly associated with psychological distress (Torre et al., 2021) and cognitive ability in childhood (age 10) which is a relevant covariate for developments throughout the life course (see section A1 in Appendix paper 2).

Statistical analysis

Our research involves exploratory analyses based on a variety of predictors, followed by confirmatory analyses to establish effect sizes. For the purpose of exploration based on many variables, we combine the machine learning (ML) algorithm of Random Forest (RF) for variable selection with established regression methods which provide effect estimation and confidence intervals (Fife & D'Onofrio, 2023). This combination of different analysis methods helps overcome issues of regression models with a large number of variables such as multicollinearity and overfitting and provides an in-built triangulation of our findings throughout statistical approaches (Wiemken & Kelley, 2020).

In the first step (description), the dataset is split into two analysis groups (stable vs. decline in mental health), and the distribution of the social determinants at age 34 and 26 in both groups is compared using simple t-tests. In the second step (variable selection), the goal is to identify the most predictive variables of being in the group of mental health decline. We use a Random Forest algorithm which is well suited for exploratory analyses with a high number of potential explanatory factors and addressing multicollinearity issues (Wiemken & Kelley, 2020). This technique was used in previous analyses of predicting self-reported health based on several social and genetic determinants (Hoekstra et al., 2023). We use the R package "party" and its function "cforest" which produces an ensemble of 1000 prediction trees, tailored to handle different variable types and inter-correlated predictors (Fife & D'Onofrio, 2023). This algorithm calculates the Variable Importance (VI; Root Mean Squared Error (MSE)) for each predictor that indicates which one is the most essential for accurately forecasting mental health outcomes (predicted

probability between 0 and 1 for each participant to experience a decline in mental health) across the 1000 computations. We also used LASSO regression as an alternative ML approach which verifies our findings (Figure S1 in Appendix paper 2).

In the third step (estimation of effect sizes), we select the twelve predictors with the highest Variable Importance in step 2. For each of these variables, we construct logistic regression models with a theoretically appropriate set of control variables to reveal effect sizes as Odds Ratios and predicted probabilities of mental health decline depending on each identified predictor and all predictors combined (see section A3 in Appendix paper 2 for details on covariate selection). Finally, we calculate the same estimates for the age shift in mental health from 26–34 to analyse if the identified predictors of decline are specific to the age period of 34–42 or are also associated with changes in the previous age period.

All participants who provided a valid answer to the question on mental distress at ages 34 and 42 are included in our analyses (N= 6992) and we impute missing data on all other covariates using the R package RandomForest. Details on our handling of missing values can be found in Appendix paper 2 (section B3).

Table 3.1. Descriptive statistics by survey wave (before imputation of missing values).

General sample characteristics				
Social class at birth	High	1406 (21.6%)		
	Medium	3860 (59.3%)		
	Low	1246 (19.1%)		
Cognitive ability age 10	mean (sd)	16.42 (5.16)		
Sex	Male	3232 (46.2%)		
	Female	3760 (53.8%)		
Variables in adulthood		**Age 26**	**Age 34**	**Age 42**
Psychological distress	Mean Malaise score (SD)	1.7 (1.7)	1.6 (1.9)	1.8 (2)
Education	University degree	n.a.	2516 (36.0%)	
	Completed A-levels		674 (9.6%)	
	GCSE and below		3797 (54.3%)	
Income as the total take-home pay in British Pounds (monthly)	Mean (sd)	1,774 (4,739)	2,109 (10,036)	
	Working parttime	400 (7.6%)	1121 (16.0%)	
	Unemployed	162 (3.1%)	116 (1.7%)	
	Having a disability	70 (1.3%)	140 (2.0%)	
	Looking after home/family	509 (9.7%)	689 (9.9%)	
Job security	High	n.a.	5460 (78.3%)	
	Low		411 (5.9%)	
	Not applicable		1104 (15.8%)	
Job satisfaction	High	n.a.	4745 (67.9%)	
	Medium		644 (9.2%)	
	Low		499 (7.1%)	
	Not applicable		1104 (15.8%)	
Working multiple jobs	Yes	n.a.	5514 (93.6%)	
	No		374 (6.4%)	
Marital status	Married	1678 (32.3%)	3909 (55.9%)	
	Divorced	106 (2.0%)	238 (3.4%)	
	Never married	3418 (65.7%)	2833 (40.5%)	
	Widowed	1 (0.0%)	9 (0.1%)	
Number of children	1 child	n.a.	1571 (22.5%)	
	2-3 children		2481 (35.6%)	
	four or more children		115 (1.6%)	
	No children		2811 (40.3%)	
Physical multimorbidity	Yes	1086 (20.6%)		
	No	4180 (79.4%)		
Regular exercise	Yes	n.a.	5587 (79.9%)	
	No		1405 (20.1%)	
Weekly smoking	Yes	1812 (34.8%)	4945 (70.7%)	
	No	3398 (65.2%)	2046 (29.3%)	

3. Results

In line with previous research, psychological distress increased from age 34 (M= 1.67, SD=1.9 on the 9-point Malaise Inventory) to 42 (M = 1.86; SD=2.0) with t-tests revealing a significant difference between these values ($p < 0.001$), while there is no further increase to the age of 46 (M= 1.77). Descriptive statistics on all variables are shown in Table 3.1. The variables are shown for the different waves 26 and 34. For the age of 42, only the variable "psychological distress" is shown as we only included predictor variables up to the age of 34.

Characteristics of decline vs. stable groups (step 1)

First, we divided the sample into those who experienced a decline in mental health (i.e., an increase in psychological distress) and explored group differences based on the different social determinants of health. Table 3.2 reveals the results for the predictors at age 34 (for age 26, results are shown in Table S1, Appendix paper 2). T-tests reveal that the group of declining mental health consists of significantly more individuals from low social class backgrounds compared to the stable group (23.5% vs. 17.8%; $t = 4.23$; $p< 0.01$). It also contains fewer individuals with high income at age 34 (11.4% vs 15.6%; $t = 4.07$; $p< 0.01$), more unemployed people (2.4% vs. 1.5%; $t = 1.97$; $p = 0.049$) and taking care of home/family (12.0 vs 9.4%; $t= 2.56$; $p = 0.01$). Those who decline in mental health are also less frequently reported regular exercise (77.1% vs. 80.5%; $t= 2.66$; $p< 0.01$).

Table 3.2. Description of the groups of stable mental health and mental health decline

Social determinants (all at age 34)	Share in group of **stable mental health**	Share in group of **mental health decline**	Difference	p-value (t-test)
Sex: female	53.4%	55.5%	2.1%	0.179
Social class				
Low birth social class	**17.8%**	**23.5%**	**5.7%**	**0.000***
High birth social class	21.9%	20.1%	-1.8%	0.173
Education				
University education	36.5%	33.6%	-2.9%	0.051
Income and employment				
Income quintile 5 (highest)	**15.6%**	**11.4%**	**-4.2%**	**0.000***
Income quintile 1 (lowest)	13.3%	15.0%	1.7%	0.129
Working full-time				
Working part-time	16.2%	15.5%	-0.7%	0.557
Unemployed	**1.5%**	**2.4%**	**0.9%**	**0.049***
Having a disability	2.1%	1.8%	-0.3%	0.489
Looking after home/family	**9.4%**	**12.0%**	**2.6%**	**0.010***
Working conditions				
High job security	93.1%	92.4%	-0.7%	0.445
High job satisfaction	80.6%	80.5%	-0.1%	0.922
Working multiple jobs	6.3%	6.7%	0.5%	0.588
Family factors				
Having children	59.4%	60.4%	1.0%	0.531
Being divorced	3.4%	3.4%	0.1%	0.927
Being married	56.4%	54.0%	-2.4%	0.125
Physical and behavioural factors				
Physical multimorbidity	7.9%	9.3%	1.4%	0.128
Regular exercise	**80.5%**	**77.1%**	**-3.5%**	**0.008***
Weekly smoking	29.0%	30.7%	1.8%	0.220

Notes: Decline in mental health is defined as an increase in psychological distress on the Malaise scale by at least two points (=1 Standard Deviation) from the age of 34 to 42; all other individuals are included in the "stable mental health" group.

Identifying main predictors of mid-life decline (step 2)

Next, a Random Forest algorithm was used to identify which social determinants are the best predictors of decline in mid-life mental health. The result of this algorithm is shown in Figure 3.1 as a Variable Importance plot. The Random Forest's Variable Importance (VI; Root Mean Squared Error (MSE)) shows which variables were the most important for the algorithm to

improve prediction accuracy. Besides the "baseline value" of psychological distress score at age 34 (strongest predictor for the mental health decline; VI = 0.047), the five strongest predictors were social class at birth (VI = 0.027), income quintile at age 34 (VI = 0.027), job security (VI = 0.021) and job satisfaction (VI = 0.018). Income at age 26, education, sex and physical morbidity, marital status, cognitive ability as well as employment status (working part-time and taking care of home) are also included in the twelve main predictors. This indicates that a broad distribution of social determinants is associated with mid-life mental health changes.

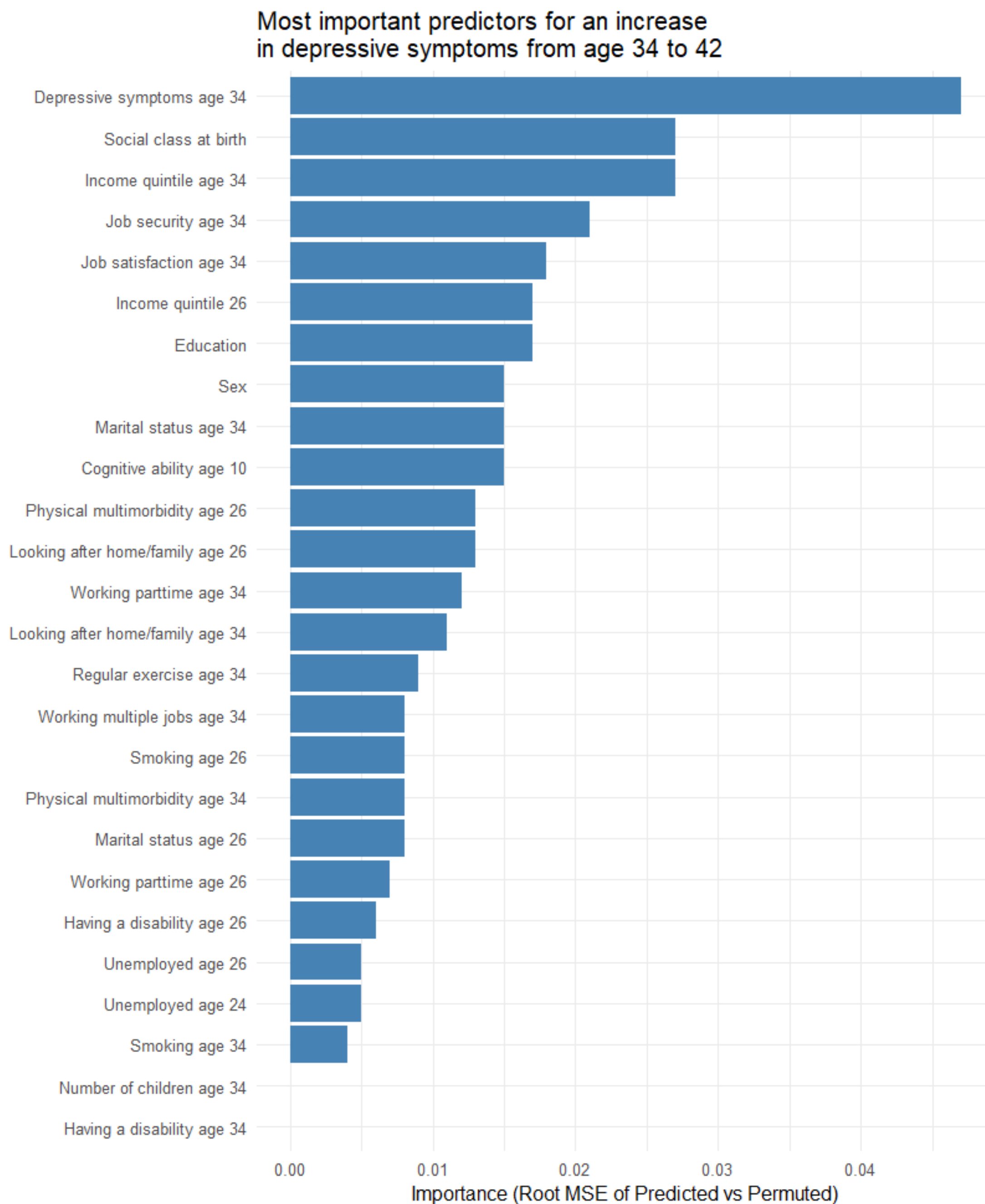


Figure 3.1. Variable importance (mean decrease in accuracy when permuted) based on Random Forest to predict the mid-life decline in mental health.

Overall contribution of social determinants (step 3)

We selected the twelve most important predictors identified by the Random Forest model (beyond depressive symptoms at age 34) and used logistic regression models to determine the estimate of effect sizes and population contribution of the social determinants. If a predictor was chosen at both ages 26 and 34, we used the stronger one with higher Variable Importance in our

regression model. For each of the models, we select relevant covariates as outlined in Appendix paper 2 (section A4). As shown in Table 3.3 (model M1), being born into a low social class family is associated with an increased probability of an increase in psychological distress (OR = 1.51, CI:[1.25 – 1.83]) while being male is linked to a lower probability (OR = 0.87, CI:[0.87 – 0.98]). Being in the highest income quintile at age 34 (see M3) is associated with a lower probability (OR = 0.68, CI:[0.53 – 0.88]). Education (M2), employment (M4) and working conditions (M5; job security and satisfaction) are associated in the expected direction but are not statistically significant (e.g., association of high job security with probability of mental health decline is OR = 0.90, CI:[0.69 – 1.18]). As for family factors (M6), neither being married (OR = 0.94, CI:[0.67 – 1.34]) nor the number of children is significantly associated with experiencing a mental health decline. Finally, having physical multimorbidity at age 26 (M7) is associated with a significantly increased probability of mental health decline (OR = 1.25, CI:[1.06 – 1.48]). Overall, social class at birth, sex, income at age 34 and physical multimorbidity at age 26 were identified as significant predictors of the mid-life mental health decline.

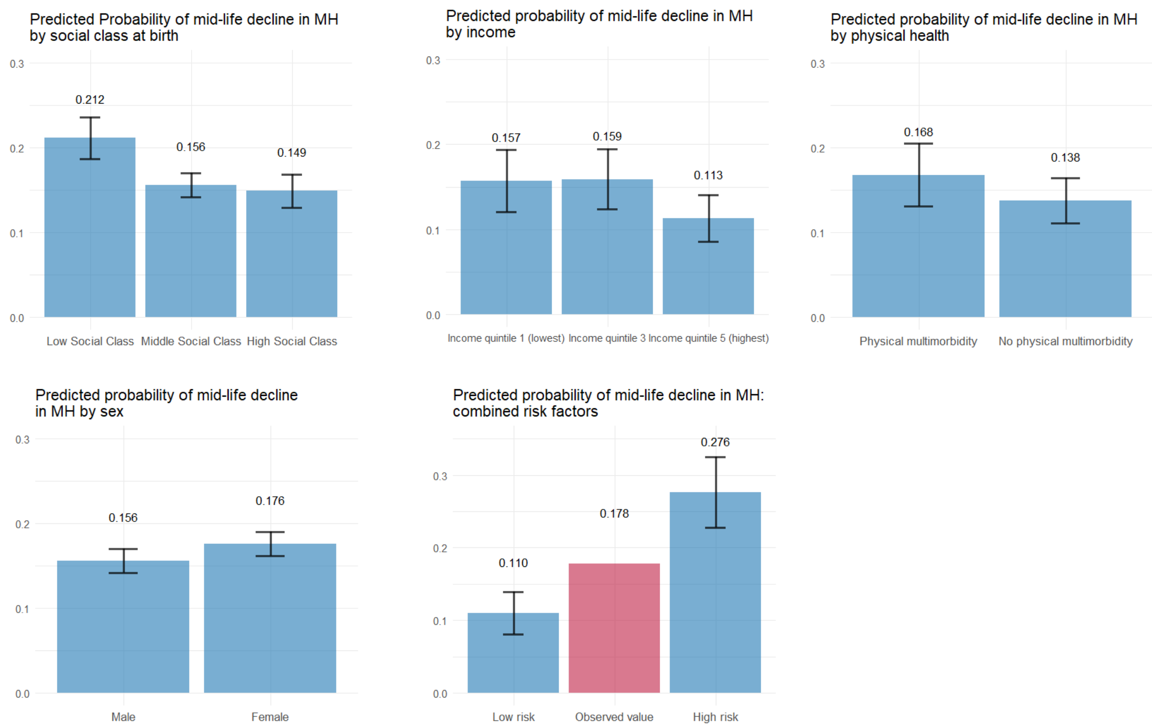
Table 3.3. Logistic regression; outcome: the likelihood of experiencing a mid-life decline in mental health from age 34 to 42 (Odds Ratios)

	M1 Social class	M2 Education	M3 Income	M4 Employment status	M5 Work conditions	M6 Family factors	M7 Physical health
Social class							
Low social class at birth: (ref=high)	**1.53**** [1.27–1.85]	**1.42**** [1.16–1.73]	**1.40**** [1.15–1.72]	**1.40**** [1.15–1.71]	**1.38**** [1.13–1.69]	**1.41**** [1.16–1.73]	**1.42**** [1.16–1.74]
Medium social class at birth: (ref=high)	1.09 [0.93–1.28]	1.04 [0.88–1.23]	1.04 [0.88–1.23]	1.04 [0.88–1.23]	1.03 [0.88–1.22]	1.04 [0.88–1.23]	1.04 [0.88–1.23]
Income and employment							
Income quintile 2 (ref= q1)			0.87 [0.69 – 1.10]	0.88 [0.69 – 1.10]	0.87 [0.69 – 1.10]		
Income quintile 3 (ref= q1)			1.02 [0.81 – 1.27]	1.01 [0.81 – 1.27]	1.01 [0.81 – 1.27]		
Income quintile 4 (ref= q1)			**0.77*** [0.60 – 0.98]	**0.77*** [0.60 – 0.97]	**0.76*** [0.60 – 0.97]		
Income quintile 5 (ref= q1)			**0.68**** [0.53 – 0.88]	**0.67**** [0.52 – 0.87]	**0.67**** [0.52 – 0.87]		
Looking after home/family (ref= all other)				1.15 [0.90 – 1.47]			
Working parttime				0.87 [0.70 – 1.08]			
Working conditions							
Job satisfaction high (ref = low)					0.83 [0.65 – 1.07]		
Job security high (ref = low)					0.90 [0.69 – 1.18]		
Family factors							
Being married at age 34 (ref= unmarried)						0.94 [0.67 – 1.34]	
Having no children aged 34 (ref=1 child)						0.91 [0.77 – 1.08]	
Having 2-3 children (ref=1 child)						0.94 [0.80 – 1.11]	
Having four or more children						0.93 [0.55 – 1.51]	
Behavioural factors and physical health							
Having physical multimorbidity aged 26 (ref = no)							**1.26**** [1.06–1.49]
Covariates							
Mental health age 34	**0.88**** [0.85–0.92]	**0.88*** [0.85–0.91]	**0.87**** [0.83–0.91]	**0.87**** [0.84–0.91]	**0.87**** [0.83–0.90]	**0.88**** [0.84–0.91]	**0.87**** [0.84–0.91]
Sex (being male)	**0.87*** [0.77–0.98]	**0.86*** [0.76–0.97]	0.92 [0.81–1.05]	0.90 [0.78–1.05]	0.95 [0.83–1.09]	**0.86*** [0.75–0.97]	**0.88*** [0.77–0.99]
University education aged 34 (ref= low education)		0.90 [0.78–1.05]	0.99 [0.85–1.16]	1.00 [0.85–1.16]	0.99 [0.85–1.16]	0.91 [0.78–1.05]	0.91 [0.78–1.05]
Cognitive ability aged 10		0.99 [0.98–1.00]	0.98 [0.97–1.01]	0.99 [0.98–1.01]	0.99 [0.98–1.01]	0.99 [0.98–1.00]	0.99 [0.97–1.00]

Notes: *p < 0.05; ** p < 0.01. N = 6,992 for all analyses.

Based on these four significant predictors and models (M1: social class and sex, M3: income, M7: physical multimorbidity), we calculate the predicted probability of a mental health decline for three scenarios each: one with the most positive level of the risk factor (e.g., income quintile = 5), one with the most adverse level (e.g., income quintile = 1) and one with the mean in the population. All other control variables in the model were set to the mean in the population. Additionally, we include one "combined model" where all or no risk factors are assumed. Figure 3.2 shows the results.

Social determinants of mid-life mental health decline (age 34 – 42)



Social determinants of mental health decline between ages 26 - 34

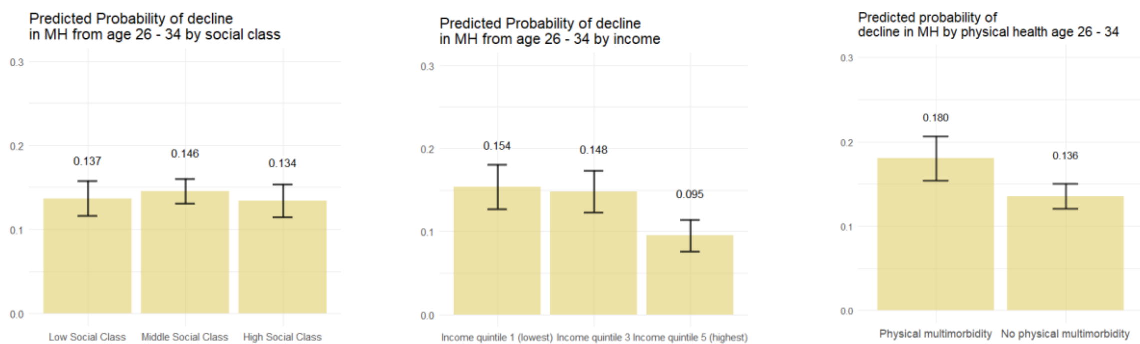


Figure 3.2. Predicted probabilities based on the logistic regression models shown in Table 3.3

For low social class at birth (top left in Table 3.3), the predicted probability of mid-life mental health decline is 0.212 (CI:[0.187 – 0.236]), but 0.156 (CI:[0.142 – 0.171]) for medium social class and 0.149 (CI:[0.129 – 0.168]) for high social class. For income, being in quintiles 1 and 3 have similar probabilities (0.159 CI:[0.124–0.194] for quintile 3), but being in the income quintile 5 at age 34 is associated with a lower probability of 0.113 (CI:[0.085 – 0.141]). The "all risk factors

combined" analysis reveals that a favourable value of all risk factors (i.e., high social class, income quintile 5, being male and not having physical multimorbidity) has a predicted probability of mental health decline of 0.11(CI:[0.081 – 0.139]), whereas an adverse value all risk factors has a decline probability of 0.28 (CI:[0.227 – 0.324]) – compared to the 17.8% decline risk observed in our sample.

Finally, we explored whether the identified variables are also predictive of changes in mental health in the earlier life period. This allows us to examine whether the identified predictors are unique to the changes during mid-life or are also relevant during the earlier life period. Therefore, we perform equivalent logistic regression analyses and predicted probabilities for social class, income and physical multimorbidity on the decline in mental health from the ages of 26 – 34. The predicted probabilities are shown in the lower part of Figure 3.2. The results show that income and physical health at age 26 are predictive of decline age 26 – 34 as they are for the 34 – 42 period. This suggests that, consistent with other work, that compositional effects may partly explain the decline in mental health during mid-life. However, the association with social class at birth is different. Being born into a low social class does not predict a mental health decline from age 26-34 (low social class predicted prob. = 0.137; CI:[0.116 – 0.158]; medium social class = 0.146 CI:[0.131 – 0.16]; high social class = 0.134; CI:[0.114 – 0.154]), which indicates that the effect of social class on mental health varies as people approach mid-life. The full regression analysis (equivalent to Table 3.3) can be found in Table S2 in Appendix paper 2.

4. Discussion

Our study investigated the contribution of the social determinants of health to the mid-life decline in mental health. We find that social class at birth, income, physical multimorbidity and sex are the strongest predictors of the mental health decline, and thereby induce social inequalities in mental health during this life stage. Taken together, these social determinants could reduce the risk of mental health decline from 18% (observed) to 11%, and up to 28% if

risk constellation changes in the population. We identify social class at birth as one potentially pivotal factor, which is strongly associated with mental health as people approach mid-life but is not associated with mental health changes in the previous life stage. Notably, these findings are focussed on developments in psychological distress at the population level, as commonly associated with common mental health problems (e.g., anxiety or depression symptomology), rather than on severe and medically diagnosed mental health conditions for which different psychological measures would need to be used.

Our findings confirm income as one of the most crucial determinants of health as it both signals social status and directly enables access to resources (Gondek et al., 2022; Lang et al., 2011). Our research is also in line with findings that women have a higher risk for a mental health decline in mid-life and the bidirectional relationship between physical health and mental health (Gondek et al., 2022; Torre et al., 2021). However, while working conditions (such as job security and satisfaction) were predictors of mental health decline in our machine learning model, they did not remain relevant when controlling for income and other confounders. Similarly, family factors such as marital status or having children at age 34 did not determine who experiences a mid-life decline in the following years. Hence, the majority of identified social determinants (social class at birth, gender, income quintile) are not novel to mid-life and remain relatively stable over the observed period. On the other hand, many factors associated with frequent life events in mid-life (e.g., getting married, having children, working part-time) did not appear to drive the change in population or inequalities in the mid-life decline. Together, these results suggest that *effect heterogeneity* is critical for understanding mid-life decline. In this view, certain pre-existing life circumstances start to have a stronger impact on mental health during mid-life and it does not seem to be the case that this decline is driven by specific life events becoming more common (Lang et al., 2011). This could particularly be the case for social class at birth which was identified as a latent risk factor and which has a distinct relationship with mental health in the

age period between 34 and 42, (but not the previous age period between 26–34) (Gondek, Moltrecht, et al., 2021; Manzoni & Mooi-Reci, 2020).

This raises another question: what is it about social class origins that start to affect people in mid-life? One explanation could that the opportunity for upward social mobility starts to close as you approach mid-life. When growing up in conditions of socio-economic disadvantage, early adulthood can – albeit too infrequently – offer chances for upward social mobility. But these opportunities diminish over time as it becomes harder to get the training or make other choices which might enable to change their economic circumstances (Elman, 2011). These changing circumstances could have negative consequences for mental health for those who were not upwardly mobile. This is in line with evidence suggesting that moving out of hardship later in life (compared to early adulthood) is more difficult and does not entail the same health benefits (Willson & Shuey, 2016) (McLoughlin et al., 2023). Another explanation speaks to an increased exposure to social stressors in mid-life of those growing up in a lower social class. That is, the cohort's members' parents coming from poorer backgrounds, are less likely to be in good health. Thus, they might require more support – both financially and in terms of care responsibilities – in addition to caring for their own children with less disposable income (Stewart, 2012). Furthermore, families are unlikely to possess various forms of financial capital in terms of housing or inheritance, which is likely to become apparent in the mid-life stages. The combination of such additional demands could induce or reduce protection from psychological distress in the mid-life period. Notably, this explanation would speak for a combination of effect heterogeneity mechanisms through an increased concentration of stressors in mid-life.

Several limitations need to be noted. First, our study sample lacks ethnic diversity and associated social determinants of health (World Health Organization, 2010). Our findings need to be verified for a more ethnically diverse population as well as different birth cohorts and countries. Second, we only include social determinants until age 34 to be prognostic of the subsequent

change in mid-life and avoid reversed causality issues. Therefore, we do not investigate direct changes between the ages 34 and 42, which would be needed in future research to further test different theoretical assumptions (e.g., heterogeneity vs. life events perspectives). Third, each statistical method used (e.g., Random Forest and logistic regressions) entails their own weaknesses (e.g., Random Forests have been criticised due to the lack of transparency in its algorithm). We attempted to use our methods in a complementary way to compensate for each other's weaknesses (Fife & D'Onofrio, 2023; Wiemken & Kelley, 2020).

Acknowledgements

We thank Dr Dawid Gondek for sharing his great expertise in this field of research, brainstorming research questions and for sharing the idea to use data-driven methods to predict whose mental health is likely to decline in their 30s and 40s, and whose is not.

Conflict of interest

All authors declare no conflict of interest.

References

Alegría, M., NeMoyer, A., Bagué, I. F., Wang, Y., & Alvarez, K. (2018). Social Determinants of Mental Health: Where We Are and Where We Need to Go. *Current Psychiatry Reports 2018 20:11*, *20*(11), 1–13. https://doi.org/10.1007/S11920-018-0969-9

Bambra, C. (2011). Health inequalities and welfare state regimes: Theoretical insights on a public health 'puzzle'. *Journal of Epidemiology & Community Health*, *65*(9), 740–745. https://doi.org/10.1136/JECH.2011.136333

Blair, A., & Siddiqi, A. (2022). The social determinants of substance use associated with deaths of despair: Individual risks and population impacts. *Preventive Medicine*, *164*, 107327. https://doi.org/10.1016/j.ypmed.2022.107327

Blanchflower, D. G. (2021). Is happiness U-shaped everywhere? Age and subjective well-being in 145 countries. *Journal of Population Economics*, *34*(2), 575–624. https://doi.org/10.1007/S00148-020-00797-Z/FIGURES/15

Brassen, S., Gamer, M., Peters, J., Gluth, S., & Büchel, C. (2012). Don't look back in anger! Responsiveness to missed chances in successful and nonsuccessful aging. *Science*, *336*(6081), 612–614. DOI: 10.1126/science.1217516

Demiral, Y., Ihle, T., Rose, U., Conway, P. M., & Burr, H. (2022). Precarious Work as Risk Factor for 5-Year Increase in Depressive Symptoms. *International Journal of Environmental Research and Public Health, 19*(6), 3175. https://doi.org/10.3390/IJERPH19063175

Elliott, J., & Shepherd, P. (2006). Cohort profile: 1970 British birth cohort (BCS70). *International Journal of Epidemiology*, *35*(4), 836–843. https://doi.org/10.1093/ije/dyl174

Elman, C. (2011). The Midlife Years: Human Capital and Job Mobility. In R. A. Settersten & J. L. Angel (Eds.), *Handbook of Sociology of Aging* (pp. 245–261). Springer New York. https://doi.org/10.1007/978-1-4419-7374-0_16

Fife, D. A., & D'Onofrio, J. (2023). Common, uncommon, and novel applications of random forest in psychological research. *Behavior Research Methods*, *55*(5), 2447–2466. https://doi.org/10.3758/s13428-022-01901-9

Furnham, A., & Cheng, H. (2015). The stability and change of malaise scores over 27 years: Findings from a nationally representative sample. *Personality and Individual Differences*, *79*, 30–34. https://doi.org/10.1016/j.paid.2015.01.027

Gondek, D., Bann, D., Patalay, P., Goodman, A., McElroy, E., Richards, M., & Ploubidis, G. B. (2021). Psychological distress from early adulthood to early old age: Evidence from the 1946, 1958 and 1970 British birth cohorts. *Psychological Medicine, 52(8), 1471-1480.* https://doi.org/10.1017/S003329172000327X

Gondek, D., Lacey, R. E., Blanchflower, D. G., & Patalay, P. (2022). How is the distribution of psychological distress changing over time? Who is driving these changes? Analysis of the 1958 and 1970 British birth cohorts. *Social Psychiatry and Psychiatric Epidemiology*, *57*(5), 1007–1016. https://doi.org/10.1007/S00127-021-02206-6/FIGURES/4

Gondek, D., Moltrecht, B., & Ploubidis, G. (2021). Mental health crisis in midlife – a proposed research agenda. *Research Ideas and Outcomes*, *7*. https://doi.org/10.3897/RIO.7.E62024

Henseke, G. (2018). Good jobs, good pay, better health? The effects of job quality on health among older European workers. *The European Journal of Health Economics*, *19*(1), 59–73. https://doi.org/10.1007/s10198-017-0867-9

Hoekstra, J., Lenssen, E. S., Wong, A., Loef, B., Herber, G.-C. M., Boshuizen, H. C., Strak, M., Verschuren, W. M., & Janssen, N. A. (2023). Predicting self-perceived general health status using machine learning: An external exposome study. *BMC Public Health*, *23*(1), 1027. https://doi.org/10.1186/s12889-023-15962-8

Lang, I., Llewellyn, D., Hubbard, R., Langa, K., & Melzer, D. (2011). Income and the midlife peak in common mental disorder prevalence. *Psychological Medicine*, *41*(7), 1365–1372. DOI: https://doi.org/10.1017/S0033291710002060

Mackenbach, J. P. (2012). The persistence of health inequalities in modern welfare states: The explanation of a paradox. *Social Science & Medicine*, *75*(4), 761–769. https://doi.org/10.1016/J.SOCSCIMED.2012.02.031

Manzoni, A., & Mooi-Reci, I. (2020). The cumulative disadvantage of unemployment: Longitudinal evidence across gender and age at first unemployment in Germany. *PloS One*, *15*(6), e0234786. https://doi.org/10.1371/journal.pone.0234786

McLoughlin, S., Präg, P., Bartley, M., Kenny, R. A., & McCrory, C. (2023). Intergenerational social mobility and allostatic load in midlife and older ages: A diagonal reference modeling approach. *The Journals of Gerontology: Series B*, *78*(1), 154–166. https://doi.org/10.1093/geronb/gbac122

Parsons, S. (2014). Childhood cognition in the 1970 British cohort study. *CLS Data Note*.

Ploubidis, G. B., Sullivan, A., Brown, M., & Goodman, A. (2017). Psychological distress in mid-life: Evidence from the 1958 and 1970 British birth cohorts. *Psychological Medicine*, *47*(2), 291–303. https://doi.org/10.1017/S0033291716002464

Rodgers, B., Pickles, A., Power, C., Collishaw, S., & Maughan, B. (1999). Validity of the Malaise Inventory in general population samples. *Social Psychiatry and Psychiatric Epidemiology*, *34*, 333–341. https://doi.org/10.1007/s001270050153

Stewart, L. M. (2012). Family Care Responsibilities and Employment. *Http://Dx.Doi.Org/10.1177/0192513X12437708*, *34*(1), 113–138. https://doi.org/10.1177/0192513X12437708

Sullivan, A., Brown, M., Hamer, M., & Ploubidis, G. B. (2023). Cohort profile update: The 1970 British cohort study (BCS70). *International Journal of Epidemiology*, *52*(3), e179. https://doi.org/10.1093/ije/dyac148

Torre, J. A. la, Ronaldson, A., Prina, M., Matcham, F., Hatch, S. L., Pickles, A., Hotopf, M., Dregan, A., London, S., Nhs, M., Torre, J. A. la, Ronaldson, A., Prina, M., Matcham, F., Pereira, S. M. P., Hatch, S. L., Armstrong, D., Pickles, A., Hotopf, M., & Dregan, A. (2021). *Depressive symptoms during early adulthood and the development of physical multimorbidity in the UK: an observational cohort study*. https://doi.org/10.1016/S2666-7568(21)00259-2

University College London, UCL Social Research Institute, Centre for Longitudinal Studies. (2024). *1970 British Cohort Study*. [data series]. *11th Release.* UK Data Service. SN: 200001, DOI: http://doi.org/10.5255/UKDA-Series-200001

Weiss, A., King, J. E., Inoue-Murayama, M., Matsuzawa, T., & Oswald, A. J. (2012). Evidence for a midlife crisis in great apes consistent with the U-shape in human well-being. *Proceedings of the National Academy of Sciences*, *109*(49), 19949–19952. https://doi.org/10.1073/pnas.1212592109

Wiemken, T. L., & Kelley, R. R. (2020). Machine learning in epidemiology and health outcomes research. *Annu Rev Public Health*, *41*(1), 21–36. https://doi.org/10.1146/annurev-publhealth-040119-094437

Willson, A. E., & Shuey, K. M. (2016). Life course pathways of economic hardship and mobility and midlife trajectories of health. *Journal of Health and Social Behavior*, *57*(3), 407–422. https://doi.org/10.1177/0022146516660345

World Health Organization. (2010). *A conceptual framework for action on the social determinants of health*. WHO IRIS. https://iris.who.int/handle/10665/44489

Yusuf, F. M., San Sebastián, M., & Vaezghasemi, M. (2023). Explaining gender inequalities in overweight people: A Blinder-Oaxaca decomposition analysis in northern Sweden. *International Journal for Equity in Health*, *22*(1), 159. https://doi.org/10.1186/s12939-023-01973-9

Paper 3: Benefit conditionality, sanctions and the self-rated health of the unemployed: a longitudinal analysis of European countries

Authors: Christoph Henking and Aaron Reeves

Abstract

Background

The health effects of unemployment vary across European countries. One explanation lies in differences in the generosity of unemployment insurance across countries. However, generosity alone is not the only aspect of social security policy that varies across countries: behavioural conditionality – pertaining to job-search requirements, availability criteria, and sanctions – also differs between countries and may impact the health effects of job loss. In this paper, we examine whether differences in these dimensions explain cross-national variation in the health consequences of unemployment – and which of these aspects of behavioural conditionality matter most.

Methods

We combined longitudinal panel data from the European Union Statistics on Income and Living Conditions (EU-SILC, 2014 – 2019) with OECD indicators on activation policy strictness in 30 countries (898,598 observations in total; n = 4992 per country and year). Using first-difference regression models with country-level clustering, we estimated the effect of becoming unemployed on changes in self-rated health (measured on a 5-point scale) and tested whether this effect was moderated by the strictness of each policy dimension. Models controlled for individual-level characteristics and macroeconomic variables, including GDP, unemployment rate, and benefit generosity.

Results

Across Europe, becoming unemployed had a small but significant association with self-rated health (−0.05, 95% CI[−0.06, −0.04]). This association varied depending on the strictness of the sanction regime (Interaction effect = −0.04 [−0.09, −0.004]), with the predicted decline in self-rated health ranging from −0.053 [−0.098, −0.017] in low-sanction countries (e.g., Hungary, Cyprus) to −0.105 [−0.135, −0.078] in countries with higher sanctions (e.g., Croatia, Poland). Job-search and availability requirements did not significantly moderate this association.

Interpretation

Our findings indicate that stricter sanction rules are associated with worse self-rated health among job seekers. Reducing reliance on sanctions and ensuring adequate income support and accessible, high-quality employment services could protect job seekers' health and support their labour market outcomes.

1. Introduction

Unemployment is detrimental to mental and physical health, but the extent of its impact varies considerably across country contexts (Murphy & Athanasou, 1999; Picchio & Ubaldi, 2024; Tøge & Blekesaune, 2015). Part of this variation in the relationship between experiencing unemployment and health outcomes seems to be connected to cross-national differences in unemployment benefit generosity and public spending on labour market programmes (Huijts et al., 2015; Tøge, 2016b; Voßemer et al., 2018). However, generosity is not the only aspect of social security policy that can vary across countries: behavioural benefit conditionality – specifically the behavioural demands and sanctions tied to unemployment support – varies greatly and this may influence the health effects of job loss. We hypothesise that the strictness of behavioural conditionality (job-search and job availability requirements) and sanction rules (financial penalties for non-compliance) in a country's unemployment system moderates the impact of job loss on individuals' health (Immervoll & Knotz, 2018; Knotz, 2020). Using panel data from the European Union Statistics on Income and Living Conditions (EU-SILC) for 30 countries (2014 – 2019) combined with OECD country-level indicators of activation policy strictness, we estimate within-person models to assess changes in health following unemployment entry under varying policy conditions. We find that the strictness of sanction rules is associated with the change in health during job loss: in countries with stricter sanction rules, the negative effect of unemployment on self-rated health is more pronounced. By contrast, other forms of behavioural conditionality, such as job-search and availability requirements, did not yield statistically significant moderation effects. These results highlight the need to better understand how punitive elements of unemployment systems may exacerbate the health consequences of job loss across different types of welfare states.

Unemployment and health

The negative consequences of unemployment on health are widely documented. A large body of research demonstrates that unemployment adversely affects multiple dimensions of health and well-being, such as depression and anxiety, self-perceived health and mortality (Picchio & Ubaldi, 2024). These adverse effects are more pronounced among men, younger workers and older adults, and tend to become stronger during periods of long-term unemployment (Paul et al., 2018; Picchio & Ubaldi, 2024). Moreover, unemployment can have a "scarring effect" on health, where health and well-being do not return to the same levels after re-employment (Knabe & Rätzel, 2011). While there is some debate about the possibility of reverse causality driving these associations (i.e., poor health increasing the risk of job loss), longitudinal evidence suggests a bi-directional and mutually reinforcing relationship between unemployment and health (Chandola & Zhang, 2018; Gedikli et al., 2023; Schmitz, 2011).

Two dominant theories are often used to explain the health effects of unemployment: psycho-social and material perspectives. The psycho-social perspective stems from Jahoda's "latent deprivation theory", which holds that unemployment causes the deprivation of five central latent functions to well-being, namely: time structure, social contact, collective purpose, status and activity (Bambra & Eikemo, 2018; Jahoda, 1982). This deprivation, in turn, leads to social isolation, stigmatisation and psychological distress that causes health to deteriorate (Bambra & Eikemo, 2018; Selenko et al., 2011). The material perspective posits that health is primarily harmed by the loss of income and reduced access to material resources and services (Paul et al., 2018). The material loss is accompanied by a reduction of control over one's life and self-esteem (Bambra & Eikemo, 2018; Fryer, 1986).

While the negative effects of job loss on health are well-documented, the magnitude of that association is not uniform across societies. Tøge and Blekesaune (2015) examined the impact of unemployment on self-rated health in European countries between 2008 and 2011, with varying results depending on the country. The study found that transitioning into unemployment was

associated with declines in self-perceived health in several countries such as Sweden, Romania, and Croatia; but had no significant effect in others like Denmark and Cyprus. Somewhat counterintuitively, they even found that job loss could be associated with improvements in health in a few cases, such as Spain. Similarly, evidence from studies based on the European Social Survey shows strong variations in the health of the unemployed (Vahid Shahidi et al., 2016) as well as differences by region and welfare state type (Bambra & Eikemo, 2009; Paul et al., 2018).

Unemployment protection and the generosity of social spending

One possible explanation for these cross-national differences are variations in the design and generosity of unemployment protection. Since the 1990s, European countries have increasingly structured their unemployment protection systems around Active Labour Market Policies (ALMP), which aim to both qualify and incentivise unemployed individuals to re-enter the workforce swiftly (de Beer & Schils, 2009; Immervoll & Knotz, 2018; Raffass, 2017; Thelen, 2012). That is, unemployed individuals are required to engage with national employment services to seek job opportunities actively, and in turn, receive access income support (Knotz, 2020). Unemployment protection across Europe typically follows a two-tiered system: the first tier consists of contributory social insurance, which replaces a share of the prior income for a fixed period, and a second tier provides means-tested social assistance that serves as a minimum safety net (Ábrahám et al., 2023; Asenjo & Pignatti, 2019; Immervoll & Knotz, 2018; Renahy et al., 2018). Eligibility for the contributory system depends on prior employment, such as having worked a minimum of one or two years (Immervoll & Knotz, 2018). Countries differ significantly in the magnitude and duration of benefits job seekers may receive (Pallage et al., 2013). Several studies suggest that more generous unemployment systems are associated with smaller health penalties during job loss. For instance, two studies across European countries showed that the effect of unemployment on self-rated health is partly mediated by the benefits received by job seekers (Huijts et al., 2015; Tøge, 2016a). A further study demonstrated that

higher public spending on unemployment mitigates the negative health effects of unemployment (Tøge, 2016b). This indicator captures not only income replacement but also expenditures on training, employment services, and the broader supportive components of ALMPs. Similarly, further evidence from European countries found that higher ALMP spending buffers the effects of unemployment on mental well-being (Voßemer et al., 2018) and on suicides during economic crises (Reeves et al., 2015; Stuckler et al., 2009). These findings extend beyond Europe: Cylus, Glymour, and Avendano (2015) reported that more generous unemployment insurance in U.S. states offset the adverse health effects of job loss.

Beyond generosity: behavioural conditionality and sanctions

While generous unemployment protection and a supportive regime is associated with better health outcomes among the unemployed, this finding does not sufficiently consider the demanding and punitive elements that can be a part of ALMPs. To fully understand the relationship between unemployment policy design and health, it is necessary to look beyond generosity and consider how support is delivered. A key feature of ALMP is that unemployment benefits are conditional upon behavioural requirements from job seekers (Asenjo & Pignatti, 2019; Immervoll & Knotz, 2018; Immervoll & Scarpetta, 2012) in order to incentivise job search (Liepmann & Pignatti, 2024). Namely, countries impose three sets of behavioural conditions on job seekers: searching for jobs (job search requirements), being available for work when it is offered (availability requirements), and imposing sanctions if requirements are not met (Immervoll & Scarpetta, 2012; Venn, 2012).

As described by Knotz (2020) and Immervoll & Knotz (2018), job search and monitoring requirements demand job seekers to prove job search at a certain frequency (e.g., monthly or weekly) and document job search activity. Availability requirements pose rules regarding the types of jobs that job seekers must accept when offered by employment services, even if they involve (unwanted) geographical or occupational mobility. Sanctions are financial penalties that

allow job centres to reduce or withdraw benefits if certain conditions are not met – such as refusal of job offers or insufficient cooperation with employment services. The severity of sanctions can range from partial reductions in benefit amounts or duration to a complete loss of entitlement. These rules apply to both tier one and tier two benefit levels, and the strength of all three dimensions of benefit conditionality differs significantly between European countries (Immervoll & Knotz, 2018).

While there is mixed evidence on whether behavioural conditionality and sanctions successfully foster re-employment (Knotz, 2020; Pattaro et al., 2022), there is a growing concern about the adverse impact on both the labour market and health (Reeves, 2017; Reeves & Loopstra, 2017). Benefit conditionality is criticised for creating negative stereotypes of job seekers as lazy or work-shy (De Vries et al., 2022; Koch & Reeves, 2021; Raffass, 2017). Further, strict job search and availability requirements have been found to reduce the autonomy of job seekers and cause downward job mobility (Pattaro et al., 2022). Punitive sanctions have been linked to worse health of job seekers (Loopstra et al., 2018; Reeve, 2017; Williams, 2021) and criticised for inducing societal stigma of job seekers are perceived of lazy and undeserving (Pattaro et al., 2022).

This evidence on the implications of behavioural requirements and sanctions, however, has been collected through single-country contexts. These insights have not yet been systematically used to explain cross-national variation in the health consequences of unemployment, which has largely focused on investigating the generosity of financial support. Our paper therefore addresses the following research question: **Does the strength of behavioural conditionality and sanction regimes help explain the variation in health effects of unemployment across European countries?** We hypothesise that greater behavioural conditionality – encompassing job search requirements, availability and sanction rules – is associated with more adverse effects of unemployment on health. We expect that this association will hold even when also including known indicators of the generosity of unemployment protection in our analysis.

Which of the behavioural requirements matters most for health?

Our research includes all three components of behavioural conditionality, drawing on data combined by Knotz (2020) and Venn (2012). This allows us to investigate which of the dimensions of conditionality matters the most for self-perceived health. Each of these dimensions may reflect different mechanisms through which policy design affects health. For job search and availability requirements, the negative implications might particularly stem from a loss in autonomy to make one's own decisions. If prescribed with strict conditions on how many jobs to apply for and which ones must be accepted, job seekers might be under extensive pressure to prove their efforts as well as psychological stress about their career to deteriorating if they are forced to accept positions below their educational qualifications (Koen et al., 2016; Verlaat et al., 2021). In short, we would expect these mechanisms to be significant moderators if the psycho-social account of job loss was most salient in this context. For sanction rules, however, the impact on health might be both materialist and psycho-social. On the one hand, sanctions will, if implemented, result in financial loss and reduced ability to make ends meet – thereby harming physical and mental health through material deprivation (Bambra & Eikemo, 2018; Thomson et al., 2022). However, in most European countries, only a small fraction of job seekers are actually subjected to such material sanctions (Lombardi, 2019). On the other hand, there is strong evidence that the threat of sanctions works through inducing fear and psychological stress, which, even if not enforced on a particular individual, cause mental health to deteriorate (Dwyer et al., 2020, 2022; Geiger, 2017; Pattaro et al., 2022). In other words, if the sanction rules (and the threat of them) moderate the association between job loss and health, the material and psycho-social explanations would not be entirely distinguishable.

In this study, we combine individual-level panel data from the EU statistics on income and living conditions (EU-SILC) with OECD data on behavioural conditionality across 30 EU countries.

By running first difference regression models with policy levels as moderators, we test which type of conditionality mitigates the effect of becoming unemployed on self-rated health

2. Methodology

Sample and data sources

The individual-level data for our study is based on panel data from Eurostat, EU Statistics on Income and Living Conditions (EU-SILC), from 2014 to 2019. The study years were chosen to be situated in years of stable economic growth in the EU (between 1.6 and 2.8% yearly across EU countries) and declining unemployment rates (Eurostat, n.d.; World Bank, n.d.). This is done to draw conclusions for stable, non-crisis contexts, rather than from evidence from most existing studies on this topic that specifically focus on the years of economic crisis and growing unemployment rates from 2008 to 2012 (Huijts et al., 2015; Tøge, 2016a; Tøge & Blekesaune, 2015). EU-SILC is a rotating household panel with representative samples of the European population in each year and across 31 countries (Arora et al., 2015). Serbia was excluded, as it does not include crucial data on benefit conditionality in the OECD dataset, which was merged with the EU-SILC data for our main analysis. As we are interested in transitions from employment into unemployment, compared to those who remain in employment, our analytical sample includes individuals of working age (18 to 65 years old) who are included in at least two study waves and are either part of the workforce (employed or self-employed) or unemployed and who have given valid responses to the item on self-perceived health

Table 4.1. Descriptive statistics of the analytical sample (pooled 2014 – 2019 across countries)

		All	Employed	Unemployed
Employment status	N (%)	898,598 (100%)	794,260 (88.4%)	104,338 (11.6%)
General health	Mean (sd)	4 (0.8)	4.06 (0.76)	3.85 (0.92)
Age	Mean (sd)	43.4 (11.6)	43.7 (11.4)	41.1 (13.2)
Gender	Number (and percentage) of women	432,620 (48.1%)	381,524 (48.0%)	51,096 (49.0%)
Marital status	Married (n, %)	497,763 (55.4%)	454,882 (57.3%)	42,881 (41.1%)
	Never married (n, %)	299,858 (33.4%)	251,281 (31.6%)	48,577 (46.6%)
	Divorced (n, %)	72,773 (8.1%)	63,685 (8.0%)	9,088 (8.7%)
	Separated (n, %)	12,219 (1.4%)	10,448 (1.3%)	1,771 (1.7%)
	Widowed (n, %)	15,985 (1.8%)	13,964 (1.8%)	2021 (1.9%)
Education	Number and Percentage with tertiary education	300,161 (33.4%)	281,723 (35.5%)	18,438 (17.7%)

Table 4.2. Descriptive statistics, country level. Country sample sizes aggregated for the years 2014 - 2019

Country	Sample size	ALMP total spending as % of GDP, 2017	GDP per capita 2017	Unemployment rate	Replacement rate	Overall strictness	Sanction rules	Job search requ.	Availability requ.
Austria	23,420	2.2	47,429.2	5.4	51	3.03	0.69	1.33	1.0
Belgium	26,500	2.1	44,198.5	7.2	81	2.92	1.17	1.0	0.75
Czechia	20,492	0.5	20,636.2	3.7	14	2.56	1.0	0.56	1.0
Denmark	9,272	2.9	57,610.1	5.9	85	3.23	0.72	1.13	1.38
Estonia	20,819	0.8	20,437.8	6.1	45	4.14	1.56	1.33	1.25
Finland	21,243	2.5	46,412.1	8.3	58	2.74	1.07	0.83	0.83
France	56,292	2.9	38,781.0	9.6	68	3.17	0.96	1.17	1.05
Germany	29,928	1.4	44,652.6	4.0	59	3.14	0.72	1.17	1.25
Greece	63,997	0.7	18,582.1	22.1	45	1.96	0.78	0.33	0.85
Hungary	27,375	1.1	14,621.2	5.2	16	2.36	0.56	0.59	1.22
Iceland	9,626	n/a	72,010.1	3.5	54	3.06	0.89	1.0	1.17
Ireland	17,955	1.2	70,150.7	7.9	39	2.73	0.69	1.0	1.03
Italy	79,755	1.5	32,406.7	11.3	60	3.18	1.44	0.57	1.17
Latvia	21,485	0.6	15,695.1	8.8	13	3.43	1.22	1.33	0.88
Lithuania	15,138	0.5	16,885.4	7.9	22	3.0	1.0	1.17	0.83
Luxembourg	18,940	1.3	110,193.2	5.9	84	4.13	1.65	1.39	1.08
Netherlands	25,927	2.1	48,675.2	5.4	66	3.2	0.89	1.1	1.21
Norway	14,153	1.0	76,131.8	4.0	68	3.26	1.01	0.67	1.58
Poland	55,231	0.6	13,815.5	5.8	34	3.08	1.33	0.33	1.42
Portugal	48,285	1.5	21,490.4	10.0	68	3.79	1.67	1.06	1.07
Slovak Republic	27,543	0.6	17,585.2	8.9	12	3.47	1.22	1.17	1.08
Slovenia	18,782	0.7	23,514.0	14.8	40	3.86	1.53	1.17	1.17
Spain	52,718	2.2	28,185.3	18.8	54	2.67	1.33	0.5	0.83
Sweden	11,983	1.6	53,791.5	7.0	64	3.36	0.78	1.33	1.25
Switzerland	26,316	n/a	82,254.4	4.7	71	3.53	0.94	1.33	1.25
United Kingdom	48,945	0.5	40,572.1	4.7	18	3.61	1.03	1.50	1.11
Bulgaria	31,309	0.6	8,381.9	7.3	77	2.89	1.22	0.83	0.83
Croatia	28,963	0.6	13,655.5	12.1	38	4.17	1.67	1.17	1.33
Cyprus	20,167	0.6	26,697.0	11.9	44	2.17	0.67	0.67	0.83
Romania	26,039	0.1	10,728.0	5.4	37	3.75	1.67	0.83	1.25

Dependent variable

The outcome variable in this study is *change in self-rated health*. Self-rated health is measured through the question *"How is your health in general?"* on a scale from 1 (very bad) to 5 (very good), and is included in every survey year. Previous studies suggest that the item possesses good psychometric properties in test–retest reliability and predictive validity for both service use and mortality (Miilunpalo et al., 1997; Jylhä, 2009). The item captures both physical and mental health, and has a strong association with mortality and mental health outcomes (Jylhä, 2009). The outcome variable is also used in similar studies on the impact of unemployment on health, making our findings comparable across studies (Huijts et al., 2015; Tøge & Blekesaune, 2015). Our study outcome is change in self-rated health within individuals form one study year to another, capturing a change score rather than absolute levels (see section *statistical analysis*).

Independent variable

Our main independent variable is change in employment status. EU-SILC uses both administratively recorded and self-reported employment status. The results reported in the main text are based on the self-reported measure, but the findings are consistent when using the administrative measure. To allow running our first difference model as intended, unemployment is coded as "1", and being at work is coded as "0". We then contrast the group of people who stayed at work between survey waves with the group of people who transitioned from being employed to unemployed. In consequence, our outcome variable is employment status, coded as "1" for becoming unemployed, "0" for stable employment and "-1" for becoming employed after unemployment (re-employment). This definition of employment transitions is in line with previous research on the EU-SILC dataset, which we are building on (Tøge & Blekesaune, 2015). This variable is then used as an interaction effect with our country level variables in behavioural conditionality to capture our moderation effects.

Individual-level covariates

We included several individual-level variables as controls in our regression models, all of which have a low share of missing values. They include age (0% missing), gender (0% missing), marital status (0.9% missing) and education (2.15% missing). Details on these variables are found in Table 4.1.

Country level indicators on benefit conditionality and sanctions

Our main interest lies in understanding how country-level activation requirements shape the relationship between unemployment and health. In this study, we focus on the average national scores of strictness of conditionality (also referred to as *strictness of activation requirements*) as provided by the Organisation for Economic Cooperation and Development (OECD). The data was downloaded from the OECD data explorer (OECD, n.d.).

The core variables to measure the strictness of conditionality include three dimensions of activation policy: (a) strictness of job-search requirements and monitoring procedures, (b) availability requirements, and (c) sanction legislation. Each of these dimensions is scored separately, and an overall composite indicator of activation strictness is calculated by combining them into a weighted average (overall strictness indicator) ranging from 1 (least strict) to 5 (most strict) (Immervoll & Knotz, 2018; Immervoll & Scarpetta, 2012; Langenbucher, 2015; Venn, 2012). The strictness scores were developed by the OECD based on a standardised expert survey (Immervoll & Knotz, 2018; Immervoll & Scarpetta, 2012). Respondents include policy officials from OECD and EU member states, specifically delegates to the OECD Employment, Labour and Social Affairs Committee and the EU's Social Protection Committee. These experts completed a detailed, open-ended questionnaire assessing national rules regarding job availability, job-search requirements, and sanctions in place as of the reference year. The OECD then coded

and scored these responses according to a predefined scheme. Notably, the resulting scores reflect statutory rules rather than their enforcement in practice (Immervoll & Knotz, 2018; Langenbucher, 2015; Venn, 2012).

In this study, we focus on the conditionality in first-tier unemployment insurance schemes, as they are the primary mechanism providing income support to individuals during the first year of unemployment (Immervoll & Knotz, 2018) and as we are focusing on transitions into unemployment from one year to another. Further, given their standardised structure and immediate impact on the newly unemployed, first-tier unemployment benefit indicators offer a consistent basis for cross-national analysis of unemployment policies (Langenbucher, 2015). Scores are provided for the years 2014, 2017 and 2020. As there is little variation across time (97.4% of variation in the strictness indicators is attributed to between-country differences; only 2.6% within-country variation), our regression models include the average score for these years to capture between-country differences accurately. Table 4.3 outlines the indicators and weights used to construct the overall strictness score, with separate scores calculated for each dimension. Country-level values of each indicator are shown in Table 4.2. Full scoring definitions are provided in Appendix paper 3.

Additional country-level variables

In addition to activation policy scores, we also include net replacement rates as a control for benefit generosity. These were downloaded from the OECD Data Explorer (OECD, n.d.) (OECD, n.d.) and refer to the share of previous income replaced by unemployment benefits for a single individual earning the average wage. We also include the total public expenditure on labour market policies as percentage of GDP from the European Commission (European Commission, n.d.) as well as variables from the Comparative Welfare Entitlements Project Data Set (Scruggs, 2022). Both sets of variables are used as supplementary analysis in the Appendix paper 3 and confirm that our main results remain stable with these additional covariates. Finally,

we include indicators on GDP per capita for the year 2017 as well as unemployment rates for that same year derived from the World Bank. (World Bank, 2022). All country-level variables for each country are shown in Table 4.2 and 4.3.

Table 4.3. Indicators on the strictness of behavioural conditionality and sanctions

Dimension	Item	Score = 1 (Lenient)	Score = 5 (Strict)	Weight in Index
Availability Requirements	Availability during ALMP participation	No availability required	Must be available and actively searching during ALMPs	0.08
	Occupational mobility	Can refuse jobs in other occupations indefinitely	Must accept any job one is capable of doing	0.08
	Geographical mobility	No commuting or relocation requirements	Must commute 4+ hours/day or relocate	0.08
	Other valid reasons for refusal	5+ valid reasons (e.g., family, ethics, health)	Two or less valid reasons accepted	0.08
Job-Search Requirements	Frequency of job-search monitoring	No checks of job-search activity	Weekly or biweekly prove required	0.17
	Documentation of job-search activity	No formal requirement	Written employer confirmations required	0.17
Sanction rules	Voluntary resignation from job	0 – 4 weeks suspension (or reduction)	Permanent ineligibility for benefits	0.11
	Refusal of suitable job (1st offence)	0 – 4 weeks suspension (or reduction)	Loss of full entitlement	0.06
	Repeated refusal of suitable job	0 – 4 weeks suspension (or reduction)	Loss of full entitlement	0.06
	Refusal of ALMP participation	0 – 4 weeks suspension (or reduction)	Loss of full entitlement	0.06
	Repeated refusal of ALMP participation	0 – 4 weeks suspension (or reduction)	Loss of full entitlement	0.06

Notes: The weight is used to create an overall index on the strictness of conditionality.
Source: Immervoll & Knotz (2018)

Statistical analysis

Our main statistical analyses are first difference regression models, in which we measure the effect of individual-level changes in employment on changes in self-rated health across countries. Being closely related to a fixed effects model, the first difference model focuses on individual-level changes, while controlling for time-invariant individual-level factors (Baltagi & Baltagi, 2008). This modelling strategy also allows adding country-level moderators into our main analysis.

As a first step, we compute this change for each country separately to measure the variation in the health changes following unemployment for the years 2014 to 2019, similar to Tøge and Blekesaune (2015) who did a similar analysis for the years 2008 – 2012.

Next, our main analysis (models 2 – 5) adds the cross-level interaction effects for the measures of country-level behavioural conditions and individual-level employment transitions (see Table 4.2). As described above, to fully represent the between-country variation in these measures. We also include various control measures at both the individual and country levels. In our main models presented in Table 4.3, we control for GDP and benefit replacement rates at the country level. This approach avoids overextending the model and ensures consistency, as data for these variables are available for all 30 countries. Additional models included in the appendix incorporate country-level spending on ALMP (see Appendix paper 3), which reduces the country sample to 28 due to data limitations. The results of our main analysis remain stable when adding these additional controls. Our first-difference models are specified as follows (see Model 2 in Table 4.4):

$$\Delta Health_i = \beta_0 + \beta_1 \Delta Employment_i + \beta_2 Strict_i + \beta_3 (\Delta Unemp_i \times Strict_i)$$

$$+ \beta_4 Age_i + \beta_5 Sex_i + \beta_6 Educ_i + \beta_7 UnempRate_i$$

$$+ \beta_8 log(GDP_i) + \beta_9 ReplacementRate_i + \epsilon_i i$$

The standard errors for all analyses in Table 4.3 were clustered at the country level − a clear and straightforward, yet conservative, strategy to account for within-country correlations and ensure that confidence intervals and p-values are not underestimated (Bryan & Jenkins, 2013).

Finally, based on the regression models, we compute predicted values of health change following unemployment, comparing countries with the most lenient and the most stringent activation policies (see Figure 4.2 and Figure 4.3). This was done using the predict() function in R, combined with a clustered bootstrap approach implemented via the "boot" package, in order to ensure that we capture country-clustered confidence intervals (Bryan & Jenkins, 2013; Cameron et al., 2008). Covariates in the regression models were set to the mean (for all numerical variables) or mode (for categorical variables such as gender and education). All regression models use complete-case analysis because the share of missing values is low (as described above) and focus only on individuals who provided data on at least two waves on their employment status and self-rated health.

3. Results

Participant flow and final sample

The initial dataset included 1,566,401 observations from the EU-SILC years 2014 – 2019. 1,093,041 (69.8%) participants were either working or unemployed, while those retired and otherwise inactive (e.g., those in education) (27.6%) and missing values (2.7%) were excluded. Additionally, only valid responses to the variable on *self-rated health* were kept as they are essential to my analytical model, removing a further 15.8% missing values. After further data cleaning and removal of missing cases in key demographic data (e.g., age, gender or education), this yielded a total analytical sample of 898,598 observations and n = 4,992 per country and year. Descriptive statistics on both individual and country-level data is included in Table 4.1 and Table 4.2 respectively.

Cross-country variation in unemployment effects

As a first step of our analysis, we estimate the effect of transitioning into unemployment on self-rated health across all countries and participants using a simple first-difference model. The estimated effect of experiencing unemployment on self-rated health is −0.05 (95% CI[−0.06, −0.04, $p < 0.001$]). Thus, becoming unemployed is associated with a significant decline of 0.05 points on a self-rated health scale. Given the standard deviation of 0.8 on the self-perceived health scale, this corresponds to a small but systematic overall deterioration in health, which is in line with previous research using the EU-SILC dataset (Huijts et al., 2015; Tøge & Blekesaune, 2015).

We then estimate the effect of unemployment separately for each country (not controlling for individual-level covariates in this case). Figure 4.1 displays the country-specific coefficients. In 27 out of 31 countries, the estimated effect of unemployment on health is negative. Slovakia, the United Kingdom, and the Czech Republic show the largest negative effects. These results demonstrate meaningful cross-national variation in the health consequences of unemployment. This variation provides the basis for further analysis of how institutional factors, such as the strictness of behavioural conditionality, might help explain these differences.

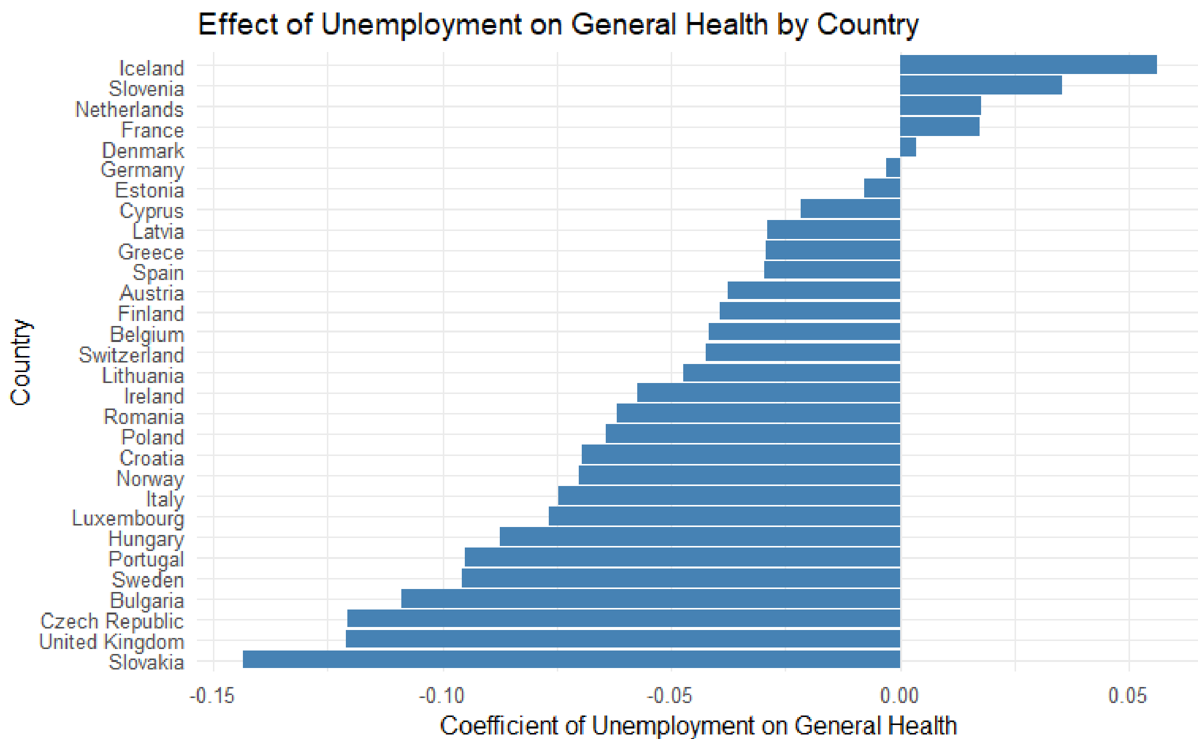


Figure 4.1. Effect of unemployment on self-rated health, years 2014 - 2019

Main regression models

To investigate our research question, we estimate a series of regression models that examine how the health consequences of unemployment are shaped by the strictness of behavioural conditionality across countries. The results are reported in Table 4.4, alongside the control variables used in each model.

Model (1) is a basic model that includes only individual-level data. It identifies the main effect and examines its consistency with previous research – with the coefficient already discussed above.

Model (2) includes an interaction term between unemployment transition and the overall strictness of activation requirements. The effect is in the expected direction — higher overall strictness is associated with a stronger deterioration in health following unemployment — but

the confidence interval includes zero, and the interaction is not statistically significant (Interaction in Model (2): −0.02, CI:[−0.03, 0.005]) with $p = 0.13$.

Model (3) estimates the interaction between unemployment transition and the strictness of sanction rules. Here, we find a statistically significant interaction effect, which indicates that stricter sanction regimes are associated with worse health outcomes following unemployment. The main effect of unemployment disappears in this model, suggesting the moderating role of sanctions (Interaction in Model (3): −0.04, CI:[−0.08,−0.004, $p = 0.029$]).

Models (4) and (5) estimate interactions between unemployment transition and, respectively, job-search requirements and availability requirements. Both interaction terms are not statistically significant. Model (4) shows a near-zero interaction (−0.001, CI:[−0.05, 0.03]), and Model 5 shows a small and non-significant negative interaction (−0.03, CI:[−0.09, 0.03]). These results suggest that the effect of unemployment on health does not vary systematically with the strictness of job-search or availability requirements for job seekers.

Overall, the results indicate a significant interaction effect between conditionality and health change only in the case of sanction rules. The stricter these sanction rules are across countries, the more harmful unemployment tends to be for self-rated health. This reflects between-country variation: in countries with stricter sanction rules, becoming unemployed is associated with a significantly greater deterioration in health.

Robustness models in the Appendix paper 3 (see Table S1 and S2) include different measures of public spending on active labour market policies (as an indicator of country-level generosity). The results remain stable: the interaction between unemployment and sanction strictness remains statistically significant, suggesting that the observed effect is not driven by broader policy generosity.

Table 4.4. First difference model for the transition of unemployment. Dependent variable: Change in self-rated health.

	(1) **Individual benefits only**	(2) **Overall strictness**	(3) **Sanction rules**	(4) **Job-search requirements**	(5) **Availability requirements**
Individual level variables					
Unemployment transition (becoming unemployed)	- 0.05** (-0.06, -0.04)	- 0.002 (-0.06, 0.05)	0.00 (-0.05, 0.05)	- 0.05** (-0.09, -0.02)	- 0.02 (-0.09, 0.04)
All models control for individual-level *gender, age, education* and *marital status.*					
Country-level activation requirements					
Overall strictness of activation requirements		- 0.004 (-0.02, 0.01)			
Overall strictness × unemployment transition		- 0.02 (-0.03, 0.005)			
Sanctions			0.006 (-0.02, 0.03)	✓	✓
Sanctions × unemployment transition			- 0.04* (-0.08, -0.004)		
Job-search requirements			✓	- 0.01* (-0.024, -0.001)	✓
Job-search requirements × unemployment transition				- 0.001 (-0.05, 0.03)	
Availability requirements			✓	✓	- 0.02 (-0.04, -0.01)
Availability requirements × unemployment transition					- 0.03 (-0.09, 0.03)
Country-level controls					
Replacement rate (% of income after six months of unemployment)		✓	✓	✓	✓
GDP (log)		✓	✓	✓	✓
Unemployment rate		✓	✓	✓	✓

Notes. *p < 0.05; **p < 0.01. 95% confidence intervals indicated in brackets below each estimate.
✓ = control variable included in the model

Visualising effect sizes

To demonstrate the effect sizes and interpret the results of the regression models presented in Table 4.3, we calculated predicted values based on countries with the highest and lowest levels of conditionality. We focus on Model (2), which includes the aggregate measure and overall conditionality, as well as Model (3), which yielded a significant interaction between

unemployment and sanction rules. The results are visualised in Figures 4.2 and 4.3. We display the visualisation for the remaining non-significant interactions in models (4) and (5) in Appendix Paper 3 (see Figure S1 and Figure S2). For overall strictness (see Figure 4.2), in countries with the lowest levels of conditionality, such as Cyprus or Greece, job loss was associated with a predicted decrease of -0.051 points in self-rated health (95% CI:[-0.105 ,-0.005]). In countries with the highest levels of strictness, such as Estonia or Croatia, the predicted decline was more than twice as large, at - 0.111 points (95% CI: [-0.148, -0.075]). Notably, while the direction of these predicted values is in the same direction as in the main first-difference regression analysis (see Table 4.4), the regression pointed to a non-significant interaction (p = 0.13; see above). In contrast, the predicted values (see Figure 4.2) now suggest that the confidence intervals for "highest strictness" do not overlap with the point estimate of "lowest strictness" – a sign of statistically significance difference. These slight differences in statistical inference might have resulted from the set average values for the prediction (e.g., education and gender set to the mode; other values to the mean), or due to the conservative method of calculating cluster-robust standard errors in the main analysis – resulting in findings outside the norm of statistical significance in Table 4.4.

For sanction rules (see Figure 4.3), job loss was associated with a significant decline in self-perceived health under both low and high levels of sanction strictness. In countries with lower sanctioning rules, such as Hungary or Cyprus, the predicted health decline was -0.053 (95% CI:[-0.098, -0.017]). In countries with stricter sanction rules, such as Croatia or Poland, the predicted decline was more than twice as large with non-overlapping confidence intervals at 0.105 (95% CI:[-0.135 to -0.078]). In this case, the findings fully support the moderating relationship of unemployment transitions and sanction rules, as indicated by the significant interaction term in model (3) in Table 4.4.

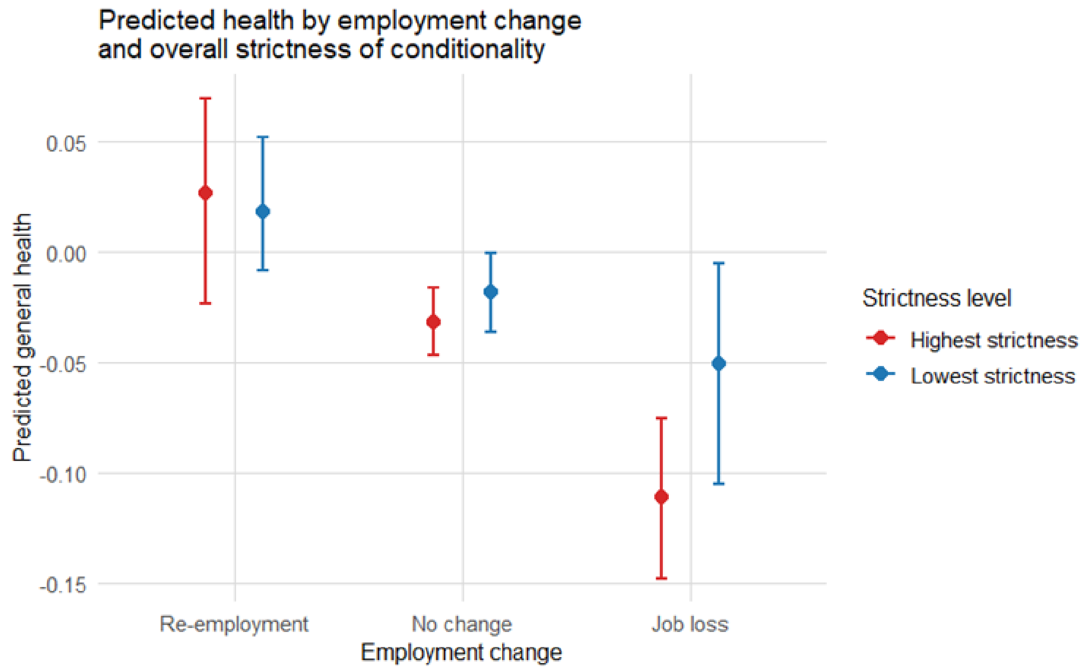


Figure 4.2. Predicted health change depending on the overall strictness of behavioural conditionality. 95% CIs clustered at the country level

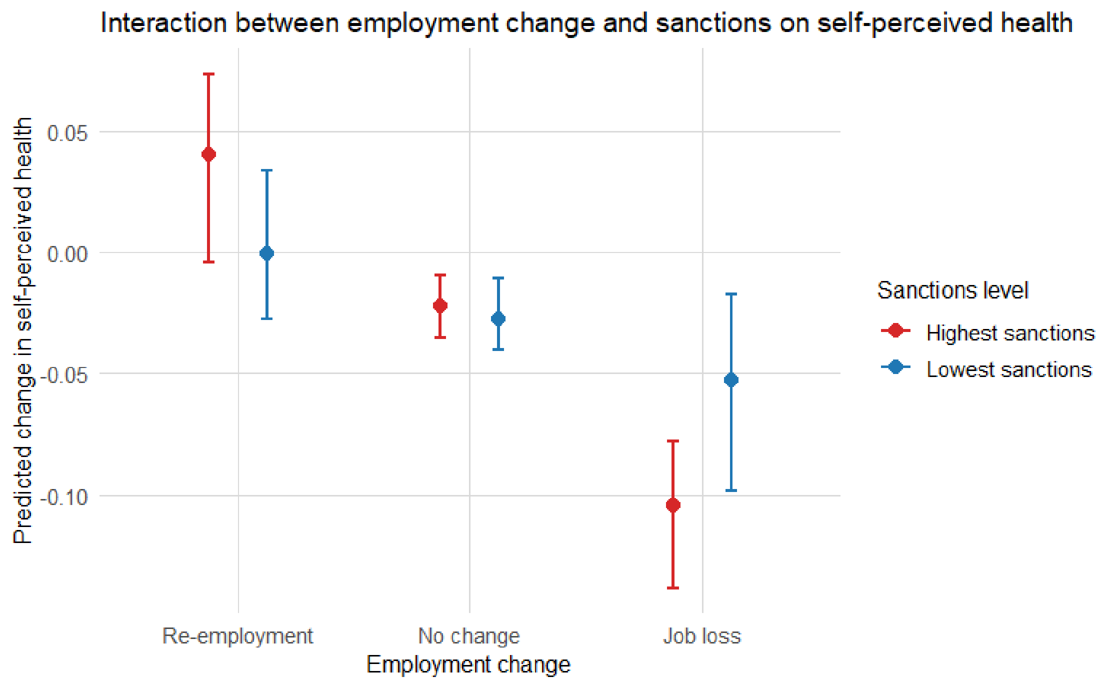


Figure 4.3. Predicted health change depending on sanction rules. 95% CIs clustered at the country level

4. Discussion

In this paper, we investigated whether the strictness of behavioural conditionality for access to unemployment protection is associated with the self-rated health of individuals who become unemployed. To explore this, we combined individual-level panel data from the EU-SILC with country-level data from the OECD on behavioural conditionality regimes across 30 EU countries. We hypothesised that in countries with stricter behavioural requirements (such as job search obligations and availability criteria, and sanction rules), becoming unemployed would be associated with a steeper decline in health, and this is what we find. Indeed, we find that sanction-related rules are particularly relevant: countries with stricter sanction regimes in tier-one unemployment protection (i.e., unemployment insurance) show significantly worse self-rated health outcomes among newly unemployed individuals. In countries with lower sanctioning rules, such as Hungary or Cyprus, the predicted health decline was -0.053. In countries with stricter sanction rules, such as Croatia or Poland, the predicted decline was more than twice as large at -0.105 points in self-rated health. Given the Standard Deviation of 0.8 (with mean = 4.0) on the self-perceived health measures similar to the values reported in previous research (Huijts et al., 2015; Tøge & Blekesaune, 2015). Notably, while these effects are small on the individual level, they are meaningful when considered at the population level. Given that 11.6% of working-age people in our sample experience unemployment, and this applies to several million individuals across the combined population of 30 European countries, a change in the effect from -0.05 to -0.1 in self-perceived health (based on the observed distribution with mean = 4.0 and SD = 0.8, where values ≤3 correspond to fair or poor health) could translate into an increase in the prevalence of fair or poor health among the newly unemployed of approximately 1.2 and 2.5 percentage points, respectively (equivalent to 12,000 to 25,000 cases per one million job seekers in Europe). Even such modest average differences could therefore result in thousands of additional individuals reporting poor health under stricter sanction regimes, with

potential consequences for future employability, personal and family mental health and mortality (Jylhä, 2009; Mariano et al., 2025; Picchio & Ubaldi, 2024).

Other dimensions apart from sanction levels, such as job search requirements or availability criteria, did not yield statistically significant results in our models.

Understanding the role of sanctions

Our results suggest that countries with stronger sanction rules have a steeper decline in self-rated health for individuals who enter unemployment. For example, strict sanction rules can entail a complete loss of benefit entitlement for the entire period of unemployment if a suitable job is not accepted or if participation in ALMP services is deemed insufficient (Immervoll & Knotz, 2018). More lenient sanction regimes would impose no or limited financial penalties for similar issues (e.g., up to 4 weeks of penalty; see Table 4.1).

Before interpreting this finding further, it is essential to contextualise our result: the measure of sanction strictness in our study refers to statutory rules in each country, rather than the enforcement of these sanctions. While this is an important limitation, it is crucial to note that the actual enforcement is based on these statutory rules, which likely have a relevant impact as well (Knotz, 2020). Additionally, the mechanisms of sanctions on health, particularly mental health, relate to the fear and stress caused by the possibility of significant sanctions rather than experiencing sanctions themselves (Dwyer et al., 2020; Koch & Reeves, 2021; Reeve, 2017). Our study provides evidence for such psycho-social mechanism and aligns with evidence suggesting that the threat of sanctions induces psychological stress and fear, leading to deterioration of self-rated health (Bambra & Eikemo, 2018; Dwyer et al., 2020).

Policy implications

Our findings should be viewed within the wider academic and policy debate on welfare states perceive and treat job seekers. Previous studies have found that countries that have higher

spending on unemployment protection and benefits have better health outcomes for those who become unemployed (Huijts et al., 2015; Tøge, 2016b; Voßemer et al., 2018). In our study, we complement this finding by highlighting that, in addition to having generous spending on unemployment benefits and labour market services, the punitive elements of unemployment protection should be reconsidered to protect the health of job seekers. This has important implications for the design of unemployment systems: if the health of job seekers deteriorates too severely, it may hinder re-employment prospects (Koen et al., 2016) or even lead to labour market exit altogether, especially among vulnerable groups (Dwyer et al., 2022). While behavioural conditionality is intended to incentivise job search and promote re-employment, our results suggest that particularly the punitive aspect of sanctions, could undermine these goals. Social policymakers aiming to enhance health and labour market outcomes should provide sufficient financial and job search support to job seekers instead of imposing punitive measures. This idea corresponds with typology of the implementation of conditionality suggested by Geiger (2017), characterised as a system offering substantial rehabilitation and training support but with lower conditionality. Countries that manage to strike this balance, even with limited unemployment spending, are more likely to achieve favourable outcomes in both employment and public health.

Limitations and future research

This study is the first to use the OECD dataset on activation requirements for job seekers and connect it with individual-level data across Europe. Our analytical approach entails several key limitations and at the same time, point to future research agendas for this topic.

First, our analysis provides a high-level assessment of cross-national patterns, showing that stricter sanction regimes are associated with worse self-rated health among the unemployed, even after controlling for key factors such as GDP, unemployment rates, and benefit generosity. However, we cannot establish a clear causal mechanism or rule out additional unobserved

country-level confounders. As noted by Knotz (2020), stricter activation rules may themselves be a result of broader political or economic trends. Future studies should build on our findings by using policy changes over time or quasi-experimental methods to identify causal effects.

Second, as already noted, our analysis relies on data capturing legislative rules and formal policy design, but does not measure how these rules are enforced in practice.

Third, our analysis examines the strictness of first-tier unemployment protection systems, which are most crucial for individuals during early job loss. This focus is important for understanding transitions into unemployment but does not consider the health effects of second-tier or means-tested assistance schemes. Future studies should explore how conditionality impacts the health of long-term unemployed individuals.

Fourth, self-rated health is a reliable measure of physical and mental well-being, but may miss specific mental health impacts like anxiety or depression. Since the threat of sanctions is particularly prone to cause psychological stress, future studies should include direct mental health indicators, if possible.

Overall, this paper shows that, to understand the health effects of labour market policies on job seekers, we need to look beyond the generosity of unemployment protection and the funding of labour market services. The study shows that behavioural benefit conditionality, a key policy element in how unemployment protection is delivered, can play a crucial role in shaping health outcomes across Europe. Sanction legislation appears to be particularly relevant, with stricter sanction rules being associated with a stronger decline in self-rated health among individuals following job loss across 30 European countries. Further studies should use causal inference methodologies and natural experiments to expand on these findings.

References

Ábrahám, Á., de Sousa, J. B., Marimon, R., & Mayr, L. (2023). On the design of a European unemployment insurance system. *European Economic Review*, *156*, 104469. https://doi.org/10.1016/j.euroecorev.2023.104469

Arora, V. S., Karanikolos, M., Clair, A., Reeves, A., Stuckler, D., & McKee, M. (2015). Data resource profile: The European Union statistics on income and living conditions (EU-SILC). *International Journal of Epidemiology*, *44*(2), 451–461. https://doi.org/10.1093/ije/dyv069

Asenjo, A., & Pignatti, C. (2019). *Unemployment insurance schemes around the world: Evidence and policy options*. International Labour Office Geneva, Switzerland. http://sarkoups.free.fr/ilo723778.pdf

Baltagi, B. H., & Baltagi, B. H. (2008). *Econometric analysis of panel data* (Vol. 4). Springer.

Bambra, C., & Eikemo, T. A. (2009). Welfare state regimes, unemployment and health: A comparative study of the relationship between unemployment and self-reported health in 23 European countries. *Journal of Epidemiology & Community Health*, *63*(2), 92–98. https://doi.org/10.1136/jech.2008.077354

Bambra, C., & Eikemo, T. A. (2018). Insecurity, unemployment, and health: A social epidemiological perspective. *The Oxford Handbook of Job Loss and Job Search*, 111–125.

Bryan, M. L., & Jenkins, S. P. (2013). *Regression analysis of country effects using multilevel data: A cautionary tale*. ISER working paper series. https://hdl.handle.net/10419/91694

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2008). Bootstrap-based improvements for inference with clustered errors. *The Review of Economics and Statistics*, *90*(3), 414–427. https://doi.org/10.1162/rest.90.3.414

Chandola, T., & Zhang, N. (2018). Re-employment, job quality, health and allostatic load biomarkers: Prospective evidence from the UK Household Longitudinal Study. *International Journal of Epidemiology*, *47*(1), 47–57. https://doi.org/10.1093/ije/dyx150

Cylus, J., Glymour, M. M., & Avendano, M. (2015). Health effects of unemployment benefit program generosity. *American Journal of Public Health*, *105*(2), 317–323. https://doi.org/10.2105/AJPH.2014.302253

de Beer, P., & Schils, T. (2009). Introduction: Achieving an optimal social policy mix. In *The Labour Market Triangle*. Edward Elgar Publishing.

De Vries, R., Reeves, A., & Geiger, B. (2022). Social class bias in welfare sanctioning judgements: Experimental evidence from a nationally representative sample. *Social Policy & Administration*, *56*(5), 843–858. https://doi.org/10.1111/spol.12812

Dwyer, P., Scullion, L., Jones, K., McNeill, J., & Stewart, A. B. (2022). Unintended outcomes? The wider impacts of compulsion and benefit sanctions in social security. In *The Impacts of Welfare Conditionality* (pp. 116–136). Policy Press. https://doi.org/10.51952/9781447343721.ch006

Dwyer, P., Scullion, L., Jones, K., McNeill, J., & Stewart, A. B. R. (2020). Work, welfare, and wellbeing: The impacts of welfare conditionality on people with mental health impairments in the UK. *Social Policy & Administration*, *54*(2), 311–326. https://doi.org/10.1111/SPOL.12560

European Commission. (n.d.). *Statistics | Employment, Social Affairs & Inclusion | European Commission*. Retrieved 22 June 2025, from https://webgate.ec.europa.eu/empl/redisstat/databrowser/explore/all/lmp?lang=en&display=card&sort=category

Eurostat. (n.d.). *Unemployment statistics and beyond*. Retrieved 16 April 2025, from https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Unemployment_statistics_and_beyond

Fryer, D. (1986). Employment deprivation and personal agency during unemployment: A critical discussion of Jahoda's explanation of the psychological effects of unemployment. *Social Behaviour, 1(1), 3–23*. https://psycnet.apa.org/record/1989-24290-001

Gedikli, C., Miraglia, M., Connolly, S., Bryan, M., & Watson, D. (2023). The relationship between unemployment and wellbeing: An updated meta-analysis of longitudinal evidence. *European Journal of Work and Organizational Psychology*, *32*(1), 128–144. https://doi.org/10.1080/1359432X.2022.2106855

Geiger, B. B. (2017). Benefits conditionality for disabled people: Stylised facts from a review of international evidence and practice. *Journal of Poverty and Social Justice*, *25*(2), 107–128. https://doi.org/10.1332/175982717X14939739331010

Huijts, T., Reeves, A., McKee, M., & Stuckler, D. (2015). The impacts of job loss and job recovery on self-rated health: Testing the mediating role of financial strain and income. *The European Journal of Public Health*, *25*(5), 801–806. https://doi.org/10.1093/eurpub/ckv108

Immervoll, H., & Knotz, C. (2018). *How demanding are activation requirements for jobseekers?* [OECD Policy Report]. IZA Discussion Paper. https://www.oecd-ilibrary.org/docserver/2bdfecca-en.pdf?expires=1725485200&id=id&accname=guest&checksum=6F8D0351F88D95007416F20C3F217811

Immervoll, H., & Scarpetta, S. (2012). Activation and employment support policies in OECD countries. An overview of current approaches. *IZA Journal of Labor Policy*, *1*, 1–20. https://doi.org/10.1186/2193-9004-1-9

Jahoda, M. (1982). Employment and unemployment. *Cambridge Books*.

Jylhä, M. (2009). What is self-rated health and why does it predict mortality? Towards a unified conceptual model. *Social Science & Medicine*, *69*(3), 307–316. https://doi.org/10.1016/j.socscimed.2009.05.013

Knabe, A., & Rätzel, S. (2011). Scarring or Scaring? The Psychological Impact of Past Unemployment and Future Unemployment Risk. *Economica*, *78*(310), 283–293. https://doi.org/10.1111/J.1468-0335.2009.00816.X

Knotz, C. M. (2020). Does demanding activation work? A comparative analysis of the effects of unemployment benefit conditionality on employment in 21 advanced economies, 1980–2012. *European Sociological Review*, *36*(1), 121–135. https://doi.org/10.1093/esr/jcz041

Koch, I., & Reeves, A. (2021). From social security to state-sanctioned insecurity: How welfare reform mimics the commodification of labour through greater state intervention. *Economy and Society*, *50*(3), 448–470. https://doi.org/10.1080/03085147.2020.1844936

Koen, J., van Vianen, A. E., van Hooft, E. A., & Klehe, U.-C. (2016). How experienced autonomy can improve job seekers' motivation, job search, and chance of finding reemployment. *Journal of Vocational Behavior*, *95*, 31–44. https://doi.org/10.1016/j.jvb.2016.07.003

Langenbucher, K. (2015). *How demanding are eligibility criteria for unemployment benefits, quantitative indicators for OECD and EU countries*. https://www.oecd.org/en/publications/how-demanding-are-eligibility-criteria-for-unemployment-benefits-quantitative-indicators-for-oecd-and-eu-countries_5jrxtk1zw8f2-en.html

Liepmann, H., & Pignatti, C. (2024). Welfare effects of unemployment benefits when informality is high. *Journal of Public Economics*, *229*, 105032. https://doi.org/10.1016/j.jpubeco.2023.105032

Lombardi, S. (2019). *Threat effects of monitoring and unemployment insurance sanctions: Evidence from two reforms*. Working Paper. https://hdl.handle.net/10419/227842

Loopstra, R., Fledderjohann, J., Reeves, A., & Stuckler, D. (2018). Impact of welfare benefit sanctioning on food insecurity: A dynamic cross-area study of food bank usage in the UK. *Journal of Social Policy*, *47*(3), 437–457. https://doi.org/10.1017/S0047279417000915

Mariano, C., Henking, C., Gondek, D., & Bernardi, L. (2025). The effects of parental unemployment on children's wellbeing–results from Switzerland and the United Kingdom. *Social Science & Medicine*, 118609. https://doi.org/10.1016/j.socscimed.2025.118609

Miilunpalo, S., Vuori, I., Oja, P., Pasanen, M., & Urponen, H. (1997). Self-rated health status as a health measure: the predictive value of self-reported health status on the use of physician services and on mortality in the working-age population. *Journal of clinical epidemiology*, *50*(5), 517-528. https://doi-org.ezproxy-prd.bodleian.ox.ac.uk/10.1016/S0895-4356(97)00045-0

Murphy, G. C., & Athanasou, J. A. (1999). The effect of unemployment on mental health. *Journal of Occupational and Organizational Psychology*, *72*(1), 83–99. https://doi.org/10.1348/096317999166518

OECD. (n.d.). *OECD Data Explorer*. Retrieved 17 April 2025, from https://data-explorer.oecd.org/?fs[0]=Topic%2C1%7CEmployment%23JOB%23%7CBenefits%252C%20earnings%20and%20wages%23JOB_BW%23&pg=0&fc=Topic&bp=true&snb=21

Pallage, S., Scruggs, L., & Zimmermann, C. (2013). Measuring unemployment insurance generosity. *Political Analysis*, *21*(4), 524–549. https://doi.org/10.1093/pan/mpt011

Pattaro, S., Bailey, N., Williams, E., Gibson, M., Wells, V., Tranmer, M., & Dibben, C. (2022). The impacts of benefit sanctions: A scoping review of the quantitative research evidence. *Journal of Social Policy*, *51*(3), 611–653. https://doi.org/10.1017/S0047279421001069

Paul, K. I., Hassel, A., & Moser, K. (2018). Individual consequences of job loss and unemployment. *Oxford Handbook of Job Loss and Job Search*, 57–85.

Picchio, M., & Ubaldi, M. (2024). Unemployment and health: A meta-analysis. *Journal of Economic Surveys*, *38*(4), 1437–1472. https://doi.org/10.1111/joes.12588

Raffass, T. (2017). Demanding activation. *Journal of Social Policy*, *46*(2), 349–365. https://doi.org/10.1017/S004727941600057X

Reeve, K. (2017). Welfare conditionality, benefit sanctions and homelessness in the UK: ending the 'something for nothing culture' or punishing the poor? *Journal of Poverty and Social Justice*, *25*(1), 65–78. https://doi.org/10.1332/175982717X14842281240539

Reeves, A. (2017). Does sanctioning disabled claimants of unemployment insurance increase labour market inactivity? An analysis of 346 British local authorities between 2009 and 2014. *Journal of Poverty and Social Justice*, *25*(2), 129–146. https://doi.org/10.1332/175982717X14939739331029

Reeves, A., & Loopstra, R. (2017). 'Set up to fail'? How welfare conditionality undermines citizenship for vulnerable groups. *Social Policy and Society*, *16*(2), 327–338. https://doi.org/10.1017/S1474746416000646

Reeves, A., McKee, M., Gunnell, D., Chang, S.-S., Basu, S., Barr, B., & Stuckler, D. (2015). Economic shocks, resilience, and male suicides in the Great Recession: Cross-national

analysis of 20 EU countries. *The European Journal of Public Health*, *25*(3), 404–409. https://doi.org/10.1093/eurpub/cku168

Renahy, E., Mitchell, C., Molnar, A., Muntaner, C., Ng, E., Ali, F., & O'Campo, P. (2018). Connections between unemployment insurance, poverty and health: A systematic review. *European Journal of Public Health*, *28*(2), 269–275. https://doi.org/10.1093/EURPUB/CKX235

Schmitz, H. (2011). Why are the unemployed in worse health? The causal effect of unemployment on health. *Labour Economics*, *18*(1), 71–78. https://doi.org/10.1016/j.labeco.2010.08.005

Scruggs, Lyle. (2022). *Comparative Welfare Entitlements Project Data Set, Version 2022-12* (Version 2022-12) [Dataset]. https://www.cwep.us/home/data

Selenko, E., Batinic, B., & Paul, K. (2011). Does latent deprivation lead to psychological distress? Investigating Jahoda's model in a four-wave study. *Journal of Occupational and Organizational Psychology*, *84*(4), 723–740. https://doi.org/10.1348/096317910X519360

Stuckler, D., Basu, S., Suhrcke, M., Coutts, A., & McKee, M. (2009). The public health effect of economic crises and alternative policy responses in Europe: An empirical analysis. *The Lancet*, *374*(9686), 315–323. https://doi.org/10.1016/S0140-6736(09)61124-7

Thelen, K. (2012). Varieties of capitalism: Trajectories of liberalization and the new politics of social solidarity. *Annual Review of Political Science*, *15*(1), 137–159. https://doi.org/10.1146/annurev-polisci-070110-122959

Thomson, R. M., Igelström, E., Purba, A. K., Shimonovich, M., Thomson, H., McCartney, G., Reeves, A., Leyland, A., Pearce, A., & Katikireddi, S. V. (2022). How do income changes impact on mental health and wellbeing for working-age adults? A systematic review and

meta-analysis. *The Lancet Public Health*, *7*(6), e515–e528. https://doi.org/10.1016/S2468-2667(22)00058-5

Tøge, A. G. (2016a). Health effects of unemployment in Europe (2008–2011): A longitudinal analysis of income and financial strain as mediating factors. *International Journal for Equity in Health*, *15*, 1–12. https://doi.org/10.1186/s12939-016-0360-6

Tøge, A. G. (2016b). Health effects of unemployment in Europe during the great recession: The impact of unemployment generosity. *International Journal of Health Services*, *46*(4), 614–641. https://doi.org/10.1177/0020731416664688

Tøge, A. G., & Blekesaune, M. (2015). Unemployment transitions and self-rated health in Europe: A longitudinal analysis of EU-SILC from 2008 to 2011. *Social Science & Medicine*, *143*, 171–178. https://doi.org/10.1016/j.socscimed.2015.08.040

Vahid Shahidi, F., Siddiqi, A., & Muntaner, C. (2016). Does social policy moderate the impact of unemployment on health? A multilevel analysis of 23 welfare states. *The European Journal of Public Health*, *26*(6), 1017–1022. https://doi.org/10.1093/eurpub/ckw050

Venn, D. (2012). *Eligibility criteria for unemployment benefits: Quantitative indicators for OECD and EU countries*.

Verlaat, T., Rosenkranz, S., Groot, L. F. M., & Sanders, M. (2021, June 21). *Conditionality vs. autonomy: What works best in social assistance?* SSRN. https://doi.org/10.2139/ssrn.3720953

Voßemer, J., Gebel, M., Täht, K., Unt, M., Högberg, B., & Strandh, M. (2018). The effects of unemployment and insecure jobs on well-being and health: The moderating role of labor market policies. *Social Indicators Research*, *138*, 1229–1257. https://doi.org/10.1007/s11205-017-1697-y

Williams, E. (2021). Unemployment, sanctions and mental health: The relationship between benefit sanctions and antidepressant prescribing. *Journal of Social Policy*, *50*(1), 1–20. https://doi.org/10.1017/S0047279419000783

World Bank. (n.d.). *World Bank Open Data—GDP growth (annual %)—European Union*. World Bank Open Data. Retrieved 16 April 2025, from https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG?end=2019&locations=EU&start=2014

World Bank. (2022). *World Bank Open Data*. https://data.worldbank.org/

Paper 4: What shapes trust in healthcare? Socio-economic and structural determinants of trust in formal and traditional health providers across 111 countries

Author: Christoph Henking

Abstract

Background

Public trust in healthcare professionals is crucial for effective healthcare systems and impacts service use and health outcomes. This study explores global variations in trust, assessing how national income (GDP) and individual socio-economic status relate to trust in healthcare professionals and trust in traditional medicine practitioners. It also analyses whether broader healthcare and political factors beyond GDP help explain these differences.

Methods

The study combines cross-sectional data from the Wellcome Global Monitor 2020 (N = 117,088) covering 111 countries with country-level indicators on healthcare expenditure, quality of care, and corruption perception. I used multilevel regression models to estimate the associations between trust in healthcare professionals and traditional healers (both measured on single-item 4-point scales with SD = 0.8) with a range of individual and country-level predictors.

Findings

Across all countries, individuals in the highest within-country income quintile reported more trust in health professionals (0.04, 95% CI[0.03, 0.06]), but significantly less trust in traditional healers (–0.08, [–0.09, –0.06]) compared to the lowest within-country income quintiles. In middle- and high-income countries there is a strong positive relationship between GDP and trust in healthcare professions in middle- and high-income countries, whereas this association is absent in low-income settings. Similarly, the within-country income gradient with trust is absent

in low/lower-middle income countries. Finally, lower levels of corruption were positively associated with trust in healthcare professionals (0.15, [0.07, 0.23]), while higher health expenditure was linked to lower trust in traditional healers (–0.14, [–0.27, –0.01]).

Interpretation

Trust in formal healthcare providers is highest among the richest individuals in the wealthiest countries, but these relationships are more nuanced and absent in low/lower-middle income countries. Corruption levels might explain the link between GDP and trust, and should be studied in future research. Within countries, trust in traditional medicine practitioners follows an inverse socio-economic pattern, with higher trust among poorer individuals and lower income countries.

1. Introduction

In paper 1 of this DPhil thesis ("*Global inequalities in mental health problems*"), I found that trust in health professionals is associated with crucial mental health outcomes (Henking et al., 2023). Across 111 countries, individuals with higher trust in healthcare professionals (e.g., medical doctors and nurses) were more likely to utilise treatment for mental health problems and find treatment more helpful. Given that mental health remains a stigmatised topic in many parts of the world, these findings underline the importance of building trust in healthcare systems as a public health strategy (Bracke et al., 2019).
These results align with a growing body of evidence linking trust in healthcare providers to a range of crucial health outcomes. Public trust in healthcare professions is an essential component of effective healthcare systems and a key requirement for producing positive health outcomes (Birkhäuer et al. 2017; Dougliiass and Calnan 2016). Conversely, low trust is associated with reduced healthcare utilisation, lower treatment satisfaction, and worse health outcomes (Birkhäuer et al., 2017; Douglass & Calnan, 2016; Henking et al., 2023).

However, trust in healthcare professionals is not universal. Less than half of the world's populations report high levels of trust in health professionals (Moucheraud et al., 2021). Trust tends to be lower in disadvantaged socio-economic groups (Antinyan et al., 2021; Brown et al., 2009). The COVID-19 pandemic may have further influenced these dynamics. Research suggests that the impact of the pandemic on trust depended on how effectively health systems managed the crisis (Lazarus et al., 2022).

Despite increasing recognition of the importance of healthcare trust, three major gaps remain in the literature. This chapter addresses each in turn: First, while there is some evidence on socio-economic gradients (Antinyan et al. 2021; Brown et al. 2009), it is unclear if greater affluence at country or individual level is consistently associated with higher trust. I examine whether national

income (GDP per capita) and individual-level socio-economic status (SES) are systematically associated with trust in healthcare professionals across different country contexts.

Second, the role of trust in traditional and complementary medical providers is underexplored. Across many countries and cultures, traditional and alternative medicine is used to replace or supplement biomedically trained healthcare professionals (Puckree et al., 2002; Van der Schee & Groenewegen, 2010; Xu & Yang, 2009). Yet, the socio-economic determinants of trust in these alternative healthcare providers are not well understood in a global, cross-national context and in contrast to conventional biomedical providers.

Third, beyond personal and national economic prosperity, healthcare system and political factors such as quality of care, healthcare investment and corruption may determine trust (Naher et al., 2020; Radin, 2013). These factors could help explain why higher national income does not uniformly translate into higher trust.

In this study, I address these three research gaps using a cross-national dataset of 111 countries, and analyse the determinants of trust in biomedical and traditional healthcare providers. I demonstrate that GDP is positively associated with trust in healthcare professionals, but only when a certain threshold of economic development is reached (i.e., upper-middle income countries). In contrast, the relationship between GDP and trust in traditional health practitioners is much flatter and statistically weak. When it comes to personal income, higher within-country income is associated with higher trust in healthcare professionals and lower trust in traditional/alternative healthcare providers. Higher perceptions of corruption are associated with lower trust in healthcare professionals.

Background and research questions

The determinants of trust in healthcare professionals

Trust in health professionals is situated in the broader context of social trust. Social trust is the belief that others in society generally act with benevolence and competence (Ben-Ner & Halldorsson, 2010). Research suggests that social trust is hierarchical: people tend to place the most trust in their family and neighbours, while trust in professionals and public figures varies substantially (Delhey et al., 2011). Trust in health professionals – such as doctors and nurses – ranks highly relative to other occupational groups and institutions, but there is strong variation within and between countries (McAndrew, 2020; Moucheraud et al., 2021). Further, research suggests that trust in physicians is declining as healthcare is becoming increasingly commercialised (Huang et al., 2018).

Higher socio-economic status (SES), as measured by education, income, or occupational position, is consistently associated with higher levels healthcare-specific trust (Cologna et al., 2025; Delhey & Newton, 2003; McAndrew, 2020). Furthermore, people with socio-economic advantage are more likely to access high-quality medical treatments, especially in wealthy countries (Fjaer et al., 2017). Positive experiences with healthcare services may also play an important role. individuals with more satisfying encounters with the healthcare system are more likely to trust doctors (Ward, 2018). In contrast, those experiencing financial hardship and members of marginalised societal groups excluded from high level quality of care exhibit lower levels of trust in health professionals (Akafu et al., 2023; Majumder et al., 2015).

At the country level, countries with greater national wealth tend to have more resources to invest in their health systems which is expected to foster greater trust in formal health professionals (Baltagi et al., 2017; Watkins et al., 2018). However, evidence suggests that the translation of national prosperity into trust in health is not straightforward and varies between regions (Moucheraud et al., 2021): for example, people in East Asia, rather than more prosperous European countries, were the most likely to have high trust in doctors and nurses. A related study on the determinants of trust in scientists in 67 countries found that GDP was a relevant

predictor (Cologna et al., 2025). Further, we do not know if socio-economic gradients in trust vary by country and national income. Some European evidence suggests that inequalities in trust may be less pronounced in countries with more universal healthcare systems (Wendt et al., 2010), but no research has illustrated the SES gradients in trust across a global context across country income groups.

The first goal of this study is to clarify whether wealth, measured as national GDP per capita and individual-level SES, is consistently associated with trust in healthcare professionals. I test whether richer countries and richer individuals tend to express higher trust, or whether this assumption does not hold globally.

Research Question 1 (individual SES, national income and trust in health professionals): What is the global relationship between personal SES, national income (GDP) and trust in healthcare professionals?

The determinants of trust in traditional and complementary health practitioners

Traditional and complementary medicine represent important facets of healthcare systems worldwide. Its meaning and usage varies between global regions (Fakih et al., 2022). Particularly in African, Asian and Latin American countries, traditional health practitioners often practice herbal or faith oriented health practices (Fakih et al., 2022; World Health Organization, 2019). In African contexts, traditional healers rather than biomedical healthcare often constitute the primary point of care, particularly in rural areas (Ae-Ngibise et al., 2010; Krah et al., 2018). China, Japan, Korea and India have a high usage of traditional medicine and have a good integration into the public health system (Fakih et al., 2022; Xu & Yang, 2009), while in Western countries, non-conventional medicine is mainly represented by complementary and alternative medicine. These include different types of care such as natural, herbal, homeopathic or manual therapeutic practices – typically used to complement rather than substitute conventional healthcare (Van der Schee & Groenewegen, 2010; von Schoen-Angerer et al., 2023). The World

Health Organization (2013) initiated a strategy for 2014 – 2023 (to be updated for 2025 – 2034), aiming to set standards in education, quality assurance and evaluation. We have limited knowledge of the determinants of trust in health practitioners and how it varies across socioeconomic groups. Some evidence suggests that within low- and middle-income countries (LMICs), lower SES individuals tend to use traditional medicine more frequently, while in high-income countries (HICs), alternative forms of medicine might be used by higher SES individuals who have the means to pay out of pocket for treatment in additional to conventional care (World Health Organization, 2019).

Improving our knowledge of what drives trust in traditional and alternative medicine provides an important missing piece in our understanding of global health. With millions of people relying on such forms of healthcare worldwide, there is little systematic evidence on how public perceptions and trust in biomedical providers differ from those in traditional healers (Fakih et al., 2022; World Health Organization, 2019). Trust in traditional medicine practitioners has also been neglected in much of the research on the political economy of healthcare and discussions on trust in healthcare institutions. This study is the first to systematically investigate these questions using cross-national population-based data. Contrasting the drivers of trust in traditional practitioners with those in conventional biomedical health professions will allow us to contextualise similarities and differences.

Research question 2 (individual SES, national income and trust in traditional health practitioners): What is the global relationship between personal SES, national income (GDP) and trust in traditional medicine practitioners?

Beyond personal SES and GDP: What political and healthcare-specific factors determine trust?

While national income and within-country socioeconomic advantage are expected to be important determinants of trust, they are unlikely to tell the full story. I also investigate whether healthcare-specific and political factors help explain variation in trust.

One country-level characteristic is the quality and coverage of healthcare systems. Lower trust in professionals in LMICs may stem from limited availability of services and poorer quality of care (Antinyan et al., 2021). This is particularly the case for chronic conditions (Zhang et al., 2010). More prosperous countries, by contrast, are able to provide universal healthcare to all citizens and invest in long-term care (Baltagi et al., 2017). These differences do not only shape patient experiences and from an institutional theory perspective, but also influence perceptions of institutional competence, fairness, and integrity (Gilson, 2003). Negative perceptions reflect not only on healthcare institutions as a whole but also on the healthcare professionals who operate within them (Gilson, 2006; Mackey & Liang, 2012). Thus, healthcare quality and coverage might act as a mediating factor between national income and trust in healthcare professionals and workers, which is crucial for improvements to national income to translate into higher trust in healthcare professionals. Besides quality of care and coverage, high personal out-of-pocket costs for treatment could increase scepticism towards medical decision-making and reducing (Cunningham, 2009; Yuan & Lee, 2022). Where formal biomedical care is inaccessible and connected to higher costs, trust may instead shift toward traditional healers if they are locally more available and affordable (World Health Organization, 2013).

Moreover, the broader political context, corruption and weak governance are expected to be an important barrier to both trust in conventional care and traditional health practitioners. From an institutional theory perspective, corruption undermines the legitimacy of healthcare institutions by signalling to the public that the health system does not operate according to fair and predictable rules (Glynn, 2022; Thompson, 2018). Similar to the argument on quality of care, this is likely to deteriorate the perception of healthcare workers' integrity and qualification operating within the system (Mackey & Liang, 2012). Empirically, countries with weaker governance and higher corruption levels tend to have lower levels of trust in general and across professions (Delhey & Newton, 2003; Uslaner, 2017). Corruption, for instance in the form of informal

payments or bribery, has also been linked to reduced trust in both healthcare systems and professionals in settings (Naher et al., 2020; Radin, 2013). Therefore, it is expected that corruption levels are an important determinant of trust in healthcare professions.

On the other hand, there is no evidence as to whether higher corruption levels might erode trust in traditional health practitioners as well, or whether they might be seen as a sought-after alternative where the formal health system is affected by high levels of corruption. For both trust in biomedical care and traditional care, such political and healthcare-specific factors have not yet been systematically explored in a global study. I therefore aim to address this aspect in Research Question 3.

Research question 3 (healthcare and political factors): Beyond national income, what political and healthcare-specific country characteristics (e.g., health system performance, health expenditure or corruption) are associated with trust in healthcare professionals and traditional medicine practitioners?

Taken together, using an individual dataset with representative data from 111 countries, this study investigates to what extend GDP and individual-level socio-economic position determine (RQ 1) trust in healthcare professionals, (RQ 2) trust in traditional medicine practitioners, (RQ 3) and how county-level differences might be driven by healthcare and political system characteristics beyond GDP.

2. Methodology

Individual-level sample

The analysis is based on the cross-sectional global survey Wellcome Global Monitor 2020 (Wellcome Trust, 2020), which collected representative samples in 113 countries. Data was collected between August 2020 and January 2021 using telephone interviews. In line with

previous work reported in paper 1 of this DPhil thesis, the final dataset resulted in 111 countries (N = 117,088) due to missing data in Tajikistan and Venezuela. Details on the participating countries and descriptive statistics per country can be found in Table S1 and S2 in the Appendix paper 4. The data collection is situated during the Covid-19 pandemic which might have impacted levels of trust in health professionals. I ran sensitivity analyses for the main multilevel regression model in Appendix paper 4 (Table S3), where I include Covid-19-specific indicators such as lockdown intensity and Covid-19 mortality rates. This analysis shows that my results remain stable when including these factors.

Variables

Outcome variable

Trust in health professionals was measured using the item "How much do you trust the following? Doctors and nurses in this country" on a scale from 1 = not at all, 2 = not much, 3 = some, 4 = a lot. Trust in traditional health practitioners was measured on the same scale from 1 to 4, using the item "How much do you trust the following? Trust in traditional healers in this country". Notably the survey item may be interpreted differently across cultural and regional contexts. In LMICs, the term typically refers to herbal, spiritual, or community-based healers, while in HICs, it may be understood more broadly to include complementary or alternative medicine providers such as homeopaths or naturopaths (Fakih et al., 2022; Van der Schee & Groenewegen, 2010; World Health Organization, 2019). For the main analysis, the variable was treated as numerical to use the full variance of this item. To validate whether the results are sensitive to a different modelling choice, I also coded binary variables for the trust variables where one category was comprised of the "not at all" or "not much" (coded as 0) and another category as "some" or "a lot) (coded as 1). Based on this alternative coding, I ran logistic regression models in correspondence with the models shown in the main analysis of this paper

(see Table 5.2). The results are shown in Appendix paper 4 (Table S4) and indicate that the findings remain consistent with the main analysis shown in Table 5.2.

Individual-level factors

Socio-economic status was measured through education (Primary school or less; completed secondary school; completed tertiary education) and household income (Per Capita Income Quintiles within countries). The study includes “trust in neighbours” as indictor for general societal trust outside the health sector (measured from 1 = not at all to 4 = a lot). Gender and age are also included as control variables because both may influence trust and healthcare-seeking behaviour.

Country-level factors

National income was measured using gross domestic product per capita (GDP) and it was downloaded from the World Bank (2022) open data website alongside health expenditure as percentage and out-of-pocket health expenditure (both as percentage of GDP). The Healthcare Access and Quality (HAQ) index, created by the Institute for Health Metrics and Evaluation (IHME) at the University of Washington was used to measure quality of care. It was downloaded for the last available year of 2015 from the EU Joint Research Center website (EU Joint Research Centre, 2025). Finally, I used the Transparency International Corruption Perception Index for the year 2020 which uses a scale from 1 – 100 to measure the level of perceived corruption per country. Higher values indicate lower levels of corruption in each country (Transparency International, 2021). All country level values for these indicators are shown in Appendix paper 4 (Table S2).

Statistical analysis

To test the three research questions, I ran a multilevel regression analysis where individuals are nested in countries and the main outcome variables are (a) trust in health professionals and (b)

trust in traditional healers. Following my analyses in paper 1, I first established a random intercept model, and then added predictors according to the variables shown in Table 5.2 (see paper 1 for a similar model using the same dataset). To increase comparability between vastly different scales, several country-level predictors (health expenditure, out of pocket payments, and corruption and quality of care indices) were standardised so that a change of "1" equals to 1 SD.

I ran eight separate models for the two outcomes "trust in health professionals" (M1 - M4) and "trust in traditional healers" (M5 - M8). Models M1 – M3 investigate research question 1, the relationship between national income (GDP), personal SES and trust in health professionals. I contrast household income quintiles 1,3 and 5 as main indicators for within-country socio-economic gradients. Model M1 only uses simple, linear predictors in the model. Models 2 and M3 then add an interaction term and a quadratic term for the relationship on household income and GDP respectively. This is done to test whether the personal income gradient differs by country prosperity and if the relationship between GDP and trust might not be linear but quadratic. The models M4 - M7 are used to examine research question 2, the relationship between national income (GDP), personal SES and trust in traditional healers. The models follow the same construction as M1 - M3.

Models M4 and M8 are used to examine research question 3, the political and healthcare related country determinants of trust. This is done by adding the country-level predictors of health expenditure, out-of-pocket health spending, quality of care and the corruption index to my model for both types of trust. "Trust in neighbors" is added as control variable to control for general trust in other life domains. Gender and age are also used as control variables throughout all models to isolate the effect of demographic factors on trust.

3. Results

Descriptive statistics and correlations

Levels of trust in health professionals and traditional health practitioners globally are shown as maps in Figure 5.1 and Figure 5.2 (darker colour indicates higher levels of trust). Figure 5.1 reveals some regional patterns, where most Western European countries as well as North America display high levels of trust in health professionals. Additionally, descriptive statistics per variables, across all 111 countries, are shown in Table 5.1. Notably, trust in healthcare professionals is considerably higher (M = 3.3, SD = 0.8) than trust in traditional healers (M = 2.3, SD = 1.0) across the whole sample of 111 countries.

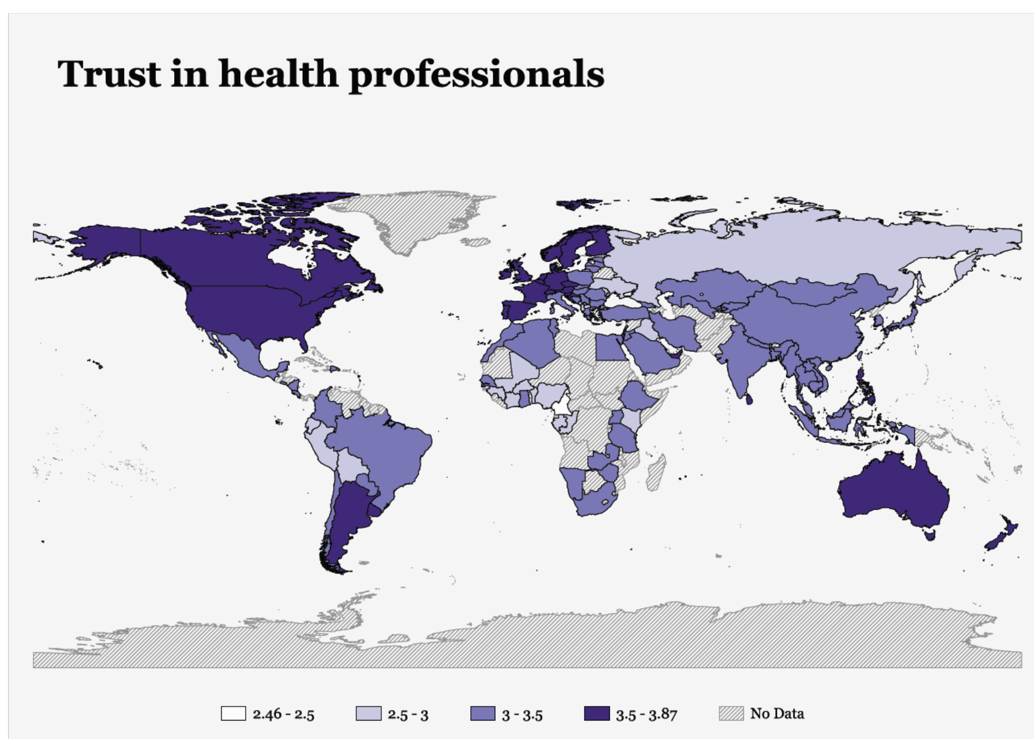


Figure 5.1. Mean trust in healthcare professionals by country

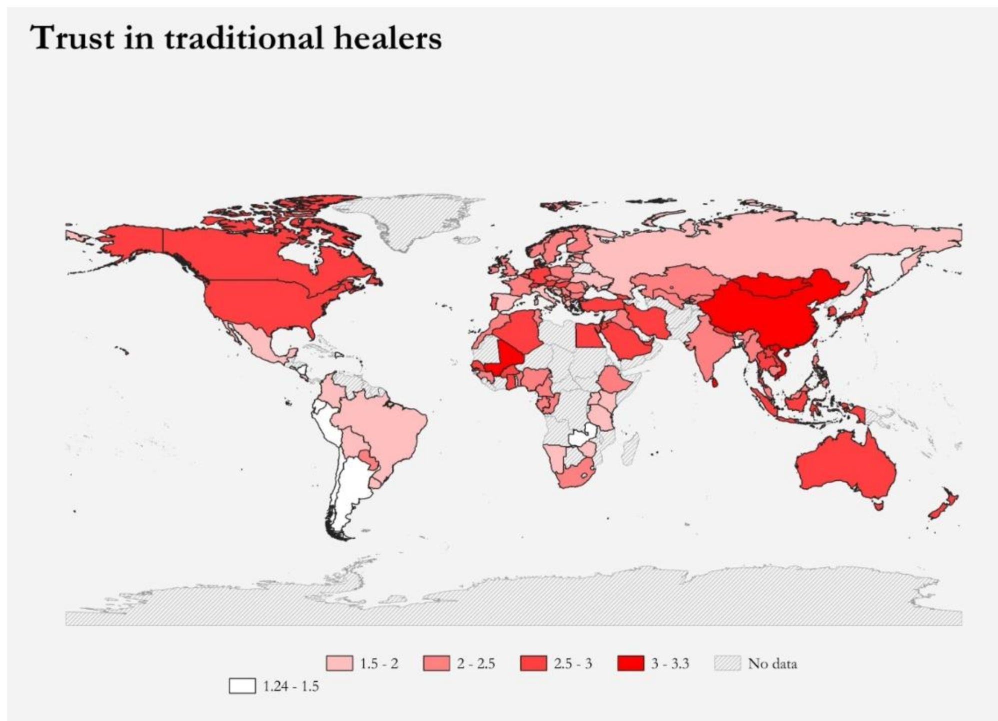


Figure 5.2. Mean trust in traditional health practitioners by country

Further, I calculated the mean values of trust for each individual country as shown in Appendix paper 4 (Table S1). Additionally, I calculated the within-country correlation coefficients between different types of trust to provide a descriptive overview of the variables in the study. As shown in Table S1, Belgium has the highest level of trust in healthcare professionals (M = 3.87), whereas Cameroon has the lowest trust (M = 2.48). In all 111 countries, trust in health professionals (as a person) is higher than trust in hospitals (as a health institution). Within all countries, there is a positive correlation between trust in health professionals and trust in hospitals, ranging from r = 0.11 in Spain to r = 0.69 in Russia. Trust in traditional healers is highest in China (M = 3.30) and lowest in Argentina (M = 1.42). Mean trust in healthcare professionals is higher than trust in traditional healers in all countries, with the exception of China and Mali. The overall correlation between trust in health professionals and trust in healers is modest (r =0.11). The correlation coefficient is highest in China (r = 0.42) and the lowest in Spain (r = -0.11). This suggests that these two types of trust only have a low correlation and there are substantive differences between countries.

Table 5.1. Descriptive statistics.

		All countries	**High income countries**	**Low- and middle-income countries**
Socio-demographic characteristics	Countries, N	111, N= 117,088	43, N= 43,201	70, N= 73,887
	Gender	F = 50.9%, M = 49.1%	F = 50.7%, M = 49.3%	F = 48.1%, M = 51.9%
	Age (mean, sd)	40.2 years (17.3)	49.1 years (18.1)	35.0 years (12.8)
Country-level indicators	GDP per capita in USD (mean, SD)	15,862 (18,908)	35,340 (18,750)	2,165 (1,034)
	GDP (log) (mean, sd)	8.9 (1.3)	10.3 (0.5)	8.1 (0.8)
	Healthcare Access and Quality (HAQ) index	68.6 (15.3)	83.6 (5.9)	60 (12)
	Corruption index (mean, sd). Note: higher scores indicate lower corruption	46.6 (17.9)	65.9 (13.2)	35.5 (8)
	Health expenditure as % of GDP (mean, SD)	6.6 (2.6)	8.5 (2.3)	4.6 (1.6)
	% Out of pocket healthcare expenditure	32.3 (15.5)	21.2 (8.9)	44.9 (15.2)
Education (individual level)	Elementary or less	13.3%	7.5%	16.7%
	Secondary	55.1%	53.2%	56.3%
	Tertiary	31.5%	39.3%	27.0%
	Number of responses	116,352	42,980	73,372
Trust in health practitioners (doctors and nurses)	mean (SD)	3.3 (0.8)	3.5 (0.7)	3.1 (0.8)
Trust in traditional healers	mean (SD)	2.3 (1)	2.3 (1)	2.2 (1.1)
Trust in clinics	mean (SD)	3 (0.9)	3.3 (0.8)	2.8 (0.9)
Trust in neighbours	mean (SD)	3 (0.9)	3.2 (0.8)	2.8 (0.9)

Multilevel-analysis regression analyses

Research question 1 (relationship between individual SES, national income and trust in traditional health practitioners)

Models M1, M2 and M3 are used to investigate research question 1 and examine the association between personal SES, country-level GDP and trust in health professionals. Model M1 shows that higher household income is linked to higher levels of trust in health professionals across the 111 countries (quintile 3: 0.033, 95% CI:[0.02, 0.04]; quintile 5: 0.04, CI[0.03, 0.06]). Model M2 shows that there is a significant interaction between individual-level household income and GDP (quintile 3 * log(GDP) = 0.03 CI:[0.02, 0.04]; quintile 5 * log(GDP) = 0.04,CI:[0.03, 0.05]). This suggests that the income-trust gradient becomes steeper in richer countries. Model M3 shows that the quadratic term for GDP is also statistically significant (log(GDP)^2: 0.06, 95% CI:[0.03, 0.09]), indicating that the association between GDP and trust has a quadratic shape. This finding is further illustrated and visualised in the section below (see Figure 5.3) where a steep incline of trust is shown as GDP rises. Overall, the effect sizes and visualisation also suggest that GDP matters more to explain trust compared to personal, within-country income. Figure 5.3 and Figure 5.4 below help illustrate these findings in more detail.

Research question 2 (relationship between personal SES, national income and trust in traditional healers)

Models M5, M6 and M7 are used to investigate research question 2, the association between SES, GDP and trust in traditional healers. Contrary to M1 (for healthcare professionals), M5 shows that being in a higher within country income quintile (quintile 3: -0.04, 95% CI:[-0.06, -0.02]; quintile 5: -0.08, 95% CI:[-0.09, -0.06]) is associated with lower trust in traditional healers. Further, model M6 shows no direct relationship between GDP and trust in traditional health practitioners, and no interaction between household income and trust. This suggest a weak relationship between GDP and trust in traditional health practitioners. However, similar to trust in health professionals, M7 shows that the quadratic term for GDP and trust in traditional health

practitioners is significant (log(GDP)^2: 0.07, 95% CI:[0.01, 0.12]). Figure 5.3 and 5.4 – as described further below – will help illustrate these associations in more detail to help make sense of the findings derived from model M6 and M7.

Research question 3 (healthcare and political factors)

Finally, models M4 and M8 focus on the role of broader country-level factors for both types of trust. Model M4 shows that lower corruption perception (higher corruption index: 0.15, 95% CI:[0.07, 0.23]) is significantly associated with greater trust in health professionals. Other health system characteristics, including health expenditure, out-of-pocket expenditure, and quality of care, are not significantly associated with trust in health professionals. Model M8 shows that only health expenditure is significantly and negatively associated with trust in traditional healers (-0.14, CI:[-027, -0.01]), meaning that an increase of 1 SD in health expenditure is related to a 0.14 decease on the 4-point-scale in trust in traditional health practitioners. Notably, in both model M4 and M8, the associations between GDP and trust become non-significant. This suggests that the addition of healthcare and political predictors interferes with this relationship and, especially corruption (for healthcare professionals) and health expenditure (for traditional healers), might mediate the relationship of GDP and trust outcomes. While causal mediation is difficult to test in cross-sectional data (Schuler et al., 2025), future longitudinal research should investigate these pathways.

Table 5.2. Multi-level regression model.

	Outcome: Trust in health professionals				Outcome: Trust in traditional healers			
Individual-level factors	**M1** (individual level)	**M2** (income *GDP)	**M3** (quadratic model)	**M4** (country-level)	**M5** (individual level)	**M6** (Income* GDP)	**M7** (quadratic model)	**M8** (country-level)
Age	**.02*** [.01 – .02]	x	x	x	**-.05*** [-.06 – .05]	x	x	x
Gender (being male)	**-.02**** [-.03 – -.01]	x	x	x	**-.03**** [-.04 – -.02]	x	x	x
Primary school or less (ref= secondary school)	-.01 [-.02 – .00]	x	x	x	**.07**** [.06 – .09]	x	x	x
University education (ref= secondary school)	**.04**** [.03 – .05]	x	x	x	**-.08**** [-.10 – -.06]	x	x	x
Household income quintile 3 (ref= quintile 1)	**.03**** [.02 – .04]	**-.20**** [-.30 – -.10]	**.04**** [.02 – .05]	x	**-.04**** [-.06 – -.02]	-.08 [-.21 – .05]	**-.03**** [-.05 – -.01]	x
Household income quintile 5 (ref= quintile 1)	**.04**** [.03 – .06]	**-.31**** [-.41 – -.21]	**.05**** [.03 – .06]	x	**-.08*** [-.09 – -.06]	-.01 [-.14 – .11]	**-.07**** [-.09 – -.05]	x
Quintile 3 * Log(GDP)		**.03**** [.02 – .04]				-.01 [-.01 – .02]		
Quintile 5 * Log(GDP)		**.04**** [.03 – .05]				-.01 [-.02 – .01]		
Trust in neighbours	**.20**** [.19 – .20]			x	**.14**** [.13 – .14]			x
Country-level factors								
Log(GDP)		**.11**** [.08 – .15]	**-1.01**** [-1.52 – -.49]	-.02 [-.08 - .14]		.06 [-.01 – .13]	**-1.12*** [-2.11 – -.12]	-.01 [-.21 - .20]
Log(GDP)^2			**0.06**** [.03 – .09]				**0.07*** [.01 – .12]	
Corruption index				**.15**** [.07 – .23]				.15 [-.02 – .32]
Health expenditure as % of GDP				.01 [-.05 - .07]				**-.14*** [-.27– -.01]
% Out of Pocket healthcare expenditure				-.02 [-.08 - .03]				.05 [-.06 – .17]
Quality of care index				.03 [-.08 – .14]				.10 [-24 – .07]
Marginal R^2	0.053	0.057	0.069	0.121	0.018	0.006	0.015	0.033
Conditional R^2	0.167	0.152	0.150	0.190	0.207	0.201	0.202	0.214

Notes. "x" indicates that the variable was included as control variable in the model; 111 countries included. Several country-level factors (corruption index, healthcare expenditure, out of pocket expenditure and quality of care) were standardised so that a change of 1 level = 1 SD.

Visualising the relationship of individual income, GDP and trust

The multilevel regression model (Table 5.2) revealed that both interaction and quadratic terms are substantial for understanding the relationship between individual income, GDP, and both types of trust. To make these relationships more transparent, I used the underlying regression models to plot the predicted values of trust in health professionals and traditional healers as a function of GDP and income, and included both quadratic and interaction terms (see Figure 5.3). Additionally, I plotted the income gradients of trust separately for low/middle-, upper-middle, and high-income country groups to illustrate the magnitude and direction of socio-economic gradients (see Figure 5.4).

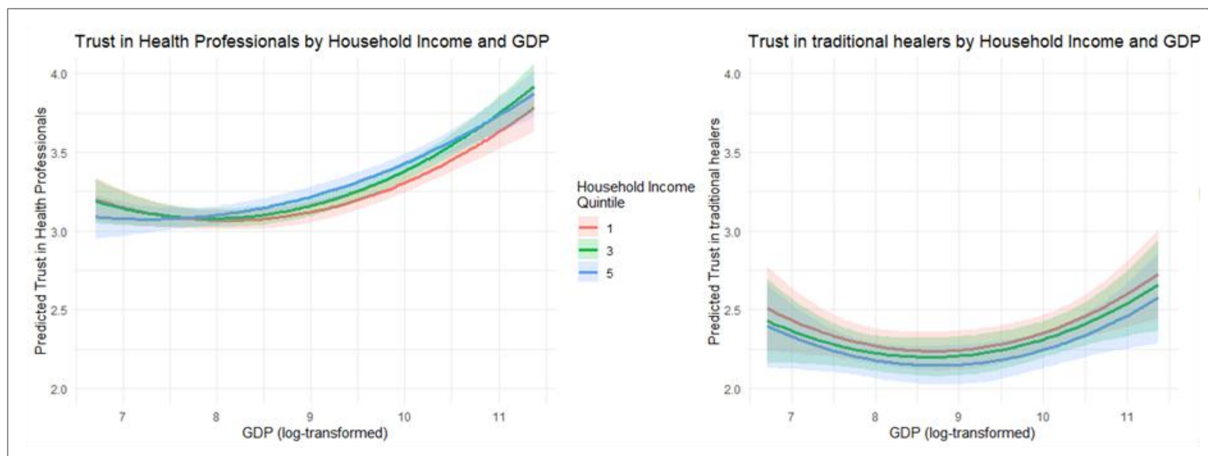


Figure 5.3. Predicted probabilities of trust in health professionals and traditional healers as a function of GDP and within country income quintile (95% CIs)

For trust in healthcare professionals (left panel of Figure 5.3), the relationship with GDP appears to be relatively flat across lower levels of GDP but then rises more sharply for richer countries. Figure 5.4 shows that the income gradient (higher-income households have higher trust in health professionals) becomes apparent only in medium- and especially in high-income countries but is absent in low/lower-middle income countries. In combination, this suggests that only when countries reach a certain threshold of economic development does trust in health professionals start to rise, and within-country socio-economic gradients begin to emerge and widen.

For trust in traditional healers (right panel of Figure 5.3), the association with GDP is much flatter compared to the graph on the right. The relationship follows a U-shaped pattern: trust initially declines as GDP rises from lower levels (with a low point at the medium GDP level) but begins to increase again once GDP reaches higher levels. The individual-level income quintiles (as shown in Figure 5.4) consistently show that people with lower incomes within countries have higher levels of trust in traditional healers.

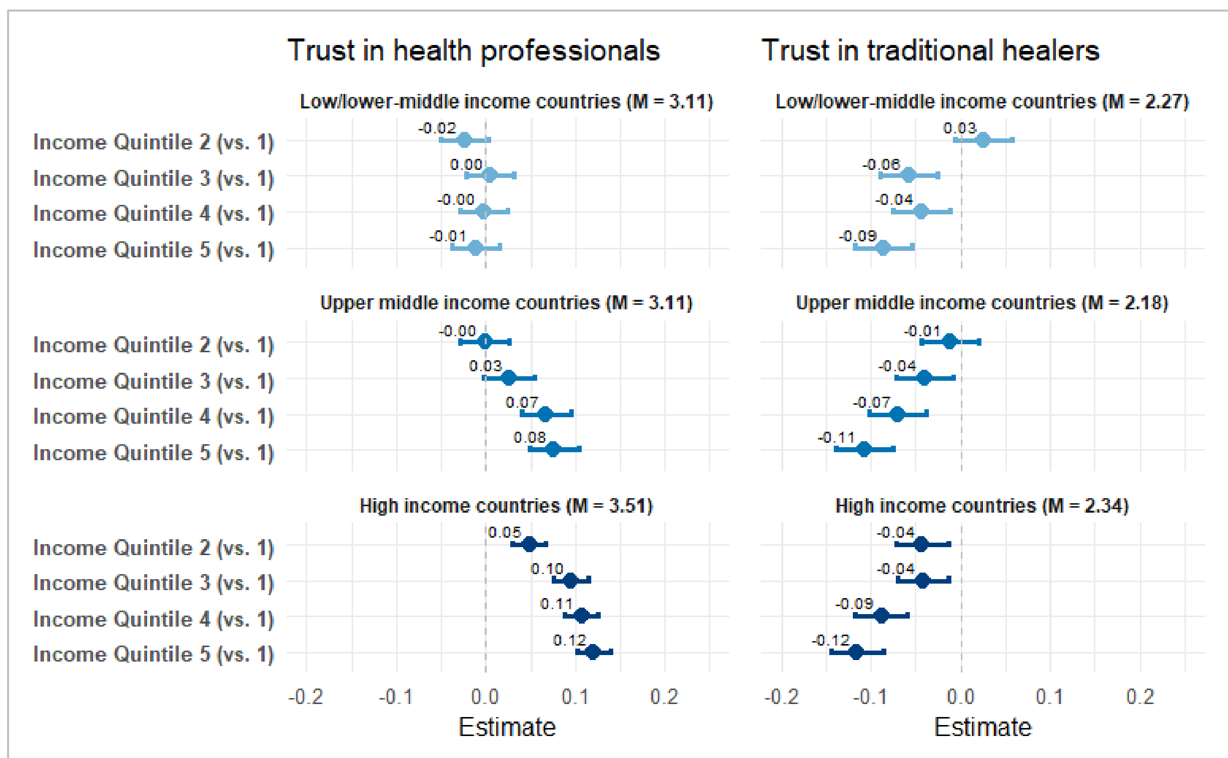


Figure 5.4. Predicted probabilities of within country household income quintiles, country groups and trust (95% CIs around each predicted value). Income Quintile 1 is used as reference category.

4. Discussion

Understanding the global variation of trust in healthcare professionals – both biomedical and traditional healthcare providers – is an important missing piece in the global study of healthcare systems. Trust in health professionals is essential for functioning healthcare systems and has shown to predict treatment utilisation and health outcomes (Birkhäuer et al., 2017; Douglass & Calnan, 2016; Henking et al., 2023).

This study investigated the social determinants of trust in healthcare professionals and traditional medicine practitioners across 111 countries. I considered household income and national income (GDP) as main socio-economic predictors, and also examined political and healthcare-specific determinants at the country level.

The study finds that trust in healthcare professionals (such as doctors and nurses) is higher than trust in traditional medicine practitioners in all countries – with the exception of China and Mali. I show that GDP is positively associated with trust in healthcare professionals, but only when a certain threshold of economic development is reached (i.e., upper-middle income countries). From that point, trust rises steeply as GDP increases. In contrast, the relationship between GDP and trust in traditional health practitioners is much flatter and statistically imprecise. The relationship forms a U-shaped pattern: somewhat higher levels of trust in traditional health practitioners were found in both low- and high-income countries, with a dip in upper-medium-income countries.

When it comes to personal income, higher within-country income is associated with higher trust in healthcare professionals in upper-middle and higher income countries. For trust in traditional health practitioners, the economic gradient is reversed: people with lower personal income have higher trust and this is consistent across all levels of national development (lower, middle and higher income countries).

Finally, I found that lower levels of perceived corruption are strongly associated with higher levels of trust in healthcare professionals, while no significant relationship was observed for traditional healers. Moreover, health expenditure was not significantly associated with trust in healthcare professionals, but in higher health expenditures was linked to lower trust in traditional healers. This suggests that political and healthcare factors have distinct implications for the two types of trust.

Trust in healthcare professionals

This study shows, in line with previous research (Akafu et al., 2023; Delhey & Newton, 2003; McAndrew, 2020), that more affluent individuals living in richer countries tend to have more trust in biomedical healthcare providers. However, the results highlight that the relationship between personal income and trust is shaped by the country's level of economic development: while there is a personal income gradient in trust in middle- and high-income countries, there is no personal income gradient in low/lower-middle income countries. Evidently, this is especially true in high-income countries (e.g., in Europe and North America), where both national wealth and individual socio-economic status align to result in higher levels of trust. In contrast, several of the lowest-income countries in my sample (e.g., Ethiopia, Mali, Uganda, Congo Brazzaville) share regional similarities. This includes a low availability of health services, which is an important contributor to trust (Antinyan et al., 2021; Zhang et al., 2010). Further, these countries have legacies of colonial medical campaigns, which have lowered overall trust in healthcare providers across generations for the entire population rather than specific socio-economic groups (Lowes & Montero, 2021). These findings highlight the need for further research focused specifically on trust in healthcare providers within low/lower-middle-income country contexts.

These differences in trust levels are likely to manifest in social inequalities in healthcare utilisation and treatment uptake – specifically for mental health (Birkhäuer et al., 2017; Douglass & Calnan, 2016). Moreover, it is important to highlight that trust is not the only psychosocial

determinant of health outcomes and healthcare utilisation, but it is interlinked with other mechanisms such as stigma. As I show in paper 1 of this dissertation, and as supported by previous studies (e.g., Bracke et al., 2019), stigma and trust share common socio-economic patterns in relation to health-seeking behaviours. That being said, I argue that improving trust in healthcare providers may also serve as an important mechanism to reduce stigmatisation, and vice versa: as societal stigma declines, trust is likely to grow as well. Future research should therefore take into account the bi-directional relationship between these two important psychosocial dimensions.

The role of corruption

The study also shows that there is a strong relationship between perceived corruption and trust in healthcare professionals. Notably, this study shows that corruption levels, rather than healthcare-specific factors such as health expenditure and healthcare quality measures (Baltagi et al., 2017; Cunningham, 2009; Zhang et al., 2010), are associated with trust in health providers globally. I propose two explanations.

First, corruption erodes generalised trust across society, affecting confidence in institutions and people throughout society (Delhey & Newton, 2003; Lavallée et al., 2008; Uslaner, 2017). While the study controls for levels of neighbourhood trust as a proxy for general trust, this is unlikely to account for all relevant variation. Thus, it is likely that broader mistrust generated by poor governance spills over into the healthcare system.

Second, there is a more direct pathway: in countries with higher corruption levels, the healthcare system itself suffers from bribery, informal payments and other unethical practices (Naher et al., 2020; Radin, 2013). Corruption also leads to overpaying, mismanagement of cases and resources, which likely erodes trust in health system and providers (Holmberg & Rothstein, 2011; Lewis, 2006).

The specific relationship between economic development, corruption and trust should be addressed in future research. One potential hypothesis derived from my research is that corruption might be a mediator in the relationship between GDP and trust. However, causal mediation is difficult to test in cross-sectional data (Schuler et al., 2025), and requires future longitudinal studies to investigate these pathways.

Trust in traditional medicine practitioners

This study is the first to investigate socio-economic and country-level predictors of trust in traditional healers across such a large global sample. Previous evidence has only insufficiently described the drivers of trust in such healthcare providers, despite millions of people relying on traditional and alternative forms of healthcare (Fakih et al., 2022; World Health Organization, 2019). The study demonstrates that the determinants differ from those of conventional biomedical healthcare providers. The relatively flat and slightly U-shaped relationship between GDP and trust in traditional health practitioners, which I found in this study, may again relate to the composition of low-income countries in the sample.

Countries in sub-Saharan Africa, which fall in the category of lowest GDP, tend to have a stronger use of traditional medicine, such as herbal medicine or spiritual healing practices (Krah et al., 2018; Puckree et al., 2002; World Health Organization, 2019). This is partly due to the unavailability and unaffordability of conventional biomedical care and greater reliance on informal care (Ae-Ngibise et al., 2010; World Health Organization, 2019). This could explain why trust is generally higher in low-income countries than in middle-income ones, where the healthcare landscape is more mixed. As countries grow wealthier, it is likely that again higher general trust drives up the U-shape (Delhey & Newton, 2003; Uslaner, 2017).

It is also important to consider that individuals in different countries and cultural contexts may interpret the concept of "traditional healer" differently, which may influence how they respond to the survey item.. That is, in high-income countries, nonconventional medicine is most

typically referred to as "supplementary and alternative medicine" rather than "traditional healing". The questionnaire item in this study, asking participants about their trust in traditional healers, might therefore have been less appropriate for such respondents. It is unclear if they interpreted the item more broadly, as referring to alternative therapies such as acupuncture or herbal medicine, or more spiritual practices. In either case, it is likely that these were seen more as supplementary care, rather than a replacement for conventional care (Van der Schee & Groenewegen, 2010; von Schoen-Angerer et al., 2023). Future research should capture such definitional differences more clearly (see limitations section below).

I also found a negative within-country socio-economic gradient in trust in traditional healers across all levels of GDP. This is in line with previous evidence from low- and middle-income countries (World Health Organization, 2019), but a novel finding for high-income countries, though definitional limitations could still play a role here.

Finally, I show that higher healthcare expenditure is associated with lower trust in traditional healers. This evidence may support the idea that investments in formal healthcare systems may reduce reliance on traditional healing practices. Similar to the argument on corruption made above, a potential mediating relationship should be investigated in future longitudinal research.

Limitations and conclusion

This study has several important limitations, two of which have already been highlighted in the discussion above. First, there may be differences in the interpretation of "trust in traditional healers," which likely captures something different from the use of alternative medicine in high-income countries, where it is unclear how this item was understood. Similarly, the item "how much do you trust doctors and nurses" carries some ambiguity and is measured using a single item. Second, the cross-sectional nature of this study hinders the causal interpretation of the relationships between the variables in this study. Additionally, it should be noted that the country sample is somewhat limited. In particular, the selection of low-income countries includes only a

small number of cases. Finally, while my analysis focuses on trust, a highly important indicator in health systems and sociological research, it does not capture the resulting implications for health behaviours and outcomes. Future research should use longitudinal designs, better measurement tools, and diverse country samples and link variations in trust to health outcomes.

In conclusion, this paper reveals global patterns and determinants of trust in both biomedical healthcare providers (e.g., doctors and nurses) and traditional healthcare providers. The study demonstrates that trust in biomedical healthcare providers is highest among the richest individuals in the wealthiest countries, however, these socio-economic gradients are largely absent and much less clear in low/lower-middle income countries. Beyond GDP, perceived corruption levels were identified as an important correlate of trust in healthcare professionals – and future studies should investigate whether corruption might mediate the relationship between GDP and trust. Within countries, trust in traditional medicine practitioners follows an inverse socio-economic pattern whereby trust is higher among poorer individuals. In times of rising political polarisation and growing public distrust in science, these patterns need to be recognised and monitored closely.

References

Ae-Ngibise, K., Cooper, S., Adiibokah, E., Akpalu, B., Lund, C., Doku, V., & Mhapp Research Programme Consortium. (2010). 'Whether you like it or not people with mental problems are going to go to them': A qualitative exploration into the widespread use of traditional and faith healers in the provision of mental health care in Ghana. *International Review of Psychiatry*, *22*(6), 558–567. https://doi.org/10.3109/09540261.2010.536149

Akafu, W., Daba, T., Tesfaye, E., Teshome, F., & Akafu, T. (2023). Determinants of trust in healthcare facilities among community-based health insurance members in the Manna district of Ethiopia. *BMC Public Health*, *23*(1), 171. https://doi.org/10.1186/s12889-023-15124-w

Antinyan, A., Bassetti, T., Corazzini, L., & Pavesi, F. (2021). Trust in the health system and COVID-19 treatment. *Frontiers in Psychology*, *12*, 643758. https://doi.org/10.3389/fpsyg.2021.643758

Baltagi, B. H., Lagravinese, R., Moscone, F., & Tosetti, E. (2017). Health care expenditure and income: A global perspective. *Health Economics*, *26*(7), 863–874. https://doi.org/10.1002/hec.3424

Ben-Ner, A., & Halldorsson, F. (2010). Trusting and trustworthiness: What are they, how to measure them, and what affects them. *Journal of Economic Psychology*, *31*(1), 64–79. https://doi.org/10.1016/j.joep.2009.10.001

Birkhäuer, J., Gaab, J., Kossowsky, J., Hasler, S., Krummenacher, P., Werner, C., & Gerger, H. (2017). Trust in the health care professional and health outcome: A meta-analysis. *PloS One*, *12*(2), e0170988. https://doi.org/10.1371/journal.pone.0170988

Bracke, P., Delaruelle, K., & Verhaeghe, M. (2019). Dominant Cultural and Personal Stigma Beliefs and the Utilization of Mental Health Services: A Cross-National Comparison. *Frontiers in Sociology*, *4*, 40. https://doi.org/10.3389/FSOC.2019.00040/BIBTEX

Brown, P., Calnan, M., Scrivener, A., & Szmukler, G. (2009). Trust in Mental Health Services: A neglected concept. *Http://Dx.Doi.Org/10.3109/09638230903111122*, *18*(5), 449–458. https://doi.org/10.3109/09638230903111122

Cologna, V., Mede, N. G., Berger, S., Besley, J., Brick, C., Joubert, M., Maibach, E. W., Mihelj, S., Oreskes, N., & Schäfer, M. S. (2025). Trust in scientists and their role in society across 68 countries. *Nature Human Behaviour*, 1–18. https://doi.org/10.1038/s41562-024-02090-5

Cunningham, P. J. (2009). High Medical Cost Burdens, Patient Trust, and Perceived Quality of Care. *Journal of General Internal Medicine*, *24*(3), 415–420. https://doi.org/10.1007/s11606-008-0879-3

Delhey, J., & Newton, K. (2003). Who trusts?: The origins of social trust in seven societies. *European Societies*, *5*(2), 93–137. https://doi.org/10.1080/1461669032000072256

Delhey, J., Newton, K., & Welzel, C. (2011). How general is trust in "most people"? Solving the radius of trust problem. *American Sociological Review*, *76*(5), 786–807. https://doi.org/10.1177/0003122411420817

Douglass, T., & Calnan, M. (2016). Trust matters for doctors? Towards an agenda for research. *Social Theory & Health*, *14*, 393–413. https://doi.org/10.1057/s41285-016-0010-5

EU Joint Research Centre. (2025). *Healthcare Access and Quality Index | Indice profile | Composite Indicators & Scoreboards Explorer*. Healthcare Access and Quality Index | Indice Profile | Composite Indicators & Scoreboards Explorer. https://composite-indicators.jrc.ec.europa.eu/explorer/indices/haqi/healthcare-access-and-quality-index

Fakih, M., Perbawati, C., & Monalisa. (2022). Relevance of WHO traditional medicine strategy (2014-2023) with traditional health care policy in the perspective of national law and international law. *Asian Journal of Legal Studies*, *1*(1), 25–34. https://doi.org/10.53402/ajls.v1i1.117

Fjaer, E. L., Balaj, M., Stornes, P., Todd, A., McNamara, C. L., & Eikemo, T. A. (2017). Exploring the differences in general practitioner and health care specialist utilization according to education, occupation, income and social networks across Europe: Findings from the European social survey (2014) special module on the social determinants of health. *European Journal of Public Health*, *27*(suppl_1), 73–81. https://doi.org/10.1093/EURPUB/CKW255

Gilson, L. (2003). Trust and the development of health care as a social institution. *Social Science & Medicine*, *56*(7), 1453–1468.

Gilson, L. (2006). Trust in health care: Theoretical perspectives and research needs. *Journal of Health Organization and Management*, *20*(5), 359–375. https://doi.org/10.1016/S0277-9536(02)00142-9

Glynn, E. H. (2022). Corruption in the health sector: A problem in need of a systems-thinking approach. *Frontiers in Public Health*, *10*, 910073. https://doi.org/10.3389/fpubh.2022.910073

Henking, C., Reeves, A., & Chrisinger, B. (2023). Global inequalities in mental health problems: Understanding the predictors of lifetime prevalence, treatment utilisation and perceived helpfulness across 111 countries. *Preventive Medicine*, *177*, 107769. https://doi.org/10.1016/j.ypmed.2023.107769

Holmberg, S., & Rothstein, B. (2011). Dying of corruption. *Health Economics, Policy and Law*, *6*(4), 529–547. https://doi.org/10.1017/S174413311000023X

Huang, E. C.-H., Pu, C., Chou, Y.-J., & Huang, N. (2018). Public Trust in Physicians—Health Care Commodification as a Possible Deteriorating Factor: Cross-sectional Analysis of 23 Countries. *Inquiry: A Journal of Medical Care Organization, Provision and Financing*, *55*, 0046958018759174. https://doi.org/10.1177/0046958018759174

Krah, E., de Kruijf, J., & Ragno, L. (2018). Integrating traditional healers into the health care system: Challenges and opportunities in rural northern Ghana. *Journal of Community Health*, *43*, 157–163. https://doi.org/10.1007/s10900-017-0398-4

Lavallée, E., Razafindrakoto, M., & Roubaud, F. (2008). *Corruption and trust in political institutions in sub-Saharan Africa*. 21.

Lazarus, J. V., Wyka, K., White, T. M., Picchio, C. A., Rabin, K., Ratzan, S. C., Parsons Leigh, J., Hu, J., & El-Mohandes, A. (2022). Revisiting COVID-19 vaccine hesitancy around the world using data from 23 countries in 2021. *Nature Communications*, *13*(1), 3801.

Lewis, M. (2006). Governance and corruption in public health care systems. *Center for Global Development Working Paper*, *78*. https://hal.science/hal-01765960/

Lowes, S., & Montero, E. (2021). The legacy of colonial medicine in Central Africa. *American Economic Review*, *111*(4), 1284–1314. https://doi.org/10.1257/aer.20180284

Mackey, T. K., & Liang, B. A. (2012). Combating healthcare corruption and fraud with improved global health governance. *BMC International Health and Human Rights*, *12*, 1–7. https://doi.org/10.1186/1472-698X-12-23

Majumder, P., O'Reilly, M., Karim, K., & Vostanis, P. (2015). 'This doctor, i not trust him, I'm not safe': The perceptions of mental health and services by unaccompanied refugee adolescents. *International Journal of Social Psychiatry*, *61*(2), 129–136. https://doi.org/10.1177/0020764014537236

McAndrew, S. (2020). *Institutional Trust, Trust in Scientists and Medical Professionals, and Vaccine Acceptance: Analyses of the Wellcome Monitor Studies*. https://osf.io/ujbwh

Moucheraud, C., Guo, H., & Macinko, J. (2021). Trust In Governments And Health Workers Low Globally, Influencing Attitudes Toward Health Information, Vaccines: Study examines changes in public trust in governments, health workers, and attitudes toward vaccines. *Health Affairs*, *40*(8), 1215–1224. https://doi.org/10.1377/hlthaff.2020.02006

Naher, N., Hoque, R., Hassan, M. S., Balabanova, D., Adams, A. M., & Ahmed, S. M. (2020). The influence of corruption and governance in the delivery of frontline health care services in the public sector: A scoping review of current and future prospects in low and middle-income countries of south and south-east Asia. *BMC public health, 20*(1), 880. https://doi.org/10.1186/s12889-020-08975-0

Puckree, T., Mkhize, M., Mgobhozi, Z., & Lin, J. (2002). African traditional healers: What health care professionals need to know. *International Journal of Rehabilitation Research*, *25*(4), 247–251.

Radin, D. (2013). Does corruption undermine trust in health care? Results from public opinion polls in Croatia. *Social Science & Medicine*, *98*, 46–53. https://doi.org/10.1016/j.socscimed.2013.08.033

Schuler, M. S., Coffman, D. L., Stuart, E. A., Nguyen, T. Q., Vegetabile, B., & McCaffrey, D. F. (2025). Practical challenges in mediation analysis: A guide for applied researchers. *Health Services and Outcomes Research Methodology*, *25*(1), 57–84. https://doi.org/10.1007/s10742-024-00327-4

Thompson, D. F. (2018). Theories of institutional corruption. *Annual Review of Political Science*, *21*(1), 495–513. https://doi.org/10.1146/annurev-polisci-120117-110316

Transparency International. (2021, January 28). *2020 Corruption Perceptions Index*. Transparency.Org. https://www.transparency.org/en/cpi/2020

Uslaner, E. M. (2017). Political trust, corruption, and inequality. In *Handbook on political trust* (pp. 302–315). Edward Elgar Publishing. https://doi-org.ezproxy-prd.bodleian.ox.ac.uk/10.4337/9781782545118

Van der Schee, E., & Groenewegen, P. P. (2010). Determinants of public trust in complementary and alternative medicine. *BMC Public Health*, *10*, 1–12. https://doi.org/10.1186/1471-2458-10-128

von Schoen-Angerer, T., Manchanda, R. K., Lloyd, I., Wardle, J., Szöke, J., Benevides, I., Martinez, N. S. A., Tolo, F., Nicolai, T., & Skaling-Klopstock, C. (2023). Traditional, complementary and integrative healthcare: Global stakeholder perspective on WHO's current and future strategy. *BMJ Global Health*, *8*(12), e013150. https://doi.org/10.1136/bmjgh-2023-013150

Ward, P. (2018). Trust and communication in a doctor-patient relationship: A literature review. *Arch Med*, *3*(3), 36. DOI: 10.4172/2472-1654.100146

Watkins, D. A., Yamey, G., Schäferhoff, M., Adeyi, O., Alleyne, G., Alwan, A., Berkley, S., Feachem, R., Frenk, J., Ghosh, G., Goldie, S. J., Guo, Y., Gupta, S., Knaul, F., Kruk, M., Nugent, R., Ogbuoji, O., Qi, J., Reddy, S., … Summers, L. H. (2018). Alma-Ata at 40 years: Reflections from the Lancet Commission on Investing in Health. *The Lancet*, *392*(10156), 1434–1460. https://doi.org/10.1016/S0140-6736(18)32389-4

Wellcome Trust. (2020). *Wellcome Global Monitor 2020* [Dataset]. https://wellcome.org/reports/wellcome-global-monitor-mental-health/2020

Wendt, C., Kohl, J., Mischke, M., & Pfeifer, M. (2010). How Do Europeans Perceive Their Healthcare System? Patterns of Satisfaction and Preference for State Involvement in the

Field of Healthcare. *European Sociological Review*, *26*(2), 177–192. https://doi.org/10.1093/esr/jcp014

World Bank. (2022). *World Bank Open Data*. https://data.worldbank.org/

World Health Organization. (2013). *WHO traditional medicine strategy: 2014-2023*. https://www.who.int/publications/i/item/9789241506096

World Health Organization. (2019). *WHO global report on traditional and complementary medicine 2019*. World Health Organization.

Xu, J., & Yang, Y. (2009). Traditional Chinese medicine in the Chinese health care system. *Health Policy*, *90*(2–3), 133–139.

Yuan, Y., & Lee, K. S. (2022). General trust in the health care system and general trust in physicians: A multilevel analysis of 30 countries. *International Journal of Comparative Sociology*, *63*(3), 91–104. https://doi.org/10.1177/00207152221085571

Zhang, P., Zhang, X., Brown, J., Vistisen, D., Sicree, R., Shaw, J., & Nichols, G. (2010). Global healthcare expenditure on diabetes for 2010 and 2030. *Diabetes Research and Clinical Practice*, *87*(3), 293–301. https://doi.org/10.1016/j.diabres.2010.01.026

General Discussion

This DPhil thesis produced new evidence on social inequalities in mental health from three main perspectives: (1) how mental health inequalities differ between countries (global perspective), (2) how they evolve over time for individuals (life-course perspective), and (3) how unemployment protection policies can contribute to addressing health inequalities (labour market perspective). Each of these perspectives was addressed in a separate paper, with an additional follow-up analysis in Paper 4 that further explores the global dimension, investigating the determinants of public trust in healthcare providers. In this discussion section, I first provide a summary of the findings of each paper, discuss the wider academic contributions and policy recommendations, and conclude with limitations and avenues for future research.

Summary of main findings

Paper 1 adopted a global perspective on social inequalities in mental health across 111 countries. The study revealed socio-economic and psycho-social inequalities in three crucial mental health outcomes (lifetime prevalence of depression/anxiety symptomology, treatment utilisation and treatment helpfulness). The key finding of the study is a global triple inequality in mental health, whereby the disadvantages of low SES individuals (compared to higher SES individuals) persist in each of these three health outcomes. The triple inequality finding is stable in both HICs and LMICs and moderated by individual and country-level factors: trust in health practitioners and stigma perceptions are highly associated with treatment utilisation and perceived helpfulness. The study also discovered that the 'triple inequality in mental health' depends on the type of treatment and does not persist for pharmacological treatment: In LMICs, richer and more educated individuals were less likely to take prescribed medication when affected by mental health problems.

Paper 2 investigated the social determinants of the mid-life decline in mental health, a phenomenon well-documented across academic disciplines. The study examined the specific

social factors associated with the decline as well as their overall contribution to population mental health in midlife. Using data from the British Cohort Study 1970 and applying a Machine Learning approach, the study identified four key predictors of experiencing a mid-life decline, which are present by the age of 34, just before the midlife period. These predictors are low social class at birth, sex (being female), low income at the start of the midlife period, and experiencing physical multimorbidity in early adulthood. Overall, these four social determinants could reduce the risk of mental health decline from 18% (observed) to 11%, and up to 28% if risk constellation changes from favourably to unfavourably in the population. Knowledge of these risk factors provides a basis for public health policy to engage in prevention and intervention efforts.

Study 3 adopts a Labour Market perspective to investigate whether the health impacts of unemployment in Europe depend on country-level differences in active labour market policies. Previous research has mainly focused on how much money countries spend on unemployment protection and services. This study extends this discussion by asking whether differences in unemployment health outcomes depend on the strictness of benefit conditionality and sanctions for job seekers set across countries. The study focused on 30 European countries for the years 2014-2019, combining an individual-level household panel with country-level indicators on the conditionality of unemployment protection provided by the OECD. These OECD indicators included measures on the strictness of job-search and availability requirements as well as the strictness of sanction laws. Becoming unemployed had a small but significant association with self-rated health. This association varied depending on the strictness of the sanction regimes: having stricter sanction rules was associated with a steeper decline in health when becoming unemployed. Such an association was not found for the other two measures of behavioural conditionality (availability and job-search requirements for job seekers). The findings suggest that

countries should consider reducing their focus on sanctions and ensure adequate income support and accessible, high-quality employment services to protect job seekers' health.

Paper 4 extends the global perspective on mental health inequalities. Paper 1 identified trust in healthcare professionals as a crucial psycho-social factor linked to mental health treatment use, but no global study has examined its determinants. This study examines global variations in trust in healthcare professionals and traditional healers across 111 countries. It uses country-level and individual-level factors to identify the predictors of trust in healthcare professionals (doctors and nurses) as well as traditional health practitioners. The study showed that in upper and middle income countries, GDP is positively associated with trust in healthcare professionals and weakly associated with trust in traditional health practitioners. Moreover, the study found that individuals with higher income had higher trust in healthcare professionals and lower trust in alternative/traditional health providers. Higher perceptions of corruption were also associated with lower trust in healthcare professionals. Overall, these findings emphasise that GDP, personal socio-economic factors and corruption perceptions shape global patterns of trust in health providers. Understanding and addressing these dynamics is crucial importance to ultimately improve equitable access to mental health care.

Wider academic contributions

There are a number of broader academic contributions that extend into wider academic debates and theory. In this section, I discuss four of these contributions.

1. **Socio-economic inequalities across countries and health outcomes: towards a context-sensitive application of the Fundamental Cause Theory**

Socio-economic inequalities in mental health are persistent across societies and have profound consequences for society (Marmot, 2015; McNamara et al., 2017). The least affluent individuals carry a proportionally high and unjust burden of mental health problems such as depression and

anxiety. Social inequalities in mental health are deeply consequential when it comes to educational attainment, labour market outcomes and society stigma – as those affected by mental health problems often experience adverse outcomes across life domains (Lund et al., 2010). Understanding how social inequalities are stratified and what could be done to reduce them is therefore highly important for researchers and policymakers alike.

Previous research has shown a *treatment gap* in mental health conditions, whereby people with lower socio-economic status are less likely to access mental healthcare (Fjaer et al., 2017; Harris et al., 2020; Knesebeck, 2015). I showed that these *pro-rich inequalities* exist globally across over 100 countries and that these inequalities are also consistently present in self-reported treatment helpfulness. Similarly, Study 2 of this DPhil showed that socio-economic disadvantage (low social class at birth and low income before midlife) is a key predictor of experiencing a midlife decline in mental health. In this way, my research aligns with existing theories on social inequality in mental health – and particularly the fundamental cause theory. The fundamental cause theory posits that socio-economic status is a root cause of health outcomes because it gives access to "health-enhancing resources" such as money, power, knowledge or social connections (Phelan et al., 2010). These resources, due to their flexible nature, affect health outcomes through a broad range of "linking mechanisms" such as treatment innovations or health behaviour – whenever new methods or knowledge becomes available (Phelan & Link, 2005). For example, when treatments for heart conditions become available, they are first accessed by high SES individuals who had the necessary knowledge, connection to doctors and financial resources – and thereby improving their cardiovascular health outcomes of these individuals (Chang & Lauderdale, 2009; Reich et al., 2016). In line with the theory, treatment utilisation and helpfulness of mental healthcare can be considered "linking mechanisms" and contribute to better mental health of high SES individuals.

However, this DPhil also showed interesting exceptions to these *pro-rich* social inequalities especially in healthcare contexts – which poses novel implications for the fundamental cause theory. Paper 1 showed that there is an exception in terms of which socio-economic groups are most likely to use pharmaceutical treatments when affected by depression or anxiety. Here, there is no clear association between income and treatment use in HICs. In LMICs, individuals with low income and education are more likely than richer people to report taking medicine for anxiety and depression – a reversed social gradient. In the paper, I discuss several reasons for this being the case, including that antidepressant medication tends to be cheaper and easier to access for healthcare providers than specialist care and talking therapy (Lewer et al., 2015; Vos et al., 2016). Similarly, my investigation into trust in healthcare providers (paper 4) showed that trust in formal providers tends to be lower among disadvantaged groups, while trust in traditional medicine is higher among poorer individuals compared to richer individuals.

From a fundamental cause perspective, the reversed socio-economic gradients in low resource contexts for certain types of treatments and healthcare providers have important implications. The fundamental cause theory presumes that "health enhancing resources" (such as money, power, social connections or knowledge) are relatively stable across different contexts, and that individuals know how to use them to access the optimal "linking mechanisms" (e.g., health behaviours or medical treatments) (Phelan et al., 2010; Phelan & Link, 2005). In fact "knowledge of what is helpful" is itself seen as a key health-enhancing resource, making high SES individuals more likely to choose and benefit from those better medical options (Shim, 2010).

My findings challenge this assumption. In low-resource settings, the definition of what constitutes the best medical option might not be fixed and universally shared. In contexts where formal medical infrastructure is unavailable or not trusted, the available and trusted forms of care might include lower-cost medications (e.g., for mental health problems) or traditional health practitioners. These might still be perceived as legitimate "linking mechanisms" to better health

by different groups in society, but it might be the case that those with lower socio-economic status perceive them as more viable. In contrast, what might otherwise be considered the "best treatment option" (such as medically trained mental health practitioners) might be unavailable altogether or only accessible to the societal elite. Such dynamics could help explain the reversed social gradients observed in my study.

Taken together, these findings do not undermine central principles of the fundamental cause theory, however, they do suggest that the theory should be applied with a greater sensitivity to the cultural and economic context. In global and low-resource contexts, access to care is mediated not just by income or education, but also by trust, cultural acceptability, and health system configuration. Future research should explicitly theorise these deviations about the core assumptions of the theory as applied to global health and low-resource contexts.

2. Conceptual contribution: a demand-side perspective in the political economy of healthcare systems

The discussion around the cultural and contextual sensitivity of healthcare choices go beyond the fundamental cause theory and are relevant to the broader literature on the political economy of healthcare (Langheim, 2014; Shah et al., 2021). Mental healthcare systems, the way they are designed, financed and interact with patients, are crucial. But mental healthcare systems worldwide are under-equipped to deal with the global burden of diseases (Evans-Lacko et al., 2018; Thornicroft & Tansella, 2013). Healthcare has long been discussed in the context of the political economy of health inequalities. However, it has largely focused on the supply side of health systems, how health systems are financed, whether they are privatised and accessible – and who profits from medical treatments (Bambra, 2005; Costa-Font et al., 2023; Gabani et al., 2023; Riman & Akpan, 2012). Key studies have shown the consequences of healthcare privatisation for population health (Goodair & Reeves, 2022). Another study showed that investments in universal healthcare or medical innovation can improve health outcomes (Reeves et al., 2015).

In covering these research perspectives, the debates in the political economy of healthcare are largely focused on the supply side of healthcare systems – implicitly assuming that health systems directly produce population health outcomes. However, it is also important to consider the "demand side" of healthcare systems, which have gained much less attention in that branch of literature than the healthcare system setup.

When healthcare systems are reformed or more treatment options become available, who in the population will accept and adopt these changes? What kind of changes and health systems do healthcare users want? Some insights on these questions are discussed in health economics when it comes to healthcare affordability as well as the fundamental cause theory as discussed above (Olsen, 2017; Phelan et al., 2010). Other demand-side factors that determine if citizens interact with changing healthcare systems are broadly discussed in the health psychology literature such as health literacy, risk perceptions or attitudes (Andersen, 1995; Dey & Jorm, 2016; Nutbeam & Lloyd, 2021). For example, the behavioural theory of healthcare access describes resources, attitudes and perceived needs as central demand-side factors of healthcare use (Andersen, 1995).

While these topics have often been discussed in disciplinary silos, I argue that they could be integrated into a more coherent demand-side perspective within the political economy of healthcare. My dissertation offers several angles to support such integration. For example, the study of trust in healthcare providers can reveal as a key component of the demand side. As shown in my research, in the context of mental health, trust in healthcare professionals is closely linked to both treatment uptake and perceived helpfulness. Trust levels, in turn, are influenced by broader political and institutional factors, including perceived corruption and healthcare system governance. Further, alternative healthcare providers play an important role, particularly in less developed healthcare systems, and might in some cases be preferred and trusted more highly by different population groups. These findings raise some important questions about what might happen when healthcare systems are changed through reform or when new healthcare

institutions are introduced in lower-income countries. To what extent are trust in healthcare providers and other demand side factors barriers or facilitators to important healthcare system reform? Is there a "moderation effect" whereby healthcare system changes are only accepted by those with previously high trust in healthcare systems, thereby fostering health inequalities? And do successful reforms of healthcare system ultimately help establish trust? Similar arguments and questions can be raised about other psychosocial factors on the demand side, such as stigma perceptions – which play a unique role in mental health and are considered an important barrier to mental healthcare system reform (Bracke et al., 2019; Evans-Lacko et al., 2012).

By establishing theoretical and empirical links between the demand side and the healthcare system side, future research could shed much more light on the dynamics of health inequalities within healthcare systems. Overall, the literature would benefit from a political economy of healthcare that encompasses both the supply/system side and the demand side, and that examines how the two interact. Advancing such an integrated perspective should be a key aim of future research.

3. Labour market policy as a political driver of health inequalities

The political economy of health inequalities studies how political and economic institutions shape population health. Besides healthcare as a political determinant of mental health inequalities – as discussed in the section above –labour market dynamics are a major theme of my research.

My DPhil makes an empirical contribution. Labour market systems are a mechanism by which political systems influence health – with policies typically set at the national level (Bambra, 2011; Lynch, 2023). For example, governments can implement labour market protection for those who become unemployed, improve working conditions, or support wage setting institutions and collective bargaining (Bambra & Eikemo, 2018; Reeves, 2021). My DPhil suggests that the way

unemployment is delivered – and specifically through behavioural requirements and sanctions – plays a key role in shaping health outcomes.

By testing what type of activation requirements (availability requirements, job-search requirements or sanctions) are associated with the health of the unemployed population, my research offers a novel perspective on the mechanisms through which such health effects occur. In this research field, opposing views argue whether it is important to be tough on job seekers and push them into employment more forcefully, while another view emphasises support and avoidance of punitive approaches (Knotz, 2020). Paper 3 finds that the punitive sanctions – rather than the activation or job-search requirements – are associated with worse health outcomes among job seekers. This finding aligns with previous research on the harmful effects of sanctions that was observed in the United Kingdom (Koch & Reeves, 2021; Williams, 2021). Sanctions largely create fear and stress caused by the possibility of significant sanctions rather than experiencing sanctions themselves (Dwyer et al., 2020; Koch & Reeves, 2021; Reeve, 2017). In fact, only a small fraction of job seekers actually experience material sanctions in most European countries, suggesting that the psychological mechanism is indeed driving the effects on health (Lombardi, 2019). My study therefore provides evidence for such a psycho-social mechanism and aligns with evidence suggesting that the threat of sanctions induces psychological stress and fear, leading to deterioration of self-rated health (Bambra & Eikemo, 2018; Dwyer et al., 2020). Study designs that capture both "threat of sanctions" and "implementation of sanctions" separately would make it possible to disentangle the pathway of stress more clearly.

Moreover, my DPhil makes a methodological contribution. The literature has proposed several approaches to explain the pathways through which politics shapes health. One of them is the welfare regime perspective, based on the work of Esping-Andersen, that distinguishes between different types of welfare regimes, including liberal (e.g. United States, the United Kingdom), conservative (e.g. Germany, France), and social democratic (e.g. Sweden, Denmark, Norway)

regimes (Esping-Andersen, 1989). Based on these distinctions, scholars have investigated how health inequalities differ across those different regimes. With an emphasis on European countries, research by Bambra and colleagues found that unemployment is associated with worse health everywhere but the health gap between the unemployed and employed is smaller in more generous welfare states – indicating that social democratic institutions buffer the harmful effects of job loss (Bambra & Eikemo, 2009; Ribanszki et al., 2022; Lynch, 2023). This line of research has informed the development of the institutional theory that conceptualises the welfare states as an institutional set of "rules of the game" which distribute the social determinants of health throughout the population (Beckfield et al., 2015).

An alternative perspective focuses on economic shocks and policy changes as "natural experiments", as seen in the work of Stuckler, Reeves and colleagues. This approach looks at how abrupt changes in the macroeconomic context or specific policy interventions (such as recessions, austerity measures, or increases in minimum wage) causally affect health (Lynch, 2023; Reeves, 2017; Sigaud et al., 2022; Stuckler et al., 2009). Studies following this lens have leveraged temporal changes within countries to isolate effects – for instance, by examining the impact of the Great Recession or strict disability benefit reforms on mental health and mortality (Reeves et al., 2014).

Each of these two approaches offers valuable insights, but they operate at different levels. One compares broader institutional regimes across countries, while the other has been particularly valuable addressing criticisms about the lack of causal evidence in the field of health inequalities (Lynch, 2023; Mackenbach, 2019, 2020).

This thesis (particularly paper 3) sits in between these two approaches, incorporating a cross-national lens while focusing on a specific and measurable policy instrument. Rather than categorising countries into broad welfare state types, I focus on one particular aspect of active labour market policy: the strictness of behavioural requirements and the use of sanctions in

unemployment benefits based on quantitative indicators compiled by the OECD. In doing so, my approach aims to be more specific and quantifiable than traditional regime-based classifications, yet still embedded in a comparative cross-country perspective. The focus of this approach on a concrete policy lever, rather than on broader regime type, enables my research to capture changes over time – which welfare rime typologies often fail to capture – and generate clear policy recommendations and insights into the specific debate of unemployment protection and health inequalities.

My approach to the research attempts to be a useful middle ground between the two approaches above, but naturally comes with limitations. My study does not provide the institutional breadth of qualitative welfare regime analyses, nor does it achieve the level of causal identification typical of natural experiment designs (Beckfield et al., 2015; Humphreys et al., 2016). Particularly the latter aspect could be directly improved by incorporating changes in policy dimensions over time or by incorporating causal difference-in-differences strategies across multiple countries – which is getting increasing possible as causal inference methodology improves (Callaway, 2023; Callaway & Sant'Anna, 2021). I discuss these future research ideas in a section on avenues for future research below.

4. The importance of the midlife period and the *effect heterogeneity* mechanisms in lifecourse research

My DPhil makes new contributions to the life-course literature. It affirms that midlife is an important period for development in mental health and provides new evidence on the social determinants of this life period, such as social class, relative income position, gender, and physical health. Notably, these determinants are largely of a population-wide, stable character that is not specific to the midlife period. This provides evidence that these elements grow in importance in that life period, speaking to a type of e*ffect heterogeneity* mechanism. For example, a poorer upbringing is a predictor of experiencing a mental health decline in midlife – even when

considering many other social determinants of health such as employment status or health behaviours. On the other hand, the *concentration of life events* would suggest that the distribution of critical life events in midlife, such as children or differences in marital status, might determine changes in mental health. However, my study did not find evidence for this mechanism.

While my study provides some evidence of the two theoretical views, more research is needed to disentangle them. My study has the limitations that it covers these social predictors only at the onset of the midlife period (at the of 34 years) and that the predictors are not completely stable, particularly as physical health tends to become worse as people age. Furthermore, my findings of predictors in midlife decline are interesting to observe in relation to my findings in paper 3, where I investigated the effect of unemployment transitions on health. Why did unemployment play a role for health across European countries in study 3, but not in the population change in study 2? The answer likely lies in the different perspectives covered by the two studies. Unemployment is a more specific social exposure that affects only a proportion of the population, with unemployment rates being around 7% in Europe in 2019 (Eurostat, n.d.). In contrast, the predictors of midlife trends in Study 2 are population-wide factors that are more likely to be associated with population-wide phenomena such as the midlife decline or U-shape in mental health.

For research and policy, both population-wide risk factors and more specific exposures, such as unemployment, are important and might require different approaches. Specific exposures offer clearer policy angles (such as unemployment protection and the design of active labour market policies), while addressing the population could require a broader response through the healthcare sector. Both approaches are outlined in the policy recommendations below.

Policy recommendations

Besides the academic contributions, my DPhil entails recommendations for policymakers in public health and social policy.

1. **Scale up mental healthcare and social interventions to address the needs of disadvantaged socio-economic groups**

Mental healthcare should be scaled up and improved worldwide. Currently, only 2% of healthcare investments worldwide are dedicated to mental health – which is inadequate to meet the burden of mental health conditions (World Health Organization, 2022). Guidance to scale up high-quality mental health services for both low and high-resource settings is given elsewhere (Thornicroft & Tansella, 2013; World Health Organization, 2022) – striving for a useful balance of hospital and community-based mental healthcare. However, as my research shows, it is crucial that investments in mental healthcare benefit the most vulnerable groups in society and do not exacerbate mental health inequalities further. My research shows that people with low levels of income and education have the highest treatment needs, yet are the least likely to access mental healthcare or benefit from treatment. Therefore, it is likely that affluent individuals will benefit the most from healthcare investments if no specific attention is given to services that reach those in disadvantaged socio-economic positions. To improve the health equality effects of mental health services, I suggest four specific steps.

First, reduce the barriers to accessing quality mental health care. In lower resource settings, mental health services and health insurance coverage are often entirely unavailable (Thornicroft & Tansella, 2013). And even in higher resource settings, such as European healthcare systems, there are often long wait times to access services or stigma and disadvantages for having mental healthcare records (e.g., for career prospects in certain professions) (Brohan & Thornicroft, 2010; Subotic-Kerry et al., 2025; Wiegand et al., 2025). As a result, many individuals end up

paying out of pocket for mental healthcare, which is an unaffordable option for many. Health policymakers should substantially reduce these barriers to enable a successful expansion and improvement of services.

Second, healthcare services should increase the diversity of mental healthcare professionals to cater to a more diverse range of socioeconomic groups. Most mental health professionals in Western countries, such as psychotherapists and psychiatrists, are women from middle- or upper-class backgrounds, which might make health professionals less relatable for some service users (Bartoli et al., 2018; Holman, 2014; Pietrantonio, 2013). Mental health services should attempt to include more people from minority backgrounds, people of colour, and working-class backgrounds (Ajluni & Michalopoulou, 2025). Men are also underrepresented in mental healthcare and should be encouraged to work in mental health professions.

Third, mental healthcare needs should cater for the social aspect and psycho-social stressors. There has been a successful integration of psychiatric services with the welfare system and social workers, besides psychological therapies, who can support those affected with mental health problems with other aspects such as family problems, housing or accessing social benefits (Bland et al., 2021). Such integration is important not merely to treat symptoms, but to make improvements on the social determinants of health.

Finally, as digital health interventions become more widespread, they should also be leveraged to address mental health problems – for example, through online counselling, mental health apps or specified Large Language Models (Graham et al., 2020). While such initiative – often private and for-profit – can successfully complement existing mental healthcare systems, they must be broadly accessible and not merely serve as a substitute for individuals who cannot access publicly funded mental healthcare (Lattie et al., 2022). Similar to other intervention efforts, digital programmes should be monitored from a health equity perspective, so that they do not exacerbate existing inequalities (Reininghaus et al., 2024; Spanakis et al., 2021).

2. **Implement non-punitive and supportive unemployment protection systems to produce better outcomes for job seekers**

Unemployment is a critical risk factor for mental health, well-being and suicide (Milner et al., 2014). Active labour market policies should be designed in a way that supports, trains, and motivates job seekers, not to punish them. Providing sufficient financial and job search support, instead of imposing punitive measures, is key to enhancing both health and labour market outcomes. Protecting job seekers health can also facilitate re-employment and therefore has important implications for the design of unemployment systems: If the health of job seekers deteriorates too severely, it may hinder re-employment prospects (Koen et al., 2016) or even lead to labour market exit altogether, especially among vulnerable groups (Dwyer et al., 2022).

While behavioural conditionality is intended to incentivise job search and promote re-employment, my results suggest that the punitive aspect of sanctions could undermine these goals. Countries with less restrictive sanction laws fare better when it comes to the health implications of unemployment. This complements previous findings showing that decent unemployment benefits and investments in training are crucial for protecting the health of those who lose their jobs (Huijts et al., 2015; Tøge, 2016; Voßemer et al., 2018). Countries that combine protection, effective training, with non-invasive sanction possibilities are likely to have the best outcomes for job seekers.

3. **Recognise mid-life as a critical period in the life-course and engage healthcare professionals to provide targeted support around the age of 40**

The midlife period of working-aged adults, broadly defined around the ages 35 – 55, should receive more attention in public health settings as a critical time for the development of mental health problems. My research confirms that this is a time where we see some deterioration in mental health on the average population level, and an increase in socioeconomic inequalities (Blanchflower, 2021; Gondek et al., 2022). Public mental health policy and healthcare services do

not typically address this demographic group with any specific attention (Johnson et al., 2022). My research suggests that it should do so, and introduce some measures that specifically help support mental health in midlife – and specifically for those with lower income, low social class background, women, and those experiencing physical health problems.

One practical example is what is already done by GPs in their routine discussions or questions around well-being and mental health (Thombs et al., 2021). For example, regular health check-ups could include some special attention to these higher-risk groups in midlife. It could also be a useful idea to introduce a mental health check-in for people around the 40-year mark, which includes psychological and psycho-social questions. Similar to the psychiatric services mentioned above, or social prescribing options, healthcare providers could then provide targeted support (Cooper et al., 2022).

4. **Strengthen public trust in healthcare providers and ensure the quality of alternative healthcare practices**

Health policymakers should pay attention and make efforts to increase trust in healthcare providers. My research shows that trust is a prerequisite for investments and scale-up efforts in the mental health system to be successful. Trust in healthcare professionals is associated with higher mental healthcare use and the helpfulness of treatment. My research also found that trust varies considerably between and within countries. For trust to be built, it is essential to ensure quality healthcare and combat corruption in the healthcare system and beyond. My research found higher corruption levels linked with lower trust in healthcare providers. A formalised health insurance system that avoids out-of-pocket payments could be one important way to ensure this, in addition to good pay and working conditions for healthcare personnel (Glynn, 2022; Lewis, 2006). Another method to enhance trust is to ensure health professionals come from diverse backgrounds and represent various population groups, making them more relatable and credible to different segments of the population (Egede-Nissen et al., 2019). Research found

that traditional and alternative medicine practitioners are used as alternative – and trusted particularly by low SES individuals. Policymakers can ensure regulations of traditional and alternative medicine practitioners are in place so they do good and avoid harm (Fakih et al., 2022; World Health Organization, 2013).

5. **Strengthen mental health monitoring systems and set targets to reduce social inequalities**

This DPhil revealed social and structural inequalities across different health outcomes and population groups. Most prominently, it demonstrated the "triple inequality in mental health" where socio-economic inequalities persist in depression prevalence, treatment use and helpfulness. To address these deeply rooted in qualities and improving the health of disadvantaged groups, progress needs to be intentional and closely monitored. For this purpose, adequate data systems should be created. For example, Germany started to build up mental health surveillance at the Robert Koch Public Health Institute in 2018 which offered regular updates of mental health changes for different social groups throughout the pandemic (Thom et al., 2023). The UK has recently implemented a monitoring system for the evaluation system to assess the effectiveness of digital interventions for children and adolescents within the NHS (Morris et al., 2023). When data and monitoring systems are not feasible for specific countries, they could use existing household and health surveys to monitor changes in mental health.

Monitoring should be accompanied by targets and measures of how progress could be made on different goals of population mental health, such as:

(a) closing disparities between the most and least disadvantaged groups,

(b) improving the health of the most disadvantaged group, and,

(c) improving overall (average) population mental health.

Priority groups for population mental health should be created at national and international levels. Finally, coordination and alignment of targets could be achieved at the international level through the World Health Organization, or the European Union should strengthen its role by supporting the use of cross-national studies and harmonised indicators to track progress and foster accountability across countries.

Limitations

Each paper has its own strengths and weaknesses, discussed in detail in the individual chapters above. Here, I highlight three limitations.

Limitations in causal claims

One important limitation lies in the needed caution in the causal interpretation of findings. The Wellcome Global Monitor dataset, which is the foundation of Paper 1 and 4, is a cross-sectional survey across 111 countries. Therefore, the results from these papers are associative in nature, and findings need to be verified using longitudinal datasets. Relatedly, paper 2 and 3 do contain longitudinal datasets – and they do have causal and explanatory elements by using regression models and time gaps between exposures and outcomes. However, they also have substantive limitations and do not contain full causal identification strategies as they had other priorities. Therefore, natural experiments or evaluations that use methods such as Difference-in-Difference, Regression Discontinuity, or Instrumental Variable approaches should be used to substantiate causal claims in future research.

Limitations in cross-cultural experiences

Three of my four papers in this dissertation used cross-national datasets. This has been discussed as a major strength and academic contribution by learning from policy experiences in different contexts. However, the cross-cultural nature of research also comes with substantive limitations. That is, survey items used in cross-national research are likely interpreted differently based on

different cultures and country norms (Davidov et al., 2014; Heine et al., 2002). Cross-national household surveys cannot fully unpack differences between regions, religious beliefs or colonial experiences of countries, and how these might have affected dynamics of mental health and social trust. When presenting my work at academic conferences, this also turned out to be the most frequent question: *how do you ensure your items on mental health are interpreted in similar ways across countries, and might this variation drive your results?* I addressed this limitation by using items that were constructed based on cross-cultural testing and adjusting research questions to minimise the potential impact of differences in interpretation (e.g., focusing on within-country socio-economic gradients rather than average values). Despite these efforts, uncertainties around the issue of cultural comparability cannot be fully resolved. Relatedly, statistical indicators on healthcare characteristics cannot fully capture the lived qualitative differences in healthcare systems. My research, therefore, needs to be complemented by specific country examples and investigations within certain regions in the future.

Limitations in measurement

This thesis relies on secondary data and self-reported mental health survey items. All items have their limitations – from the single-item use in the Wellcome Global Survey, to the Malaise Questionnaire, and the general health measure. Therefore, my findings should be complemented by future research that uses more modern mental health measures such as the Patient Health Questionnaire (PHQ-9). As pointed out at the beginning of this dissertation, I attempted to ensure that the items still adequately capture health outcomes and build on previous studies that had used the same items (Gondek et al., 2022; Tøge & Blekesaune, 2015). In some cases, it can even be argued that findings might be statistically stronger, rather than weaker, if different items had been used. For example, in paper 3, a specific mental health measure (rather than self-perceived health) could have resulted in even more decisive or stronger results, as unemployment is expected to influence mental health most directly (Bambra & Eikemo, 2018; Williams, 2021).

Nevertheless, measurement uncertainty needs to be addressed in future research as well as complemented by healthcare-specific or administrative data beyond household surveys.

Avenues for future research

This DPhil offers many potential avenues for future research. Based on the diverse nature of the studies and the cross-national scope of the work, the areas are plentiful – many of which are discussed in separate chapters above. To conclude, I will highlight four key areas.

First, my research points to various research questions and findings that could be investigated using causal designs. For example, would improvements in trust in healthcare providers translate into increased use of mental health services? Or would income support and better mental healthcare in midlife decrease the risk of mental health deterioration? If possible, natural experiments and/or policy evaluations could be used to address these causal questions derived from my research.

Second, having identified socio-economic inequalities in mental healthcare use and treatment helpfulness worldwide, what would work to improve mental healthcare for disadvantaged groups? In my policy recommendations, I propose four approaches: reducing barriers to therapy (e.g., cutting out-of-pocket payments and wait times), developing a more diverse mental healthcare workforce, and integrating social work as part of social psychiatry concepts. Research could investigate which of these solutions has the greatest effect, and once again, policymakers should be encouraged to implement trials and policy changes that would enable policy evaluations.

Third, my research found an interesting variation of socio-economic gradients in low- and middle-income countries, where poorer people are more likely to take medication for mental health conditions. Relatedly, I show that the dynamics of trust in healthcare providers differ between relatively poorer and richer countries. Existing theories – such as the theory of

fundamental causes – do not fully account for the context-sensitive nature of these findings. At the same time, the vast majority of research on health inequalities and mental health service use comes from higher-income countries (Evans-Lacko et al., 2018; Ma et al., 2024), often implicitly assuming similar behavioural responses across contexts. More research should be done in lower resource settings and consider public perceptions, trust and stigma as demand side factors – and to build the "demand side perspective" in the study of the political economy, which I discuss above.

Fourth, there are some crucial research perspectives on the issue of unemployment protection, work, and mental health. My research findings that sanctions are associated with worse transitions of mental health into unemployment offer several important research perspectives. Research should identify specific reforms in countries and use natural experiments – for example, if a country introduces a reform that increases or reduces sanctions for job seekers, what is the effect on the unemployed population? Research should identify concrete policies and natural experiments to evaluate these questions. Further, as public employment services increasingly use algorithmic decision-making and digital profiling (Allhutter et al., 2020; Brioscú et al., 2024), it is important to explore how these technologies impact access to services, reinforce (or mitigate) inequalities, and shape the implementation of behavioural conditionality. Lastly, observing and evaluating ongoing policy changes is of high research interest. Labour market policies and unemployment continue to be a dynamic field where policy changes often occur following elections and changes in government. For example, Germany moved toward reducing sanctions job seekers in the Bürgergeld reform in 2021 (Beckmann et al., 2022), only to propose an increase in strictness and a tougher for the newly elected government in 2025. Investigating the consequences of such policy changes, providing evidence-based recommendations, as well as the accompanying public discourse, would be of high importance.

To conclude, this dissertation contributes to our understanding of mental health inequalities. It shows the breadth and depth in which social inequalities shape mental health within and across societies – from healthcare systems to life-course phenomena and the labour market. I started this DPhil by stating that mental health is highly political. I want to conclude with the message that this observation offers great potential. The political and societal nature of mental health, which goes beyond biological and psychological determinants, means that there is a lot we can do to promote mental well-being in society and work towards equity in mental health. As my findings illustrate, the way healthcare systems and labour markets are set up and operated – and the trajectories in which social disadvantage develops over the life-course – are real levers for improvements in population mental health. I hope that my dissertation can contribute to action and further research in the field of public mental health, which offers so much potential to improve our lives and society.

References

Ajluni, V., & Michalopoulou, G. (2025). Addressing the Underrepresentation of African American Mental Health Professionals: A Call to Action. *Journal of Patient Experience*, *12*, 23743735241307382. https://doi.org/10.1177/23743735241307382

Allhutter, D., Cech, F., Fischer, F., Grill, G., & Mager, A. (2020). Algorithmic profiling of job seekers in Austria: How austerity politics are made effective. *Frontiers in Big Data*, *3*, 5. https://doi.org/10.3389/fdata.2020.00005

Andersen, R. M. (1995). Revisiting the behavioral model and access to medical care: Does it matter? *Journal of Health and Social Behavior*, *36*(1), 1–10. https://doi.org/10.2307/2137284

Bambra, C. (2005). Worlds of welfare and the health care discrepancy. *Social Policy and Society*, *4*(1), 31–41. https://doi.org/10.1017/S1474746404002143

Bambra, C. (2011). Work, worklessness and the political economy of health inequalities. *Journal of Epidemiology & Community Health*, *65*(9), 746–750. https://doi.org/10.1136/jech.2009.102103

Bambra, C., & Eikemo, T. A. (2009). Welfare state regimes, unemployment and health: A comparative study of the relationship between unemployment and self-reported health in 23 European countries. *Journal of Epidemiology & Community Health*, *63*(2), 92–98. https://doi.org/10.1136/jech.2008.077354

Bambra, C., & Eikemo, T. A. (2018). Insecurity, unemployment, and health: A social epidemiological perspective. *The Oxford Handbook of Job Loss and Job Search*, 111–125.

Bartoli, E., Bentley-Edwards, K. L., García, A. M., Michael, A., & Ervin, A. (2018). What do white counselors and psychotherapists need to know about race? White racial socialization in counseling and psychotherapy training programs. In *Whiteness and White Privilege in Psychotherapy* (pp. 80–96). Routledge.

Beckfield, J., Bambra, C., Eikemo, T. A., Huijts, T., McNamara, C., & Wendt, C. (2015). An institutional theory of welfare state effects on the distribution of population health. *Social Theory & Health*, *13*, 227–244. https://doi.org/10.1057/sth.2015.19

Beckmann, F., Heinze, R. G., Schad, D., & Schupp, J. (2022). From Hartz IV to Bürgergeld: Reform preferences of the long-term unemployed. *DIW Weekly Report*, *12*(29/31), 183–192. https://hdl.handle.net/10419/263224

Blanchflower, D. G. (2021). Is happiness U-shaped everywhere? Age and subjective well-being in 145 countries. *Journal of Population Economics*, *34*(2), 575–624. https://doi.org/10.1007/s00148-020-00797-z

Bland, R., Drake, G., Drayton, J., & Tullgren, A. (2021). *Social work practice in mental health: An introduction*. Routledge.

Bracke, P., Delaruelle, K., & Verhaeghe, M. (2019). Dominant Cultural and Personal Stigma Beliefs and the Utilization of Mental Health Services: A Cross-National Comparison. *Frontiers in Sociology*, *4*. https://doi.org/10.3389/fsoc.2019.00040

Brioscú, A., Lauringson, A., Saint-Martin, A., & Xenogiani, T. (2024). *A new dawn for public employment services: Service delivery in the age of artificial intelligence*. OECD Publishing. https://doi.org/10.1787/5dc3eb8e-en

Brohan, E., & Thornicroft, G. (2010). Stigma and discrimination of mental health problems: Workplace implications. *Occupational Medicine*, *60*(6), 414–415. https://doi.org/10.1093/occmed/kqq048

Callaway, B. (2023). Difference-in-differences for policy evaluation. *Handbook of Labor, Human Resources and Population Economics*, 1–61. https://doi.org/10.1007/978-3-319-57365-6_352-1

Callaway, B., & Sant'Anna, P. H. C. (2021). Difference-in-Differences with multiple time periods. *Journal of Econometrics*, *225*(2), 200–230. https://doi.org/10.1016/J.JECONOM.2020.12.001

Chang, V. W., & Lauderdale, D. S. (2009). Fundamental cause theory, technological innovation, and health disparities: The case of cholesterol in the era of statins. *Journal of Health and Social Behavior*, *50*(3), 245–260. https://doi.org/10.1177/002214650905000301

Cooper, M., Avery, L., Scott, J., Ashley, K., Jordan, C., Errington, L., & Flynn, D. (2022). Effectiveness and active ingredients of social prescribing interventions targeting mental health: A systematic review. *BMJ Open*, *12*(7), e060214. https://doi.org/10.1136/bmjopen-2021-060214

Costa-Font, J., Batinti, A., & Turati, G. (2023). *Handbook on the political economy of health systems*. Edward Elgar Publishing.

Davidov, E., Meuleman, B., Cieciuch, J., Schmidt, P., & Billiet, J. (2014). Measurement equivalence in cross-national research. *Annual Review of Sociology*, *40*(1), 55–75. https://doi.org/10.1146/annurev-soc-071913-043137

Dey, M., & Jorm, A. F. (2016). Social determinants of mental health service utilization in Switzerland. *International Journal of Public Health 2016 62:1*, *62*(1), 85–93. https://doi.org/10.1007/S00038-016-0898-5

Dwyer, P., Scullion, L., Jones, K., McNeill, J., & Stewart, A. B. (2022). Unintended outcomes? The wider impacts of compulsion and benefit sanctions in social security. In *The Impacts of Welfare Conditionality* (pp. 116–136). Policy Press.

Dwyer, P., Scullion, L., Jones, K., McNeill, J., & Stewart, A. B. R. (2020). Work, welfare, and wellbeing: The impacts of welfare conditionality on people with mental health

impairments in the UK. *Social Policy & Administration*, *54*(2), 311–326. https://doi.org/10.1111/SPOL.12560

Egede-Nissen, V., Sellevold, G. S., Jakobsen, R., & Sørlie, V. (2019). Minority healthcare providers experience challenges, trust, and interdependency in a multicultural team. *Nursing Ethics*, *26*(5), 1326–1336. https://doi.org/10.1177/0969733017752546

Esping-Andersen, G. (1989). The three political economies of the welfare state. *Canadian Review of Sociology/Revue Canadienne de Sociologie*, *26*(1), 10–36.

Eurostat. (n.d.). *Unemployment statistics and beyond*. Retrieved 16 April 2025, from https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Unemployment_statistics_and_beyond

Evans-Lacko, S., Aguilar-Gaxiola, S., Al-Hamzawi, A., Alonso, J., Benjet, C., Bruffaerts, R., Chiu, W.-T., Florescu, S., de Girolamo, G., & Gureje, O. (2018). Socio-economic variations in the mental health treatment gap for people with anxiety, mood, and substance use disorders: Results from the WHO World Mental Health (WMH) surveys. *Psychological Medicine*, *48*(9), 1560–1571. https://doi.org/10.1017/S0033291717003336

Evans-Lacko, S., Brohan, E., Mojtabai, R., & Thornicroft, G. (2012). Association between public views of mental illness and self-stigma among individuals with mental illness in 14 European countries. *Psychological Medicine*, *42*(8), 1741–1752. https://doi.org/10.1017/S0033291711002558

Fakih, M., Perbawati, C., & Monalisa. (2022). Relevance of WHO traditional medicine strategy (2014-2023) with traditional health care policy in the perspective of national law and international law. *Asian Journal of Legal Studies*, *1*(1), 25–34. https://doi.org/10.53402/jals.v1i1.117

Fjaer, E. L., Balaj, M., Stornes, P., Todd, A., McNamara, C. L., & Eikemo, T. A. (2017). Exploring the differences in general practitioner and health care specialist utilization according to education, occupation, income and social networks across Europe: Findings from the European social survey (2014) special module on the social determinants of health. *European Journal of Public Health*, *27*(suppl_1), 73–81. https://doi.org/10.1093/EURPUB/CKW255

Gabani, J., Mazumdar, S., & Suhrcke, M. (2023). The effect of health financing systems on health system outcomes: A cross-country panel analysis. *Health Economics*, *32*(3), 574–619.

Glynn, E. H. (2022). Corruption in the health sector: A problem in need of a systems-thinking approach. *Frontiers in Public Health*, *10*, 910073. https://doi.org/10.1002/hec.4635

Gondek, D., Lacey, R. E., Blanchflower, D. G., & Patalay, P. (2022). How is the distribution of psychological distress changing over time? Who is driving these changes? Analysis of the 1958 and 1970 British birth cohorts. *Social Psychiatry and Psychiatric Epidemiology*, *57*(5), 1007–1016. https://doi.org/10.1007/S00127-021-02206-6/FIGURES/4

Goodair, B., & Reeves, A. (2022). Outsourcing health-care services to the private sector and treatable mortality rates in England, 2013–20: An observational study of NHS privatisation. *The Lancet Public Health*, *7*(7), e638–e646. https://doi.org/10.1016/S2468-2667(22)00133-5

Graham, A. K., Lattie, E. G., Powell, B. J., Lyon, A. R., Smith, J. D., Schueller, S. M., Stadnick, N. A., Brown, C. H., & Mohr, D. C. (2020). Implementation strategies for digital mental health interventions in health care settings. *American Psychologist*, *75*(8), 1080. https://doi.org/10.1037/amp0000686

Harris, M. G., Kazdin, A. E., Chiu, W. T., Sampson, N. A., Aguilar-Gaxiola, S., Al-Hamzawi, A., Alonso, J., Altwaijri, Y., Andrade, L. H., Cardoso, G., Cía, A., Florescu, S., Gureje, O.,

Hu, C., Karam, E. G., Karam, G., Mneimneh, Z., Navarro-Mateu, F., Oladeji, B. D., … Kessler, R. C. (2020). Findings From World Mental Health Surveys of the Perceived Helpfulness of Treatment for Patients With Major Depressive Disorder. *JAMA Psychiatry*, *77*(8), 830–841. https://doi.org/10.1001/JAMAPSYCHIATRY.2020.1107

Heine, S. J., Lehman, D. R., Peng, K., & Greenholtz, J. (2002). What's wrong with cross-cultural comparisons of subjective Likert scales?: The reference-group effect. *Journal of Personality and Social Psychology*, *82*(6), 903. https://doi.org/10.1037/0022-3514.82.6.903

Holman, D. (2014). 'What help can you get talking to somebody?' Explaining class differences in the use of talking treatments. *Sociology of Health & Illness*, *36*(4), 531–548. https://doi.org/10.1111/1467-9566.12082

Huijts, T., Reeves, A., McKee, M., & Stuckler, D. (2015). The impacts of job loss and job recovery on self-rated health: Testing the mediating role of financial strain and income. *The European Journal of Public Health*, *25*(5), 801–806. https://doi.org/10.1093/eurpub/ckv108

Humphreys, D. K., Panter, J., Sahlqvist, S., Goodman, A., & Ogilvie, D. (2016). Changing the environment to improve population health: A framework for considering exposure in natural experimental studies. *J Epidemiol Community Health*, *70*(9), 941–946. https://doi.org/10.1136/jech-2015-206381

Johnson, P. J., Mentzer, K. M., Jou, J., & Upchurch, D. M. (2022). Unmet healthcare needs among midlife adults with mental distress and multiple chronic conditions. *Aging & Mental Health*, *26*(4), 775–783. https://doi.org/10.1080/13607863.2021.1904830

Knesebeck, O. V. D. (2015). Concepts of social epidemiology in health services research. *BMC Health Services Research*, *15*(1), https://doi.org/10.1186/s12913-015-1020-z

Knotz, C. M. (2020). Does demanding activation work? A comparative analysis of the effects of unemployment benefit conditionality on employment in 21 advanced economies, 1980–2012. *European Sociological Review*, *36*(1), 121–135.

Koch, I., & Reeves, A. (2021). From social security to state-sanctioned insecurity: How welfare reform mimics the commodification of labour through greater state intervention. *Economy and Society*, *50*(3), 448–470. https://doi.org/10.1093/esr/jcz041

Koen, J., van Vianen, A. E., van Hooft, E. A., & Klehe, U.-C. (2016). How experienced autonomy can improve job seekers' motivation, job search, and chance of finding reemployment. *Journal of Vocational Behavior*, *95*, 31–44. https://doi.org/10.1016/j.jvb.2016.07.003

Langheim, F. J. (2014). Poor access to health care as a social determinant of mental health. *Psychiatric Annals*, *44*(1), 52–57. https://doi.org/10.3928/00485713-20140108-09

Lattie, E. G., Stiles-Shields, C., & Graham, A. K. (2022). An overview of and recommendations for more accessible digital mental health services. *Nature Reviews Psychology*, *1*(2), 87–100. https://doi.org/10.1038/s44159-021-00003-1

Lewer, D., O'Reilly, C., Mojtabai, R., & Evans-Lacko, S. (2015). Antidepressant use in 27 European countries: Associations with sociodemographic, cultural and economic factors. *The British Journal of Psychiatry*, *207*(3), 221–226. https://doi.org/10.1192/BJP.BP.114.156786

Lewis, M. (2006). Governance and corruption in public health care systems. *Center for Global Development Working Paper*, *78*. http://dx.doi.org/10.2139/ssrn.984046

Lombardi, S. (2019). *Threat effects of monitoring and unemployment insurance sanctions: Evidence from two reforms*. Working Paper. https://hdl.handle.net/10419/227842

Lund, C., Breen, A., Flisher, A. J., Kakuma, R., Corrigall, J., Joska, J. A., Swartz, L., & Patel, V. (2010). Poverty and common mental disorders in low and middle income countries: A systematic review. *Social Science & Medicine*, *71*(3), 517–528. https://doi.org/10.1016/j.socscimed.2010.04.027

Lynch, J. (2023). The political economy of health: Bringing political science in. *Annual Review of Political Science*, *26*(1), 389–410. https://doi.org/10.1146/annurev-polisci-051120-103015

Ma, J., Wu, J., & Marois, G. (2024). Socioeconomic inequalities in depression and the role of job conditions in China. *Frontiers in Public Health*, *12*, 1464187. https://doi.org/10.3389/fpubh.2024.1464187

Mackenbach, J. P. (2019). *Health inequalities: Persistence and change in European welfare states*. Oxford University Press.

Mackenbach, J. P. (2020). Re-thinking health inequalities. *European Journal of Public Health*, *30*(4), 615–615. https://doi.org/10.1093/EURPUB/CKAA001

Marmot, M. (2015). The health gap: The challenge of an unequal world. *The Lancet*, *386*(10011), 2442–2444. https://doi.org/10.1016/S0140-6736(15)00150-6

McNamara, C. L., Balaj, M., Thomson, K. H., Eikemo, T. A., Solheim, E. F., & Bambra, C. (2017). The socioeconomic distribution of non-communicable diseases in Europe: Findings from the European Social Survey (2014) special module on the social determinants of health. *European Journal of Public Health*, *27*(suppl_1), 22–26. https://doi.org/10.1093/EURPUB/CKW222

Milner, A., Page, A., & Lamontagne, A. D. (2014). Cause and effect in studies on unemployment, mental health and suicide: A meta-analytic and conceptual review. *Psychological Medicine*, *44*(5), 909–917. https://doi.org/10.1017/S0033291713001621

Morris, A. C., Ibrahim, Z., Moghraby, O. S., Stringaris, A., Grant, I. M., Zalewski, L., McClellan, S., Moriarty, G., Simonoff, E., Dobson, R. J., & Downs, J. (2023). Moving from development to implementation of digital innovations within the NHS: myHealthE, a remote monitoring system for tracking patient outcomes in child and adolescent mental health services. *DIGITAL HEALTH*, *9*, 20552076231211551. https://doi.org/10.1177/20552076231211551

Nutbeam, D., & Lloyd, J. E. (2021). Understanding and Responding to Health Literacy as a Social Determinant of Health. *Annu. Rev. Public Health*, *42*(1), 159-173. https://doi.org/10.1146/annurev-publhealth

Olsen, J. A. (2017). *Principles in health economics and policy*. Oxford University Press.

Phelan, J. C., & Link, B. G. (2005). Controlling Disease and Creating Disparities: A Fundamental Cause Perspective. *The Journals of Gerontology: Series B*, *60*(Special_Issue_2), S27–S33. https://doi.org/10.1093/GERONB/60.SPECIAL_ISSUE_2.S27

Phelan, J. C., Link, B. G., & Tehranifar, P. (2010). Social Conditions as Fundamental Causes of Health Inequalities: Theory, Evidence, and Policy Implications. *Journal of health and social behavior, 51(1_suppl),* S28-S40. https://doi.org/10.1177/0022146510383498

Pietrantonio, K. R. (2013). *Class is out: Mental health professionals' social class identification and classist attitudes toward low-income clients*. The University of North Dakota.

Reeve, K. (2017). Welfare conditionality, benefit sanctions and homelessness in the UK: ending the 'something for nothing culture' or punishing the poor? *Journal of Poverty and Social Justice*, *25*(1), 65–78. https://doi.org/10.1332/175982717X14842281240539

Reeves, A. (2017). Does sanctioning disabled claimants of unemployment insurance increase labour market inactivity? An analysis of 346 British local authorities between 2009 and

2014. *Journal of Poverty and Social Justice*, *25*(2), 129–146. https://doi.org/10.1332/175982717X14939739331029

Reeves, A. (2021). The health effects of wage setting institutions: How collective bargaining improves health but not because it reduces inequality. *Sociology of Health & Illness*, *43*(4), 1012–1031. https://doi.org/10.1111/1467-9566.13272

Reeves, A., Gourtsoyannis, Y., Basu, S., McCoy, D., McKee, M., & Stuckler, D. (2015). Financing universal health coverage—Effects of alternative tax structures on public health systems: Cross-national modelling in 89 low-income and middle-income countries. *The Lancet*, *386*(9990), 274–280. https://doi.org/10.1016/S0140-6736(15)60574-8

Reeves, A., Karanikolos, M., Mackenbach, J., McKee, M., & Stuckler, D. (2014). Do employment protection policies reduce the relative disadvantage in the labour market experienced by unhealthy people? A natural experiment created by the Great Recession in Europe. *Social Science & Medicine*, *121*, 98–108. https://doi.org/10.1016/j.socscimed.2014.09.034

Reich, A. D., Hansen, H. B., & Link, B. G. (2016). Fundamental interventions: How clinicians can address the fundamental causes of disease. *Journal of Bioethical Inquiry*, *13*, 185–192. https://doi.org/10.1007/s11673-016-9715-3

Reininghaus, U., Reinhold, A. S., Priebe, S., Rauschenberg, C., Fleck, L., Schick, A., Schirmbeck, F., Myin-Germeys, I., Morgan, C., & Hartmann, J. A. (2024). Toward equitable interventions in public mental health: A review. *JAMA Psychiatry*, *81*(12), 1270–1275. https://doi.org/10.1001/jamapsychiatry.2024.3206

Ribanszki, R., S Taylor, K., Scheutzow, J., Saez Fonseca, J. A., & Ponzo, S. (2022). Welfare systems and mental health in OECD and EEA countries: A scoping review. *Humanities and Social Sciences Communications*, *9*(1), 431. https://doi.org/10.1057/s41599-022-01391-2

Riman, H. B., & Akpan, E. S. (2012). Healthcare financing and health outcomes in Nigeria: A state level study using multivariate analysis. *International Journal of Humanities and Social Science, 2*(15), 296–309. https://mpra.ub.uni-muenchen.de/55215/

Shah, N., Walker, I. F., Naik, Y., Rajan, S., O'Hagan, K., Black, M., Cartwright, C., Tillmann, T., Pearce-Smith, N., & Stansfield, J. (2021). National or population level interventions addressing the social determinants of mental health – an umbrella review. *BMC Public Health*, *21*(1), 1–14. https://doi.org/10.1186/s12889-021-12145-1

Shim, J. K. (2010). Cultural health capital: A theoretical approach to understanding health care interactions and the dynamics of unequal treatment. *Journal of Health and Social Behavior*, *51*(1), 1–15. https://doi.org/10.1177/0022146509361185

Sigaud, L., Daley, A., Rubin, J., & Noblet, C. (2022). The effects of recent minimum wage increases on self-reported health in the United States. *Social Science & Medicine*, *305*, 115110. https://doi.org/10.1016/j.socscimed.2022.115110

Spanakis, P., Peckham, E., Mathers, A., Shiers, D., & Gilbody, S. (2021). The digital divide: Amplifying health inequalities for people with severe mental illness in the time of COVID-19. *The British Journal of Psychiatry*, *219*(4), 529–531. https://doi.org/10.1192/bjp.2021.56

Stuckler, D., Basu, S., Suhrcke, M., Coutts, A., & McKee, M. (2009). The public health effect of economic crises and alternative policy responses in Europe: An empirical analysis. *The Lancet*, *374*(9686), 315–323. https://doi.org/10.1016/S0140-6736(09)61124-7

Subotic-Kerry, M., Borchard, T., Parker, B., Li, S. H., Choi, J., Long, E. V., Batterham, P. J., Whitton, A., Gockiert, A., & Spencer, L. (2025). While they wait: A cross-sectional survey on wait times for mental health treatment for anxiety and depression for

adolescents in Australia. *BMJ Open*, *15*(3), e087342. https://doi.org/10.1136/bmjopen-2024-087342.

Thom, J., Walther, L., Eicher, S., Hölling, H., Junker, S., Peitz, D., Wilhelm, J., & Mauz, E. (2023). Mental Health Surveillance am Robert Koch-Institut – Strategien zur Beobachtung der psychischen Gesundheit der Bevölkerung. *Bundesgesundheitsblatt - Gesundheitsforschung - Gesundheitsschutz*, *66*(4), 379–390. https://doi.org/10.1007/s00103-023-03678-4

Thombs, B. D., Markham, S., Rice, D. B., & Ziegelstein, R. C. (2021). Does depression screening in primary care improve mental health outcomes? *Bmj*, *374*. https://doi.org/10.1136/bmj.n1661

Thornicroft, G., & Tansella, M. (2013). The balanced care model: The case for both hospital- and community-based mental healthcare. *The British Journal of Psychiatry*, *202*(4), 246–248. https://doi.org/10.1192/BJP.BP.112.111377

Tøge, A. G. (2016). Health effects of unemployment in Europe during the great recession: The impact of unemployment generosity. *International Journal of Health Services*, *46*(4), 614–641.

Tøge, A. G., & Blekesaune, M. (2015). Unemployment transitions and self-rated health in Europe: A longitudinal analysis of EU-SILC from 2008 to 2011. *Social Science & Medicine*, *143*, 171–178. https://doi.org/10.1177/0020731416664688

Vos, T., Corry, J., Haby, M. M., Carter, R., & Andrews, G. (2016). Cost-Effectiveness of Cognitive–Behavioural Therapy and Drug Interventions for Major Depression. *Australian & New Zealand Journal of Psychiatry, 39*(8), 683-692. https://doi.org/10.1080/J.1440-1614.2005.01652.X

Voßemer, J., Gebel, M., Täht, K., Unt, M., Högberg, B., & Strandh, M. (2018). The effects of unemployment and insecure jobs on well-being and health: The moderating role of labor

market policies. *Social Indicators Research*, *138*(3), 1229-1257. https://doi.org/10.1007/s11205-017-1697-y

Wiegand, H. F., Hölzel, L., Tüscher, O., Lieb, K., Falkai, P., & Adorjan, K. (2025). Mental health services in Germany–Structures, outcomes and future challenges. *International Review of Psychiatry*, *37*(3–4), 253–270. https://doi.org/10.1080/09540261.2025.2479601

Williams, E. (2021). Unemployment, sanctions and mental health: The relationship between benefit sanctions and antidepressant prescribing. *Journal of Social Policy*, *50*(1), 1–20. https://doi.org/10.1017/S0047279419000783

World Health Organization. (2013). *WHO traditional medicine strategy: 2014-2023*. https://www.who.int/publications/i/item/9789241506096

World Health Organization. (2022). *World mental health report: Transforming mental health for all*. World Health Organization. https://iris.who.int/bitstream/handle/10665/356119/9789240049338-eng.pdf?sequence=1

Appendices

Appendix Paper 1

Appendix 1A: Country-level variables

The appendices for this paper are split into two sections. In Appendix A, we provide all details regarding the country-level indicators, including values and sources for each individual country. In Appendix B, we present supplementary analyses that offer additional details related to the results reported in the main text.

Analysis of country-level variation

First, a null model was used to test if the probability of "Ever experienced anxiety/depression (= Yes)" varies as a function of countries (i.e., a random intercept model without fixed effects). The analysis indicate that the intercept does vary by country (SD = 0.56; logit(Intercept) = −1.43). The Inter Class Correlation was low ($ICC = 0.042$) for the "ever experienced anxiety/depression" outcome variable, but higher for the other outcome variables ("talking to mental health professional": $ICC = 0.16$; "Taking prescribed medication": $ICC = 0.079$). Overall, the results illustrate that there is a relatively small but substantial degree of cross-country variation. Further, as our research question is explicitly focused on country-level predictors and countries are a conceptually different level of analysis as individuals, we decided that our analyses warrant a multi-level regression models.

Data sources

Table S3 and S4 show all countries and country-level indicators used in this study. In Table S3, country-level indicators are derived from the World Bank. In four out of the 111 countries (Taiwan, Hong Kong, Bahrain, and Kosovo), some or all of the World Bank data were missing and substituted by national statistics. In these select cases, we conducted literature searches to

find validated national-level statistics either from government websites or peer-reviewed publications. These sources are indicated in footnotes below Table S3.

The Covid-19 variables are displayed in Table S4. Covid-19-related deaths per 100,000 inhabitants, Covid-19 infection rates, and lockdown stringency were all based on data from January 31st, 2021, which aligns with the data collection period of the Wellcome survey (completed in all countries by this date). These variables were derived from the website Our World in Data (2023) and the Oxford Covid-19 Government Response Tracker (OxCGRT) (2023) at https://github.com/OxCGRT/covid-policy-dataset. For these Covid analyses, we have data available for only 108 countries, as three countries were missing Covid data (Hong Kong, Kyrgyzstan, and Taiwan). Consequently, we decided not to include them in the main text to maintain a sample size of 111 countries.

Table S3. Country-level data

	Sample size in survey dataset (n)	Gini co-efficient	Year, source	GDP per capita (current US$)	Year, source	Health expenditure (% of GDP)	Year, source	Out-of-pocket expenditure (% of health exp.)	Year, source
Albania	1,000	33.2	2017, WB[1]	5,246	2020, WB[1]	5.2	2019, WB[1]	44.6	2018, WB[1]
United Arab Emirates	1,002	26	2018, WB[1]	3,6285	2020, WB[1]	4.3	2019, WB[1]	12.5	2019, WB[1]
Argentina	1,001	42.9	2019, WB[1]	8,579	2020, WB[1]	9.5	2019, WB[1]	27.7	2019, WB[1]
Australia	1,001	34.4	2014, WB[1]	51,693	2020, WB[1]	9.9	2019, WB[1]	16.0	2019, WB[1]
Austria	1,000	30.8	2018, WB[1]	48,587	2020, WB[1]	10.4	2019, WB[1]	19.1	2019, WB[1]
Belgium	1,001	27.2	2018, WB[1]	45,159	2020, WB[1]	10.7	2019, WB[1]	18.2	2019, WB[1]
Benin	1,007	47.8	2015, WB[1]	1,291	2020, WB[1]	2.4	2019, WB[1]	47.0	2019, WB[1]
Burkina Faso	1,002	35.3	2014, WB[1]	858	2020, WB[1]	5.5	2019, WB[1]	34.7	2019, WB[1]
Bangladesh	1,011	32.4	2016, WB[1]	1,962	2020, WB[1]	2.5	2019, WB[1]	72.7	2019, WB[1]
Bulgaria	1,007	41.3	2018, WB[1]	10,079	2020, WB[1]	7.1	2019, WB[1]	39.0	2019, WB[1]
Bahrain	1,005	34.9	2015, [2]	20,410	2020, WB[1]	4.0	2019, WB[1]	29.7	2019, WB[1]

[1] WB World Bank. (n.d.). World Bank Open Data | Data. Retrieved April 4, 2022, from https://data.worldbank.org/
[2] Hammar, O., & Waldenström, D. (2017). Global earnings inequality, 1970-2015.

Bosnia Herzegovina	1,002	33	2011, WB[1]	6,080	2020, WB[1]	9.0	2019, WB[1]	29.4	2019, WB[1]
Bolivia	1,002	41.6	2019, WB[1]	3,133	2020, WB[1]	6.9	2019, WB[1]	23.9	2019, WB[1]
Brazil	1,000	53.4	2019, WB[1]	6,797	2020, WB[1]	9.6	2019, WB[1]	24.9	2019, WB[1]
Canada	1,010	33.3	2017, WB[1]	43,295	2020, WB[1]	10.8	2019, WB[1]	14.9	2019, WB[1]
Switzerland	1,000	33.1	2018, WB[1]	87,097	2020, WB[1]	11.3	2019, WB[1]	25.3	2019, WB[1]
Chile	1,021	44.4	2017, WB[1]	13,232	2020, WB[1]	9.3	2019, WB[1]	32.8	2019, WB[1]
China	3,502	38.5	2016, WB[1]	10,435	2020, WB[1]	5.4	2019, WB[1]	35.2	2019, WB[1]
Cote d'Ivoire	1,005	41.5	2015, WB[1]	2,326	2020, WB[1]	3.3	2019, WB[1]	37.3	2019, WB[1]
Cameroon	1,006	46.6	2014, WB[1]	1,537	2020, WB[1]	3.6	2019, WB[1]	72.5	2019, WB[1]
Congo Brazzaville	1,009	48.9	2011, WB[1]	1,846	2020, WB[1]	2.1	2019, WB[1]	45.9	2019, WB[1]
Colombia	1,000	51.3	2019, WB[1]	5,335	2020, WB[1]	7.7	2019, WB[1]	14.9	2019, WB[1]
Costa Rica	1,001	48.2	2019, WB[1]	12,141	2020, WB[1]	7.3	2019, WB[1]	22.3	2019, WB[1]
Cyprus	1,012	32.7	2018, WB[1]	27,528	2020, WB[1]	7.0	2019, WB[1]	30.6	2019, WB[1]
Czech Republic	1,000	25	2018, WB[1]	22,931	2020, WB[1]	7.8	2019, WB[1]	14.2	2019, WB[1]
Germany	1,000	31.9	2016, WB[1]	46,208	2020, WB[1]	11.7	2019, WB[1]	12.8	2019, WB[1]
Denmark	1,000	28.2	2018, WB[1]	61,063	2020, WB[1]	10.0	2019, WB[1]	14.2	2019, WB[1]
Dominican Republic	1,000	41.9	2019, WB[1]	7,268	2020, WB[1]	5.9	2019, WB[1]	42.9	2019, WB[1]
Algeria	1,020	27.6	2011, WB[1]	3,307	2020, WB[1]	6.2	2019, WB[1]	33.4	2019, WB[1]
Ecuador	1,000	45.7	2019, WB[1]	5,600	2020, WB[1]	7.8	2019, WB[1]	30.9	2019, WB[1]
Egypt	1,004	31.5	2017, WB[1]	3,569	2020, WB[1]	4.7	2019, WB[1]	62.7	2019, WB[1]
Spain	1,000	34.7	2018, WB[1]	27,063	2020, WB[1]	9.1	2019, WB[1]	21.8	2019, WB[1]
Estonia	1,013	30.3	2018, WB[1]	23,027	2020, WB[1]	6.7	2019, WB[1]	24.0	2019, WB[1]
Ethiopia	1,003	35	2015, WB[1]	936	2020, WB[1]	3.2	2019, WB[1]	37.9	2019, WB[1]
Finland	1,000	27.3	2018, WB[1]	48,745	2020, WB[1]	9.2	2019, WB[1]	17.4	2019, WB[1]
France	1,000	32.4	2018, WB[1]	39,030	2020, WB[1]	11.1	2019, WB[1]	9.3	2019, WB[1]
Gabon	1,005	38	2017, WB[1]	6,882	2020, WB[1]	2.8	2019, WB[1]	23.1	2019, WB[1]
United Kingdom	1,000	35.1	2017, WB[1]	41,059	2020, WB[1]	10.2	2019, WB[1]	17.1	2019, WB[1]
Georgia	1,000	35.9	2019, WB[1]	4,267	2020, WB[1]	6.7	2019, WB[1]	46.8	2019, WB[1]
Ghana	1,000	43.5	2016, WB[1]	2,206	2020, WB[1]	3.4	2019, WB[1]	36.2	2019, WB[1]
Guinea	1,009	33.7	2012, WB[1]	1,194	2020, WB[1]	4.0	2019, WB[1]	59.2	2019, WB[1]
Greece	1,006	32.9	2018, WB[1]	17,623	2020, WB[1]	7.8	2019, WB[1]	35.2	2019, WB[1]

Hong Kong	1,004	53.9	2016, [3]	46,324	2020, WB[1]	6.5	2019, [4]	30.0	2019, WB[5]
Croatia	1,000	29.7	2018, WB[1]	14,134	2020, WB[1]	7.0	2019, WB[1]	11.5	2019, WB[1]
Hungary	1,000	29.6	2018, WB[1]	15,981	2020, WB[1]	6.4	2019, WB[1]	28.2	2019, WB[1]
Indonesia	1,023	38.2	2019, WB[1]	3,870	2020, WB[1]	2.9	2019, WB[1]	34.8	2019, WB[1]
India	3,045	35.7	2011, WB[1]	1,928	2020, WB[1]	3.0	2019, WB[1]	54.8	2019, WB[1]
Ireland	1,000	31.4	2017, WB[1]	85,268	2020, WB[1]	6.7	2019, WB[1]	11.7	2019, WB[1]
Iran	1,007	42	2018, WB[1]	2,422	2020, WB[1]	6.7	2019, WB[1]	39.5	2019, WB[1]
Iraq	1,009	29.5	2012, WB[1]	4,146	2020, WB[1]	4.5	2019, WB[1]	50.1	2019, WB[1]
Israel	1,063	39	2016, WB[1]	44,169	2020, WB[1]	7.5	2019, WB[1]	21.0	2019, WB[1]
Italy	1,000	35.9	2017, WB[1]	31,714	2020, WB[1]	8.7	2019, WB[1]	23.3	2019, WB[1]
Jordan	1,005	33.7	2010, WB[1]	4,283	2020, WB[1]	7.6	2019, WB[1]	30.3	2019, WB[1]
Japan	1,012	32.9	2013, WB[1]	40,193	2020, WB[1]	10.7	2019, WB[1]	12.9	2019, WB[1]
Kazakhstan	1,000	27.8	2018, WB[1]	9,122	2020, WB[1]	2.8	2019, WB[1]	33.9	2019, WB[1]
Kenya	1,002	40.8	2015, WB[1]	1,879	2020, WB[1]	4.6	2019, WB[1]	24.3	2019, WB[1]
Kyrgyzstan	1,000	29.7	2019, WB[1]	1,174	2020, WB[1]	4.5	2019, WB[1]	46.2	2019, WB[1]
Cambodia	1,000	36.6	2018, WB[1]	1,544	2020, WB[1]	7.0	2019, WB[1]	64.4	2019, WB[1]
South Korea	1,009	31.4	2016, WB[1]	31,631	2020, WB[1]	8.2	2019, WB[1]	30.2	2019, WB[1]
Laos	1,000	38.8	2018, WB[1]	2,630	2020, WB[1]	2.6	2019, WB[1]	41.8	2019, WB[1]
Lebanon	1,035	31.8	2011, WB[1]	4,650	2020, WB[1]	8.6	2019, WB[1]	33.5	2019, WB[1]
Sri Lanka	1,011	39.3	2016, WB[1]	3,681	2020, WB[1]	4.1	2019, WB[1]	45.6	2019, WB[1]
Lithuania	1,001	35.7	2018, WB[1]	20,234	2020, WB[1]	7.0	2019, WB[1]	32.3	2019, WB[1]
Latvia	1,005	35.1	2018, WB[1]	17,726	2020, WB[1]	6.6	2019, WB[1]	35.7	2019, WB[1]
Morocco	1,012	39.5	2013, WB[1]	3,059	2020, WB[1]	5.3	2019, WB[1]	46.8	2019, WB[1]
Moldova	1,005	25.7	2018, WB[1]	4,547	2020, WB[1]	6.4	2019, WB[1]	35.7	2019, WB[1]
Mexico	1,000	45.4	2018, WB[1]	8,329	2020, WB[1]	5.4	2019, WB[1]	42.1	2019, WB[1]
North Macedonia	1,019	33	2018, WB[1]	5,917	2020, WB[1]	7.3	2019, WB[1]	40.4	2019, WB[1]
Mali	1,002	33	2009, WB[1]	862	2020, WB[1]	3.9	2019, WB[1]	31.4	2019, WB[1]
Malta	1,002	28.7	2018, WB[1]	27,885	2020, WB[1]	8.2	2019, WB[1]	34.6	2019, WB[1]
Myanmar	1,000	30.7	2017, WB[1]	1,468	2020, WB[1]	4.7	2019, WB[1]	76.0	2019, WB[1]
Montenegro	1,027	38.5	2016, WB[1]	7,677	2020, WB[1]	8.3	2019, WB[1]	38.6	2019, WB[1]
Mongolia	1,000	32.7	2018, WB[1]	4,061	2020, WB[1]	3.8	2019, WB[1]	34.8	2019, WB[1]

[3] Census and Statistics Department Hong Kong: https://www.censtatd.gov.hk/en/EIndexbySubject.html?scode=459&pcode=D5321605 (retrieved, 22 April 2022)
[4] https://www.healthbureau.gov.hk/statistics/download/dha/en/table1_1920.pdf
[5] https://www.healthbureau.gov.hk/statistics/en/dha/dha_summary_report.htm#:~:text=Analysed%20by%20financing%20scheme%2C%2053

Mauritius	1,000	36.8	2017, WB[1]	8,628	2020, WB[1]	6.2	2019, WB[1]	45.7	2019, WB[1]
Malaysia	1,004	41.1	2015, WB[1]	10,412	2020, WB[1]	3.8	2019, WB[1]	34.6	2019, WB[1]
Namibia	1,007	59.1	2015, WB[1]	4,179	2020, WB[1]	8.5	2019, WB[1]	8.2	2019, WB[1]
Nigeria	1,002	35.1	2018, WB[1]	2,097	2020, WB[1]	3.0	2019, WB[1]	70.5	2019, WB[1]
Nicaragua	1,000	46.2	2014, WB[1]	1,905	2020, WB[1]	8.4	2019, WB[1]	34.4	2019, WB[1]
Netherlands	1,000	28.1	2018, WB[1]	52,397	2020, WB[1]	10.1	2019, WB[1]	10.6	2019, WB[1]
Norway	1,000	27.6	2018, WB[1]	67,330	2020, WB[1]	10.5	2019, WB[1]	13.9	2019, WB[1]
Nepal	1,000	32.8	2010, WB[1]	1,155	2020, WB[1]	4.4	2019, WB[1]	57.9	2019, WB[1]
New Zealand	1,000	34.9	2014, WB[1]	41,441	2020, WB[1]	9.7	2019, WB[1]	12.2	2019, WB[1]
Peru	1,001	41.5	2019, WB[1]	6,127	2020, WB[1]	5.2	2019, WB[1]	28.1	2019, WB[1]
Philippines	1,000	42.3	2018, WB[1]	3,299	2020, WB[1]	4.1	2019, WB[1]	48.6	2019, WB[1]
Poland	1,002	30.2	2018, WB[1]	15,721	2020, WB[1]	6.4	2019, WB[1]	20.4	2019, WB[1]
Portugal	1,004	33.5	2018, WB[1]	22,176	2020, WB[1]	9.5	2019, WB[1]	30.5	2019, WB[1]
Paraguay	1,000	45.7	2019, WB[1]	5,001	2020, WB[1]	7.2	2019, WB[1]	41.6	2019, WB[1]
Romania	1,006	35.8	2018, WB[1]	12,896	2020, WB[1]	5.7	2019, WB[1]	18.9	2019, WB[1]
Russia	2,002	37.5	2018, WB[1]	10,127	2020, WB[1]	5.6	2019, WB[1]	36.6	2019, WB[1]
Saudi Arabia	1,013	45.9	2013, WB[1]	20,110	2020, WB[1]	5.7	2019, WB[1]	16.5	2019, WB[1]
Senegal	1,025	40.3	2011, WB[1]	1,472	2020, WB[1]	4.1	2019, WB[1]	51.0	2019, WB[1]
El Salvador	1,000	38.8	2018, WB[1]	3,799	2020, WB[1]	7.2	2019, WB[1]	28.4	2019, WB[1]
Serbia	1,000	36.2	2017, WB[1]	7,721	2020, WB[1]	8.7	2019, WB[1]	37.0	2019, WB[1]
Slovakia	1,004	25	2018, WB[1]	19,267	2020, WB[1]	7.0	2019, WB[1]	19.2	2019, WB[1]
Slovenia	1,001	24.6	2018, WB[1]	25,517	2020, WB[1]	8.5	2019, WB[1]	11.7	2019, WB[1]
Sweden	1,000	30	2018, WB[1]	52,274	2020, WB[1]	10.9	2019, WB[1]	13.9	2019, WB[1]
Thailand	1,000	34.9	2019, WB[1]	7,187	2020, WB[1]	3.8	2019, WB[1]	8.7	2019, WB[1]
Tunisia	1,006	32.8	2015, WB[1]	3,522	2020, WB[1]	7.0	2019, WB[1]	37.9	2019, WB[1]
Turkey	1,000	41.9	2019, WB[1]	8,536	2020, WB[1]	4.3	2019, WB[1]	16.9	2019, WB[1]
Tanzania	1,000	40.5	2017, WB[1]	1,076	2020, WB[1]	3.8	2019, WB[1]	22.2	2019, WB[1]
Uganda	1,027	42.8	2016, WB[1]	822	2020, WB[1]	3.8	2019, WB[1]	38.3	2019, WB[1]
Ukraine	1,000	26.6	2019, WB[1]	3,725	2020, WB[1]	7.1	2019, WB[1]	51.1	2019, WB[1]
Uruguay	1,003	39.7	2019, WB[1]	15,438	2020, WB[1]	9.3	2019, WB[1]	15.5	2019, WB[1]
United States	1,001	41.4	2018, WB[1]	63,593	2020, WB[1]	16.8	2019, WB[1]	11.3	2019, WB[1]
Uzbekistan	1,000	35.3	2003, WB[1]	1,751	2020, WB[1]	5.6	2019, WB[1]	57.7	2019, WB[1]
Vietnam	1,000	35.7	2018, WB[1]	2,786	2020, WB[1]	5.2	2019, WB[1]	43.0	2019, WB[1]

Kosovo	1,004	29	2017, WB[1]	4,347	2020, WB[1]	4.5	2017, [6]	33.3	2014, [7]
South Africa	1,004	63	2014, WB[1]	5,656	2020, WB[1]	9.1	2019, WB[1]	5.7	2019, WB[1]
Zambia	1,005	57.1	2015, WB[1]	985	2020, WB[1]	5.3	2019, WB[1]	10.2	2019, WB[1]
Zimbabwe	1,002	50.3	2019, WB[1]	1,215	2020, WB[1]	7.7	2019, WB[1]	24.4	2019, WB[1]
Taiwan	1,000	33.9	2019, WB[1]	28,358	2020, [8]	6.1	2017, [9]	34.0	2016, [10]

Table S4: Covid-19 data

Summary of Covid Data for the 111 countries in the study. All data derived from the Our World in Data website and the Oxford Covid-19 Government Response Tracker (OxCGRT)

	Sample size in survey dataset (n)	**Covid-19 total infections** (until 31st Jan 2021)	**Covid-19 total deaths** (until 31st Jan 2021)	**Lockdown stringency** (31st Jan 2021)
Albania	1,000	26861.878	477.779	60.19
United Arab Emirates	1,002	31845.843	88.76	62.04
Argentina	1,001	43804.39	1180.304	79.17
Australia	1,001	1100.605	35.259	70.83
Austria	1,000	45366.373	1037.852	82.41
Belgium	1,001	60611.073	1831.258	62.96
Benin	1,007	283.535	3.595	26.39
Burkina Faso	1,002	471.117	5.292	22.22
Bangladesh	1,011	3126.061	47.475	81.02
Bulgaria	1,007	32235.248	1331.18	53.7
Bahrain	1,005	69707.527	252.677	58.33
Bosnia Herzegovina	1,002	37695.955	1452.283	42.59
Bolivia	1,002	17456.643	836.543	30.56
Brazil	1,000	42349.935	1034.148	69.91
Canada	1,010	20044.376	511.308	75.46

[6] Kosovo National Health Accounts Report for 2017 https://msh.rks-gov.net/wp-content/uploads/2019/10/Raporti-p%C3%ABr-NHA-ENG.pdf

[7] Arenliu Qosaj, F., Froeschl, G., Berisha, M., Bellaqa, B., & Holle, R. (2018). Catastrophic expenditures and impoverishment due to out-of-pocket health payments in Kosovo. *Cost effectiveness and resource allocation*, *16*(1), 1-12.

[8] https://www.statista.com/statistics/727592/gross-domestic-product-gdp-per-capita-in-taiwan/

[9] https://www.healthaffairs.org/do/10.1377/forefront.20190206.305164/#:~:text=National%20health%20expenditure%20(NHE)%20in,the%20average%20for%20OECD%20countries.

[10] https://www.commonwealthfund.org/international-health-policy-center/countries/taiwan

Switzerland	1,000	59758.908	1048.57	60.19
Chile	1,021	36875.624	935.485	79.17
China	3,502	70.815	3.382	78.24
Cote d'Ivoire	1,005	1000.62	5.433	17.59
Cameroon	1,006	1085.921	16.98	35.19
Congo Brazzaville	1,009	1349.987	20.434	43.52
Colombia	1,000	40051.507	1027.181	81.02
Costa Rica	1,001	37305.948	502.622	66.67
Cyprus	1,012	34852.406	223.213	84.26
Czech Republic	1,000	94689.055	1596.533	81.48
Germany	1,000	26643.676	849.516	83.33
Denmark	1,000	33676.688	358.026	70.37
Dominican Republic	1,000	18929.236	235.644	62.04
Algeria	1,020	2385.619	64.316	72.22
Ecuador	1,000	13875.839	825.01	69.44
Egypt	1,004	1490.385	83.458	48.15
Spain	1,000	60133.647	1395.73	71.3
Estonia	1,013	37550.224	372.531	39.79
Ethiopia	1,003	1110.562	16.948	51.85
Finland	1,000	8221.097	126.517	52.31
France	1,000	45354.125	1236.41	63.89
Gabon	1,005	4498.959	28.464	65.74
United Kingdom	1,000	57484.642	1917.08	87.96
Georgia	1,000	68932.815	848.738	83.33
Ghana	1,000	2024.802	12.666	38.89
Guinea	1,009	1048.534	5.917	47.69
Greece	1,006	15514.534	560.907	80.56
Hong Kong	1,004	n/a	n/a	71.3
Croatia	1,000	57585.412	1240.087	47.22
Hungary	1,000	36879.18	1256.508	72.22
Indonesia	1,023	3914.006	108.885	68.06
India	3,045	7582.83	108.86	61.57
Ireland	1,000	38814.614	708.525	87.96

Iran	1,007	15942.653	653.739	80.09
Iraq	1,009	13909.571	293.082	44.44
Israel	1,063	67778.813	504.286	87.04
Italy	1,000	43053.724	1495.305	74.07
Jordan	1,005	28856.779	381.362	75.93
Japan	1,012	3142.498	45.615	49.54
Kazakhstan	1,000	12092.433	156.459	76.85
Kenya	1,002	1863.403	32.483	50.93
Kyrgyzstan	1,000	n/a	n/a	41.67
Cambodia	1,000	27.791		55.56
South Korea	1,009	1515.04	27.405	63.89
Laos	1,000	5.844		22.22
Lebanon	1,035	54449.351	552.12	85.19
Sri Lanka	1,011	2938.648	14.474	79.17
Lithuania	1,001	67070.222	1026.16	75.93
Latvia	1,005	35792.212	736.496	64.81
Morocco	1,012	12565.842	220.487	76.85
Moldova	1,005	48736.126	1106.327	57.41
Mexico	1,000	15189.713	1460.274	71.76
North Macedonia	1,019	44290.091	1612.529	0
Mali	1,002	357.137	14.606	44.44
Malta	1,002	34341.347	532.54	52.78
Myanmar	1,000	2586.688	57.79	70.37
Montenegro	1,027	95383.06	1106.713	0
Mongolia	1,000	533.785	0.589	73.61
Mauritius	1,000	437.099	7.695	19.44
Malaysia	1,004	6333.833	21.981	77.31
Namibia	1,007	13221.536	139.461	38.89
Nigeria	1,002	597.402	7.221	58.33
Nicaragua	1,000	718.439	24.322	8.33
Netherlands	1,000	55963.327	816.897	82.41
Norway	1,000	11632.174	103.601	73.15
Nepal	1,000	8870.063	96.963	57.41

New Zealand	1,000	375.678	4.821	22.22
Peru	1,001	33065.745	3020.859	66.67
Philippines	1,000	4548.447	92.325	74.54
Poland	1,002	38024.476	934.789	71.3
Portugal	1,004	66781.866	1245.368	87.96
Paraguay	1,000	19450.075	397.154	55.56
Romania	1,006	36975.839	929.027	76.85
Russia	2,002	26607.359	505.703	46.76
Saudi Arabia	1,013	10102.304	175.013	53.7
Senegal	1,025	1513.763	35.862	50.46
El Salvador	1,000	8520.463	254.719	46.3
Serbia	1,000	57322.9	582.111	56.48
Slovakia	1,004	44283.688	822.546	73.15
Slovenia	1,001	78742.152	1819.474	75.93
Sweden	1,000	54387.621	1155.522	69.44
Thailand	1,000	261.963	1.074	52.78
Tunisia	1,006	16790.713	540.623	71.3
Turkey	1,000	28953.186	303.077	80.56
Tanzania	1,000	7.771	0.321	6.48
Uganda	1,027	837.658	6.794	54.63
Ukraine	1,000	29701.139	508.718	54.63
Uruguay	1,003	11840.904	124.167	64.81
United States	1,001	76452.287	1336.496	71.76
Uzbekistan	1,000	0.26	n/a	34.26
Vietnam	1,000	18.526	0.356	67.59
Kosovo	1,004	33606.698	831.596	n/a
South Africa	1,004	24196.728	733.814	72.22
Zambia	1,005	2665.245	37.217	43.52
Zimbabwe	1,002	2038.597	73.098	84.26
Taiwan	1,000	n/a	n/a	n/a

Appendix 1B: Supplementary analyses

Strategy for supplementary analyses

Our strategy and approach for supplementary analyses follows three main purposes. The first purpose is to show all socio-economic effects for both income quintiles and education levels in a high level of detail. The second purpose is to assess the stability of the outcome variables of treatment helpfulness. As the third purpose is to demonstrate the stability of the study's findings when adding county-level Covid-19 variables. In the sections below, we briefly describe the analyses and findings for each of these three purposes.

Triangulation of income and education as SES predictors

While we present most of the SES effects in the main text using income quintiles, we include equivalent analyses for education in the supplementary analyses. This approach allows us to triangulate the socio-economic effect sizes for both income and education and provides confidence in our results based on the two measures in as much detail as possible. In Figure S2, we first present the specific predictions for the effect of income on the three mental health outcomes segregated by HICs and LMICs as a supplement to Figure 1 in the main text. Next, we show the same analysis for the association between education (instead of income) and mental health in Figures S3 and S4. The results for education show the same pattern as was shown for income. Finally, we include Table S5, where we replicate the same analysis as shown in the main text as Table 2 but use Education as the main predictor. In this case, we do not control for income because it might mediate between the effect of education and mental health and should therefore not be included as a control. Table S5 shows that the association between education levels and mental health varies notably in each country; therefore, we considered income quintiles the better measure for the main analysis.

For education, the result show very similar patterns of results as was shown for income, and we also show the 'triple inequality in mental health'. Individuals with university (tertiary) education are less likely to experience symptoms of depression and anxiety (OR= 0.76, CI:[0.73-0.79]), are more likely to talk to a mental health professional (OR=1.41[1.30-1-64]) and to find this treatment helpful (OR=1.17[1.04-1.31]). Notably, the size of association for education is higher with "talking to a mental health professional" (OR=1.41) than it was for income (OR=1.25 for richest vs. poorest quintile).

Different variable coding of treatment helpfulness

The second purpose is to assess the stability of the outcome variables of treatment helpfulness. As described in the main text, we used the grouping of 'Somewhat helpful' and 'not helpful' as one category labelled 'not entirely helpful.' This helps account for the distribution of results, as relatively few participants chose 'somewhat helpful,' and even fewer chose 'not helpful,' while 63% answered with 'very helpful' in the question on the helpfulness of talking to a mental health professional. However, it is important to test whether this decision of grouping leads to substantially different results than the alternative coding of 'somewhat helpful' and 'very helpful' together in one group, as well as the alternative of not merging categories at all and running a linear regression rather than a logistic regression. We tested both alternative variations, and the results are shown in Table S7 below. Table S7 shows that all scenarios yield very similar results. The strength of the effect remains very similar (potentially slightly bigger if we merge "somewhat helpful" and "very helpful", and statistical significance and confidence intervals also remain stable across the different models.

Covid-19 analysis

As our data were collected during the Covid-19 pandemic in 2020 through telephone interviews, it is important to assess the robustness of our results when considering the effects of the

pandemic. One way to do this is to include country-level indicators that measure consequences and policy responses as part of the analysis to see if the results are substantially affected.

To achieve this, we re-ran our main regression models and incorporated country-level effects related to Covid-19. These effects include Covid-19-related deaths per 100,000 inhabitants (as of January 31st, 2021), which aligns with the data collection period of the Wellcome survey. Additionally, we included Covid-19 infection rates and a lockdown stringency indicator for the same date. These variables were obtained from the Our World in Data (2023) the Oxford Covid-19 Government Response Tracker (OxCGRT) available at https://github.com/OxCGRT/covid-policy-dataset.

The findings of this analysis are presented in Table S7. Table S7 reveals that Covid-19 variables exhibit minimal association with the outcome variables of our study. We demonstrate that Covid-19 deaths and the lockdown stringency index are not significantly associated with the prevalence, utilization, and helpfulness of talking to a mental health professional. Furthermore, they do not substantially change the direction and statistical significance of the other country-level or individual-level predictors.

Regarding these Covid-19 analyses, we had data available for only 108 countries, as three countries were missing Covid data (Hong Kong, Kyrgyzstan, and Taiwan). Consequently, we made the decision to not include them in the main text, allowing us to maintain a sample size of 111 countries.

1. Inequality in prevalence

Predicted probability of suffering from anxiety or depression (lifetime)

wbi.2groups = 1

Household_Income_factor	Predicted	95% CI
1	0.27	[0.26, 0.28]
2	0.24	[0.24, 0.25]
3	0.22	[0.21, 0.23]
4	0.20	[0.20, 0.21]
5	0.19	[0.19, 0.20]

wbi.2groups = 2

Household_Income_factor	Predicted	95% CI
1	0.22	[0.21, 0.23]
2	0.19	[0.18, 0.20]
3	0.17	[0.16, 0.18]
4	0.17	[0.16, 0.18]
5	0.15	[0.15, 0.16]

wbi.2gourps = 1
Low- and middle-income countries

wbi.2gourps = 2
High income countries

2. Inequality in treatment utilisation

Predicted prob. of "talking to MH professional"

wbi.2groups = 1

Household_Income_factor	Predicted	95% CI
1	0.32	[0.30, 0.34]
2	0.32	[0.30, 0.34]
3	0.33	[0.31, 0.34]
4	0.35	[0.33, 0.36]
5	0.37	[0.36, 0.39]

wbi.2groups = 2

Household_Income_factor	Predicted	95% CI
1	0.58	[0.55, 0.60]
2	0.61	[0.58, 0.63]
3	0.62	[0.60, 0.65]
4	0.63	[0.60, 0.65]
5	0.67	[0.65, 0.69]

Predicted prob. of "taking prescribed medication"

wbi.2groups = 1

Household_Income_factor	Predicted	95% CI
1	0.46	[0.44, 0.48]
2	0.44	[0.42, 0.46]
3	0.41	[0.40, 0.43]
4	0.41	[0.39, 0.42]
5	0.40	[0.39, 0.42]

wbi.2groups = 2

Household_Income_factor	Predicted	95% CI
1	0.54	[0.52, 0.57]
2	0.58	[0.55, 0.60]
3	0.59	[0.56, 0.61]
4	0.57	[0.54, 0.59]
5	0.57	[0.55, 0.59]

3. Inequality in treatment helpfulness

Predicted prob. of rating "talking to MH professional" as very helpful

wbi.2groups = 1

Household_Income_factor	Predicted	95% CI
1	0.65	[0.62, 0.68]
2	0.63	[0.60, 0.66]
3	0.64	[0.61, 0.67]
4	0.66	[0.63, 0.69]
5	0.69	[0.67, 0.71]

wbi.2groups = 2

Household_Income_factor	Predicted	95% CI
1	0.56	[0.52, 0.59]
2	0.58	[0.54, 0.61]
3	0.62	[0.59, 0.65]
4	0.64	[0.61, 0.67]
5	0.63	[0.60, 0.66]

Predicted prob. of rating "taking prescribed medication" as very helpful

wbi.2groups = 1

Household_Income_factor	Predicted	95% CI
1	0.59	[0.56, 0.61]
2	0.57	[0.54, 0.60]
3	0.61	[0.58, 0.64]
4	0.58	[0.55, 0.61]
5	0.61	[0.58, 0.63]

wbi.2groups = 2

Household_Income_factor	Predicted	95% CI
1	0.52	[0.49, 0.56]
2	0.51	[0.48, 0.55]
3	0.53	[0.50, 0.56]
4	0.56	[0.52, 0.59]
5	0.52	[0.49, 0.55]

Figure S2. *Exact predicted probabilities and CIs as supplement for Figure 1 in the main text*

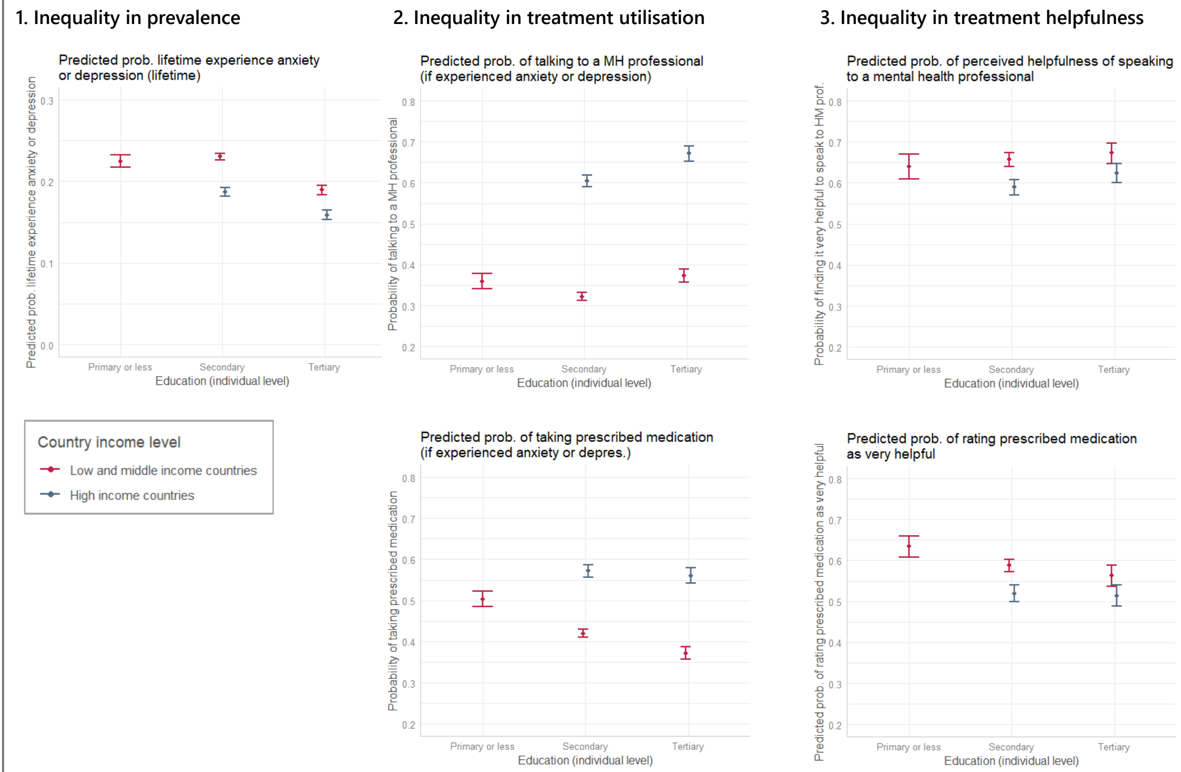


Figure S3. *Predicted probabilities of prevalence, utilisation and helfpuless by educational attainment (95% confidence intervals provided around each predicted value). For HICs, the "primary school or less" category was omitted due to the small nuber of participants in this category (only 2.4% of participants)*

Predicted probabilities - Education

1. Inequality in prevalence

Predicted probability of suffering from anxiety or depression (lifetime)

```
# wbi.2groups = 1

Education.factor.prime | Predicted |       95% CI
--------------------------------------------------
1                      |      0.22 | [0.22, 0.23]
2                      |      0.23 | [0.23, 0.23]
3                      |      0.19 | [0.18, 0.19]

# wbi.2groups = 2

Education.factor.prime | Predicted |       95% CI
--------------------------------------------------
2                      |      0.19 | [0.18, 0.19]
3                      |      0.16 | [0.15, 0.16]
```

2. Inequality in treatment utilisation

Predicted prob. of "talking to MH professional"

```
# wbi.2groups = 1

Education.factor.prime | Predicted |       95% CI
--------------------------------------------------
1                      |      0.36 | [0.34, 0.38]
2                      |      0.32 | [0.31, 0.33]
3                      |      0.37 | [0.36, 0.39]

# wbi.2groups = 2

Education.factor.prime | Predicted |       95% CI
--------------------------------------------------
2                      |      0.60 | [0.59, 0.62]
3                      |      0.67 | [0.65, 0.69]
```

Predicted prob. of "taking prescribed medication"

```
# wbi.2groups = 1

Education.factor.prime | Predicted |       95% CI
--------------------------------------------------
1                      |      0.50 | [0.48, 0.52]
2                      |      0.42 | [0.41, 0.43]
3                      |      0.37 | [0.36, 0.39]

# wbi.2groups = 2

Education.factor.prime | Predicted |       95% CI
--------------------------------------------------
2                      |      0.57 | [0.56, 0.59]
3                      |      0.56 | [0.54, 0.58]
```

3. Inequality in treatment helpfulness

Predicted prob. of rating "talking to MH professional" as very helpful

```
# wbi.2groups = 1

Education.factor.prime | Predicted |       95% CI
--------------------------------------------------
1                      |      0.64 | [0.61, 0.67]
2                      |      0.66 | [0.64, 0.67]
3                      |      0.67 | [0.65, 0.70]

# wbi.2groups = 2

Education.factor.prime | Predicted |       95% CI
--------------------------------------------------
2                      |      0.59 | [0.57, 0.61]
3                      |      0.62 | [0.60, 0.65]
```

Predicted prob. of rating "taking prescribed medication" as very helpful

```
# wbi.2groups = 1

Education.factor | Predicted |       95% CI
--------------------------------------------
1                |      0.63 | [0.61, 0.66]
2                |      0.59 | [0.57, 0.60]
3                |      0.56 | [0.54, 0.59]

# wbi.2groups = 2

Education.factor | Predicted |       95% CI
--------------------------------------------
2                |      0.52 | [0.50, 0.54]
3                |      0.51 | [0.49, 0.54]
```

wbi.2gourps = 1
Low- and middle-income countries

wbi.2gourps = 2
High income countries

Figure S4. *Exact predicted probabilities and CIs as supplement for Figure S3*

Table S5

Logistic regression results for experience of mental health problems, treatment utilisation and perceived treatment helpfulness with education as main socio-economic predictor

Predictors	**Dependent variable 1:** Lifetime experience of anxiety or depression (= Yes)	**Dependent variable 2a:** 'Talking to a mental health professional' (= Yes)		**Dependent variable 2b:** 'Taking medication prescribed by a healthcare professional' (=Yes)		**Dependent variable 3a:** Rating 'talking to mental health professional' as very helpful (=Yes)		**Dependent variable 3b:** Rating 'taking medication prescribed by a healthcare professional' as very helpful (=Yes)	
Individual-level socio-economic factors	**Full model**	**Simple model**	**Full model**	**Simple model**	**Full model**	**Simple model**	**Full model**	**Simple model**	**Full model**
Primary school or less (ref = secondary school)	1.14** [1.10–1.19]	0.94 [0.87–1.01]	0.96 [0.89–1.03]	1.05 [0.98–1.03]	1.09* [1.02–1.17]	0.84** [0.75–0.94]	0.89 [0.80–1.01]	1.02 [0.93–1.13]	1.06 [0.95–1.17]
Tertiary education (ref = secondary school)	0.76** [0.73–0.79]	1.41** [1.30–1.54]	1.41** [1.29–1.54]	0.86** [0.80–0.93]	0.87** [0.80–0.94]	1.17** [1.04–1.31]	1.14** [1.01–1.28]	1.04 [0.93–1.17]	0.98 [0.87–1.11]
Psycho-social factors									
Perception of local mental health stigma			0.93** [0.90–0.97]		0.93** [0.89–0.96]		0.77** [0.72–0.81]		0.80** [0.76 – 0.85]
Belief in science to treat mental health conditions			1.08** [1.05–1.12]		1.08** [1.05–1.11]		1.32** [1.26–1.39]		1.33** [1.27–1.39]
Trust in health practitioners (doctors and nurses)			1.10** [1.06–1.14]		1.07** [1.04–1.11]		1.32** [1.26–1.39]		1.27** [1.21–1.34]
Country-level factors									
GDP per capita (log)	1.02 [0.94–1.12]	1.23** [1.05–1.44]	1.25** [1.07–1.46]	0.95 [0.84–1.08]	0.98 [0.86–1.11]	0.75** [0.65–0.87]	0.78** [0.67–0.90]	0.78** [0.68–0.90]	0.80** [0.70–0.93]
GINI coefficient	1.02* [1.00–1.03]	0.99 [0.98–1.01]	1.00 [0.98–1.01]	0.99 [0.98–1.01]	0.99 [0.98–1.01]	1.01 [1.00–1.03]	1.02 [1.00–1.03]	1.01 [0.99–1.02]	1.01 [1.00–1.03]
Health expenditure as % of GDP		1.12** [1.05–1.20]	1.11** [1.04–1.18]	1.07* [1.01–1.13]	1.05 [1.00–1.11]	1.03 [0.97–1.10]	1.02 [0.97–1.09]	0.96 [0.91–1.02]	0.94 [0.89–1.00]
% Out of Pocket healthcare expenditure		0.99 [0.98–1.00]	0.99 [0.98–1.00]	0.99 [0.99–1.00]	1.00 [0.99–1.00]	0.99 [0.98–1.00]	0.99 [0.98–1.00]	0.99* [0.98–1.00]	0.99* [0.98–1.00]
All models above also control for age and gender									
Observations (n)	115,121	23,340	21,677	23,359	21,692	9,929	9,387	10,809	10,154

Notes. Values reflect unstandardised regression coefficients; * $p < 0.05$; ** $p < 0.01$. Country sample is N = 111 for all analyses. "Simple models" are for the optimal interpretation of the association of education and mental health outcomes.

Table S6: Sensitivity Tests for helpfulness variables

Sensitivity tests for "helpfulness variables" with alternative variable coding (logistic regressions) as well as on an outcome scale from 1 – 3 using linear mixed effects models

Predictors	**Dependent variable 3a:** Rating 'talking to mental health professional' as very helpful (=Yes) **Simple model in main text**	**Dependent variable 3a:** Rating 'talking to mental health professional' at least somewhat helpful	**Dependent variable 3a (scale from 1 – 3):** 'Helpfulness of talking to mental health professional' on a scale from 1 – 3 (linear mixed effects model)	**Dependent variable 3b:** Rating 'taking medication prescribed by a healthcare professional' as very helpful (=Yes) **Simple model in main text**	**Dependent variable 3b:** Helpfulness of 'taking prescribed medication' at least somewhat helpful	**Dependent variable 3b:** Helpfulness of 'taking prescribed medication' on a scale from 1 – 3 (linear mixed effects model)
Individual-level socio-economic factors						
Household income quintile 2 (ref= quintile 1)	0.88 [0.78–0.99]	1.36* [1.10–1.68]	−0.004 [-0.03–0.03]	0.89* [0.80-1.00]	1.03 [0.86-1.23]	−0.02 [-0.06–0.01]
Household income quintile 3 (ref= quintile 1)	1.01 [0.89–1.15]	1.13 [0.92–1.40]	0.01 [-0.02– 0.05]	1.11 [0.98–1.23]	1.12 [0.92–1.35]	−0.03 [-0.01–0.07]
Household income quintile 4 (ref= quintile 1)	1.19* [1.04–1.35]	1.63** [1.29–2.05]	0.08** [0.04–0.11]	1.02 [0.90–1.15]	1.11 [0.91–1.35]	0.03 [-0.02–0.05]
Household income quintile 5 (ref= quintile 1)	1.23** [1.07–1.40]	1.44** [1.14–1.81]	0.07** [0.03–0.11]	1.06 [0.94–1.21]	0.87 [0.71–1.05]	0.0002 [-0.04–0.04]
Country-level factors						
GDP per capita (log)	0.76** [0.66–0.88]	0.97** [0.80–1.18]	−0.06** [-0.10– -0.03]	0.78** [0.68–0.90]	0.83* [0.70–0.99]	−0.07** [-0.11– -0.03]
GINI coefficient	1.01 [1.00–1.03]	1.03* [1.00–1.05]	0.004 [-0.00– 0.01]	1.01 [0.99–1.02]	1.02* [1.00–1.04]	0.003 [-0.01– -0.00]
Health expenditure as % of GDP	1.03 [0.97–1.10]	0.97 [0.90 – 1.04]	0.005 [-0.01– 0.02]	0.96 [0.91–1.02]	0.88** [0.82–0.94]	−0.02* [-0.04– -0.00]
% Out of Pocket healthcare expenditure	0.99 [0.98–1.00]	1.00 [0.99–1.01]	−0.002 [-0.01– 0.00]	0.99* [0.98–1.00]	0.99 [0.98–1.01]	−0.003* [-0.01– -0.00]

Notes. Values reflect unstandardised regression coefficients; * $p < 0.05$; ** $p < 0.01$. All models above also control for age and gender

Table S7
Covid-19 sensitivity analyses using logistic regression models of experience of mental health problems, treatment utilisation and perceived treatment helpfulness including Covid-19 country effects

Predictors	**Dependent variable 1:** Lifetime experience of anxiety or depression (= Yes)		**Dependent variable 2a:** 'Talking to a mental health professional' (= Yes)		**Dependent variable 2b:** 'Taking medication prescribed by a healthcare professional' (=Yes)		**Dependent variable 3a:** Rating 'talking to mental health professional' as very helpful (=Yes)		**Dependent variable 3b:** Rating 'taking medication prescribed by a healthcare professional' as very helpful (=Yes)	
Individual-level socio-economic factors	**Simple model**	**With Covid data**	**Simple model**	**With Covid data**	**Simple model**	**With Covid data**	**Simple model**	**With Covid data**	**Simple model**	**With Covid data**
Household income quintile 2 (ref= quintile 1)	0.83** [0.79–0.86]	0.81** [0.78–0.85]	1.00 [0.93–1.09]	1.02 [0.94–1.11]	0.99 [0.92–1.08]	1.00 [0.93–1.08]	0.88 [0.78–0.99]	0.86 [0.76–0.98]	0.89* [0.80-1.00]	0.90 [0.80-1.01]
Household income quintile 3 (ref= quintile 1)	0.73** [0.70–0.76]	0.72** [0.68–0.75]	1.02 [0.94–1.12]	1.02 [0.94–1.11]	0.93 [0.86–1.01]	0.94 [0.86–1.02]	1.01 [0.89–1.15]	1.00 [0.88–1.14]	1.11 [0.98–1.23]	1.11 [0.98–1.25]
Household income quintile 4 (ref= quintile 1)	0.69** [0.66–0.72]	0.67** [0.64–0.71]	1.10* [1.01–1.20]	1.11* [1.02–1.22]	0.90* [0.86–0.99]	0.90* [0.83–0.98]	1.19 [0.89–1.15]	1.18 [1.03–1.34]	1.02 [0.90–1.15]	1.02 [0.91–1.16]
Household income quintile 5 (ref= quintile 1)	0.67** [0.64–0.70]	0.66** [0.63–0.69]	1.25** [1.14–1.36]	1.25** [1.14–1.37]	0.97 [0.89–1.06]	0.97 [0.89–1.06]	1.23** [1.07–1.40]	1.21** [1.06–1.39]	1.06 [0.94–1.21]	1.09 [0.96–1.24]
Country-level factors										
GDP per capita (log)	1.01 [0.93–1.11]	0.99 [0.90–1.09]	1.24** [1.06–1.45]	1.25** [1.04–1.49]	0.95 [0.84–1.08]	1.00 [0.87–1.14]	0.76** [0.66–0.88]	0.79** [0.66–0.93]	0.78** [0.68–0.90]	0.84* [0.72–0.98]
GINI coefficient	1.02* [1.00–1.03]	1.02* [1.01–1.04]	0.99 [0.98–1.01]	0.99 [0.97–1.01]	0.99 [0.98–1.01]	0.99 [0.98–1.01]	1.01 [1.00–1.03]	1.02* [1.00–1.03]	1.01 [0.99–1.02]	1.01 [0.99–1.03]
Health expenditure as % of GDP			1.12** [1.05–1.20]	1.12** [1.04–1.20]	1.07* [1.01–1.12]	1.07* [1.01–1.12]	1.03 [0.97–1.10]	1.01 [0.95–1.08]	0.96 [0.91–1.02]	0.95 [0.89–1.01]
% Out of Pocket healthcare expenditure			0.99 [0.98–1.00]	0.99 [0.98–1.00]	0.99 [0.99–1.00]	0.99 [0.98–1.01]	0.99 [0.98–1.00]	0.99 [0.98–1.00]	0.99* [0.98–1.00]	0.99* [0.98–1.00]
Covid-19 indicators (country-level)										
Total Covid-19 deaths per million inhabitants (log)		1.04 [0.99–1.10]		1.02 [0.95–1.10]		0.99 [0.99–1.10]		1.03 [0.98–1.10]		1.02 [0.96–1.09]
Lockdown stringency index		1.00 [0.99–1.01]		0.99 [0.99–1.00]		0.99* [0.99–1.00]		1.00 [0.99–1.01]		0.99* [0.99–1.00]
All models above also control for individual level education, age and gender										
Observations (n)	115,121	108,221	23,340	22,483	23,359	23,222	9,929	9,708	10,809	10,377

Notes: Values reflect unstandardised regression coefficients; * $p < 0.05$; ** $p < 0.01$.

Appendix paper 2

Section A1

This appendix has the purpose of providing additional information on the variable descriptions and descriptive analyses. Section A1 provides additional information on the predictors used in the main analysis. Section A2 provides the descriptive statistics for the different waves of all variables used in the dataset. Section A3 provides additional analysis of Research Question 1 ("Characteristics of decline vs. stable groups"), by providing an overview of the predictors at age 26. Section A4 provides more details on the RandomForest algorithm used in the main text. Finally, section A5 provides more details on the reasoning for the selection of co-variation in the regression analysis.

Section A1: Additional information on the predictors

Job security was measured using the question "Would you say your current job is... "very secure", "fairly secure" (both classified as "secure job"), "not very secure" ("low job security"). Having multiple jobs was "How many jobs do you have?" and classified as "multiple jobs" or "single job". Job satisfaction was measured using the item "how satisfied or dissatisfied are you with your present job overall" and categorised into "high" (Very satisfied or satisfied) "medium" (Neither satisfied nor dissatisfied) or "low" (Very dissatisfied or dissatisfied). As family factors, following (Blair & Siddiqi, 2022), marital status was categorised into "never married", "married", "divorced" and "widowed". Having children was measured as "number of cohort member's natural children in household". As behavioural factors, smoking was categorised into "current smokers" and "non-smokers". Exercise was measured whether participants exercise regularly (at least once a month) which classified as "yes" or "no".

Having physical multimorbidity was defined as self-reporting at least two chronic medical conditions following previous research(Torre et al., 2021). These conditions include: asthma; backache; bladder or kidney conditions; cancer; cardiovascular conditions; convulsions or

epilepsy; diabetes; hearing conditions; migraine as well as stomach, bowel, or gall conditions(Torre et al., 2021). Finally, cognitive ability in childhood (at age 10) was measured using the "British Ability Scales" (BAS), examining Inductive, non-verbal reasoning (28 items; 1 point for each question) (Parsons, 2014), which is a relevant covariate for developments in mid-life.

Research question 1 for age 26 predictors

For the first research question, we divided the sample into those who experienced a decline in mental health (i.e., an increase in psychological distress) and explored group differences based on the different social determinants of health. The main text shows the results for the predictors of age 34 in Table 1. Below, we provide the same results for the predictor variables at age 26. Among the variables, only having "physical multimorbidity" is significantly higher in the group of people with declining mental health (M=23.2% vs. 20.1%; p=0.04). All other predictors are not statistically significant. This finding aligns with later results from the main text, which identify physical multimorbidity as a main predictor of the mid-life decline in mental health.

Table S1. Description of the groups of stable mental health and mental health decline at age 26

Social determinants (all at age 26)	Share in group of **stable mental health**	Share in group of **mental health decline**	Difference	p-value (t-test)
Cognitive ability in childhood (mean score)	16.5	16.3	0.2	0.264
Income and employment				
Income quintile 5 (highest)	17.0%	15.1%	1.9%	0.16
Income quintile 1 (lowest)	15.1%	17.4%	-2.3%	0.09
Working part-time	7.7%	7.1%	0.6%	0.50
Unemployed	3.1%	3.1%	0.0%	0.95
Having a disability	2.1%	1.8%	-0.3%	0.489
Looking after home/family	9.3%	11.3%	-1.9%	0.08
Family factors				
Being married	32.7%	30.4%	2.3%	0.17
Physical and behavioural factors				
Physical multimorbidity	**20.1%**	**23.2%**	**-3.1%**	**0.04***
Weekly smoking	29.0%	30.7%	1.8%	0.220

Notes: Decline in mental health is defined as an increase in psychological distress on the Malaise scale by at least two points (=1 Standard Deviation) from the age of 34 to 42; all other individuals are included in the "stable mental health" group

A3: Additional information on the RandomForest algorithm

In this section, we provide some additional information on the Random Forest algorithm in the main analysis section. The Random Forest algorithm was used to identify the variables which are most predictive of the mental health decline in mid-life. As suggested by Fife and D'Onofrio (2023), our paper uses R package "party" and its function "cforest". The cforest function establishes the Random Forest model using an ensemble of 1000 prediction trees (including all suggested Social Determinants of Health as possible predictors) and the function "estimates" to derive the Variable Importance for each variable. Besides the Variable Importance (VI; Root Mean Squared Error (MSE)) for each predictor, the algorithm also produces a score of overall prediction accuracy (Out of Bag accuracy of prediction) and R Squared, which are of less relevance for our research questions as our goal is variable selection rather than overall prediction accuracy and the R squared of predicting individuals' level of change is expected to be low. As expected, the overall prediction of predicted probability was low (R^2= 1.01%), showing that individual changes in health cannot be predicted with high accuracy. The social determinants selected therefore provide a measure of population-level trends, rather than an accurate risk prediction for each individuals. By additionally controlling for the Malaise score at age 34 throughout all analyses, we ensure that the decline is not dependent on the baseline level.

A4: Selection of co-variates for the regression analyses performed in Table 2

- **M1 (Social class):** This model focuses on estimating the association between of social class at birth and the mid-life decline. It only includes sex as additional control variable. All other variables temporarily lay between birth factors and mental health in mid-life, and could therefore be potential mediators of the relationship. We keep social class as control variable in the models M2 – M7.

- **M2 (Education):** For interpreting the association between education and mental health, we control for background factors of social class, sex and cognitive ability at age 10, which happened earlier in people's lifetime. Other factors are likely become mediators for the link of education and mental health, and are therefore not included in the model.
- **M3 (Income):** Income is added to the control variables of social class, sex, cognitive ability and education, which are all likely to be confounders for the relationship between income and mental health. Other factors are likely to be mediators or competing exposures and are not included in model M3. They are however included in the models M4 and M5, where income remains statistically significant even if such potential mediators and competing exposures area added.
- **M4 (Employment status) and M5 (work conditions):** Employment status and work conditions are included in addition to previous control variables (social class, sex, cognitive ability and education). We also control for income so that effects of work conditions and employment status needs to be relevant beyond income differences.
- **M6 (Family factors) and M7 (Physical health):** We control for the background factors which happen earlier in life (social class, sex, cognitive ability and education).

A5: Predictors of mental health decline from age 26 – 34

We perform equivalent logistic regression analyses and predicted probabilities (as produced in Table 2 in the main text) for social class, income and physical multimorbidity on the decline in mental health from the ages of 26 – 34 (replicating model M1, M3 and M7 as S1, S3 and S7). The results of this analysis are shown in Table S2. As reported in the main text (lower part of Figure 2), the table shows that low social class at birth is not significantly associated with a decline in mental health from the age of 26 – 34 (OR = 1.03 ; CI[0.83–1.28]. On the other hand, income (OR = 0.58; [0.44 – 0.76]) and physical health (1.40;[1.19–1.65]) are significantly associated with the decline in mental health from age 26 – 34.

Table S2. Logistic regression; outcome: the likelihood of experiencing a mid-life decline in mental health from age 26 to 34(Odds Ratios)

	S1 **Social class**	**S3** **Income**	**S7** **Physical health**
Social class and education			
Low social class at birth: (ref=high)	1.03 [0.83–1.28]	0.84 [1.15–1.72]	0.96 [0.76–1.19]
Medium social class at birth: (ref=high)	1.12 [0.94–1.33]	1.04 [0.88–1.23]	1.07 [0.90–1.27]
Income and employment			
Income quintile 2 (ref= q1)		0.98 [0.76 – 1.25]	
Income quintile 3 (ref= q1)		0.96 [0.76 – 1.22]	
Income quintile 4 (ref= q1)		0.81 [0.62 – 1.04]	
Income quintile 5 (ref= q1)		**0.58**** [0.44 – 0.76]	
Looking after home/family (ref= all other)			
Working parttime			
Working conditions			
Job satisfaction high (ref = low)			
Job security high (ref = low)			
Family factors			
Being married at age 34 (ref= unmarried)			
Having no children aged 34 (ref=1 child)			
Having 2-3 children (ref=1 child)			
Having four or more children			
Behavioural factors and physical health			
Having physical multimorbidity aged 26 (ref = no)			**1.40**** [1.19–1.65]
Covariates			
Mental health age 26	**0.88**** [0.85–0.92]	0.86** [0.82–0.90]	0.86 [0.82–0.90]
Sex (being male)	**0.97** [0.85–0.12]	1.04 [0.90–1.21]	**0.99** [0.86–1.13]
Cognitive ability aged 10		0.99 [0.97–1.00]	0.97 [0.96–0.99]

Notes: *p < 0.05; ** p < 0.01. N = 6,992 for all analyses.

Section B: Supplementary statistical analyses: Supplementary statistical analyses

Section B has the purpose of providing various supplementary statistical analyses on the robustness of the results displayed in the main text above. There are three main supplementary analyses performed.

Section B1 outlines the results for an alternative coding of mental health decline. Section B2 provides a LASSO regression as an alternative analytical tool. Section B3 provides more details on the handling of missing data in this paper and provides a full-cases analysis as an alternative to the main text.

B1: Alternative coding of mental health decline

In the main text, we defined the decline in mental health as an increase in psychological distress on the Malaise scale by at least two points (one standard deviation) between the ages of 34 to 42. In the alternative coding, Decline in mental health is defined as being under the threshold at age 34, and declining in mental health by at least 2 points (i.e., one standard deviation) on the Malaise scale from 34 – 42. Stable mental health is defined as being under the threshold for mental distress at age 34 (Malaise score <4 and not having a decline in mental health). We repeated the main analysis shown in Table S4 based on this alternative coding. The results are shown in Table S4 below. The findings in terms of the significant factors are consistent with Table 2 in the main text.

Table S3. Logistic regression; outcome: the likelihood of experiencing a mid-life decline in mental health from age 34 to 42 (Odds Ratios)

	M1 **Social class**	**M2** **Education**	**M3** **Income**	**M4** **Employment status**	**M5** **Work conditions**	**M6** **Family factors**	**M7** **Physical health**
Social class and education							
Low social class at birth (ref=high)	**1.52**** [1.25–1.85]	**1.38**** [1.12–1.71]	**1.37**** [1.11–1.69]	**1.36**** [1.10–1.68]	**1.35**** [1.10–1.67]	**1.38**** [1.12–1.70]	**1.39**** [1.12–1.71]
Medium social class at birth (ref=high)	1.02 [0.87–1.00]	0.97 [0.81–1.15]	0.97 [0.82–1.16]	0.97 [0.82–1.15]	0.96 [0.81–1.15]	0.96 [0.81–1.15]	0.97 [0.81–1.15]
Income and employment							
Income quintile 2 (ref= q1)			0.84 [0.66 – 1.07]	0.85 [0.66 – 1.08]	0.84 [0.66 – 1.07]		
Income quintile 3 (ref= q1)			0.98 [0.77 – 1.24]	0.92 [0.72 – 1.19]	0.98 [0.77 – 1.24]		
Income quintile 4 (ref= q1)			**0.78*** [0.61 – 1.01]	**0.73*** [0.56 – 0.95]	0.78 [0.60 – 1.00]		
Income quintile 5 (ref= q1)			**0.68**** [0.52 – 0.89]	**0.64**** [0.48 – 0.85]	**0.68**** [0.52 – 0.88]		
Looking after home/family (ref= all other)				1.06 [0.81 – 1.39]			
Working parttime				0.84 [0.66 – 1.05]			
Working conditions							
Job satisfaction high (ref = low)					0.80 [0.61 – 1.05]		
Job security high (ref = low)					0.91 [0.69 – 1.22]		
Family factors							
Being married at age 34 (ref= unmarried)						0.91 [0.64 – 1.32]	
Having no children aged 34 (ref=1 child)						0.92 [0.77 – 1.11]	
Having 2-3 children (ref=1 child)						0.96 [0.80 – 1.14]	
Having four or more children						1.05 [0.60 – 1.74]	

Behavioural factors and physical health							
Having physical multimorbidity aged 26 (ref = no)							**1.28**** [1.07–1.54]
Covariates							
Mental health age 34	**0.98** [0.92–1.05]	**0.97** [0.91–1.04]	**0.97** [0.91–1.03]	**0.97** [0.91–1.03]	**0.96** [0.90–1.03]	**0.97** [0.91–1.03]	**0.97** [0.91–1.03]
Sex (being male)	**0.87*** [0.77–1.00]	**0.86*** [0.76–0.99]	0.92 [0.80–1.06]	0.89 [0.76–1.05]	0.97 [0.84–1.12]	**0.87*** [0.76–0.99]	**0.88** [0.77–1.00]
University education aged 34 (ref= low education)		0.88 [0.75–1.02]	0.96 [0.82–1.13]	0.97 [0.82–1.15]	0.96 [0.82–1.14]	0.88 [0.76–1.03]	0.88 [0.75–1.03]
Cognitive ability aged 10		0.99 [0.97–1.00]	0.99 [0.98–1.01]	0.99 [0.98–1.01]	0.99 [0.98–1.01]	0.99 [0.98–1.00]	0.99 [0.97–1.00]

Notes: $p < 0.05$; ** $p < 0.01$. N = 6,992 for all analyses.

B2: LASSO Regression as alternative analysis

To verify the results acquired from the Random Forest, we also computed a LASSO regression suing the R package "caret". The results are shown in Figure S3. The results show a very similar list of predictors compared to Figure 2 in the main text. "Low social class" and "income at age 34" are also among the top 3 predictors as the RandomForest in the main text. Physical multimorbidity, ranks at place 2 in the LASSO regression, and is also one of the key predictors identified in the main text which remains statistical significant in the main logistic regression analysis (see Table 2 in the main text). Overall, all variables which play a key role in the main text and stay statistically significant throughout all analyses are also detected by this alternative Machine Learning technique.

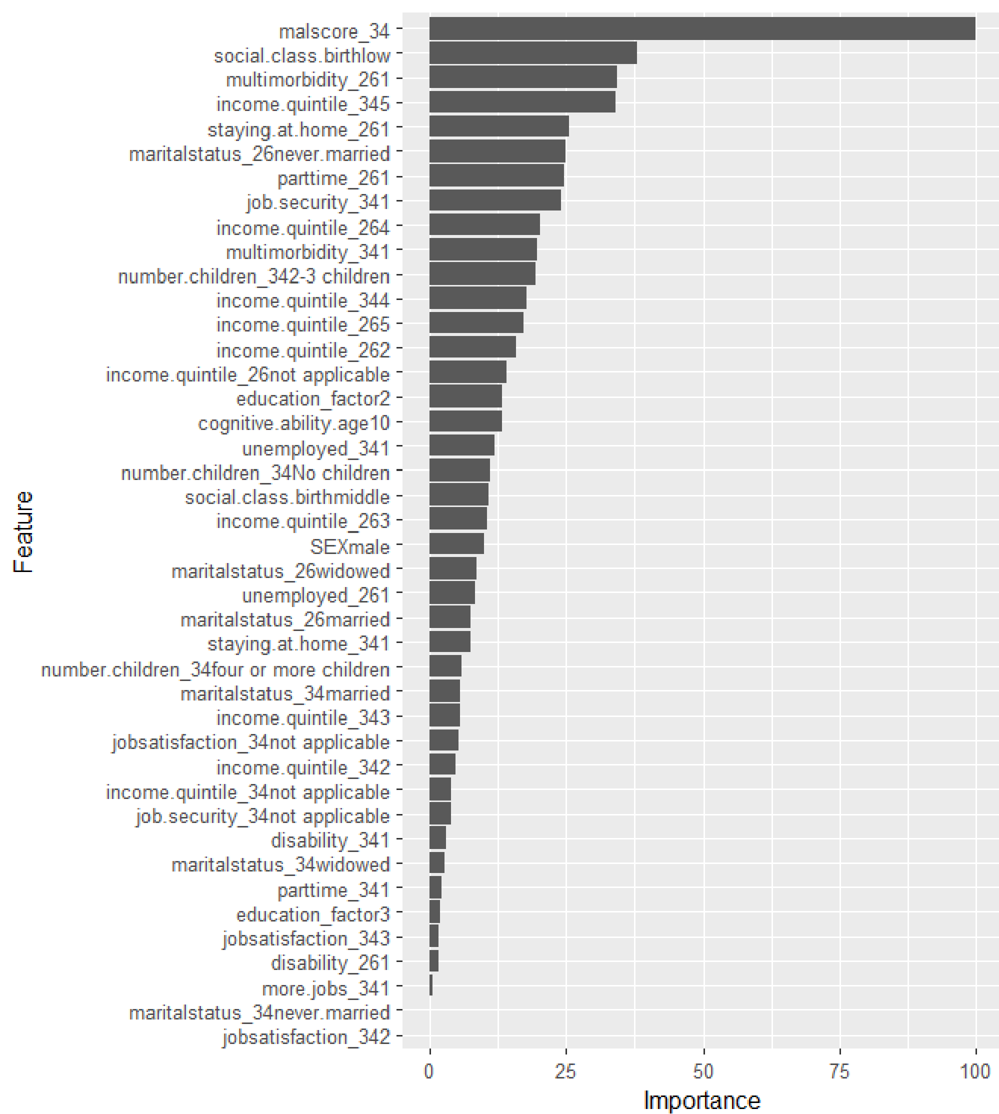


Figure S1. Alternative Machine Learning analysis using LASSO regression

B3: Handling of missing values

The full sample consists of all participants who provided a valid answer to question on mental distress at ages 34 and 42 (N= 6992). Before conducting step 2 and 3 of the analysis, missing values in all explanator y variables were imputed. To do so, we used the R package RandomForest, which predictor missing values with adequate error rates in prediction (NRMSE = 0.35 for imputing quantitative and PFC= 0.116 for categorical variables). This approach allows to be consistent between analysis step 2 and 3.

Finally, we also conducted a full-case analysis without the imputation of missing values. The findings are shown in Table S5 and remain stable in terms of statistical significance as shown in Table 2 of the main text.

Table S4. Full-case analysis; Logistic regression; outcome: the likelihood of experiencing a mid-life decline in mental health from age 34 to 42 (Odds Ratios)

	M1 **Social class**	**M2** **Education**	**M3** **Income**	**M4** **Employment status**	**M5** **Work conditions**	**M6** **Family factors**	**M7** **Physical health**
Social class and education							
Low social class at birth (ref=high)s	**1.46**** [1.20–1.78]	**1.38**** [1.10–1.74]	**1.37**** [1.09–1.72]	**1.37**** [1.09–1.72]	**1.35**** [1.10–1.70]	**1.38**** [1.10–1.73]	**1.47**** [1.13–1.92]
Medium social class at birth (ref=high)	1.02 [0.88–1.22]	0.99 [0.82–1.20]	0.99 [0.82–1.20]	0.99 [0.82–1.20]	0.98 [0.81–1.19]	0.99 [0.82–1.19]	1.04 [0.84–1.30]
Income and employment							
Income quintile 2 (ref= q1)			0.96 [0.73 – 1.24]	0.96 [0.74 – 1.25]	0.97 [0.75 – 1.27]		
Income quintile 3 (ref= q1)			1.12 [0.86 – 1.46]	1.07 [0.82 – 1.41]	1.14 [0.88 – 1.48]		
Income quintile 4 (ref= q1)			**0.85** [0.64 – 1.12]	0.81 [0.61 – 1.09]	0.86 [0.65 – 1.13]		
Income quintile 5 (ref= q1)			**0.70**** [0.52 – 0.94]	**0.67*** [0.49 – 0.91]	**0.70*** [0.52 – 0.95]		
Looking after home/family (ref= all other)				1.00 [0.75 – 1.34]			
Working parttime				0.87 [0.68 – 1.12]			
Working conditions							
Job satisfaction high (ref = low)					0.84 [0.63 – 1.13]		
Job security high (ref = low)					0.94 [0.69 – 1.29]		
Family factors							
Being married at age 34 (ref= unmarried)						0.97 [0.65 – 1.51]	
Having no children aged 34 (ref=1 child)						0.91 [0.75 – 1.11]	
Having 2-3 children (ref=1 child)						0.92 [0.76 – 1.12]	
Having four or more children						1.09 [0.75 – 1.11]	
Behavioural factors and physical health							

Having physical multimorbidity aged 26 (ref = no)							**1.25**** [1.02–1.52]
Covariates							
Mental health age 34	**0.88**** [0.85–0.92]	**0.86**** [0.82–0.90]	**0.85**** [0.82–0.89]	**0.85**** [0.81–0.89]	**0.85**** [0.81–0.89]	**0.85**** [0.82–0.89]	**0.84**** [0.79–0.88]
Sex (being male)	**0.87*** [0.77–0.99]	**0.84*** [0.72–0.97]	0.90 [0.77–1.72]	0.87 [0.74–1.04]	0.94 [0.80–1.11]	**0.83*** [0.72–0.97]	**0.86** [0.73–1.02]
University education aged 34 (ref= low education)		0.96 [0.82–1.14]	1.05 [0.88–1.26]	1.06 [0.89–1.26]	1.05 [0.88–1.25]	0.97 [0.82–1.15]	1.07 [0.88–1.29]
Cognitive ability aged 10		0.99 [0.98–1.01]	0.99 [0.98–1.01]	0.99 [0.98–1.01]	0.99 [0.98–1.01]	0.99 [0.98–1.01]	0.99 [0.98–1.01]
N	6512	5209	5209	5208	5196	5195	3946

Notes: *p < 0.05; ** p < 0.01.

Appendix paper 3

This Appendix for paper 3 provides some additional analyses to provide evidence on the robustness of results presented in the main analyses. That is, Table S1 and S2 replicate the main regression analysis presented in Table 4 in the main text, but adding additional covariates and interaction effects. First, Table S1 includes total ALMP spending per country as a covariate in the main models (S6 and S10) and shows that the interaction effects of unemployment transitions and sanctions remains stable with additional controls (see model S8). Model S11 in the same table shows that there is an interaction between unemployment transition and total ALMP spending: higher spending is associated with better health outcomes of the unemployment transition. Second, Table S2 includes additional covariates from the SCUP social policy database Comparative Welfare Entitlements Project Data Set. These include a combined generosity index and an unemployment generosity index (see Table S3 for values on each country). The methodology for these indicators are provided by Scruggs (2022). Again, the results remain stable despite fewer countries in the sample (especially the interaction effect between unemployment and sanctions; model S14). Third, the appendix shows supplementary graphs to visualise the relationships between activation requirements, job-search requirement and unemployment transitions. Finally, I provide details on the activation measures used in this study, providing details on all measurements and scoring provided by the OECD.

Table S1. Control table including ALMP spending interactions on the country level

	(S6) Individual benefits only	**(S7) Overall strictness**	**(S8) Sanctions**	**(S9) Job-search requirements**	**(S10) Availability requirements**	**(S11) ALMP spending**
Individual level variables						
Unemployment transition (becoming unemployed)	- 0.05** (-0.06, -0.05)	- 0.00 (-0.06, 0.06)	- 0.001 (-0.05, 0.05)	- 0.05** (-0.09, -0.02)	- 0.03 (-0.09, 0.03)	- 0.09* (-0.12, -0.05)
All models control for *gender, age, education* and *marital status.*						
Country-level activation requirements						
Overall strictness of activation requirements		- 0.006 (-0.018, 0.006)				✓
Overall strictness × unemployment transition		- 0.02 (-0.04, 0.003)				
Sanctions			0.002 (-0.02, -0.03)	✓	✓	
Sanctions × unemployment transition			- 0.04* (-0.08, -0.004)			
Job-search requirements			✓	- 0.01 (-0.02, 0.002)	✓	
Job-search requirements × unemployment transition				- 0.002 (-0.05, 0.04)		
Availability requirements			✓	✓	0.003 (-0.08, 0.08)	
Availability requirements × unemployment transition					- 0.02 (-0.08, 0.04)	
Country-level controls						
ALMP spending						-0.009 (-0.02, -0.03)
ALMP spending × unemployment transition						0.03* (0.006, 0.04)
Replacement rate (% of income after six months of unemployment)		✓	✓	✓	✓	✓
GDP (log)		✓	✓	✓	✓	✓
Unemployment rate		✓	✓	✓	✓	✓

Notes: *p < 0.05; ** p < 0.01.

✓ = control variable included in the model

Table S2. Sensitivity analysis with variables from the Comparative Welfare Entitlements Project Data Set

	(S12) Individual benefits only	(S13) Overall strictness	(S14) Sanctions	(S15) Job-search requirements	(S16) Availability requirements
Individual level variables					
Unemployment transition (becoming unemployed)	- 0.04** (-0.06, -0.03)	0.08 (-0.07, 0.22)	0.007 (-0.02, 0.2)	- 0.03 (-0.07, 0.01)	- 0.04 (-0.14, 0.06)
All models control for *gender, age, education* and *marital status*.					
Country-level activation requirements					
Overall strictness of activation requirements		0.001 (-0.02, 0.02)			
Overall strictness × unemployment transition		- 0.04 (-0.09, 0.01)			
Sanctions			0.001 (-0.01, 0.02)	✓	✓
Sanctions × unemployment transition			- 0.10** (-0.16, -0.03)		
Job-search requirements			✓	- 0.03 (-0.06, 0.01)	✓
Job-search requirements × unemployment transition				- 0.02 (-0.10, 0.07)	
Availability requirements			✓	✓	0.01 (-0.05, 0.06)
Availability requirements × unemployment transition					- 0.07 (-0.13, 0.12)
Country-level controls					
Unemployment Generosity Index (Scruggs, 2022)		✓	✓	✓	✓
Combined Generosity Index (Scruggs, 2022)		✓	✓	✓	✓
Replacement rate (% of income after six months of unemployment)		✓	✓	✓	✓
GDP (log)		✓	✓	✓	✓
Unemployment rate		✓	✓	✓	✓

Notes: *p < 0.05; ** p < 0.01.

✓ = control variable included in the model

Supplementary graphs

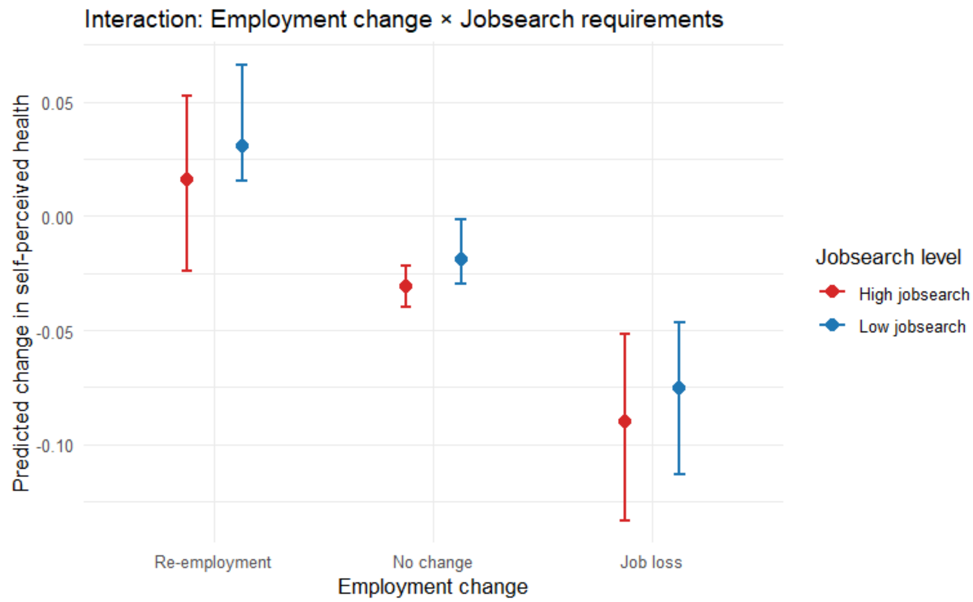


Figure S1. Interaction between unemployment transitions and job-search requirements

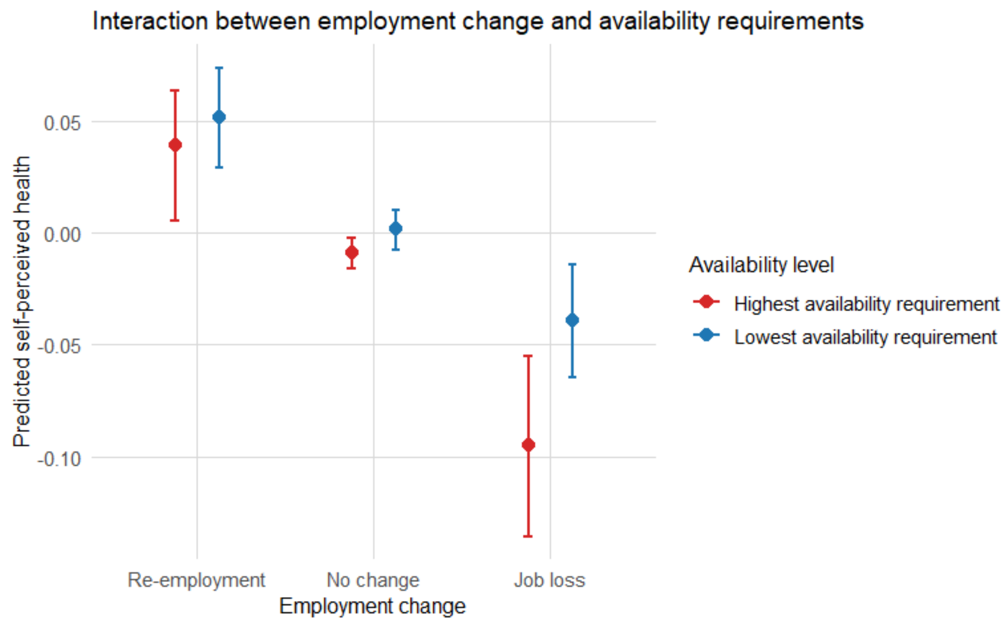


Figure S2. Interaction between unemployment transitions and availability requirements

Details on the activation measures

OECD Activation Requirement Indicator Scoring

This section provides anoverview of the OECD scoring system for evaluating the strictness of activation requirements in unemployment benefit systems. Each item is scored from 1 (least strict) to 5 (most strict) based on statutory rules, and weighted to create composite indicators for availability requirements, job-search monitoring, and sanctioning strictness (Langenbucher, 2015; Immervoll & Knotz, 2018).

Availability during ALMP participation (Weight: 0.08)

Score	Description
1	1 – No demands on availability for work during participation in ALMPs
2	2 – Participation in some ALMPs requires availability for work
3	3 – Participation in most ALMPs requires availability for work
4	4 – The unemployed should always be available for work while participating in ALMPs, but are not required to actively search for work
5	5 – The unemployed should always be available and actively searching for work while participating in ALMPs

Demands on occupational mobility(Weight: 0.08)

Score	Description
1	1 – The unemployed can refuse job offers in other occupational areas or with lower wages indefinitely
2	2 – The unemployed can refuse job offers in other occupational areas or with lower wages for a limited period of 6 months or more
3	3 – The unemployed can refuse job offers in other occupational areas or with lower wages for a period of less than 6 months
4	4 – No explicit reservations but the unemployed person's qualifications, previous remuneration and the length of the unemployment spell are taken into account
5	5 – The unemployed must accept all job offers that he/she is capable of doing

Demands on geographical mobility (Weight: 0.08)

Score	Description

1	1 – No demands on geographical mobility The unemployed must accept a daily commuting
2	2 – The unemployed must accept a daily commuting time of up to 2 hours per day
3	3 – The unemployed must accept a daily commuting time of up to 4 hours per day
4	4 – The unemployed must accept a daily commuting time of 4+ hours per day
5	5 – The unemployed must be willing to move

Other valid reasons for refusing jobs (Weight: 0.08)

Score	**Description**
1	Countries with five valid types of reason for refusing jobs
2	
3	Countries with three or four valid types of reason for refusing jobs
4	
5	5 Countries with two or less valid types of reason for refusing jobs

Frequency of job-search monitoring (Weight: 0.17)

Score	**Description**
1	1 – No check of job-search activity
2	2 – Infrequent or ad-hoc checking of job-search activity
3	3 – Frequency of job-search activities varies for different jobseekers and/or during the unemployment spell (on average less that quarterly)
4	4 – All unemployed must regularly prove job-search activity (monthly or quarterly)
5	5 – All unemployed must often i.e. every week or every second week prove job search

Documentation of job-search activity (Weight: 0.17)

Score	**Description**

1	1 – No formal requirement
2	2 – The person must regularly affirm that he or she has undertaken some actions to find work without specifying what these were
3	3 – The person must regularly affirm that he or she has undertaken some actions to find work and specify what these were (e.g. keeping a jobsearch diary)
4	4 – The person must regularly supply the name and address (or equivalent documentation) of employers that he or she has contacted
5	5 – The person must regularly produce declarations by employers that he or she has applied to them for work

Sanctions for voluntary resignation (Weight: 0.11)

Score	**Description**
1	1 – 0-4 weeks (including benefit reductions)
2	2 – 5–9 weeks
3	3 – 10–14 weeks
4	4 – More than 14 weeks
5	5 – Ineligible for benefits

Sanctions for refusing job offers (1st) (Weight: 0.06)

Score	**Description**
1	1 – 0-4 weeks (including benefit reductions)
2	2 – 5–9 weeks
3	3 – 10–14 weeks
4	4 – More than 14 weeks
5	5 – Loss of remaining benefit entitlement

Sanctions for repeated refusal of job offers (Weight: 0.06)

Score	**Description**
1	1 – 0-4 weeks (including benefit reductions and sanctions until compliance)
2	2 – 5–9 weeks

3	3 – 10–14 weeks
4	4 – More than 14 weeks
5	5 – Loss of remaining benefit entitlement

Sanctions for refusal of ALMP participation (Weight: 0.06)

Score	Description
1	1 – 0-4 weeks (including benefit reductions and sanctions until compliance)
2	2 – 5–9 weeks
3	3 – 10–14 weeks
4	4 – More than 14 weeks
5	5 – Loss of remaining benefit entitlement

Sanctions for repeated refusal of ALMP participation (Weight: 0.06)

Score	Description
1	1 – 0-4 weeks (including benefit reductions and sanctions until compliance)
2	2 – 5–9 weeks
3	3 – 10–14 weeks
4	4 – More than 14 weeks
5	5 – Loss of remaining benefit entitlement

References

Immervoll, H., & Knotz, C. (2018). How demanding are activation requirements for jobseekers? [OECD Policy Report]. IZA Discussion Paper. https://www.oecd-ilibrary.org/docserver/2bdfecca-en.pdf?expires=1725485200&id=id&accname=guest&checksum=6F8D0351F88D95007416F20C3F217811

Langenbucher, K. (2015). *How demanding are eligibility criteria for unemployment benefits, quantitative indicators for OECD and EU countries*. https://www.oecd.org/en/publications/how-demanding-are-eligibility-criteria-for-unemployment-benefits-quantitative-indicators-for-oecd-and-eu-countries_5jrxtk1zw8f2-en.html

Table S3. Comparative Welfare Entitlements Project Data (Scruggs, 2022)

Country	Combined Generosity Index (TOT_GEN), year 2017	Unemployment Generosity Index (UE_GEN), year 2017
Austria	37	11
Belgium	41	15
Czechia	n.a.	n.a.
Denmark	34	10
Estonia	n.a.	n.a.
Finland	37	11
France	39	11
Germany	33	11
Greece	26	11
Hungary	n.a.	n.a.
Iceland	n.a.	n.a.
Ireland	30	11
Italy	31	12
Latvia	n.a.	n.a.
Lithuania	n.a.	n.a.
Luxembourg	n.a.	n.a.
Netherlands	36	12
Norway	40	14
Poland	n.a.	n.a.
Portugal	39	11
Slovak Republic	n.a.	n.a.
Slovenia	n.a.	n.a.
Spain	34	11
Sweden	37	14
Switzerland	37	14
United Kingdom	25	6
Bulgaria	n.a.	n.a.
Croatia	n.a.	n.a.
Cyprus	n.a.	n.a.
Romania	n.a.	n.a.

Appendix paper 4

The appendix presents country-level statistics on trust in different types of healthcare providers in Table S1. Furthermore, Table S2 and Table S3 present sensitivity analyses for the main analysis in the main text (shown in Table 2). Table S2 demonstrates that the results of the main regression analysis remain stable when adding Covid-19-specific predictors on lockdown stringency and Covid-19 deaths. The results – the demonstrated relationships between GDP, personal income, and trust – remain stable as discussed in the main section of the paper. Notably, there are some significant relationships between the Covid-19 indicators and trust. Namely, countries with higher lockdown stringency tend to have higher levels of trust in healthcare providers, whereas higher death rates are associated with higher trust. These findings should be further investigated in future research, as they were not part of the main focus of this paper.

Table S3 uses a logistic regression model to replicate the main analysis (shown in Table 2) with an alternative variable coding (where 0 represents low trust and 1 represents some or a lot of trust). The findings and levels of statistical significance remain consistent with the results shown in the main text – demonstrating that the findings are not sensitive to the specific variable coding.

Table S1. Descriptive statistics as a ranking, sorted by the mean county-level value of trust in doctors and nurses

#	Country	Trust in doctors & nurses	Trust in hospitals & clinics	Trust in traditional healers	Correlate trust doctors and trust clinics	Correl. Doctors & trad. healers	#	Country	Trust in doctors & nurses	Trust in hospitals & clinics	Trust in trad. healers	Correl. Doctors & clinics	Correl. Doctors & trad. healers
1	Belgium	**3.87**	3.75	2.68	.52	.06	56	Italy	**3.26**	3.06	1.59	.26	.00
2	Norway	**3.86**	3.80	2.36	.56	-.02	57	South Korea	**3.26**	3.21	2.82	.62	.29
3	Malta	**3.86**	3.66	3.21	.31	.20	58	Slovakia	**3.25**	2.98	2.18	.59	.00
4	Netherlands	**3.82**	3.74	2.30	.62	-.04	59	Cambodia	**3.24**	3.21	2.49	.43	.06
5	Finland	**3.80**	3.80	2.09	.58	.05	60	Colombia	**3.24**	2.69	1.78	.39	.11
6	Switzerland	**3.80**	3.74	2.59	.19	.02	61	Egypt	**3.23**	2.59	2.77	.40	.16
7	Australia	**3.78**	3.66	2.58	.52	.07	62	Nepal	**3.22**	3.13	2.78	.40	.06
8	France	**3.77**	3.58	2.24	.16	-.06	63	Hong Kong	**3.22**	3.05	2.84	.39	.20
9	Spain	**3.77**	3.61	1.52	.11	-.11	64	Senegal	**3.21**	3.08	2.55	.45	.16
10	New Zealand	**3.75**	3.50	2.58	.49	-.05	65	Lithuania	**3.20**	3.01	1.99	.62	-.06
11	Denmark	**3.74**	3.65	2.55	.62	-.04	66	Ethiopia	**3.20**	2.98	2.33	.41	.07
12	Austria	**3.74**	3.69	2.63	.15	-.03	67	El Salvador	**3.19**	2.81	1.70	.46	.15
13	Germany	**3.72**	3.62	2.51	.18	.03	68	Mongolia	**3.19**	2.94	3.09	.43	.27
14	Canada	**3.69**	3.47	2.71	.56	.08	69	Latvia	**3.19**	2.98	1.78	.61	.08
15	Sri Lanka	**3.65**	3.41	3.29	.41	.08	70	Poland	**3.16**	2.78	2.26	.59	.01
16	Ireland	**3.65**	3.28	2.35	.12	-.09	71	Kyrgyzstan	**3.14**	2.96	2.37	.54	.21
17	United States	**3.64**	3.51	2.67	.57	.04	72	Nicaragua	**3.13**	2.98	1.49	.52	.09
18	Czech Republic	**3.63**	3.50	2.39	.61	-.01	73	Bulgaria	**3.12**	2.62	2.16	.50	.07
19	Slovenia	**3.63**	3.45	2.14	.60	.01	74	Jordan	**3.12**	2.87	2.83	.58	.09
20	Sweden	**3.63**	3.46	2.08	.68	.03	75	Zambia	**3.11**	2.79	1.49	.34	.00
21	United Kingdom	**3.61**	3.48	2.18	.12	-.03	76	Serbia	**3.11**	2.82	2.09	.62	.06
22	Philippines	**3.60**	3.28	2.34	.40	.14	77	Lebanon	**3.09**	2.47	2.33	.57	.22
23	Argentina	**3.60**	3.23	1.42	.49	-.01	78	Kazakhstan	**3.09**	3.00	2.02	.54	.15
24	Israel	**3.60**	3.44	2.64	.60	.07	79	Uganda	**3.09**	2.77	1.66	.41	.11
25	Croatia	**3.58**	3.30	1.99	.49	.03	80	Ghana	**3.07**	2.87	2.56	.45	.18
26	Uruguay	**3.58**	3.40	1.60	.54	.01	81	Tunisia	**3.07**	2.41	2.27	.44	.06

27	Portugal	**3.54**	3.28	2.77	.51	.19
28	United Arab Emirates	**3.54**	3.44	2.91	.45	.37
29	Malaysia	**3.49**	3.37	2.01	.38	.09
30	Tanzania	**3.47**	3.29	1.89	.35	.00
31	Thailand	**3.45**	3.16	2.65	.33	.11
32	Turkey	**3.44**	3.15	2.77	.48	.27
33	Costa Rica	**3.43**	3.27	1.58	.56	.09
34	Uzbekistan	**3.42**	3.26	2.23	.61	.24
35	Taiwan	**3.42**	3.44	2.69	.53	.16
36	Laos	**3.41**	3.30	2.94	.44	.17
37	Estonia	**3.41**	3.42	2.01	.58	.06
38	Mexico	**3.41**	2.89	1.73	.42	.01
39	India	**3.41**	3.13	2.06	.46	.12
40	Iran	**3.39**	2.97	2.87	.36	.17
41	South Africa	**3.39**	2.96	2.39	.31	.16
42	Chile	**3.36**	2.91	1.43	.46	.04
43	Myanmar	**3.35**	3.12	2.28	.43	.14
44	Hungary	**3.35**	2.86	2.52	.55	.07
45	Dominican Republic	**3.33**	2.90	1.24	.38	.00
46	Vietnam	**3.32**	3.25	3.03	.48	.39
47	Japan	**3.30**	3.14	2.53	.54	.15
48	Brazil	**3.30**	2.81	1.86	.44	.10
49	Bahrain	**3.30**	n/a	2.72	n/a	.10
50	Bangladesh	**3.30**	3.09	1.48	.48	.01
51	China	**3.29**	3.14	3.30	.47	.42
52	Saudi Arabia	**3.28**	3.17	2.63	.54	.20
53	Zimbabwe	**3.27**	2.90	1.95	.51	.06
54	Greece	**3.27**	2.88	2.00	.51	.05
55	Cyprus	**3.26**	2.89	2.61	.54	.15
82	Romania	**3.07**	2.48	2.12	.54	.15
83	Algeria	**3.06**	2.80	2.96	.60	.03
84	Morocco	**3.03**	2.37	2.24	.53	.00
85	Georgia	**3.03**	2.84	2.53	.58	.21
86	Namibia	**3.03**	2.74	1.72	.32	.03
87	Indonesia	**3.02**	3.06	2.77	.43	.29
88	Paraguay	**3.02**	2.68	2.33	.44	.10
89	Bosnia Herzegovina	**3.01**	2.60	1.96	.58	.11
90	Burkina Faso	**3.00**	2.70	2.64	.42	.26
91	Montenegro	**2.98**	2.77	2.04	.61	.06
92	Mauritius	**2.98**	2.89	2.33	.54	.28
93	Kenya	**2.97**	2.76	2.00	.34	.17
94	Kosovo	**2.97**	2.62	2.05	.55	.17
95	Mali	**2.95**	2.91	3.02	.48	.32
96	Peru	**2.92**	2.46	1.35	.40	-.01
97	Ecuador	**2.87**	2.55	1.48	.43	.07
98	North Macedonia	**2.86**	2.43	2.24	.54	.24
99	Albania	**2.84**	2.46	2.22	.58	.18
100	Bolivia	**2.82**	2.56	1.99	.40	.02
101	Nigeria	**2.79**	2.51	2.11	.36	.12
102	Russia	**2.74**	2.52	1.57	.69	.11
103	Moldova	**2.73**	2.47	1.73	.62	.09
104	Benin	**2.71**	2.54	2.19	.45	.17
105	Ukraine	**2.71**	2.40	1.64	.62	.11
106	Ivory Coast	**2.69**	2.50	2.47	.45	.13
107	Guinea	**2.69**	2.54	2.28	.38	.20
108	Iraq	**2.68**	2.17	2.49	.46	.17
109	Congo Brazzaville	**2.60**	2.45	2.28	.44	.11
110	Gabon	**2.59**	2.35	2.03	.42	.12
111	Cameroon	**2.48**	2.33	2.02	.39	.17

Table S2. Country-level statistics

	Sample size in survey dataset (n)	GDP per capita (current US$)	Year, source	Health expen-diture (% of GDP)	Year, source	Out-of-pocket expenditure (% of health expen-diture)	Year, source	Qaulity of care index	Corruption perception index
Albania	1,000	5,246	2020, WB[1]	5.2	2019, WB[1]	44.6	2018, WB[1]	78.2	36
United Arab Emirates	1,002	3,6285	2020, WB[1]	4.3	2019, WB[1]	12.5	2019, WB[1]	72.2	71
Argentina	1,001	8,579	2020, WB[1]	9.5	2019, WB[1]	27.7	2019, WB[1]	68.4	42
Australia	1,001	51,693	2020, WB[1]	9.9	2019, WB[1]	16.0	2019, WB[1]	89.8	77
Austria	1,000	48,587	2020, WB[1]	10.4	2019, WB[1]	19.1	2019, WB[1]	88.2	76
Belgium	1,001	45,159	2020, WB[1]	10.7	2019, WB[1]	18.2	2019, WB[1]	87.9	76
Benin	1,007	1,291	2020, WB[1]	2.4	2019, WB[1]	47.0	2019, WB[1]	43	41
Burkina Faso	1,002	858	2020, WB[1]	5.5	2019, WB[1]	34.7	2019, WB[1]	42.9	40
Bangladesh	1,011	1,962	2020, WB[1]	2.5	2019, WB[1]	72.7	2019, WB[1]	51.7	26
Bulgaria	1,007	10,079	2020, WB[1]	7.1	2019, WB[1]	39.0	2019, WB[1]	71.4	44
Bahrain	1,005	20,410	2020, WB[1]	4.0	2019, WB[1]	29.7	2019, WB[1]	79	42
Bosnia Herzegovina	1,002	6,080	2020, WB[1]	9.0	2019, WB[1]	29.4	2019, WB[1]	78.2	35
Bolivia	1,002	3,133	2020, WB[1]	6.9	2019, WB[1]	23.9	2019, WB[1]	59.2	31
Brazil	1,000	6,797	2020, WB[1]	9.6	2019, WB[1]	24.9	2019, WB[1]	64.9	38
Canada	1,010	43,295	2020, WB[1]	10.8	2019, WB[1]	14.9	2019, WB[1]	87.6	77
Switzerland	1,000	87,097	2020, WB[1]	11.3	2019, WB[1]	25.3	2019, WB[1]	91.8	85
Chile	1,021	13,232	2020, WB[1]	9.3	2019, WB[1]	32.8	2019, WB[1]	76	67
China	3,502	10,435	2020, WB[1]	5.4	2019, WB[1]	35.2	2019, WB[1]	74.2	42
Cote d'Ivoire	1,005	2,326	2020, WB[1]	3.3	2019, WB[1]	37.3	2019, WB[1]		
Cameroon	1,006	1,537	2020, WB[1]	3.6	2019, WB[1]	72.5	2019, WB[1]	44.4	25
Congo Brazzaville	1,009	1,846	2020, WB[1]	2.1	2019, WB[1]	45.9	2019, WB[1]	43.5	19
Colombia	1,000	5,335	2020, WB[1]	7.7	2019, WB[1]	14.9	2019, WB[1]	67.8	39
Costa Rica	1,001	12,141	2020, WB[1]	7.3	2019, WB[1]	22.3	2019, WB[1]	72.9	57
Cyprus	1,012	27,528	2020, WB[1]	7.0	2019, WB[1]	30.6	2019, WB[1]	85.3	57
Czech Republic	1,000	22,931	2020, WB[1]	7.8	2019, WB[1]	14.2	2019, WB[1]	84.8	54
Germany	1,000	46,208	2020, WB[1]	11.7	2019, WB[1]	12.8	2019, WB[1]	86.4	80
Denmark	1,000	61,063	2020, WB[1]	10.0	2019, WB[1]	14.2	2019, WB[1]	85.7	88
Dominican Republic	1,000	7,268	2020, WB[1]	5.9	2019, WB[1]	42.9	2019, WB[1]	62.5	28

Algeria	1,020	3,307	2020, WB[1]	6.2	2019, WB[1]	33.4	2019, WB[1]	63.7	36
Ecuador	1,000	5,600	2020, WB[1]	7.8	2019, WB[1]	30.9	2019, WB[1]	61.2	39
Egypt	1,004	3,569	2020, WB[1]	4.7	2019, WB[1]	62.7	2019, WB[1]	61	33
Spain	1,000	27,063	2020, WB[1]	9.1	2019, WB[1]	21.8	2019, WB[1]	89.6	62
Estonia	1,013	23,027	2020, WB[1]	6.7	2019, WB[1]	24.0	2019, WB[1]	81.4	75
Ethiopia	1,003	936	2020, WB[1]	3.2	2019, WB[1]	37.9	2019, WB[1]	44.2	38
Finland	1,000	48,745	2020, WB[1]	9.2	2019, WB[1]	17.4	2019, WB[1]	89.6	85
France	1,000	39,030	2020, WB[1]	11.1	2019, WB[1]	9.3	2019, WB[1]	87.9	69
Gabon	1,005	6,882	2020, WB[1]	2.8	2019, WB[1]	23.1	2019, WB[1]	51.4	30
United Kingdom	1,000	41,059	2020, WB[1]	10.2	2019, WB[1]	17.1	2019, WB[1]	84.6	77
Georgia	1,000	4,267	2020, WB[1]	6.7	2019, WB[1]	46.8	2019, WB[1]	62.1	56
Ghana	1,000	2,206	2020, WB[1]	3.4	2019, WB[1]	36.2	2019, WB[1]	49.7	43
Guinea	1,009	1,194	2020, WB[1]	4.0	2019, WB[1]	59.2	2019, WB[1]	38.6	28
Greece	1,006	17,623	2020, WB[1]	7.8	2019, WB[1]	35.2	2019, WB[1]	87	50
Hong Kong	1,004	46,324	2020, WB[1]	6.5	2019, [11]	30.0	2019, WB[12]		
Croatia	1,000	14,134	2020, WB[1]	7.0	2019, WB[1]	11.5	2019, WB[1]	81.6	47
Hungary	1,000	15,981	2020, WB[1]	6.4	2019, WB[1]	28.2	2019, WB[1]	79.6	44
Indonesia	1,023	3,870	2020, WB[1]	2.9	2019, WB[1]	34.8	2019, WB[1]	49.2	37
India	3,045	1,928	2020, WB[1]	3.0	2019, WB[1]	54.8	2019, WB[1]	44.8	40
Ireland	1,000	85,268	2020, WB[1]	6.7	2019, WB[1]	11.7	2019, WB[1]	88.4	72
Iran	1,007	2,422	2020, WB[1]	6.7	2019, WB[1]	39.5	2019, WB[1]	71.1	25
Iraq	1,009	4,146	2020, WB[1]	4.5	2019, WB[1]	50.1	2019, WB[1]	60.1	21
Israel	1,063	44,169	2020, WB[1]	7.5	2019, WB[1]	21.0	2019, WB[1]	85.5	60
Italy	1,000	31,714	2020, WB[1]	8.7	2019, WB[1]	23.3	2019, WB[1]	88.7	53
Jordan	1,005	4,283	2020, WB[1]	7.6	2019, WB[1]	30.3	2019, WB[1]	76.5	49
Japan	1,012	40,193	2020, WB[1]	10.7	2019, WB[1]	12.9	2019, WB[1]	89	74
Kazakhstan	1,000	9,122	2020, WB[1]	2.8	2019, WB[1]	33.9	2019, WB[1]	61.1	38
Kenya	1,002	1,879	2020, WB[1]	4.6	2019, WB[1]	24.3	2019, WB[1]	48.7	31
Kyrgyzstan	1,000	1,174	2020, WB[1]	4.5	2019, WB[1]	46.2	2019, WB[1]	60.4	31
Cambodia	1,000	1,544	2020, WB[1]	7.0	2019, WB[1]	64.4	2019, WB[1]	50.7	21
South Korea	1,009	31,631	2020, WB[1]	8.2	2019, WB[1]	30.2	2019, WB[1]	85.8	61
Laos	1,000	2,630	2020, WB[1]	2.6	2019, WB[1]	41.8	2019, WB[1]	44.9	29

[11] https://www.healthbureau.gov.hk/statistics/download/dha/en/table1_1920.pdf

[12] https://www.healthbureau.gov.hk/statistics/en/dha/dha_summary_report.htm#:~:text=Analysed%20by%20financing%20scheme%2C%2053

Lebanon	1,035	4,650	2020, WB[1]	8.6	2019, WB[1]	33.5	2019, WB[1]	80	25
Sri Lanka	1,011	3,681	2020, WB[1]	4.1	2019, WB[1]	45.6	2019, WB[1]	72.8	38
Lithuania	1,001	20,234	2020, WB[1]	7.0	2019, WB[1]	32.3	2019, WB[1]	76.6	60
Latvia	1,005	17,726	2020, WB[1]	6.6	2019, WB[1]	35.7	2019, WB[1]	77.7	57
Morocco	1,012	3,059	2020, WB[1]	5.3	2019, WB[1]	46.8	2019, WB[1]	61.3	40
Moldova	1,005	4,547	2020, WB[1]	6.4	2019, WB[1]	35.7	2019, WB[1]	73.1	34
Mexico	1,000	8,329	2020, WB[1]	5.4	2019, WB[1]	42.1	2019, WB[1]	62.6	31
North Macedonia	1,019	5,917	2020, WB[1]	7.3	2019, WB[1]	40.4	2019, WB[1]	76	35
Mali	1,002	862	2020, WB[1]	3.9	2019, WB[1]	31.4	2019, WB[1]	45.6	30
Malta	1,002	27,885	2020, WB[1]	8.2	2019, WB[1]	34.6	2019, WB[1]	85.1	53
Myanmar	1,000	1,468	2020, WB[1]	4.7	2019, WB[1]	76.0	2019, WB[1]	48.4	28
Montenegro	1,027	7,677	2020, WB[1]	8.3	2019, WB[1]	38.6	2019, WB[1]	80.7	45
Mongolia	1,000	4,061	2020, WB[1]	3.8	2019, WB[1]	34.8	2019, WB[1]	58.5	35
Mauritius	1,000	8,628	2020, WB[1]	6.2	2019, WB[1]	45.7	2019, WB[1]	65.7	53
Malaysia	1,004	10,412	2020, WB[1]	3.8	2019, WB[1]	34.6	2019, WB[1]	66.6	51
Namibia	1,007	4,179	2020, WB[1]	8.5	2019, WB[1]	8.2	2019, WB[1]	53.7	51
Nigeria	1,002	2,097	2020, WB[1]	3.0	2019, WB[1]	70.5	2019, WB[1]	51.3	25
Nicaragua	1,000	1,905	2020, WB[1]	8.4	2019, WB[1]	34.4	2019, WB[1]	64.3	22
Netherlands	1,000	52,397	2020, WB[1]	10.1	2019, WB[1]	10.6	2019, WB[1]	89.5	82
Norway	1,000	67,330	2020, WB[1]	10.5	2019, WB[1]	13.9	2019, WB[1]	90.5	84
Nepal	1,000	1,155	2020, WB[1]	4.4	2019, WB[1]	57.9	2019, WB[1]	50.8	33
New Zealand	1,000	41,441	2020, WB[1]	9.7	2019, WB[1]	12.2	2019, WB[1]	86.2	88
Peru	1,001	6,127	2020, WB[1]	5.2	2019, WB[1]	28.1	2019, WB[1]	69.6	38
Philippines	1,000	3,299	2020, WB[1]	4.1	2019, WB[1]	48.6	2019, WB[1]	52	34
Poland	1,002	15,721	2020, WB[1]	6.4	2019, WB[1]	20.4	2019, WB[1]	79.6	56
Portugal	1,004	22,176	2020, WB[1]	9.5	2019, WB[1]	30.5	2019, WB[1]	84.5	61
Paraguay	1,000	5,001	2020, WB[1]	7.2	2019, WB[1]	41.6	2019, WB[1]	60.4	28
Romania	1,006	12,896	2020, WB[1]	5.7	2019, WB[1]	18.9	2019, WB[1]	74.4	44
Russia	2,002	10,127	2020, WB[1]	5.6	2019, WB[1]	36.6	2019, WB[1]	71.7	30
Saudi Arabia	1,013	20,110	2020, WB[1]	5.7	2019, WB[1]	16.5	2019, WB[1]	79.4	53
Senegal	1,025	1,472	2020, WB[1]	4.1	2019, WB[1]	51.0	2019, WB[1]	44.4	45
El Salvador	1,000	3,799	2020, WB[1]	7.2	2019, WB[1]	28.4	2019, WB[1]	64.4	36
Serbia	1,000	7,721	2020, WB[1]	8.7	2019, WB[1]	37.0	2019, WB[1]	75.4	38
Slovakia	1,004	19,267	2020, WB[1]	7.0	2019, WB[1]	19.2	2019, WB[1]	78.6	49
Slovenia	1,001	25,517	2020, WB[1]	8.5	2019, WB[1]	11.7	2019, WB[1]	87.4	60

Sweden	1,000	52,274	2020, WB[1]	10.9	2019, WB[1]	13.9	2019, WB[1]	90.5	85
Thailand	1,000	7,187	2020, WB[1]	3.8	2019, WB[1]	8.7	2019, WB[1]	70.8	36
Tunisia	1,006	3,522	2020, WB[1]	7.0	2019, WB[1]	37.9	2019, WB[1]	70.1	44
Turkey	1,000	8,536	2020, WB[1]	4.3	2019, WB[1]	16.9	2019, WB[1]	76.2	40
Tanzania	1,000	1,076	2020, WB[1]	3.8	2019, WB[1]	22.2	2019, WB[1]	49.9	38
Uganda	1,027	822	2020, WB[1]	3.8	2019, WB[1]	38.3	2019, WB[1]	42.9	27
Ukraine	1,000	3,725	2020, WB[1]	7.1	2019, WB[1]	51.1	2019, WB[1]	72.7	33
Uruguay	1,003	15,438	2020, WB[1]	9.3	2019, WB[1]	15.5	2019, WB[1]	72	71
United States	1,001	63,593	2020, WB[1]	16.8	2019, WB[1]	11.3	2019, WB[1]	81.3	67
Uzbekistan	1,000	1,751	2020, WB[1]	5.6	2019, WB[1]	57.7	2019, WB[1]	62.3	26
Vietnam	1,000	2,786	2020, WB[1]	5.2	2019, WB[1]	43.0	2019, WB[1]	66.3	36
Kosovo	1,004	4,347	2020, WB[1]	4.5	2017, [13]	33.3	2014, [14]		
South Africa	1,004	5,656	2020, WB[1]	9.1	2019, WB[1]	5.7	2019, WB[1]	52	44
Zambia	1,005	985	2020, WB[1]	5.3	2019, WB[1]	10.2	2019, WB[1]	41.6	33
Zimbabwe	1,002	1,215	2020, WB[1]	7.7	2019, WB[1]	24.4	2019, WB[1]	48.7	24
Taiwan	1,000	28,358	2020, [15]	6.1	2017, [16]	34.0	2016, [17]	77.6	65

[13] Kosovo National Health Accounts Report for 2017 https://msh.rks-gov.net/wp-content/uploads/2019/10/Raporti-p%C3%ABr-NHA-ENG.pdf

[14] Arenliu Qosaj, F., Froeschl, G., Berisha, M., Bellaqa, B., & Holle, R. (2018). Catastrophic expenditures and impoverishment due to out-of-pocket health payments in Kosovo. *Cost effectiveness and resource allocation*, *16*(1), 1-12.

[15] https://www.statista.com/statistics/727592/gross-domestic-product-gdp-per-capita-in-taiwan/

[16] https://www.healthaffairs.org/do/10.1377/forefront.20190206.305164/#:~:text=National%20health%20expenditure%20(NHE)%20in,the%20average%20for%20OECD%20countries.

[17] https://www.commonwealthfund.org/international-health-policy-center/countries/taiwan

Table S3. Multi-level regression model with Covid controls.

	Outcome: Trust in health professionals				Outcome: Trust in traditional health practitioners			
Individual-level factors	**M1 (individual level)**	**M2 (income *GDP)**	**M3 (quadratic model)**	**M4 (country-level)**	**M5 (individual level)**	**M6 (Income* GDP)**	**M7 (quadratic model)**	**M8 (country-level)**
Age	**.02*** [.01 – .02]	x	x	x	**-.05*** [-.06 – .05]	x	x	x
Gender (being male)	**-.02**** [-.03 – -.01]	x	x	x	**-.03**** [-.04 – -.02]	x	x	x
Primary school or less (ref= secondary school)	-.01 [-.02 – .00]	x	x	x	**.07**** [.06 – .09]	x	x	x
University education	**.04**** [.03 – .05]	x	x	x	**-.08**** [-.10 – -.06]	x	x	x
Household income quintile 3 (ref= quintile 1)	**.03**** [.02 – .04]	**-.19**** [-.30 – -.09]	**.04**** [.03 – .06]	x	**-.04**** [-.06 – -.02]	-.11 [-.25 – .02]	**-.04**** [-.05 – -.02]	x
Household income quintile 5 (ref= quintile 1)	**.04**** [.03 – .06]	**-.28**** [-.39 – -.18]	**.05**** [.04 – .07]	x	**-.08*** [-.09 – -.06]	.01 [-.12 – .15]	**-.07**** [-.09 – -.05]	x
Quintile 3 * Log(GDP)		**.03**** [.02 – .04]				-.01 [-.01 – .02]		
Quintile 5 * Log(GDP)		**.04**** [.03 – .05]				-.01 [-.02 – .01]		
Trust in neighbours	**.20**** [.19 – .20]			x	**.14**** [.13 – .14]			x
Country-level factors								
Log(GDP)		**.13**** [.09 – .18]	**-.97**** [-1.51 – -.44]	-.04 [-.04 - .14]		**.13**** **[.05 – .21]**	-.39 [-1.41 – .63]	-.01 [-.21 - .20]
Log(GDP)^2			**.06**** [.03 – .09]				0.03 [-.03 – .08]	
Corruption index				**.14**** [.06 – .22]				.04 [-.13 – .21]
Health expenditure as % of GDP				.04 [-.02 - .11]				-.02 [-.16– .11]
% Out of Pocket healthcare expenditure				-.04 [-.10 - .01]				.05 [-.06 – .16]
Quality of care index				.03 [-.06 – .13]				.18 [-.02 – .38]
Covid-19 indicators								
Lockdown stringency		**.07**** [.02 – .12]	**.08**** [.03 – .12]	**.08**** [.03 – .12]		**.10**** [.01 – .19]	**.10**** [.01 – .19]	.09 [.01 – .19]
Covid-19 deaths		**-.03**** [-.06 – -.01]	**-.02** [-.04 – -.01]	**-.03*** [-.05 – -.00]		**-.11**** [-.16 – -.07]	**-.11**** [-.15 – -.06]	**-.12**** [-.17 – -.06]
Marginal R^2	0.053	0.057	0.069	0.121	0.018	0.006	0.015	0.033
Conditional R^2	0.167	0.152	0.150	0.190	0.207	0.201	0.202	0.214

Notes: "x" indicates that the variable was included as control variable in the model; 111 countries included. Several country-level factors (corruption index, healthcare expenditure, out of pocket expenditure and quality of care, lockdown stringency) were standardised so that a change of 1 level = 1 SD.

Table S4. Logistic regression model on the probability of high trust in healthcare providers

	Outcome: Trust in health professionals				**Outcome: Trust in traditional health practitioners**			
Individual-level factors	**M1 (individual level)**	**M2 (income *GDP)**	**M3 (quadratic model)**	**M4 (country-level)**	**M5 (individual level)**	**M6 (Income* GDP)**	**M7 (quadratic model)**	**M8 (country-level)**
Age	**1.05**** [1.02 – 1.07]	x	x	x	**0.90**** [0.89 – 0.92]	x	x	x
Gender (being male)	**0.86**** [0.83 – 0.90]	x	x	x	**0.94**** [0.91 – 0.97]	x	x	x
Primary school or less (ref= secondary school)	**0.82**** [0.78 – 0.86]	x	x	x	**1.11**** [1.07 – 1.15]	x	x	x
University education	**1.30**** [1.21 – 1.39]	x	x	x	**0.82**** [0.79 – 0.86]	x	x	x
Household income quintile 3 (ref= quintile 1)	**1.14**** [1.08 – 1.21]	**0.44**** [0.28 – 0.68]	**1.17**** [1.10 – 1.23]	x	**0.92**** [0.88 – 0.97]	1.00 [0.74 – 1.35]	**0.94*** [0.90 – 0.98]	x
Household income quintile 5 (ref= quintile 1)	**1.21**** [1.13 – 1.28]	**0.25**** [0.16 – 0.40]	**1.22**** [1.15 – 1.29]	x	**0.87**** [0.83 – 0.92]	1.19** [0.87 – 1.63]	0.88 [0.85 – 0.92]	x
Quintile 3 * Log(GDP)		**1.12**** [1.07 – 1.18]				0.99 [0.96 – 1.03]		
Quintile 5 * Log(GDP)		**1.20**** [1.14 – 1.27]				0.97 [0.93 – 1.00]		
Trust in neighbours	**1.66**** [1.63 – 1.70]			x	**1.32**** [1.30 – 1.34]			x
Country-level factors								
Log(GDP)		**1.40**** [1.23 – 1.59]	0.03 [0.00 – 2.75]	0.90 [0.63 – 1.28]		1.11 [0.96 – 1.28]	0.16 [0.02 – 1.15]	0.87 [0.61 – 1.24]
Log(GDP)^2			1.25 [0.97 – 1.60]				1.11 [1.00 – 1.25]	
Corruption index				**1.66**** [1.24 – 2.23]				1.33 [0.96 – 1.86]
Health expenditure as % of GDP				1.04 [0.83 – 1.30]				**0.77*** [0.60 – 0.99]
% Out of Pocket healthcare expenditure				1.01 [0.83 – 1.22]				1.12 [0.90 – 1.40]
Quality of care index				1.17 [0.78 – 1.75]				1.30 [0.88 – 1.92]
Marginal R^2	0.062	0.103	0.121	0.171	0.019	0.005	0.012	0.034
Conditional R^2	0.254	0.258	0.249	0.284	0.220	0.212	0.212	0.220

Notes: "x" indicates that the variable was included as control variable in the model; 111 countries included. Several country-level factors (corruption index, healthcare expenditure, out of pocket expenditure and quality of care, lockdown stringency) were standardised so that a change of 1 level = 1 SD.