INCOME-RELATED INEQUALITY IN HEALTH SYSTEMS: A MULTI-COUNTRY STUDY ON ACCESS, UTILISATION, AND VACCINATION DURING THE COVID-19 PANDEMIC

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Abstract

Introduction The COVID-19 pandemic placed unprecedented strain on global health systems, however, income-related health inequalities during the period remain underexplored. This thesis investigates income-related inequality in healthcare access, healthcare utilisation, and vaccination in 16 socioeconomically diverse countries during the pandemic. This thesis aims to: (1) situate the research in the literature, (2) assess income-related inequality in healthcare, (3) compare inequality across countries, (4) examine variation within countries, and (5) explore novel equality and efficiency approaches in healthcare. This thesis contributes to understanding inequalities during disruptions, offering insights to promote equitable access.

Methods I conduct a replicable literature review on quantitative assessment of inequality in access, utilisation of health services, and vaccination, and apply variants of the concentration index to estimate income-related inequality in these areas. I then assess inequality-efficiency trade-offs in a financial incentives vaccination case study, and investigate sociodemographic characteristics associated with vaccine sentiment consistency. Finally, I conduct a synthesis of inequalities in health systems considering the estimates produced in this thesis.

Results Significant pro-rich inequalities were identified in each country, particularly in lower and middle-income settings. Access and utilisation of appointments exhibited pro-rich inequality. Hospitalisation was utilised pro-poorly after overcoming access barriers. Vaccine sentiment was initially pro-rich, though inequality reduced over time. Financial incentives did not alter inequality in vaccination, but illustrate the importance of inequality measurement, while stated intention was the strongest predictor of vaccine uptake.

Conclusion This thesis contextualises and quantifies income-related health inequality in several settings, finding a degree of inequality in each country. To address income-related inequality in healthcare, equality-sensitive policy makers need to adopt measures that focus on the vulnerable, and are based on recent and reliable evidence. This thesis sets out several considerations and implications to address inequality in healthcare.

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List of Acronyms

Adj. R^2	Adjusted coefficient of variation
AIC	Akaike Information Criterion
ANOVA	Analysis of variance
AR	Autonomous region
ATE	Average Treatment Effects
AUS	Australia
BIC	Bayesian Information Criterion
BRA	Brazil
CAN	Canada
CANDOUR	Covid-19 vaccine preference and opinion survey
CDC	Centre for Disease Control
CHL	Chile
CHN	China
CI	Confidence interval
CIx	Concentration index
COL	Colombia
COVID-19	Coronavirus disease 2019
DCEA	Distributional Cost Effectiveness Analysis
df	Degrees of freedom
DTE	Distributional Treatment Effects
EQZ	Equality score
ESP	Spain
EU	European Union
F	F statistic or score
FH	Fisher-Hayter
FN	False Negative
FP	False Positive
FRA	France
GBR	United Kingdom of Great Britain and Northern Ireland
GCI	Generalized Concentration Index
GHA	Ghana
GNI	Gross national income
GP	General practitioner
GPS	Global Positioning System

HDI	Human development index
HESG	Health Economists' Study Group
HIV	Human immunodeficiency virus
HPV	Human papillomavirus
HSPA	Health System Performance Assessment
IMD	Index of multiple deprivation
IND	India
IPSC	International Pandemic Sciences Conference
IQR	Interquartile range
ITA	Italy
JHU	Johns Hopkins University
JPN	Japan
MS	Mean square
MSE	Mean squared error
NHS	National Health Service
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary least squares
OR	Odds ratio
PPP	Purchasing power parity
R^2	Coefficient of variation
RCT	Randomised controlled trial
RIF	Recentered influence function
RII	Relative index of inequality
SD	Standard Deviation
SII	Slope index of inequality
SS	Sum of squares
SVI	Social vulnerability index
TN	True Negative
TP	True Positive
UGA	Uganda
UK	United Kingdom of Great Britain and Northern Ireland
UN	United Nations
USA	United States of America
VERSE	Vaccine Economics Research for Sustainability and Equity
WHO	World Health Organisation
ZAF	South Africa
ZIP	Zone improvement plan

Publications and presentations linked to this thesis

Publications

- Abel ZDV, Roope LSJ, Duch R, Clarke PM. Access to healthcare services during the COVID-19 pandemic: a cross-sectional analysis of income and user-access across 16 economically diverse countries. *BMC Public Health*. 2024;24(1):2678. doi:10.1186/s12889-024-20147-y *(Chapter 4)*
- Abel ZD, Roope LS, Duch R, Cole S, Clarke PM. Inequality in COVID-19 vaccine acceptance and uptake: A repeated cross-sectional analysis of COVID vaccine acceptance and uptake in 13 countries. *Health Policy*. 2025;153:105251. doi:10.1016/j.healthpol.2025.105251 *(Chapter 6)*
- Abel ZD, Roope LS, Violato M, Clarke PM. Accuracy of online surveys in predicting COVID-19 vaccine uptake and demand: A cohort study investigating vaccine sentiments and switching in 13 countries from 2020-2022. *Vaccine. 62, 127450.* https://doi.org/10.1016/j.vaccine.2025.127450 *(Chapter 7)*

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Co-author Releases

All co-authors listed above have confirmed that the works listed and included in this thesis were led, authored, and produced by Zachary Abel. Co-authors may have provided input or reviews consistent with the levels appropriate for a dissertation. Full releases are contained in the appendix.

1. Introduction

1.1 Background

Good health is a naturally desirable state for individuals and nations. Many individuals and nations also desire equity in health. Health is a function of a wide range of determinants, including social and genetic factors. Discrepancies in the quality and amount of care received, if one believes at all in the curative or preventative properties of modern health care also impact health. It follows that for equivalent needs, if one individual has access to care and the other doesn't, the individual with access to health systems is likely to face more favourable health outcomes, ceteris paribus. The process of accessing healthcare can be broken down into several stages. Levesque et al.'s framework couches the healthcare journey from the patient's perspective, and disaggregates health access into its constituent parts.[1] This process begins with the development of a healthcare need, and terminates with the consequences of care, encompassing the intermediate stages of perceiving the need for care, seeking care, reaching care, and utilising care.[1] Health systems operate under varying principles across countries.[2] The principles governing health systems shape patients' healthcare experience, differentiating patient's experiences by country. The stages in the healthcare process may be blended or distinct from each other depending on different health system processes. Internal or external barriers at each stage can cause individuals to abandon the care-seeking process.

Inequity is defined by Fleurbaey and Schokkaert, amongst many contemporaries, as unfair differences in health care delivery or consumption for equal health needs,[3] while Wagstaff, van Doorslaer and Paci define horizontal equity as the receipt of equal delivery of health care for those in equal (health) need, irrespective of ability to pay for that care.[4] Inequality on the other hand refers to differences in health care delivery without considering or adjusting for health needs. As such, inequity comprises a moral value judgement to determine what is fair and what constitutes fair variation in delivery for different health needs, whereas inequality is a more descriptive measure. This dissertation focuses on the latter, particularly due to possible differences in how the countries included in this work may account for differences in health needs and their own adopted moral value judgements and frameworks.

Inequality and inequity in healthcare are prevalent in many countries, to the extent that equitable healthcare for all is the third of the United Nations' Sustainable Development Goals.[5] However, the study of inequality and inequity in healthcare during health system disruptions is limited. The COVID-19 pandemic represents a health system disruption, marked by periods of increased demand for health services, constrained supply of health services in some regions, and changes in utilisation patterns of health services as a result. I use the COVID-19 pandemic as a case study in which I investigate income-related health inequality during a global health systems disruption. Health systems are most important in the moments they are tested, and the pandemic saw increased and sustained pressure which threatened to collapse national health systems around the world.[6,7] Some countries managed these pressures better than others through preparedness, containment measures, and vaccination efforts. Apart from anecdotal evidence and reviews of national vaccination rates, studies which investigate the cross-country income-related experiences of individuals during the pandemic had not yet entered the public domain at the commencement of this thesis.

Three key areas remain underexplored in the literature, offering opportunities to contribute to research and guide policymakers in delivering equitable healthcare. 1) Do health systems grant preferential access based on income levels during disruptions, such as pandemics?; 2) Do the experiences differ across countries?; 3) Does income-related inequality vary within countries across different stages of the healthcare-access process, potentially leading to points of stepwise attrition? With these 3 questions in mind, this thesis aims to investigate income-related inequality in healthcare to answer my research objectives below within 3 spheres during health system disruptions: between countries, within countries, and across the stages of care.

1.2 Research objectives

The overarching objective of this thesis is to investigate global income-related inequality in healthcare during the COVID-19 pandemic. I examine inequality at several stages across the health access framework as defined by Levesque et al's[1] *Patient-centred access to health care: conceptualising access at the interface of health systems and populations* during the pandemic to understand how health systems contend with disruptions. To accomplish this, I select a number of points across the health access framework and investigate income-related inequality at these points. The analysis employs robust mathematical methods to estimate inequality, primarily the concentration index and its variations. The analysis is applied to several socioeconomically diverse countries to provide a broad perspective of experiences around the world during the pandemic. Specifically, this thesis seeks to:

1) Review the literature pertaining to methods of socioeconomic and income-related inequality and inequity in healthcare within the context of the proposed investigations, situating this thesis within the broader literature, and ensuring the novel contribution of each component of this thesis.
2) Estimate income-related inequality in healthcare in access, utilisation, and vaccination during the COVID-19 pandemic in selected countries.
3) Assess differences in estimated income-related inequality in healthcare between countries to develop a perspective on the different experiences of national health systems during the pandemic.
4) Explore income-related inequality in healthcare within health systems, and the extent of inequality at different stages of the healthcare access framework within countries.

5) Investigate the application of novel methodological concepts in equality and efficiency to the COVID-19 pandemic context based on learnings and need identified in this dissertation.

1.3 Methodological framework and thesis structure

This thesis is guided in part by the Levesque et al.'s 2013 framework, which defines patient-centred access to healthcare along a broad range of dimensions throughout the health system (figure 1A).[1] The purpose of this thesis is to investigate income-related inequality in health system engagement during the COVID-19 pandemic. I aim, per my research objectives, to investigate inequality during health system disruptions between countries, and within the national health systems of each country I survey.

While guided by Levesque et al.'s framework, I adjust this slightly to include specific points of interest within health systems that are particularly relevant to the COVID-19 pandemic, such as vaccination. The framework of analysis for this dissertation is shown in figure 1B below.

Figure 1A: Definition of healthcare access by Levesque et al., 2013.[1]

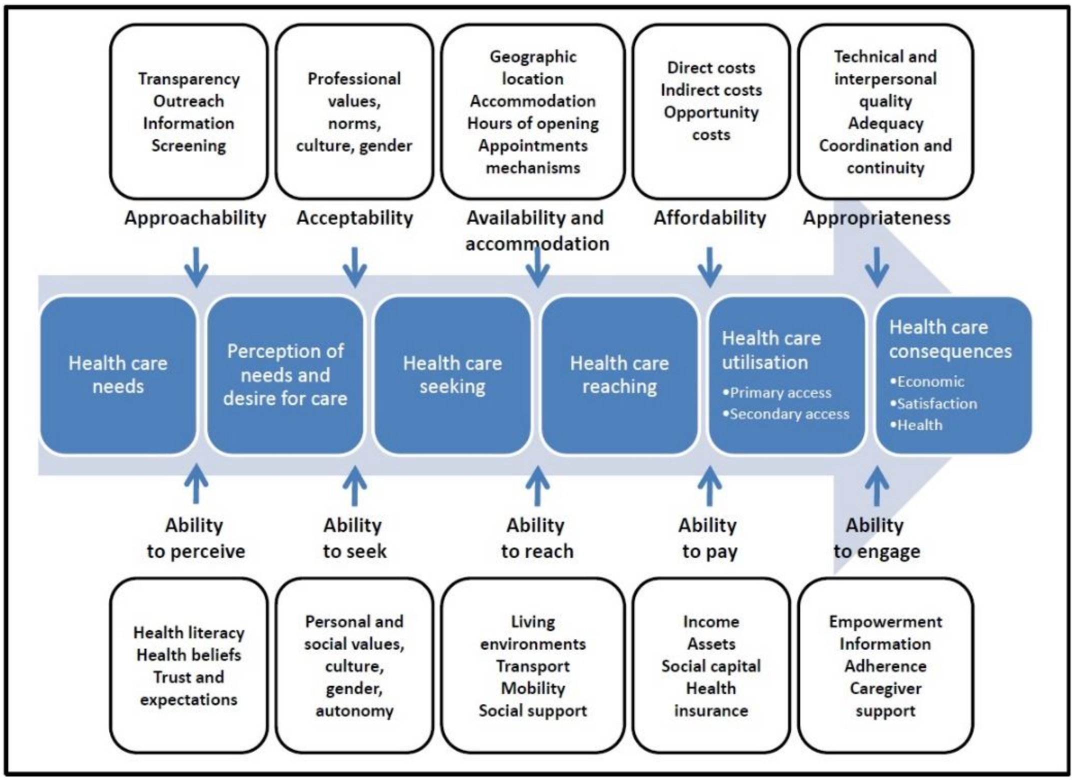
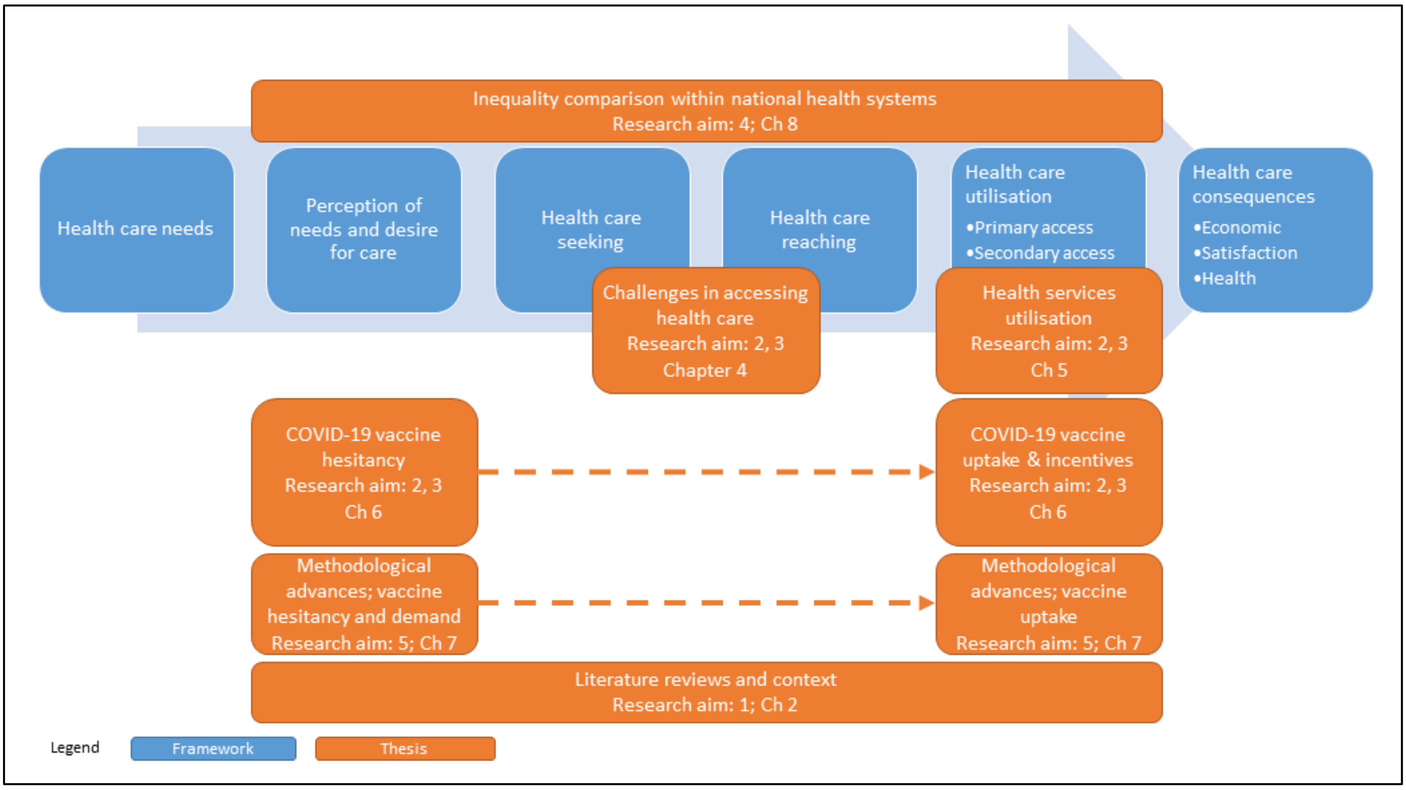


Figure 1B: Dissertation framework of analysis



This thesis covers each intermediate stage of the Levesque et al.'s framework. The initial and terminal stages are excluded due to the large body of literature that has already been produced on the topics related to the Coronavirus pandemic (e.g., prevalence of Coronavirus amongst socioeconomic groups; COVID-19 mortality).

In Chapter 2, I conduct a review of the methods of mathematical measurement and estimation of socioeconomic inequality and inequity in health. This is followed by separate structured reviews of socioeconomic and income-related inequality and inequity in a) access, b) utilisation, and c) vaccination around the time of the COVID-19 pandemic. This positions the thesis within the broader literature and identifies the gaps which this thesis aims to fill with its novel contributions to the field, covering each of the intermediate stages of the framework which are focal points within this thesis. I explain the data and the key variables employed in the production of this thesis in Chapter 3.

In Chapter 4, I begin an assessment of income-related inequality in healthcare, covering *Healthcare seeking and healthcare reaching*. I conduct my assessment on needs-adjusted inequality in access across different types of care (in-person general practitioner (GP); internet or telephone care; and hospital admission or clinic visits), which is set at the point after prospective patients begin to seek care, but before care is reached. I compare my estimates between countries using a variety of aggregate measures to determine if country characteristics influence the levels of inequality in access.

Health care utilisation is covered both by utilisation of all health services during the COVID-19 pandemic (Chapter 5) and COVID-19 vaccine uptake – a specific COVID-19 care utilisation in Chapter 6. In Chapter 5, I estimate the income-related needs adjusted inequality in the utilisation of health services across five different types of care. The types of care considered are in-person GP appointments, telephone appointments, internet appointments, hospital admissions, and clinic visits. I use the perfectly decomposable Level Index to estimate the sources of inequality between and within countries, to compare inequality in the utilisation of each of these types of care across countries, and to compare types of care within countries.

In addition to covering a form of utilisation in Chapter 6, I also cover *Perceptions of needs and desire for care* in Levesque et al.'s framework with a joint investigation of inequality in vaccine hesitancy and vaccine uptake, determining individuals' desire for specific COVID-19 care (e.g., vaccination) during the pandemic. I assess how attitudes change over the course of the pandemic, and identify, using a re-centred influence function (RIF) regression decomposition approach, the potential factors that are associated with these changes.

In Chapter 7, I turn to novel methodological concepts in the inequality and efficiency realms based on observations during the literature review and empirical work. This work covers both *Perceptions of needs and desire for care* with elements on vaccine hesitancy and demand, and *health care utilisation* with elements on vaccination. Through the course of this dissertation, I have noticed two avenues where contributions could strengthen the literature: 1) Producing more inequality or distributional measurements where possible to expand the evidence base. Doing so enables the illustration of possible trade-offs between equality and efficiency. These measurements can be applied to the introduction of new medical technologies (e.g., the Coronavirus vaccine); and 2) Improving efficiency of new medical technology (e.g., vaccines) deployment to reduce wastage and offer more equitable opportunity for vaccination (or new medical technologies, generally speaking). I apply these thoughts to COVID-19 data using two cohort analyses. In the first, I illustrate how distributional measures can be incorporated into existing analyses with a randomised controlled trial as a case study. I present the equality efficiency trade-off in evaluation trials which is often left under investigated, pointing to the notion that if efficiency (or uptake) is the primary outcome, there may be unconsidered equality implications which could lead to unintended, and potentially harmful, consequences. I use a dataset of a financial incentives trial in COVID-19 vaccination in rural Ghana to illustrate this and adopt novel methods to analyse subgroup heterogeneity. Secondly, I look to a subset of the CANDOUR study who were sampled repeatedly across waves, questioning attitudes related to vaccination at different stages of the COVID-19 pandemic. I look at the accuracy of survey-based tools in predicting demand for new health technologies, and aim to determine sociodemographic factors which may contribute to switching vaccine sentiments between the *perception of needs* and *utilisation* stages in the health system, which could allow improved targeting and efficient deployment through the use of simple online survey-based tools.

Before concluding in Chapter 8, I synthesise the work completed across the dissertation and the health systems studied covering each intermediate stage of the framework. I identify archetypes based on inequality estimates produced within each country, and the implications of changes in inequality between stages in the healthcare process. I highlight the relevant policy implications, summarise the limitations of this work, and explore avenues for future extensions.

2. A review of socioeconomic inequality and inequity in health

2.1 Background

The examination of existing literature surrounding the topics contained in this thesis is a necessary and important step. Reviewing the available literature provides background context to the researcher, informs study designs and approaches based on best practices, and provides a perspective on the novelty of the work – allowing me as the researcher to calibrate the research prior to beginning. This ensures that valuable contributions are made to the field, and gaps in knowledge are filled. Furthermore, by anchoring on the existing literature, I can draw on existing studies to compare with my own results where there are valid comparators.

There is a large and growing body of research on inequity and inequality in health. The research spans topics ranging from perceived needs of healthcare to mortality. Levesque et al. have developed a conceptual framework which consists of the continuum of healthcare, from identifying healthcare needs, through to the consequences, including intermediate steps of perceiving needs, seeking care, reaching care, and in the penultimate step, utilising care.[1] I use this framework to guide the structure of the thesis and the metrics I investigate. There are a wide variety of methods available to analyse inequality and inequity in these environments, and an associated body of literature expressly devoted to its measurement and appropriate methods.

In reviewing the literature associated with my thesis topic, I take a modular approach for two reasons. The approach splits the review into constituent elements of healthcare (e.g., access, utilisation, vaccination, and further thoughts on inequality in healthcare). Firstly, the literature on inequality and inequity in healthcare is vast. A single literature review which attempts to combine the topics of works contained in this thesis would prove unwieldly and unnecessarily broad. Such a broad literature review may not even achieve the desired purpose of outlining knowledge gaps, which is the second reason for a modular review approach.

Identifying gaps in the knowledge from a focused perspective is more rigorous, and will more clearly identify the existence of knowledge gaps and how they can be filled.

I begin my literature review by researching the methods employed in the field. Examining the methods available identifies the analyses that are possible at present, and potential methodological advances. Perhaps most importantly, beginning with the methods grounds the work in the realm of income-related inequality in healthcare without ambiguity. I outline the history of measurement and the approaches taken in the methods section, leading to the methods available today and their use in this dissertation.

After discussing a brief history of the methods, I turn to the application of the methods in the literature; reviewing literature related to each chapter of my thesis: namely inequalities in access, utilisation, and vaccination. Each review examines the existing literature through a rigorous search and synthesis. I then identify areas where I can contribute to the field, and undertake this work in my thesis in the associated chapters. I focus on contributing novel quantitative estimates of inequality related to the coronavirus pandemic.

2.2 A history of the measurement of socioeconomic and income-related inequalities and inequities in healthcare

This section contains the history of measurement of socioeconomic and income-related inequality (and inequity) in health as far as it is relevant to the analyses conducted in the thesis.

Background

Corrado Gini pioneered inequality measurement with his 1914 paper *On the measurement of concentration and variability of characters* that forms the foundation of the Gini coefficient as we know it today.[8,9] Piketty and Chancel have measured income and wealth inequality dating as far back as 1820,[10] using historical records to produce backward-looking estimates, and are perhaps the most famous practitioners in modern times. In the United Kingdom, income inequality estimates exist from as early as the 1300s.[11] A number of methods are available to measure inequalities. Many are derived from the Lorenz curve, Gini's 1914 and other works,[8,9,12] and generalized entropy indices – borrowing from the study of thermodynamics.[13] The measurement of inequality in health economics borrows and builds on several concepts employed in the measurement of income, wealth, and labour inequalities. Often these methods require augmentation to make the methods appropriate for varied measurement scales and health outcome ranges, which often differ from those used in income, wealth, and labour analyses.

Univariate and bivariate measurement

Measurements such as the Gini coefficient, or the function from which it is derived, the Lorenz Curve,[9] measure distributional properties of a single variable. The second through fourth statistical moments (variance, skewness, and kurtosis) can also be used to describe the shape of a population's distribution curve for a single variable. Health inequality is measured using single variables in many instances.[14] Measuring the proportions of good health held by the healthiest portion of the population relative to the least healthy portion of the population is analogous to the Gini coefficient or Lorenz curve.[15] The dissimilarity index, which measures the different proportions of health held by a proportion of the population relative to another, has also been used alongside the Gini coefficient and Lorenz curve in measuring inequality in health.[16] Range measures, which explore differences between groups, are also commonly employed (e.g., difference in prostate cancer mortality rates between black and white populations in Harper et al. 2010.[17]) As these measures are concerned with location and/or dispersion of a single variable, they are described as univariate measures, and are an important family of measures used in the measurement of inequality in health.[18,19] Univariate measures describe the distribution and inequality in mortality (or its inverse, life expectancy), or general health levels, and are valuable tools in inequality measurement.

Univariate measures can only be used to measure variation in both socioeconomic status and health status in a relatively crude fashion (e.g., range - health of richest quintile against health of the poorest quintile). In a discussion on the (six) different measures used to measure inequality in health in use in 1991, Wagstaff, Paci, and van Doorslaer describe the differences between measures that reflect the "socioeconomic dimension to inequalities in health" and those that do not.[20] These measures that consider the distribution of health *and* another (socioeconomic) variable are termed bivariate measures.[20] Robson, O'Donnell, and van Ourti conduct an experiment to determine if aversion levels differ between univariate inequality, defined as "…differences in health between individuals irrespective of their non-health characteristics.." and bivariate inequality, defined as "…systematic differences in health between individuals distinguished by income…" In this work, they refer to univariate health inequality as pure health inequality (that is, inequality in health), and socioeconomic-status linked inequality in health (the bivariate measure) as income-related health inequality.[21] They go further to look at income-caused health inequality, however this goes beyond the scope of the review. Using univariate measures can be better categorized as measuring inequality within health, or pure-health inequality as used by Robson et al. in their experiment,[21] whereas bivariate measures, which are the focus of this thesis going forward, can be used to measure socioeconomic health inequality, or income-related inequality in health. This is not to diminish the use of univariate measures, which as described above are important and valuable tools. However, without a bivariate measure, one cannot infer or describe the relationship between the distribution of socioeconomic status (such as income) and the distribution of health,[20] as Sydenstricker, Warren, and Schereschewsky investigated in 1916.[22,23]

The slope and relative indices of inequality (SII and RII) are examples of bivariate measures of inequality, as they account for the socioeconomic dimension as well as the health dimension, and conventionally do so by calculating mean health levels in ranked socioeconomic groups, though can also calculate over individuals continuously. The health concentration index was introduced by Kakwani in 1980.[24,25] The concentration index also consists of a ranking by socioeconomic status, similar to the SII and RII; however the analysis can also be conducted on an individual basis, rather than by socioeconomic groups.[20] While the concentration index is often calculated using discrete approximations, it conceptually calculates inequality over the entire distribution of constituent individuals, rather than discrete groups, and in doing so offers a better approximation of inequality, though the extent to which the approximation is better is not necessarily large.[26] While the measurement of inequality in the distribution of health outcomes is important, the joint distribution of health outcomes and socioeconomic status is what defines socioeconomic health inequality. In cases where an income measure is used, this refers to income-related inequality of health, though these terms are often used interchangeably in the literature. Socioeconomic health inequality attempts to define and explain health inequality as it is related to socioeconomic inequality. As such I require a bivariate measure to conduct the analyses in this thesis to answer my research questions.

The concentration index is a key component of health inequality analysis today – and is closely related to the SII and RII, the family of which are deemed normatively appealing measures of inequality by thought leaders.[20,26]

$$C(h) \equiv \frac{2}{n^2\mu_h}\sum_{i=1}^{n}(z_i h_i) \qquad (1)$$

The concentration index, (equation 1) above, considers the socioeconomic rank of individuals (z, $where\ z_i = r_i - \frac{(n+1)}{2}, and\ r_i\ is\ the\ socioeconomic\ rank\ of\ individual\ i$) and his or her individual health levels (h_i) relative to the overall distribution of the population (n) and mean health levels (μ_h), and is applied widely in health economics as a means of assessing inequality.[26–29] Several variations of the concentration index have been proposed and adopted to address various methodological concerns rising from the properties of the index and the nature of the data being analysed.[25,30,31] Much of the discussion on suitable measurement methods and the associated implications is contained in Erreygers and van Ourti's *Measuring socioeconomic inequality in health, health care and health financing by means of rank-dependent indices: a recipe for good practice,*[32] and Contoyannis, Hurley, & Walli-Attaei's *When the technical is also normative: a critical assessment of measuring health inequalities using the concentration index-based indices*,[29] alongside the other works cited in this dissertation.

Relative and absolute inequalities

Measuring inequality has previously been seen as a value-neutral process involving the observation and description of a distribution. However, this is untrue.[29] Inequality measures necessarily make implicit value judgements in their calculations, embodying these value judgements in the degree of inequality they find.[33] After reducing the available methods to those which fit the measurement scale of the data, the researcher is faced with the question of measuring relative or absolute inequality, which may seem trivial at first.[20,32,34] However, the choice to measure absolute or relative inequalities may impact the magnitude and even the direction of the result.[17,35] Harper et al. illustrate this with an example of prostate cancer mortality between sub-groups, where the rate-ratio (a relative measure) increases while the rate difference (an absolute measure) decreases.[17] Relative and absolute measures can behave differently based on the overall level of the measure and its distance from the measurement bounds,[35] due to the mathematical ceilings and floors employed in the calculation – which remain prevalent in some bounded iterations of the concentration index.[25]

The decision to employ either a relative or absolute measure thus requires the researcher to define the normative significance of inequality within the context of the analysis.[36] A relative measure depends on the change from original position and does not consider the absolute levels of health of the population,[17] whereas an absolute measure includes information on the overall mean health levels of the population.

If analysing inequality across multiple populations, the choice of relative or absolute inequality has further consequences, particularly around the value of the means, and varying sensitivity to means in the calculation that are treated differently by absolute and relative measures.[37] The mean is a function of the absolute levels of health in given populations, and can influence the outcome of the measurements. A relative measure will only yield a decrease in inequality if the health of the less fortunate increases proportionately more than the health of the more fortunate, whereas an absolute measure will yield a decrease in inequality if the absolute difference in health between the less and more fortunate decreases. The choice of measure remains a value judgement for the researcher based on the purpose of the analysis and the mathematical merits of the case, and as such, the measurement of inequality may be less value-neutral than originally anticipated.[38] Ultimately, the decision should be made based on the context considering the implications of each decision. Reporting a secondary measure is also an option, and may enrich the analysis. Moving from perceived value neutrality to overt non-neutrality, one example is the addition of an inequality aversion parameter to health inequality measurement by Wagstaff, enabling explicit value judgements on the desired distribution to be included in the measurement process (discussed in more detail in chapter 7).[39]

The concentration index as a family of measures (e.g., inclusive of generalised, standard, and other variations) is widely used to measure health inequality.[26] In concentration index literature, a generalized concentration index (equation 2) enables the analyst to allow sensitivity to mean health levels, and is analogous to the absolute Gini coefficient, which looks at absolute inequalities in univariate variables.[40]

$$V(h) \equiv \mu_h C(h) \tag{2}$$

Bounded health variables

The standard concentration index (equation 1) assesses relative inequalities.[20] The standard concentration index is sensitive to measuring attainment or shortfall. In some instances, the standard index produces different estimates for the equivalent, transformed datasets (e.g., health and ill-health).[41] For example, if health is measured, and morbidity is taken as the maximum value minus health, one may expect or desire equal inequality results for health and morbidity, however this is seldom the case. While income inequality is often measured in relative terms due to different scales (e.g., currency), time periods, and countries, health can often be measured on the same scale, which is bounded in some cases. Erreygers and Wagstaff address this with their adjusted indices and mirror conditions, which yield the same outcome whether health or ill-health is measured (equation 3 and 4 below).[25]

$$W(h) \equiv \frac{2(b_h - a_h)}{n^2(b_h - \mu_h)(\mu_h - a_h)} \sum_{i=1}^{n} (z_i h_i) \tag{3}$$

$$E(h) \equiv \frac{8}{n^2(b_h - a_h)} \sum_{i=1}^{n}(z_i h_i) \quad (4)$$

Where b_h and a_h are the upper and lower bounds respectively, and z_i retains the weighting function described in equation 1.

Choosing to measure morbidity or health could influence the outcomes and magnitudes of a non-mirror condition relative inequality measure, although they are two sides of the same coin. Using an absolute measure of inequality, such as the generalised concentration index, or an index with quasi-absolute properties in the case of binary variables,[32] addresses this problem by satisfying the mirror condition.[41] Though the Wagstaff index (equation 3) satisfies the mirror condition, it is neither an absolute nor quasi-absolute measure.[42] The mirror condition cannot be combined with a relative index owing to different starting values in attainment or shortfall (e.g., self-assessed health of 70 on a scale of 1-100 equates to a shortfall of 30, and a change in 10 units on bases of 70 or 30 yields different results), on which relative indices are dependent. Beyond the mirror condition, neither the standard concentration index nor the generalized index are the best-fit to accurately measure binary health outcomes in their conventional form, though they can be used with adjustment to make them appropriate for binary measurement. In several instances in this thesis, the outcome variable investigated is binary, and I seek to employ a measure best suited for analysing a binary variable in these instances. For non-binary variable measures, the approach taken depends on whether the variable is bounded, and the desired (relative or absolute, rank or level) inequality analysis.

Wagstaff shows that the range of the concentration index of a binary outcome variable is determined by the mean of the binary variable, with higher means leading to narrow ranges of the standard concentration index of a bounded variable.[43] Wagstaff uses immunisation coverage as an example, showing that higher inequality can still be prevalent with higher overall coverage. This may be counter-intuitive, however, to explain this further – coverage levels of

0% result in zero inequality, whereas coverage of x%, if only for the wealthiest x% of the population, is as unequal as possible. Wagstaff proposes caution when viewing concentration index inequality outcomes of a binary outcome, and suggests normalisation to return the bounds of the concentration index to [-1:1], resulting in the Wagstaff index (equation 3). Erreygers proposes a corrected index, addressing four issues: transfer; level independence; cardinal invariance; and mirror (symmetry) in response to Wagstaff's index.[25] Erreygers' corrected index (equation 4) includes these properties, addressing what he deems to be the shortcomings of the standard concentration index, and going further than the Wagstaff Index and generalised concentration indices which address only elements of the issues Erreygers identifies.[25]

Wagstaff and Erreygers responded in turn after the initial publications, citing issues or non-desirable properties of each other's indices.[31,32,42,44–46] Wagstaff pointed out that Erreygers' index is an absolute measure of inequality, analogous to the generalised concentration index,[44] borne of the desire to satisfy level independence, and that an absolute measure is not necessarily the correct measure to employ. Wagstaff's index captures neither relative nor absolute inequality because of the rescaling related to bounds and means.[30] The satisfaction of the mirror property of both Wagstaff and Erreygers' index precludes both from being termed pure relative measures in the case of binary measures.[45] Erreygers further contests that his measure is suitable for measuring overall inequality, not just absolute inequality, and that his measure is not dependent on means, whereas Wagstaff's measure overstates inequality when the means approach the bounds of the variable in question.[45]

Through a number of replies and retorts between the academics, something approaching a consensus emerged. Erreygers and van Ourti provide a useful paper which characterises scenarios fitting the different indices, and when each should be employed based on the nature of the data and desired properties.[32] Binary variables can be used for health inequality measurement, and quasi-relativity and quasi-absoluteness may be helpful notions through which to view bounded-variable indices.[42]

Kjellsson and Gerdtham summarise the exchange, critique a number of the properties, and conclude that the choice of indices is not merely semantic – but importantly dictated by the value judgement the researcher wishes to impose, once again highlighting the lack of value-neutrality in measurement.[30] Imposing a more absolute perspective should steer the researcher to the Erreygers' index. For relative inequalities, Wagstaff's index may be more desirable, however, there remain possible inconsistencies in the measurement of health and ill-health using Wagstaff's index due to its status as neither an absolute nor a relative measure.[30]

Rank and Level dependent indices

The measures explained above each describe the association between the ranked socioeconomic (often income) position and the rank of a health variable, and as such are termed rank-dependent indices. Erreygers and Kessels propose an alternative family of indices which utilise levels of socioeconomic status, rather than ranks, e.g., income magnitude opposed to ranked income.[47] Where rank dependent indices use the rank of the individual in the socioeconomic distribution as the basis for the weighting function for the concentration index, level-dependent indices employ a weighting function proportional to the deviation of the individual's socioeconomic level relative to the mean socioeconomic *level* of the distribution. Other weighting functions based on the relative value (level) of the variable can also be employed.[47] This approach retains more of the available information of the socioeconomic variable, rather than reducing this information to ranks. Level-dependent indices include the properties of coherence and continuity, where rank-dependent indices do not. Coherence implies an increase (decrease) in the concentration index if there is an undoubted increase (decrease) in the positive (negative) bivariate correlation. Continuity implies the change of the index continuously, rather than a change in stepwise levels resulting from a change in either of the considered distributions, as may be the case when ranks are tied. In particular, level-dependent indices are preferred in measuring inequality across countries or population groups, and over time. Population-weighted rank dependent indices can produce unwanted results which are highly sensitive to changes in the socioeconomic variable if population weights are sufficiently disparate in magnitude.[48] The Level Index is preferred for analysis in this dissertation where future waves of analysis may be considered, which is true of Chapter 5 when the CANDOUR 3rd wave is available. Continuity is particularly useful for comparisons over time where changes in national income levels are dealt with more smoothly than by rank dependent indices. If China and Botswana were ranked subsequently in a sample by income (by some narrow margin) and had largely different health outcomes, a change in income ranking would significantly alter a rank-dependent index despite a possibly small increase in income levels, whereas the Level Index would deal with this more smoothly. This could lead to a large shift in measured inequality, despite a relatively small change in observed income levels.[48] Level-dependent indices with the properties of continuity would not produce such markedly discrete differences, a desirable property in the context of global inequality comparisons using countries of varying populations, especially over time.

Decomposing indices

In many cases, the interests of the researcher extend beyond the level of inequality to its underlying causes. Decomposition techniques allow researchers to explore the possible causes of inequality.[49] This is particularly important in driving to actionable research outputs which can be used to address inequality in policy.[50,51]

After the seminal works on decomposition in labour economics by Oaxaca,[52] and Blinder,[53] which resulted in the now commonly used Oaxaca-Blinder technique, Shorrocks pioneered the modern decomposition of income inequality.[50,54–56] Some sort of decomposition method, which allows a sum value to be disaggregated into its parts is present in many computed indices employed to identify inequality today.[54] The mathematical logic behind this family of decompositions is relatively intuitive – by disaggregating inequality into its constituent contributing parts, one can identify the likely sources from where inequality is coming.[28] Inequality can be decomposed according to contributing factors (i.e., covariates) and, in cross-population studies the sources of inequality can be disaggregated into between population inequality, and within population inequality – both of which can offer useful insights into priority areas for policy makers.[57]

Wagstaff, van Doorslaer, and Watanabe[58] have developed a popular decomposition approach for use with bivariate concentration indices in health economics, while Erreygers and Kessels[59,60] have also developed approaches which are less widely used. Despite accepted usage in the literature, there are several problems associated with decomposition, well documented by Fortin et al.[61] Decomposition techniques are not only accounting exercises of disaggregation as is indicated by the mathematical technique, though without satisfying identifying assumptions, decomposition is merely a disaggregation. Interpretation of decompositions are often undertaken as though the assumptions were met, however, rendering the results as invalid estimates of underlying causal parameters, as in the case with OLS due to unclear identification assumptions.[61,62] Results using different decomposition techniques can produce varied results, without any clear indication as to which may be more accurate.[61,62] The recentered influence function (RIF) regression decomposition approach proposed by Firpo et al.,[63] addresses several of these critiques, though is not immune to challenging identification assumptions. In practice, after estimating the RIF regression, it is similar to the Oaxaca-

Blinder approach. The primary drawback of the RIF regression is that coefficients can only offer a local approximation of effects on the index. Accuracy is thus determined by the context of the analysis, or indeed the covariate in question.[61] Heckley et al. provide a general method of decomposition using the RIF decomposition technique, applicable to bivariate rank dependent indices, which addresses the identification issues which are raised by Fortin et al.[61,62]

While the above refers to factor decomposition, Erreygers et al. show that the decomposition of the level-index is perfectly decomposable between subgroups into a between and within component,[64] analogous to the univariate Theil index.[65] Where the decomposition literature has until this point focused on rank-dependent indices – including Heckley et al.'s general method,[62] the decomposition of a level-dependent index produces favourable results without residuals, and likely more accurate within-inequality estimates.[64] However, while the decomposition of level indices appears to produce more reliable results than rank-dependent indices, the method remains an accounting exercise of disaggregation, and the user should remain cautious in interpretation. In all measures of decomposition, it would be cautious to interpret the results as a correlation with the observed inequality, rather than a causal influence.

Decompositions are helpful in another sense; moving from inequality to inequity. Inequity is defined by Fleurbaey and Schokkaert as unfair differences (in the health variable) for equal needs.[3] In a decomposition analysis, variables that contribute to inequality that are deemed unfair (e.g., education, area of residence) can be stripped out. The resulting value is composed of "fair" variation based on equal need, identifying how inequality and inequity relate to each other in a given context. A secondary approach to calculating inequity is to adjust for need based variables through standardization prior to estimating the concentration index.[28] The two methods should produce the same results.

In this dissertation, I employ the concentration index and its extensions in several analyses, and this forms the methodological underpinning for this work. The exact variation of the index used depends on the data and the desired analysis – whether I want to measure relative or absolute inequality; whether the outcome variable is binary or a count variable; the richness of the data and the analysis that enables, and the desire for decomposability. In each instance, the measure of inequality I employ is discussed in the methods section of the relevant chapter of analysis, with a rationale for the choice of measure.

2.3 A review of socioeconomic and income-related inequality and inequity in healthcare literature

2.3.1 Methods of review

Following Khan et al.'s and Tawfik et al.'s review guide,[66,67] I outline the process for the review below. In this review, I adhere to the key principles outlined by Khan et al. and Tawfik et al.[66,67] Khan et al. provide a broad 5 step strategy, while Tawfik et al. offer a granular, step-by-step approach to conduct a review.[66,67]

Step 1 is framing the review using key questions. Khan et al. identify four key structured questions to inform the review, defined by populations, interventions or exposures, outcomes, and study designs.[66]

The populations: Adult populations (ideally nationally representative) engaging with health systems in countries studied in this thesis.

The exposures: Engagement occurred during, or pertains to the COVID-19 pandemic in one of the key research areas. Namely access, utilisation, or vaccination.

The outcomes: Disparities in user engagement with health systems on the basis of socioeconomic status, including income measures.

The study designs: Pulling the above together to inform the designs, I search for studies of any design which a) examine socioeconomic and income-related health inequalities or disparities in an issue, related to the adult population which is contained as a specific study on income-related health inequality in this thesis (access, utilisation, vaccination); (b) using quantitative methodologies which are at least comparable to the concentration index, with a sample size exceeding 500 individual respondents; c) in a country included in this thesis; d) where the engagement with health systems occurred during the COVID-19 pandemic time period; (e) with an equivalent or approximate approach to measure distributional elements of socioeconomic or income-related inequality in health. The thesis comprises each of the design elements a through e. With this context, I search separately for each of the specific studies contained within this thesis (i.e., access, utilisation, vaccination).

Step 2 is defining the search strategy and inclusion and exclusion criteria. I impose inclusion criteria based on the study designs section above, of (a) **and** (b) **and** (e), and **at least one of** (c) **or** (d), which I believe will contribute to the review in a meaningful way, either as comparator data to this study, or as counterfactual data which examines inequality outside of this study time-period or locations. To ensure the study is limited to relevant and recent studies in the changing landscape of global health, I restrict the search to studies published from 2020 onwards. I search the PubMed, EMBASE, and EconLit databases using the identified search strategy.

Step 3 is assessing the quality of the studies returned in the search, based on the pre-stated acceptable level as defined in the search strategy. The first stage I will employ is title screening. Studies that pass this stage will proceed to abstract screening. The studies that are included according to the criteria for relevance after abstract screening will progress to full text reading, whereafter a final inclusion decision will be made based on the full text.

Step 4 is summarizing the evidence, including comparing study characteristics, identifying effects (in this case, pro-poor or pro-rich impacts), magnitudes, and population overlap with the samples used in this study.

Step 5 is interpretation, and will include the discussion of the works included in the study. This step is important as it will identify the gap in the literature which this thesis aims to address.

I conduct the literature reviews in a stepwise process for each chapter. This allows me to focus on the literature relevant to the chapter without expanding the search unnecessarily. There are of course links between access, utilisation, and vaccination. I account for these links in the search. The specific process for each review is explained below.

Each review is conducted using Rayyan online screening software.

2.3.2 Socioeconomic and income-related inequalities and inequities in access to healthcare

For the literature review on socioeconomic inequalities in access to healthcare, I employed the following search terms, filtered to items published from 2020 onwards, on PubMed, EMBASE, and EconLit: ((socioeconomic inequality of health) OR (income related inequality of health) OR (socioeconomic health inequity) OR (socioeconomic health equity)) AND (access) AND (index OR curve) (from 2020:2024). The search terms offer a relatively broad perspective to begin the search, focusing on the inclusion of access, a measure of quantitative measurement, and an income gradient relative to health.

Healthcare access can be defined by several stages, and is conceptualised by Levesque et al. in their 2013 study, which I use extensively in this thesis.[1] The framework breaks healthcare access into 6 steps, beginning with healthcare needs, through perception of needs, seeking care, reaching care, utilisation, and outcomes or consequences. The question I propose for this chapter is focused in the intermediate stage between seeking and reaching care; I ask respondents if they had difficulty obtaining an appointment. At this stage, respondents are seeking care, but have yet to reach or utilise care. Similar studies have been undertaken by Gordon et al., Tapager et al., Houghton et al., and Alamneh et al.[68–71] The principles are similar to those employed by Fjaer et al. who adopt a retrospective approach,[72] and Cylus and Papanicolas who use a forward-looking approach.[73]

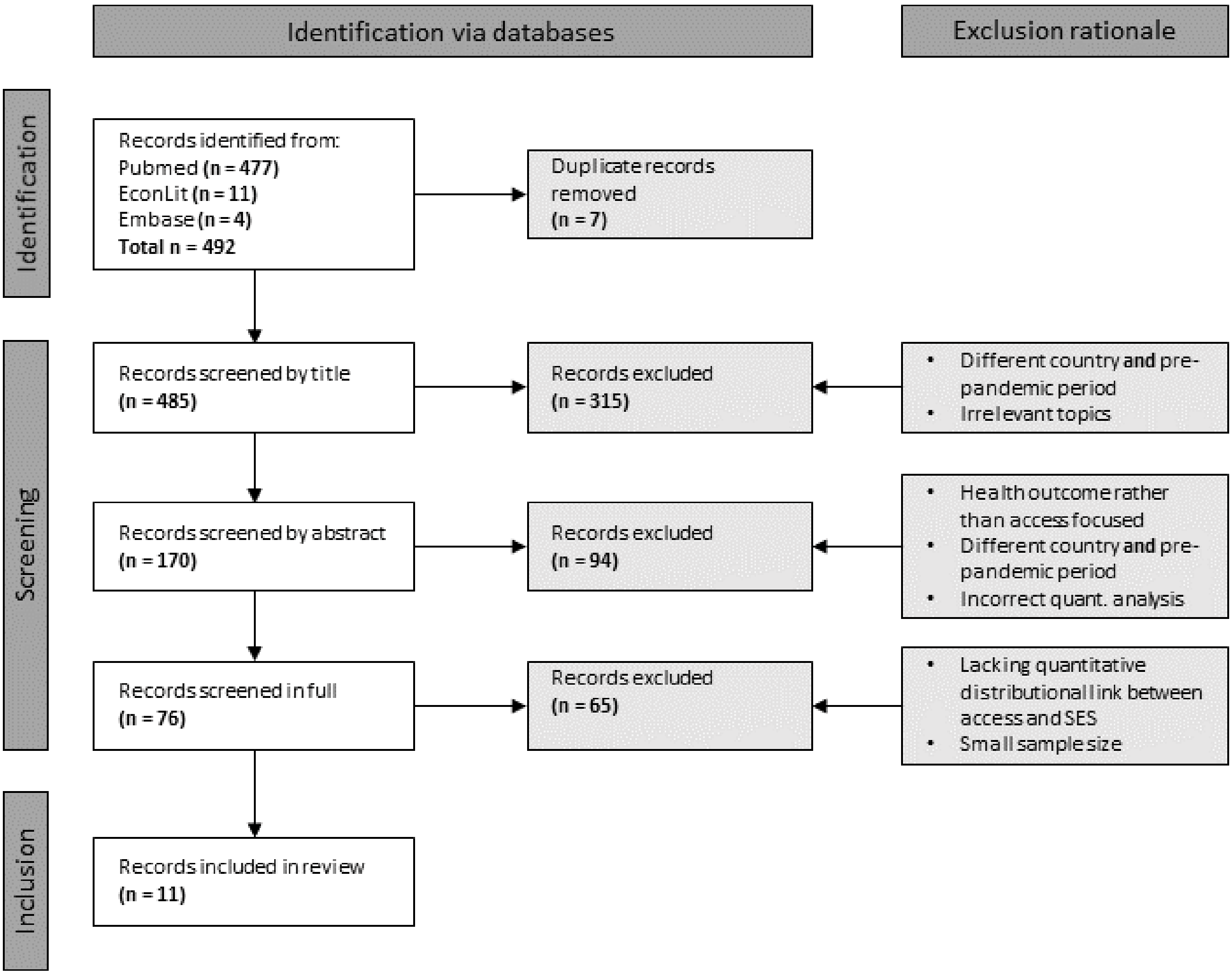
I screen outcome (e.g., inequality in patient response to surgery) focused papers closely to determine if they can add context to the particular question at hand, though many outcome-oriented articles do not include enough information to determine socioeconomic relationships with access at any stage of the framework mentioned above. Similarly, many papers purport to analyse access when in fact the focus is on utilisation, or coverage using utilisation as the underlying metric. Though it is true that to utilise healthcare, access must exist, and care need be reached. Utilisation studies that include an element of access are thus also screened carefully to establish if they may contribute to the literature on socioeconomic inequality and inequity in access in a meaningful way. While there may be a socioeconomic gradient in utilisation, analysis at the utilisation stage (which I conduct in *chapter 5*) omits those who have been unable to gain access to health systems, leading to potential compounding effects. Although inferences can be drawn, I aim to maintain specificity in this review, and leave utilisation comparisons to subsequent chapters. Specialist services (e.g., dental care) are excluded, as the services are deemed sufficiently different from those incorporated in the corresponding chapter of analysis in this dissertation (e.g., in-person GP appointments), and usually require different channels to access, making comparison adjacent at best.

An initial search was conducted in June 2023. Revisions and updates to the search were conducted in early 2024. The final search was conducted on the 3 March 2024. In the initial title screening, I include articles explicitly linked to utilisation if they may still meet search criteria (c) (country relevance) or (d) (time-period relevance; e.g., during the COVID-19 pandemic), as these articles may include information on access measures which could prove insightful.

A summary of the search process is presented in figure 2A. The search returned 492 results, the majority of which were found on PubMed. I removed 7 duplicate articles before beginning title screening, resulting in 485 articles. The first step, as outlined in my screening strategy, is a title screening. Titles that clearly did not pass the search criteria were excluded, totalling 315 articles. The remaining 170 articles, including ambiguous titles, proceeded to abstract screening. Common reasons for exclusion at the first stage included non-relevance (non-health system related, non-access related), or clearly out of country and time-period scope.

Of the 170 articles which progressed to abstract screening, a further 94 were excluded on the basis of a narrow focus on outcome, not meeting quantitative standards, desired country or time-period characteristics, or a focus on specialty care (e.g., dental care). The remaining 76 articles progressed to full-text screening. The dominant reason for exclusion during full text screening was related to the focus of the study. Excluded articles focused predominantly on utilisation or health outcomes, and failed to establish a clear quantitative relationship between socioeconomic status and access to healthcare. 11 papers were retained for review after full-text screening.

Figure 2A: Search strategy flowchart for socioeconomic and income-related inequalities and inequities in access to healthcare literature review



The 11 papers retained for review, shown in Table 2A at the end of this section, covered 7 countries included in my analysis; namely China, Colombia, Ghana, India, Spain, South Africa, and Uganda. One paper focused on Thailand, and was the only paper retained which assessed a metric of access during the COVID pandemic. The other 10 papers used data sourced from surveys conducted between 2010 and 2019. Each paper exhibited some signs of inequality in access favouring the rich, while 3 papers also had additional measures with pro-poor findings leading to mixed results overall.

Five papers focused explicitly on barriers to access and unmet need. Unmet need is defined as needing care and not receiving care, either as a self-determined requirement in works by Gordon et al., Houghton et al., and Wu et al.,[68,71,74] or if referred to care by a doctor in Zhuoga et al. work.[75] Alamneh et al. define a challenge to access if respondents faced financial constraints, long distances to facilities, did not receive permission to consult a health practitioner, or did not want to attend an appointment by themselves.[70] Alamneh et al. investigate barriers in accessing maternal care in Sub-Saharan Africa.[70] Ghana, Uganda, and South Africa are included in the study alongside 30 other African countries which find pro-rich inequality in accessing care. Estimates at the country level were not available. A single full-sample estimate is produced with aggregated regional effects in a regression. Houghton et al. conduct an analysis on access barriers in four Latin American countries, including Colombia. Lower-income respondents faced increased barriers relative to wealthier respondents, with significant results observed from 2010-2016 using the slope index of inequality. The relative index of inequality returned greater pro-rich inequality, however the relative results were not statistically significant. Minimal variation in absolute inequality was observed between 2010 and 2016. Wu et al. investigate unmet need for inpatient and outpatient care in China from 2011-2015, while Zhuoga et al. investigate unmet need for hospitalization (inpatient) in Tibet.[74,75] Wu et al. find inequality favouring the rich for both inpatient and outpatient unmet need due to financial constraints, but find the poor were less affected than the rich by non-financial constraints, implying financial barriers reduce care-seeking more than non-financial barriers for low-income earners.[74] Zhuoga et al. find pro-rich inequality in unmet need, implying the poor had disproportionately more unmet need, though the result did not achieve statistical significance. The pro-rich inequality decreased marginally over the study period (2013-2018). Gordon et al. find pro-rich inequality in unmet need in South Africa using a 2012 study. Similarly, postponement of healthcare was also inequitably concentrated amongst less-wealthy households.[68]

Three of the 11 papers retained focus on access and adherence to medication. A 2021 study in Thailand by Nontarak et al. studies new modes of medication delivery during the pandemic.[76] Chipanta et al. focus on access and adherence to antiretroviral therapy in 12 Sub-Saharan African countries, including Uganda in 2016/17.[77] Guo et al. investigate adherence to hypertension and diabetes medication in Taizhou city, China from 2011-2016.[78] Nontarak et al. found that regular services for non-communicable disease patients exhibited pro-rich inequalities during the pandemic. However, new modes of medication access such as primary care facility collection, postal delivery, and delivery by volunteers exhibited pro-poor inequalities.[76] Chipanta et al. find pro-rich inequality in accessing antiretroviral therapy in Uganda,[77] and Guo et al. find pro-rich inequality in high adherence to medication at baseline (2011-2012). However, after implementation of the full coverage policy for essential medicines which aimed to increase access to essential medications, pro-poor inequality in high adherence was observed in each of the three subsequent years, with increasing pro-poor magnitude.[78]

Three articles focus on access to maternal health. There is a wealth of literature on maternal health, though most papers focus on utilisation and relate this to coverage, or availability, which is used as a proxy for access. Alamneh et al. conduct their study on barriers to maternal care, the results of which are described above. Leventhal et al. conduct a comprehensive study on reproductive, maternal, newborn, and child health interventions in low and middle-income countries – including India and Uganda.[79] Alongside several other metrics of utilisation, Leventhal et al. analyse demand satisfied by modern family planning. Pro-rich inequality is observed using the concentration index and slope index of inequality, however this is a pooled result between 36 countries, with no country-specific results available. Bobo et al. evaluate equity across the maternal healthcare continuum in 25 sub-Saharan African countries.[80] The focus of the study, like several other maternal care studies – is on utilisation. However, the study includes estimates of inequality for different numbers of antenatal care contacts, which allows access to be inferred – and includes country specific estimates for Ghana, Uganda, and South Africa. Inequality is pro-rich for any (1+) antenatal contacts in Uganda and Ghana, while the South African estimates straddle equality. Estimates of inequality in Ghana in 2014 are increasingly pro-rich from 1 antenatal contact to 4+ antenatal contacts. Similar results are observed in Uganda in 2016, though the 95% confidence interval for having between 1 and 3 antenatal contacts just crosses the equality line, while more than 4 antenatal contacts is significantly pro-rich. In South Africa, 1-3 antenatal contacts are distributed equitably, while 4+ antenatal contacts are more pro-rich. The gradient in inequality between no contacts, 1-3 contacts and 4+ contacts implies an access issue in each of the three countries.[80]

The final paper retained for review investigates health literacy in Valencia, Spain. Tamayo-Fonseca et al. study the determinants of health literacy and find a relationship between low socioeconomic status and poor health literacy.[81] They then investigate the relationship between health literacy levels and engagement with health systems, and healthcare needs not met. They find that there is marginally more unmet need amongst those with inadequate or problematic levels of health literacy, however the differences to those with sufficient health literacy are not statistically significant.

The papers reviewed cover a range of elements that deal with access, either explicitly or in ways that can be inferred. The unmet need papers investigate whether or not patients attempted to seek care after perceiving, or being informed of the need for care, and possible reasons for not seeking care. The retained papers use data collected between 2010 and 2019, aside from the work conducted on medication delivery during the COVID pandemic in Thailand. Several studies report pooled estimates without reporting specific within-country inequality estimates.

At the time of initial and subsequent searches, and submission for publication, a clear gap in the literature could be addressed by the estimation of CANDOUR country-specific inequality indices on access during the COVID-19 pandemic. Focusing the work on barriers to access for those actively seeking care would further address an existing gap in the literature. Preceding literature focuses on inequalities before and after this stage of the health search continuum. Investigating inequalities at this stage is important, particularly in the context of health systems coming under extreme pressure, as many did during the COVID-19 pandemic. It is important to understand how health systems responds to individuals during these times of sustained health system pressure (e.g., ability to provide timeous care), in addition to previous research which focuses on barriers to health systems (e.g., financial, educational, or geographic constraints, amongst others).

I focus my work in this chapter on providing quantitative estimates of inequality in access to care, at the stage of seeking care and interacting with health systems. I undertake this work in the CANDOUR wave 2 countries during the COVID-19 pandemic, which addresses the current gaps in the literature, namely; 1) quantitative inequality estimates for the CANDOUR countries, which account for approximately 50% of the global population; 2) estimates of inequality in access during the COVID-19 pandemic; 3) estimates of inequality at the stage of seeking care and interacting with health systems.

Table 2A: Included studies for socioeconomic and income-related inequalities and inequities in access to healthcare literature review

Author	Relevant Country	Sub-population	Study time-period	Study focus	Methodology employed	Findings
Alamneh et al.[70]	Ghana, Uganda, South Africa	Mothers	2014-2016	Maternal care	Erreygers adjusted concentration index	Pro-rich results
Bobo et al.[80]	Ghana, Uganda, South Africa	Mothers	2014-2016	Maternal care	Concentration index	Pro-rich results
Chipanta et al.[77]	Uganda	HIV patients	2015-2018	Medication access	Concentration index	Pro-rich results
Gordon et al.[68]	South Africa		2012	Multiple	Erreygers adjusted concentration index	Pro-rich results
Guo et al.[78]	China	Hypertensive and Diabetic patients	2011-2016	Medication access	Concentration index	Mixed results
Houghton et al.[71]	Colombia		2010-2016	Access barriers	Slope and relative index of inequality	Pro-rich results
Leventhal et al.[79]	India; Uganda	Mothers	2010-2019	Maternal care	Slope index of inequality and concentration index	Pro-rich results
Nontarak et al.[76]	Thailand		2021	Medication access	Concentration index	Mixed results
Tamayo-Fonseca et al.[81]	Spain		2016	Health literacy	Income stratification	Pro-rich results
Wu et al.[74]	China		2011-2015	Inpatient and outpatient care	Concentration index	Mixed results
Zhuoga et al.[75]	China, Tibet Autonomous region (AR)		2013-2018	Inpatient care	Concentration index and horizontal inequity index	Pro-rich results

2.3.3 Socioeconomic and income-related inequalities and inequities in utilisation of healthcare services

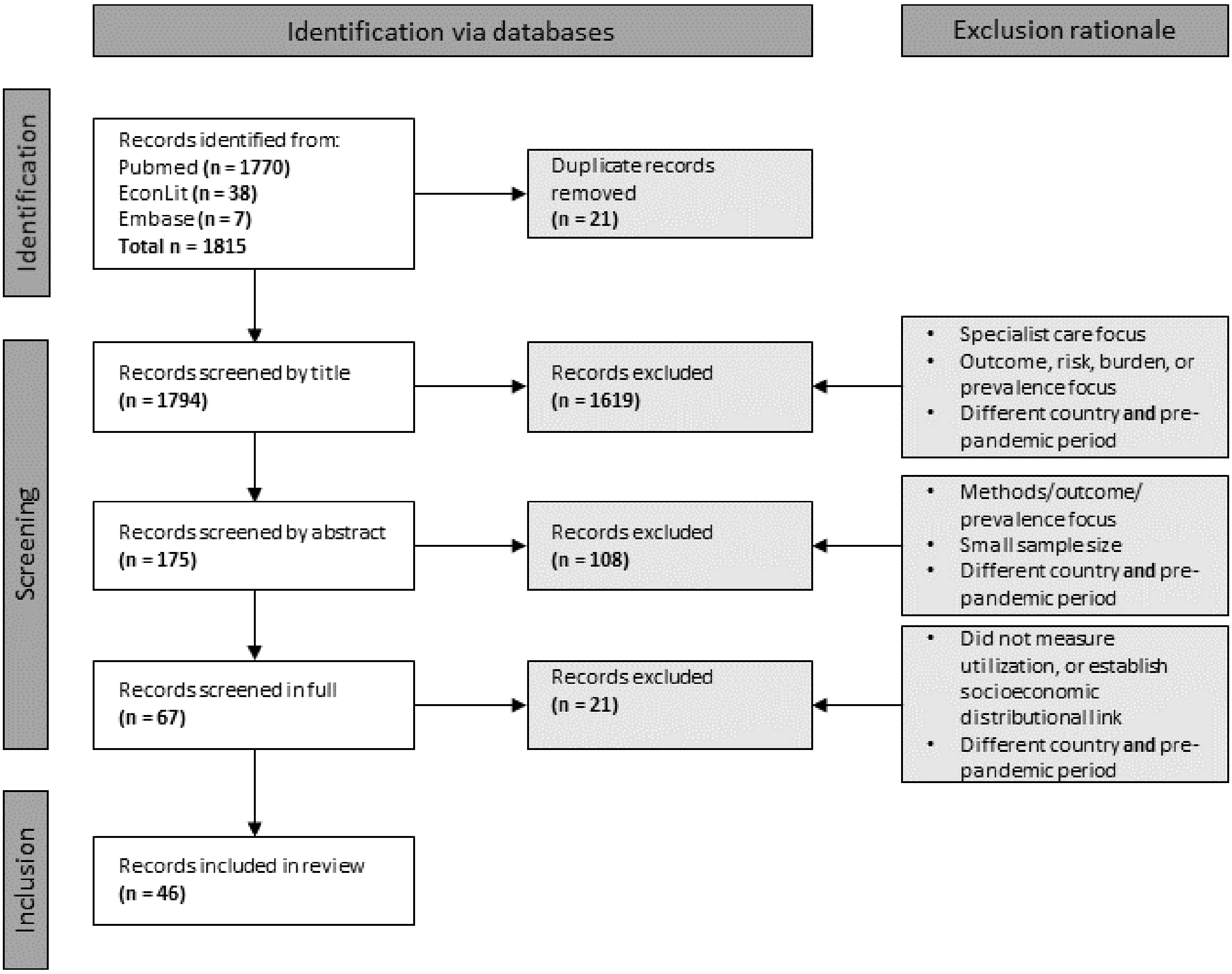
In reviewing the literature on socioeconomic and income-related inequalities in the utilisation of healthcare services, I employed the following search terms, filtered to items published from 2020 onwards, on PubMed, EMBASE, and EconLit: ((socioeconomic inequality of health) OR (income related inequality of health) OR (socioeconomic health inequity) OR (socioeconomic health equity)) AND (utilisation OR utilization OR consumption OR usage OR hospitalization) AND (index OR curve) (from 2020:2024). The search terms offer a relatively broad perspective to begin the search, focusing on the utilisation or consumption of health, a measure of quantitative measurement, and an income gradient relative to health.

Levesque et al. define healthcare access in a 6-step framework, a framework employed by Gordon et al. in their assessment of the South African healthcare system.[1,68] In the previous chapter, I focus on the step between seeking and reaching care. In this chapter, I focus on the utilisation of care – the step after reaching care in Levesque's framework, thereby following in logical order.[1]

The search follows the process outlined in the *methods of review* section. The search is focused on quantitative, distributional estimates of adult inequality or inequity on the basis of socioeconomic or income-level status in the utilisation or consumption of health services, in any of the CANDOUR countries, or in any location where the study uses data collected from the beginning of 2020 (i.e., during the COVID pandemic).

The first search was conducted in June 2023. A subsequent search was conducted on 12th April 2024. As of 12th April 2024, the search strategy had identified a total of 1,815 records, 1,770 of which were on PubMed, 38 on EconLit, and 7 on EMBASE. 21 of these were duplicates. 1,794 records remained and entered the screening process. The search strategy flowchart is presented in figure 2B below.

Figure 2B: Search strategy flowchart for socioeconomic and income-related inequalities and inequities in utilisation of healthcare services literature review



In title screening, I exclude specialist health services (e.g., dental, maternal), child health services, and outcome, risk, burden, prevalence, or expenditure focused studies, in addition to the criteria specified in the methods of review section. The focus of the review is narrowly on the utilisation or consumption of health services, and the presence of a socioeconomic gradient in this utilisation.

At the title screening stage, common reasons for exclusion included a focus on body mass index, obesity, adiposity, or weight related factors, alcohol or tobacco consumption, fruit and vegetable consumption, risk factors, prevalence and incidence, mortality, allostatic load, and activity or exercise. Many excluded papers also contained data collected in non-target countries out of the considered time period. In total, 1,619 articles were excluded at the title screening stage. The 175 remaining papers proceeded to abstract screening.

At the abstract screening stage, 108 papers were excluded. Several papers were methods focused, outcome or prevalence focused, mismatched in either country or time-period studied, or had small samples that were below the threshold for consideration. The 67 papers remaining were screened in full. During full text screening, 21 papers were excluded, leaving 46 papers for inclusion in the review. A table of included papers can be found at the end of this review in table 2B. 11 excluded papers did not measure utilisation, but another measure (e.g., probability of utilisation). 5 papers did not measure socioeconomic or income-related inequality in utilisation, 4 papers were not in the country or time period catchment, and 3 papers did not include a distributional perspective.

12 of the CANDOUR countries were covered directly in studies included in the review. The most frequently studied country was China, which was included 18 times. Australia and India followed with 6 and 5 appearances respectively. Each type of care was covered in the review, with a rich literature in inpatient and outpatient utilisation investigations, comparable to the hospital admissions and clinic visits in the CANDOUR study. GP utilisation was also covered frequently, while studies focusing on telephone and internet contacts were less frequent. The data used in the studies is predominantly from before the COVID-19 pandemic, however a number of studies include data from the pandemic time period. The studies are conducted between 1998 and 2022. A substantial number (11) of the studies focused on middle-aged and elderly subgroups, while several studies focused on an indigenous sample of the population, the urban rural divide, or disease-specific subgroups (e.g., hypertension, diabetes).

I report the review results by country in alphabetical order to allow convenient comparison at the country level in the analysis chapter.

6 studies included in the review investigated inequality or inequity in utilisation in Australia. Yeatman et al. conduct a study on the use of psychiatric care, finding that utilisation was pro-rich, however trending towards pro-poor results marginally over the study period (2015-2021).[82] Video-linked utilisation was significantly more unequal than telephone and face-to-face contact. Both video and telephone utilisation of psychiatric services were more inequitably utilised in 2020-21 than in 2019-20.[82] Hashmi et al. conduct a similar review, finding pro-poor results in psychiatric utilisation in 2009 and pro-rich utilisation in 2017, though results were not statically significant.[83] Pulok, van Gool, and Hall conduct a number of studies on inequity in utilisation of health services in Australia. The studies focus predominantly on specialist visits, but include general physician and any physician components, as well as inpatient and outpatient services.[84–87] The authors find pro-rich utilisation of GP and specialist services, equity in hospital admissions and outpatient visits which was formerly pro-poor.[85] Additional work finds pro-rich utilisation for specialists, including in the non-remote indigenous population, except when there is no out-of-pocket payment, where utilisation is pro-poor.[84,86,87] The probability of visiting any physician is pro-rich too, however the number of GP visits, and the number of non-zero (conditional on attending at least one) GP visits of found to be pro-poor, while no inequity was observed for conditional specialist visits.[87]

Three studies were conducted in Brazil, two of which were in the pandemic period. One study investigated the use of counselling services for those who had tested positive for COVID-19, and found pro-rich results in their utilisation.[88] A second study investigated the use of specialist services after symptomatic COVID-19 in Southern Brazil and found pro-rich results for any specialist, but pro-poor results for psychiatric services utilisation.[89] The third investigation looked at those who suffered from back pain and found pro-rich inequality in the use of follow-up appointments with health professionals and the use of physiotherapy.[90]

Like Brazil, three studies in the review were conducted in Canada. Each of the studies were completed prior to the COVID-19 pandemic, however. One focused on a general population, while two focused on specific subgroups, namely the elderly, and First Nations respondents. In the general population study, pro-rich results were found from 2000-2014 in GP and specialist utilisation, however hospital admissions were pro-poor.[91] In the elderly-focused study conducted between 1998 and 2011, the probability of visiting a GP, specialist, or any physician was pro-rich, as was the number of visits, however there was some variation in the number of GP visits, which presented with pro-poor utilisation in the number of visits between 2002 and 2005.[92] In the First Nations' people study, pro-rich inequality was observed in both the primary care and specialist care routes.[93]

18 studies conducted in China were included in the review. 8 studies focused on general, regional, or disease constrained samples. The remaining 10 studies focused on the middle-aged and elderly. Yang & Erreygers employ both level and rank indices to analyse inequality in utilisation of services from 2000-2015. They find pro-rich inequality in city hospital admissions and preventative care, while pro-poor results for the utilisation of folk doctors, community health clinics, admission to town hospitals, and general formal care. The results were similar using both rank and level methodology.[94] Guo et al. find pro-rich utilisation in inpatient and outpatient care in both rural and urban settings in the general Chinese population in 2008.[95] This result is supported by the works of Zhang et al. who find similarly in economically underdeveloped areas in Northeast China a decade later, and by Tang et al. and Liu et al. who find pro-rich outpatient and inpatient care for hypertensive patients between 2011 and 2018 and 2015-2019 respectively.[96–98] Zhuoga et al. find similar pro-rich inequality in inpatient care utilisation, though decreasing over the study period which ran from 2013-2018, a similar trend to that observed by Tang et al. and Liu et al.[75,97,98] In a study on internal migrants in 2014, Wang et al. find pro-rich inequality in inpatient service utilisation.[99] The only pro-poor

estimates for non-elderly focused studies in China comes from Xu et al., who find pro-poor estimates in rural China from 2010-2018 for inpatient and outpatient utilisation.[100]

Looking specifically to the elderly population in China, Su et al. find pro-rich use of health examinations for the elderly overall, however, they find a pro-poor utilisation in rural areas for unadjusted concentration indices; mirroring trends seen by Xu et al.[100,101] When adjusting for need, pro-rich results are found for the period 2011-2018, but statistical significance is not achieved. In a 2016 study, Li et al. find pro-poor utilisation in the concentration index and the horizontal inequality index of outpatient and inpatient care for both rural residents, and rural to urban migrant workers.[102] Wu and Liu find pro-rich utilisation of physical examinations amongst the elderly in Henan, though the result doesn't hold in Shandong, as in 2018 Huang et al. find pro-poor physical examination utilisation, and pro-rich utilisation of family doctors for first visits.[103,104]

Zhang et al., Fu et al., and Fu, Fang, & Dong each find evidence of pro-rich utilisation in inpatient and / or outpatient utilisation in the period 2011-2018.[105–107] Zhang et al. results trend toward equity, but remain pro-rich for utilisation in both inpatient and outpatient services for people with multiple chronic diseases.[105] Fu et al. study from 2011-15 found that in the sample of elderly patients with non-communicable chronic diseases, higher income patients used more inpatient services than lower-income counterparts, resulting in a pro-rich inequality.[106] Fu, Fang, & Dong find pro-rich results in the utilisation of inpatient and preventative care.[107] In outpatient care, they find pro-poor results from 2011-2013, but pro-rich results from 2015-2018. When disaggregating the results by socioeconomic group, they find inequality within the upper-income group to be substantially larger than in the lower income group – which shows results approaching equity in 2015 for each of the three types of care.[107]

In two 2018 studies conducted by Zhao et al. and Sun, Lyu, & Lyang, pro-rich results were found for inpatient utilisation.[108,109] Zhao et al. also find pro-rich results for outpatient care in their study of individuals with chronic disease. They find pro-poor utilisation for those who suffer from musculoskeletal and digestive related chronic diseases, however this is outweighed by pro-rich utilisation by those who suffer from respiratory, cardiovascular, and hypertension related diseases. The hypertension results support those found by Tang et al. and Liu et al. for the overall population.[97,98]

Fan et al. find pro-poor utilisation of inpatient services from 2013-2018, with a pro-rich finding in 2011.[110] This result stands in contrast to most of the research conducted in China, which consistently finds pro-rich inequality in utilisation apart from rural-focused studies.

A study in Colombia found inequality in the use of GP visits and screening for men and women for the elderly. Inequality was not found in inpatient care, however the result was not statistically significant.[111] An English study found pro-poor utilisation in inpatient care between 2017 and 2019, defined as at least one overnight stay. Admissions from any referral channel were considered (e.g., planned surgery, emergency, GP referral).[112] A 2013-2015 Europe-wide study on the uptake of cervical, mammography and colorectal screening found pro-rich results for each type of screening in each European region. The results were observed using both relative and absolute measures of inequality.[113] A 2017 study in France of Alzheimer's and related disease patients found pro-rich utilisation of private neurologist, psychiatrist, preventative care, and specialist consultations.[114] There was a clear gradient in the use of GP consultations from quintile 2-5, decreasing with income, however quintile 2 consumed more GP services than quintile 1 (highest-income). Unplanned and avoidable hospital admissions were more concentrated among lower-income quintiles, as were emergency room presentations.[114]

5 studies were conducted in India, covering inpatient and outpatient care, screening practices, utilisation of health services by those suffering from cardiovascular disease, and diabetes treatment practices. Inequality was observed for both public and private inpatient and outpatient care following Indian health policy reform. Inequality worsened over the study

period (2004-2018) in the private sector and for public outpatient utilisation, however public inpatient inequality reduced during the course of the study.[115] Pro-rich results were observed in both breast-examination utilisation (2015-16), and cervical cancer screening practices.[116,117] These pro-rich results were observed across the country, apart from cervical screening in the central region, which exhibited pro-poor uptake between 2019-2021.[117] In a disease specific analysis, Akhtar & Chowdhury find pro-rich utilisation and horizontal inequity in the utilisation of health services for cardiovascular disease patients, while Maiti et al. find pro-rich utilisation in diabetes treatment in all Indian states aside from 2.[118,119]

In Italy, Di Girolamo et al. find generally pro-rich results in hospital utilisation between 2018 and 2020. Estimates were more pro-rich for women than men, though emergency utilisation was pro-poor for men and women. Certain surgeries were pro-poor (e.g., surgery for prostatic hyperplasia, breast cancer surgeries). Limited variation was seen in the 2018 and 2020 estimates.[120] In Japan, employers are mandated to provide employee routine health check-ups. The utilisation in these general check-ups was pro-rich, an unsurprising result given the link to employment.[121] Two studies investigate the uptake of organised and opportunistic screening for colorectal and gastric cancers in Korea between 2009 and 2021/2022. Both studies find pro-poor estimates for organised screening uptake, and pro-rich opportunistic screening uptake.[122,123] In colorectal screening, organized screening was the most pro-rich in the study period in 2020 during the height of the pandemic. Organized screening showed a trend moving towards equity, becoming less pro-poor, while opportunistic screening also showed a trend towards equity, becoming less pro-rich.[122] In gastric screening, there is a trend in organised screening towards equity, as with colorectal screening. Opportunistic screening was most pro-poor in 2020, reducing the general inequality during the pandemic before returning to trend levels.[123] Gordon et al. find pro-rich utilisation of the private health system in South Africa in 2012, but pro-poor use of the public system – mirroring results in India, and showing the disparities present in public-private health system countries.[68,115] In the United Kingdom, Vestesson et al. find a generally pro-poor utilisation of health services, and narrowing of socioeconomic inequalities during the pandemic, as consultations increased with deprivation.[124] There was a pro-poor shift in the use of remote consultations, as the most deprived consumed relatively more than the least deprived. However, in face-to-face consultations, the most deprived faced a steeper reduction in contacts than the least deprived.[124]

The literature on the utilisation of health services is extensive. The majority of studies find pro-rich results in the utilisation, or consumption of health services, with 43 of the 46 papers included exhibiting evidence of pro-rich inequality. However, in certain countries, inpatient utilisation appears to be the nearest to equity, with exceptions (e.g., China, India). Some evidence of pro-poor inequality was found in 20 of the papers reviewed. Study designs are often similar, with most studies included containing an analysis of inequality, and attempting to identify its causes. Several studies employ the concentration index, a method of decomposition, and the horizontal inequity index. A number of studies rely on either the slope or relative indices of inequality, or differentiation by quintile and a simple analysis on the differences in utilisation between these groups. Several studies were focused on sub-populations, including the elderly, regional areas, and those who suffer from certain diseases. Several longitudinal studies were conducted, as well as a number of cross-sectional analyses. Only one study included in the review considered more than 1 country, and investigated socioeconomic inequality in cancer screening around Europe.[113]

At the time of review, the literature does not appear to include work on comparisons between countries. While work comparing countries does exist, these works are often restricted to specific types of care (e.g., maternal care). As such, a cross-country study that analyses the socioeconomic inequality in utilisation of (general) health services would contribute to the existing literature. As limited research into the utilisation of services during the COVID-19 pandemic exists in certain countries, this also presents an opportunity to produce novel estimates for these countries. While single country estimates for inequality in utilisation have been produced, comparisons between countries that identify if inequality lies in the differences between countries, or in differences between individuals within countries have also not been undertaken. These gaps in the literature can be filled using data collected in the CANDOUR study as intended, and form the basis for the chapter on socioeconomic inequality in utilisation.

Table 2B: Included studies for socioeconomic and income-related inequalities and inequities in utilisation of healthcare services literature review

Author	Relevant country	Sub-population	Study time-period	Methodology employed	Findings
Akhtar & Roy Chowdhury[118]	India	Cardiovascular patients	2014-2018	Erreygers adjusted concentration index and horizontal inequity index	Pro-rich results
Bozhar et al.[113]	France, Italy, Spain		2013-2015	Slope and relative index of inequality	Pro-rich results
Couret et al.[114]	France	Alzheimer's & related disease patients	2017	Income quintile stratification	Mixed results
Di Girolamo et al.[120]	Italy	30+ in 2011	2018-2020	Relative index of inequality	Mixed results
Fan et al.[110]	China	Middle-aged and elderly (45+)	2011-2018	Concentration index and horizontal inequity index	Mixed results
Fu et al.[106]	China	Middle-aged and elderly with chronic NCDs	2011-2015	Concentration index and horizontal inequity index	Pro-rich results
Fu, Fang, & Dong[107]	China	Middle-aged and elderly (45+)	2011-2018	Concentration index	Mixed results
Garcia-Ramirez, Nikoloski, & Mossialos[111]	Colombia	Elderly (60+)	2015	Concentration index	Mixed results
Gordon et al.[68]	South Africa		2012	Erreygers adjusted concentration index	Mixed results
Guo et al.[95]	China		2008	Horizontal inequity index	Pro-rich results
Hajizadeh et al.[93]	Canada	First Nations	2017	Horizontal inequity index	Pro-rich results
Hashmi et al.[83]	Australia		2009-2017	Regression and Gini models	Pro-rich results
Hirello, Pulok, & Hajizadeh[91]	Canada		2000-2014	Horizontal inequity index	Mixed results
Huang et al.[104]	China	Elderly (65+)	2018	Concentration index	Mixed results
Li et al.[102]	China	Elderly (50+, rural, and rural-to-urban migrant)	2016	Concentration index and horizontal inequity index	Pro-poor results
Liu et al.[98]	China	Hypertensive patients in Pearl River	2015-2019	Concentration index and horizontal inequity index	Pro-rich results

Luu et al.[122]	Korea	50-74 year olds	2009-2021	Slope and relative index of inequality	Mixed results
Luu et al.[123]	Korea	50-74 year olds	2009-2022	Slope and relative index of inequality	Mixed results
Maiti et al.[119]	India	Diabetic patients	2019-2021	Concentration index	Pro-rich results
Muthuramalingam & Muraleedharan[117]	India	Women	2019-2021	Concentration index and slope index of inequality	Pro-rich results
Negi & Nambiar[116]	India	Women	2015-2016	Concentration index and slope index of inequality	Pro-rich results
Pulok & Hajizadeh[92]	Canada	Elderly (65+)	1998-2011	Horizontal inequity index	Mixed results
Pulok, van Gool, & Hall[85]	Australia		2011-2015	Horizontal inequity index	Mixed results
Pulok, van Gool, & Hall[84]	Australia	Urban indigenous	2012-2013	Horizontal inequity index	Pro-rich results
Pulok, van Gool, & Hall[86]	Australia		2014-2015	Concentration index	Pro-rich results
Pulok, van Gool, & Hall[87]	Australia		2014-2015	Horizontal inequity index	Mixed results
Rocha et al.[88]	Brazil	COVID positive; South Brazil	2020-2021	Concentration index and slope index of inequality	Pro-rich results
Saes et al.[90]	Brazil	Individuals with back-pain	2019	Concentration index and slope index of inequality	Pro-rich results
Selvaraj et al.[115]	India		2004-2018	Concentration index	Pro-rich results
Shimoda et al.[121]	Japan		2015-2016	Slope and relative index of inequality	Pro-rich results
Su et al.[101]	China	Middle-aged and elderly	2011-2018	Horizontal inequity index	Mixed results
Sun, Lyu, & Yang[109]	China	Elderly (60+)	2018	Concentration index	Pro-rich results
Tang et al.[97]	China	Hypertensive patients	2011-2018	Concentration index	Pro-rich results
Toal et al.[112]	England		2017-2020	Index of multiple deprivation stratification	Pro-poor results
Vestesson et al.[124]	United Kingdom		2018-2022	Index of multiple deprivation stratification	Mixed results
Vieira et al.[89]	Brazil	South Brazil	2021	Concentration index and Slope index of inequality	Mixed results

Wang et al.[99]	China	Internal migrants	2014	Concentration index	Pro-rich results
Wu and Liu[103]	China	Elderly (65+), Henan Province	2015	Concentration index	Pro-rich results
Xu et al.[100]	China	Rural	2010-2018	Concentration index and horizontal inequity index	Mixed results
Yang & Erreygers[94]	China		2000-2015	Erreygers adjusted concentration index and level-dependent index	Mixed results
Yeatman et al.[82]	Australia		2015-2021	Concentration index	Pro-rich results
Zhang et al.[105]	China	Middle-aged and elderly with chronic conditions (45+)	2011-2018	Concentration index and horizontal inequity index	Pro-rich results
Zhang et al.[96]	China	Northeast China; economically underdeveloped	2018	Concentration index and horizontal inequity index	Pro-rich results
Zhao et al.[108]	China	Elderly with chronic disease	2018	Concentration index and horizontal inequity index	Pro-rich results
Zhuoga et al.[75]	China, Tibet AR		2013-2018	Concentration index and horizontal inequity index	Pro-rich results

2.3.4 Socioeconomic and income-related inequalities in vaccination and immunisation

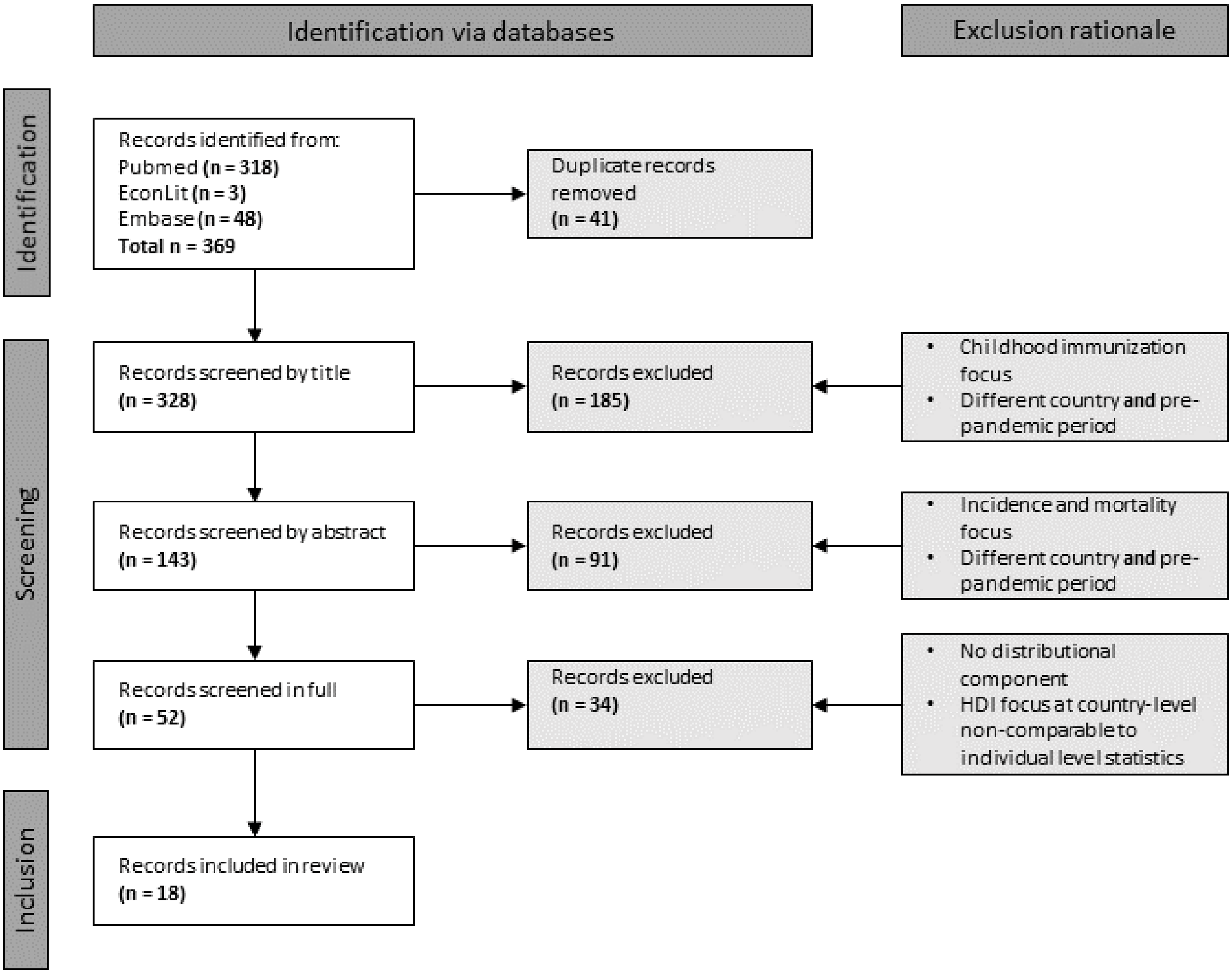
For the literature review on socioeconomic inequalities in vaccination during the COVID-19 pandemic, I employed the following search terms, filtered to items published from 2020 onwards, on PubMed, EMBASE, and EconLit: ((socioeconomic inequality) OR (income related inequality) OR (inequity)) AND (vaccination OR immunisation OR immunization OR hesitancy OR acceptance) AND (index OR curve) (from 2020:2024).

Having conducted searches for access and utilisation, I turn to a particular element of utilisation of healthcare services; vaccination. This is particularly pertinent to the COVID-19 pandemic, where vaccination hesitancy and uptake was a key barrier to exiting the pandemic.

I follow the same methods as in previous searches, defined by the *methods of review* section. I focus my search on quantitative, distributional estimates of adult inequality or inequity on the basis of socioeconomic status or income level in hesitancy, acceptance, or vaccine uptake, in any of the CANDOUR countries, or in any location where the study uses data collected from the beginning of 2020. In this search, I keep the focus narrow on inequality and equity considerations, however I also conduct a semi-structured search for levels of uptake and hesitancy, the results of which are contained in the main chapter of analysis.

The first search was conducted in November 2023. A subsequent search was conducted on 12th March 2024 to prepare for submission of a publication on acceptance and vaccination inequality. By this date, 369 papers had been identified through searches, 318 of which were on PubMed, 3 on EconLit, and 48 on EMBASE. 41 of these were duplicated records, leaving 328 articles to the screening process. I present an overview of the search process in figure 2C.

Figure 2C: Search strategy flowchart for socioeconomic and income-related inequalities vaccination and immunisation literature review



143 papers were retained after title screening. A focus on childhood immunisation was a primary reason for exclusion at this stage. Non-relevance to the search also resulted in exclusions, as well as timing and geographic mismatches. 91 papers were excluded during abstract screening. The main reasons for exclusion at the abstract screening phase were around incidence and mortality focused articles, or timing and geographic mismatches. This process left 52 papers remaining for full text screening. 18 papers were retained after the full text screening, which are presented in table 2C at the end of the section. A lack of distributional analysis resulted in several exclusions. Several papers comprised interesting studies, notably

Patenaude's use of the Vaccine Economics Research for Sustainability and Equity (VERSE) toolkit – using an expanded deprivation criteria to rank individuals rather than pure income-related measures, however the application was limited to childhood immunisation.[125,126] Several papers compared uptake levels with Human Development Index levels in ecological studies, however these papers did not distinguish income levels from other indicators, nor did they include a distributional analysis. While these studies may be interesting for cross-country comparison through an ecological lens, they do not reach the threshold for inclusion in the review for this chapter, unless they contained a quintile analysis which could be used to inform a perspective on socioeconomic gradients.

The resulting 18 papers covered several countries investigated in the CANDOUR study. The USA was the most frequently investigated, with 8 papers focusing on the country. 3 articles focused on Brazil, making it the second most frequently investigated country. 2 articles looked at the global context, one of which was a systematic review, and another 2 investigated the UK. The remaining 3 papers studied Italy, Spain, and Korea. 15 papers focused specifically on COVID vaccines, with data collected from 2020 onwards. 1 paper focused on uptake of the flu vaccine during the pandemic relative to prior periods, and 2 systematic reviews focused on immunisation from 2000-2010 and 2011 onwards respectively. Each paper found pro-rich inequality in uptake, though the two included systematic reviews also found mixed results in the constituent papers included for review, and two further country or regional studies found signs of pro-poor alongside pro-rich results.

10 papers conducted ecological analyses. The ecological studies covered the USA (6), Brazil (3), and one global study. The global investigation by Miranda-Soberon et al. calculates between country inequality using a number of socioeconomic ranking variables.[127] Country competitiveness, fragility, and human development indices are employed, alongside corruption indices, doctor density, and demographic profiles (e.g., age and life expectancy). Pro-rich results

are found for each measure apart from corruption. The findings suggest that vaccination doses are concentrated in countries with better socioeconomic indicators, though this does little to explain within country variation. When disaggregated by continent, Africa consistently has the greatest inequality by each of the variables considered (competitiveness, human development, and fragility). The Americas had the lowest observed inequalities between countries across the measures, followed by Asia/Oceania, and Europe, and lastly Africa.

The American focused ecological studies covered Connecticut, St. Louis and Kansas City, Texas, California, a selection of 16 large cities, and a nationwide county study.[128–133] Each study found pro-rich results in vaccine allocation. All of the USA based studies use the Social Vulnerability Index (SVI) as the socioeconomic variable, though some disaggregate the index into its constituent themes.[129,131–133] Barry et al., in a study which includes 3,129 of the USA's 3,143 counties, find a clear gradient between SVI quartiles and vaccination, with less vulnerable counties having greater vaccination coverage. Disaggregated socioeconomic status produced the highest disparities from quartile 1 to quartile 4 relative to other SVI themes across the country.[130] Bilal et al., in their study of 16 large cities across the country, found that the most vulnerable neighbourhoods had 75% vaccination coverage relative to the least vulnerable, significant for both absolute and relative measures.[129] Mody et al. find that the most vulnerable zip codes had lower vaccination rates relative to less vulnerable zip codes. The result was observed in all races studied (Black, Hispanic, White) apart from Asian residents in both the primary vaccination series and the booster campaign.[133] In Texas, Mofleh et al. find that adults living in poverty and with lower education had lower vaccination rates, based on a spatial analysis of zip codes and SVI, consistent with prior stated hesitancy among the same groups.[131] In California, Bruckhaus et al. find that uptake is related to SVI, with significant gaps based on overall SVI. Bruckhaus et al. find that the vaccination rates by overall SVI and socioeconomic disparities (theme 1) attenuated over time, while those counties with more minority status residents were likely to achieve higher overall vaccination coverage over time.[132] Wang et al. investigate vaccination coverage amongst the elderly in Connecticut. The analysis is disaggregated for age groups 65-74 and 75 and over. Significant differences are found between the top and bottom quartiles along six SVI indicators for both age groups. The indicators were poverty, education, disability, minority, vehicle access and language. Poverty accounted for the second largest difference between quartiles for the 65-74 age group, and the third largest for the 75 and over age group.[128]

The three ecological studies conducted in Brazil relied on the Human Development Index (HDI), Income per capita, and income inequality amongst other measures. Bastos et al. find that low and medium HDI were associated with lower vaccine coverage relative to high HDI municipalities, though this was mitigated by high primary healthcare coverage.[134] Li et al. find a decreasing probability of receiving the second dose of the vaccine course associated with decreasing municipal income per capita.[135] Boing et al. show that municipalities with the lowest vaccine coverage generally have poorer sociodemographic indicators. A greater proportion of municipalities in the low-coverage group had high income inequality, and fewer years of schooling.[136]

Of the non-ecological or systematic studies, 2 were conducted in the UK, and one in each of Italy, Spain, the USA, and Korea. Both UK studies focused on the city of Manchester, one with a special focus on patients on renal replacement therapy, and the other a general cohort study on influenza vaccine uptake over time.[137,138] Poulikakos et al. find a socioeconomic gradient in first dose vaccination by Index of Multiple Deprivation (IMD) quintiles in the Greater Manchester clinically extremely vulnerable adult population. A mixed gradient is observed in the Salford cohort, which was the subject of a targeted, locally evidence-based strategy to increase vaccination uptake. A 3.1 percentage point difference (Salford) is observed between the most and least deprived quintiles, less than the 7.2 percentage point difference observed in the total of Greater Manchester clinically extremely vulnerable population, which was not subject to specifically tailored vaccination uptake strategies.[137] Watkinson et al. study inequality in influenza vaccination uptake, and find inequalities in uptake of the flu vaccine increased at the start of the pandemic among adults aged 65 and over, with a marked jump in the slope index of inequality.[138]

In the Umbria region of Italy, Primieri et al. find that non-adherence to the vaccination series, and failure to receive a booster shot increased with deprivation, however, the differences were not significant.[139] In urban Catalonia, Spain, Roel et al. conduct an investigation into adult vaccination, infection and hospitalization.[140] Vaccination coverage was higher in the least deprived areas, by 8 percentage points (85 vs 77). Deprivation was associated with vaccination coverage among the 40-64 year age group, though there was no association amongst retirement age individuals of 65 years and over.[140] Brewer et al. find that income is associated with an increased likelihood to obtain seasonal influenza vaccine in the USA, with high income earners (>$75,000 annually) more likely to receive flu vaccines than lower income categories.[141] Jeon et al. conduct an analysis of inequality in infection and vaccination in Korea. They find that vaccination is less concentrated among lower income groups using the slope index of inequality, with the lowest income group 4.52% less likely to be vaccinated than the highest income group.[142]

Two systematic reviews were included in the literature review. Sacre et al. conduct a global umbrella review on socioeconomic inequalities in vaccination, while Murfin et al. conduct a study on influences on uptake of cervical cancer prevention strategies.[143,144] Murfin et al.'s work is included in the systematic review by Sacre et al., which I parcel out in this review.[143] Sacre et al.'s review comprises several types of vaccination, including Human Papillomavirus (HPV) Vaccination, Influenza and pneumococcal immunisation, routine vaccines, and childhood vaccinations. Excluding childhood studies based on the prior stated exclusion criteria, Sacre et al. include 15 studies (inclusive of Murfin et al.)[143] 3 of the included studies find pro-rich inequality across country income levels for HPV and influenza or pneumococcal vaccinations. 2 studies find pro-poor inequality for HPV and influenza or pneumococcal vaccinations in high-income countries. The remaining 10 studies found mixed results, including Murfin et al. Seven of the mixed result studies focused primarily on HPV. The remaining 3 studies with mixed results focused on influenza or pneumococcal vaccination, or routine childhood and adult vaccinations.[143] Murfin et al. analysed 8 studies, 6 of which studied vaccination, and find income to be a significant factor in vaccination uptake in 4 of the studies. Only one paper found a pro-poor inequality, while the remaining paper was inconclusive.[144] Overall, the results of the systematic reviews are mixed, with a tendency towards pro-rich inequality, particularly in lower income countries..

Overall, the articles included in the literature review can be allocated to three groups; ecological studies using aggregated data to conduct spatial inequality analyses relating to COVID-19 vaccination within or across countries; studies investigating inequality in vaccination in a single country or area; and systematic reviews investigating non-COVID related vaccination. The majority of results in the review are pro-rich, though there are a handful of mixed results. Based on the review and at the time of writing, there is not yet research that focuses on comparable within-country inequality using distributional techniques in several of the countries included in the CANDOUR dataset. Furthermore, existing studies that compare across countries use aggregated metrics (such as HDI, or per capita income), and do not contain the same depth of information that utilising the concentration index would enable. Given this, a study which investigates distributional inequality in COVID-19 acceptance and uptake, and produces quantitative estimates, would fill an existing gap in the current literature.

Table 2C: Included studies for socioeconomic and income-related inequalities in vaccination and immunisation literature review

Author	Relevant country	Sub-population	Study time-period	Methodology employed	Findings
Barry et al.[130]	USA		2020-2021	Social vulnerability index stratification	Pro-rich results
Bastos et al.[134]	Brazil		2021	Human development index stratification	Pro-rich results
Bilal et al.[129]	USA		2020-2021	Slope and relative index of inequality	Pro-rich results
Boing et al.[136]	Brazil		2021-2022	Slope and relative index of inequality on multiple measures	Pro-rich results
Brewer et al.[141]	USA		2020	Income stratification	Mixed results
Bruckhaus et al.[132]	USA	California	2020-2021	Social vulnerability index stratification	Pro-rich results
Jeon et al.[142]	Korea		2020-2022	Slope index of inequality	Pro-rich results
Li et al.[135]	Brazil		2021	Income stratification	Pro-rich results
Miranda-Soberón et al.[127]	Global		2020-2022	Concentration index	Pro-rich results
Mody et al.[133]	USA	St Louis, Kansas	2020-2022	Social vulnerability index stratification	Pro-rich results
Mofleh et al.[131]	USA	Texas	2021	Social vulnerability index stratification	Pro-rich results
Murfin et al.[144]	USA	HPV vaccine focus, systematic review	2000-2010	Multiple	Mixed results
Poulikakos et al.[137]	UK	Manchester, Renal replacement patients	2021-2022	Index of multiple deprivation stratification	Pro-rich results
Primieri et al.[139]	Italy	Umbria	2022	Deprivation index stratification	Pro-rich results
Roel et al.[140]	Spain	Catalonia, 40+	2020-2021	Socioeconomic deprivation index stratification	Mixed results
Sacre et al.[143]	Global	Multiple	2011-2023	Multiple	Mixed results
Wang et al.[128]	USA	Elderly, Connecticut	2021	Social vulnerability index stratification	Pro-rich results
Watkinson et al.[138]	UK	Manchester, Flu, 65+	2015-2022	Slope index of inequality	Pro-rich results

3. Data used in the production of the thesis

3.1 CANDOUR Study

The COVID-19 Vaccine Preference and Opinion Survey (CANDOUR) study consists of an online, multi-country survey of adults aged 18 and above. To date, the survey has been fielded in three waves, however, the third wave was not available for the purposes of this thesis, as it only went to field in mid-2025. The CANDOUR study uses quota sampling to ensure representative samples for gender, age, education, and geography in each country. Where imbalances remained, post-stratification weighting was adopted in individual waves. The surveys are available in Appendix Y.

Wave 1

The first CANDOUR wave was conducted in 14 economically diverse countries using anonymous online surveys from November 2020 to May 2021. 16,746 responses were collected, averaging 1,196 per country, ranging from 1,022 to 1,424. The following countries were included in the survey: Australia, Brazil, Canada, Chile, China, Colombia, France, India, Italy, Russia, Spain, Uganda, United States of America, and the United Kingdom.

Wave 2

The second CANDOUR wave was conducted in 16 economically diverse countries using anonymous online surveys from March to November 2022. 22,150 responses were collected, averaging 1,385 per country, ranging from 1,266 to 1,907. Russia, which had been included in wave 1, was not included in wave 2. Ghana, Japan, and South Africa were the additional countries included in wave 2. All other countries from wave 1 were retained in wave 2.

Convenience longitudinal sub-sample

Drawing from wave 1 and wave 2, a convenient sub-sample of repeatedly sampled individuals is formed. 5,454 respondents participated in both wave 1 and wave 2, and provide a longitudinal component of the CANDOUR data. However, the convenient sub-sample is not representative by any measure, and is only used for direct ex-ante and ex-post comparison in section 7.2.

Reweighting processes

In some instances, the CANDOUR data sample sizes were reduced due to incomplete data (e.g., not answering vaccination questions). To retain a nationally representative sample, I adjusted individual sample weights in each country. Individuals within each country are assigned a weighting subgroup based on their age, gender, education level, and geographic location. Through the reweighting process, I attempt to hold constant each subgroup's weighting to ensure that the subgroups reflect its share of the national adult population. This is possible unless all individuals from a weighting subgroup are excluded, however the process does naturally place greater weights on those who remain in the sample.

3.2 The Ghana financial incentives data

The Ghana Financial Incentives Trial investigates the influence of cash incentives on COVID-19 vaccination uptake in six rural Ghanaian districts.[145] The study conducted a two-stage randomised controlled trial (RCT) with four treatment arms consisting of a video message embedded in the survey: placebo, Centre for Disease Control (CDC)-styled informative health message, low cash incentive (20 Ghana cedis / $3) and high cash incentive (60 Ghana cedis / $10). Data were collected in various stages from 5 February 2022 to 30 November 2022. 5,900 respondents were interviewed across the treatment arms in phase 1 after randomising villages for treatment within districts based on ranked population. Phase 2 involved collecting reported vaccination status from phase 1 respondents. Phase 3 attempted to collect any outstanding reported vaccination statuses from phase 1 respondents. 4,101 phase 1 respondents were contacted in phases 2 and 3. Phase 3 also collected data to identify possible spillovers. Spillovers refer to the impacts experienced due to an independent event. In this case, it refers to the effect of offering financial incentives for vaccination to some individuals on the behaviour of those not offered incentives. In phase 4, health workers at district hospitals reconciled official health records to the participant list (5,900 original respondents and 1,101 spillover respondents) to verify vaccination status. 3,075 records were verified. A full description of the study is available in Duch et al.[145] A link to the survey instrument is available in appendix Y.

3.3 Secondary data sources

Several data sources are utilised on an ad-hoc basis. Secondary data supplements the primary data, or validate it using external sources. Where additional data are employed, a note is made in the relevant chapter, and the data are cited appropriately. Full descriptions can be found in Appendix Z.

3.4 Key variable descriptions

The variables used in the analysis in this thesis are split into groups according to their use in the analysis. Where variables have been transformed, a detailed explanation follows. Variables are split into 4 overarching groups; outcome variables, income-related variables, sociodemographic variables, and variables used for sensitivity analysis, which include those used for external verification and validation. Variables may be used in one or several chapters of this dissertation. The chapter(/s) in which each variable appears is clearly defined at the end of each description. The outcome variables and income variables are described below. Additional variables are described in appendix Z.

3.4.1 Outcome variables

Inequality in each of the outcome variables is analysed at the particular stage of the Levesque et al. framework.[1] Analysis is restricted to those who have engaged with health systems in their respective countries, and so is in a sense conditional, however, the analysis is conditioned on engagement in the given stage, rather than pass-through of the previous stage of the framework. I do not condition on the previous stage because national health systems vary, stages may be blended or distinct in different systems, and individuals may be subject to different (internal or external) barriers in different regions.

3.4.1.1 Access to healthcare services

Respondents were asked the extent to which they agreed or disagreed with a statement (e.g., getting a face-to-face appointment has been difficult) from strongly agree to strongly disagree, with five inclusive ordinal steps. Responses of "strongly agree" and "agree" were classified as having faced challenges for each type of care. Participants who did not attempt to make appointments were excluded from the analysis of the relevant type of care. This question was repeated for face-to-face appointments, telephone or internet appointments, and hospital admissions or clinic visits. Outcomes were standardized to account for health need and subjectivity. The standardization process is explained in the methods section. *Used in chapter 4.*

3.4.1.2 Utilisation of health services

Respondents were asked to indicate the number of contacts they had had with various health professionals *since the beginning of the pandemic,* ranging from 0 to 10 or more in five different types of care. The types of care included in the study are hospital admissions (overnight stays), clinic visits, face-to-face contacts with a doctor, telephone contacts with a health professional, and internet contacts with a health professional. Outcomes were standardized for health need and normalized to equivalent time periods. *Used in chapter 5.*

3.4.1.3 Vaccination acceptance

CANDOUR Respondents were asked their intended actions if an effective COVID-19 vaccine were to become available. Respondents could select between the following options; "definitely get it"; "probably get it"; "probably not get it"; "definitely not get it"; "do not know"; "prefer not to say". Responses of "definitely get it" and "probably get it" were coded as accepting. Responses of "prefer not to say" were excluded. The remaining options, including "do not know", were coded as hesitant. *Used in chapter 6, 7.*

In the Ghana financial incentives trial, vaccine acceptance data was collected by asking respondents, "Do you think you will get a first shot of a COVID-19 vaccine within the first 6 weeks after the vaccine becomes available to you?" immediately after watching the treatment video. Respondents could answer "yes", "no", "do not know", or "prefer not to say." Responses of "yes" were coded as vaccine accepting. *Used in chapter 7.*

3.4.1.4 Vaccination uptake

Respondents were asked if they had received a COVID-19 vaccine. Respondents who had received at least one shot of any COVID vaccine were deemed vaccinated. Respondents who had not been offered a vaccine, who were still waiting for a vaccination, or who had declined the vaccination were deemed non-vaccinated. I excluded respondents with missing vaccination data. *Used in chapter 6, 7.*

In the Ghana financial incentives trial, self-reported vaccine uptake was collected in phases 2 (telephone survey) and 3 (in-person interview). Respondents were asked if they had received at least one shot of a COVID-19 vaccine. Possible responses were "Yes, I have received at least one shot of a COVID-19 vaccine", or "No, I have not received at least one shot of a COVID-19 vaccine." Responses of "Yes…" were coded as reported vaccinated, while responses of "No…" were coded as unvaccinated. Reported vaccination was not limited to the 6 weeks immediately after treatment, with collection occurring in April and June respectively. *Used in chapter 7.*

3.4.1.5 Verified vaccination uptake

In the Ghana financial incentives trial, verified vaccine uptake was recorded by using verified data from official health records, and reconciling these records with study participant lists. In order to be deemed vaccinated, vaccination was required to have taken place within 6 weeks of the initial treatment. *Used in chapter 7.*

3.4.2 Income-related variables

The variables below are used as ranking or level variables in concentration indices, or as measures to test between country inequalities, and form a key component of the analyses in this thesis. Additional measures are contained in the sensitivity variables section.

3.4.2.1 Equivalised household income

Respondents in the CANDOUR survey were asked to select the band (from >10 bands) in which their household income fell for a given time period, including all sources of income received by the household. While household income may not be the best measure for socioeconomic status, it is frequently used as a proxy in the literature. Different relationships between household income and socioeconomic status that vary systematically between countries could introduce further measurement error between countries despite equivalisation and PPP adjustments (e.g., greater coarsening error in one country relative to another will have implications on cross-country comparisons, where greater coarsening error will artificially reduce inequality in that country); however, these issues cannot easily be addressed, and the CANDOUR data does not include a viable alternative to the categorical income data, which although with limitations, is often used for the purpose of concentration index calculation. As there are >10 income groups in the survey, bias is likely lower than if there were fewer income groups, however, bias is likely still present to some extent.[146] Although the bands are adjusted in each country to account for similar proportions of the populations (e.g., are made context appropriate), countries that are more income-concentrated will have larger downward biases as within income group inequality is flattened. More discussion on possible biases and cross-country comparison implications are contained in the concluding chapter. While a correction approach exists, shown by Clarke and van Ourti,[146] I seek to develop a continuous measure that can be equivalised. Midpoints are an appropriate measure where a firm upper and lower bound to the income band is present.[147] Midpoints are taken for all bands aside from the lowest and highest income bands. Methods exist to impute midpoints of the highest and lowest bands; however, this can over specify and introduce false precision to the analysis. To this end, I take a simple but accepted route of adding a fixed percentage to the lower bound of the highest income band, and subtracting a fixed percentage to the higher bound of the lowest income band.[147] Given the methods of the (rank) concentration index – this is not problematic. Rank indices deal with all equal values in the same manner, and the income smoothing adopted for the level indices adjusts for this. I select a highest midpoint value of 150% (50% premium) of the lower bound of the highest band; and a lowest midpoint of 66.66% (33.33% discount) of the higher bound of the lowest band. However, as the data are categorical, the assumptions implemented to attain a continuous income measure can introduce measurement errors, particularly at the extremes of the distribution. The midpoints are converted into purchase power parity (PPP) dollars, and I equivalise the income levels. Household incomes are equivalised to account for the composition and size of a household.[148,149] There are several equivalence scales which can be employed. Based on the availability of data, I employ the square root scale, which transforms household income by the square root of the number of adult and child residents in the household,[150] up to the maximum truncated value of 8, as described in the household size variable. *Used in chapter 4,5,6.*

3.4.2.2 Equivalised household income (median)

The median income variable is taken as the median of the weighted equivalised household income variable described directly above in each country. *Used in chapter 4.*

3.4.2.3 Percentile income

Respondents are ordered into percentiles based on their equivalised household income after considering sample weights; aiming to achieve 100 groups of equal weight based on the approach by Erreygers and Kessels.[47] Due to sample weights and tied incomes, some groups may only approximate 1% of the population, and in reality represent slightly more or slightly less than 1%. A mid-interval value for each percentile is calculated, taken as

$$Interval\ Income_{ij} = Y_{min_{ij}} + (Y_{max_{ij}} - Y_{min_{ij}})/2$$

Where the minimum and maximum are of the associated income percentile i in country j. This value is then assigned to each respondent in the percentile, and is used as the ranking variable in the Level Index, although it is a somewhat contrived continuous income measure. Using the Level Index on what was initially categorical income data is likely to underestimate true inequality within each income group, and likely faces similar measurement error between adjacent groups (e.g., could increase the difference between individuals on either side of a group boundary by taking the midpoints, and instead of using a rank which minimises this possible discrepancy, weights the difference more so using relative values. The same of course could be true between two people, one at the highest end of income group n, and the second at the highest end of group n+1. The Level Index would reduce this difference, and given even distributions the weighting distortions may balance, but remain distortionary). While the categorical data is converted into a continuous measure and equivalised, there remains a limitation that this is not the intended authentic continuous data for which the level index is designed. The equivalisation process similarly introduces scope for further measurement error within income bands. While I also adopt rank-dependent indices in sensitivity analyses in the chapter and do not find marked differences, there remains a limitation on the use of the Level Index for categorical income measures. *Used in chapter 5.*

3.4.2.4 Equivalised weekly food expenditure

In the Ghana financial incentives trial, the socioeconomic variable is based on weekly food expenditure. Respondents were asked, "How much on average does your household spend in a typical week on food?" While a total expenditure variable is also available in the data, this variable was significantly noisier, as expected, as large, irregular purchases are likely to be included. The mean non-food / food expenditure ratio was 0.29, while outliers in some cases reached ratios as high as 80, which would have outsized influence on the Level Index computation, particularly compared to rank dependent indices. Food expenditure has a 95% correlation with total (food and non-food) expenditure, and does not exhibit the same noise and large outliers. Though the outliers were few, the effect on a Level dependent index can be material. As the Level Index is used for this analysis, the inclusion of large outliers can materially alter the results. For this reason, I selected food expenditure as the socioeconomic variable, however, I include an analysis using the total expenditure variable in appendix D, figure D2. Food expenditure is equivalised using the Organisation for Economic Co-operation and Development (OECD) modified equivalence scale, which accounts for the number of adults and children in the household.[151] *Used in chapter 7.*

4. Income-related inequality in access to healthcare services during the COVID-19 pandemic

4.1 Introduction

The onset of the COVID-19 pandemic saw many health systems overwhelmed in ways that few would have expected. At its extremes, when care was required, certain systems, e.g., Italy and India, among others, were unable to provide care adequately due to the number of COVID patients requiring attention.[6,152] The concept of limited resources in healthcare is familiar to many health systems and practitioners who work in these systems. In these systems, it is often necessary to take decisions that prioritise resources, which can result in individuals receiving, postponing, or being refused care – as in triage environments. While changes in overall utilisation of healthcare during the pandemic have been documented,[153] how these changes translated to challenges for individuals in accessing care at different levels of income has not been studied in depth. It is possible that re-prioritisation associated with the pandemic may have led to changes in how equitably care was provided. Understanding the experiences of patients in diverse contexts is necessary to determine where inequality lies, and take the required steps to address inequality.

Health economics studies frequently employ the concentration index or related measures to quantify inequalities in access to different forms of healthcare, after adjusting for need.[28] However these studies are often limited in their use for global comparisons due to differences in methodology (e.g., different variants of inequality measure), focus (types of access), and timing.

Healthcare access itself can be defined conceptually in several ways. As discussed in the introduction, in their 2013 study, Levesque et al. develop a framework that breaks healthcare access into 6 stages, beginning with healthcare needs, through perception of needs, seeking care, reaching care, utilisation, and outcomes or consequences.[1] The stage I seek to investigate in this chapter is reaching care, conditional on having sought care. I investigate the extent to which people perceive difficulties in reaching care, and how this is associated with socioeconomic status. This chapter includes individuals' subjective perceptions on the difficulties in accessing care and, in this regard, is similar to works by Fjaer et al. and Cylus and Papanicolas.[72] [73]

The literature on cross-country health access comparison is largely concentrated in specialised pathways, (e.g., maternal and child care, elderly care, insurance coverage) or within constrained geographic regions (e.g., Sub-Saharan Africa, OECD, Latin America).[70,154–157] I conducted a literature search focused on the quantitative assessment of socioeconomic or income-related inequalities in access to health services, which is contained in Chapter 2.3.2 of this dissertation.

Current COVID-related cross-country research focuses predominantly on health outcomes and utilisation rather than challenges in access.[158–160] None of the papers identified in the literature search that focused on unmet need used data from the COVID pandemic period. This quantitative multi-country study aims to address this gap in the literature. I apply the Erreygers concentration index to assess inequality in the perceived challenges faced in accessing needed care during the COVID-19 pandemic.[25] The results of this investigation display how healthcare users experienced their country's healthcare system during a period of the COVID-19 pandemic, and can provide insight into future health system disruptions. I investigate healthcare challenges after seeking care and before reaching care, as per Levesque et al. conceptualisation of access,[1] across three types of care: in-person GP appointments; telephone *or* internet (digital) appointments; and surgical *or* clinical admissions. Individuals rated the ease with which they were able to obtain appointments (if required) in each type of care, and these responses were analysed with respect to household income to determine inequality levels. The subjective nature of this question separates this study from previous work. This chapter focuses on challenges accessing care for those actively seeking care, rather than on general and persistent barriers to care, which is the focus of many studies. After estimating within-country inequality in each of the three investigated types of care, I analyse patterns between country inequalities with respect to median national household income, using Spearman's correlation tests.

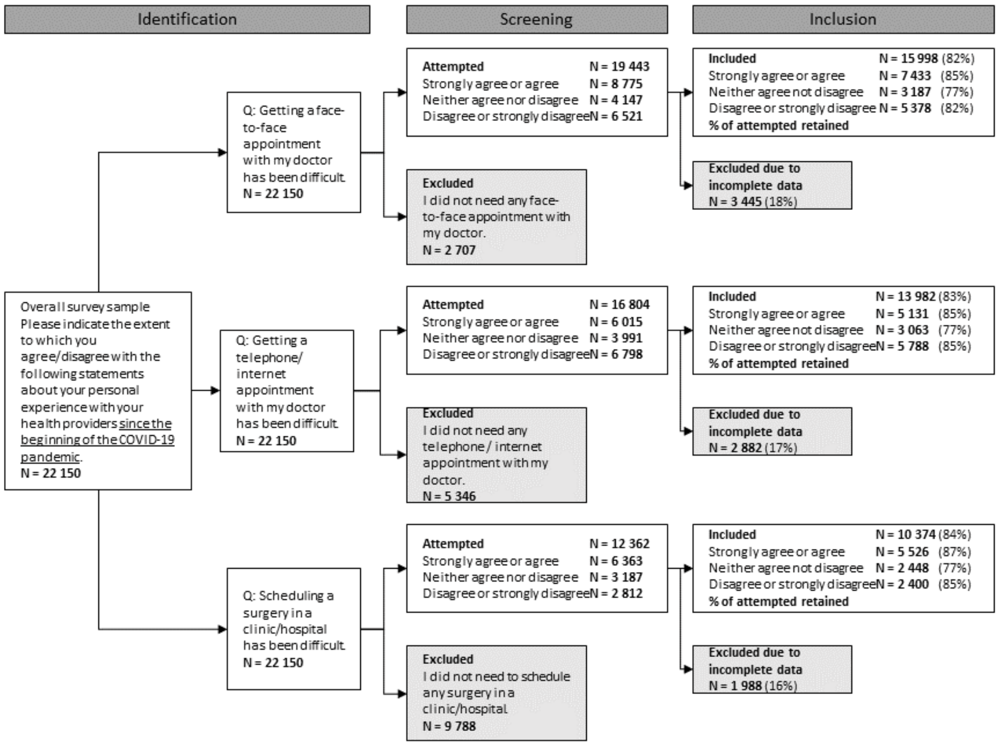
4.2 Data

This investigation was conducted using data collected in the second wave of the COVID-19 Vaccine Preference and Opinion Survey (CANDOUR) study. CANDOUR is an online, multi-country survey for adults aged 18 and over. All participants provided informed written consent before beginning the survey. The wave 2 survey was developed for this and other studies as a follow-on to CANDOUR wave 1. The second wave of the CANDOUR study was expanded from vaccine preferences to investigate public attitudes related to the COVID-19 pandemic more broadly, and included questions specifically developed to assess public attitudes on difficulties in accessing care during the pandemic.

The wave 2 survey was conducted in 16 economically diverse countries using anonymous online surveys from March to November 2022. 22,150 responses were collected, averaging 1,385 per country, ranging from 1,266 to 1,907. The CANDOUR study used quota sampling to ensure representative samples in terms of gender, age, education, and geography in each country. Where imbalances remained, post-stratification weighting was adopted. Analysis was restricted to individuals who attempted to engage with each type of care, and with complete data for the demographic and health standardization variables (discussed in methods). This limited respondents for each of the challenge types to 15,998 for face-to-face GP challenges, 13,982 for digital appointments, and 10,374 for surgical/clinical appointments. The selection methodology and exclusion criteria are presented in figure 4A.

Respondents were asked to rate their experience of getting an appointment in each of the three types of care since the beginning of the COVID-19 pandemic to assess challenges in accessing care. Respondents were asked the extent to which they agreed or disagreed with a statement (i.e., "getting a face-to-face appointment has been difficult") from "strongly agree" to "strongly disagree", with five inclusive ordinal steps, and an option if they did not need care. Responses of "strongly agree" and "agree" were classified as having faced challenges for each type of care. Participants who did not attempt to make appointments were excluded from the analysis of the relevant type of care. Annual household income was self-reported in income bands. This metric was equivalised using the square-root of household size,[150] and converted to purchasing power parity values to allow comparison between countries. All other individual variables used were self-reported in the survey, while a number of sources were used for external aggregate data for the purpose of comparison and validation.

Figure 4A: Individual respondent criteria for inclusion in Chapter 4 analysis flowchart



4.3 Methods

4.3.1 Theoretical framework

I aim to investigate inequality in the challenges that individuals faced in attempting to access care. To assess this inequality quantitatively, I select the Erreygers adjusted concentration index for the analysis due to the desirable properties of the adjusted index; particularly its mirror properties, scale invariance (important for cross-country comparison, which may otherwise obfuscate results based on different means),[25,29,43] and its suitability given the binary characteristics of the transformed barrier to access variable. I conduct a sensitivity analysis using the Wagstaff index and find no notable differences. I elaborate in the sensitivity analysis section.

Following estimation of the concentration indices using the Erreygers adjusted index, I test for correlation between the national indices and national median income using the Spearman's rank correlation coefficient test. In so doing, I explore the relationship between income levels and barriers to equitable healthcare across the sample. Given the nature of the collected data which lacks a prior counterfactual, I do not attempt to draw causal inferences, opting instead to assess whether a relationship exists and its strength at the time of investigation.

4.3.2 Empirical estimation

4.3.2.1 Descriptive analysis

A descriptive analysis was conducted on the sample. The selected variables were also employed for the needs-standardization as health-need variables or controls. The variables described for each country are self-reported gender, age, household size, education level, political leaning, marital status, household income, labour force participation, current health condition, number of chronic conditions, COVID risk and willingness to engage in behaviours that could pose health risks. Age, political ideology, education level, and household income are reported as median values, while the remaining variables are reported as mean values. Where variables are binary – the stated figures represent the percentage of individuals in a country with the stated attribute. A full explanation of each of the variables can be found in the variable description section. Further descriptive statistics were reported for each of the contact and challenge types after standardization, which are employed for the bulk of the analysis contained in this chapter. These were reported as mean values and stratified by income quintile within each country.

4.3.2.2 Indirect standardization

The challenge variables were standardized for health needs indirectly using non-linear regression methods within each country to maintain specificity for the purpose of cross-country comparison. Country specific standardization was conducted accounting for gender, age, current health level, number of chronic conditions, COVID risk, and willingness to risk health. I include the COVID risk and willingness to risk health variables to account for individual likelihood of seeking appointments, as self-reported attitudes to risk have been shown to play a role in health related behaviour and are likely to play a role here.[161,162] For instance, individuals less willing to risk health and at higher perceived risk of contracting COVID may be more likely to seek medical appointments. I further controlled for education level, marital status, political ideology, labour force participation, and household size within each country. I use an expanded set of variables for standardization to account for differences in how respondents may perceive challenges in accessing care.[28] I provide the rationale for inclusion of variables in the expanded standardization set (Appendix Z), and use a restricted standardization of age, gender, and health status as a robustness and sensitivity analysis, both of which are reported in supplementary materials (figures A2-A4).

The standardisation is run using a logistic regression, accounting for the binary nature of the dichotomized challenge variable. Sample weights are included in the regression. Demographic variables (x_{nij}) and non-confounding control variables (z_{mij}) are regressed on the health variable (h_{ij}) – where i is the individual respondent in country j, and α, β and γ are parameter vectors.

$$\Pr\left(h_{ij} = 1 \mid x_{nij}, z_{mij}\right) = \frac{1}{1 + e^{[-(\alpha + \sum_n \beta_{nj} x_{nij} + \sum_m \gamma_{mj} z_{mij})]}}$$

Using logistic parameter estimates $\hat{\alpha}$, $\widehat{\beta_{nj}}$ and $\widehat{\gamma_{mj}}$; actual individual values x_{ij}; and sample means of the non-confounding $\bar{z}_{mj}$ variables per country, I predict the x-expected values of the health variable, $\widehat{h^x}$. Mean values of $\bar{z}_{mj}$ are taken rather than alternatives (such as the maximum observed per country, or some target value). The choice of $\bar{z}_{mj}$ is particularly important as the logit model is not additively separable. I select the mean level to standardize non-need differences within each country for a country specific control. Though for some variables (e.g., education, which is categorical) this does not have an innate meaning, it still has statistical content. The mean considers the entire distribution of a country's non-needs variables. Choosing maximums, target quintiles (e.g., 90th percentile), or even medians could smooth over the distribution if countries achieve similar maximums or are centred around the same point, and impose a benchmark not reflective of the population; either by considering the tails exclusively, or by not considering them enough. Such measures also rely more on normative reasoning, whereas the mean provides a distribution weighted reference value unique to each country.

$$\widehat{h^x} = \frac{1}{1 + e^{[-(\hat{\alpha} + \sum_n \hat{\beta}_{nj} x_{nij} + \sum_m \hat{\gamma}_{mj} \bar{z}_{mj})]}}$$

The standardized health variable, $\widetilde{h^s}$ is thus taken as the difference between actual and x-expected health variable, plus the sample mean per country.

$$\widetilde{h^s} = h_{ij} - \widehat{h^x} + \overline{h_j}$$

4.3.2.3 Concentration indices

Concentration indices are calculated for each country and each challenge variable, yielding a total of 48 (16 countries x 3 types of care) indices. Indices are calculated using the Erreygers adjusted index. The Erreygers adjusted concentration index was utilised given the desirable properties for binary variables.[25] The index is calculated as follows:

$$E_j(\mathrm{h_j}) = \frac{8}{n_j{}^2\,(b_h - a_h)} \sum_{j=1}^{j} \sum_{i=1}^{n} z_{ij} h_{ij}$$

Where i is the individual respondent; j is the country; h_{ij} is the measure of the standardized health variable (challenge status); b_{hj} and a_{hj} are the upper and lower bounds of h_{ij} respectively; n_j is the sample size and z_{ij}, a weighting variable of relative socioeconomic rank (equivalised household income in this analysis).[25]

The health variable used for the analysis is a dichotomised variable asking the extent to which the respondent agreed or disagreed with the statement that "getting a [*care type*] appointment has been difficult." The full question and response set is available in the variable description. The health variable is standardised using indirect standardisation techniques,[28] accounting for both confounding variables and non-confounding control variables. Indirect standardisation was implemented within each country, effectively allowing for country-specific relationships with covariates to be retained in the analysis for later comparison between countries, without introducing artificial controls, and allowing country level differences in health need norms through the health-need and control variables to be accounted for. The standardization accounts for gender, age, education level, marital status, political ideology, household size, health levels, number of chronic conditions, and perceived COVID risk.

4.3.2.4 Multivariable regression

I run a multiple regression using a range of country level aggregate independent variables regressed on the 16 country inequality indices in each of the three types of care. I aim to identify possible explanatory variables which are correlated with within country inequality as measured by the concentration index, and thus can be used to explain between-country variation. I include median household income as calculated from the survey, national health expenditure, COVID containment policy index, health worker density, internet access, and corruption levels.

I test the variables for their joint and separate relationship with the defined inequality indices by combining the variables in a multiple linear regression. The regression is specified below:

$$Y_{ij} = \beta_{ij} x_{ij} + \varepsilon_j$$

Where Y_{ij} is the calculated concentration index per challenge in each type of care in country j, and x_{ij} are the proposed explanatory variables.

4.3.2.5 Correlation computation

Extending the analysis from within-country (which is completed with the concentration index), I seek to identify if there is a systematic relationship between (inequality within) countries based on income. Establishing a causal relationship given the size and characteristics of the dataset at the country level is not feasible. The sample size (16 countries, when aggregated into indices) simply does not allow for the level of detail in confounding variables that would be required to fully model the relationship without introducing omitted variable bias. Identification assumptions are unlikely to be met even with a significantly larger number of countries included, making it unlikely that such a method could establish a causal relationship. As such, I have chosen to use a correlation measure. In so doing, I can establish if there is a relationship which can be further investigated, rather than ascribing spurious causality.

The correlation coefficient used is the standard Spearman's rank correlation coefficient, testing for a monotonic relationship between the within-country concentration index and national median household income. I employ the Spearman test over the Pearson test, as the result of monotonicity is deemed more valuable than linearity in the interpretation of results and answering the question at hand – of whether a relationship (that needn't be linear) exists between country health inequality and country income levels.

The Spearman's rank correlation coefficient is defined as:

$$\rho_j = 1 - \frac{6 \sum {d_{ij}}^2}{n_j({n_j}^2 - 1)}$$

Where d_{ij} is the difference between the two ranks of observation i in country j, and n_j is the number of observations in country j. The associated significance level, or p-value, is thus the likelihood of obtaining a relationship as monotonic as that observed in the data if the underlying population is in fact non-monotonically related.

4.3.3 Sensitivity analysis

4.3.3.1 Alternative concentration index specification

While I believe the Erreygers adjusted concentration index is the best fitting index to use for the analysis, I nonetheless compare the output of the Erreygers test against the Wagstaff index, also suitable for binary variables. I do this both within each country and across the countries in the dataset. The primary difference between the two indices is that for feasible uniform changes, Wagstaff's inequality changes whereas Erreygers' remains invariant. That is to say, if all respondents were 3% more likely to be challenged in obtaining an appointment (provided the maximal likelihood before was <97% for each country); the Erreygers index would produce the same index value under both circumstances, whereas inequality would change using the Wagstaff index, giving it quasi-relative characteristics, whereas the Erreygers' index is quasi-absolute.[42]

4.3.3.2 Restricted standardization

In the standardization presented in the analysis, I use an expanded set of demographic and health variables. I do this to account for subjectivity in the answer to the key question of the chapter. However, I also run a restricted standardization including only self-reported health, age, and gender – and do not control for other potential confounding variables as I do in the main analysis.

4.3.3.3 Alternative income measures

I test several other income measures against the CANDOUR survey-sourced household median income measure. I do this as a means of external validation, comparing externally sourced aggregate country income data against the CANDOUR income measure. I test this simply by running correlation tests between the survey-based household median income with the external income measures and comparing results. For this test, I employ median annual household consumption data and Gross National Income (GNI) per capita in purchase power parity dollars (at both current and 2017 constant prices) against the survey-based median income measure. I report both the Pearson correlation coefficients for these income measures. GNI does not quite reflect the measure I want, being a mean value; and the median daily (converted to annual) household income/consumption figure is aged (2019) – however the metrics stand to validate my own income measures.

4.3.3.4 Testing alternative correlations

I test several other variables against within-country inequality using Spearman's correlation rank coefficient test. This is to determine if other variables may have as strong a relationship with within-country inequality as national median household income. The variables selected for testing are national spend on healthcare services; mean containment and severity levels of COVID-19 lockdowns; number of medical practitioners; internet access; and perceived corruption. The test is conducted using a Pearson's correlation coefficient test. A full description of the variables used in this chapter is found in the variable description appendix Z.

4.4 Results

4.4.1 Descriptive overview of the sample

The full wave 1 sample descriptive statistics are displayed in table 4A, while sub-group sample descriptive statistics are available in the appendix (tables A1-A3). Some of these subgroups show variation in the descriptive variables across countries. This is due to the restricted sample employed for the analysis, and in some cases a result of the original sampling which did not achieve full representativeness. The variation has implications for the representativeness and generalisability of the work where certain countries do not mirror the overall population in the subsample (e.g., Ghana has only ~19% female respondents). All selected variables were reported as mean values apart from age, household income, education level, and political ideology, which were reported as medians. I report standard deviations alongside means and interquartile ranges alongside medians. Where variables are binary, the stated values represent the percentage of individuals in a country with the stated attribute. The overall study sample is 50% female. The median respondent has completed secondary education and is 39 years old. 70% of the sample is economically active in the labour force. Average self-reported health on a scale of 0-100 (where 100 is perfect health) is 68.9%. The average respondent had 0.6 chronic conditions, with an average willingness to risk health of 3.5/10. The samples within individual countries in table 4A varied. Comparisons between countries and subgroups can be completed using tables 4A and A1-A3. Respondents that attempted to seek any care (n=16,367), and thus were included in this study, are on average lower income earners, in worse self-perceived health, younger, more likely to be employed, slightly better educated, more likely to be male, and more willing to take risks with their health than those who did not attempt to seek care (n=5,783). Results of statistical tests between the sub-samples, and the observed differences are available in table A4.

The subgroup descriptive statistics (tables A1-A3) enable a perspective of differences between the individual respondents who interacted, or attempted to interact with each type of care. Demographic comparisons are drawn against the overall sample to show the differences between those who attempted to interact contrasted with those who did not. Distinctions between the sub-groups are evident in the tables.

Most countries had higher median ages in the subgroups than for the overall samples. Ghana and South Africa had the same median ages for each of the subgroups and overall samples. The USA was the only country which had consistently younger subgroups (those who sought care) compared to the overall sample. France, India, Italy, and Uganda each presented with subgroups at least the same age or younger than the overall sample. Japan was the only country with a mixed difference – as those seeking in person GP appointments were on average older than the total sample, those seeking surgical admissions or digital appointments were younger. The remaining countries presented older or at least as old subgroup populations, with the in-person GP subgroup having the greatest average median age of 43 years.

Table 4A: Overall sample descriptive statistics

	Median Age (years)	Female (%)	Median Education level[2]	Med. Income (PPP$ '000s)	Labour force participation (%)	Self-reported health (%)	No. Chronic conditions (n)	Willingness to risk health[3]	Sample size (n)
Overall	39(27-55)	50(50)	3(3-4)	14.7(4-32)	70.0(46)	68.9(27)	0.60(0.9)	3.5(2.9)	22,150
Australia	41(28-56)	59(49)	3(3-4)	28.6(16-57)	67.8(46)	64.7(25)	0.74(0.9)	4.1(2.9)	1,907
Brazil	33(26-54)	54.9(49)	3(1-3)	5.3(2-9)	53.7(49)	66.8(26)	0.62(0.9)	3.2(3.0)	1,301
Canada	30(23-55)	65.8(47)	4(3-4)	35.7(14-50)	74.4(43)	70.8(25)	0.59(0.8)	3.4(2.4)	1,350
Chile	32(25-43)	57.8(49)	3(3-4)	12.2(8-20)	68.8(46)	72.6(20)	0.72(0.7)	3.2(2.6)	1,390
China	43(28-53)	49.2(50)	3(3-3)	20.5(13-28)	73.1(44)	78.3(21)	0.35(0.6)	3.3(3.1)	1,363
Colombia	48(31-60)	49.7(50)	3(2-3)	8.9(4-14)	65.5(47)	59.7(35)	0.58(0.8)	3.4(2.6)	1,332
France	49(35-61)	58.7(49)	3(3-4)	29.2(15-46)	54.1(49)	68.9(25)	0.53(0.7)	3.5(2.8)	1,343
Ghana	30(26-34)	19.8(39)	4(3-4)	0.9(0.5-5)	75.7(42)	84.6(17)	0.17(0.4)	3.3(3.2)	1,266
India	31(25-40)	45(49)	4(2-4)	3.5(2-10)	87(33)	49.5(35)	0.75(1.0)	5.5(2.8)	1,444
Italy	52(40-62)	57.6(49)	3(3-3)	24.1(16-37)	56.7(49)	69.8(22)	0.65(0.8)	2.9(2.8)	1,428
Japan	55(36-65)	52.2(49)	3(3-4)	31(12-45)	77.2(41)	69.1(23)	0.66(0.9)	3.9(2.5)	1,364
South Africa	36(27-47)	46.8(49)	3(2-3)	8.9(0.1-24)	79.4(40)	69.2(27)	0.77(1.2)	2.6(2.4)	1,330
Spain	44(33-61)	48.4(49)	4(3-4)	30.5(22-54)	47.3(49)	70.7(28)	0.48(0.7)	2.8(2.7)	1,342
Uganda	28(25-36)	25(43)	3(3-3)	0.2(0.06-0.5)	91.3(28)	73.8(22)	0.34(0.7)	3.1(2.6)	1,292
UK	42(32-51)	52.9(49)	3(3-4)	23.5(11-41)	76.8(42)	64.5(23)	0.68(0.9)	4.2(2.9)	1,383
US	44(28-59)	52(49)	3(3-4)	35(18-51)	70.4(45)	69.5(23)	1.02(1.0)	3.4(2.8)	1,315

1. Figures are presented as mean(Standard Deviation (SD)) and median(Interquartile Range (IQR))
2. 1 = less than primary completed; 2 = primary school completed; 3 = secondary school completed; 4 = university completed
3. Respondents were asked how willing they were to risk their health from 0 to 10.

The subgroup samples were significantly more male dominated than the overall sample. Spain and South Africa were the only countries to have consistently greater female proportions in the subgroups. Colombia presented with more females in the surgical admissions subgroup and

India had marginally more females in both the surgical and digital subgroups than the overall sample. Uganda had a 20% higher proportion of females in the in-person GP subgroup than in the country. Overall, the subgroups were on average 3.5 – 4.5 percentage points more male than the overall sample, implying that males were more likely to seek care than females within the sample.

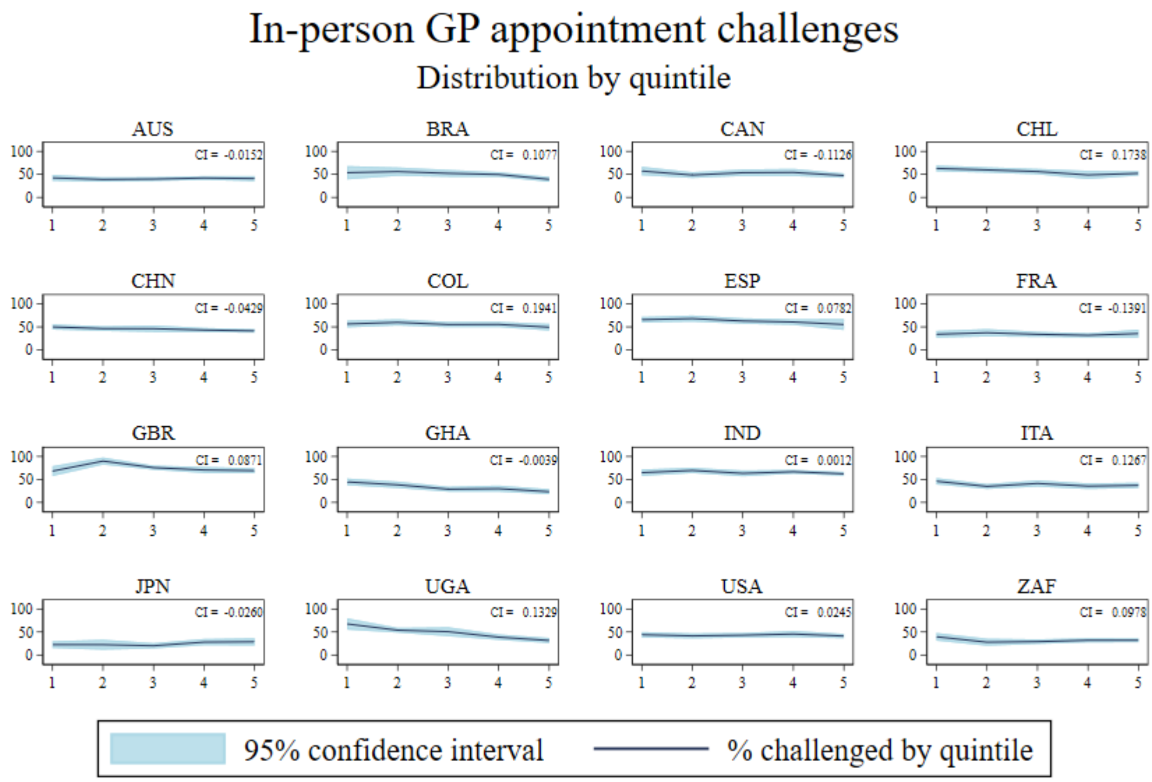
Australia, Brazil, Ghana, India, South Africa, Spain, and the United States all reported consistently higher levels of general health in the subgroups seeking care than in the overall sample. Canada, Chile, China, Colombia, France, and Italy all had lower levels of self-reported health among those seeking care. The United Kingdom, Uganda, and Japan were mixed. Each of the UK and Uganda had generally higher levels, apart from in the in-person GP subgroup (UK) and digital appointment subgroup (Uganda). Japan had higher self-reported health levels only in the in-person GP subgroup.

In terms of median income, Australia, Brazil, France, the UK, and the USA all had higher median incomes across the subgroups than the overall sample. Only Chile and Colombia had consistently lower median incomes across the subgroups, while Uganda and Italy remained the same, but had lower median income in the surgical admission subgroup. Contrasting the self-reported health differences and the income differences from the subgroups to the overall sample indicate that within the sample, there may be a bias for those seeking care to generally be healthier and earn higher-incomes. This variation is not captured in the subsequent inequality analysis, however, it is nonetheless an additional layer pointing to inequality in a number of these systems even before patients begin the process of *accessing care*. This is prevalent most notably in the USA, followed by Brazil and Australia based on the health and median income levels of the subgroups relative to the overall samples in this study.

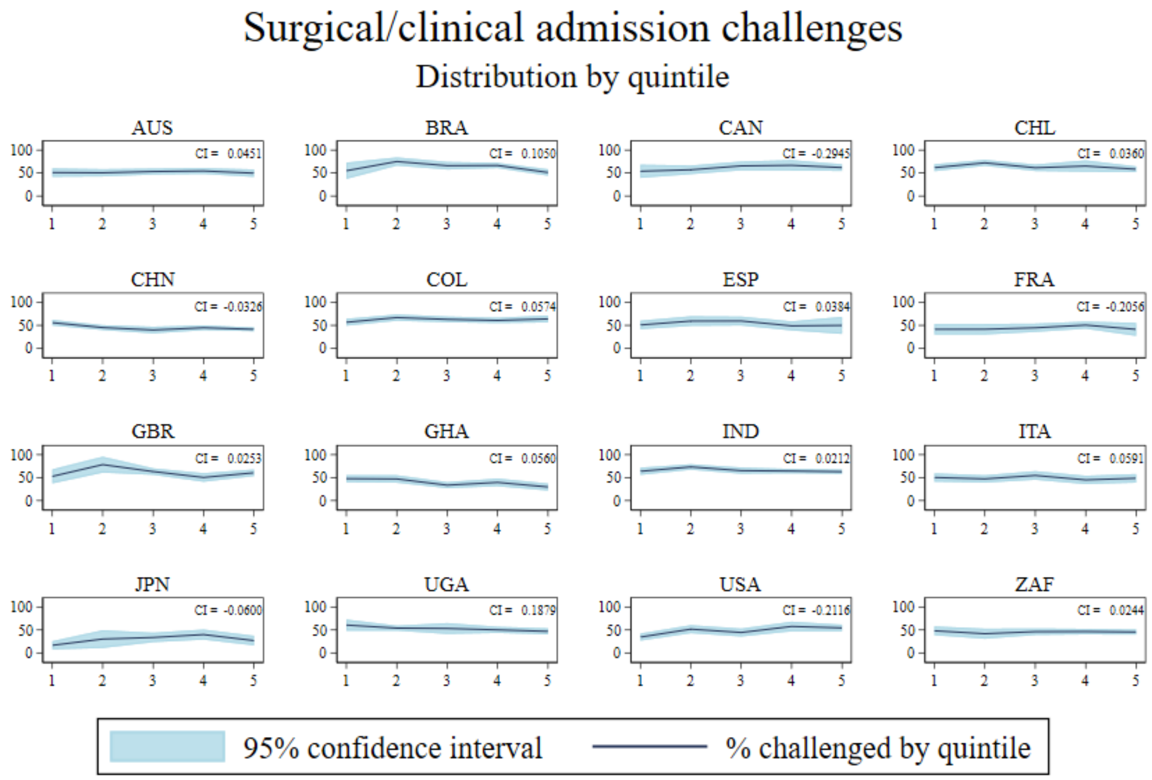
4.4.2 Within country inequality gradients

Healthcare challenges to access were investigated across income quintiles (Q1 = lowest income quintile; Q5 = highest income quintile) within each country, conditional on attempting to interact with the respective type of care. I observe ranges in the proportion of populations challenged while seeking care from 21% (Japan Q3) to 89% (United Kingdom Q2); 17% (Japan Q1) to 78% (United Kingdom Q2); and 10% (Japan Q1) to 63% (Spain Q2) in the in-person GP, surgical or clinical, and digital care types respectively. These results, shown graphically in figure 4B, present the gradient of inequality within each country across each of the types of care. Uganda and Ghana show increasing ease of access with income across each type of care, evidenced by the downward sloping "challenged" lines. Concentration indices were calculated, and are estimated on each of the panels in figure 4B, providing firm numerical estimates of within country inequality.

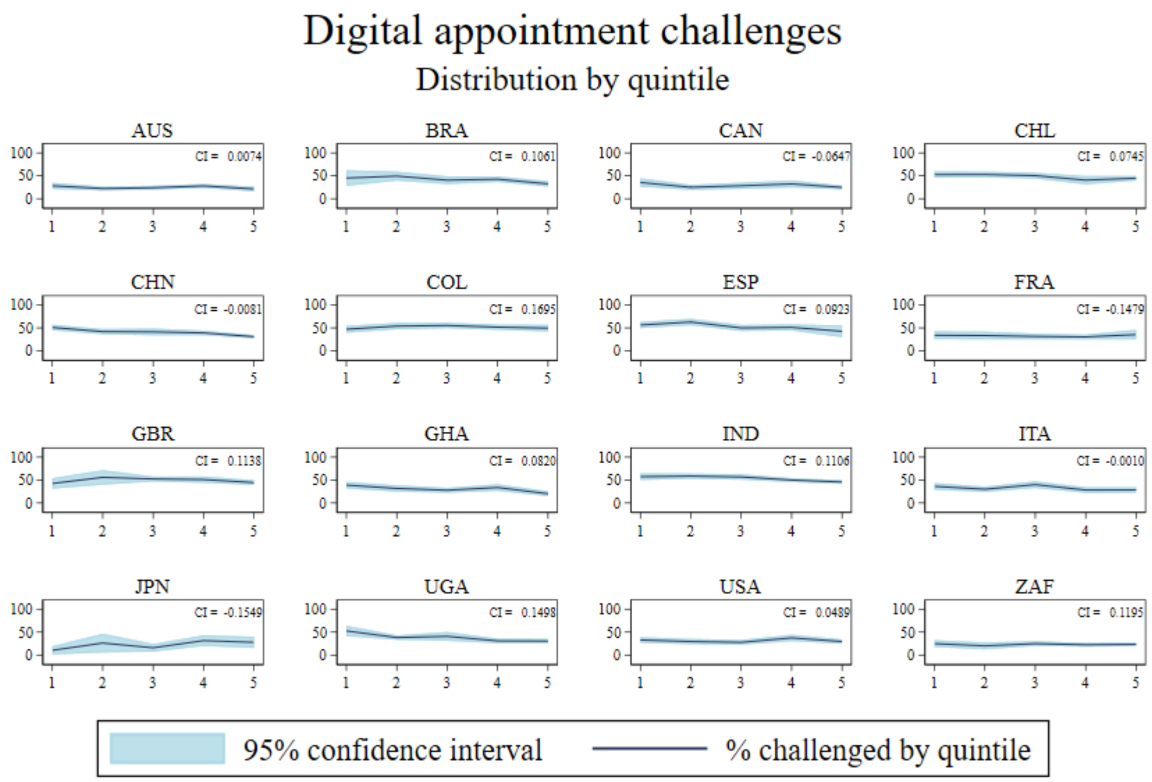
Figure 4B: Graphical representation challenge statistics by type of care, quintile, and country



Proportion of quintile facing challenges in obtaining an appointment
Erreygers concentration index reported



Proportion of quintile facing challenges in gaining admission
Erreygers concentration index reported



Proportion of quintile facing challenges in obtaining an appointment
Erreygers concentration index reported

4.4.3 Regression identifying correlations with inequality

I run a simple multiple regression of possible explanatory variables on inequality in each of the types of care. I include median household income as calculated from the survey, national health expenditure, COVID containment policy, health worker density, internet access, and corruption levels in the regression. The results are presented in table A5. In each type of care, national median income is significant. The result is small, however the value reflects the impact of individual purchasing power parity (PPP) dollars on the concentration index. In reality, differences between country median incomes are larger, leading to the impact effect being magnified. For example, a $1,250 increase in PPP dollars (roughly the difference between French and Spanish median incomes in the data) represents a decrease of the inequality index of ~0.01 across each of the challenge pathways – significantly larger than the other covariates. The effect of income is always negative, as expected given the graphical quintile results.

Medical practitioner density is the only other variable of significance in the regression. It is positively associated with inequality, producing an unexpected result, though non-significant in the digital channel. Containment and internet access also produced negative associations with each of the challenge variables, with meaningful, though insignificant effects. Corruption is found to have a positive effect on inequality, confirming existing literature, though I did not find significance in this analysis.

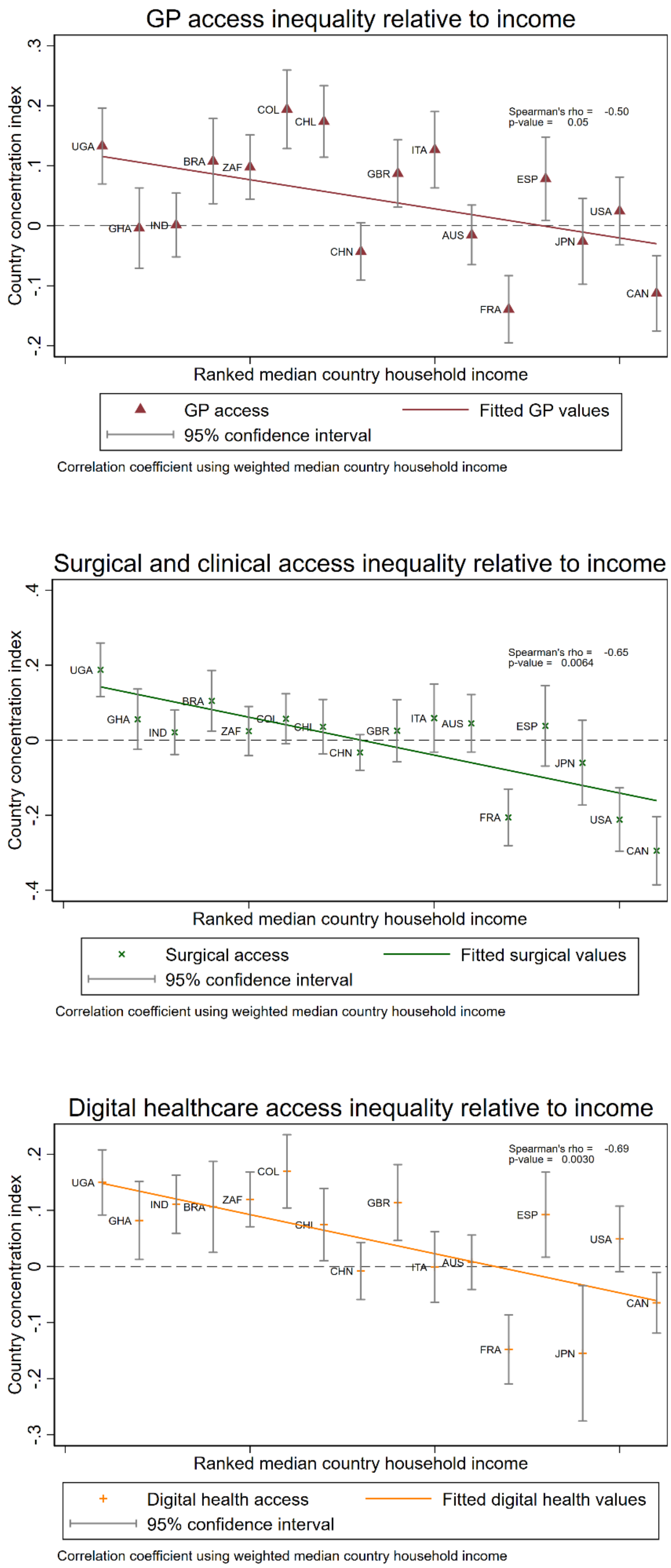
4.4.4 Between country inequality

The results of the computed concentration indices between countries are reported against median income graphically in figure 4C. A sensitivity analysis on medical practitioner density is included in the appendix. Within country inequality in figure 4C is presented with the country's concentration index, plotted on the chart as a point on the y-axis, with a 95% confidence interval. Results using the restricted standardization are reported in the appendix (figures A2-A4). Correlations on income are robust to standardization, however correlations on medical practitioner density weaken using a restricted standardization. I observe ranges in the inequality indices from 0.19 (Colombia) to -0.14 (France); 0.19 (Uganda) to -0.29 (Canada); and 0.17 (Uganda) to -0.15 (Japan) in the in-person GP, surgical or clinical, and digital care types respectively.

Between-country inequality is shown in figure 4C by the trend-line and the correlation measure between the inequality indices and median national household income. Results are negatively sloped in each of the types of care investigated. Median income has the largest observed correlation in the digital care-type, with a calculated Spearman's correlation coefficient of -0.69 and p-value of 0.003. The surgical/clinical type of care follows closely with a correlation of -0.65 and p-value of 0.006. Results in the GP channel are weaker. The negative monotonic relationship between median income and inequality is observed across each of the variables investigated, effectively implying that lower median country income is associated with higher inequality in reported challenges to accessing care during the COVID-19 pandemic.

When comparing between countries on the basis of medical practitioner density in figures A5-A7*,* the results are similar to the median income comparison, though with weaker correlations. These results are more dependent on the standardization method used. Results are negative in the digital care type, with a Spearman's correlation of -0.47 and p-value of 0.06. The relationships in the in-person GP challenge and surgical or clinical admission types of care are weak and flat. Using restricted standardization produced much weaker correlations (Appendix figures A8-A10).

Figure 4C: Challenge inequality by type of care and country-ranked median income levels



4.4.5 Sensitivity analysis

4.4.5.1 Alternative concentration index specification

In table 4B, I report the Erreygers and Wagstaff indices for the challenge variable in each type of care respectively. Although computation and interpretation of the Erreygers index (and other absolute indices) has nuances relative to the standard concentration index (and other relative indices), given that the rankings do not materially differ under both the Wagstaff and Erreygers' index, I do not feel this is material in this instance.[27]

Table 4B: Comprehensive computed concentration index results

	Erreygers Index			Wagstaff Index		
	In person GP challenge	Surgical/clinical challenge	Digital challenge	In person GP challenge	Surgical/clinical challenge	Digital challenge
Australia	-0.015	0.045	0.007	-0.016	0.045	0.010
Brazil	0.108	0.105	0.106	0.108	0.115	0.108
Canada	-0.113	-0.295	-0.065	-0.120	-0.295	-0.099
Chile	0.174	0.036	0.074	0.176	0.038	0.075
China	-0.043	-0.033	-0.008	-0.045	-0.035	-0.009
Colombia	0.194	0.057	0.17	0.195	0.060	0.172
France	-0.139	-0.206	-0.148	-0.155	-0.210	-0.169
Ghana	-0.004	0.056	0.082	-0.004	0.056	0.087
India	0.001	0.021	0.111	0.001	0.023	0.112
Italy	0.127	0.059	-0.001	0.130	0.060	-0.001
Japan	-0.026	-0.06	-0.155	-0.038	-0.071	-0.204
South Africa	0.098	0.024	0.12	0.114	0.026	0.161
Spain	0.078	0.038	0.092	0.084	0.039	0.093
Uganda	0.133	0.188	0.15	0.157	0.211	0.166
UK	0.087	0.025	0.114	0.124	0.032	0.114
US	0.024	-0.212	0.049	0.025	-0.212	0.058

In most cases, these differences are small, however in some cases they are more marked than others. The largest relative differences are in Digital challenges for Canada (52%); in-person GP challenges for Japan (46%); Digital challenges for Australia (43%); and in-person GP challenges in the UK (43%). The Wagstaff index produces estimates that are on average 10%, 7%, and 14% higher than the Erreygers Index for in-person GP, surgical/clinical, and digital challenges respectively.

However, there are only two changes in the ranks of the indices across all measures. Under the Erreygers index; Brazil ranks 5th least equal for in-person GP challenges, while the UK ranks 7th. Under the Wagstaff Index, these rankings are reversed, while the remainder of the countries maintain their previous ranking order. This change is due to the difference in means of the two countries, as the UK has a significantly higher mean proportion of respondents being challenged, which alters the index calculation between absolute and relative measures (seen in figure A1).[29] The only other change is in the surgical/clinical admissions challenge area. Italy reported an inequality index of 0.059, and Colombia of 0.057, ranking them 3rd and 4th most unequal under the Erreygers index. Using the Wagstaff index, both countries report values of 0.060, ranking 3.5.

Overall, while the index values themselves do deviate using either the Erreygers of Wagstaff index, the relative positioning is largely unimpacted under either calculation. As I am searching for monotonic relationships between income and inequality, the output remains unchanged, apart from a minor difference in the in-person GP type of care.

4.4.5.2 Restricted standardization

In figures A2 – A4 (Appendix A), I present the between country results using the restricted standardization. In these figures the impact of standardization both within and between countries compared to the full standardization in the main body of work is evident. It is clear that the method of standardization does have some impact on the results. This is particularly true for the correlations between inequality and number of medical practitioners in each country, and for the in-person GP correlations against income. The digital and surgical or clinical challenges are relatively robust to the standardization, though both variables do see a decrease in significance and strength of correlation. I do not believe the restricted standardization fully captures the income-related inequalities due to the subjective nature of the question posed. The confounding variables which are often associated with income (e.g., education) may obfuscate the true impact of income in the analysis. By failing to control for a number of (these) sociodemographic factors, which may also be social determinants of health, the effect of income on the bivariate measure of inequality is clouded amongst these other measures. The *true* measure of inequality could lie within the bounds of the two standardizations I utilise in this chapter. While I accept that these estimations are imperfect tools, I believe these to be fair bounding approximations of the inequality in the sample given the data and methods available.

4.4.5.3 Alternative income measures

Using external measures of income, I seek to externally validate my own income measure as calculated in the survey.

Table 4C: Alternative income measure correlations

Variables	(1)	(2)	(3)	(4)
(1) PPP Median household income	1.000			
(2) PPP Median annual consumption	0.923*** (<0.001)	1.000		
(3) PPP GNI per capita at 2017 constant prices	0.941*** (<0.001)	0.973*** (<0.001)	1.000	
(4) PPP GNI per capita at current prices	0.934*** (<0.001)	0.970*** (<0.001)	0.999*** (<0.001)	1.000

**** p<0.01, ** p<0.05, * p<0.1*

Each of the external variables is strongly and significantly correlated to the constructed median household income data based on the survey data. The weakest correlation is between the PPP annual consumption variable and median household income. The PPP annual consumption variable is the variable most similar in nature to the selected household median income variable, and the only other median income variable that was accessible. While the correlation is the weakest shown, it remains a strong correlation that is statistically significant, and provides strong evidence that the survey measure is externally valid. Difference in measurement periods, sampling bias, and different measurement techniques could all account for the difference shown. However, as a means of external validation, the variables are close enough foils to externally validate the CANDOUR income measure.

When I correlate the various income measures against the inequality indices across countries, I see that median household income remains the most correlated option. In addition to this, only the median values are significant across each of the three types of care. Median household income is marginally more significant than median annual consumption in each of the types of care. These results indicate that median household income is the best variable of those considered for the analysis at hand.

Table 4D: Correlating alternative income measures to inequality

	In-person GP Challenge Inequality	Surgical / clinical admission Challenge Inequality	Digital Challenge Inequality
Variables	(1)	(2)	(3)
(1) PPP Median household income	-0.501**	-0.721***	-0.678***
	(0.048)	(0.002)	(0.004)
(2) PPP Median annual consumption	-0.468*	-0.652***	-0.630***
	(0.068)	(0.006)	(0.009)
(3) PPP GNI per capita at 2017 constant prices	-0.385	-0.661***	-0.573**
	(0.141)	(0.005)	(0.020)
(4) PPP GNI per capita at current prices	-0.379	-0.661*	-0.570**
	(0.148)	(0.005)	(0.021)

**** p<0.01, ** p<0.05, * p<0.1*

4.4.5.4 Testing alternative correlations

I find household median income to be the most consistent and most strongly correlated variable with each of the three inequality indices produced across the 16 sample countries. A similar analysis is contained within the earlier regression analysis, which jointly tests the proposed variables and finds median household income to be the best explanatory variable across the challenge indices. National health spend is also correlated to the surgical and digital variables, albeit with less strength and significance. However, it comes close to median income in the surgical or clinical admissions type of care. The perceived corruptions index is also significant and strongly correlated with inequality in the surgical or clinical and digital challenge types of care, however it is insignificant with the in-person GP type of care. Given the results of the regression which jointly test the variables and find significance in only median household income and number of medical practitioners, I find there is insufficient cause to further investigate the variables below apart from those already selected (Median household income and medical practitioner density).

Table 4E: Alternative correlations testing

	In-person GP Challenge Inequality	Surgical / clinical admission Challenge Inequality	Digital Challenge Inequality
Variables	(1)	(2)	(3)
(1) PPP Median household income	-0.501**	-0.721***	-0.678***
	(0.048)	(0.002)	(0.004)
(2) National health spend per capita	-0.371	-0.676***	-0.444*
	(0.157)	(0.004)	(0.085)
(3) COVID policy response containment index	0.027	0.003	0.023
	(0.920)	(0.990)	(0.933)
(4) Number of medical practitioners in country per capita	-0.076	-0.309	-0.377
	(0.780)	(0.243)	(0.151)
(5) Internet penetration level	-0.232	-0.505**	-0.381
	(0.388)	(0.046)	(0.145)
(6) Perceived corruption index	-0.421	-0.616**	-0.617**
	(0.104)	(0.011)	(0.011)

**** p<0.01, ** p<0.05, * p<0.1*

4.5 Discussion

4.5.1 Summary of results

This study investigated the relationship between income levels and inequality in accessing health services in three different care pathways across 16 socioeconomically diverse countries. In around half the countries studied, I observe significant inequalities in access to care based on the difficulties in accessing care reported by respondents. In terms of understanding global patterns of inequality between countries, a regression analysis indicated that country level median income was most strongly correlated with inequalities in access. For example, I observe a correlation of -0.69 between the measure of national median household income and inequality in challenges to access to internet or telephone (digital) appointments, and a correlation of -0.65 in challenges in obtaining surgical or clinical admissions, suggesting that citizens in lower- and middle-income health systems faced greater inequality in accessing care during the COVID-19 pandemic (the World Bank country income classification is available in table A6).

4.5.2 Comparisons to existing studies

While there is a significant literature on inequality for particular types of care within individual countries and regions,[70,85,154–157,163] globally representative quantitative analyses during and post the COVID-era are rare. Though there is a growing body of research linking inequality in health outcomes during the pandemic, investigations on access (a precursor to outcomes) remain limited. The strength of this study lies in the ability to compare inequality across 16 countries, accounting for roughly half of the world's population, for challenges in three different types of care (in-person GP care, surgical or clinical care, and digital care). The three types of care investigated cover a significant portion of patients' primary care contacts with the healthcare system, making them important markers of initial and subsequent access. The countries included in the analysis cover each of the World Bank country classifications by income, and are geographically diverse, covering each of the six continents (excluding Antarctica).

In person-GP and surgical or clinical admissions inequalities in context

Research on access to healthcare during the COVID-19 pandemic is sporadic across countries and types of care. Several previous studies provide additional context or support to the results of this study. Research has found temporarily heightened inequalities in GP consultation utilisation in the UK,[164] consistent with my estimates for inequality in challenges to in-person GP appointments during the pandemic. In the UK, the most deprived areas faced marginally larger reductions in hospital admissions than the least deprived areas, despite the higher incidence and mortality of COVID-19 among lower socioeconomic status groups.[165–167] These results and other previous work showing a socioeconomic gradient to accessing surgical care,[168] support the surgical or clinical access inequality point estimate. Research has found that in Uganda, lack of financial resources was the primary reason cited for being unable to access medical treatment,[169] consistent with my broadly unequal results found in each care type in the country. Research in South Africa suggests that observed worsening health inequalities during the pandemic were due to effects of lockdown, felt and borne disproportionately by the poor.[170] This study supports the hypothesis that inequalities were borne more by the poor. Canada, Italy, Japan, and Spain each took measures to reach vulnerable groups during the pandemic, reducing challenges to access across the health system.[171] I reported pro-poor point-estimates in half of the instances concerning these four countries excluding the digital channel. Inequitable results broadly supporting my findings were observed in the south of Brazil for specialised health services, though I cannot perfectly match the types of care to my own.[89] A 2021 report addressing differences in health systems between the US and other high-income countries found Australia to provide the most equitable access to care, care process, and administrative efficiency.[172] The UK, France, and Canada followed, with the USA performing the worst and placing last. The 2021 study also investigated access to care in detail, combining metrics of affordability and timeliness. The UK placed first in access, driven by the affordability of the National Health Service (NHS) system, followed by France, Australia, Canada, and the USA.[172] While it is difficult to draw direct comparison with my results due to the specific nature of the metrics used in each study, it is necessary to note the disparities. On average, across the three types of care I investigate, France and Canada are the most equitable, followed by the USA, Australia, and the UK. A possible explanation is that this study focuses on those who attempt to gain access to health systems and face challenges, but does not incorporate those who do not seek care initially due to affordability and other barriers, which is captured in the corresponding report.[172] A second potential reason for the observed disparities, aside from the metrics measured, are the methods employed; the 2021 report compares equity with only two income groups; above and below the median income,[172] compared to my more granular measure using several income groups across the distribution.

Contextualising the digital healthcare results

Digital health inequalities were not found in Japan in previous work during the pandemic, contrary to my own findings which showed pro-poor accessibility of digital services.[173] The surveys used in this study were conducted two years after the previous work in Japan, offering timing as a possible explanation for the different results observed. Previous work has found that low-income Zone improvement plan (ZIP) codes were still less likely to seek care digitally compared to better-off counterparts in the USA during the pandemic,[174] which is consistent with my finding in digital care in the USA. Temporarily increased inequalities in the use of tele-health services were found in the UK during the earlier stages of the pandemic,[175] but this returned to equitable levels in subsequent months.[164] It is notable that several high-income countries took steps to improve digital accessibility during the pandemic to reach vulnerable citizens, including reimbursement and subsidisation of teleservices, practice guidelines, and removing requirements for in-person assessment for sick certificates.[171] This study finds pro-poor digital challenge inequality estimates for three of the four countries that took measures to improve accessibility, suggesting that such policies may reduce health inequalities.

4.5.3 Policy implications

Low income levels have been associated with higher incidence and mortality rates of COVID-19.[166,167] Many factors affect access to healthcare. In some cases, these factors are dependent on the definition of access, which varies in the literature.[1] Some factors that are frequently associated with socioeconomic status and are known to affect health access are affordability, proximity to health facilities, transport accessibility, education levels, and media exposure, amongst many others[70,176] With higher incidence and reduced access to healthcare, as shown in this study, in certain countries, it follows that poor health outcomes will continue to be disproportionately distributed amongst the economically vulnerable.[177] This would result in a double burden of ill-health compared to wealthier counterparts, resulting in a "*syndemic pandemic".*[177] This double burden will remain persistent unless policy can be implemented to expand and protect access to healthcare services and systems for the poor, addressing the inverse care law and ensuring horizontal equity.[178] Based on the monotonic relationships observed between national median income and inequality, lower-income countries in the study (on average) were less able to provide equitable care to citizens. Possible causes for this result include the existence of strong private systems accessible only to wealthier individuals in low-income countries (e.g., the case of South Africa), or the heightened presence of corruption associated with lower income countries, which may enable those who engage in corrupt activities to gain preferential access to health systems in times of need.[179] The development and implementation of digital health services offers a policy opportunity to address these inequities. These digital services (i.e., telephone and internet-based consultations) presently show large inequalities in lower-income countries, but may simultaneously offer future paths to mitigate inequality and inequity. Specifically, a digital offering can circumvent barriers in transport, logistics, and overall consultation duration to reduce required time off work. Digital distance-based services require only an internet or phone connection, access to which is increasing in developing countries.[180]

Digital health services expanded rapidly during the pandemic to promote safety and protect healthcare workers.[181,182] However, the role of digital health in the post-pandemic world is unclear and will continue to evolve. Unlocking the potential inequity-mitigating effects of digital and distance services is likely to require significant support in implementation, particularly in resource-constrained systems. Lower-income countries in this study did not provide equitable digital services, while higher-income countries were more able to do so, and in some instances took specific interventions to improve digital access.[171] One such implementation support lever could involve the prioritisation of digital and distance services for rural (by distance from practice) patients, if not explicitly by income level.

As much of the world returns to pre-pandemic practices, the now-known possibilities of digital health will be included in the care offering available to patients. It is necessary that low-income countries and low-income communities are supported to improve access to digital health services to reduce inequality and possible inequities. Digital services offer an opportunity to reduce and reverse inequality if policy and initiatives surrounding rollout are well-managed and targeted, ensuring that marginal groups are not left behind.[175,183]

4.5.4 Sensitivity analysis

An extensive sensitivity analysis is undertaken. There appears to be no material difference in the use of the Erreygers index relative to the Wagstaff index. The restricted standardization returns weaker correlations, though the digital and surgical/clinical estimates remain relatively robust. The in-person GP estimates are the most affected. Despite the variability, I believe that the overall estimates lie between the two values produced, and given the robustness of two of the three measures, I do not believe the standardization employed changes the overarching narrative of the analysis. The alternative income measures are all strongly correlated with the income measure used from the CANDOUR survey, offering external validation for the sampling processes of the CANDOUR survey. The alternative aggregated measures posed did not appear to explain inequality better than median equivalised household income. National health spend and the corruption index were both significant in two of the three cases, though at a lower significance level. I do not believe this gives cause to alter direction of analysis, given the strong observed significance and relationship between equivalised median income and inequality estimates. The ANOVAs (available in appendix A6-8) find results consistent with the previous findings, showing disparities based on national income; with stronger associations observed in the digital and surgical and clinical types of care. Evidence of regional disparities was also found, however I did not observe disparities in the digital care type. Differences in the surgical and clinical type of care were mainly ascribed to differences between North America and other regions, whereas South America was primarily responsible for the observed differences in the in-person GP type of care. Overall, the sensitivity analyses are consistent with the main analysis, and add additional context with which one can view the main results.

4.5.5 Limitations

There are five limiting factors to consider in this study:

(1) Survival bias. The survey asks respondents if they had difficulty in obtaining an appointment or admission in three different care types. The analysis conducted assesses inequalities in challenges to obtaining access, but does not incorporate those who did not attempt to gain access to health systems but needed to, which may be due to traditional barriers to care, such as proximity, affordability, and time constraints.[70,176] This could lead to comparisons of different populations across countries, which are dependent on the barriers faced in each country. If the decision to seek care is correlated with the standardizing variables, which is not implausible, a bias is introduced. (2) The use of indices. It is important to note that the concentration index is a summary measure, and does not necessarily reflect intermediate information along the distribution. Examining the index value alongside a graphic aid is useful in understanding the overall distribution of inequality. Visuals may show switches between

equality and inequality, whereas the index nets these values, such as in the case of separated public and private health systems accessed by different income groups.[184] (3) The cross-sectional nature of the study. This survey was conducted from March – November 2022, however this study lacks a prior counterfactual. As such, I can only infer that the observed inequalities were present during the period from the onset of the COVID-19 pandemic to the end of the study period. Without a prior counterfactual, I cannot ascertain the direction in which inequalities may have changed. I am similarly unable to ascertain whether the pandemic, or associated health system restructurings (e.g. increased digital consultations), had a causal impact, in either direction, on these inequalities and inequities. Further research to address the state of inequality following the pandemic is planned, employing subsequent waves of the CANDOUR survey. (4) Survey limitations. Respondents may misremember certain elements of their interactions with health systems over the ~2 year study period. Such recall errors would bias the results, though research has found that longer recall periods minimise bias.[185] The same research found greater measurement errors in lower-income groups. I recognise that the countries studied did not face the same infection or restriction profiles and, at the time they were surveyed, respondents may have found themselves in varying contexts. However, the ~2 year study period allows respondents to provide an overview of their experiences in accessing care in their country, from the beginning of the pandemic to the date of survey, which remained in the global health emergency phase of the COVID-19 pandemic as defined by the World Health Organisation (WHO).[186,187] Respondents (or respondent groups) may have subjective views over what constitutes a challenge in accessing care, which may bias the results if systematically prevalent among groups. This subjectivity could be built on expectations and prior experiences with national health systems or social desirability biases. In cross country comparisons, this can confound true differences if these subjectivities, biases, experiences and expectations vary systematically (either with a covariate within a country, or between countries). The subjectivity in this response is the underlying reason for inclusion of the expanded standardization set, aiming to collect information on respondents' subjectivity based on a wider array of variables and control for this. Restricting the sample to those who accessed care had some implications on the representativeness of the work in certain countries where sample populations of the subgroups did not mirror actual populations in reality. In these countries (e.g., Ghana) generalisability is cautioned. (5) Sample power at aggregate level. In testing between country differences I reduce the sample to 16 observations per type of care, rather than pooling the responses. This necessarily reduces the power of the test, which with a limited number of degrees of freedom may be unable to provide significant results despite indicated correlations.

4.6 Conclusion

These limitations notwithstanding, this study adds to the existing literature on inequality in access and challenges to care. The paper goes beyond a single-country analysis by exploring the relationships between three different types of care and income levels across 16 economically diverse countries. In doing so, it finds strong relationships between median income and healthcare accessibility challenges in digital healthcare services and surgical or clinical admissions. Given the rise of digital healthcare during the pandemic and its potential to alleviate inequality in healthcare access, the digital health services results in this paper should be given due consideration. Policymakers may be able to alter inequality gradients with intentional digital interventions, mirroring those countries that have successfully implemented equitable digital services.

Having investigated inequality in access (seeking and reaching care) to health systems, I turn my attention to inequality in the utilisation of health services. It is a prerequisite that to utilise, or to consume health services, an individual must have gained access by seeking and reaching care. Utilisation is the subsequent stage in an individual's healthcare journey, as defined by Levesque et al.[1] Investigating inequality in utilisation of health services is interesting in its own right, and a measure used frequently in analysis of the equality of health systems. By partnering the analysis with the investigation into access, I am able to investigate the relationship between inequality in access and utilisation contextually within each country. Studying these metrics alongside each other enables me to define the persistency of inequality across stages of the healthcare journey, which is incorporated into this dissertation in chapter 8.

5. Income-related inequality in the utilisation of healthcare services during a health shock

5.1 Introduction

In the previous chapter I investigated income-related inequalities in access to care, at the point after seeking care but before reaching care, as defined by Levesque et al.'s framework.[1] Having observed varied inequality in access to care across countries, it is a natural progression that the next chapter should investigate the subsequent stage – utilisation of care, having reached care. This sequenced study offers a perspective into the consistency of inequality through health system(s) during the COVID-19 pandemic, which I revisit in chapter 8.

The COVID-19 pandemic placed severe strains on national healthcare systems. Beyond understanding how patients may have faced challenges in gaining access to health systems, understanding the income-related dynamics of utilisation conditional on gaining access is similarly important. If patients could gain access to systems, did they receive the care they required relative to their health needs, was this influenced by income level, and did this experience differ by country?

Several studies investigate socioeconomic inequality and inequity in the utilisation of healthcare. A great number of studies focus on a single country, a specific disease-group within that country, an age group, or a specific type of care (see utilisation literature review in section 2.3.3). A number of studies take a broader geographic approach, but limit the types of care examined. Most typically this is the case for maternal and child health utilisation or coverage studies.[79,80] Limited work has been conducted examining inequality and inequity in the utilisation of services during the COVID-19 pandemic from a cross-country perspective, or in a way that allows comparisons across countries outside of specialised channels of care.

In this chapter, my objectives are to: 1) measure socioeconomic inequality in the utilisation of health services during the COVID-19 pandemic and 2) assess to what extent inequalities in utilisation are driven by within country versus between country inequalities. While inequalities can only be addressed at the national level, it remains of interest to see how inequality behaves between different countries, at the very least for policy makers to understand inequality benchmarks in counterpart or desirable health systems. The COVID pandemic was characterised by limited international collaboration, and many health systems were left to fend for themselves while wealthier nations hoarded critical supplies like ventilators and vaccines.[188–191] The decomposition investigates if privileged access extended into the utilisation of healthcare services between countries, or if similar inequality gradients were observed within each country. In effect this looks at the question of whether more privileged health system interaction was afforded to those in wealthier countries, or to the wealthy within countries. This is an important area of research as health care influences health outcomes, and adds qualitative explanatory power to the inequality in health observed throughout the pandemic. Though little can be done to address global inequality in health care save for targeted health system strengthening programmes, understanding the extent to which differences between countries plays a role in observed inequality is not meaningless. The degree of between inequality in fact outlines a possible bound for the reduction in overall inequality if global collaboration were increased to a maximum. The results of the between component of the decomposition also inform us of the differences faced, for example, by the mean individual in each country.

To complete this analysis, I estimate needs adjusted income-related inequality in the utilisation of health services using the Level Index, which retains more information than traditional rank indices, and is suitable for the data in wave 2 of the CANDOUR study (see also chapter 3 on income variables which explains certain limitations).[47,64] While I estimate the previous and subsequent chapters with rank-dependent indices, the Level Index's property of continuity with the prospect of follow-up data from CANDOUR wave 3 and a comparison analysis, and the perfect decomposition property make it desirable for the analysis at hand. I estimate inequality in 5 different types of care (as investigated in the previous chapter, albeit separately in certain instances, accounting for the expansion from 3 to 5 types of care), based on the total number of visits, contacts, or nights stayed. The 5 types of care are in-person GP appointments, telephone appointments with a health professional, internet (video) appointments with a health official, overnight hospital stays (inpatient care), or clinic visits (outpatient care). I conduct an inequality analysis in each of the 16 countries in wave 2 of the CANDOUR study to identify the magnitude and direction of inequality within each country. I decompose these global estimates into their constituent parts in order to identify if within or between country differences in the utilisation of health services were the primary driver of inequality during the pandemic.

5.2 Data

I use data from CANDOUR wave 2 for this analysis. Respondents in wave 2 were asked to indicate the number of contacts they had had with various health professionals *since the beginning of the pandemic,* ranging from 0 to 10 or more (truncated) in five different types of care. The percentage of truncated observations is in brackets after each type of care below. The types of care included in the study are hospital admissions (inpatient overnight stays) (0.99% truncated observations), outpatient clinic visits (3.83% truncated observations), face-to-face contacts with a doctor (7.76% truncated observations), telephone contacts with a health professional (3.15% truncated observations), and internet contacts with a health professional (1.69% truncated observations). The income measure used as the socioeconomic ranking variable is the same variable as in the previous chapter – namely purchase power parity equivalised household income (see limitations of its use and possible measurement error in chapter 3, which could be exacerbated by use of a level dependent index opposed to a rank dependent index). The number of contacts is normalized by country, to account both for the date of survey, and the effective start date (date of first case) of the coronavirus pandemic in each country. Quota sampling was adopted during the survey field-work, and where imbalances remained – post stratification weighting was employed. In elements of the analysis the sample size is reduced due to missing or incomplete data. In such instances, weightings are recomputed to maintain a representative sample where feasible.

5.3 Methods

5.3.1 Theoretical framework

In this chapter I aim to investigate inequality in the utilisation of healthcare services during the COVID-19 pandemic. There are two sources of inequality that are of interest; within country inequality, and between country inequality. In selecting the methods to employ for the quantitative inequality analysis, I consider the following data factors; the socioeconomic variable is ratio-scale, while the standardized health variable (number of contacts) is fixed-scale and true zero.[32]

There are a number of rank dependent indices which can be applied to a bounded health variable. While number of visits is normally unbounded, the responses were truncated in data collection at 10. The generalized concentration index and the Erreygers index with absolute properties, or the concentration index and the Wagstaff index with relative properties could each suffice. As the socioeconomic and health data are both in level form (i.e., value rather than rank), the use of a level dependent index is also a possibility. The level dependent family of indices has several desirable properties, chiefly the retention of information by not reducing the socioeconomic variable to a rank, its continuity over time for multiple analyses, and its properties in decomposition. However, as the income measure was categorical before transformation into an equivalised continuous variable, the Level Index weighting function may introduce more measurement error than a rank-dependent index, though this is attenuated to some degree with the income smoothing process described in section 5.3.2.4. A fuller description of the Level Index is found in the history of measurement section (2.2).

As the nature of the data allows, I employ the (absolute) Level Index, which is perfectly decomposable into within and between sub-components, and minimises the loss of information, effectively incorporating the marginal income distribution in the inequality calculation. Estimating inequality with the Level Index offers a clear perspective on the sources of inequality due to the property of perfect subgroup decomposability.[64] The decomposition describes the sources of inequality either as coming from within countries or between countries. Rank dependent indices have been shown to be hypersensitive to changes in inequality when considering population weighted estimates over time.[48] As this wave of data may be followed by another which would enable a follow-up analysis, the Level Index's properties of continuity (see section 2.2 – *Rank and level dependent indices*) are also advantageous and lend rationale for the Level Index's use over rank dependent indices.

I begin by estimating inequality within each country using the Level Index to gain insight into the observed inequality for each of the countries studied. I then turn to estimating the sources of inequality using a within-and between decomposition across the sample.

Due to issues around the representativeness of the CANDOUR sample in certain countries discussed earlier in this thesis, the application of population weights to the sample in a pooled analysis may exacerbate these issues. In assigning population weights to the samples for pooled analysis, each country's relative weighting is adjusted by a factor of its population to the total population of the sample countries. In this instance, countries with larger populations (e.g., India, China, USA) take on significantly greater weightings in the calculation. This has two effects; 1) the inequality findings within these countries are given more importance than countries with lower populations, and 2) the between component is also adjusted relative to these weights. Gluschenko provides an example of this, using inequality estimates in Mainland China and SAR Macao.[192] Mainland China's population exceeds Macao's by 1.376 billion people in Gluschenko's work, yielding population adjusted weights of 99.96% for Mainland China and 0.04% for Macao. A global interpersonal inequality measure that assesses inequality between all individuals would effectively yield the same (weighting) results as above. Population weights can amplify (or attenuate) measurement error based on the relative weights and degree of error. If, for example, there is known measurement error in Mainland China, weighting these results highly amplifies the error. While this approach may exacerbate measurement error that is inherent in survey collection, particularly where full representativeness could not be achieved, it remains an interesting research question to investigate (see 5.1) to understand if global inequality during the pandemic was due to differences between countries, or predominantly due to factors within each country's control.

I conduct the analysis on three levels (1) health-needs adjusted health care utilisation metrics with control variables, (2) age, gender, health level standardized metrics, and (3) on raw health care utilisation estimates. Comparing the resulting inequality outputs offers further insight into how each national health system functions.

5.3.2 Empirical estimation

5.3.2.1 Sample reweighting

Approximately 15% of the data is incomplete due to missing income data. It would be inappropriate and infeasible to conduct the desired analysis with the incomplete data which is missing key variables required to estimate outcomes without accounting for this in some form; particularly where population weightings are being applied. There are four possibilities available; complete case analysis, which excludes the missing data completely; complete case analysis with reweighting of remaining samples to ensure a representative sample; coding all missing values as a "missing income" variable, though this is not appropriate for concentration indices which rely on an income figure; or multiple imputation, which imputes the missing values. While imputation has been shown to produce viable estimates, in cases where a significant amount of data is missing, the procedure may produce unreliable estimates.[193] I opt instead for a complete case analysis and reweighting procedures to maintain representativeness.[194] I find this a superior option given the challenges faced in imputation with the extent of missing income data, and the alternative of excluding without reweighting.

The sample size is reduced to 18 760 respondents. For inclusion, each respondent requires income data and health contact data. To maintain representativeness and external validity, the sample must be re-weighted to account for the excluded respondents. To reweight the sample, I assign to each existing individual weight within each country a weighting type, which uniquely identifies the characteristics of the individual(s) within the country as a *demographic weighting type*. I sum the weights of each weighting type per country to get the relative contribution of each weighting type in each country which I aim to hold constant through the reweighting process. I tag the variables which are complete and included in the analysis, and calculate the sum of the weights per weighting type of tagged variables to be included in the analysis. I calculate the ratio of the sum of weights of tagged identifications to total identifications per weighting type, to derive an expansion factor unique to each weighting type in each country. I multiply the existing weights by the expansion factor. Provided no *demographic types* are entirely excluded, the new weights will be representative. However, if an entire *demographic type* is excluded, the new weights will necessarily not sum to 1. The *weighting types* will maintain the absolute contributions as they did in the original sample, apart from those types that have been excluded in full due to missing data. Relative weights are also maintained between *demographic types* that are included in the sample. In most cases, the reweighting procedure achieves near complete representation, though there are some countries where representativeness cannot be maintained. Table B1 details the achieved reweighted sample weights, where 100% implies full representativeness.

5.3.2.2 Descriptive statistics

A descriptive analysis was conducted on the reweighted sample. The variables selected present an overview of the sample that is used in this chapter. I use several of the same variables as descriptors as in the previous chapter relating to access challenges. The variables described for each country are self-reported gender, age, household size, education level, political ideology, marital status, household income, labour force participation, current health condition, and number of chronic conditions. Age, political ideology, education level, and household income are reported as median values. The remaining variables are reported as mean values. Where variables are binary the stated figures represent the percentage of individuals in a country with the stated attribute. A full explanation of each of the variables can be found in the variable description section.

I also calculate mean number of (health-needs adjusted) contacts per country and for the overall sample, to begin to develop an idea of the utilisation of healthcare systems across different countries.

5.3.2.3 Standardization and normalisation

The health contact variables are standardized for health needs indirectly using a negative binomial regression within each country. This process means the computed concentration index will estimate health-needs adjusted inequality, rather than inequality, though I also present inequality outcomes on the non-standardized estimates. While health-needs adjusted inequality is often referred to as inequity in the literature, this implies normative assumptions on fairness based on the standardizing variables.[3] As the CANDOUR data does not, for example, contain a workable ethnicity variable across countries, and ethnicity has been shown to be an important factor in healthcare inequity[166] (see limitations section), I do not ascribe normative assumptions on fairness and extend the analysis to inequity. Instead, I go so far as to call this health-needs adjusted inequality, which does not go so far as to pass comment on fairness, despite following the same analytical steps. In doing so, I avoid implicitly assigning normative assumptions across countries to get a measure of fairness.

The negative binomial regression is employed due to the over dispersion of the health contact variables.[195] Over dispersion is characterised by variation greater than the mean, which is true in each case of the contact variables. Country specific standardization was conducted accounting for gender, age, health levels, and number of chronic conditions and controlling for education level, marital status, labour force participation, and household size.

The standardisation is run using a negative binomial regression for the reasons described above,[28] accounting for the over dispersed count contact variables.[196] Sample weights are included in the regression. Demographic variables (x_{nij}) and non-confounding control variables (z_{mij}) are regressed on the health variable (h_{ij}) using a maximum likelihood estimation – where i is the individual respondent in country j, θ is a parameter vector, h_{ij} is the number of appointments utilised by individual i in country j, and μ_j is the mean number of appointments utilised in country j.[195]

$$f(h_{ij}|x_{nij}; z_{mij}) = \frac{\Gamma\left(h_{ij} + \frac{1}{\theta_j}\right)}{h_{ij}!\ \Gamma\left(\frac{1}{\theta_j}\right)} \left(\frac{\theta_j \mu_j}{1 + \theta_j \mu_j}\right)^{h_{ij}} \left(\frac{1}{1 + \theta_j \mu_j}\right)^{\frac{1}{\theta_j}},$$

$$h_{ij} = 0, 1, 2, \dots; i = 1, 2, \dots, n; j = 1, 2, \dots k$$

Using the negative binomial parameter estimates $\hat{\theta}$; individual values x_{ij}; and sample means of the non-confounding $\bar{z}_{mj}$ variables per country, I predict the x-expected values of the health variable, $\widehat{h^x}$. Mean values of $\bar{z}_{mj}$ are taken to reflect the average individual in each country, giving a distribution weighted reference value unique to each country, and how the average individual's control variables would affect health needs. Further discussion on this is contained in the indirect standardization section in chapter 4.

The standardized health variable, $\widetilde{h^s}$ is thus taken as the difference between actual and x-expected health variable, plus the sample mean per country.

$$\widetilde{h^s} = h_{ij} - \widehat{h^x} + \overline{h_j}$$

There are several considerations in selecting the variables used for standardization. Primarily, these variables are used to adjust the number of contacts within each country relative to individual's health needs. As the process is undertaken within each country, adjustment is done on a health system basis. For example, if the UK implemented priority access for older individuals and this was utilised in practice and Ghana did not, the standardization would lead to a higher need for the elderly in the UK based on observed increased usage, but not in Ghana. The variables selected in standardization adjust the raw data, and in this way, variable selection is a normative process based on what the researcher determines impacts health needs, and is not a purely technical process, although technical considerations need also be considered.[3] The standardization process becomes increasingly normative when comments on inequity are made, as the variables form the underlying basis for what constitutes fair and unfair variation.

There are two further practical implications to consider when selecting variables to include in the standardization (beyond the rationale for variable selection on health-needs in the existing literature). Both implications result from the reduced sample size inherent in complete case standardization methods (e.g., standardization by regression). While power reduction due to a smaller sample could be a concern, given the large sample size, this does not come into effect materially in this study. Some of the potential descriptive variables were less complete than others. This could be due to the nature of data collection (e.g., not all participants participated in certain experiments), or, in certain cases, I hypothesize that the missing data was the result of unwillingness to answer. Including these variables with lower response rate for any reason in the standardization results in the exclusion of respondents from the sample, though a missing dummy variable could be implemented. In certain countries the reduced sample resulting from inclusion of some potential standardizing variables led to less variation of the sample, and particular exclusion of those who utilised health services. The result of this was that the number of zeros in the data relative to the number of non-zero count values increased, and with reduced non-zero values, the negative binomial standardization failed to converge. Note this occurred in the overnight hospital type of care in select countries, where there is already a significant number of zero outcomes. The presence of zeros varied in each of the 5 types of care. ~25% of individuals had zero in-person GP contacts before standardization. The other types of care had higher proportions of zero values (~50% in telephone and clinic contacts), up to approximately 70% in the hospital nights stayed and internet appointments. However, as the means were also low, the negative binomial model sufficed, and was not significantly outperformed by the zero-inflated negative binomial model to the extent that replacement was warranted. For consistent analysis across the sample (and viability of accurate between country decomposition results), standardization should include the same variables in each country, removing the prospect of country-specific standardization which could alter individual estimates differently.

A smaller sample could also impact the representativeness of the sample, and this is my second consideration in the standardization variable selection. A further reduced sample (based on descriptive variables, rather than the primary concentration index forming variables, e.g., equivalised income inputs, the health variable, and health needs variables) would require further reweighting due to additional exclusions and changing composition of the sample. In certain countries, the effects of further respondent exclusion were such that representativeness could not be maintained. A standardization with fewer variables (e.g., excluding certain experimental and reported risk variables, which were peripheral to the analysis) was employed rather than sacrificing external validity through reduced representativeness. As such, the variables selected above balance the needs for standardization (controls) against the needs for representativeness in a pragmatic manner.

I use the same standardization set across each of the 5 types of care. While those presenting for clinic visits may differ from those using internet-based appointments, the variables affecting health need are not likely to change, but the parameter values associated with each variable for each type of care would differ to accommodate these different patterns. While certain variables such as proximity to nearest hospital or digital literacy would be optimal to include in the standardizations for hospital nights and internet appointments respectively, variables of this nature were not available in the CANDOUR dataset.

In selecting the variables for standardization, I thus opt for variables that are valid consistently across the five types of health contacts rather than selecting different variables for different types of health contacts, in doing this I maintain consistency in both the standardization and the sample across the analysis. Maintaining the same sample across the analysis allows differences in utilisation across care types to be observed for the same respondents, a property I deem valuable.

Having standardized the variables for health need, I normalise the contact variables to a 12-month time period. The normalization process is to account for disparities in data collection dates and start dates of the pandemic within each country. Surveys were conducted in different countries at slightly different times, and the pandemic reached different countries at varying dates too. However, the question posed asked respondents their utilisation since the beginning of the pandemic. The normalization brings all responses into a common appointments per time variable that accounts for both the start date of the pandemic and collection date of the data.

5.3.2.4 Income smoothing

Following the approach adopted by Erreygers and Kessels, I employ an income smoothing function for the Level Index.[47] I order respondents into percentiles based on equivalised income, after considering sample weights; aiming to achieve 100 groups of equal weight in each country. Due to the nature of the sample weights, groups may only approximate 1%. Not all groups will equal exactly 1% due to the irregular nature of the weights used. Within each group (by country), I calculate the mid-interval of the equivalised income variable. This is taken as

$$Interval\ Income_{ij} = Y_{min_{ij}} + (Y_{max_{ij}} - Y_{min_{ij}})/2$$

Where the minimum and maximums are of the associated income percentile i in country j. This value is then assigned to each respondent in the percentile, and is used as the ranking variable in the Level Index.

5.3.2.5 Population weighting

I employ population weights from 2022 as published in the United Nations' World Population Prospects 2024 report and associated data sources. The figures used are available in Table B2.[197]

5.3.2.6 Level Index

The Level Index can be expressed in several forms, as is the case with several variations of the concentration index. The index is expressed below algebraically, and in its convenient covariance form, where y_i is the income of individual *i*, h_i is the number of appointments utilised by individual *i,* and μ_y is the mean income level.[47]

$$L = \frac{1}{n}\sum_{i=1}^{n}\frac{y_i - \mu_y}{\mu_y}h_i = \frac{Cov(y,h)}{\mu_y}$$

I analyse the within country inequality for each of the 16 countries included in the analysis. I focus on country specific estimates within which there are no defined groups in this analysis. Between estimates are still possible within each country, however would rely on defining subgroups (e.g., age groups, employment groups, ethnicities, etc), which, though useful, go beyond the scope of this analysis and chapter objectives. I explore subgroup definitions and decompositions in more detail in chapter 7.

The below formula displays the property of perfect subgroup decomposition between countries, which I undertake after the within country analysis. The Level Index can be split into two terms representing inequality within groups and inequality between groups, denoted simply below, where *W* is within-group and *B* between group inequality.[64] In this analysis, groups are represented by countries.

$$L = L_W + L_B$$

Erreygers and Kessels show that within country inequality is given by the equation below:[64]

$$L_W = \frac{1}{n\mu_y}\sum_{i=1}^{n} y_i h_i - \sum_{j=1}^{k} s_j \mu_{h_j}$$

Where n is the sample size, y is the socioeconomic variable, h is the health variable (standardized for health needs), μ is the mean for the associated variable, i is the individual respondent and j is the subgroup (country), where s is the weighting function (adjusted by population weights for the relevant analysis), given by the below expression for the absolute version of the index, equal to each country's share of total income:

$$s_j = \frac{n_j \mu_{y_j}}{n\mu_y}$$

The between country (or subgroup) inequality is thus given as:

$$L_B = \sum_{j=1}^{k} s_j \mu_{h_j} - \mu_h$$

Where total inequality L can then be defined by the expression:

$$L_W + L_B = \frac{1}{n\mu_y} \sum_{i=1}^{n} y_i h_i - \mu_h = L$$

I adopt this specification for the analysis requiring decomposition, where I analyse the sources of inequality and decompose this into a between and within country component.

5.3.2.7 Use of restricted standardization and absent standardization

Although standardization is well supported in the literature, and is required to produce estimates of unfair differences in utilisation based on healthcare need, it is still a reality that standardization transforms the variable.[28] As such, I re-run the analysis in two instances – the first with a restricted standardization that includes only age, gender, and health levels, without any control variables. In the second re-run, I conduct the analysis with unstandardized (after cleaning and time normalization) outcome variables. Conducting this analysis twice in this manner offers a perspective on the effects of standardization. I report the results of the standalone within country level indices, which form the foundation for the within and between calculations. I then apply the within and between decomposition to the newly computed indices.

5.3.3 Sensitivity analysis

5.3.3.1 Alternative concentration index specification

I conduct a sensitivity analysis on the **standalone within-country** inequality estimates using alternative concentration index specifications.

In addition to the Level Index, which retains the most information, I estimate within-country inequality using the Erreygers adjusted concentration index (which I use in the chapter 8 synthesis for consistency), the Generalized concentration index (together with the Erreygers index is also an absolute measure of inequality), and the concentration index, which is a relative measure. For each of the types of care studied, I compute and compare ranks of each variation of the concentration index. This exercise is undertaken to determine the sensitivity of the results to the method of measurement.[47] To provide a summary measure of the ranks relative to each other measure, I produce a value, which I call the rank similarity percentage. This percentage is taken simply as the percentage of ranks which are the same as another index, similar to a measure of concordance (e.g., Kendall's correlation testing) without adding complications. As such, the rank similarity percentage is expressed as S_{ij}, where i and j denote the indices used. Where i = j; S_{ij} = 100%. This would, rather unhelpfully, represent the comparison of the same index against itself. I also calculate the rank correlations using a Spearman's correlation test, which is defined in section 4.3.2.5.

5.4 Results

5.4.1 Descriptive overview of the pooled sample

Table 5A outlines the characteristics of the sample with internal country sampling weights but without between-country weights applied. Approximately 49% of the sample is female. The sample has a self-reported mean health level of ~70 (on a scale of 0-100). The average respondent lives in a household of 3.5 people, and 54% of the sample is married or lives with a partner. The median age of the sample is 40 years old, and the median respondent is both university educated, and centrally-located on the political spectrum. The median household income of the sample is 13,706 PPP equivalised dollars. Disparities in the sample by country are evident (e.g., Australia vs Ghana female respondents, Japan vs India or Uganda age profile.) In most cases, a roughly representative sample has been maintained. However, data collection faced challenges in certain countries (Ghana, India, Uganda) and a representative sample was unobtainable. After accounting for those who answered the questions needed to conduct the study the restricted data used in this study further reduces the representativeness of the sample. Reweighting attempts are made to keep appropriate sample weights to maintain external validity and representativeness where possible, and were largely successful. However, reweighting procedures in Spain left the country non-representative. Reweighting results are available in appendix table B1.

Table 5A: Sample descriptive statistics

	Female (%)	Median Age (years)	Household size	Median Education level[2]	Median Ideology level[3]	Married (%)	Med. Income (PPP$ '000s)	Labour force participation (%)	No. Chronic conditions (n)	Self-reported health (%)
Overall	49.1 (50)	40 (28-56)	3.5 (8.5)	3 (3-4)	5 (4-7)	54.4 (50)	13.7 (3-31)	70.7 (45)	0.5 (0.8)	70.5 (26)
Australia	70.7 (46)	32 (24-49)	2.1 (0.8)	3 (3-4)	5 (5-6)	75.8 (43)	41.3 (29-83)	58.7 (49)	0.6 (0.7)	65.9 (18)
Brazil	50.6 (50)	35 (25-50)	5.9 (15.1)	3 (2-3)	6 (1-7)	41 (49)	3.7 (2-9)	50.9 (50)	0.4 (0.6)	69.6 (27)
Canada	64.2 (48)	39 (23-59)	2.1 (1)	3 (3-4)	5 (4-7)	33.4 (47)	28.9 (14-50)	70.2 (46)	0.7 (0.9)	68 (26)
Chile	60.7 (49)	31 (22-39)	2.5 (0.9)	3 (3-4)	3 (2-4)	41.4 (49)	6.1 (4-12)	49.8 (50)	0.5 (0.7)	80.7 (18)
China	48.5 (50)	44 (29-54)	3.5 (7.6)	3 (3-3)	5 (5-5)	74.7 (44)	18.6 (15-30)	74.2 (44)	0.3 (0.6)	78.6 (21)
Colombia	46.2 (50)	45 (32-62)	2.9 (2.4)	3 (2-3)	5 (2-7)	55.8 (50)	9.1 (4-16)	72 (45)	0.5 (0.7)	62.1 (34)
France	55.4 (50)	53 (40-64)	2 (0.9)	3 (2-4)	5 (4-8)	55 (50)	23 (13-38)	57.1 (50)	0.5 (0.7)	67.2 (26)
Ghana	19.1 (39)	30 (27-35)	4.3 (2.3)	4 (3-4)	5 (5-7)	54.3 (50)	0.9 (0-3)	77.7 (42)	0.2 (0.4)	84.1 (17)
India	56.5 (50)	28 (27-35)	11 (27.1)	3 (2-4)	7 (6-8)	38.7 (49)	2.3 (2-9)	87.2 (33)	0.6 (0.8)	46.1 (37)
Italy	54.7 (50)	53 (41-62)	2.4 (1.3)	3 (3-3)	5 (3-7)	66.7 (47)	24.1 (16-37)	57.3 (49)	0.5 (0.7)	69.4 (23)
Japan	49 (50)	58 (43-65)	2.4 (0.8)	3 (3-4)	5 (5-5)	71.8 (45)	31.1 (0-45)	75.1 (43)	0.7 (0.8)	79 (22)
South Africa	38.9 (49)	40 (28-44)	2.8 (1.8)	3 (2-3)	5 (0-6)	51.2 (50)	5.2 (1-20)	83 (38)	0.7 (1.1)	73.9 (21)
Spain	51.2 (50)	49 (36-62)	2.4 (2)	3 (3-4)	4 (2-6)	66.8 (47)	30.5 (19-44)	63.7 (48)	0.5 (0.7)	74.6 (23)
Uganda	17.9 (38)	28 (25-36)	5 (4.3)	3 (2-3)	5 (4-7)	40.3 (49)	0.2 (0-1)	92 (27)	0.3 (0.6)	73.4 (19)
UK	50.4 (50)	45 (39-55)	2 (0.8)	3 (3-4)	5 (4-7)	49.2 (50)	19.2 (9-41)	77.5 (42)	0.4 (0.7)	63.2 (23)
US	51.8 (50)	50 (35-61)	2.3 (2.5)	3 (3-4)	5 (3-7)	58.3 (49)	25 (9-51)	81.9 (39)	0.8 (1)	73.1 (24)

1. Figures are presented as mean(SD) and median(IQR)
2. 1 = less than primary completed; 2 = primary school completed; 3 = secondary school completed; 4 = university completed
3. Respondents were asked to rate their political ideology where 10 was as conservative / right leaning as possible, 5 was centre, and 1 was left.

In table 5B, I present a summary of the standardized outcome measures – the mean number of contacts within each type of care, namely telephone and internet contacts, in-person GP contacts, and overnight hospital stays and clinic visits. The in-person GP type of care was the most routinely used across the sample, despite the pandemic restrictions imposed in many countries, with respondents visiting a general practitioner 1.5 times on average over the course of the pandemic. Telephone appointments and day visits to clinics followed in frequency, with an average of just over 1 interaction or appointment per type of care. Internet appointments and overnight hospital stays were less frequently utilised, both with means of under 1 appointment or overnight stay.

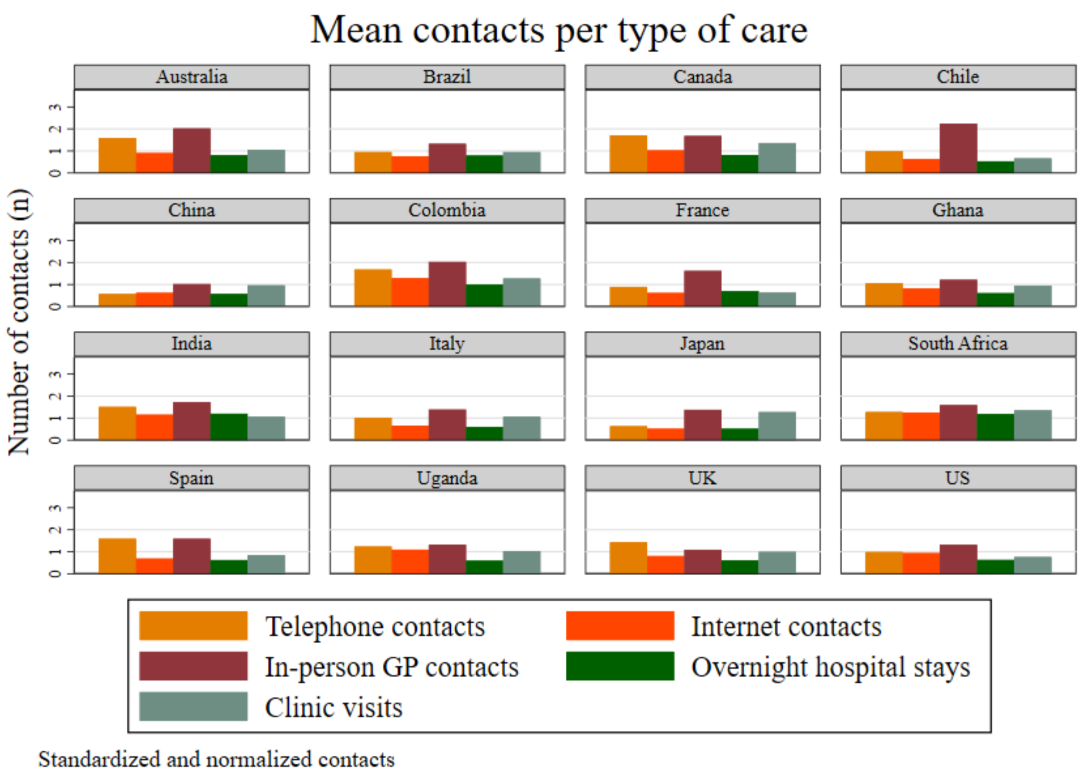
Table 5B: Mean contacts by type of care and country

	Telephone contacts	Internet contacts	In-person GP contacts	Overnight hospital stays	Clinic visits
Overall	1.2 (1)	0.9 (0.8)	1.5 (1.2)	0.7 (0.7)	1 (1)
Australia	1.6 (0.9)	0.9 (0.8)	2 (1.1)	0.8 (0.5)	1.1 (0.8)
Brazil	1 (0.7)	0.8 (0.6)	1.3 (0.9)	0.8 (0.8)	1 (0.8)
Canada	1.7 (1.2)	1 (0.7)	1.7 (1.1)	0.8 (0.7)	1.4 (1.3)
Chile	1 (0.7)	0.6 (0.7)	2.2 (1.6)	0.5 (0.5)	0.7 (0.7)
China	0.6 (0.5)	0.6 (0.5)	1 (0.9)	0.6 (0.5)	1 (0.9)
Colombia	1.7 (1.3)	1.3 (1.2)	2 (1.3)	1 (0.9)	1.3 (1)
France	0.9 (0.6)	0.6 (0.4)	1.6 (1.4)	0.7 (0.6)	0.6 (0.5)
Ghana	1.1 (1.1)	0.8 (0.9)	1.2 (0.9)	0.6 (0.5)	1 (0.9)
India	1.5 (0.9)	1.2 (0.9)	1.7 (0.9)	1.2 (0.8)	1.1 (0.8)
Italy	1 (1)	0.7 (0.7)	1.4 (1.1)	0.6 (0.6)	1.1 (1)
Japan	0.6 (0.6)	0.5 (0.3)	1.4 (1.3)	0.5 (0.4)	1.3 (1.3)
South Africa	1.3 (1.3)	1.3 (1.3)	1.6 (1.2)	1.2 (1.4)	1.4 (1.4)
Spain	1.6 (1.1)	0.7 (0.7)	1.6 (1.1)	0.6 (0.6)	0.8 (0.8)
Uganda	1.2 (1.1)	1.1 (0.9)	1.3 (1.1)	0.6 (0.6)	1 (0.8)
UK	1.4 (1.1)	0.8 (0.7)	1.1 (0.9)	0.6 (0.5)	1 (1)
US	1 (0.9)	0.9 (0.8)	1.3 (1.1)	0.6 (0.5)	0.8 (0.7)

Figures are presented as mean(SD), and are standardized and normalised for length of time.

Means across countries appear to deviate. Half of the countries analysed average more than 1 appointment for every type of care. The maximum mean usage for each type of care was spread across countries, as Canada, Colombia, Chile, India, and South Africa had the highest mean utilisation for telephone, internet, in-person, inpatient overnight hospital stays, and outpatient clinic visits respectively. Minimum utilisation was more concentrated, as China reported the lowest mean usage levels of telephone and in-person appointments, and Japan reported the lowest internet and overnight hospitalization utilisations. France reported the lowest mean clinic visits. Structural differences in national health systems could account for these discrepancies. Figure 5A is a graphic representation of table 5B, allowing a visual perspective across countries and types of care. In most countries in-person appointments remained the most utilised means of interacting with health systems.

Figure 5A: Mean contacts by type of care by country



Canada, Spain, and the United Kingdom were the only countries where another type of care exceeded in-person GP utilisation. In each case, it was telephone appointments. In Canada and Spain, the differences were marginal, whereas in the UK the difference was more pronounced. Hospital utilisation was the least utilised type of care in each country except in Brazil and France, where internet appointments were accessed less frequently on average. Mean clinic visits exceeded overnight hospital stays in all countries except for France and India. Mean clinic visit utilisation was higher than internet-based appointments across the sample, an interesting result given the restrictions enacted in many countries and the desire for remote consultations.

5.4.2 Within country inequality

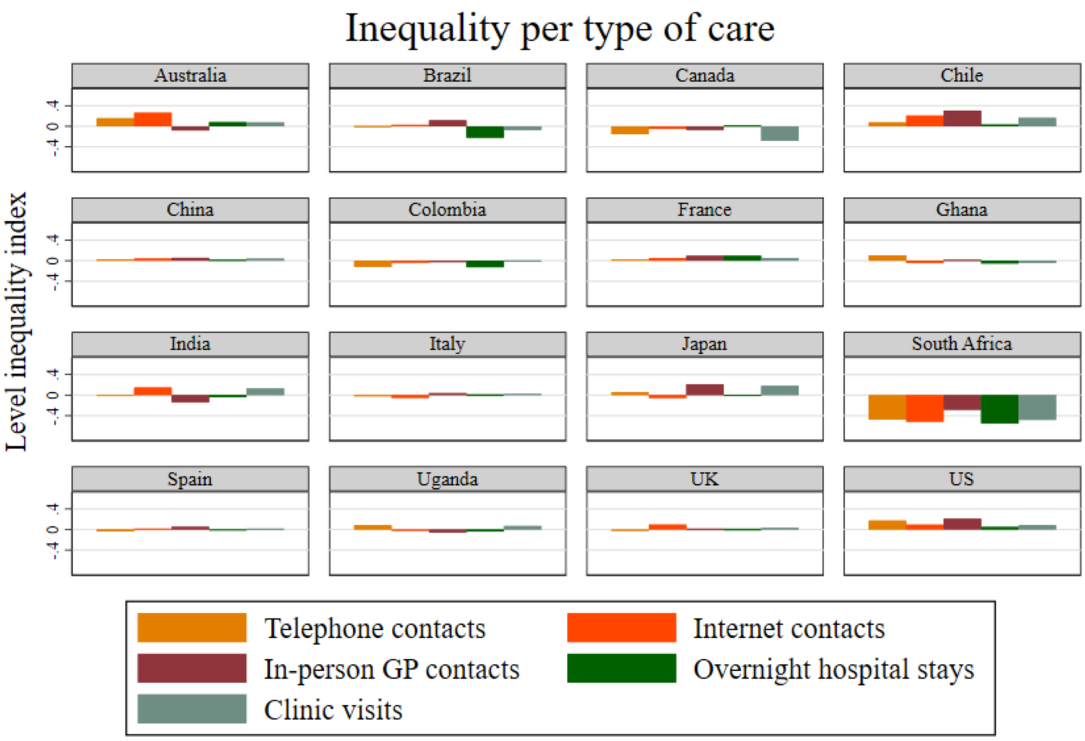
Before investigating the sources of inequality (within or between), it is important to understand inequality within each country as a standalone entity for each type of care. Within country estimates are an important metric which can contribute to our understanding of experiences during the pandemic in a significant way. This is not to be confused with the within inequality calculated in the decomposition in the following section. This measure calculates the inequality in each country, rather than ascribing elements of total inequality to within or between components. These measures are of course linked, however.

The results are presented in table 5C and figure 5B. As is perhaps expected with 80 estimates, the results vary substantially across countries and types of care. The most consistently pro-poor estimate is in the overnight hospital stay type of care, which produces 10 pro-poor (negative) estimates. 8 and 7 pro-poor estimates are reported for telephone and internet contacts respectively, followed by in-person GP and clinic visits with 6 and 5 respectively. South Africa and Colombia are the only countries that report consistently negative (pro-poor) estimates across each type of care, while Canada reported pro-poor estimates in all care types apart from overnight hospital stays. At the other end of the spectrum, Chile, China, France, and the United States report consistently pro-rich (positive) estimates, implying higher-income earners used more than their health-needs adjusted share of health services in each type of care in these countries. Chile and the United States reported the highest average pro-rich inequalities, and had high inequality in the in-person GP contacts type of care. Australia reported pro-rich estimates with in-person GP appointments excepted. Pro-rich inequality was high for telephone and internet contacts in Australia, significantly more so than in other types of care that required in-person attendance. The remaining countries had varied estimates, with 2 or 3 pro-poor estimates. Comparisons within each type of care are available in appendix figures B1-B5.

Table 5C: Within country inequality across each type of care per country

	Telephone contacts	Internet contacts	In-person GP contacts	Overnight hospital stays	Clinic visits
Australia	0.158	0.264	-0.081	0.082	0.079
Brazil	-0.009	0.029	0.117	-0.221	-0.072
Canada	-0.153	-0.046	-0.069	0.011	-0.282
Chile	0.08	0.209	0.307	0.033	0.164
China	0.026	0.042	0.057	0.015	0.041
Colombia	-0.12	-0.038	-0.027	-0.127	-0.01
France	0.022	0.052	0.097	0.096	0.051
Ghana	0.105	-0.043	0.012	-0.054	-0.042
India	-0.019	0.148	-0.138	-0.039	0.129
Italy	-0.023	-0.053	0.038	-0.004	0.023
Japan	0.056	-0.056	0.209	-0.013	0.18
South Africa	-0.476	-0.516	-0.285	-0.55	-0.481
Spain	-0.038	0.009	0.053	-0.017	0.007
Uganda	0.084	-0.024	-0.056	-0.04	0.068
UK	-0.026	0.096	0.004	-0.002	0.032
US	0.174	0.095	0.21	0.05	0.088

Figure 5B: Level Index inequality per type of care per country



Level index

5.4.3 Between country inequality

Clearly, some countries were able to provide more services, or more services were demanded of certain health systems by the populations, as defined by table 5B and figure 5A. An income-related inequality lens is applied to these figures in table 5C and figure 5B, specific to each country.

Having already estimated income-related inequality within each country, I turn to the sources of inequality across countries. I employ the Level Index on the overall sample, aiming to determine the levels of health needs adjusted inequality across each type of care, and its sources of variation. This analysis describes where inequality is prevalent by type of care, and from where that inequality comes through a decomposition analysis.

Table 5D breaks down the observed inequality using the Level Index into within and between components. One of the primary perks of the Level Index is that it is perfectly decomposable, allowing full allocation to either within or between variation without a residual term.

Table 5D: Within and between inequality

	Telephone contacts		Internet contacts		In-person GP contacts		Overnight hospital stays		Clinic visits	
	Values	%	Values	%	Values	%	Values	%	Values	%
Total	-1.042	100%	-0.875	100%	-1.391	100%	-0.829	100%	-1	100%
Within	-0.883	84.76%	-0.778	88.96%	-1.275	91.68%	-0.687	82.86%	-0.959	95.94%
Between	-0.159	15.24%	-0.097	11.04%	-0.116	8.32%	-0.142	17.14%	-0.041	4.06%

5.4.3.1 Interpersonal inequality

The country population weighted results are presented in table 5D. Total observed health-needs adjusted inequality in each type of care is pro-poor. The largest driver of this is India's large population and pro-poor estimates in the telephone, in-person GP and overnight hospital stays types of care, however each weighted country of course plays a role. India's large influence is somewhat problematic given the issues with the Indian sampling weights and internal representativeness of the sample. Between inequality is in the same direction as overall inequality in each type of care.

Pro-poor inequality was greatest in the in-person GP type of care, which was also the most frequently used care pathway (per table 5B). The levels of inequality follow the same trend as overall utilisation; where utilisation is higher, so too is inequality. Telephone contact follows in-person GP contact inequality. Clinic visits and internet contacts follow thereafter, with decreasing levels of pro-poor inequality. Overnight hospital stays, the least utilised service of the 5 types of care studied, has the lowest observed pro-poor inequality.

Across each type of care, the majority of inequality comes from within-country inequality, with the lowest component being ~82% in overnight hospital stays. That is to say, differences in utilisation based on income levels are more prevalent within each country than between countries. The meaningful variation comes from higher-income earners within each country accessing more health services than lower income earners. This is an important result in the context of global inequalities, which is discussed further in the discussion section.

5.4.4 Effects of standardization

The results below compare the estimates using the full standardization to estimates found using restricted (age, gender, health level, without controls) and no standardization in the data preparation process.

Differences are expected, as standardization transforms the data to account for health needs. In the restricted standardization, I estimate inequality without controlling for education level, marital status, labour force participation, and household size. Despite standardization being a necessary step to estimating health needs adjusted inequality with well-grounded support in the literature, it can nonetheless alter the results.[28] Understanding the extent to which this occurs is an important component of the analysis.

5.4.4.1 Within country inequality

I present the standalone country Level Index results using the different standardization sets in table 5E. I observe 6 sign switches in the internet contacts type of care, 5 in the telephone contacts and overnight hospital stays care types, 4 in the clinic visits, and none in in-person GP contacts. While there is variation, in the least consistent type of care, 8 countries reported indices with the same sign at each level of standardization. At a country level, Australia, Chile, India, Japan, and Spain were the most affected by the method of standardization; each observing multiple sign-switches from unstandardized to fully standardized outputs. Canada, Italy, and Uganda reported 1 each. The remaining countries (China, Colombia, France, Ghana, South Africa, and the US) were consistent across the methods, and only the magnitude of the reported estimate varied. South Africa was one such example, where the estimated index became increasingly pro-poor with each level of increased standardization. Clear monotonic trends were not perceptible in any of the other countries.

Table 5E: Within inequality using Level Index and alternative standardization methods

	Telephone contacts inequality			Internet contacts inequality			In person GP contacts inequality			Inpatient hospital stay inequality			Outpatient clinic visits inequality		
	F	R	N	F	R	N	F	R	N	F	R	N	F	R	N
Average	-0.01	0.03	-0.04	0.01	0.04	-0.02	0.03	0.06	0.07	-0.05	-0.01	-0.04	0.00	0.03	-0.02
Australia	0.16	0.19	-0.03	0.26	0.2	-0.08	-0.08	-0.07	-0.14	0.08	0.08	0.07	0.08	0.1	0.07
Brazil	-0.01	0.04	-0.1	0.03	0.07	-0.05	0.12	0.15	0.28	-0.22	-0.13	-0.18	-0.07	0.00	-0.04
Canada	-0.15	-0.18	-0.23	-0.05	-0.04	-0.07	-0.07	-0.08	-0.04	0.01	0.01	-0.01	-0.28	-0.3	-0.14
Chile	0.08	0.06	-0.04	0.21	0.17	0.05	0.31	0.25	0.43	0.03	0.02	-0.05	0.16	0.14	-0.07
China	0.03	0.03	0.02	0.04	0.05	0.04	0.06	0.06	0.05	0.01	0.02	0.01	0.04	0.05	0.04
Colombia	-0.12	-0.12	-0.14	-0.04	-0.03	-0.07	-0.03	-0.04	-0.07	-0.13	-0.12	-0.18	-0.01	-0.02	-0.09
France	0.02	0.02	0.01	0.05	0.05	0.07	0.1	0.09	0.11	0.1	0.1	0.07	0.05	0.05	0.04
Ghana	0.11	0.11	0.1	-0.04	-0.02	-0.02	0.01	0.01	0.01	-0.05	-0.05	-0.1	-0.04	-0.05	-0.02
India	-0.02	0.02	-0.17	0.15	0.14	-0.17	-0.14	-0.07	-0.15	-0.04	-0.01	-0.27	0.13	0.13	-0.14
Italy	-0.02	-0.02	-0.04	-0.05	-0.05	-0.06	0.04	0.04	0.02	0.00	0.00	-0.02	0.02	0.03	0.00
Japan	0.06	0.46	0.23	-0.06	0.32	0.23	0.21	0.5	0.22	-0.01	0.37	0.23	0.18	0.48	0.22
South Africa	-0.48	-0.38	-0.38	-0.52	-0.41	-0.24	-0.29	-0.22	-0.18	-0.55	-0.44	-0.21	-0.48	-0.39	-0.22
Spain	-0.04	-0.05	0.07	0.01	0.01	-0.06	0.05	0.04	0.56	-0.02	-0.02	-0.06	0.01	0.00	-0.1
Uganda	0.08	0.12	0.07	-0.02	0.02	-0.03	-0.06	-0.02	0.00	-0.04	-0.03	-0.09	0.07	0.09	0.06
UK	-0.03	0.00	-0.11	0.1	0.15	0.05	0.00	0.05	0.01	0.00	0.05	0.04	0.03	0.09	0.05
US	0.17	0.17	0.1	0.09	0.09	0.08	0.21	0.21	0.06	0.05	0.05	0.02	0.09	0.09	0.05

F = full standardization; R = Restricted standardization (age, gender, health); N = No standardization

5.4.4.2 Sources of inequality

The results of the Level Index decomposition using each standardization are presented in table 5F. In each of the standardization versions, the directions of impacts are the same, implying at least that the standardizations do not alter the data to the extent that the headline results are impacted.

Table 5F: Within and between country inequality under different standardization methods

Full standardization

	Telephone contacts		Internet contacts		In-person GP contacts		Overnight hospital stays		Clinic visits	
	Values	%	Values	%	Values	%	Values	%	Values	%
Total	-1.042	100%	-0.875	100%	-1.391	100%	-0.829	100%	-1.000	100%
Within	-0.883	84.76%	-0.778	88.96%	-1.275	91.68%	-0.687	82.86%	-0.959	95.94%
Between	-0.159	15.24%	-0.097	11.04%	-0.116	8.32%	-0.142	17.14%	-0.041	4.06%

Restricted standardization (age, gender, health)

	Telephone contacts		Internet contacts		In-person GP contacts		Overnight hospital stays		Clinic visits	
	Values	%	Values	%	Values	%	Values	%	Values	%
Total	-1.029	100.00%	-0.879	100.00%	-1.357	100.00%	-0.814	100.00%	-0.975	100.00%
Within	-0.870	84.60%	-0.777	88.46%	-1.246	91.86%	-0.673	82.68%	-0.928	95.17%
Between	-0.158	15.40%	-0.101	11.54%	-0.110	8.14%	-0.141	17.32%	-0.047	4.83%

No standardization

	Telephone contacts		Internet contacts		In-person GP contacts		Overnight hospital stays		Clinic visits	
	Values	%	Values	%	Values	%	Values	%	Values	%
Total	-1.061	100.00%	-0.974	100.00%	-1.428	100.00%	-0.874	100.00%	-1.078	100.00%
Within	-0.940	88.58%	-0.835	85.79%	-1.410	98.74%	-0.722	82.68%	-0.959	88.96%
Between	-0.121	11.42%	-0.138	14.21%	-0.018	1.26%	-0.151	17.32%	-0.119	11.04%

No standardization (inequality in actual use) shows greater pro-poor inequality than the needs-adjusted standardized data in all types of care. This implies that lower income earners were able to utilise more services, but when accounting for health-needs, this diminished slightly. Having said this, the overall picture remains materially pro-poor in this analysis, and the sources of contribution are largely similar between the standardization methods. The restricted standardization that accounts for only age, gender, and health is the least pro-poor, apart from in the telephone contacts type of care. In-person GP contacts has the largest deviation in contributing sources, with the no standardization between component reducing substantially from 8.32% with full standardization to 1.26%. That in general these results are similar is positive, despite controlling for additional variables, the overall result has not been altered to a great degree. This does not indicate evidence of overfitting the standardization model. The magnitude of results is also reasonably similar across the standardizations.

5.4.5 Sensitivity analysis

5.4.5.1 Alternative concentration index specification

I introduce 3 variations of the concentration index to test the sensitivity of the results. In addition to the Level Index employed for the main body of the analysis, which I hold as the comparator, I employ the Erreygers adjusted index (which is used in chapter 8 for consistency across chapters for the synthesis) and the Generalized concentration index, which hold quasi-absolute or absolute properties respectively, and the concentration index, which has relative properties. It is important to consider how the results may vary using these measures. Within each type of care and each variant of the concentration index, I rank the results for convenient interpretation in table 5G. The Generalized concentration index is not presented in rank form, as it is a linear transformation of the Erreygers adjusted index and the ranks remain the same. However, these and all other values are available in table B3 in the appendices.

Table 5G: Ranked alternative concentration index variations per type of care per country

	Telephone contacts inequality rank			Internet contacts inequality rank			In person GP contacts inequality rank			Overnight hospital stays inequality rank			Clinic visits inequality rank		
	L	E	C	L	E	C	L	E	C	L	E	C	L	E	C
Australia	15	15	14	16	16	16	3	2	2	15	15	15	12	12	10
Brazil	8	6	6	9	11	11	13	9	9	2	2	2	3	3	3
Canada	2	2	2	4	4	4	4	3	3	11	14	14	2	1	1
Chile	12	12	13	15	14	15	16	16	16	13	12	12	15	15	16
China	10	8	8	10	7	8	11	10	12	12	9	9	9	8	8
Colombia	3	3	3	6	5	5	6	6	5	3	3	3	5	4	4
France	9	9	9	11	12	12	12	13	13	16	16	16	10	9	14
Ghana	14	13	12	5	8	7	8	12	11	4	6	6	4	5	5
India	7	11	10	14	15	14	2	4	4	6	10	10	14	14	12
Italy	6	5	5	3	2	2	9	8	8	9	7	7	7	7	7
Japan	11	10	11	2	3	3	14	15	14	8	8	8	16	16	15
South Africa	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2
Spain	4	4	4	8	6	6	10	11	10	7	4	4	6	6	6
Uganda	13	16	16	7	10	9	5	7	7	5	5	5	11	11	9
UK	5	7	7	13	13	13	7	5	6	10	11	11	8	13	11
US	16	14	15	12	9	10	15	14	15	14	13	13	13	10	13

L = Level Index; E = Erreygers adjusted index; C = Concentration index

5.4.5.1.1 Trends

Looking first to the signs (positive or negative) of the results (table B3), I find that in each type of care apart from clinical visits, there is only one change of sign between the Level Index and the Erreygers index estimates. In the clinic visits type of care, there are two sign changes. That across 160 estimates there are only 6 differences of signs is positive, and provides insight into the general level of robustness of the results. The values of each country's estimates for each type of care are available in the appendix in full.

To go further in investigating the differences between the indices, I utilise the rank similarity percentage, defined in the methods section, to provide a summary on the similarity of the ranks. I apply this to table 5G. The Erreygers and Generalized concentration indices produce exactly the same ranks in each type of care. This is an expected result, as the Erreygers index is equal to the product of the Generalized concentration index and a scaling factor ($\frac{4}{h^u-h^l}$), where h^u and h^l refer to the upper and lower bounds of the health variable respectively. For convenience, I will refer to the Erreygers index, though these produce the same results in rank terms in each instance. This gives a rank similarity percentage of 100%.

Overall, the rank similarity indices are as follows:

S_{LE} = 36.25% (Level to Erreygers)

S_{LR} = 35% (Level to relative)

S_{EG} = 100% (Erreygers to Generalized)

S_{ER} = 66.25% (Erreygers to relative)

In the sample, approximately 1/3rd of estimated level ranks are the same as the Erreygers or relative concentration index ranks. The Erreygers and relative ranks are more similar, which is unsurprising given the shared rank methodology. That there are still differences between the Erreygers and relative measures is informative of how quasi-absolute and relative measures can produce different results.

Of course, low percentages do not necessarily mean that the indices produce vastly different results. As in this case many of the ranks that are not precise replicas are perhaps 1 or 2 ranks away. It is also expected that the Level Index, which uses more information, produces different estimates compared to the rank dependent estimates.[47] Further details within each type of care are contained in table B4 of the appendix.

Using Spearman's correlation test, I find that the average correlation between the Level Index and the Erreygers index is 0.93. This is taken as the average correlation of country ranks for each type of care investigated. The average rank correlation between the Level Index and the Concentration index is 0.94, and the correlation between the Erreygers index ranks and the concentration index ranks is 0.98 – all offering high degrees of rank correlation. Results per type of care are also available in table B4 in the appendix.

5.5 Discussion

5.5.1 Summary of results

In this chapter, I investigate the relationship between the utilisation of healthcare services and income levels in 16 countries using the Level Index to estimate inequality. I investigate this relationship across 5 different types of care to provide a broad perspective of the health systems investigated during the COVID-19 pandemic. Within country results were mixed, with varied estimates observed across countries and types of care. I find that the primary source of inequality in each type of care stems from inequality observed within each country, rather than differences between countries. This indicates that social gradients within countries played a greater role in the inequality of utilising care than social gradients between countries. Differences between actual use and health-needs standardized use were marginal in most types of care, but did indicate slightly less pro-poor inequality in the utilisation of health services after adjusting for health needs. At the country level, more changes were observed between the full standardization and raw use, with 15 shifts between pro-rich and pro-poor across the 80 statistics estimated.

5.5.2 Contextualising the results within the literature (standalone within metrics)

The following section examines the literature in the 16 countries included in this chapter. Results from this chapter are compared to previous work. However, even with these quasi-counterfactuals, it is difficult to say what gives rise to differences in every case and the counterfactuals are not direct enough to compare and make causal inferences. Ultimately of interest is the inequality landscape during the COVID-19 pandemic. Understanding the limitations of these quasi-counterfactuals, where differences are observed in prior time periods, possible reasons are examined where feasible.

Pro-rich results in the utilisation of telephone and internet linked services in Australia are supported by findings in Yeatman et al. (though specific to psychiatric uses).[82] Pulok, van Gool, and Hall have studied inequality and inequity in utilisation in Australia in several studies.[84–87] My findings during the pandemic are consistent with their estimates for the pro-poor use of unconditional GP visits. However, my results for overnight hospital stays and outpatient visits were both marginally pro-rich using both level and rank indices (under all levels of standardization). Where Pulok, van Gool, and Hall find near equitable results having observed less pro-poor results over time, I observe marginally pro-rich results – perhaps being exacerbated during the pandemic and following a similar trajectory as noted by Pulok, van Gool, and Hall, though this is conjecture.

The literature in Brazil has to date not focused on general interaction with health systems, but in areas such as counselling, psychiatry, physiotherapy, and with other specialists. In most cases, these results were pro-rich, apart from post-COVID psychiatric services in Southern Brazil.[88–90] The general pro-rich results mirror my estimates, where I find pro-rich inequality in all types of care aside from overnight hospital stays, and the rank index estimate of outpatient clinic visits. Given the approach adopted by Brazil, which was largely business as usual, it is not surprising that prior trends were largely maintained during the pandemic.

Previous work in Canada has found pro-rich use of GP services in population-wide and elderly studies, while similar pro-rich results were observed for First Nations' primary care and specialist care interactions. Overnight hospital admissions were pro-poor between 2000 and 2014.[91–93] My estimates in Canada are not consistent with the literature, which finds marginally pro-rich estimates for overnight hospital stays (pro-poor with no standardization), and pro-poor estimates in each other type of care using both level and rank index methodologies. The public orientation of Canada's health system may have made the system more agile in responding to the pandemic in a pro-poor fashion, mirroring pro-poor in-person GP estimates between 2002 and 2005. Furthermore, restricted samples used in the comparator studies (First Nations and elderly), and standardization processes might account for differences observed between the works.

A substantial body of literature exists related to inequality and inequity in utilisation of services in China. My estimates are pro-rich in all instances. In the literature, the general theme supported by several papers is also of pro-rich inequality and inequity in utilisation – particularly of inpatient and outpatient services.[75,94–98] However, a small handful of niche studies find some pro-poor estimates when disaggregating the country (e.g., rural areas, rural elderly, migrant workers).[100,102,104] Only one study identified in the literature focusing on the elderly between 2013 and 2018 finds consistent pro-poor utilisation,[110] and stands in contrast to several studies conducted on similar population groups and similar time periods.[101,103–109] While the magnitudes are not necessarily comparable between my work and these studies, the narrative of pro-rich inequality appeared to remain consistent during the pandemic period.

In Colombia, inequality has been observed in the elderly's utilisation of GP visits, while inpatient care was neither pro-rich nor pro-poor with statistical significance.[111] In my estimates, I find pro-poor results for each type of care. That the CANDOUR study includes all ages, while the reference case is only the elderly could feasibly explain the observed differences.

In England and the wider UK, I find pro-rich results in each type of care except the level estimate of telephone services. The literature finds pro-poor use of inpatient care between 2017 and 2019 in England.[112] In the COVID period, a study finds pro-rich use of GPs and medical helplines, while estimates for inpatient and outpatient care were insignificant, which is more in-line with my own findings.[164] Vestesson et al. find pro-poor utilisation of services during the pandemic, but do not compute an index, and so analysis is limited to quintile comparisons.[124] More deprived quintiles used more remote consultations, supported by my telephone services results, however my internet results were oppositional. Vestesson et al. also see a steeper reduction in the use of GP services for more deprived individuals, supporting my pro-rich GP estimates.[124]

The French estimates in my study are all pro-rich, and are supported by a 2017 study which found pro-rich utilisation across a range of health services for those suffering from Alzheimer's and related diseases.[114] However, the study did not compute indices, and so I rely on quintile comparisons. Furthermore, the specifically focused study group is not representative of the population, limiting the support gained from such a study.

My inequality estimates in India were pro-rich apart from in-person GP utilisation and overnight hospital stays using the Level Index. In the literature, inpatient and outpatient care were both found to be pro-rich using rank index methodology, though inequality decreased over time up to 2018 – supporting my rank index result in hospitalisation, and indicating the feasibility of the pro-poor level estimate in overnight hospital stays.[115] However, the pro-poor estimates I find for GP utilisation are not supported elsewhere in the literature. Problems with representativeness in India in my data may have contributed to discrepancies, though there is some support for my results based on prior trends and feasible future outcomes in the pandemic period if trends were maintained or accelerated.

My Italian estimate of pro-rich use of hospital services is supported by Di Girolamo et al., who find similar results from 2018-2020,[120] while my pro-rich estimates in Japan are also supported in the literature.[121] Both suggest a continuation of pro-rich inequality during the pandemic, rather than abatement of any sort. In South Africa, the public system is shown to be pro-poor, while the private system is pro-rich.[68] My pro-poor results in all types of care could thus indicate that the survey response was disproportionately completed by users of the pro-poor public health system.

With Canada excepted, my results are generally consistent with those found in the literature, though I lack reference estimates in Uganda, Ghana, Spain, and the United States.

5.5.3 Effects of standardization

In the standardization analysis, it is interesting to note how country estimates change given the degree of standardization which accounts for the level of need that the analysis considers. Countries that produce pro-poor estimates prior to standardization but sign-switch with standardization have systems that are pro-poor in serving populations on an income basis only, but *may* not meet the principle of horizontal equity for equal need (providing equivalent services at equivalent needs, regardless of income), as pro-poor inequality disappears as the level of need is considered. It is important to understand what is being measured, and what result is sought. In this case, the needs adjusted utilisation is important to understand how individuals of different incomes interact with systems given equivalent needs, and this can be compared to inequality in the actual use (no standardization). Though some estimates do change, this is not unexpected, and the incidence is observed in several instances in similar studies cited in the literature review of the utilisation section. The estimates are consistent in ~80% of cases, adding to the robustness of the study. The within-between decomposition across different standardization sets was also largely consistent, with marginal changes moving towards slightly less pro-poor inequality, offering the same implication as above, albeit still resulting in pro-poor inequality.

5.5.4 Sensitivity analysis

Under alternative concentration index specifications, I find overwhelming consistency in the signs of inequality between the estimates using the Erreygers and the level indices, with 10 instances in 80 where estimates are of different signs. When looking to the consistency of ranks using the Erreygers, Level, and relative indices, there is more variation. This is not unexpected, and does not cause alarm. The Spearman's correlations between ranks are also high, with the lowest observed rank correlation between indices of 0.92. It is important to note that in the interpretation of concentration indices, different specifications should be considered as the results can vary; as shown in select examples in this chapter. Presenting results with only a single index can offer a narrative with false specificity. However, each index does also measure a slightly different concept, and knowing which is fit for purpose is key. In this analysis, though there are disparities in the ranks, I take confidence from the fact that the signs are consistent between the level and Erreygers index, which both fit the purpose of the analysis given their absolute and quasi-absolute properties.

5.5.5 Policy implications

The majority of inequality observed in the study comes from within country-variation in the utilisation of services. This implies that the greatest driver of inequality during the pandemic does not lie in differences between countries. In aiming to reduce global interpersonal income-related inequality in the utilisation of healthcare, a primary focus should be given to within country inequality, and ensuring equitable access first within each country before trying to bring countries in line with each other. Without a global government, this is already the only feasible solution to address inequality.

The measurement of inequalities and inequities plays an important role in decision making. This chapter shows how different methods can, in certain instances, shift narratives, though in most cases the results are consistent. Researchers and policy makers should consider this in their decision-making process, and ensure that the selected method is fit for purpose. Policy makers that choose to analyse inequality rather than inequity could implement starkly different programmes if the estimates diverge sufficiently. A broad perspective that incorporates different types of care and different measures is necessary to support informed decision-making.

5.5.6 Limitations

There are six limitations in this investigation. (1) This study does not include metrics focused on quality of care, or differences due to government guidelines and health system specific issues. While the analysis focuses on the number of appointments utilised, it is true that in some countries, more care may be provided in 1 appointment (quality), requiring two appointments in another country for equivalent care, hypothetically speaking. It is also true that certain countries implemented guidelines prioritising certain age groups for appointments and health system access, and that reduced utilisation due to these regulations or other self-excluding decisions (e.g., self-care, fear of interacting with systems) is not included in this analysis. There are of course differences between those who did not need health systems, and those who did need health systems but elected not to engage for whatever reason. In this analysis both are treated as zero utilisation which fails to capture the whole picture. (2) The truncation in initial data collection of number of visits or appointments, although applied to a small proportion of observations in most types of care except in-person GP appointments (7.76% of observations), leads to a downward bias in the mean of the health utilisation variable, and ultimately to a non-defined mean of the variable due to the truncation. This creates challenges for both rank and level dependent indices that depend on the mean value of the health utilisation variable in this analysis. As absolute / quasi-absolute indices are employed in this analysis (apart from the concentration index in the sensitivity analysis), the effects of the truncation are likely to reduce the magnitude of the observed indices as a result of an artificially reduced mean, however I proceed with the analysis given the generally low number of truncated observations. (3) Respondents may misremember certain elements of their interactions with health systems over the ~2 year study period. Such recall errors would bias the results, though research has found that longer recall periods minimise bias.[185] Nevertheless, in a count variable taken over the full pandemic period, it is likely there was some measurement error resulting from recall bias. It is likely that this bias was not directional, and may have resulted in something approximating a zero mean error. (4) Using the Level Index with initial categorical income variables may create measurement error that is exacerbated relative to rank-dependent methods. Though this should be attenuated to an extent by the income smoothing process, it does not remove the possible error. (5) As with many surveys, representativeness with missing data can become a concern. In this chapter, Spain faced significant exclusion of individuals due to missing data, and reweighting sample weights was not able to achieve representativeness. The remaining countries achieved acceptable representation in reweighting. However, survey sampling challenges in Uganda and India limit the external validity of the results. This issue is exacerbated due to the inclusion of population weights, which are based on the original sample weights. (6) The sixth limitation relates to the non-inclusion of an ethnicity variable in the investigation. Ethnicity has been shown to influence behaviours around care seeking, attitudes towards the pandemic, and morbidity.[166,198,199] The CANDOUR study collected ethnicity variables in a manner that makes cross country comparison challenging, and more suited to individual country study on a granular level. As such, I cannot include ethnicity in this study which focuses on cross-country comparisons, though I do acknowledge that its inclusion would strengthen the research.

5.6 Conclusion

Despite limitations, this study adds a significant body of work to the literature on inequality in the utilisation of health services. This chapter adds a novel perspective on utilisation of health services across 5 different types of care during the Coronavirus pandemic in 16 countries. While some studies have been conducted in similar focus areas prior to the pandemic, several countries and types of care have not been studied at the time of writing, either during the pandemic or beforehand. I find that the majority of observed income-related inequality in utilisation during the COVID-19 pandemic is due to within-country inequality, rather than inequalities present between countries. Inequality was largest for in-person GP appointments, and lowest for overnight hospital stays across the sample. Within country estimates varied substantially. I find reasonable support for the estimates in these chapters from previous work conducted outside of the pandemic in several countries, however I lack strong counterfactuals in a number of the countries I study which prohibits me from making causal inferences on the effect of the pandemic.

6. Income-related inequality in vaccine uptake and acceptance during the COVID-19 pandemic

6.1 Introduction

Continuing with my investigation into income-related inequality in healthcare during the Coronavirus pandemic, I next turn my attention to an element of utilisation specific to the pandemic: COVID-19 vaccination. Viewing inequalities in vaccine uptake alongside utilisation provides an interesting snapshot of engagement with pandemic-specific functions of health systems during the pandemic; whereas the utilisation chapter also encompasses the "business as usual" side of health services during the pandemic period. Further discussion comparing these metrics is available in chapter 8.

The pandemic period was a time of worldwide disruption, leading many governments to impose lockdown restrictions. These restrictions were intended to minimise Coronavirus infections and were seen as an immediate solution to reduce mortality and prevent overwhelming national health systems.[200] Mass immunisation was touted as a viable measure to allow a return to normality, provided sufficient vaccination rates could be achieved to reduce virus transmission.[201] Global vaccine shortages led to inequalities and inequities in vaccine procurement and activity, particularly for Global South countries.[188,191] Shortages were driven by hoarding, vaccine nationalism, and the enforcement of intellectual property rights which restricted vaccine production, amongst other factors.[188–191] While the importance of sufficiently high overall vaccination rates to reduce transmission was recognised, failure to achieve sufficient coverage in any population sub-group risked the emergence of vaccine-resistant escape variants of the Coronavirus.[202–204] An effective vaccine rollout depended on overcoming two challenges; first of global disparities in allocation caused by shortages, which garnered much attention, and then of local disparities in allocation, caused by hesitancy across diverse populations.[205] There is an extensive literature on the global allocation of COVID vaccines, but investigations have often overlooked the socioeconomic-related distributional inequality perspective, particularly at the national level. This chapter seeks to fill this gap by analysing the distributional inequality of COVID-19 vaccine sentiment in 13 national contexts.

I use waves 1 and 2 of the COVID-19 Vaccine Preference and Opinion Survey (CANDOUR), which collected online responses from adults in 14 countries in 2020/2021 in wave 1, and in 16 countries in 2022 in the second wave. This study population focuses on the 13 countries sampled in both waves. However, I also include an analysis on the inequality in vaccine uptake for the 3 additional countries sampled in wave 2, as I use these estimates later in the thesis. In this chapter, I aim to quantitatively investigate income-related inequality in prior acceptance and subsequent reported vaccination using the difference, ratio, and Erreygers adjusted concentration index in each of the countries studied. Building on chapters 4 and 5, I analyse inequality in self-reported vaccine acceptance in 2020/2021 (a pandemic specific example of stage 2 of Levesque et al.'s access framework on *perception of needs and desire for care*[1]) and self-reported vaccination status in 2022 (stage 4 of the healthcare access framework, a pandemic specific lens on *healthcare utilisation*) to determine how hesitancy changed over the course of the pandemic. I further investigate possible sources of observed inequality using recentred influence function (RIF) regression decomposition methods. Finally, I compare covariate associations from the RIF regressions with inequality in acceptance prior to vaccine availability to associations with inequality in reported vaccine uptake.

6.2 Methods

6.2.1 Study design and population

This study was conducted using data from the first and second waves of the COVID-19 Vaccine Preference and Opinion Survey (CANDOUR) study. CANDOUR is an online, multi-country survey for adults aged 18 and over. All participants provided informed written consent before beginning the survey. Wave 1 data were collected from 14 countries between November 2020 and January 2021. Wave 2 data were collected in 16 countries between March and November 2022. I restricted analysis for the comparison between acceptance and uptake to the 13 countries surveyed in both waves to enable ex ante and ex post comparison, namely: Australia, Brazil, Canada, Chile, China, Colombia, France, India, Italy, Spain, Uganda, United Kingdom (UK), and the United States of America (US); however I include an uptake analysis on Ghana, Japan, and South Africa. The sample population is 15,337 observations in wave 1, and 18,189 in wave 2. Quota sampling was employed to ensure representative samples across gender, age, education and geographic setting per country. Post-stratification weighting was adopted if imbalances remained. Despite these efforts, sample representativeness in Uganda or India could not be achieved. Participants with missing household income or vaccination data were excluded, resulting in effective sample sizes of 13,090 (85%) in wave 1 and 16,161 (89%) in wave 2. I employed a re-weighting process to maintain representative samples after exclusion, available in the supplementary materials (table C1).

6.2.2 Data collection

In wave 1, participants were asked their intended actions if an effective COVID-19 vaccine were to become available. Respondents could select the following options: definitely get it; probably get it; probably not get it; definitely not get it; do not know; prefer not to say. "Definitely get it" and "Probably get it" were coded as accepting. "Prefer not to say" was excluded. The remaining options, including "do not know" were coded as hesitant. In wave 2, participants were asked if they had received a COVID-19 vaccine. Respondents who had received at least a single shot of any COVID vaccine were deemed vaccinated. Respondents who had not been offered a vaccine, who were still waiting for a vaccination, or who had declined the vaccination were deemed non-vaccinated. Annual household income was self-reported in bands, which I equivalised using square root equivalisation[150]. I excluded respondents with missing vaccination or income data. Health levels were self-reported on a scale of 0-100, where 100 represents perfect health. Ideology was also self-reported, where a score of 10 represented the greatest possible affiliation with right-leaning political ideology; whereas a score of 0 was associated with left-leaning ideology. Education is coded from 1 to 4, where 4 represents completion of tertiary or university education; 3: completion of secondary education; 2: completion of primary, and 1: less than primary education completed.

6.2.3 Statistical analysis

I aim to determine if there is a difference in income-related inequality between vaccination uptake and ex-ante vaccination intention (acceptance), and identify factors associated with inequality in each country. I use absolute differences and relative rate ratios in uptake and acceptance between the highest and lowest income quintiles in each country for an initial assessment of inequality. I then investigate across the full distribution using concentration indices, the bivariate extension of the Gini coefficient, which are employed frequently in health economics to measure the relationship between socioeconomic (e.g., income) and health-related variables. The index estimates a measure of dispersion based on the covariance between two variables. Positive values represent a concentration of higher values of the health-related variable amongst higher income earners (pro-rich, if the health value is desirable, e.g., good health), while negative values represent a concentration of higher values of the health-related variable amongst lower income earners. A value of 0 indicates perfect equality. Greater absolute values indicate deviations to pro-poor inequality (-1) or pro-rich inequality (1). A fuller discussion is contained in the methods review in chapter 2. I compute concentration indices within each country for dichotomized vaccine acceptance and vaccination uptake variables in waves 1 and 2 respectively. I then compare and test the vaccine acceptance indices (2020/21) with the vaccine uptake indices in each country (2022). I assess covariate associations with inequality using the recentered influence function (RIF) regression decomposition approach. The RIF regression decomposition assesses the average influence of covariates on the bivariate distributional inequality index, rather than on the uptake or acceptance variables. The RIF approach estimates how the concentration index changes if an individual were removed from the calculation (the influence function). It assesses the average contribution of each covariate by removing individuals, and observing how their covariate values impact the index. Interpretation of the RIF decomposition is analogous to ordinary least squares (OLS) regression, where coefficients are the effect on the index if every individual moved 1 unit of the covariate. I consider age, health levels, presence of chronic diseases, gender, marital status, education, and political ideology in the decomposition.

In analysing the inequality in the dichotomized uptake and acceptance variables, I employ a binary specific method. The Wagstaff (quasi-relative) and Erreygers (quasi-absolute) adjusted concentration indices have both been developed to analyse binary variables.[32] Discrepancies in mean vaccination uptake levels (due to varying timelines of national vaccine rollout) can impact the magnitude of relative measures, particularly as means approach the bounds.[205] Harper et al. produce a succinct discussion on the implicit values of inequality measurement and the use of both absolute and relative measures.[17] The mirror property, which produces equal estimates for measures of health and ill-health (e.g., acceptance and hesitancy) in the same population is present in both the Wagstaff and Erreygers index. I report the Erreygers' index in the main text, due to its ability to contend with estimates that have different underlying population means (e.g., national uptake and hesitancy). I report concentration indices and ranks for both methods in the supplementary materials (table C2), allowing comparison between indices that have relative and absolute properties, respectively.[25,32]

I decompose the Erreygers adjusted index to identify covariates associated with the observed inequality and its changes. Wagstaff, van Doorslaer, Watanabe, and Erreygers and Kessels have developed popular decomposition approaches.[58,59,60,206] However, the interpretation of these decompositions is not immediately clear.[62] The RIF approach addresses critiques raised by Fortin et al. and Erreygers and Kessels, and decomposes the index itself rather than the covariance-forming variables in a general decomposition approach for bivariate rank indices using an influence function.[59,62,61] I employ the RIF-regression decomposition, which has the benefit of producing partial effects on the index, linking to conventional evaluation literature. Interpretation is akin to OLS regression, with which most readers will be familiar[62,206]. The RIF decomposition produces easily interpreted results, with coefficients interpreted as the expected change in inequality associated with a 1-unit societal (e.g., all individuals in a country) shift in the covariate. These methods provide a perspective on the distributional landscape of COVID vaccination, thereby filling the gap this paper seeks to address.

Further discussion on methods is contained in Erreygers (2008),[25] Heckley et al. (2016),[62] and Kessels and Erreygers (2019),[206] as well as in the methods review found in chapter 2.

6.3 Results

6.3.1 Descriptive statistics

The sample descriptive statistics of survey respondents are presented in Table 6A. 5,454 respondents were repeatedly sampled. Descriptive statistics are reported as means (SD) or median (IQR). Binary variables (e.g., married, female) represent the proportion of the population with the stated attribute. Wave 2 respondents were nearly 10 percentage points more likely to be vaccinated than their intentions indicated, led by Chile (98.6% uptake, 87.6% acceptance). Among the three European Union countries in the sample - France, Italy, and Spain - there was a significant increase in positive vaccine sentiment, with increases of 26, 22, and 17 percentage points respectively. Respondents in wave 2 were two years younger at the median, and four percentage points less healthy than wave 1 counterparts. Wave 2 respondents were better educated and one degree more left-leaning politically. Wave 1 respondents were more likely to be married and lived in smaller households. Mean income was $250 PPP dollars higher in wave 2. China reported the highest average health levels in both waves at approximately 80%, despite the overall decline in self-reported health levels between waves across the sample. India reported the lowest health values in each wave, and was the only country to report average health levels below 50%. Political ideology was consistent across the samples. India was the most right-wing, with self-reported median scores of 8 and 7 (where 10 is the most right-wing), compared to Spain and Chile, who reported median left-wing leanings (1 and 3, where 0 is most left-leaning). Uganda had the least female representation, with more than 80% male respondents in each wave.

6.3.2 Comparing country acceptance and uptake levels

National acceptance and uptake levels are presented in the left panel of figure 6A. Acceptance levels in wave 1 are consistently around the 80% mark. India and Brazil had the highest acceptance rates, nearing 90%. France (45%), Italy (63%), and the US (67%) had the lowest acceptance rates. Uptake levels were 10 percentage points higher on average than acceptance levels. Each country reported higher uptake than acceptance apart from Brazil. Perhaps unsurprisingly based on stated hesitancy, France and the US had the lowest uptake levels (~70%), though Italy appears to have overcome initial hesitancy to reach 86% uptake.

6.3.3 Quintile differences and rate ratios

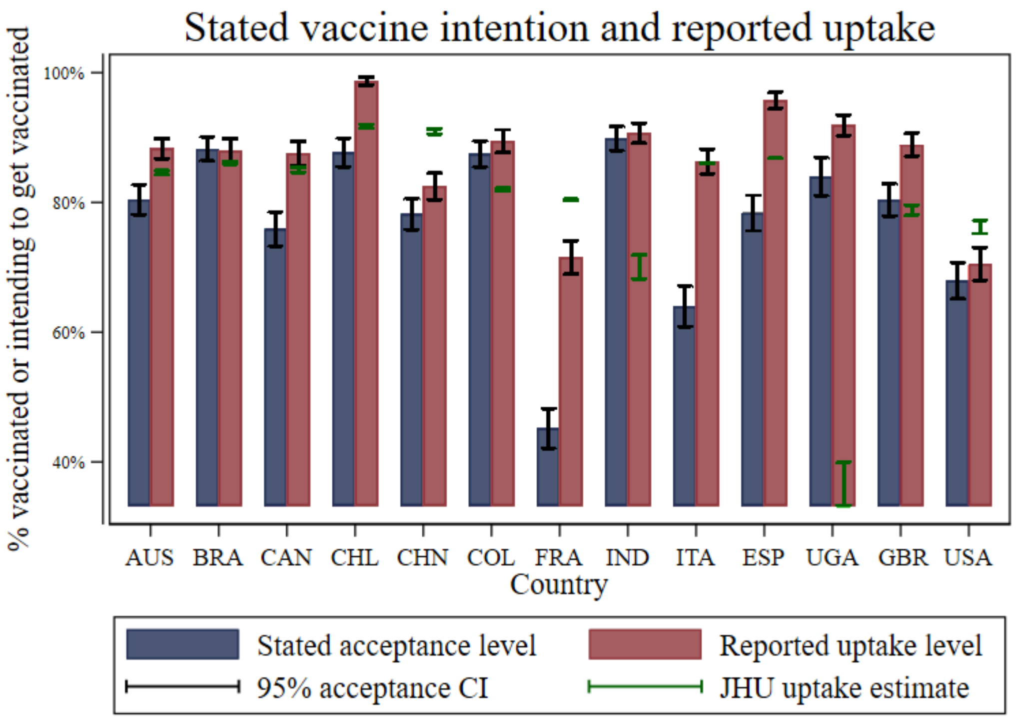
I report descriptive statistics of acceptance and uptake by income quintile (Q1 = lowest-income quintile; Q5 = highest-income quintile) in figure 6B. The top left panel shows mean acceptance per quintile, while the top right shows mean uptake per quintile. France, Italy, Spain, and the United States show the steepest inequality gradients in the quintile analysis in acceptance (left). Chile presents a relatively flat gradient for both acceptance and uptake. Italy and Spain maintain inequality gradients, and are joined by China, while the United States and France are more varied across quintiles, despite maintaining absolute differences in mean uptake between Q1 and Q5. I report absolute differences between Q5 and Q1 (in percentage points) and a relative descriptive measure employing the rate ratio in table 6B .

Table 6A: Sample descriptive statistics for acceptance (2020/21) and uptake (2022)

Panel 1	Acceptance (%)	Age* (years)	Health (%)	Chronic diseases (n)	Education level*	Ideology*	Female (%)	Household size (n)	Married (%)	Household income ('000s ppp $)
OVERALL – 2020/21	77.2 (12.0)	44 (30-59)	71.6 (23.9)	0.48 (0.49)	2 (2-4)	5 (4-7)	46.6 (49.8)	2.6 (1.5)	60.3 (48.9)	26.3 (27.5)
Australia	80.4 (39.7)	44 (31-60)	67.3 (22.4)	0.77 (0.94)	3 (2-4)	5 (5-7)	49.0 (50.0)	2.1 (1.1)	60.5 (48.9)	38.6 (33.2)
Brazil	88.2 (32.2)	41 (29-55)	75.0 (23.6)	0.52 (0.49)	3 (2-3)	6 (4-8)	47.5 (49.9)	2.6 (1.2)	54.7 (49.7)	10.9 (11.4)
Canada	75.8 (42.8)	48 (32-62)	70.4 (20.3)	0.77 (0.91)	3 (3-3)	5 (4-6)	49.2 (50.0)	2.0 (0.9)	53.6 (49.8)	37.7 (28.1)
Chile	87.6 (32.9)	39 (26-54)	73.3 (21.1)	0.66 (0.85)	3 (3-4)	5 (3-5)	45.6 (49.8)	2.8 (1.4)	53.0 (49.9)	15.0 (21.8)
China	78.1 (41.3)	49 (34-60)	80.8 (16.1)	0.44 (0.69)	2 (2-3)	-	49.8 (50.0)	2.9 (1.3)	87.6 (32.9)	22.8 (19.0)
Colombia	87.4 (33.1)	41 (28-56)	79.9 (23.2)	0.54 (0.84)	3 (2-3)	5 (4-7)	48.4 (49.9)	3.2 (1.4)	62.7 (48.3)	6.45 (5.44)
France	45.1 (49.7)	48 (33-62)	74.6 (22.0)	0.37 (0.48)	4 (3-4)	5 (4-7)	47.6 (49.9)	1.9 (0.8)	66.2 (47.3)	33.1 (17.8)
India	89.8 (30.2)	33 (25-46)	46.6 (30.7)	1.32 (1.17)	2 (1-3)	8 (5-10)	51.3 (50.0)	3.8 (2.2)	58.3 (49.3)	5.05 (6.98)
Italy	63.9 (48.0)	51 (37-62)	73.6 (21.1)	0.58 (0.80)	3 (3-3)	5 (3-7)	47.9 (49.9)	2.5 (1.1)	63.8 (48.0)	27.6 (19.1)
Spain	78.3 (41.2)	49 (35-61)	76.1 (19.7)	0.60 (0.79)	3 (3-4)	4 (2-6)	48.5 (50.0)	2.3 (0.8)	67.5 (46.8)	44.3 (28.4)
Uganda	83.9 (36.7)	25 (23-35)	77.2 (18.3)	0.94 (0.89)	3 (3-3)	5 (5-7)	12.3 (32.8)	3.7 (1.9)	22.8 (42.0)	3.35 (2.84)
United Kingdom	80.3 (39.7)	49 (34-62)	72.0 (20.9)	0.59 (0.85)	3 (3-4)	5 (4-7)	48.9 (50.0)	2.1 (0.9)	61.6 (48.6)	40.4 (30.8)
United States	67.9 (46.7)	42 (30-56)	65.7 (26.7)	0.92 (0.96)	3 (3-4)	5 (4-8)	49.5 (50.0)	2.2 (1.2)	60.5 (48.8)	48.8 (35.5)
Panel 2	UPTAKE (%)									
OVERALL - 2022	86.8 (7.8)	42 (28-56)	67.6 (25.4)	0.39 (0.48)	3 (3-4)	4 (3-7)	50.4 (49.9)	3.2 (9.0)	52.0 (49.9)	26.5 (28.6)
Australia	88.2 (32.1)	38 (29-55)	66.6 (18.7)	0.59 (0.81)	3 (3-4)	5 (4-6)	64.9 (47.7)	2.1 (1.1)	48.1 (49.9)	42.1 (35.3)
Brazil	87.9 (32.5)	39 (26-62)	70.2 (24.1)	0.64 (0.96)	5 (3-5)	6 (4-7)	53.0 (49.9)	5.8 (15.)	41.9 (49.3)	8.80 (10.4)
Canada	87.5 (33.0)	37 (24-56)	68.0 (23.7)	0.67 (0.85)	4 (3-5)	5 (4-7)	61.8 (48.5)	2.0 (0.9)	39.8 (48.9)	40.4 (29.3)
Chile	98.6 (11.4)	32 (23-43)	73.5 (21.3)	0.42 (0.65)	3 (3-4)	3 (2-5)	55.8 (49.6)	2.6 (1.2)	30.3 (46.0)	17.8 (21.0)
China	82.4 (38.0)	44 (29-53)	78.4 (21.0)	0.31 (0.59)	3 (3-3)	-	48.9 (50.0)	3.3 (6.4)	73.5 (44.0)	25.4 (24.9)
Colombia	89.4 (30.7)	45 (32-62)	62.2 (33.4)	0.51 (0.70)	4 (3-5)	5 (2-7)	46.1 (49.8)	2.8 (2.4)	55.4 (49.7)	11.7 (9.03)
France	71.5 (45.1)	53 (41-63)	68.8 (26.0)	0.50 (0.68)	3 (3-4)	5 (5-7)	55.2 (49.7)	1.9 (0.8)	58.7 (49.2)	28.6 (15.3)
India	90.6 (29.0)	31 (24-40)	49.8 (35.8)	0.62 (0.84)	4 (2-4)	7 (5-8)	45.2 (49.7)	7.0 (26.)	48.9 (50.0)	7.75 (8.69)
Italy	86.2 (34.4)	53 (41-62)	69.2 (23.2)	0.50 (0.73)	3 (3-3)	5 (3-7)	54.2 (49.8)	2.4 (1.3)	65.5 (47.5)	29.7 (17.5)
Spain	95.7 (20.2)	33 (33-53)	70.8 (18.1)	0.31 (0.63)	4 (3-4)	1 (0-5)	51.1 (50.0)	2.2 (1.5)	79.7 (40.2)	52.9 (27.6)
Uganda	91.8 (27.3)	30 (25-40)	73.9 (19.4)	0.32 (0.60)	3 (3-5)	5 (4-7)	19.6 (39.7)	5.7 (6.6)	35.4 (47.8)	0.31 (0.37)
United Kingdom	88.8 (31.4)	47 (37-59)	60.0 (23.5)	0.59 (0.83)	4 (3-5)	5 (3-7)	52.5 (49.9)	1.8 (0.7)	53.2 (49.9)	29.1 (26.9)
United States	70.4 (45.6)	42 (26-61)	66.9 (22.5)	0.97 (0.91)	3 (3-4)	5 (3-8)	47.7 (49.9)	2.2 (2.6)	44.3 (49.6)	48.4 (43.4)

Standard Errors (SE) and Interquartile Ranges (IQR) in parentheses. An asterisk (*) indicates the use of IQR in parentheses. If not stated, Standard Errors are produced.

Figure 6A: Comparison between acceptance and uptake levels



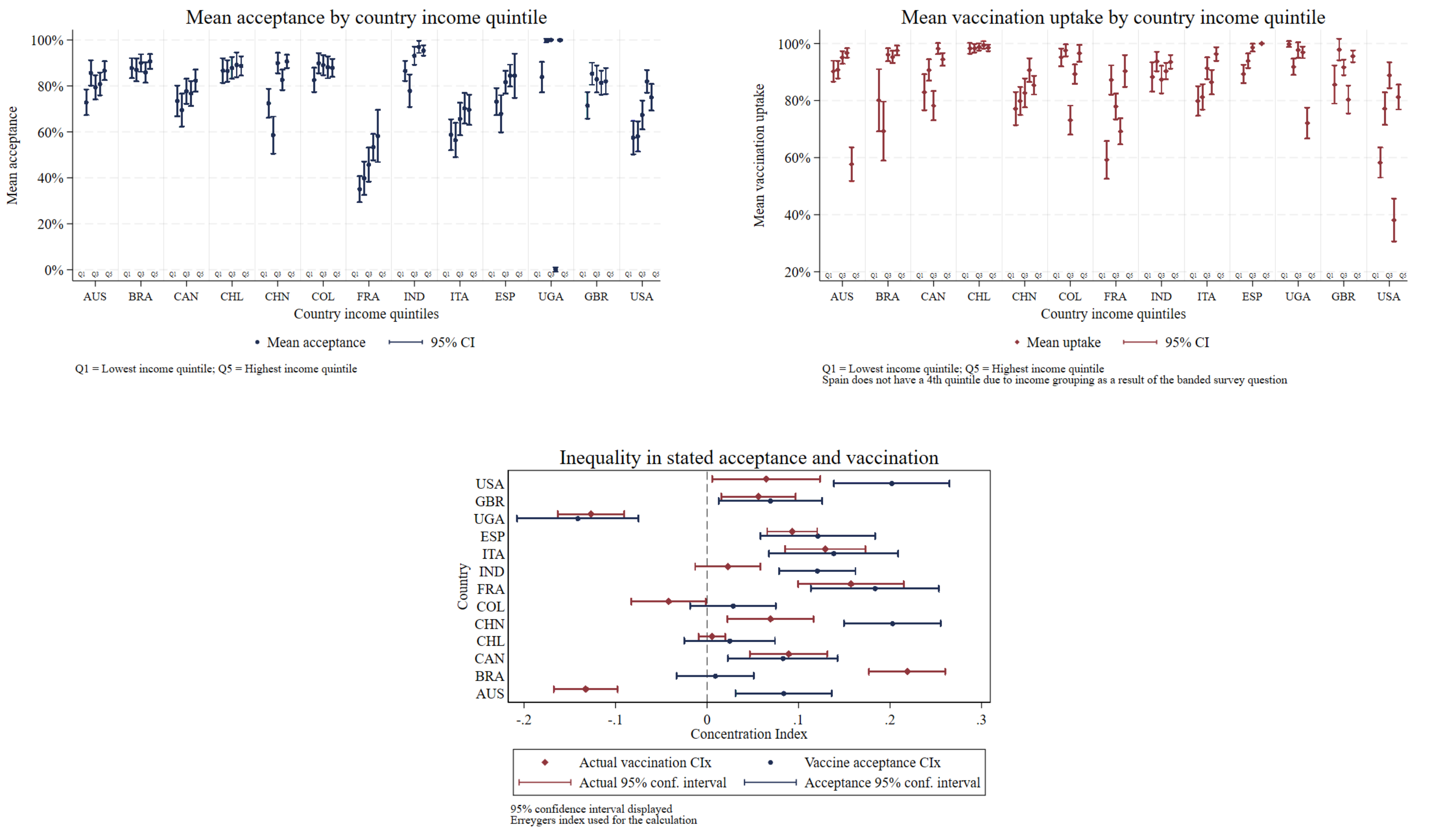
COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University
JHU interval based on rate at first survey date to rate at last survey date per country

Table 6B: Differences and rate ratios in acceptance and uptake across national income quintiles

	Vaccine acceptance		Vaccine uptake	
Country	Difference [p.p.] (95% CI)	Rate ratio (95% CI)	Difference [p.p.] (95% CI)	Rate ratio (95% CI)
Australia	0.14 (0.05 - 0.22)	1.19 (1.06 - 1.32)	-0.22 (-0.69 - 0.25)	0.76 (0.24 - 1.28)
Brazil	0.04 (-0.04 - 0.12)	1.05 (0.95 - 1.14)	0.18 (-0.18 - 0.54)	1.32 (0.39 - 2.25)
Canada	0.1 (-0.01 - 0.2)	1.14 (0.97 - 1.3)	0.07 (-0.18 - 0.33)	1.12 (0.71 - 1.52)
Chile	0.03 (-0.08 - 0.15)	1.04 (0.9 - 1.18)	0 (-0.02 - 0.02)	1 (0.98 - 1.02)
China	0.2 (0.04 - 0.36)	1.3 (0.98 - 1.63)	0.08 (-0.08 - 0.24)	1.11 (0.89 - 1.34)
Colombia	0.05 (-0.05 - 0.16)	1.07 (0.94 - 1.2)	-0.01 (-0.12 - 0.1)	0.99 (0.87 - 1.11)
France	0.23 (0.1 - 0.37)	1.69 (1.22 - 2.16)	0.3 (-0.05 - 0.64)	1.95 (-15.39 - 19.3)
India	0.1 (-0.01 - 0.2)	1.12 (0.97 - 1.26)	0.04 (-0.11 - 0.19)	1.05 (0.87 - 1.24)
Italy	0.13 (0 - 0.26)	1.23 (0.99 - 1.47)	0.15 (-0.01 - 0.31)	1.2 (0.97 - 1.43)
Spain	0.11 (0 - 0.22)	1.15 (0.99 - 1.31)	0.1 (0.05 - 0.14)	1.11 (1.06 - 1.17)
Uganda	0.07 (-0.39 - 0.53)	1.12 (0.38 - 1.87)	-0.23 (-0.66 - 0.21)	0.77 (0.33 - 1.21)
United Kingdom	0.1 (0.01 - 0.19)	1.15 (1.01 - 1.28)	0.11 (-0.19 - 0.41)	1.36 (-6.98 - 9.69)
United States	0.17 (0.07 - 0.28)	1.31 (1.09 - 1.54)	0.24 (0.11 - 0.37)	1.42 (1.16 - 1.69)

Notes: Difference calculated as (mean) Q5 (highest income) – (mean) Q1 (lowest income) in percentage points.
Rate ratio calculated as (mean) Q5/ (mean) Q1.
Positive differences and ratios indicate likelihood of pro-rich inequality between highest and lowest income groups.
Standard errors calculated using bootstrap (n=1,000) resampling methods.

Figure 6B: Inequality in stated acceptance versus actual vaccination



Top left: Mean acceptance rate by country income quintile. Top right: Mean vaccination uptake by country income quintile. Bottom: Erreygers adjusted inequality indices

All countries had higher acceptance in Q5 than Q1, though this was only significant at the 5% level (i.e., 95% CI strictly above 0) in approximately half the countries. France had the highest absolute difference in acceptance between Q5 and Q1 (23 percentage points). The South American nations of Chile, Brazil, and Colombia exhibited the lowest absolute differences, at 3, 4, and 5 percentage points respectively. France and the United States showed the largest relative differences, with ratios of 1.69 and 1.31 respectively, indicating higher vaccine acceptance amongst the highest income quintile. In uptake, France again exhibited the largest absolute and relative differences favouring the high-income quintile. Australia and Uganda presented negative differences, showing higher uptake in Q1 relative to Q5, while Chile presented a rate-ratio of 1.00, and negligible absolute differences between Q1 and Q5. While I focus on the Erreygers adjusted index to assess inequality for the remainder of this paper, further quintile comparisons can be drawn using table 6B.

6.3.4 Income-related inequality in acceptance and uptake using the Erreygers adjusted index

The bottom panel of figure 6B shows the full-distribution inequality in acceptance and hesitancy within each country. As the rankings of relative and absolute inequality measures are similar, I report and comment on the quasi-absolute Erreygers measure, with quasi-relative results available in supplementary table C2. Acceptance was concentrated among richer individuals, shown in the pro-rich (positive) concentration indices reported in 9 countries. China (0.203), the US (0.202), and France (0.184) reported the most pro-rich results. Only Uganda (-0.141) reported pro-poor (negative) acceptance levels – however this result should be viewed with caution due to the non-representativeness of the sample. Uptake was less pro-rich than acceptance. Australia (-0.133), Uganda (-0.127), and Colombia (-0.042) reported pro-poor estimates. Although 8 countries reported pro-rich uptake indices, Australia (Δ= -0.216), China (Δ= -0.133), India (Δ= -0.098), and the US (Δ= -0.137) reported more pro-poor estimates of uptake than acceptance, taken simply as the difference in index values between uptake and acceptance. Brazil (Δ= 0.210) was the only country that reported a pro-rich change across the pandemic.

6.3.5 Decomposing income-related inequality

The results of the RIF-regression decomposition are presented in tables 6C and 6D. The results are informative of: a) covariate associations of inequality in vaccine acceptance and uptake and b) changes in covariate associations over time. At this stage it is a useful reminder that these results are associations, and are not necessarily causal. Several other factors that were not included in the data collection could similarly have influenced sentiment, and its changes over time. Variables with negative (positive) coefficients are associated with pro-poor (pro-rich) influences on the concentration index. For example, if more individuals were married, inequality would decline, suggesting marriage is either associated with acceptance and lower income levels, or hesitancy and higher income levels; similar logic holds for all results. For vaccine acceptance, marital status was significantly associated with inequality in 8 countries. The coefficient was pro-poor (negative) in all countries but France. Political ideology was also significant in 8 countries, with a smaller magnitude of impact. In all sample countries apart from France and Italy, a more conservative political ideology was associated with an increase in inequality. An increased proportion of females was associated with increased inequality in acceptance everywhere but Brazil and Italy, and was significant and pro-rich in 7 countries. Age and health levels had a pro-poor association with the Erreygers adjusted index, while education had varied associations. For vaccine uptake, health levels were significant and pro-poor. Age was significant in 10 of the countries and remained a pro-poor influence except in China. Marital status was also significant in 10 countries with pro-poor effects. Political ideology was again significant in 8 countries. Political ideology did not contribute significantly in uptake in Italy and the United Kingdom despite observed significance in acceptance, while in Australia, Colombia, France, and the US, political ideology was significantly correlated with uptake and not acceptance.

6.3.6 Additional uptake estimates

Ghana, Japan, and South Africa were not sampled in wave 1. Thus, I cannot provide a comparison between acceptance and uptake. However, I estimate inequality in uptake, and present these results in figure 6C, for use in the synthesis across the healthcare process in chapter 8. The concentration indices and decompositions are available in the appendix in tables C2-C3, for comparison to the other countries in the sample.

Table 6C: Acceptance decomposition table

	Australia	Brazil	Canada	Chile	China	Colombia	France	India	Italy	Spain	Uganda	UK	US
Age	-0.0007	-0.0121***	0.0037	-0.0112*	0.0001	0.0070*	-0.0221***	0.0008	-0.0059	-0.0031	-0.0235*	-0.0086**	0.0062
	(-0.0022)	(-0.0032)	(-0.0032)	(-0.006)	(-0.0004)	(-0.0041)	(-0.0049)	(-0.0049)	(-0.0053)	(-0.0043)	(-0.0126)	(-0.0043)	(-0.0038)
Female	0.3388***	-0.0693	0.4554***	0.3211**	0.0246	0.1238	0.4605***	-0.0183	0.3931***	0.3271***	0.0942	0.0983	0.5609***
	(-0.1069)	(-0.0902)	(-0.1166)	(-0.1358)	(-0.0987)	(-0.0928)	(-0.1416)	(-0.0889)	(-0.1223)	(-0.124)	(-0.1783)	(-0.1253)	(-0.1198)
Health level	-0.0057**	-0.0063***	-0.0036	-0.0030	-0.0059*	-0.0006	0.0050	-0.0020	0.0068**	-0.0011	-0.0022	-0.0055*	-0.0005
	(-0.0023)	(-0.0022)	(-0.0031)	(-0.0038)	(-0.0033)	(-0.0022)	(-0.0031)	(-0.0017)	(-0.0031)	(-0.0033)	(-0.0027)	(-0.003)	(-0.0021)
Marital status	-0.2745**	-0.0710	-0.2954**	-0.3873**	-0.6928***	-0.0624	0.1394	-0.5754***	-0.2947**	-0.2127	-0.3971***	- 0.4350***	-0.1977
	(-0.1319)	(-0.0924)	(-0.128)	(-0.179)	(-0.1453)	(-0.1007)	(-0.1432)	(-0.1196)	(-0.1485)	(-0.134)	(-0.1522)	(-0.1373)	(-0.1338)
Education (Less than primary)	0.5303	-0.8226**	0.9034*	-0.0868	-	0.5078	-2.4059***	-	-0.8050	1.7357**	-	1.2365*	-3.7173**
	(-0.9102)	(-0.3781)	(-0.4762)	(-0.6831)	(-)	(-0.5494)	(-0.9208)	(-)	(-1.1101)	(-0.8765)	(-)	(-0.6678)	(-1.8576)
Education (Primary)	0.2886	-1.2980***	-	-0.0564	0.1521	0.6376	-0.1659	0.4778***	-0.9946	0.5280	0.2337	1.0178*	-1.9546**
	(-0.5997)	(-0.3707)	(-)	(-0.977)	(-0.2995)	(-0.559)	(-0.7329)	(-0.1651)	(-1.1332)	(-0.7393)	(-0.8445)	(-0.6013)	(-0.846)
Education (Secondary)	-0.0697	-1.4218***	0.0673	0.5963	0.3613	0.6009	-0.5249	0.7922***	-1.0219	0.5075	0.7109	0.8815	-2.5875***
	(-0.5834)	(-0.334)	(-0.3672)	(-0.4627)	(-0.3292)	(-0.5349)	(-0.7057)	(-0.1823)	(-0.9285)	(-0.7396)	(-0.7822)	(-0.5848)	(-0.7576)
Education (University)	-0.7125	-1.8870***	-0.2272	0.0338	-0.4004	0.7856	-0.7518	0.4543***	-1.3196	0.3538	0.4583	0.5870	-3.1571***
	(-0.5776)	(-0.3351)	(-0.3866)	(-0.4452)	(-0.3001)	(-0.5395)	(-0.7067)	(-0.1409)	(-0.932)	(-0.7392)	(-0.7908)	(-0.5841)	(-0.7518)
Chronic disease	-0.1094	0.0875	-0.0735	-0.2803**	-0.2254**	-0.0916	-0.1576	0.0213	-0.3605***	-0.3581***	-0.0077	-0.0277	-0.2586**
	(-0.1103)	(-0.0861)	(-0.1095)	(-0.1365)	(-0.1095)	(-0.1007)	(-0.1404)	(-0.1035)	(-0.1231)	(-0.112)	(-0.1384)	(-0.1263)	(-0.1161)
Political ideology	0.0342	0.0458***	0.0733***	0.0387	-	0.0425**	-0.0299	-0.0549**	0.0732***	0.0940***	0.0234	0.0476	0.0380**
	(-0.0225)	(-0.0152)	(-0.024)	(-0.0272)	(-)	(-0.0188)	(-0.0244)	(-0.0226)	(-0.0219)	(-0.0229)	(-0.0261)	(-0.0294)	(-0.0183)
Constant	-0.8176	0.3700	-1.1995**	-2.0157***	0.0789	-2.1035***	1.5203*	-1.6032***	0.1734	-0.7933	-1.9872**	-1.2017*	2.2243***
	(-0.7081)	(-0.3983)	(-0.4806)	(-0.6008)	(-0.4277)	(-0.6022)	(-0.8054)	(-0.2885)	(-0.9521)	(-0.8086)	(-0.9063)	(-0.6695)	(-0.7709)
Observations	1,158	1,203	1,041	906	1,196	1,036	1,004	1,047	935	873	607	1,006	1,078

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

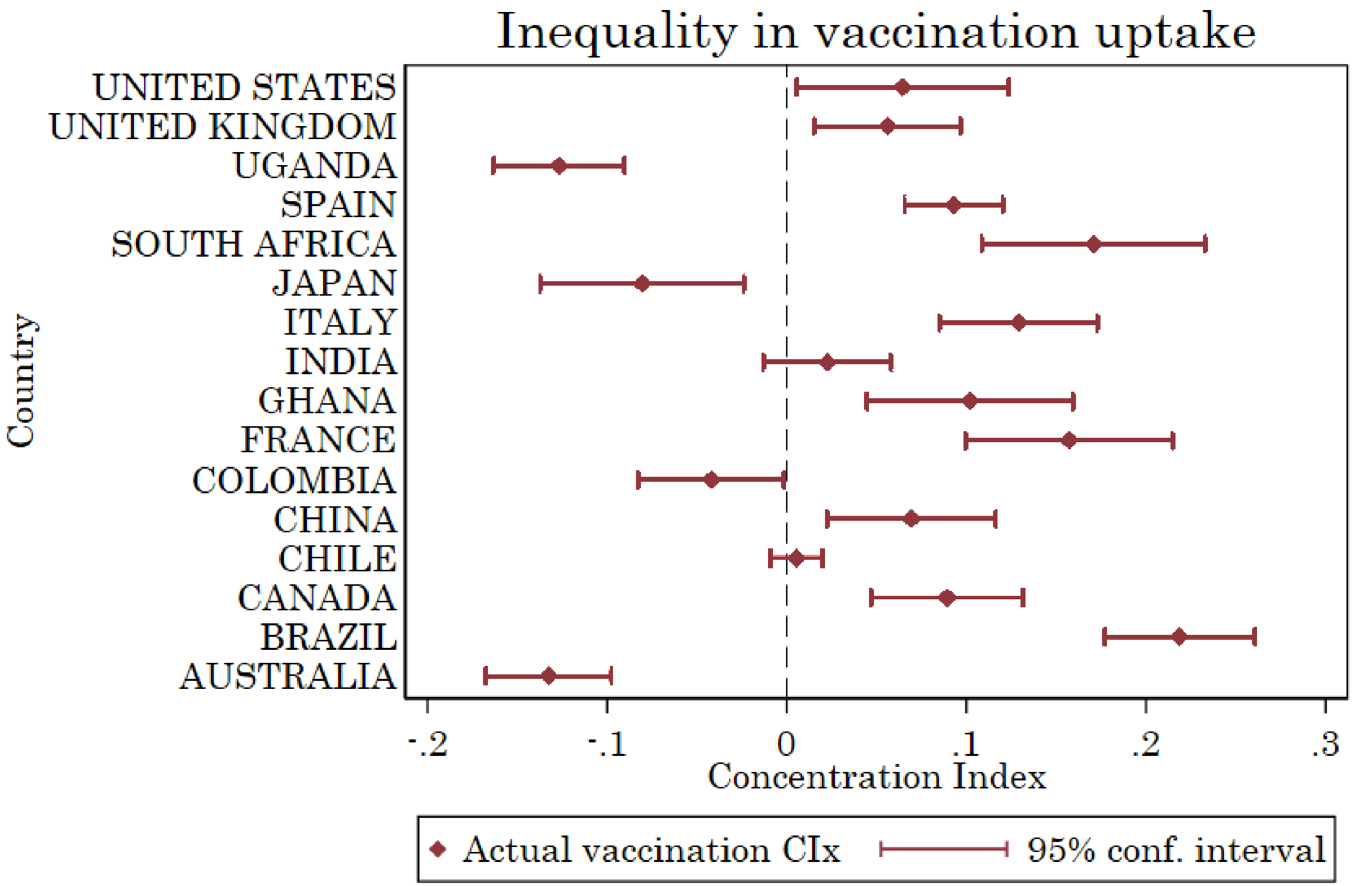
Table 6D: Uptake decomposition table

	Australia	Brazil	Canada	Chile	China	Colombia	France	India	Italy	Spain	Uganda	UK	US
Age	-0.0035	-0.0145***	-0.0045*	-0.0010	0.0208***	-0.0066**	-0.0147***	-0.0013	-0.0109***	-0.0061**	-0.0357***	-0.0171***	-0.0174***
	(-0.0029)	(-0.0033)	(-0.0027)	(-0.003)	(-0.0042)	(-0.003)	(-0.0035)	(-0.0041)	(-0.0034)	(-0.003)	(-0.0089)	(-0.0039)	(-0.0032)
Female	-0.0717	-0.1457	0.0864	0.1494*	-0.1339	-0.0355	0.0167	-0.0509	-0.0015	0.1107	-0.1046	0.0648	0.1858*
	(-0.0807)	(-0.0952)	(-0.0821)	(-0.0778)	(-0.0874)	(-0.0768)	(-0.1018)	(-0.0719)	(-0.0878)	(-0.0819)	(-0.1295)	(-0.0955)	(-0.1006)
Health level	-0.0111***	-0.0097***	-0.0068***	-0.0078***	-0.0099***	-0.0023*	-0.0098***	-0.0058***	-0.0120***	-0.0068***	-0.0186***	-0.0053*	-0.0107***
	(-0.0026)	(-0.002)	(-0.0026)	(-0.002)	(-0.0034)	(-0.0012)	(-0.0025)	(-0.0014)	(-0.0025)	(-0.0022)	(-0.004)	(-0.0028)	(-0.0025)
Marital status	-0.5091***	-0.3572***	-0.3820***	-0.2120**	-1.0325***	-0.0096	-0.2980**	-0.1857**	-0.1827*	-0.0480	-0.2741**	-0.4559***	-0.1275
	(-0.0802)	(-0.0995)	(-0.0994)	(-0.0935)	(-0.1498)	(-0.0806)	(-0.118)	(-0.0904)	(-0.1018)	(-0.0903)	(-0.1275)	(-0.1117)	(-0.1159)
Education (Less than primary)	1.1183	-0.6590	0.8573	-1.0514	0.4525	-0.2557	0.9317	-0.0906	1.7465	0.0023	0.1509	-0.1530	1.9725
	(-1.0436)	(-0.7576)	(-0.7382)	(-0.6761)	(-0.954)	(-0.5035)	(-2.0207)	(-0.8386)	(-1.7889)	(-0.2752)	(-1.2075)	(-0.4642)	(-1.3309)
Education (Primary)	0.1917	-0.6869	-	-0.3162	-0.5285	0.1155	-0.3569	-	1.3387	-	1.3616*	-0.6600*	2.0983*
	(-0.7248)	(-0.7535)	(-)	(-0.5779)	(-0.8164)	(-0.5146)	(-1.4962)	(-)	(-1.3482)	(-)	(-0.8054)	(-0.3887)	(-1.1366)
Education (Secondary)	-0.4540	-1.3872*	0.1616	-0.6038	-0.7219	-0.6505	-0.7795	-0.8148*	0.0912	-0.3285**	0.2036	-0.9328**	0.9534
	(-0.721)	(-0.7339)	(-0.7035)	(-0.5245)	(-0.8191)	(-0.4284)	(-1.4787)	(-0.432)	(-0.7854)	(-0.1354)	(-0.7302)	(-0.3627)	(-1.0832)
Education (University)	-0.7097	-1.5830**	-0.1257	-1.0409**	-1.1969	-0.4595	-0.9107	-0.5407	-0.0330	-0.3772***	0.0017	-1.1183***	0.2459
	(-0.7153)	(-0.7361)	(-0.7033)	(-0.5254)	(-0.8272)	(-0.4321)	(-1.4874)	(-0.4102)	(-0.7892)	(-0.1441)	(-0.7371)	(-0.3655)	(-1.0902)
Chronic disease	0.0655	-0.1169	-0.1139	-0.1511*	-0.0961	0.0155	-0.1808*	-0.2831***	-0.1115	-0.0254	-0.0631	0.0118	-0.2897***
	(-0.083)	(-0.0923)	(-0.083)	(-0.0812)	(-0.1078)	(-0.0819)	(-0.1012)	(-0.0735)	(-0.0941)	(-0.0799)	(-0.116)	(-0.1018)	(-0.1089)
Political ideology	0.0589***	0.0400***	0.0960***	0.0155	-	0.02553*	0.0296	-0.0133	0.0386**	0.03392**	-0.0237	0.0092	0.0480***
	(-0.0225)	(-0.0142)	(-0.0191)	(-0.0162)	(-)	(-0.0136)	(-0.019)	(-0.0153)	(-0.0161)	(-0.0164)	(-0.023)	(-0.0237)	(-0.017)
Constant	0.1020	1.0997	-0.2503	-0.3719	0.1090	0.0753	2.9489*	0.4584	1.0808	0.7462***	-0.0259	0.8740**	-0.2997
	(0.7667)	(0.7796)	(0.7465)	(0.5671)	(0.8097)	(0.4490)	(1.5183)	(0.4435)	(0.8246)	(0.2797)	(0.8546)	(0.4143)	(1.1186)
Observations	1,675	1,139	1,220	1,285	1,329	1,167	1,216	1,363	1,226	1,005	1,106	1,212	1,218

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Figure 6C: Inequality in stated vaccination uptake including Ghana, Japan, and South Africa



95% confidence interval displayed
Erreygers index used for the calculation

6.4 Discussion

6.4.1 Summary of results

This chapter examined income-related inequality and associated factors in acceptance and uptake of COVID-19 vaccination in 13 countries. My main results employing the Erreygers adjusted index suggest that acceptance and uptake were generally pro-rich. Nine countries reported pro-rich inequality in acceptance, and eight in uptake. Average inequality in uptake was lower than in acceptance by 46% ($\overline{\Delta} = -0.039$). This is a promising result, indicating that initial inequality in attitudes to vaccination in a pandemic context can be reduced over time.

Vaccine inequality and inequity vary depending on contexts. In routine immunisation, there are often inequalities based on wealth or income, gender, education and location.[207–209,125] COVID-19 vaccine inequality first became a concern due to global vaccine shortages. Income has been consistently identified as a factor influencing vaccine acceptance and uptake at both individual and national levels, with wealthier individuals being more likely to be vaccinated and wealthier nations achieving higher coverage.[127,210–213] This chapter takes an additional step from the existing literature, and investigates the distributional impacts of individual income-related hesitancy on overall income-related inequality in vaccine acceptance and uptake.

6.4.2 Validity of uptake and acceptance estimates compared to existing studies

An extensive literature has been produced on both general and COVID-19 specific vaccine hesitancy and acceptance.[207,214] To estimate income-related inequalities in vaccine uptake and acceptance, it is important that the survey tools used provide reliable estimates of baseline vaccine acceptance and uptake. I therefore compare the overall country estimates of acceptance and uptake to the literature, to anchor the validity and representativeness of the sample, and provide a basis for the inequality estimates, for which there are limited comparators. The reported levels of acceptance and uptake are largely consistent with the literature, though there are some differences which I note. Drawing on the works of Lazarus et al.,[215] Robinson et al.,[210] Sallam,[216] and others,[217–219] I find support for ten of the country-level estimates on vaccine acceptance based on previously published estimates. However, the acceptance estimates in India and Uganda, where the sample under-represented lower income earners and did not achieve full representativeness, were substantially higher than other works. My estimates for China are 5-10% lower than those in most studies, except for Zhang et al., which focused on parents and guardians.[220]

Uptake figures were compared to reliable national administrative data collated and managed by Johns Hopkins University (JHU).[221] I take administrative estimates aligned to the start and end-dates of the CANDOUR survey for each country. India and Uganda were the largest outliers relative to JHU data. This is indicative of further socioeconomic and income-related inequality in uptake, as my income-skewed sample has higher uptake than the national average. The remaining countries were similar to administrative data, though some variation was observed.

6.4.3 Inequality in COVID-19 vaccine sentiment

I observed 5 countries where differences between inequality estimates of acceptance and uptake were statistically significant, namely Australia, Brazil, China, India, and the US. Brazil (0.219) reported the most pro-rich results in uptake, and was the only country in this study that saw a statistically significant pro-rich increase in inequality in uptake relative to acceptance. Australia (-0.132) reported the most pro-poor result in this study. Differences in policy agility and effectiveness offer a potential explanation for the diverging experiences beyond the decomposition covariates I investigate. Australia controlled the initial stages of the pandemic through stringent lockdowns and restrictive travel policy, managing the spread of the virus and keeping infection numbers low, while cases soared in Brazil.[222,223] Despite different initial paths, both Australia and Brazil lagged global leaders in vaccination efforts. Australia corrected course by turning to proven healthcare structures after policy missteps in private sector and local vaccine distribution.[222] With control over case numbers and a predictable reproduction rate due to enacted restrictions, the Australian government turned its focus to economic support for its population. Measures included doubling the unemployment benefit and a wage subsidy scheme, which likely contributed to positive sentiment towards the government and its vaccine rollout from low-income earners who benefited most from these measures. This could have contributed to positive vaccine response amongst these and other groups, seeing semblances of normal life resume in Australia sooner than in other countries, potentially contributing to the pro-poor inequality observed in this study.[224] The decomposition analysis (tables 6C and 6D) suggests that reductions in female hesitancy also contributed to the reduction in inequality in uptake. Brazil, meanwhile, led by Bolsonaro who did little to hide his anti-vaccine sentiment, lacked federal coordination. The campaign was politically convoluted, polarizing, and faced consistent supply challenges due to the politicization of the rollout, which hindered the country's ability to deploy the vaccine.[223,135,225] The observed inequalities were perpetuated by hesitancy and unmet demand in low-income communities with low levels of education.[136] A study has found logistical challenges (e.g., time off work, child supervision) borne disproportionately by low-income earners to be a likely mechanism driving inequality, though elements of this were mitigated by pro-poor primary healthcare coverage.[226,134] I cannot discount missing data as a possible, or even partial cause, of the differences observed between uptake and acceptance in Brazil, as I could not achieve a fully representative sample with re-weighting, though I did achieve 93% representation (table C2).

The change in political leadership in the US in 2021 likely had an impact on the observed inequalities, as the Democratic leadership re-energised vaccine mobilisation efforts to reach previously missed targets.[227] The pro-rich association of being conservative increased in magnitude in the decomposition – implying that higher-income right-leaning respondents were more likely to get vaccinated (or low-income refusal increased), potentially speaking to Republican mistrust of vaccine incentives promulgated by states under the newly elected federal Democratic leadership.[227,228] Previous research has found associations between far-right voting and vaccine hesitancy in the European Union (EU), which appears to be replicated in these results in the US.[229] The US, like Australia, saw significant reductions in the decomposition association between female hesitancy and inequality.

China's stringency index was the highest of the countries in the sample, with mandatory vaccination administered by some local governments, which would necessarily reduce inequality if mandates were effective across income groups.[230,231] China also had the advantage of a locally manufactured vaccine, CoronaVac, thereby avoiding the shortages faced by many countries. India could similarly rely on the local manufacture of vaccines, after the de-facto ban on exports of the locally manufactured AstraZeneca vaccine in favour of local use. Increased availability in both nations is likely to have reduced inequality as a result of unmet demand. After devastating peaks in the first wave in India,[7] having a chronic disease became associated with pro-poor inequality, as individuals took additional steps to safeguard their health with vaccines relative to prior stated intention.

6.4.4 Policy implications

Various measures were adopted globally to encourage vaccination uptake; including travel limitations, vaccine passports, vaccine mandates, and differential restrictions based on vaccination status.[232] The differences between the acceptance and uptake measures indicate that these measures had some effect in achieving greater coverage and more equitable uptake than anticipated. However, these policies led to a global discourse on freedom of choice and potential rejection of COVID policies in response to strict measures.[232,233] The benefits of a tightly managed programme are illustrated in the examples of Australia and Brazil, but are not without cost. Vaccine mandates, for example, theoretically have the ability to solve social coordination problems and remove socioeconomic inequality by vaccinating all individuals regardless of income levels, but remove freedom of choice. There is a value judgement to be made by policy-makers regarding the efficacy of these policies in context, particularly amongst marginalised groups, and the possible trade-offs between equity, liberty, and societal health outcomes. Aside from moral value judgements, reduced coverage and inequality in vaccination increases the likelihood of escape variants which may render immunisation strategies redundant if the virus mutates to resist vaccines.[234,235]

Public health officials and policy makers should be prepared to deploy additional measures to achieve equality and coverage in vaccination. Context specific cash incentives have been found to increase uptake and decrease hesitancy,[145,236] while surveys can prove useful in locating and addressing hesitancy and inequality in local and specialised contexts.[137]

6.4.5 Limitations

This investigation faces two limitations: (1) I was unable to obtain fully representative samples in India and Uganda. As such, the results in India and Uganda are not generalizable. (2) I have not included an ethnicity variable in this research. The recording of ethnicity in the CANDOUR dataset varies by country to meet local needs, leaving cross-country comparison challenging. However, I make note that minority groups were found to have higher risk factors associated with COVID-19 infection and severity, and increased hesitancy rates relative to other racial groupings.[166,198,199]. Recent literature has suggested expanding the ranking variable to a multivariable measure including elements of socioeconomic status, demographics, educational attainment, sex-based characteristics, and geospatial elements.[125] Extending the analysis could add to the literature given previously observed discrepancies between such multivariable socioeconomic measures and traditional measures.[125]

6.5 Conclusion

This chapter analyses the inequality landscape of COVID-19 vaccine sentiment, using indices of income-related inequality in vaccine acceptance and uptake indices in 13 countries, and vaccine uptake in a further 3 countries for comparison later in this thesis. I estimate income-related inequality in vaccine acceptance and uptake and decompose these indices to identify associations with inequality. I find that income-related inequality in vaccination in 2022 was lower than income-related inequality in acceptance in 2020, but remained pro-rich in most cases despite varied attempts to achieve nationwide vaccination. Policy makers should be prepared to adopt additional and targeted mitigating procedures to ensure that marginalised groups are not left behind in vaccination campaigns. Coherent and coordinated policy messaging alongside effective management to procure necessary resources (where feasible) could contribute to more equitable vaccination outcomes in future campaigns.

Having looked at three separate empirical investigations into income-related inequality along the healthcare process, I turn my attention to addressing additional gaps or opportunities for novel thought I have noticed during the course of my research. I address two of these gaps, both related to vaccination in the COVID-19 pandemic, or more broadly, the introduction of new medical technologies. I address how the effects of these interventions should be considered incorporating both inequality and effectiveness in order to contribute to the evidence base, and once adopted, how roll-out can be made more efficient using simple tools.

7. An application of novel concepts in equality and efficiency related to COVID-19 vaccination efforts

During the research and production of this thesis, I identified two areas where further contributions could be valuable. Both areas relate to the real-world introduction and implementation of new medical technologies. The first relates to how the effects of intervention should be considered holistically to include distributional perspectives and thus broaden the scope of the evidence base on effects. The second relates to the efficient deployment of interventions or health technologies. Both topics have practical implications for equality and efficiency, and are centred around vaccination in the COVID-19 pandemic.

During my research, I noted that despite having the required data, many observational and some evaluation studies did not include distributional measures of inequality or inequity. Instead, analyses often relied solely on income coefficients in regressions. However, such coefficients fail to capture distributional perspectives which can be assessed with inequality or inequity indices, such as the concentration index. To broaden the distributional evidence base and make better use of the available data, I propose the inclusion of a distributional measure (such as the concentration index) to better inform policy makers. I apply this concept using data from a trial on financial incentives to increase Coronavirus vaccine uptake. I show the possible consequences of failing to include a distributional measure in assessing the impacts of interventions or new medical technologies. Additionally, I introduce a novel method for assessing heterogenous treatment effects in inequality in trial contexts.

The second issue, observed both anecdotally and in the literature around vaccine deployment, was that many countries wasted doses while others struggled to procure vaccines. Taking advantage of the repeated sampling of individuals in CANDOUR wave 1 and wave 2, I assess how individuals changed vaccination sentiments during the course of the COVID-19 pandemic. These changes could affect the efficiency of health system operations. I investigate the extent to which simple tools (such as online surveys) track sentiment changes and potentially improve efficiency in delivery, as well as socioeconomic characteristics associated with changing sentiments.

7.1 Expanding the evidence base on the distributional impact of health technology: A proposal and an application in the context of a vaccine uptake intervention trial in Ghana

7.1.1 Introduction

Intervention trials measure the average treatment effect of an intervention on a variable of interest. However, the distributional implications of interventions are rarely quantified in health system evaluation trials. This is surprising as equity and equality are often desired principles in health systems.[172] Despite increased momentum to include distributional elements in economic evaluation, this practice is still not widespread.[237–239] The measurement of a socioeconomic inequality indicator in trials enables distributional considerations alongside primary outcomes. Including distributional measures can broaden the inequality evidence base.

In this study, I explore how the inequality impact of an intervention can be quantified alongside primary trial results. My focus is on socioeconomic (income-related) inequality in health (e.g., rank and level dependent bivariate inequality indicators). I demonstrate how this can be accomplished post-hoc to augment trials if distributional concerns were not included in the original design. However, as with any post-hoc analysis, care should be taken to avoid incorrect conclusions. Unspecified post-hoc analysis increases risks of both Type I and Type II errors, resulting from increased testing (Type I), and possibly underpowered testing (Type II). I further show how the results and any potential trade-offs can be visualised in an achievement plane.[240] I then demonstrate that the decomposition of the Level Index, a perfectly subgroup decomposable index,[64] can be used to explore the presence of heterogenous treatment effects of socioeconomic inequality of health across subgroups in exploratory research if not pre-specified. In an empirical application, I describe the data and methods required for such analyses and illustrate the approach using data from a randomised COVID-19 vaccine financial incentives study in Ghana.[145] I analyse the distributional treatment effects of public health messaging, low cash incentives, and high cash incentives on socioeconomic inequality in vaccine uptake, relative to a placebo group. With appropriate adjustments, these concepts can be applied to any field concerned with the distributional impacts of interventions. I illustrate these foundations using rank-dependent indices, which are more frequently used in the literature, and then show that the Level Index can be used in an exploratory manner to identify heterogenous treatment effects in subgroups provided there is adequate power.

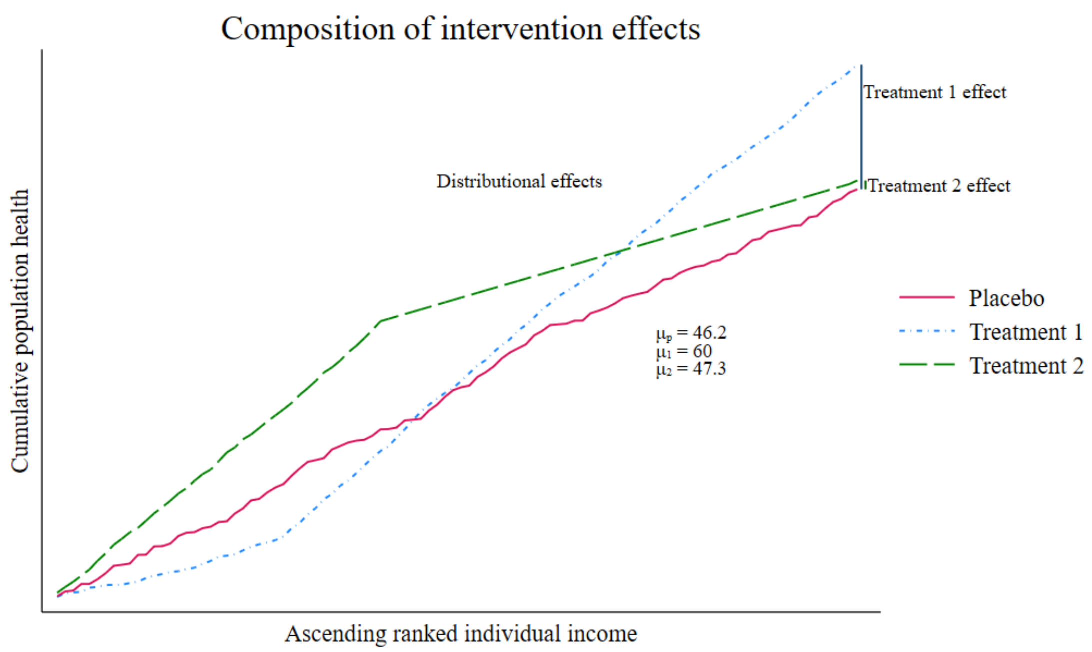
7.1.2 Socioeconomic health inequality

7.1.2.1 The case for incorporating inequality measures in evaluation trials

"To ensure healthy lives and promote well-being for all" is the third sustainable development goal, and many countries strive to provide equitable access to healthcare.[5,172] Yet opportunities to research the impacts of healthcare interventions on inequality are often missed. If health systems strive to achieve equality, at the minimum, an understanding of how policies affect socioeconomic equality, which forms an element of overall equality is required. Policy makers may be faced with trade-offs between maximising average health outcomes and reducing (or maintaining) inequalities, known as equality-efficiency trade-offs. Studies evaluating policy intervention impacts should report on (in)equality to produce more complete information for the decision-making process. However, if effects on inequality are not investigated, policymakers risk taking equality-blind decisions that could lead to undesired effects, as distributional cost effectiveness analyses (DCEA) has shown in recent years.[241] It is important to note that testing without adequate power could also introduce Type II errors, whereby the researcher fails to identify true inequality. As such, post-hoc application of the methods discussed in this paper should be exploratory, and interpretation of non-significant differences should be cautious unless there is adequate power.

Consider a hypothetical intervention trial with three treatment arms, illustrated in figure 7A. Cumulative health of the population is plotted against ascending ranked income, producing a Generalized concentration curve. Two effects are evident in the figure. The average treatment effect (ATE) is taken as the mean difference between the treatment groups (*1, 2*) and the placebo group (*p*). ATE is given by $(\mu_1 - \mu_p)$ and $(\mu_2 - \mu_p)$ for treatments 1 and 2 respectively, where μ_i is mean uptake level of group *i*, and is the conventional effect noted in trials literature. However, there are also distributional treatment effects (DTE), reflected by the deviations of the treatment curves from the placebo curve. Despite a lack of meaningful difference in mean health between treatment 2 and the placebo, there is clearly a distributional effect benefitting the lowest-income earners. Treatment 1, however, has improved average health meaningfully, despite making the poorest in society worse off – constituting an equality efficiency trade-off. Both treatments lead to different socioeconomic inequality of health outcomes compared to the placebo, which warrants further measurement and investigation.

Figure 7A: Composition of intervention effects in a hypothetical trial scenario



Inequality measures embody implicit value judgements. The choice of which measure to employ is partly subjective. Distributional comparisons depend on these choices, and particularly on the choice between absolute versus relative measures, which are conceptually very different and may give divergent results. Absolute measures consider absolute magnitudes of change, whereas relative measures consider changes relative to the starting position. Different absolute (and relative) measures can also lead to different conclusions, as they embody their own value judgements on what constitutes a desired distribution, or how sensitive one should be to inequality.[17,41,242]

A simple summary measure of socioeconomic related inequality (e.g., the concentration index, generalized concentration index, or a variation such as the Level Index) can be estimated on the basis of the distributions presented above in figure 7A. Should data and other constraints allow, the analysis can be extended further to equity analysis, dominance analyses, and full DCEAs.[241]

7.1.2.2 Data requirements and methods

7.1.2.2.1 Data requirements

To include a measure of income-related or socioeconomic inequality of health, the researcher requires data on the health variable (e.g., outcome measure), and income or socioeconomic status. The relationship over the distribution can be quantified using these two variables. The concentration index and its adjustments and extensions are frequently used in health economics literature, though alternative ordered indices such as the Slope or Relative Indices of Inequality could similarly be employed as summary measures of socioeconomic inequality of health.[243]

Ideally, respondent-level data would be used as an indicator of socioeconomic status, such as individual or family income, education level, or consumption. Data of this sort may be collected as social determinants of health or as controls in trials. If data on the participants' locations (e.g., household addresses or Global Positioning System (GPS) co-ordinates) are collected, further socioeconomic variable options include indicators of local neighbourhood deprivation (such as the English indices of multiple deprivation), luminosity data, or other combinations of proxies, provided there is enough granularity to provide sufficient variation within the sample; such measures are particularly useful for post-hoc applications.[244,245]

7.1.2.3 Measuring socioeconomic health inequality

The concentration index, the workhorse of inequality analysis in health economics, introduced by Kakwani and Wagstaff[20,24] is specified as follows:

$$C(h) \equiv 1 - \frac{\sum_{i=1}^{n}(2\lambda_i - 1)h_i}{n^2\mu_h} \quad (1)$$

The measure considers the socioeconomic rank of individuals (λ_i) and his or her individual health levels (h_i) relative to the overall distribution of the population (n) and its mean health levels (μ_h).[25] The index is extended to incorporate attitudes towards inequality in the computation of the index (Extended concentration index),[39] with the introduction of an inequality aversion parameter (v), where $v \geq 1$, with $v = 1$ indicating no concern for inequality and higher values of v reflecting an increasing aversion to inequality, which in turn affects the gradient of the underlying indifference curves.

$$C(h, v) = 1 - \frac{v}{n\mu}\sum_{i=1}^{n} h_i(1 - \lambda_i)^{v-1} \quad (2)$$

Several further extensions have been produced to provide, for example, absolute measures of socioeconomic health inequality (Generalized concentration index, multiplied through by mean health levels),[41] measures fit for binary variables (Wagstaff index,[43] and the Erreygers adjusted index,[25]), or to retain additional socioeconomic information (Level Index,[47]). Each is appropriate for different data or use cases, though relies on similar principles.[32,47]

The family of bivariate inequality measures can be used to discern summary differences in the distributions contained in figure 7A above. In order to estimate the impact of a treatment on inequality, the resultant inequality index must be compared against a counterfactual, or a placebo in the case of trials. The specific choice of measure should be dictated by the data and the desired use case (e.g., decomposition), for which different variations have useful properties.

7.1.2.4 The equality efficiency trade-off

In the hypothetical example provided in figure 7A, a policymaker may be able to select between the placebo and treatment 2, which offers similar mean health but improved health for the lowest-income earners. In this instance, treatment 2 dominates the placebo group in both equality (consistently above the placebo treatment) and efficiency (total above the placebo treatment). However, incorporating treatment 1 into the decision making process poses a problem to the equality-conscious decision maker. Average (societal) health is improved at the expense of the lowest income earners. Unless the decision maker is completely indifferent to inequality levels (i.e., v =1), there is a trade-off to be made.

In response to this trade-off, Wagstaff developed the achievement index: a measure incorporating both inequality between high and low-income earners, and average health levels,[39] retaining the inequality aversion parameter (v), defined as:

$$I(h, v) = \frac{1}{n}\sum_{i=1}^{n} h_i v(1-\lambda_i)^{v-1} \qquad (3)$$

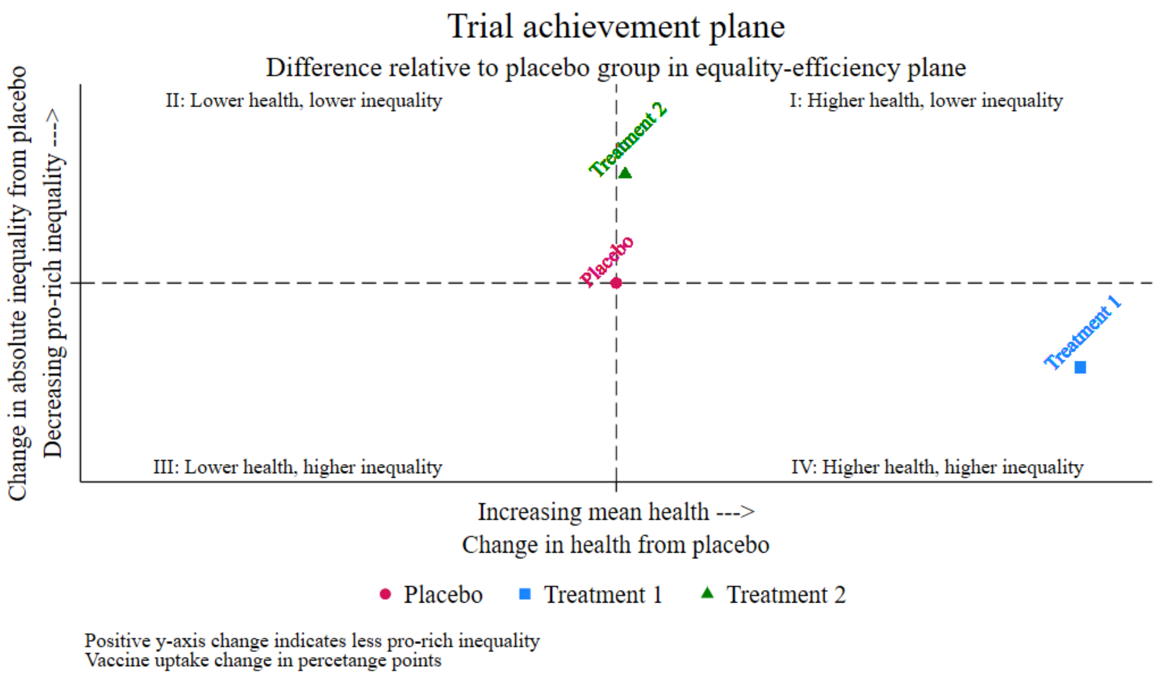
which is equivalent to:

$$I(v) = \mu\big(1 - C(h, v)\big) \qquad (4)$$

Multiplying out, this expression is $\mu - \mu C(v)$, which in turn is equivalent to $\mu - GCI$, where GCI is the generalized concentration index; the absolute version of the rank dependent concentration index (when $v = 2$),[41] and the equivalent index of the Generalized concentration curves in figure 7A. This work was extended by Clarke and Hayes who visualised the achievement index trade-off over time in 2D space, using change in (ill) health on the x-axis and change in absolute inequality on the y-axis to form an achievement plane.[240]

I apply the principle of the achievement plane to evaluation trials, plotting the differences between treatment and placebo groups in an equality-efficiency space rather than against time. I show the mean difference in health on the x-axis ($\mu_{hi} - \mu_{hp}$), and the mean difference in absolute inequality on the y-axis ($GCI_p - GCI_i$), where GCI is an index of inequality, i is treatment group and p is the placebo group. I present the evaluation trial achievement plane in figure 7B below, using the hypothetical distributions in figure 7A to explain the plane. In this case the Generalized concentration index is used, however this can be replaced with another measure of absolute income-related inequality for the purposes of populating the achievement plane.

Figure 7B: Evaluation trial achievement plane



Centring the placebo group as the origin in figure 7B, I can compare treatment inequality and efficiency trade-offs relative to the control. Treatments to the right of the placebo group indicate improved average health, while treatments above the placebo group indicate decreased pro-rich inequality. While quadrants are displayed here mirroring the cost-effectiveness plane in Cookson et al. and the achievement plane,[240,246] it is possible that trade-off treatments in

Quadrants II and IV may in some cases be preferred to those in Quadrant I due to the negative slope of the underlying social indifference curves, the gradient of which will depend on the inequality aversion parameter, v (previously defined). Treatments in Quadrants II and IV indicate a trade-off relative to the placebo group, favouring either pro-poor equality (II) or improved health (IV) at the expense of the other. Treatments in quadrant III have decreased health and increased inequality, making them unfavourable options (termed lose-lose by Cookson et al for a similar trade-off, albeit in cost-effectiveness terms.[246]) Such treatments will be dominated by the placebo group in figure 7A, lying below the placebo across the distribution. Quadrant I has both higher uptake and reduced inequality relative to the placebo group (win-win by Cookson et al.[246]) Quadrant I treatments dominate the placebo group across the distribution, as is evident in figure 1 and now in figure 7B, with treatment 2 as an example case. If the health variable is measured in ill-health, the quadrants may be reflected in the y-axis, as in the original iteration of the achievement plane,[240] unless the variable is transformed or measured using an index with the mirror property.

7.1.2.5 Investigating heterogenous treatment effects of socioeconomic inequality of health using a decomposition approach

After investigating the trade-offs between inequality and uptake using the achievement plane, socioeconomic inequality of health practitioners may be interested in the inequality landscape within each treatment in more detail. While average treatment effects capture overall trends of treatments, individuals are unlikely to each face the average effect. This could be due to observable characteristics. Investigating heterogeneity in treatment effects is an important step in the trials process.[247,248] Heterogenous treatment effects may be observed simply by stratification, or by more advanced techniques.[249] If testing for heterogenous treatment effects is not pre-specified, there is a risk of data-mining, and if testing multiple times, of Type I errors. If the sample has not been designed for subgroup testing, there is also a possibility of Type II error. Ideally, studies should be designed for subgroup testing to enable the methods below. Failing this, caution should be exercised, and the methods enclosed should be viewed as exploratory only.

The notion of heterogeneity in an inequality context is particularly important. Summary socioeconomic inequality measures capture the association of the socioeconomic variable and the health variable over the entire distribution, but subgroups may respond to treatments differently. Assessing if the socioeconomic inequality context is different across subgroups is thus an important consideration in addressing inequality, analogous to investigating ATE per subgroup for differences. The intuition here is no different to average effects in an intervention trial, albeit with an added relationship of income built in; overall uptake could conceal different uptake rates within subgroups, and warrants further investigation. The same is true of socioeconomic inequality, though adequate sample sizes and testing power for distribution testing is required.

Within the family of bivariate inequality measures, the Level Index takes its name from its level-dependence (opposed to rank dependence of the concentration index). Instead of reducing the socioeconomic variable to ranks, the Level Index retains additional information in its weighting function.[47] The Level Index can, as with rank-dependent indices, be adjusted for bounded variables, and has an absolute variant. Perhaps its most desirable property, however, is the property of perfect subgroup decomposability, which I employ to advantage to investigate heterogenous treatment effects of socioeconomic inequality in health.[64]

The Level Index (L) with simple linear weighting function is defined as follows:[47,64]

$$L = \frac{1}{n} \sum_{i=1}^{n} \frac{y_i - \mu_y}{\mu_y} h_i = L_W + L_B \tag{5}$$

Where, as in the concentration index, h_i refers to the individual health level. The weighting function considers the individual's socioeconomic deviation from the mean $\frac{y_i - \mu_y}{\mu_y}$, where y is a measure of socioeconomic status, such as household income or food expenditure, L_W refers to the component of inequality within groups, and L_B to inequality component between groups.

While any (absolute) bivariate index would suffice to produce the achievement plane in figure 7A (subject to the underlying social welfare function), the perfect subgroup decomposability property of the Level Index allows complete decomposition, and allocation to either a within-subgroup or between subgroup component. This property offers a neat mathematical approach as a first step to identifying heterogenous treatment effects in socioeconomic inequality of health. Implementing a decomposition between treatments can similarly be used to elicit evidence on treatment effects. However, the decomposition approach does not offer the most direct route to identify directional effects *between* treatments in the case of >2 treatments. In the case of >2 subgroups, only the presence of variation between groups can be identified with the decomposition approach, and further numerical or graphical investigation of subgroups is required to identify between which treatments or subgroups differences lie. In the case of 2 subgroups, if there are differences in inequality (within) in each subgroup, the between component is larger and is indicative of heterogenous treatment effects. While this is true when >2 subgroups exist, one cannot tell between which two (or more) subgroups there are differences without further analysis.

The decomposition is presented by Erreygers et al.[64] giving the within component as:

$$L_W = \frac{1}{n\mu_y} \sum_{i=1}^{n} y_i \, h_i - \sum_{j=1}^{k} s_j \, \mu_{hj} \qquad (6)$$

And the between component as:

$$L_B = \sum_{j=1}^{k} s_j \, \mu_{hj} - \mu_h \qquad (7)$$

Where the subgroup weighting function $s_j = \frac{n_j \mu_{yj}}{n\mu_y}$ is equal to the income share of the subgroups $j = 1, \ldots, k$. The between component gives the cumulative deviation of the average health within subgroups (e.g., gender or educational attainment) relative to the whole group (in this case, one of the treatment arms), weighted by subgroup population income shares. By comparing the results of this decomposition between different groups (i.e., placebo and different treatments), one can identify heterogenous treatment effects in socioeconomic inequality of health across subgroups such as gender or educational attainment.

It is evident that the between component is maximised by greater deviations in subgroup means from the whole group mean health (e.g., proportion of vaccinated individuals) and income. A greater between component indicates discrepancies in the average socioeconomic inequality of health between subgroups, and is indicative of heterogenous treatment effects in socioeconomic inequality of health. The proportion of between inequality is a function of within inequality; if uptake and socioeconomic variables are completely uniform within subgroups, but vary between subgroups, the between component will compose the entirety of inequality, and indicate differences in socioeconomic inequality of health between subgroups. The within component is a weighted average of the subgroup index values, which is informative of whether socioeconomic inequality of health within subgroups is predominantly pro-rich or pro-poor. The within component can also be compared to the magnitude and direction of the overall inequality across subgroups. The between component either reinforces (if of the same sign as the within component) or counteracts the socioeconomic inequality of health in the within component, based on subgroup weighted deviation from mean health (e.g., vaccination levels).

One can compare the decompositions across treatments to identify if socioeconomic responses to treatments varied by the selected subgroup. There is not a defined cut-off value (e.g., >b%) of the between component that indicates an unambiguous presence of heterogeneity in treatment effects. However, as the absolute value of the between component rises, so too does the likelihood of heterogenous treatment effects in socioeconomic inequality of health. Users should adopt reasonable approaches specific to the context and acceptable inequality between different subgroups. It is important to consider the full context.

To determine a social gradient between subgroups, an analysis of ordered groups numerically or graphically is required, the sign of the between component is not necessarily informative of the direction of social gradient. As such, this decomposition method offers a mathematically neat guiding point that is grounded in socioeconomic inequality of health literature, and should be familiar to many socioeconomic inequality in health practitioners, but is decidedly exploratory in nature. Sample sizes of subgroups should be considered when conducting subgroup decompositions, both for differences and for under-powered testing, to reduce the prospects of errant or chance results.

7.1.3 Empirical application

7.1.3.1 Data

7.1.3.1.1 Data description and survey design

To illustrate the approaches, I use data from the Ghana Financial Incentives Trial which investigates the influence of cash incentives on COVID-19 vaccination uptake (a binary variable) in six rural Ghanaian districts.[145] The study conducted a two-stage cluster RCT with four treatment arms consisting of a video message embedded in the survey; placebo, CDC-styled informative public health message, low cash incentive (20 Ghana cedis / $3) and high cash incentive (60 Ghana cedis / $10) from 5 February 2022. Within each of the six districts, villages were ranked by population and divided into quadruplets consisting of 4 consecutively population ranked villages. Each district had approximately 50 quadruplets, from which 13 were randomly selected, resulting in the inclusion of 310 villages in the study. Within each selected quadruplet, villages were randomly assigned to one of the 4 treatment arms. 21 households were randomly selected within each village, and a single eligible individual over 18 years old was randomly selected from each selected household to complete the survey. Eligibility required non-vaccination at the onset of the trial. 5,900 individuals were treated up to 28th February 2022.[145] As a measure of socioeconomic status, I use equivalised weekly food expenditure in this study. While a total expenditure variable is also available in the data, this was significantly noisier and food expenditure was preferred. The headline analysis using total expenditure is contained in appendix figure D2. This separates the paper somewhat from the previous analysis in this dissertation, which uses income based metrics. Respondents were asked, "How much on average does your household spend in a typical week on food?" Food expenditure is equivalised using the OECD modified equivalisation scale, which accounts for the number of adults and children in the household.[151]

Phase 2 and 3 of the trial, conducted from 13 April 2022 and 15 June 2022 respectively, attempted to follow up with Phase 1 participants to collect self-reported vaccination status in binary form. 2,082 and 2,019 participants were contacted in phase 2 and 3. Phase 3 also included identification and data collection from 1,101 non-treated, non-placebo allocated individuals in treatment villages for a spillover analysis, which is not included in this paper. Between 15 October and 30 November 2022, staff at district hospitals verified the vaccination status of all respondents to that point. 3,075 total records were verified, including the 2,271 individuals allocated to one of the four primary treatments arms that form the population for this study (placebo, CDC-styled messaging, low-cash incentive, high-cash incentive). The data used in this empirical study is limited to those individuals for whom verified vaccination records were found *and* who were participants in the treatment phase of the trial, limiting the sample to 2,271 individuals. The full sample characteristics (Table D1), including analysis on self-reported vaccination status, is available in the supplementary materials, and can be compared to the original study.

7.1.3.2 Socioeconomic inequality of health outcome indicator

I compute the inequality estimate by treatment arm using the Level Index. While any bounded absolute version of a bivariate inequality index would suffice in this context for the binary vaccination variable, I employ the Level Index owing to its desirable subgroup decomposition properties, which I use to explore the presence of heterogenous socioeconomic inequality of health subgroup treatment effects.[64] This is one of several measures that could potentially be used to provide an indication of the treatment's inequality impact. The selected measure should fit the data and desired purpose, which may lead to the use of alternative indices.[32,47,206] In the case of a binary variable, the bounded (absolute) Level Index takes on the same value as the absolute version of the index, however generalization to a non-binary bounded version can be undertaken easily. I also present results using the Erreygers adjusted concentration index, a version of the generalized concentration index, in figure D3, which shows similar results.

To determine the impact on inequality in vaccine uptake, I compare inequality in each treatment arm against the placebo group,[250] as is common in evaluation trials. I use 1,000 iterations of bootstrapping resampling in each treatment arm to develop standard errors on the resulting differences. I then visualise these results on the evaluation trials achievement plane to examine the possible trade-offs between equality and uptake. Note that as the original design was not specifically powered to detect distributional effects, these results should be viewed with caution, as there is a risk of both Type I errors from post-hoc analysis, and Type II errors from testing without pre-specified power for the purpose.

7.1.3.3 Heterogeneity of treatment effects

I employ subgroups defined by education level (coded as no schooling, up to end of primary school, and more than primary school), and gender to illustrate an investigation into treatment effect heterogeneity in socioeconomic inequality of health. I estimate the "between component" of socioeconomic inequality between the defined subgroups within each treatment. I compare these results to determine if the different treatments elicited varied socioeconomically related responses based on educational attainment and gender. The presence of substantial between subgroup inequality indicates the presence of heterogenous treatment effects in socioeconomic inequality of health. However, non-significant differences do not mean that there are no inequality effects, unless the testing has been adequately powered in the design stage to report this, as above.

7.1.3.4 Results

7.1.3.4.1 Balance

In this analysis, I use unadjusted and unweighted verified vaccine status to maintain comparison to the primary body of work. The sample is restricted to respondents with verified vaccination status and full income data. In the main work, it is shown that the unadjusted covariates fell within a standardized mean difference tolerance of 0.1 in most instances. I find similarly relative to the placebo group in most cases. Some differences are observed in employment status across treatment groups in the revised sample. Balances outside the tolerance were also observed in gender and number of children in the household (high cash). The balances are consistent with the main work for the high-cash treatment group; however, the employment imbalances were not previously observed. The weighted differences were balanced, with all but one covariate within the tolerance bounds. The balance table (Figure D1) is available in the supplementary materials.

7.1.3.4.2 Vaccination uptake

Table 7A presents the verified vaccination status per treatment group. At commencement, all individuals are unvaccinated per eligibility requirements. 6 weeks after vaccine availability, uptake was relatively similar in the placebo, CDC health message and high-cash groups (within a range of 4 percentage points), but substantially higher in the low-cash group. These figures are within 1-3 percentage points of the original work, despite small sample size differences.

Table 7A: Vaccine sentiment and status at stages of trial

Vaccine sentiment	Placebo	CDC health message	Low cash	High cash
Commencement				
Unvaccinated	702 (100%)	488 (100%)	522 (100%)	559 (100%)
After 6 weeks of availability				
Verified: Vaccinated	200 (28.4%)	117 (23.9%)	225 (43.1%)	153 (27.3%)
Verified: Not vaccinated	502 (71.6%)	371 (76.1%)	297 (56.9%)	406 (72.7%)
Original article (Duch et al., 2023)				
Verified: Vaccinated	28.4%	21.6%	40.7%	25.9%

7.1.3.4.3 Treatment equality and uptake trade-offs

The computed inequality indices are presented in figure 7C and table 7B. The figure 7C evaluation trials achievement plane visualises the equality uptake trade-off often present in policy-making decisions. While no significant differences in inequality were observed as shown by the overlapping confidence interval estimates on the y-axis (shown numerically in table 7B), the low-cash treatment had a statistically significantly higher uptake level. Non-significant differences should not be equated with equivalence. However, in this study, with no statistically significant evidence of differences in inequality, higher uptake can be tentatively prioritised, which is achieved by the low-cash treatment. In the original work, Duch et al. suggest that the low-cash incentive outperforms the high-cash incentive due to the possibility that the high-cash 60 cedis / $10 incentive (which represents approximately ~50% of average weekly food expenditure) may signal a low-quality vaccine and higher potential health risks of the vaccine, to which individuals are averse.[145]

7.1.3.4.4 Identification of heterogenous treatment effects

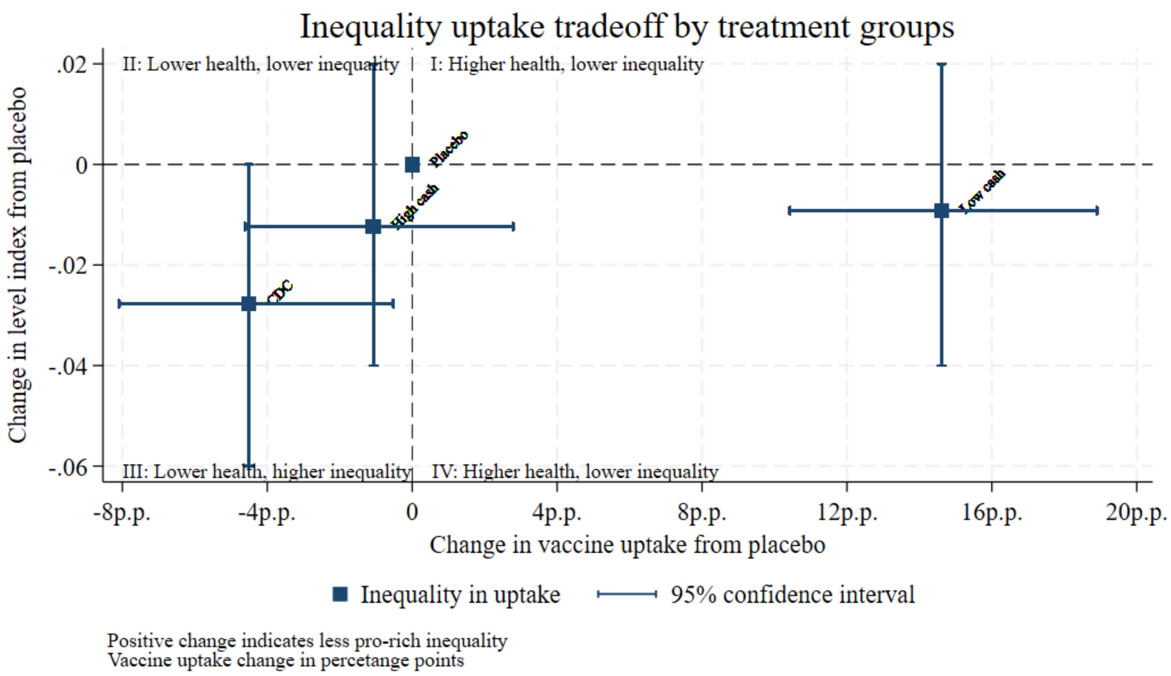
Summary statistics for the subgroup decomposition of socioeconomic inequality of health by gender and educational attainment are presented in tables 7C and 7D respectively. These statistics are used for the subgroup decomposition of socioeconomic inequality of health presented in table 7E, and the process is analogous to investigating ATEs by subgroup albeit in a socioeconomic inequality of health context.

Table 7B: Bootstrapped treatment effects using verified vaccine status

	Level Index	Treatment effect magnitude[1] [95% CI][2]
	-0.0221	
Placebo		
Treatments		
CDC	0.0054	-0.0277 [-0.06 - 0.00]
Low cash	-0.0130	-0.0092 [-0.04 - 0.02]
High cash	-0.0095	-0.0124 [-0.04 - 0.02]

Notes
1. Treatment magnitude refers to the average difference between inequality of treated in treatment villages and inequality of untreated in untreated villages 6 weeks after vaccine availability. i.e., placebo index – treatment index
2. *** p<0.001, ** p<0.01, * p<0.05

Figure 7C: Trials achievement by treatment group using Level Index



In table 7E, a counteracting within-between effect is evident in the high cash incentive for the gender and education decomposition, and the low cash incentive for the gender decomposition, while all other between components are reinforcing of the within component. The between component due to gender within treatments accounts for less than 4 absolute percentage points of total observed inequality in each treatment. This result implies little evidence that treatments were taken up differently between considering the correlation of gender and income.

Educational attainment is linked to higher absolute between components, ranging from -6.05% of variation in the high-cash group to 19.33% of total inequality within the CDC public health messaging treatment. This result indicates that there was variation in subgroup uptake and socioeconomic status, possibly due to correlations between higher educational attainment and socioeconomic status. However, to determine which groups differed, a closer investigation of table 7D is required (e.g., differences between no schooling and up to end of primary schooling). Figure 7D presents the concept of the between component graphically, where the between component is a weighted summation of the deviation from the treatment means (see formula 4). As is clear in figure 7D, those with no schooling had higher average uptake rates than other educational groups, conditional on receiving treatment, unlike in the placebo group. Note, as is evident by the proximity of the treatment mean locations relative to the >primary subgroup in figure 4, the >primary subgroup is the largest in each treatment arm (table 7C).

Table 7C: Summary statistics for subgroup decomposition by gender

	Vaccination status		Food Expenditure (Cedis)		Index	
	Mean	SD	Mean	SD	Level Index	95% Confidence interval
Placebo						
Female	0.2667	0.4428	52.82	30.8726	-0.01078	[-0.036 - 0.014]
Male	0.3058	0.4615	51.15	30.848	-0.03483*	[-0.065 - -0.005]
All	0.2849	0.4517	52.04	30.8504	-0.0221*	[-0.041 - -0.002]
CDC message						
Female	0.2363	0.4246	53.51	30.4777	0.0193	[-0.01 - 0.048]
Male	0.2441	0.4306	55.76	35.244	-0.0012	[-0.046 - 0.023]
All	0.2398	0.4274	54.49	32.6282	0.0054	[-0.016 - 0.027]
Low cash						
Female	0.4187	0.4942	51.31	31.4232	0.0105	[-0.024 - 0.045]
Male	0.4463	0.4982	55.32	33.9478	-0.0412*	[-0.076 - -0.006]
All	0.431	0.4957	53.1	32.6034	-0.013	[-0.037 - 0.011]
High cash						
Female	0.2786	0.449	53.49	34.0839	-0.0308*	[-0.057 - -0.005]
Male	0.2673	0.4436	52.59	36.9934	0.0244	[-0.017 - 0.066]
All	0.2742	0.4465	53.12	35.1852	-0.0095	[-0.033 - 0.014]

*Denotes index value is statistically significantly different to 0 at the 5% level.

Table 7D: Summary statistics for subgroup decomposition by educational attainment

	Vaccination status		Food Expenditure (Cedis)		Index	
	Mean	SD	Mean	SD	Level Index	95% Confidence interval
Placebo						
No schooling	0.2	0.4021	54.75	30.0037	-0.0052	[-0.043 - 0.032]
Up to end of primary	0.2373	0.4272	54	30.6231	-0.0459*	[-0.086 - -0.006]
More than primary	0.3129	0.4641	51.04	31.0736	-0.0177	[-0.042 - 0.007]
All	0.2849	0.4517	52.04	30.8504	-0.0221*	[-0.041 - -0.002]
CDC message						
No schooling	0.3478	0.4798	55.21	35.0647	0.0315	[-0.043 - 0.106]
Up to end of primary	0.1786	0.3853	50.13	31.2876	-0.0077	[-0.044 - 0.029]
More than primary	0.2328	0.4233	55.44	32.4485	0.0016	[-0.026 - 0.03]
All	0.2398	0.4274	54.49	32.6282	0.0054	[-0.016 - 0.027]
Low cash						
No schooling	0.5412	0.5013	50.58	32.9712	-0.0283	[-0.096 - 0.039]
Up to end of primary	0.3964	0.4914	51.68	33.1026	0.0104	[-0.046 - 0.067]
More than primary	0.4141	0.4933	54.25	32.3808	-0.0154	[-0.045 - 0.015]
All	0.431	0.4957	53.1	32.6034	-0.013	[-0.037 - 0.011]
High cash						
No schooling	0.3204	0.4689	51.66	33.9198	0.0177	[-0.037 - 0.072]
Up to end of primary	0.2258	0.4204	47.58	30.7384	-0.0084	[-0.054 - 0.037]
More than primary	0.2735	0.4464	54.96	36.4977	-0.0179	[-0.047 - 0.011]
All	0.2742	0.4465	53.12	35.1852	-0.0095	[-0.033 - 0.014]

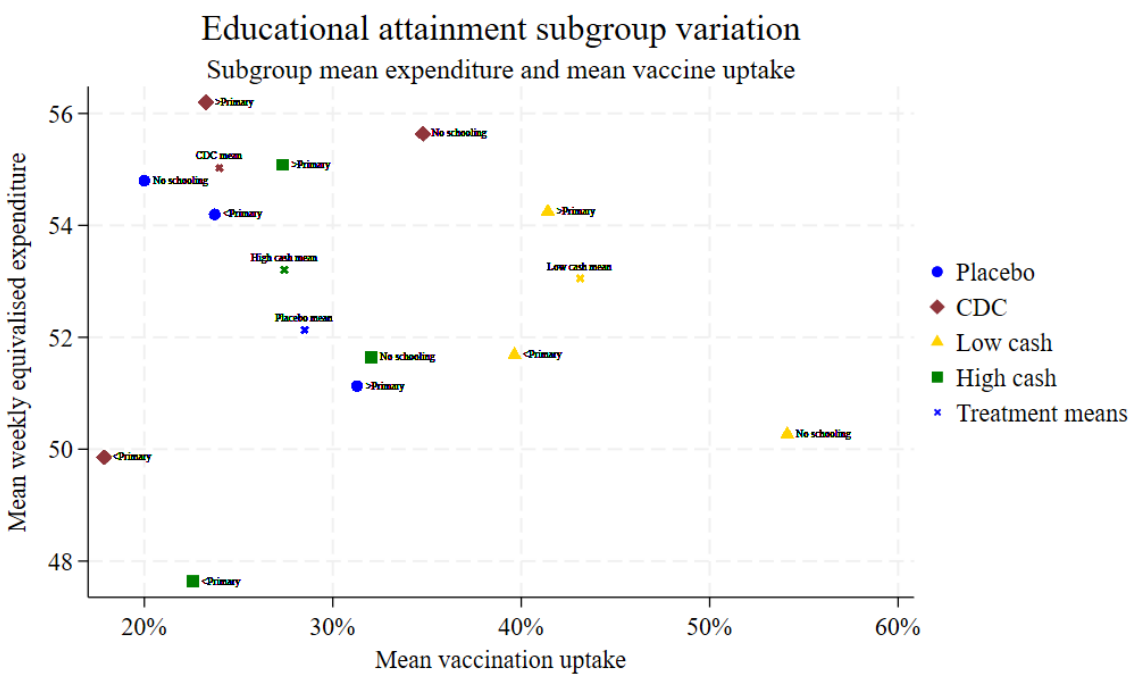
*Denotes index value is statistically significantly different to 0 at the 5% level.

Table 7E: Identification of heterogenous distributional treatment effects

	Placebo		CDC styled message		Low cash incentive		High cash incentive	
Gender[1]								
	Values	%	Values	%	Values	%	Values	%
Within	-0.0218	98.53%	0.0054	97.82%	-0.0135	103.79%	-0.0096	100.50%
Between	-0.0003	1.47%	0.0001	2.18%	0.0005	-3.79%	0.0000	-0.50%
Total	-0.0221	100.00%	0.0054	100.00%	-0.0130	100.00%	-0.0095	100.00%
Education[2]								
	Values	%	Values	%	Values	%	Values	%
Within	-0.0208	94.21%	0.0044	80.68%	-0.0120	92.39%	-0.0101	106.05%
Between	-0.0013	5.79%	0.0011	19.33%	-0.0010	7.61%	0.0006	-6.05%
Total	-0.0221	100.00%	0.0054	100.00%	-0.0130	100.00%	-0.0095	100.00%

1. Gender includes self-reported male and female respondents only, as other groups only had two verified respondents.
2. Education is split into the following groups: No schooling; up to end of primary; More than primary

Figure 7D: Educational attainment subgroup variation for between component



7.1.4 Discussion and conclusion

In this paper I have shown how socioeconomic inequality indices can be computed post-hoc in evaluation trials, but that caution should be exercised due to the risk of Type I and II errors. These results can be used first to more fully inform decision-making on the possible socioeconomic inequality implications of interventions relative to one another using an achievement plane, and second, in the special case of the perfectly decomposable Level Index (which need not be used to develop the achievement plane), to explore the presence of heterogenous socioeconomic inequality treatment effects across treatment subgroups.

In this illustrative empirical application, the results indicated that there were no evidence of significant differences between the socioeconomic distributional impacts relative to the placebo group. I did not observe heterogeneous treatment effects in socioeconomic inequality of health by subgroup, however as the subgroups were not powered for distributional testing, this serves more as an illustrative and exploratory example. Despite observing more heterogeneity by education level, with the greatest degree of heterogeneity between groups in the public health messaging treatment, I did not observe heterogenous inequality treatment effects either, though this may be due to uneven and smaller than optimal sample sizes of subgroups, and a resulting lack of statistical power. While an absence of formal education was associated with higher uptakes in each treatment, I caution the reader that this may be due to other confounding variables (see heterogeneity interaction models in the original work[145]), which would require interaction testing by subgroup to confirm. Nevertheless, that respondents without schooling responded more positively to treatments than other groups is a noteworthy response in its own right. This result cannot be generalised to the rest of Ghana, however, given the rural sample used in this dataset.

Policy makers often need to consider balancing efficiency (i.e., average uptake) and equality, of which socioeconomic inequality in health is but one part. In this case, treatments with the greatest average uptake (i.e., the low-cash incentive) should be prioritised, as there is limited evidence to suggest that there are significant distributional ramifications between treatments, but the possibility of Type II errors exists.

The primary benefit of the achievement plane and accompanying Level Index decomposition for identification of heterogenous socioeconomic inequality treatment effects is that it is a relatively simple process that can be completed with limited data (health variable, socioeconomic variable, and subgroup variables), either during the original trial analysis or post-hoc, though caution is advised in the post hoc case, and adequate power for testing should be ensured. The methods are straightforward and accessible to socioeconomic inequality of health practitioners, and are consistent when using the Level Index throughout. The achievement plane offers a simple and intuitive way of comparing multiple treatment arms through a joint socioeconomic inequality of health and average treatment effect lens. The subgroup decomposition offers a mathematically neat and simple solution which acts as a signpost as to whether socioeconomic inequality of health differs across subgroups after treatments, however, further robust investigation is required to confirm the presence of heterogenous socioeconomic inequality effects, per the distinction between exploratory and confirmatory empirical findings.[251]

In comparing the decomposition approach to other subgroup analysis methods, many of the same challenges persist. Many evaluation trials are powered to identify main effects, not subgroup differences, and like other subgroup analyses, pre-specification and powering is optimal, and often required for convincing findings.[252,253] That this method can be computed post-hoc is beneficial, but it does not detract from the fact that underpowered testing is likely to find null results (Type II error), or that testing large numbers of subgroups could turn up a chance result (Type I error) – both of which should be avoided in practice.[252]

Pocock et al. argue that interaction tests are the most useful subgroup methodology despite the oft-lamented lack of statistical power, which can in fact be helpful by recognising data limitations and inhibiting false claims. Stratified analysis and testing for differences across subgroups can be misleading according to Pocock et al, which I acknowledge, and hence suggest limiting this approach, which is effectively a stratification analysis, to an exploratory technique.[253]

It is clear that there are limitations to the subgroup decomposition method. Differential sample sizes will reduce the influence of smaller subgroups, while small subgroup sample sizes could lead to underpowered testing and chance results. More so, there is no clear level at which the between component is indicative of heterogenous treatment effects that affect socioeconomic inequality in health in subgroups. A nuanced approach to investigating differences could thus lead to researchers reaching different conclusions when faced with the same data, a naturally undesirable outcome. Guidelines could be put in place (for example, if the between component is >50%, it may be strongly indicative of heterogeneity), however further academic debate would be required to confirm the level at which this was set. In any event, further testing, either in the form of ordered numerical or graphical analysis, or of more traditional subgroup heterogeneity tests is more than likely required to complement the descriptive nature of the decomposition.

Given the limitations of the approach outlined above, the decomposition approach should be used when sample sizes of subgroups are more or less equal and large enough for conventional subgroup testing, and when socioeconomic inequality of health analysis is already being undertaken with the Level Index (e.g., plotting on the achievement plane). The approach lends itself to post-hoc analysis provided sample sizes are adequate, especially in the case when more detailed data may not be available. In this case, the decomposition approach can suffice as an exploratory indicator, rather than a confirmatory result, provided some pre-specification hypothesis exists and tests are not conducted over a large number of subgroups.[251,252] When more data are available and the option for conventional and robust subgroup analysis remains open, the decomposition approach proffered here should be used as an indicator of socioeconomic inequality of health in conjunction with commonly accepted approaches such as interaction testing.

The original trial cited limitations due to 1) potential discrepancies in the village-level rollout of vaccination, 2) results that may be specific to the study design, 3) the study being conducted in rural areas only; to this end I advise caution in the generalizability of trial inequality statistics. Without a representative dataset (in this case, entirely rural), the trial's socioeconomic inequality of health statistic should not be generalized to different populations, and its use in wider policy application should be carefully considered, 4) and the unknown potential spillover effects under scaling.[145] A further limitation relevant to this work is the uneven sample sizes of the subgroups, noted in table D3, and the lack of pre-specification and powering for distributional and subgroup testing.

Future work could involve applying social welfare foundations to the achievement plane presented in this paper, particularly for the Level Index. Bleichrodt & van Doorslaer have worked on social welfare foundations related to the (rank-based) concentration index,[254] and show that the achievement index is the abbreviated social welfare function underlying the extended concentration index. While this achievement plane places by assumption an equal weighting on average (societal) health and inequality, and in assuming so relies implicitly on the principle of income-related health transfers; where a transfer of health from someone with a higher socioeconomic status to someone of a lower socioeconomic status does not cause a change in social welfare provided there is no change of socioeconomic status rank(/level). The plausibility of the principle is challenged by Bleichrodt and van Doorslaer, especially in the case that differences in socioeconomic status are small, and the transfer occurs from a high socioeconomic status individual in poor health to a lower socioeconomic status individual in better health.[254] Further work is required to develop social welfare foundations for level dependent indices, and in so doing enable a) selection of interventions in the same quadrants and b) the possibility of redrawing the achievement plane quadrants according to the appropriate underlying social welfare function, as outcomes in quadrants II or IV may be preferred to those in quadrant I depending on the underlying function.

A second avenue for further work could include the application of joint distributions of the health outcome and socioeconomic inequality, allowing the inclusion of a measure adopting similar principles to the acceptability curve used in cost-effectiveness analysis, and thus enabling decision-making incorporating inequality and uptake jointly. Fleurbaey has worked on shifting health and income from a two-dimensional problem into a single dimension by combining the variables into a single distribution with a willingness to pay for health metric.[255]

In this work, I have explored the use of an achievement plane to jointly present the socioeconomic equality of health and efficiency trade-off in randomized trials. Treatment may have impacts on the socioeconomic distribution of health in addition to the mean, which should be considered. While incorporating this into the study design is preferred I have shown that an indicator of socioeconomic inequality of health impact and overall health achievement can be estimated post-hoc provided the relevant socioeconomic data were collected, though this should be done with caution to avoid both Type I and Type II errors. I have further contributed to the literature by presenting the use of the Level Index and its decomposition as a method to explore heterogeneity of treatment effects in socioeconomic inequality of health for application in intervention trials.

Despite not finding significant discrepancies in socioeconomic inequality of health between treatments, this study outlines the process and importance of including a socioeconomic inequality of health impact indicator alongside average treatment effects. Without a socioeconomic distributional indicator, policy makers risk equality-blind decisions which could lead to inequality-increasing policies if there is an unknown, or hidden equality efficiency trade-off. However, the use of these methods post-hoc should be employed with care, as application without adequate power could yield unwanted and even damaging results.

7.2 A note on improving the deployment efficiency of new medical technologies: Assessing the sensitivity of demand forecasting and sociodemographic characteristics associated with changing sentiments in Coronavirus vaccination over time

7.2.1 Introduction

Challenges to the global rollout of COVID-19 vaccines were forecast to include limited production capacity, affordability, allocation mechanisms, and local deployment issues (e.g., hesitancy and logistics).[190] In a perfectly coordinated system, vaccine supply would meet vaccine demand. Vaccines would be produced at scale affordably, procured, allocated efficiently, and deployed effectively to those individuals willing to accept doses, minimising vaccine waste. However, systems are not perfectly coordinated at the local, regional, national, or global level, as was evident during the COVID-19 pandemic.

On the supply side, global vaccine shortages stunted early rollout in all but a select few countries.[191] Hoarding and vaccine nationalism in wealthy and vaccine producing countries limited vaccination activity in the Global South.[188]

On the demand side, hesitancy was present to varying extents in many countries.[215,256–259] While the unusually rapid development and speed to market of COVID-19 vaccines was achieved by factors that did not compromise safety,[260] large pockets of the public perceived less investigation than usual into possible long-term effects, which left some individuals hesitant.[256] Hesitancy and logistic challenges resulted in the expiration and waste of doses in some countries while others waited for first doses.[191]

A perfectly coordinated system would eliminate waste on the bases of allocative inefficiency (demand and supply mismatch) and mismanagement. However, with full knowledge that perfectly coordinated systems are improbable, especially in times of shock, steps can be taken to increase coordination. Apart from the benefits of cost reduction due to waste, increased coordination could improve global equity and global health. For example, vaccine equity would reduce the prospects of escape variants.[202,203] Increased coordination would not come without economic cost. One such method already in wide use in academia which could improve coordination is the use of surveys for indicative demand planning. Alongside historical data, surveys are used routinely in demand forecasting in some fields of business, particularly in supply chain management and retail.[261] Demand planning or forecasting is a necessary but not sufficient condition for efficient allocation, as supply-side issues may still arise. Knowledge of accurate hesitancy and acceptance levels could improve the efficiency with which health systems deliver care, giving rise to efficiency gains in allocation and waste reduction.

The widespread interest and the extensive research conducted around the COVID-19 pandemic provides a unique opportunity to investigate the relationship between stated hesitancy and actual uptake. The body of research on hesitancy and uptake can facilitate analyses on the predictive power of surveys in eliciting future demand (uptake), and on associations between certain sociodemographic factors and consistency in vaccine preferences. This research can inform our understanding of the extent to which such surveys might assist in policy decisions.

Previous research has been conducted on differences between COVID-19 vaccine hesitancy and uptake using cohort designs.[262–267] in the United Kingdom, United States, and Kenya respectively. Similar repeated research has also been conducted on the stability of vaccine prioritisation preferences using discrete choice experiments.[268]

Yang et al. identify 16 COVID-related studies for qualitative review in a systematic review on the relationship between hesitancy and vaccination behaviour.[269] Three of the sixteen studies are longitudinal or cohort in design.[262,263,266] The remaining 13 studies are cross-sectional (12) or ecological (1), generally using a generic vaccine hesitancy scale or adjusted COVID vaccine hesitancy scale to inform models on uptake. These studies cover Australia, China (2), Germany, Israel, Saudi Arabia, Turkey, and the United States (6).[269]

Using the prospective cohort portion of the CANDOUR survey conducted in 13 countries between 2020 and 2022 (N = 5,213), I aimed firstly to investigate the extent to which individual-level surveys, undertaken prior to the availability of COVID-19 vaccines, were able to predict subsequent vaccine uptake by measuring sensitivity and specificity. I compare ex-ante and ex post sentiment towards receipt of COVID-19 vaccines at two points during the pandemic. Secondly, I aimed to identify sociodemographic characteristics associated with changes in vaccine sentiment (e.g. being ex ante vaccine hesitant but subsequently getting vaccinated (false negative), and vice versa) to illuminate whether consideration of sociodemographic characteristics holds potential for improving survey based predictions of health technology uptake. This research contributes to the literature by providing a comparison between COVID-19 vaccine hesitancy and uptake using a cohort design with new data from the CANDOUR wave 2 dataset. I further contribute by directly investigating characteristics associated with departure from stated intentions (i.e., false responses) in surveys.

7.2.2 Materials and methods

7.2.2.1 Data

7.2.2.1.1 Survey design

This investigation was conducted using data from the first and second waves of the COVID-19 Vaccine Preference and Opinion Survey (CANDOUR) study. CANDOUR is an online cross-sectional multi-country survey for adults aged 18 and above, with a convenience longitudinal sub-sample followed in both waves 1 and 2. All participants provided informed written consent before beginning the survey. In each wave of the CANDOUR study, quota sampling was employed to obtain samples broadly representative of the adult (18+) population in each country in terms of gender, age, education and geographic region. However, to enable direct ex ante and ex post comparison, the analysis in this study is restricted to the subsample of CANDOUR respondents who were surveyed repeatedly in waves 1 (November 2020 – January 2021) and wave 2 (March – November 2022), forming a cohort of 5,454 respondents from 13 countries from samples of 15,337 in wave 1 and 18,189 in wave 2 respectively. Of these, 5,213 individuals provided complete hesitancy and vaccination uptake responses, and were included in the analysis.

7.2.2.1.2 Data collection

In wave 1, survey respondents were asked if they would get a COVID-19 vaccine if an effective vaccine were to become available. Respondents who said they would "definitely get it" or "probably get it" were deemed accepting in wave 1. Respondents who selected "do not know", "probably not get it", and "definitely not get it" were deemed hesitant in wave 1. Responses of "prefer not to say" were excluded.

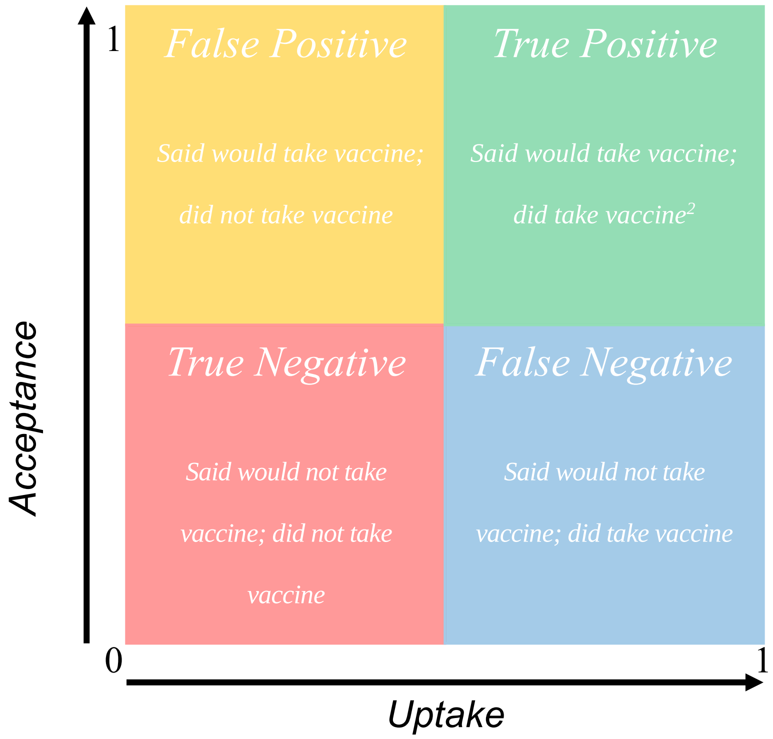
In wave 2, participants were asked if they had received a COVID-19 vaccine. Respondents who had received at least a single shot of any COVID vaccine, or who were still awaiting appointments and were willing to receive a vaccine (n=26) were deemed accepting at subsequent follow-up (wave 2). Respondents who declined the offer to be vaccinated were deemed hesitant, and those who preferred not to answer were again excluded. All other variables included in the study were self-reported in the online survey.

7.2.2.2 Methodology

I seek to answer two research questions; 1) how effective are direct survey questions as predictors of vaccine uptake? and 2) whether sociodemographic differences exist between individual respondents who provided false positive or false negative responses relative to those who provided true (consistent) responses. The second research question is exploratory in nature due to the non-representativeness and convenience sample nature of the dataset. These factors may also introduce bias, which limits the generalizability of the results, but remains a valid approach for the sample at hand.

To answer the first research question, I develop a descriptive transition matrix based on vaccine intention in wave 1 and uptake in wave 2, identifying the sentiment switching between time periods, and applying a diagnostic accuracy sensitivity-specificity framework. The matrix consists of the following outcomes, shown graphically in figure 7E - True positive (TP) – accepting in wave 1, vaccinated or still intent to be vaccinated in wave 2; True negative (TN) – accepting in wave 1, unvaccinated with no intention to get vaccinated in wave 2; False negative (FN) – hesitant in wave 1, vaccinated or vaccinated or still intent to be vaccinated in wave 2; False positive (FP) – hesitant in wave 1, unvaccinated with no intention to get vaccinated in wave 2. Sensitivity is calculated as TP/(TP+FN), and specificity is calculated as TN/(TN+FP). I then run logistic regressions to determine the predictive power of stated intention alongside several key sociodemographic variables on uptake. The sociodemographic variable set includes age, gender, education levels, chronic disease status, political ideology, income levels, marital status, presence of dependent children, employment status, and country – which captures country level effects (e.g., strength of COVID vaccine rollout; national vaccine mandates, COVID regulations). I fitted 4 models and performed selection based on Akaike and Bayesian information criterion (AIC and BIC, respectively). As I include categories such as undisclosed income, other employment status, undisclosed ideology, and other education level – which may incorporate missing responses, the sample size is held constant and the AIC and BIC do not incorporate reduced sample size and therefore do not penalise overfitting as much as usual, which is considered in model selection. Model (A)1 and (A)2 contrast the association of sociodemographic determinants with ex-ante acceptance and ex-post uptake respectively. Model (A)3 introduces ex-ante intention into model (A)2, investigating the effectiveness of stated intention as a predictor for uptake. Model (A)4 adds time-varying change variables to model (A)3; namely changes in income, marital status, employment status, and child dependent status. Adding these change variables employs the available and varying longitudinal data, and adds insight into how changes in the period affect vaccine uptake alongside static variables.

Figure 7E: Vaccine sentiment transition matrix



In answering the second research question, I construct a binary *switching* variable, coded 1 for false positives or negatives and 0 for true positives or negatives. As the transition matrix coding requires data on both the individuals' vaccine intent in Wave 1 and their vaccination uptake status in Wave 2, and the sociodemographic variables included are predominantly time-invariant, panel methods are inappropriate for analysis despite the longitudinal data. I run a logistic regression on switch status to investigate if certain sociodemographic variables may indicate a higher propensity to switch sentiment, providing guidance for future survey estimates. I repeat this analysis with disaggregated binary switch variables FN and FP responses separately. I specify four models. In model (B)1, I regress the constructed switch variable on the sociodemographic variable set. In model (B)2, I add the time varying change variables to the model, as I did in model (A)4, to retain a longitudinal perspective. In (B)3, I regress the FN variable (hesitant to accepting & received vaccine) on the (B)1 variable set, and in (B)4, I regress the binary FP variable (accepting to hesitant & refused vaccine) on the same sociodemographic variable set to determine if any sociodemographic characteristics are associated with specific directional switches. The independence of irrelevance alternatives assumption is violated, precluding the use of multinomial logistic regression or nested logistic regressions in models (B)3 and (B)4. I elect logistic regression for simplicity.

Statistical significance was set at $p < 0.05$. Analyses was conducted using Stata 18.0 (StataCorp LP; College Station, TX).

7.2.3 Results

7.2.3.1 Sample overview

A descriptive overview of the restricted (repeated) wave 1, and the full, unrestricted wave 1 sample is contained in Table 7F. The median respondent in the restricted sample is in the 40–49-year-old age group, with no chronic diseases, and a university education. 77% of the sample was vaccine accepting in wave 1, while 89% of restricted respondents had reported vaccination in wave 2, slightly more than the unrestricted sample in wave 2. The restricted sample is ~51% male and ~48% female, and draws from each of the 13 countries surveyed. Approximately 59% of the restricted sample lives with a partner, and 43% lives with a dependent child. The restricted sample is more educated (+6 percentage point more respondents with university education), in worse health (-5 percentage point fewer respondents with no chronic health conditions), and slightly less right-leaning politically (-2 percentage points right leaning). The income profile of the restricted sample mirrors the overall sample closely. In the restricted sample, 21.6% of respondents are in the lowest income quartile in their country in the full sample, 21.6% and 22.6% are in quartiles 2 and 3 in their country in the full sample respectively, and 20.1% are in the highest earning quartile in the full sample. 13.8% of restricted sample respondents did not disclose their income. Descriptive statistics for the restricted waves 1 and 2, available per country, are available in the supplementary materials.

Table 7F: Descriptive overview of the sample at wave 1

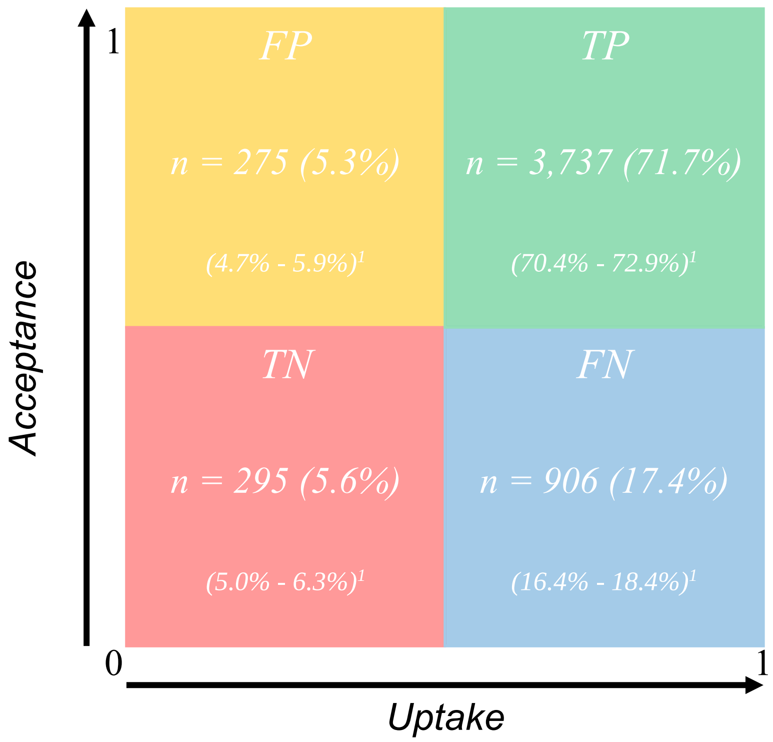
		Restricted Wave 1 (N (%))	Unrestricted Wave 1 (N (%))
	Sample size	5,213	15,337
Age group (years)	18-29	1,126 (21.5%)	3,975 (25.9%)
	30-39	1,180 (22.6%)	3,381 (22.0%)
	40-49	1,065 (20.4%)	2,651 (17.2%)
	50-59	893 (17.1%)	2,394 (15.6%)
	60-69	708 (13.5%)	2,092 (13.6%)
	70+	241 (4.6%)	839 (5.5%)
Gender	Male	2,659 (51.0%)	7,902 (51.5%)
	Female	2,524 (48.4%)	7,354 (47.9%)
	Other	30 (0.6%)	81 (0.5%)
Education level	Primary or less	412 (7.9%)	1,854 (12.0%)
	Secondary complete	2,009 (38.5%)	6,037 (39.3%)
	University complete	2,733 (52.4%)	7,128 (46.4%)
	Other education level	59 (1.1%)	318 (2.1%)
Chronic health conditions	None	2,676 (51.3%)	8,733 (56.9%)
	1	1,742 (33.4%)	4,825 (31.4%)
	2 or more	795 (15.2%)	1,779 (11.5%)
Political ideology	Left	741 (14.2%)	2,093 (13.6%)
	Centre	1,872 (35.9%)	5,402 (35.2%)
	Right	791 (15.1%)	2,683 (17.4%)
	Undisclosed ideology	1,809 (34.7%)	5,159 (33.6%)
Living with a partner	No	1,940 (37.2%)	5,841 (38.0%)
	Yes	3,093 (59.3%)	8,996 (58.6%)
	Undisclosed	180 (3.5%)	500 (3.5%)
Dependent children	No	2,967 (56.9%)	8,863 (57.7%)
	Yes	2,246 (43.0%)	6,474 (42.2%)
Employment status	Employed	2,752 (52.7%)	7,887 (51.4%)
	Unemployed	490 (9.4%)	1,449 (9.4%)
	Pension or capital income	487 (9.3%)	1,472 (9.6%)
	Other employment status	1,484 (28.4%)	4,529 (29.5%)
Income quartile in country[1]	Bottom 25%	1,129 (21.6%)	3,528 (23.0%)
	26-50%	1,131 (21.6%)	3,377 (22.0%)
	51-75%	1,180 (22.6%)	3,357 (21.8%)
	Top 25%	1,049 (20.1%)	2,902 (18.9%)
	Undisclosed income	724 (13.8%)	2,173 (14.1%)
Vaccination status	Accepting (wave 1)	4,012 (77.0%)	11,883 (77.5%)
	Received vaccine (wave 2)[2]	4,643 (89.0%)	15,762 (86.5%)[2]

1. Income quartiles non-exact due to ties of bounded categorical income question
2. Wave 2 unrestricted sample is 18,189 respondents

7.2.3.2 *The predictive power of survey intention in COVID-19 vaccine uptake*

Analysing the data in wave 1 and wave 2, I am able to place individual respondents into the 2x2 transition matrix in figure 7E in order to gain a perspective into the consistency of respondent sentiment and actions, and thus the effectiveness of surveys as tools for predicting uptake. 77.3% (95% CI: 76.2 – 78.5%) of respondents in this online, global, unweighted and quasi-convenience longitudinal sample provided true positive or true negative responses, meaning these respondents were consistent in their intention from wave 1 to wave 2, and thus using the results from the wave 1 survey could have informed supply decisions for approximately 77% in this specific, non-representative sample. The survey had a resultant sensitivity (correctly predicting vaccination) of 80.5% while specificity (correctly predicting non-vaccination) was lower, at 51.8% due to a large number of false negative responses.

Figure 7F: 2020 – 2022 Transition matrix for vaccine sentiment



1. 95% confidence interval
2. Includes 26 respondents who are vaccine willing but waiting for appointments

I employ logistic regression models (Table 7G) to estimate the predictive power of ex-ante intention in ex-post vaccination. Using AIC and BIC as selection criteria, I select model (A)3. Although model (A)4, which includes time varying lags has a lower AIC than model (A)3, the BIC is larger, penalising the model for introducing additional variables and overfitting.

Table 7G: Predictors of COVID-19 vaccine uptake

	Vaccine intention		Vaccine uptake					
	Model (A)1		Model (A)2		Model (A)3		Model (A)4	
	OR	SE	OR	SE	OR	SE	OR	SE
Vaccine intention					3.51***	(0.36)	3.61***	(0.38)
Ref: 18-29 years								
30-39	0.86	(0.11)	0.88	(0.14)	0.90	(0.14)	0.90	(0.14)
40-49	0.72*	(0.10)	1.09	(0.18)	1.17	(0.20)	1.19	(0.20)
50-59	0.99	(0.14)	1.18	(0.21)	1.17	(0.21)	1.18	(0.21)
60-69	1.19	(0.20)	1.64*	(0.37)	1.58*	(0.36)	1.51	(0.35)
70+	1.52	(0.37)	1.28	(0.40)	1.17	(0.37)	1.03	(0.33)
Ref: Male								
Female	0.75***	(0.06)	0.99	(0.10)	1.07	(0.11)	1.07	(0.11)
Other	0.73	(0.48)	1.78	(1.96)	1.65	(1.78)	1.30	(1.41)
Ref: Primary or less completed								
Secondary complete	1.09	(0.15)	1.86***	(0.30)	1.88***	(0.31)	1.84***	(0.31)
University complete	1.72***	(0.24)	2.12***	(0.35)	1.91***	(0.32)	1.88***	(0.32)
Other education level	3.40	(2.64)	1.23	(0.83)	0.94	(0.65)	0.95	(0.65)
Ref: No chronic health conditions								
1	1.47***	(0.12)	0.99	(0.10)	0.89	(0.09)	0.88	(0.09)
2 or more	1.46***	(0.16)	1.19	(0.18)	1.10	(0.16)	1.10	(0.17)
Ref: Left								
Centre	0.79*	(0.09)	0.77	(0.13)	0.82	(0.13)	0.83	(0.14)
Right	0.53***	(0.07)	0.43***	(0.08)	0.48***	(0.09)	0.50***	(0.09)
Undisclosed ideology	0.55***	(0.07)	0.48***	(0.08)	0.55***	(0.09)	0.57**	(0.10)
Ref: Living alone								
Yes	1.21*	(0.10)	1.69***	(0.18)	1.66***	(0.19)	1.66***	(0.20)
Undisclosed	1.03	(0.32)	0.76	(0.25)	0.73	(0.24)	0.78	(0.26)
Ref: No dependent child								
Yes	0.88	(0.08)	0.79*	(0.09)	0.81	(0.09)	0.73*	(0.09)
Ref: Employed								
Unemployed	0.94	(0.12)	0.67**	(0.09)	0.67**	(0.10)	0.63	(0.18)
Pension or capital income	1.13	(0.18)	1.12	(0.24)	1.09	(0.24)	1.49	(0.46)
Other employment status	0.91	(0.10)	0.89	(0.12)	0.92	(0.13)	1.03	(0.16)
Ref: Bottom quartile								
26-50%	1.03	(0.11)	1.13	(0.15)	1.13	(0.15)	1.16	(0.16)
51-75%	1.17	(0.13)	1.33*	(0.19)	1.30	(0.19)	1.32	(0.20)
Top 25%	1.44**	(0.17)	1.43*	(0.22)	1.33	(0.21)	1.40*	(0.23)
Undisclosed income	0.80	(0.11)	1.00	(0.17)	1.10	(0.19)	1.46	(0.36)
Ref: Australia								
Brazil	2.39***	(0.48)	1.45	(0.38)	1.18	(0.31)	1.15	(0.31)
Canada	0.89	(0.21)	1.31	(0.47)	1.33	(0.49)	1.23	(0.46)

Chile	1.69*	(0.35)	4.61***	(1.78)	4.03***	(1.57)	4.07***	(1.61)
China	1.17	(0.24)	0.89	(0.24)	0.81	(0.22)	0.96	(0.28)
Colombia	2.29***	(0.46)	1.88*	(0.53)	1.54	(0.44)	1.70	(0.49)
France	0.21***	(0.04)	0.41***	(0.10)	0.61*	(0.15)	0.52*	(0.14)
India	2.90**	(1.08)	3.56*	(2.00)	2.80	(1.58)	2.97	(1.69)
Italy	0.62**	(0.11)	0.48**	(0.12)	0.53*	(0.13)	0.52**	(0.13)
Spain	1.02	(0.19)	1.40	(0.38)	1.35	(0.37)	1.39	(0.40)
Uganda	3.90***	(0.97)	1.19	(0.33)	0.88	(0.25)	0.94	(0.28)
United Kingdom	1.23	(0.23)	1.11	(0.29)	1.03	(0.27)	0.91	(0.25)
United States	0.38***	(0.09)	0.34***	(0.11)	0.42**	(0.13)	0.38**	(0.13)
Ref: No income change								
Increased by >20%							0.62***	(0.08)
Decreased by >20%							0.73*	(0.11)
Undisclosed change							0.58*	(0.12)
Ref: No change in dependents								
New dependent							1.16	(0.24)
Lost dependent							0.64*	(0.13)
Ref: No employment change								
Gained job							1.36	(0.21)
Lost job							1.28	(0.40)
Retired							0.68	(0.22)
Ref: No change								
Got married							0.89	(0.20)
Got divorced							0.77	(0.18)
Constant	3.06***	(0.76)	4.76***	(1.55)	2.09*	(0.71)	2.66**	(0.93)
Observations	5,213		5,213		5,213		5,213	
AIC	4976		3362		3219		3209	
BIC	5225		3612		3475		3530	

SE in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Apart from country specific controls, vaccine intention was the variable most associated with vaccination, (OR: 3.51, 95% CI: [2.87-4.29], significant at the 0.001 level. Higher education levels were associated with a higher likelihood of vaccination uptake for both high school and university graduates. 60-69 year old respondents were more likely to be vaccinated compared to other age groups. Right-wing political ideology is associated with significantly lower vaccination uptake (OR: 0.48, 95% CI: [0.34-0.69]), while those who did not disclose political ideology were marginally more likely to be vaccinated than the self-identified right (OR: 0.55, 95% CI: [0.40-0.77]). Income categories were not found to have significant effects on vaccination uptake in the sample, however unemployed respondents were less likely to be vaccinated relative to employed individuals (OR: 0.67, 95% CI: [0.50-0.88]. In model (A)4, income changes of more than 20% (positive or negative) were both associated with decreased uptake compared to respondents with roughly constant income. Marital status was significant, with increased likelihood of vaccination for married respondents (or those living with their partner) relative to non-married respondents (OR: 1.66, 95% CI: [1.33-2.07]). Country specific effects varied widely – which naturally include an overarching control of national vaccine policy. Significant country results were observed in Chile, France, Italy, and the United States.

Models (A)1 and (A)2 show changes in factors affecting sentiment over time. The baseline odds of being vaccinated were higher than for vaccine acceptance given by the larger constant term in Model (A)2 than (A)1, indicating a positive shift towards acceptance over the study period, ceteris paribus. In (A)1, I see lower acceptance in females relative to males, whereas this all but disappears in (A)2. Ideological differences remained largely constant, however having chronic diseases was more associated with being accepting than with being vaccinated. Marriage status was a more important factor in uptake than acceptance. Income and employment were largely consistent over time, while age and education were more varied over time. Country effects varied.

7.2.3.3 Identifying false responses in survey prediction

On the basis of the AIC and BIC, I select model (B)1. Model (B)2 has higher values for both the AIC and BIC, implying an overfitted model compared to model (B)1. I present the results in Table 7H. Respondents aged 70 and over were half as likely to switch intention (i.e., provide false responses) compared to the 18–29-year-old age group. Females were 17% more likely to switch than males (OR: 1.17, 95% CI [1.01-1.35]). Respondents in the highest earning income quartile were nearly 25% (OR: 0.77, 95% CI [0.61-0.96]) less likely to switch than the lowest income quartile. Those who self-identified as right-leaning politically, or did not disclose a political status were significantly more likely (95% CI [1.28-2.13] and [1.35-2.16] respectively) to switch than politically central and left-leaning respondents. University graduates were significantly less likely to switch sentiment than other levels of education (95% CI [0.46-79]). Individuals in France and Italy showed increased likelihood of switching relative to the base country, Australia. Brazil, Chile, Colombia, India, Uganda, and the United Kingdom were each associated with reduced likelihood of switching, ranging from a 40-59% reduction relative to Australia. In models (B)3 and (B)4, I gain a perspective of sociodemographic characteristics associated with false positives and false negatives respectively. Females were 29% more likely to provide FN responses (from vaccine hesitant to accepting) than males (OR: 1.29, 95% CI [1.10-1.51]). 40-49-year-olds also showed significantly higher odds of FN responses, while respondents 70 and over showed similarly low prospects of FN responses as in model (B)1. Right-leaning respondents were approximately 50% (OR: 1.47, 95% CI [1.11-1.95]) more likely to switch to vaccine accepting than left-leaning counterparts, however these political affiliations were also associated with switching from vaccine accepting to vaccine hesitant (FP) with greater odds (OR: 1.83, 95% CI [1.13-2.97]), effectively cancelling each other out as useful predictive variables. Having chronic diseases was associated with lower odds of providing FP responses, and higher odds of FN responses respectively. Respondents living alone were less likely to switch to hesitancy over time. Country effects varied, with respondents in Canada, the UK, and the US unlikely to change sentiment to vaccine hesitancy; whereas respondents in Brazil, Canada, Italy, and the US were unlikely to become more accepting after initial hesitancy. Colombia and Spain were the only countries that reported statistically significant likelihoods of changes to acceptance.

Table 7H(I): Predictors of switching COVID-19 vaccine sentiment

	(B)1		(B)2	
	Propensity to switch		Propensity to switch	
	OR	SE	OR	SE
Ref: 18-29 years				
30-39	1.10	(0.13)	1.12	(0.14)
40-49	1.16	(0.15)	1.19	(0.15)
50-59	1.00	(0.14)	1.03	(0.14)
60-69	0.80	(0.13)	0.82	(0.14)
70+	0.50**	(0.12)	0.52**	(0.13)
Ref: Male				
Female	1.17*	(0.09)	1.16*	(0.09)
Other	1.02	(0.72)	0.97	(0.69)
Ref: Primary or less completed				
Secondary complete	0.89	(0.12)	0.89	(0.12)
University complete	0.60***	(0.08)	0.60***	(0.08)
Other education level	1.20	(0.67)	1.20	(0.67)
Ref: No chronic health conditions				
1	0.88	(0.07)	0.88	(0.07)
2 or more	0.87	(0.09)	0.86	(0.09)
Ref: Left				
Centre	1.21	(0.13)	1.21	(0.14)
Right	1.65***	(0.21)	1.65***	(0.21)
Undisclosed ideology	1.71***	(0.20)	1.71***	(0.21)
Ref: Living alone				
Yes	0.89	(0.08)	0.88	(0.08)
Undisclosed	0.59	(0.20)	0.60	(0.20)
Ref: No dependent child				
Yes	1.13	(0.10)	1.14	(0.11)
Ref: Employed				
Unemployed	1.07	(0.13)	0.93	(0.24)
Pension or capital income	0.92	(0.14)	0.85	(0.18)
Other employment status	0.99	(0.10)	1.01	(0.11)
Ref: Bottom quartile				
26-50%	0.95	(0.10)	0.94	(0.10)
51-75%	0.88	(0.09)	0.88	(0.10)
Top 25%	0.77*	(0.09)	0.77*	(0.09)
Undisclosed income	1.02	(0.14)	0.98	(0.19)
Ref: Australia				
Brazil	0.46***	(0.09)	0.47***	(0.10)
Canada	0.77	(0.19)	0.79	(0.20)
Chile	0.58*	(0.12)	0.59*	(0.13)
China	1.17	(0.23)	1.15	(0.24)
Colombia	0.49***	(0.10)	0.50***	(0.10)
France	3.04***	(0.55)	2.96***	(0.56)
India	0.41*	(0.14)	0.43*	(0.15)
Italy	1.57*	(0.29)	1.62**	(0.30)
Spain	1.02	(0.19)	1.08	(0.21)
Uganda	0.60*	(0.13)	0.61*	(0.14)
United Kingdom	0.58**	(0.11)	0.60*	(0.12)
United States	1.52	(0.38)	1.58	(0.40)
Ref: No income change				

Increased by >20%			0.94	(0.09)
Decreased by >20%			0.90	(0.10)
Undisclosed change			1.00	(0.17)
Ref: No change in dependents				
New dependent			1.02	(0.15)
Lost dependent			0.99	(0.16)
Ref: No employment change				
Gained job			1.06	(0.12)
Lost job			1.21	(0.33)
Retired			1.20	(0.27)
Ref: No change				
Got married			1.36*	(0.21)
Got divorced			1.10	(0.21)
Constant	0.35***	(0.08)	0.34***	(0.09)
Observations	5,213		5,213	
AIC	5208		5221	
BIC	5458		5536	

SE in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 7H(II): Predictors of switching COVID-19 vaccine sentiment

	(B)3 Propensity to change to accepting		(B)4 Propensity to change to hesitancy	
	OR	SE	OR	SE
Ref: 18-29 years				
30-39	1.10	(0.16)	1.07	(0.21)
40-49	1.36*	(0.19)	0.69	(0.16)
50-59	1.06	(0.16)	0.87	(0.21)
60-69	0.92	(0.17)	0.57	(0.19)
70+	0.54*	(0.15)	0.53	(0.26)
Ref: Male	1.29**	(0.10)	0.82	(0.11)
Female	1.44	(1.01)	-	-
Other	1.12	(0.17)	0.50**	(0.11)
Ref: Primary or less completed	0.71*	(0.11)	0.49**	(0.11)
Secondary complete	0.62	(0.48)	2.70	(1.88)
University complete	0.73***	(0.06)	1.47**	(0.20)
Other education level	0.78*	(0.09)	1.25	(0.25)
Ref: No chronic health conditions	1.19	(0.14)	1.19	(0.27)
1	1.47**	(0.21)	1.83*	(0.45)
2 or more	1.53**	(0.20)	1.88**	(0.44)
Ref: Left	1.00	(0.11)	0.84	(0.16)
Centre	0.94	(0.11)	0.78	(0.15)
Right	0.78	(0.10)	0.81	(0.16)
Undisclosed ideology	1.16	(0.17)	0.68	(0.18)
Ref: Living alone	1.01	(0.09)	0.66**	(0.10)
Yes	0.57	(0.23)	0.75	(0.40)
Undisclosed	1.07	(0.10)	1.26	(0.20)

Ref: No dependent child	0.90	(0.12)	1.44	(0.27)
Yes	0.94	(0.16)	0.92	(0.29)
Ref: Employed	1.01	(0.12)	0.91	(0.19)
Unemployed	0.40***	(0.09)	0.77	(0.28)
Pension or capital income	1.00	(0.26)	0.11*	(0.12)
Other employment status	0.75	(0.17)	0.19**	(0.11)
Ref: Bottom quartile	0.99	(0.22)	1.53	(0.56)
26-50%	0.48**	(0.11)	0.65	(0.25)
51-75%	3.24***	(0.63)	1.16	(0.42)
Top 25%	0.45*	(0.18)	0.42	(0.28)
Undisclosed income	1.34	(0.27)	1.92	(0.66)
Ref: Australia	1.09	(0.22)	0.78	(0.29)
Brazil	0.31***	(0.08)	1.47	(0.54)
Canada	0.66*	(0.14)	0.38*	(0.16)
Chile	1.55	(0.42)	1.14	(0.59)
China	1.10	(0.16)	1.07	(0.21)
Colombia	1.36*	(0.19)	0.69	(0.16)
France	1.06	(0.16)	0.87	(0.21)
India	0.92	(0.17)	0.57	(0.19)
Italy	0.54*	(0.15)	0.53	(0.26)
Spain	1.29**	(0.10)	0.82	(0.11)
Uganda	1.44	(1.01)	-	-
United Kingdom	1.12	(0.17)	0.50**	(0.11)
United States	0.71*	(0.11)	0.49**	(0.11)
Constant	0.19***	(0.05)	0.11***	(0.05)
Observations	5,213		5,200	
AIC	4458		2052	
BIC	4708		2294	

SE in parentheses
*** p<0.001, ** p<0.01, * p<0.05

7.2.4 Discussion and conclusion

This study investigates the use of ex-ante vaccine intention in predicting ex-post vaccine uptake. I find vaccine intention to be a strong predictor of vaccine uptake, achieving nearly 80% prediction accuracy and sensitivity in the pooled analysis. Low specificity, however, could undermine prospects of implementation due to the risk averse nature of health technology deployments. When considering sociodemographic factors, intention remains the strongest predictor of vaccine uptake apart from the country factor in Chile. Chile oversaw a successful vaccine rollout which achieved comparatively higher uptake in a short timeframe relative to regional, development level, and population size peers. In July of 2021, Chilean uptake rates also exceeded the developed nations of Spain, the United Kingdom, and the United States.[270] I found some evidence that certain factors contributed to (non-)switching tendencies. For example; older, high-income, university educated males were unlikely to switch sentiment (i.e., provide false responses), whereas right-leaning females were more likely to switch from hesitancy to vaccine accepting. However, further work on representative and large datasets is required to make general findings on switching propensities. These findings suggest that the use of ex-ante surveys as prediction tools for medical demand may improve allocative efficiency if employed.

The findings on vaccination uptake support previous findings on intention using wave 1 of the same data.[256] Higher education levels, older age, and left political leaning were associated with greater likelihood of vaccination as they were with intention. I did not find significant associations between income and uptake at the $\alpha = 0.05$ level. However, it is notable that although unemployment was associated with reduced odds of uptake, it was not associated with intention. This suggests that unemployed respondents did not follow through with their intention. Possibly due to, for example, an inability to overcome logistical challenges (e.g., time off work, childcare) to receive the vaccine.

Germann et al. and Siegler et al. find accurate prediction in 67% and 74% of instances respectively in the United States.[262,267] Germann et al. conduct their study on pregnant and postpartum individuals towards the end of March 2021, following up with individuals 3-6 months later. Siegler et al. conduct their study on a population based serosurvey cohort from the second half of 2020 (August-December) with follow up during March-April 2021. Both works have shorter study periods compared to this investigation. Despite the rate, which is comparable to that found in this study, Siegler et al. conclude that hesitancy is not a stable predictor of vaccination uptake. Latkin et al. and Rane et al. refute this, suggesting that attitudes are predictive of uptake in the United States.[263,266] Studies in United States/United

Kingdom and Kenya investigated differences in intention and uptake (as I do with models (A)1 and (A)2), but do not explicitly track changes in sentiment.[264,265]

Vaccine prioritisation frameworks that consider hesitancy by linking personal ex-ante intention from simple surveys to health system administrative profiles could predict uptake with increased accuracy, allow more efficient supply management to accurately meet demand, reduce wastage, and increase the speed of initial rollout by targeting only those who are willing to accept new technologies. This is particularly useful for the delivery of novel, urgent, and expensive technologies where delays and wastage have larger effects on public health and budgets. However, low specificity could mean those who change their minds are left without new technologies, an undesirable outcome in a risk averse context. Cost benefit analyses and pilots should be conducted to determine the extent (if any) of potential efficiency gains.

There are three limitations to this work. 1) Self-reported status is not a guarantee of actual uptake. 2) The ethnicity variable in the CANDOUR surveys is tailored to each country and unfortunately not practical to use for cross-country or pooled analyses. 3) The restricted sample of the CANDOUR dataset is not designed to be representative. Despite similarities with the unrestricted wave 1 dataset as shown in table 7F, these results cannot be generalized. A second result of the restriction to repeatedly surveyed respondents is that the per country sample size of the panel portion of the CANDOUR survey is small in certain instances, limiting the power and feasibility of conducting country-level analysis.

I highlight 4 avenues for possible further work. 1) Conducting similar analyses on new medical technologies with large, nationally representative datasets. 2) Conducting cluster or latent class analyses on representative datasets to further investigate if underlying differences exist between switchers and non-switchers. 3) Conducting cost benefit analyses incorporating the cost of running surveys and collecting data and potential increased efficiency gains. 4) Conducting comparisons of predictive efficiency between responses recorded using the vaccine hesitancy scale, COVID vaccine hesitancy scale, and direct questions (e.g., will you get vaccinated if a vaccine becomes available).

This study investigated the predictive power of ex-ante intention on vaccine uptake using online surveys. I find intention to be a strong predictor of uptake, which, if incorporated into public health rollouts, could increase efficiency and speed of delivery. I find some evidence that certain characteristics are linked to changing sentiments, however further research is required to generalize these results.

7.3 Contributions

In this chapter, I address challenges or opportunities identified during my DPhil by exploring two key ideas which could contribute meaningfully to the literature. First, I investigated how the distributional evidence base could be broadened post-hoc, using data often collected in academic studies, in relatively straightforward, non-intensive processes. I then employed this data to show the trade-off between uptake and distributional concerns in an evaluation trial setting. Second, I analysed repeated survey data to investigate the sociodemographic characteristics associated with changing vaccine sentiment, and the sensitivity and specificity of simple online surveys for use as demand forecasting tools in the rollout of medical technology. Together, these two studies investigate the equality and efficiency aspects of healthcare, further contributing to the literature.

8. Synthesis and Conclusion

After introducing this thesis in chapter 1, chapter 2 reviewed the literature on income-related inequality in healthcare in access, utilisation, and vaccination, and its measurement, covering the stages of the Levesque et al. framework addressed in this thesis. I estimated income-related inequality in access to health systems (chapter 4), utilisation of health services (chapter 5), and in vaccine attitudes and uptake (chapter 6). In each of these chapters, I conducted comparisons between different types of care and between different countries to outline the landscape of income-related inequality in healthcare during the COVID-19 pandemic. Based on needs identified during the production of these chapters, I investigated possible methodological advances that could support equality and efficiency in the introduction of new medical technologies in chapter 7. This thesis has contributed to the literature by providing numerous novel quantitative estimates of inequality in different types of care during the Coronavirus pandemic, in up to 16 countries, and offering robust comparison between countries and types of care. The final aim of my thesis is to investigate inequality within countries and across the different stages of the healthcare process, which I undertake as a means of synthesizing the work conducted, before concluding.

8.1 Inequality trends within countries: a synthesis across the healthcare process

I have investigated inequality at various stages of the healthcare process, guided by the definitions of the Levesque et al. framework.[1] Each chapter thus far has presented a cross-sectional view of the health system; the inequality at a specific point within the overall process. The exceptions are in chapter 6 and 7, which draw comparisons across the process between hesitancy/demand and uptake in vaccination. Comparisons within these chapters have largely focused on differences between countries or between different types of care at the relevant stage in the healthcare process. To develop a comprehensive view of within-country inequality based on the works of this thesis, it is necessary to synthesise these previously separate analyses. In this chapter, I focus on the estimates from each previous chapter within each country to develop a longitudinal view of the inequality landscape. This approach allows identification of whether inequality varies as a patient progresses through the healthcare system, or if it remains consistent. Understanding the dynamics of inequality at different points within health systems can assist policymakers pinpoint areas for interventions. The purpose of this chapter is not to revisit discussion on any individual estimate, but to link estimates and to discuss the possible broader implications.

To illustrate the longitudinal healthcare process, I plot the various inequality estimates as they fit into the Levesque et al. framework,[1] and investigate inequality across the stages of contact with health systems. For consistency, I use the Erreygers adjusted indices from each chapter for the analysis.

I divide the countries into indicative archetypes based on the overall aggregated performances in inequality estimates throughout the healthcare process. Countries are assigned to archetypes using a cumulative net score of the previously produced results: +1 for a pro-poor result, 0 for an indeterminate result, -1 for a pro-rich result. Each country is classified according to the country's estimated health system performance (as defined and estimated in this thesis *only, and is thus indicative*) in inequality during the COVID-19 pandemic. The three archetypes are pro-poor, non-discriminatory on an income basis (e.g., neutral), or pro-rich. I acknowledge that other factors contribute to overall system income-related inequality (e.g., incidence and outcome), however, these factors are beyond the scope of work of this thesis as is clearly outlined in chapter 1.

It would be somewhat negligent to reduce to a simplified constructed mean value the totality of estimates I have produced within each country in a dissertation that is principally about distributional statistics. Though this method does suffice for the purpose of assigning to archetypes. While it is inappropriate to investigate the comparative statistical moments of the estimates owing to differences in standardization, I incorporate qualitative discussion on distributional components of within-healthcare system inequality.

8.2 Methods

8.2.1 Data used

The analysis employs the Erreygers concentration index estimates computed in the previous chapters of this thesis. The estimates cover inequality in access to health services (chapter 4), inequality in utilisation of health services (chapter 5), and inequality in COVID-19 vaccination uptake and intention (chapter 6). Estimates from chapter 7 are excluded due to the randomised treatments undertaken on the Ghana vaccination data, and because the CANDOUR data used in chapter 7 is already included in analysis in chapter 6.

Although the main estimates in the utilisation chapter (5) are Level Index estimates, they are substantially similar to the Erreygers adjusted estimates contained in the sensitivity analysis. To ensure consistency across the chapters analysed and avoid methodological differences influencing the results, I employ the Erreygers adjusted rank-dependent version of the utilisation estimates for the comparison across the healthcare process.

8.2.2 Inequality through health systems

The purpose of this exercise is to develop an indicative perspective of inequality within systems and identify differences and gradients between the different contact points, similar to a health system performance assessment (HSPA), albeit with a narrower focus on inequality. HSPAs conduct a full assessment of system goals, stretching beyond inequality and inequity, though equity is included as a key indicator in WHO/Europe HSPAs.[271] As early as 2000, Murray &

Frenk indicated that HSPAs often fall into two traps; listing overlapping, desirable attributes to measure (top down), or looking at data availability and constructing an assessment based on readily available metrics (bottom up).[272] Given adherence to the (intermediate stages of the) Levesque et al. framework in this dissertation, this analysis falls into neither trap, though it is not intended to be an HSPA. While HSPA has been largely codified, the revised HSPA guidebook still lists indicative measures; given that measurement areas and data constraints vary by country, necessitating some degree of flexibility (e.g., Malaria indicators may be used in Sub-Saharan Africa, but not Europe).[271] Data availability and consistency for inequality (and inequity) measures is addressed in chapter 7.1, and HSPAs are a clear use case where consistent inequality and inequity metrics would be valuable as contributing metrics.

Using the data produced in this dissertation, which measures income-related inequalities consistently across the countries in this study, I develop an indicative health systems inequality performance measure using concentration indices as inputs across the Levesque et al. framework phases studied in this dissertation.[1] This work is similar to Gordon, Booysen, & Mbonigaba's work in South Africa,[68] although goes further in synthesizing a single, indexed outcome measure. I conduct a visual analysis of the previous estimates in each country using line graphs across each phase of the Levesque et al. framework.[1] For each estimate produced, I assign a score, which I term the equality score (EQZ) of +1 if the estimate is pro-poor, 0 if the estimate is not statistically significantly different from equality, and -1 if the estimate is pro-rich. I then sum these scores in each country and assign each country to an indicative archetype. I discuss different weighting systems below, however this is not exhaustive, and other systems could also be developed to combine inequality measures.

Graphically, I link inequality in vaccine intention to inequality in vaccine uptake, and inequality in access to inequality in utilisation. There are clear links between the types of services investigated in the access and utilisation chapters, though due to combinationquestions in the access chapter, these are mapped in 2:1 fashion for two of the access estimates. The five types of care I investigate in the utilisation chapter are combined into three types of care in the access chapter. In the access chapter, I produced estimates for in-person GP access, which maps 1:1 to the estimates in the utilisation chapter. However, the remaining estimates are combined into two composite metrics for comparison due to the structure of the original survey question (Appendix Y). Internet and telephone appointment utilisation must therefore be contrasted against a composite measure of access that contains the two, where the same is true for inpatient hospital admissions and outpatient clinic visits.

There are a number of reasons why some sort of weighting makes sense, though any differentiated weightings would rely on value judgements. I employ a weighting scheme that most closely resembles the Levesque et al. framework.[1] Details of the weighting schemes I considered are contained in appendix note and table E1.

Though it may appeal to rank countries against each-other on the basis of these scores, this would be unwise due to the lost information (e.g., estimate magnitudes) and potential for artificial offsetting of scores relative to the true value of the estimates (e.g., a slightly pro-rich estimate offsets a largely pro-poor estimate in the simplified framework). Despite the loss of information, the constructed indices remain useful to investigate the average incidence of income-discrimination health system users may have faced in each country.

8.2.3 Defining the archetypes

In constructing the archetypes, I assign cut-off values to the cumulative inequality scores and use these to group countries based on their reported inequality scores (using EQZ4).

The following bound values are employed:

Pro-poor: $\sum EQZ4 > 1$

Non-discriminatory on an income basis: $-1 \leq \sum EQZ4 \leq 1$

Pro-rich: $\sum EQZ4 < -1$

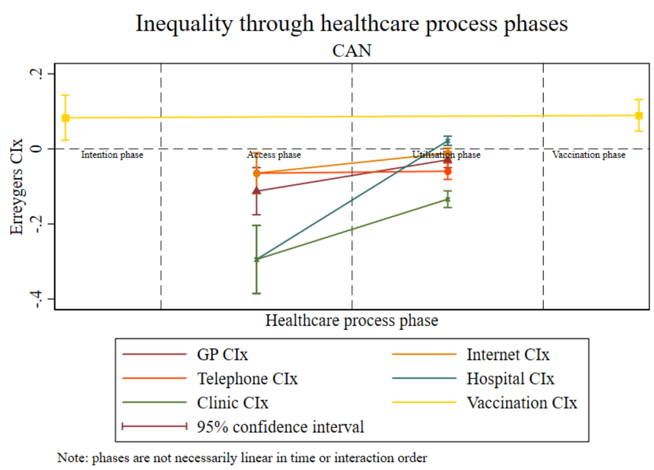
Assigning the archetypes in this manner does not allow over-indexation on any one chapter's results. The bounds of the non-discriminatory archetype allow room for offsetting at various stages of the healthcare process to retain an average perspective. It is important to note, however, that the archetypes are by definition *average* measures. As such, countries in the pro-poor archetype may include a number of pro-rich estimates, in so far as that allows an EQZ4 score that exceeds 1. Archetype assignments under different EQZ weighting schemes are available in table 8A. Note, a positive EQZ score corresponds to a negative Erreygers index value; I have reversed these signs for ease of interpretation in this exercise.

8.3 Indicative archetype assignments

8.3.1 Pro-poor

Countries where $\sum EQZ4 > 1$: Canada

Figure 8A: Inequality through the healthcare process: Canada



Notes to Figure 8A
Phases mirror Levesque et al. framework.[1]
Intention phase: Inequality in COVID-19 vaccine intention (chapter 6)
Access phase: Inequality in challenges to accessing appointments (chapter 4)
Utilisation phase: Inequality in number of appointments utilised (chapter 5)
Vaccination phase: Inequality in COVID-19 vaccine status (chapter 6)

Canada is the only country in the sample with a pro-poor EQZ4 score. All but four of the inequality estimates produced for Canada were pro-poor in nature. Both vaccination estimates were pro-rich, as was the hospital utilisation metric – though the latter result was often not supported in the literature.[91] Canada serves as a useful case study, where even though the average inequality across the health system was pro-poor, elements remained pro-rich. In this case, COVID-19 vaccination was consistently pro-rich from attitude prior to acceptance (intention phase) to vaccination uptake. In the access and utilisation phases, estimates were consistent in direction. In all access-utilisation links, apart from telephone contacts which remained consistent, inequality estimates became less pro-poor from access to utilisation. Despite this trend, the majority of estimates remained pro-poor. The gradient between access and utilisation phases is important. Although results remained pro-poor apart from in-patient hospital utilisation, the reduction in pro-poor inequality implies that it becomes less straightforward for lower-income earners to consume services as they progress through the healthcare system. While results remain pro-poor, this does not necessarily threaten access for lower-income individuals.

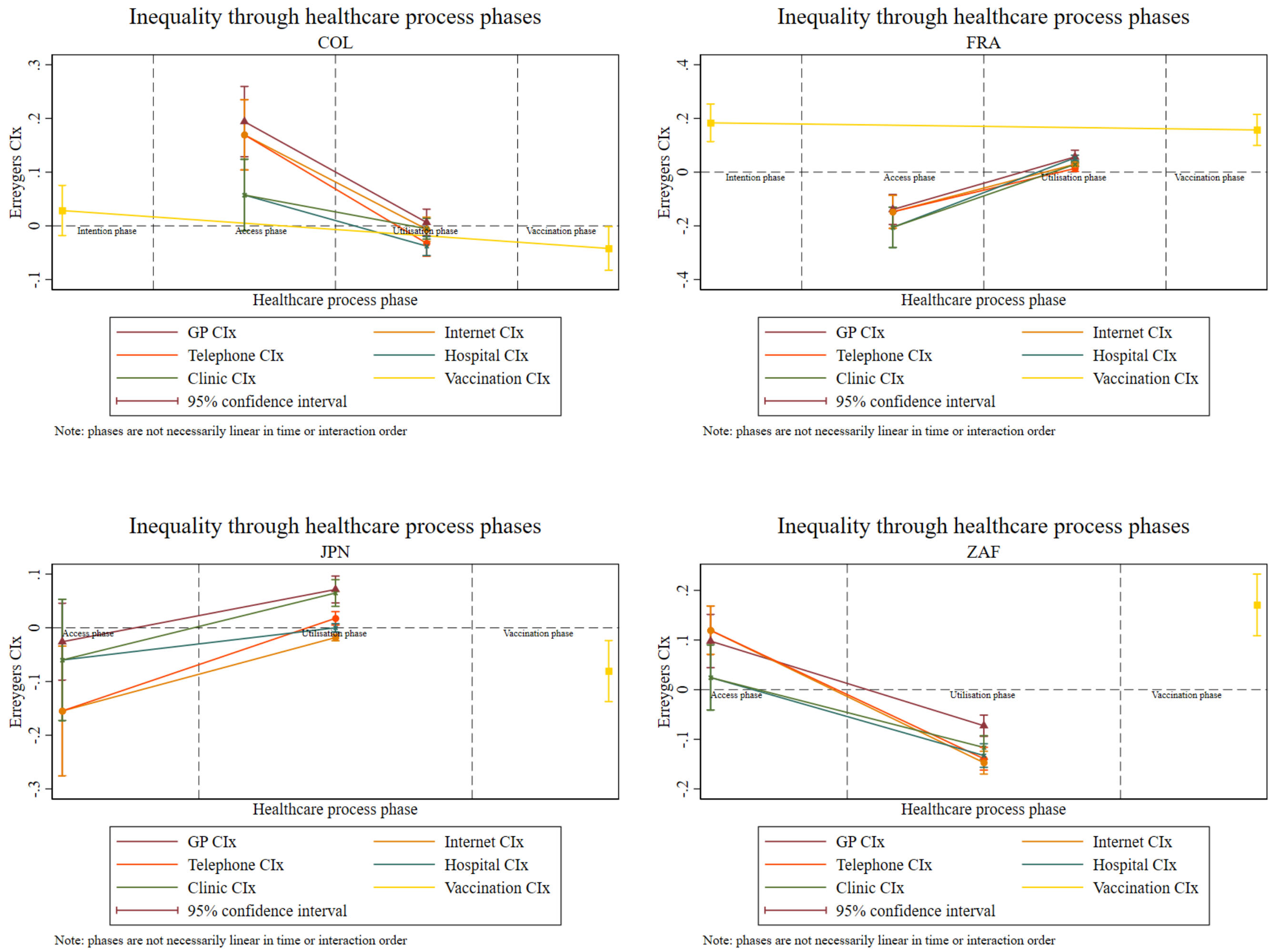
8.3.2 Non-discriminatory on an income basis

Countries where $-1 \leq \sum EQZ4 \leq 1$: Colombia, France, Japan, South Africa

Colombia, France, Japan, and South Africa each produced EQZ4 scores between -1 and 1. With the exception of South Africa, each country displays a cluster of estimates around the line of equality, and a second cluster further removed from equality in either direction. In Colombia, both utilisation and vaccination estimates are clustered around equality, whereas access estimates, aside from hospital or clinic admissions, are strongly pro-rich. There are two possibilities to fit this archetype: the first, as seen in Colombia, where the majority of estimates are neither pro-rich nor pro-poor with statistical significance. The second, as in France or South Africa, where several (even if only marginally) pro-rich estimates are offset by an almost equivalent number of pro-poor estimates, dependent on the weighting scheme. It is clear that health system user experiences in these systems may differ even if they share an archetype. France and Japan exhibit similar gradients to Canada above in the access-utilisation link, though in these cases certain estimates become pro-rich with statistical significance, implying greater difficulty in utilising services after gaining access to health systems for low income users. This can be contrasted with Colombia and South Africa, which both present pro-rich inequality in access, and reduced or pro-poor inequality in utilisation. This downward trend in inequality implies initial barriers to the health system for low-income earners, and then equal or even preferential access once the initial barrier has been overcome.

A final noteworthy point is the difference in directions of inequality in vaccination uptake and utilisation in Japan and South Africa. Despite being a form of utilisation, vaccination in South Africa remains strongly pro-rich relative to the pro-poor estimates of general health system utilisation. As the vaccine was deployed through channels outside of traditional primary healthcare delivery and required pre-vaccination registration in a separate system, it is perhaps unsurprising that the initial barriers faced by low income earners seen in access are also evident in vaccination. This once again implies that effort to gain initial access (i.e., overcome inertia outside the healthcare system) is higher and prohibitive for low income earners. The opposite is seen in Japan, where vaccination inequality is lower than general utilisation inequality. Neither Japan nor South Africa was included in wave 1 of the CANDOUR study, and thus lack inequality estimates for inequality in vaccine sentiments. Nine of the thirteen countries reported significantly pro-rich estimates for this measure. Despite allocating a score of zero to this metric so as not to bias the results, its omission could in itself be a bias.

Figure 8B: Inequality through the healthcare process: Colombia, France, Japan, South Africa

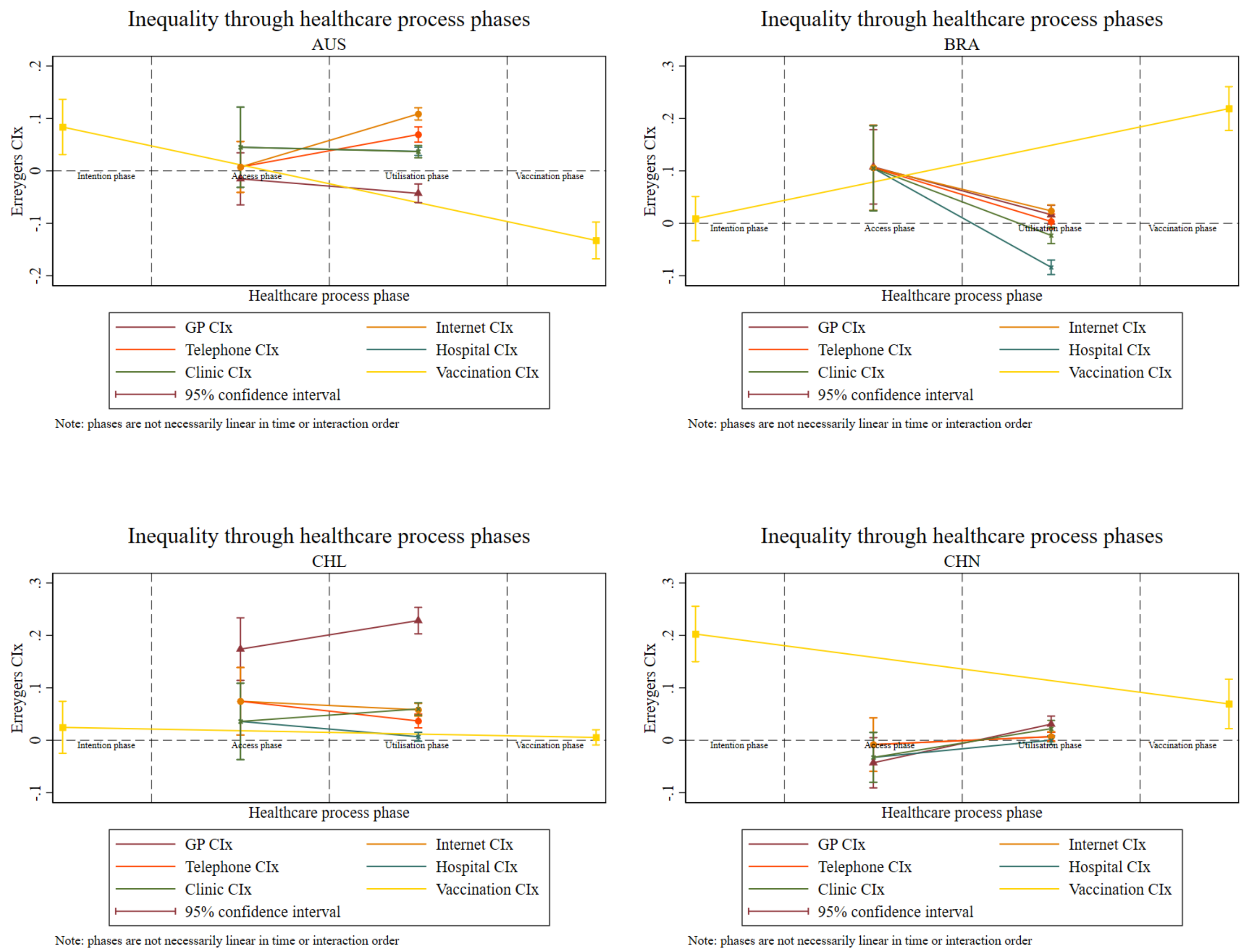


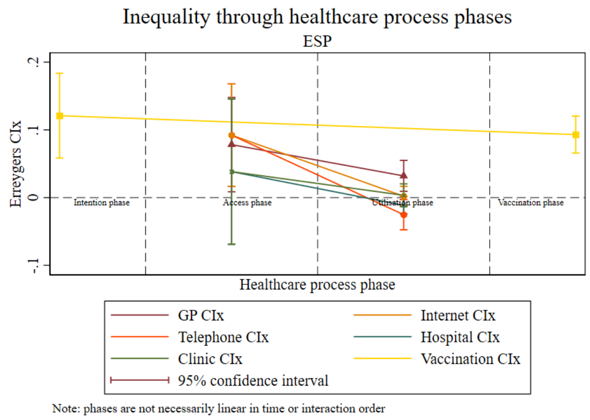
8.3.3 Pro-rich

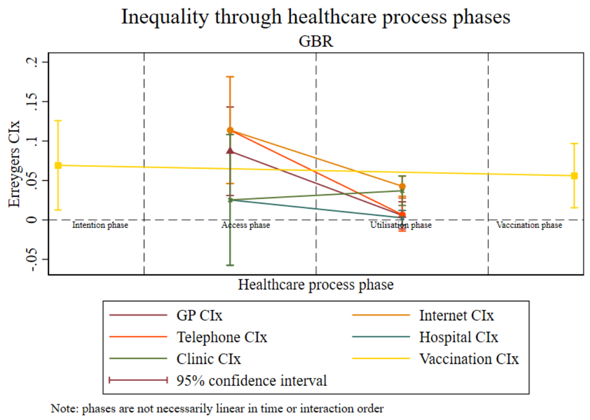
Countries where $\sum EQZ4 < -1$: Australia, Brazil, Chile, China, Spain, Ghana, India, Italy, Uganda, The United Kingdom, The United States of America.

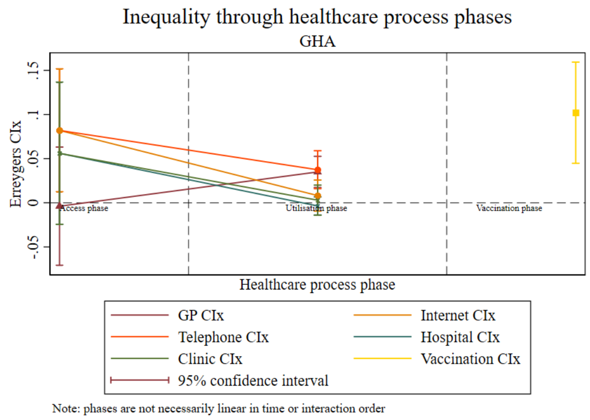
Eleven countries fall into the pro-rich archetype. However, none is pro-rich across the entire process, with all exhibiting elements of equality or pro-poor results. Chile, Uganda, and The United States are the most visually identifiable as being pro-rich on average, with the majority of inequality estimates of a pro-rich nature. The concept of gradients between phases has been discussed in the pro-poor and non-discriminatory archetype sections, and need not be re-iterated using additional examples here. The vaccination gradients evident in chapter 6 for Australia and Brazil, which are discussed at length, are clearly visible in the first two panels of figure 8C below. In Spain, the United Kingdom, India, and Italy, estimates varied. The majority of estimates in these countries are either neutral or pro-rich. The nature of the index construction leads these countries to a pro-rich archetype allocation, despite the fact that at several instances in the health system, results do not differ from equality with statistical significance, which is perhaps a limitation. China presents a similar case, where all access estimates exhibit approximate equality, as well as three of the utilisation estimates. However, both vaccination estimates and two utilisation estimates are pro-rich and statistically significant, yielding an overall pro-rich archetype.

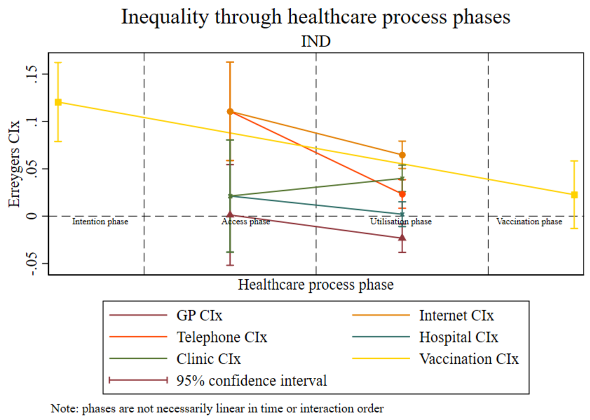
Figure 8C: Inequality through the healthcare process: Australia, Brazil, Chile, China, Spain, The United Kingdom, Ghana, India, Italy, Uganda, The United States of America

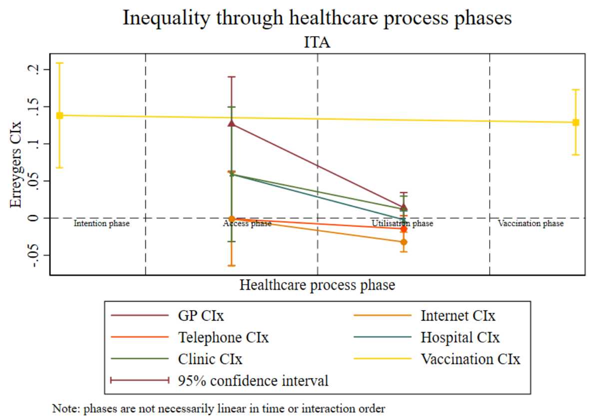


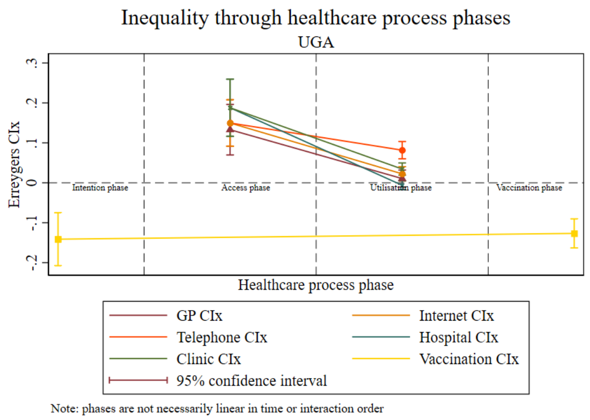

Inequality through healthcare process phases
ESP
Erreygers CIx
Intention phase
Access phase
Utilisation phase
Vaccination phase
Healthcare process phase
GP CIx
Internet CIx
Telephone CIx
Hospital CIx
Clinic CIx
Vaccination CIx
95% confidence interval
Note: phases are not necessarily linear in time or interaction order

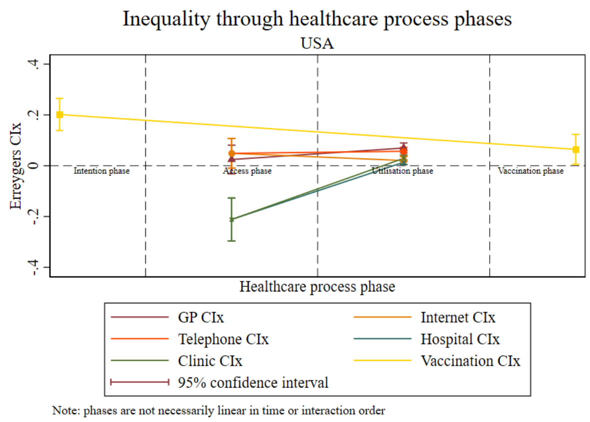

Inequality through healthcare process phases
GBR
Erreygers CIx
Intention phase
Access phase
Utilisation phase
Vaccination phase
Healthcare process phase
GP CIx
Internet CIx
Telephone CIx
Hospital CIx
Clinic CIx
Vaccination CIx
95% confidence interval
Note: phases are not necessarily linear in time or interaction order


Inequality through healthcare process phases
GHA
Erreygers CIx
Access phase
Utilisation phase
Vaccination phase
Healthcare process phase
GP CIx
Internet CIx
Telephone CIx
Hospital CIx
Clinic CIx
Vaccination CIx
95% confidence interval
Note: phases are not necessarily linear in time or interaction order


Inequality through healthcare process phases
IND
Erreygers CIx
Intention phase
Access phase
Utilisation phase
Vaccination phase
Healthcare process phase
GP CIx
Internet CIx
Telephone CIx
Hospital CIx
Clinic CIx
Vaccination CIx
95% confidence interval
Note: phases are not necessarily linear in time or interaction order


Inequality through healthcare process phases
ITA
Erreygers CIx
Intention phase
Access phase
Utilisation phase
Vaccination phase
Healthcare process phase
GP CIx
Internet CIx
Telephone CIx
Hospital CIx
Clinic CIx
Vaccination CIx
95% confidence interval
Note: phases are not necessarily linear in time or interaction order


Inequality through healthcare process phases
UGA
Erreygers CIx
Intention phase
Access phase
Utilisation phase
Vaccination phase
Healthcare process phase
GP CIx
Internet CIx
Telephone CIx
Hospital CIx
Clinic CIx
Vaccination CIx
95% confidence interval
Note: phases are not necessarily linear in time or interaction order


Inequality through healthcare process phases
USA
Erreygers CIx
Intention phase
Access phase
Utilisation phase
Vaccination phase
Healthcare process phase
GP CIx
Internet CIx
Telephone CIx
Hospital CIx
Clinic CIx
Vaccination CIx
95% confidence interval
Note: phases are not necessarily linear in time or interaction order

8.4 Sensitivity analysis

The analysis is not without limitations; however, it is intended to provide an overview of the works produced and the changes between various phases of access within health systems. I limit the sensitivity analysis here to a brief investigation into the implications of the alternative weighting schemes of the EQZ scores (see appendix table E1). However, sensitivity could be extended in various directions, including the use of different input indices for computation. This is not undertaken as I produce alternative indices in each chapter, and do not find material differences between the Erreygers adjusted and alternative indices.

Table 8A below provides the complete set of weighting results under each of the weighting schemes considered. I also indicate, by means of the letters P, N, R next to each estimate, into which archetype each country is allocated under different weighting schemes. (P = pro-poor; N = non-discriminatory on an income basis; R = pro-rich).

Table 8A: Archetype allocations and weighted EQZ scores under alternative weighting schemes

	EQZ1	EQZ2	EQZ3	**EQZ4**
AUS	-3 (R)	-0.6 (N)	-0.6 (N)	**-1.3 (R)**
BRA	-3 (R)	-1.3 (R)	-1.8 (R)	**-2 (R)**
CAN	3 (P)	0.4 (N)	-0.6 (N)	**1.2 (P)**
CHL	-6 (R)	-1.5 (R)	-1.5 (R)	**-2 (R)**
CHN	-4 (R)	-1.4 (R)	-2.4 (R)	**-1.5 (R)**
COL	1 (N)	0.2 (N)	0.7 (N)	**-0.8 (N)**
ESP	-4 (R)	-1.7 (R)	-2.7 (R)	**-2.5 (R)**
FRA	-4 (R)	-1 (N)	-2 (R)	**0 (N)**
GHA	-4 (R)	-1.2 (R)	-1.7 (R)	**-1.2 (R)**
IND	-4 (R)	-1.2 (R)	-1.7 (R)	**-2 (R)**
ITA	-2 (R)	-1.1 (R)	-2.1 (R)	**-1.7 (R)**
JPN	0 (N)	0.4 (N)	0.9 (N)	**0.5 (N)**
UGA	-4 (R)	-0.6 (N)	0.4 (N)	**-1.3 (R)**
GBR	-6 (R)	-2.1 (R)	-3.1 (R)	**-2.8 (R)**
USA	-6 (R)	-1.7 (R)	-2.7 (R)	**-1.3 (R)**
ZAF	2 (P)	-0.2 (N)	-0.7 (N)	**-0.7 (N)**

Five of the sixteen countries included in the study change archetype allocation based on the weighting scheme. Australia, Canada, France, Uganda, and South Africa could each be allocated to a different archetype under different weighting schemes. France and South Africa both fall into the non-discriminatory archetype under EQZ4. Using EQZ1, which gives a larger weighting to utilisation and reduced relative weighting to access (see appendix table E1), South Africa would move into the pro-poor archetype given the country's strong pro-poor estimates in the utilisation phase and strong pro-rich estimates in the access seeking and reaching stages. France would face the opposite, moving from the neutral archetype to the pro-rich archetype if access weightings are reduced and utilisation phase weightings increase. France achieves a non-discriminatory archetype allocation under EQZ4 when the pro-rich vaccination uptake weighting is reduced and access weightings are higher. Australia, Uganda, and Canada similarly switch archetypes based on the relative weightings. Canada is pulled to the neutral archetype when vaccination and hesitancy are given greater weights. Australia moves into the neutral archetype when utilisation is de-weighted. Uganda scores better when the relative weightings of the access phases are reduced. The remaining eleven countries were consistent in archetype allocation across each of the four weighting schemes. Details of the weighting schemes are available in appendix table E1.

8.5 Discussion

8.5.1 Summary of results

In this brief synthesis, I find that eleven countries report an average pro-rich inequality throughout their health systems. I find four countries where inequality is, on average, non-discriminatory, or neutral, and one country where there is pro-poor inequality on average. These results are relatively consistent under different weighting specifications, though some variation is observed. In countries that vary under different weighting schemes, the variation led to entry or exit from the neutral archetype depending on the relative weights of each estimate. In addition to investigating averages across the health system, I outlined possible implications of changes in inequality estimates from access to utilisation, and how these changes might be experienced by health system users.

Beyond this archetype exercise, I have produced 157 country-specific estimates of inequality in chapters 4, 5, and 6. I added four additional inequality estimates by treatment group and a further four perspectives on characteristics of individuals based on their vaccine preferences over time in chapter 7. These results vary across and within countries, and between different types of care. While certain countries have a propensity for more equal estimates, no country produced consistently pro-poor or pro-rich estimates in every estimate. This is an important outcome to note, indicating that there is space for equality-improving efforts in each of the sixteen countries included in this study.

8.5.2 Policy implications

A number of policy implications have been outlined in the previous chapters. In looking to the synthesis above, policy makers may prioritise certain interventions - for example, Brazil and Uganda, both countries that reported pro-rich systems overall, may look to reform elements of their health systems on equality grounds. Looking strictly within the utilisation phase, both countries could improve types of care to bring them in line with the most equal / pro-poor within the phase. However, doing so would neglect the access phase, which in both countries is more pro-rich. The perspective offered in this chapter theoretically allows policy makers to select interventions with the largest scope for improvement, or at least with a full contextual perspective. Interventions at earlier stages in the healthcare access framework are likely to have higher impacts than later phases, as more individuals are likely to pass through them before attrition occurs, due to socioeconomic inequality and other barriers. Different systems face different problems, of varying magnitudes, at different stages.

This thesis and this chapter, in particular, brings issues from the different stages together and contextualises these challenges alongside one another.

For policy decisions that incorporate health systems from end-to-end, viewpoints on perceptions and desire for care beyond vaccination, and sentiments towards health systems in general (i.e., further analysis of the first stage of the Levesque et al framework[1]) would be useful, and provide a richer picture which can be integrated into broader understandings on incidence (healthcare needs) and consequences of healthcare.

I highlight some clear implications for policymakers which can be gleaned from synthesizing implications and outcomes from this dissertation below.

Accurate baseline estimates are crucial to identifying changes over time. Baseline data for niche outcomes can be collected rapidly if they do not already exist, but estimates and results will only ever be as reliable as the data that produced them. Building data capabilities (e.g., administratively linked data) and expanding the evidence base could greatly improve future responses to disruptions, enabling increased efficiency and equality in actions. Integrating (simple) distributional measures into ongoing research will expand the equality-concerned evidence base, and provide comparative data (i.e., approximate counterfactuals) which may enable more informed decision making by policy makers, as discussed in chapter 7.1.

Countries only control their own response to disruptions. Different responses can lead to entirely different outcomes, and should be revised and adjusted as new evidence emerges to ensure that objectives are met. These objectives should be communicated effectively to encourage public buy-in to implemented measures.

Within countries, it is likely that there will be individuals who are better able to navigate disruptions than peers. Thoughtful support should be given to those who are less likely to be able to effectively navigate disruptions to ensure that vulnerable subgroups (e.g., low-income earners; elderly) are not marginalised by health systems, and do not face multiplicative burdens of disease. Such actions should be built into preparedness plans based on periodic assessment (e.g., through HSPA) and robust evidence generation and use. Countries that are able to prepare and develop mitigating actions that can be adjusted based on the particular disruption at hand will be much better placed to protect their populations.

This is perhaps even more pressing in contemporary times, as disruptions to global health architecture and donor fiscal constraints suggest that international aid may face increasing pressure in the post COVID-19 era. These changes are a warning that countries which have historically relied on international support may not be able to do so in times of future crisis, underscoring the importance of self-reliant preparedness and robust understandings of internal health systems.

8.5.3 Limitations

Attrition at different stages of the healthcare process can skew inequality estimates at the subsequent stages, akin to survivorship bias.[273] Individuals who provide data for access challenges as defined in this thesis, for example, need to have taken the decision to seek services, necessarily overcoming barriers (e.g., location, cost, time). Similarly, those who provide utilisation data necessarily have to overcome challenges in access. As the inequality estimates are computed only on the data available, it should be noted that if the attrition rate is related to income levels, the inequality estimates are valid only for the sample.

A second limitation for this chapter is the archetyping methodology. I have selected the weighting scheme that aligns most closely with the framework that guides this dissertation, to maintain consistency. However, other schemes and methods could similarly be used and output different results. The methods selected are consistent and appropriate - however, this does not exclude the validity of other methods which could produce alternative implications. To the greatest extent possible, I have mitigated the risk with the use of several sensitivity analyses in each chapter, which I believe provides sufficient confidence in the robustness of the results.

As I have highlighted frequently, some of the data used in this dissertation are not representative. This caused particular challenges in chapter 5, where country estimates are weighted by population sizes. Apart from the issue of representativeness, the CANDOUR study provides a solid foundation on which to build this dissertation; provided the limitations are kept in mind. The lack of a direct counterfactual prior to the pandemic is also a limitation. In chapter 7, I advocate for the inclusion of distributional measures in research such that this can be mitigated in future. However, the CANDOUR study's specific COVID-related questions compensate for this to some extent, and the panel portion allows some inference to be drawn over time and over various peaks of the pandemic in different countries. Lastly, working with what is essentially approaching a global dataset consisting of microeconomic individualised data, different interpretations of race and ethnicity in different countries reduced the feasibility of including these factors in the study. These characteristics are important, and their non-inclusion in a study of this sort is not ideal given historical associations and findings evidencing the effects of race and ethnicity in health system interactions.

Concentration indices have limitations too, as I point out at various instances in this dissertation. Indices are incredibly useful means to summarise a distribution. However, in summarising a distribution, information is necessarily lost. This is particularly true for index values near to zero, which could represent either equality, or an offsetting of pro-rich and pro-poor inequality throughout the distribution. This should be kept in mind, and concentration curves or other visual analysis tools can be used to supplement indices where appropriate.

Without a prior period counterfactual, it remains impossible to say how the pandemic impacted income-related inequalities in healthcare. While the results observed in this dissertation are specific to the COVID-19 pandemic, the policy implications and learnings from the period can be carried over to future health disruptions. Namely, prior measurement is required to measure causal impact, and that intentional programs are required to address inequalities, which require background knowledge of where the inequalities exist and which interventions may be the most impactful.

A final mathematical limitation, raised previously in chapter 3, concerns the use of transformed categorical income data as the socioeconomic variable in this thesis. Despite contextualisation in data collection (i.e., setting of income bands to reflect the distribution of the economy), a high number of income bands (>10), and post-collection cleaning, equivalization, and purchase-power-parity adjustment, the use of original categories rather than a continuous variable is nevertheless likely to introduce bias firstly in index computation, and then to some extent in cross-country comparison.

While bias for each country has been discussed in chapter 3, how this bias appears across countries will affect cross-country comparison. Simply put, if one country experiences more bias than another, this affects the cross-country comparison. For example, if each country's income distribution is evenly distributed across the original income categories, though within country bias will exist, cross-country bias will be limited, assuming similar full income metrics are captured in each country (as was requested in the survey instrument). However, in the case where countries have heterogenous distributions over the income bands, comparison will be hindered, as the degree to which bias effects the within-country estimates will vary. This effectively relies on the distribution over income bands, and thus the *effective number of income bands*. The more bands are evenly presented, the smoother and less biased the estimate will be; whereas if only one band is represented (not the case in this thesis), the estimates will be biased downwards. Practically speaking, this means that countries with a tighter income distribution are likely to be more biased downwards than those with a more evenly distributed distribution. Narrower distributions (more concentration in fewer bands) will result in greater downward bias due to coarsening within the band which flattens inequality measurement, even using rank dependent indices. This bias would be exacerbated with level-dependent indices. However, distributions with gaps and few observations in income bands will increase sampling noise. If income questions were answered systematically differently in countries (e.g., what individuals considered as income), this would similarly present a heterogonous variation and could further introduce bias between countries in comparison, though the effect of this should be mitigated due to the wording of the question in the original instrument which asked about income from *all sources* (see chapter 3).

8.5.4 Further work

There are a number of avenues for further work. The most apparent is in developing a counterfactual outside the pandemic period. While a prior counterfactual is best practice, this is not possible. A post-pandemic counterfactual would still allow for temporal comparison, and give researchers an idea of the change between pandemic period and post pandemic period inequality. A post-period counterfactual does not give evidence that the pandemic caused the results produced during the pandemic, but could add context alongside qualitative assessment of what has happened since the pandemic. A post-hoc counterfactual would not explain whether the pandemic gave rise to new inequalities or exacerbated pre-existing inequalities. However, by increasing the evidence base as suggested in chapter 7.1, future work could rely on recently developed counterfactuals and answer such questions.

An additional avenue would be to expand the VERSE toolkit, or a similar tool, to adult vaccination and health usage, and develop a more holistic and codified method to measure equity and equality. The use of surveys in demand-forecasting for (new) health technologies and services using linked administrative data also warrants further research, and could be piloted in select applications to increase efficiency of deployment and allay identified potential inequalities.

A final avenue for further work could include the investigation of joint distributions in the equality-efficiency trade-off space, to enable joint decision making in the introduction of new technologies. The field of distributional cost effectiveness analysis could provide guidance in this regard.

8.6 Conclusion

In the introduction, I outlined 5 research objectives that this thesis aims to address. I have contextualised the work with focused literature reviews on the methods of measurement and recent literature of socioeconomic and income-related inequality in healthcare. I investigated income-related inequality in access, utilisation of health services, and vaccination within each country, and compared these results across countries. I explored inequality at different stages of health systems to gain a system perspective. Finally, I investigated avenues to expand the distributional evidence base and increase efficiency of medical technology deployment through the use of surveys – both using case studies of COVID-19 vaccination.

In conducting this work, I have contributed to the literature in a meaningful way, providing quantitative estimates of inequality during the COVID-19 pandemic, a health system disruption, in 16 socioeconomically diverse countries. I have explored practical policy implications indicated by the insights generated in each chapter, and showed that there appear to be elements of inequality present in the health systems of each country studied. Despite limitations, this work addresses the research objectives in full and fills an existing gap in the academic literature. In doing so, this thesis reinforces the literature on income-related inequality in healthcare, with specific attention to health system disruptions such as the COVID-19 pandemic.

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10. Appendices

Appendix: A – Chapter 4

TABLES

FIGURES

A10 Figure: Digital challenge inequality by density of medical practitioners per 10,000 of population using restricted standardization

A11 Note: Concentration Index deviations from the line of equality

A12 Figure: Concentration Index deviations from the line of equality, In-person GP challenge inequality

A13 Figure: Concentration Index deviations from the line of equality, Surgical/clinical admission inequality

A14 Figure: Concentration Index deviations from the line of equality, Digital inequality

A1 Table: In-person GP subgroup descriptive statistics sample for analysis

	Median Age (years)	Female (%)	Household Size (n)	Married (%)	Median Ideology[2]	Median Educ. level[3]	Med. Income (PPP$ '000s)	Labour force participation (%)	Self-reported health (%)	No. Chronic conditions (n)	COVID risk (%)	Willingness to risk health[4]	Sample size (n)
Australia	44(30-59)	51.2(50)	2.3(1.4)	61.8(48)	5(4-6)	3(3-4)	34.9(20-57)	64.4(47)	69.7(21)	0.77(1.0)	52.3(27)	3.5(2.5)	1,508
Brazil	41(30-55)	49.4(50)	2.7(1.3)	61.4(48)	5(3-8)	3(2-3)	8.8(5-14)	66.7(47)	72.4(26)	0.71(0.9)	38.1(30)	3.2(3.0)	905
Canada	47(32-61)	64.4(47)	2.1(1.0)	49.6(50)	5(4-7)	3(3-4)	35.7(20-70)	63.5(48)	68.7(18)	0.85(0.9)	42.3(25)	3.9(2.4)	962
Chile	42(30-56)	52.8(49)	2.7(1.2)	52.4(49)	5(3-5)	3(2-4)	12.1(7-24)	71.4(45)	72.2(23)	0.85(0.9)	43.2(27)	3.2(2.7)	1,097
China	44(28-54)	46.5(49)	2.8(1.3)	74.4(43)	..	3(3-3)	20.5(15-32)	73.3(44)	77.4(22)	0.37(0.6)	36.2(32)	3.8(3.1)	1,080
Colombia	50(31-62)	48.8(50)	3.2(3.2)	54.6(49)	5(3-6)	3(2-3)	7.2(4-12)	71.9(44)	56.7(40)	0.50(0.9)	38.1(25)	3.6(3.1)	1,056
France	49(34-66)	56.3(49)	1.9(0.6)	68.1(46)	6(5-8)	3(2-4)	32.5(20-47)	55.7(49)	62.9(26)	0.72(0.8)	46.1(21)	3.9(3.1)	803
Ghana	30(27-35)	18.8(39)	4.3(2.2)	52.8(49)	6(5-7)	4(3-4)	1.2(0.5-5)	76.5(42)	84.7(15)	0.18(0.4)	21.9(27)	3.4(3.1)	945
India	31(25-37)	41.8(49)	6.4(8.9)	50.3(50)	7(6-9)	3(2-4)	4.5(2-13)	83.1(37)	55.2(36)	0.64(1.0)	55.4(31)	6(2.8)	1,299
Italy	52(41-62)	55(49)	2.5(1.3)	64.2(47)	5(4-7)	3(3-3)	24.1(15-42)	57.4(49)	68.6(23)	0.71(0.8)	45.2(25)	3.2(2.7)	883
Japan	59(43-65)	38.6(48)	2.1(1.2)	66(47)	5(5-6)	3(3-4)	31.1(15-45)	74.9(43)	70.3(21)	0.68(0.8)	47.6(21)	4.3(2.4)	626
South Africa	36(28-47)	47.3(49)	3.1(1.7)	69.1(46)	5(4-6)	3(2-3)	11.5(0.9-21)	76.1(42)	75.1(24)	0.66(1.4)	33.2(29)	2.9(2.5)	1,068
Spain	48(35-62)	49.6(50)	2.4(1.9)	67.4(46)	4(2-6)	3(3-4)	30.5(22-44)	66.2(47)	75.1(22)	0.68(0.8)	53(26)	2.9(2.5)	999
Uganda	28(25-34)	30.2(45)	3.5(2.4)	29.9(45)	5(4-7)	3(3-3)	0.2(0.09-0.6)	92.7(26)	78.3(19)	0.59(1.0)	18.5(20)	3.4(3.0)	999
UK	45(39-64)	36.1(48)	1.9(0.9)	66.4(47)	5(4-7)	3(3-4)	33.2(13-50)	66.8(47)	64.3(23)	0.57(0.9)	42.7(23)	4.2(2.5)	768
US	41(29-54)	49.1(50)	2.4(2.7)	62.7(48)	5(4-8)	4(3-4)	44.2(18-78)	76.7(42)	73.2(23)	0.92(1.0)	40.2(29)	4(2.9)	1,000

1. Figures are presented as mean(SD) and median(IQR)
2. Respondents were asked to rate their political ideology from 1 (left) to 10 (right). Responses were not collected in China.
3. 2 = primary schooling completed; 3 = secondary school completed; 4 = university completed
4. Respondents were asked how willing they were to risk their health from 0 to 10.

A2 Table: Surgical and clinical challenges subgroup descriptive statistics sample for analysis

	Median Age (years)	Female (%)	Household Size (n)	Married (%)	Median Ideology[2]	Median Educ. level[3]	Med. Income (PPP$ '000s)	Labour force participation (%)	Self-reported health (%)	No. Chronic conditions (n)	COVID risk (%)	Willingness to risk health[4]	Sample size (n)
Australia	41(29-55)	47.3(49)	2.3(1.7)	61.8(48)	5(5-7)	3(3-4)	34.9(19-58)	67.3(46)	68.4(22)	0.77(0.9)	53.3(26)	3.9(2.7)	782
Brazil	41(30-55)	48.1(49)	2.7(1.2)	61.5(48)	5(4-8)	3(2-3)	7.5(4-14)	68.5(46)	71.7(27)	0.70(0.9)	40(30)	3.3(3.0)	699
Canada	51(32-55)	56.7(49)	2(1.0)	48(50)	6(5-8)	3(3-4)	35.7(12-70)	58.9(49)	64.8(21)	0.62(0.9)	51.6(25)	3.8(2.5)	433
Chile	45(32-56)	52.5(49)	2.8(1.3)	60.5(48)	5(2-5)	3(2-3)	10(5-17)	68.9(46)	69(25)	0.93(0.9)	45.6(27)	3.4(2.7)	597
China	43(27-54)	49.1(50)	2.8(1.3)	73.7(44)	..	3(3-3)	20.5(15-32)	75.3(43)	77.1(23)	0.38(0.6)	39.4(32)	4.2(3.1)	919
Colombia	49(31-59)	52.7(49)	3.2(3.7)	59.8(49)	5(4-6)	3(2-3)	7.9(5-12)	81.3(39)	47.7(40)	0.53(0.9)	39.3(26)	4.1(3.1)	762
France	38(30-63)	53.5(49)	1.8(0.6)	64.7(47)	6(5-8)	3(2-3)	33.4(15-47)	65.6(47)	56(28)	0.50(0.7)	48.5(19)	5.1(3.1)	332
Ghana	30(27-34)	17.3(37)	4.3(2.2)	51.2(50)	6(5-7)	4(3-4)	0.9(0.5-4)	77(42)	85.5(15)	0.19(0.4)	22.5(28)	3.8(3.3)	671
India	30(24-35)	46.4(49)	6.8(9.1)	45.2(49)	7(6-9)	3(2-4)	3.2(2-10)	85.9(34)	51.1(36)	0.67(1.0)	56.3(31)	6.1(2.7)	1,201
Italy	51(34-61)	55.7(49)	2.5(1.5)	59.7(49)	6(5-7)	3(3-3)	23.2(16-42)	63.2(48)	65.1(25)	0.65(0.9)	46.5(24)	3.7(2.9)	560
Japan	51(36-61)	36.7(48)	2(1.4)	65.6(47)	5(5-6)	3(3-4)	31(15-44)	84(36)	65.3(23)	0.70(0.9)	49.6(21)	4.8(2.2)	314
South Africa	36(27-47)	51.8(50)	3.3(1.9)	68.5(46)	5(2-7)	3(2-3)	4.3(0.7-21)	75.1(43)	71.1(25)	0.73(1.6)	34.3(30)	3.3(2.5)	741
Spain	50(37-62)	50.4(50)	2.5(2.5)	67.9(46)	5(2-6)	3(3-4)	30.5(17-44)	65.1(47)	71.9(24)	0.71(0.9)	53.3(26)	3.3(2.7)	513
Uganda	28(25-34)	23.7(42)	3.8(2.2)	31.7(46)	6(4-7)	3(3-3)	0.2(0.06-0.4)	95.2(21)	75.7(20)	0.47(0.9)	15.9(19)	3.6(2.9)	692
UK	45(39-55)	32.4(46)	1.9(1.0)	66.5(47)	5(4-7)	3(3-4)	40.6(19-50)	79.5(40)	69(23)	0.52(0.9)	42.3(22)	4.1(2.6)	529
US	36(28-47)	44.6(49)	2.6(3.3)	65.8(47)	6(5-8)	4(3-4)	43.7(16-87)	82.4(38)	72.7(25)	0.81(1.0)	46.2(30)	4.6(3.0)	629

1. Figures are presented as mean(SD) and median(IQR)
2. Respondents were asked to rate their political ideology from 1 (left) to 10 (right). Responses were not collected in China.
3. 2 = primary schooling completed; 3 = secondary school completed; 4 = university completed
4. Respondents were asked how willing they were to risk their health from 0 to 10.

A3 Table: Digital challenges subgroup descriptive statistics sample for analysis

	Median Age (years)	Female (%)	Household Size (n)	Married (%)	Median Ideology[2]	Median Educ. level[3]	Med. Income (PPP$ '000s)	Labour force participation (%)	Self-reported health (%)	No. Chronic conditions (n)	COVID risk (%)	Willingness to risk health[4]	Sample size (n)
Australia	42(30-57)	53.2(49)	2.3(1.5)	61.3(48)	5(4-6)	3(3-4)	34.9(19-58)	66.7(47)	68.5(21)	0.78(1.0)	53(27)	3.6(2.6)	1,254
Brazil	41(30-55)	47.3(49)	2.6(1.2)	61.1(48)	5(3-8)	3(2-3)	8.8(4-14)	67.3(46)	72.2(27)	0.68(0.9)	39.4(30)	3.3(3.0)	736
Canada	46(32-61)	65.2(47)	2.1(1.0)	49.6(50)	5(4-7)	3(3-4)	35.7(20-71)	63.3(48)	68.5(19)	0.86(0.9)	42.6(26)	3.9(2.4)	880
Chile	44(31-56)	53.2(49)	2.7(1.2)	53.6(49)	5(3-5)	3(2-4)	11.7(6-20)	71.2(45)	71.5(24)	0.86(0.9)	44(27)	3.3(2.7)	966
China	44(27-56)	48.2(49)	2.9(1.3)	72.6(44)	..	3(3-3)	20.5(15-32)	71.4(45)	76.7(23)	0.38(0.6)	39.4(32)	4.1(3.2)	1,007
Colombia	50(31-62)	48.4(50)	3.2(3.3)	54.2(49)	5(3-6)	3(2-3)	7.2(4-12)	71.5(45)	56.4(40)	0.50(0.9)	38(25)	3.6(3.1)	1,036
France	43(33-63)	52.2(49)	1.8(0.6)	65.3(47)	6(5-8)	3(2-4)	32.5(15-47)	62(48)	60.9(27)	0.57(0.7)	46.3(21)	4.6(3.0)	568
Ghana	30(27-35)	17(37)	4.3(2.2)	51.9(49)	6(5-7)	4(3-4)	0.9(0.5-4)	75.8(42)	85.2(15)	0.17(0.4)	22.2(27)	3.5(3.2)	809
India	31(24-36)	45.7(49)	6.5(8.9)	46.9(49)	7(5-9)	3(2-4)	3.5(2-10)	84(36)	53.3(36)	0.65(1.0)	55(31)	5.9(2.8)	1,279
Italy	52(39-62)	55.2(49)	2.5(1.4)	64.1(48)	5(4-7)	3(3-3)	24.1(16-42)	59.4(49)	69.1(23)	0.67(0.8)	45.6(25)	3.3(2.7)	821
Japan	49(37-61)	35.2(47)	1.9(1.4)	60.9(48)	5(5-6)	3(3-4)	31.1(15-44)	80.3(39)	66.2(23)	0.51(0.7)	49.7(22)	4.7(2.3)	291
South Africa	36(26-47)	52.6(49)	3.3(1.8)	67.6(46)	5(3-7)	3(2-3)	5.2(0.8-24)	75.9(42)	72.4(25)	0.74(1.6)	33.4(31)	3.3(2.6)	857
Spain	48(35-61)	50.3(50)	2.4(1.9)	67.3(46)	4(2-6)	3(3-4)	30.5(19-44)	66.5(47)	75.1(22)	0.68(0.8)	53.2(26)	2.9(2.5)	976
Uganda	26(25-33)	21.5(41)	3.7(2.2)	40.5(49)	5(4-7)	3(3-3)	0.2(0.09-0.4)	94.5(22)	73(20)	0.54(0.8)	18.8(20)	3.9(2.9)	885
UK	46(39-58)	36.1(48)	1.9(0.9)	66.4(47)	5(4-7)	3(3-4)	39.1(23-50)	75.8(42)	69.2(22)	0.58(0.9)	42.8(22)	3.9(2.6)	770
US	39(29-52)	48.6(50)	2.5(2.9)	63.4(48)	6(4-8)	4(3-4)	43.7(18-87)	79.6(40)	73.1(23)	0.87(1.0)	43.2(29)	4.3(2.9)	847

1. Figures are presented as mean(SD) and median(IQR)
2. Respondents were asked to rate their political ideology from 1 (left) to 10 (right). Responses were not collected in China.
3. 2 = primary schooling completed; 3 = secondary school completed; 4 = university completed
4. Respondents were asked how willing they were to risk their health from 0 to 10.

A4 Table: T-test results for sub-sample difference testing

	Included in study (1)	Excluded from study (0)	Difference (0) - (1)	T-statistic	Significance level
Median age (years)	39	42	3	24.03	<0.001
Female (%)	0.496	0.514	0.018	10.51	<0.001
Educ. Level	3.265	3.185	-0.080	-12.17	<0.001
Income (PPP$ '000s)	24043.55	26506.42	2462.87	11.58	<0.001
Labour force participation (%)	0.704	0.685	-0.019	-10.36	<0.001
Self-reported health (%)	68.472	69.197	0.725	6.40	<0.001
No. Chronic conditions (n)	0.610	0.609	-0.001	-0.33	0.7451
Willingness to risk health	3.520	3.477	-0.043	-4.15	<0.001

A5 Table: Linear regression results: Challenge concentration indices on possible explanatory variables

		(1)	(2)	(3)
		In person GP challenge concentration index	Surgical/clinical challenge concentration index	Digital challenge concentration index
Median household income		-1.02e-05*	-1.05e-05**	-9.02e-06*
	SE	(4.67e-06)	(4.04e-06)	(4.45e-06)
	T statistic	-2.177	-2.605	-2.028
	p-value	(0.0575)	(0.0285)	(0.0732)
Health expenditure (2019)		6.68e-06	-1.20e-05	1.42e-05
	SE	(1.34e-05)	(1.16e-05)	(1.28e-05)
	T statistic	0.499	-1.036	1.115
	p-value	(0.630)	(0.327)	(0.294)
COVID-19 containment policy		-0.00102	-0.00360	-0.000393
	SE	(0.00348)	(0.00301)	(0.00331)
	T statistic	-0.295	-1.197	-0.119
	p-value	(0.775)	(0.262)	(0.908)
Medical practitioner density		0.00704**	0.00899***	0.00309
	SE	(0.00299)	(0.00259)	(0.00285)
	T statistic	2.354	3.474	1.084
	p-value	(0.0430)	(0.00700)	(0.306)
Internet access		-0.000538	-0.00267	0.000798
	SE	(0.00183)	(0.00158)	(0.00174)
	T statistic	-0.295	-1.694	0.459
	p-value	(0.775)	(0.124)	(0.657)
Corruption perceptions index		-0.000368	0.000939	-0.00237
	SE	(0.00312)	(0.00269)	(0.00297)
	T statistic	-0.118	0.348	-0.797
	p-value	(0.909)	(0.735)	(0.446)
Constant		0.158	0.347	0.189
	SE	(0.248)	(0.215)	(0.236)
	T statistic	0.638	1.619	0.800
	p-value	(0.539)	(0.140)	(0.444)
Observations		16	16	16
R-squared		0.566	0.807	0.613

se p-val in parentheses

*** p<0.01, ** p<0.05, * p<0.1

A6 Table: World Bank Income group classification

Income Group	Group for analysis	Countries
Low income	1	Uganda
Lower middle-income	1	Ghana; India
Upper middle-income	1	Brazil; China; Colombia; South Africa
High income	2	Australia; Canada; Chile; France; Italy; Japan; Spain; United Kingdom; United States of America

A7 Table: Regional comparison between countries

Continental group	Countries
Africa	Ghana; South Africa; Uganda
Europe	France; Italy; Spain; United Kingdom
South America	Brazil; Chile; Colombia
North America	Canada; United States of America
Australasia	Australia; China; India; Japan

A8 Table: ANOVA Results by World Bank Income Group Classification

In-person GP challenges		n = 16	Root MSE = 0.097707	R^2 = 0.0627	Adj R^2 = -0.0043
	Partial Sum of squares (SS)	df	MS	F	Prob > F
Between	0.0089357	1	0.0089357	0.94	0.3497
Within	0.13365387	14	0.00954671		
Total	0.14258957	15	0.00950597		

Surgical challenges		n = 16	Root MSE = 0.11347	R^2 = 0.2484	Adj R^2 = 0.1947
	Partial SS	df	MS	F	Prob > F
Between	0.0595787	1	0.0595787	4.63	0.0494**
Within	0.18025463	14	0.01287533		
Total	0.23983333	15	0.01598889		

Digital challenges		n = 16	Root MSE = 0.084157	R^2 = 0.3154	Adj R^2 = -0.2665
	Partial SS	df	MS	F	Prob > F
Between	0.04569006	1	0.04569006	6.45	0.0236**
Within	0.09915453	14	0.00708247		
Total	0.14484459	15	0.00965631		

A9 Table: ANOVA Results by continental classification

In-person GP challenges		n = 16	Root MSE = 0.078552	R^2 = 0.5240	Adj R^2 = 0.3509
	Partial SS	df	MS	F	Prob > F
Between	0.07471559	4	0.0186789	3.03	0.0655*
Within	0.06787399	11	0.00617036		
Total	0.14258958	15	0.00950597		

Surgical challenges		n = 16	Root MSE = 0.82091	R^2 = 0.6909	Adj R^2 = 0.5785
	Partial SS	df	MS	F	Prob > F
Between	0.16570418	4	0.04142604	6.15	0.0075***
Within	0.07412915	11	0.00673901		
Total	0.23983333	15	0.01598889		

Digital challenges		n = 16	Root MSE = 0.091369	R^2 = 0.3660	Adj R^2 = 0.1355
	Partial SS	df	MS	F	Prob > F
Between	0.05301378	4	0.01325345	1.59	0.2457
Within	0.0918308	11	0.00834825		
Total	0.14484458	15	0.00965631		

A10 Table: Fisher-Hayter (FH) pairwise comparisons

In-person GP challenge pairwise comparisons

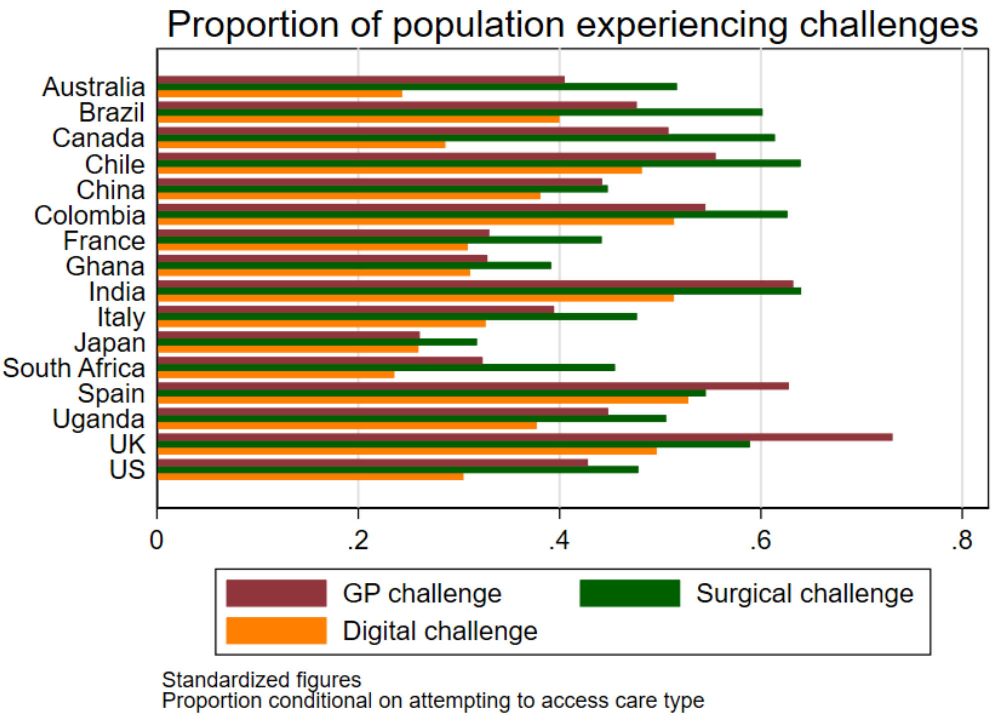
	Group means			
Comparison	**Left**	**Right**	**Difference**	**FH-test**
Africa vs Europe	0.0756	0.0382	0.0374	0.8815
Africa vs South America	0.0756	0.1585	-0.0829	1.828
Africa vs North America	0.0756	-0.0441	0.1197	2.3604
Africa vs Australasia	0.0756	-0.0207	0.0963	2.2707
Europe vs South America	0.0382	0.1585	-0.1203	2.8357
Europe vs North America	0.0382	-0.0441	0.0823	1.7107
Europe vs Australasia	0.0382	-0.0207	0.0589	1.5006
South America vs North America	0.1585	-0.0441	0.2026	3.9954*
South America vs Australasia	0.1585	-0.0207	0.1792	4.2249*
North America vs Australasia	-0.0441	-0.0207	-0.0234	0.4855

Surgical challenge pairwise comparisons

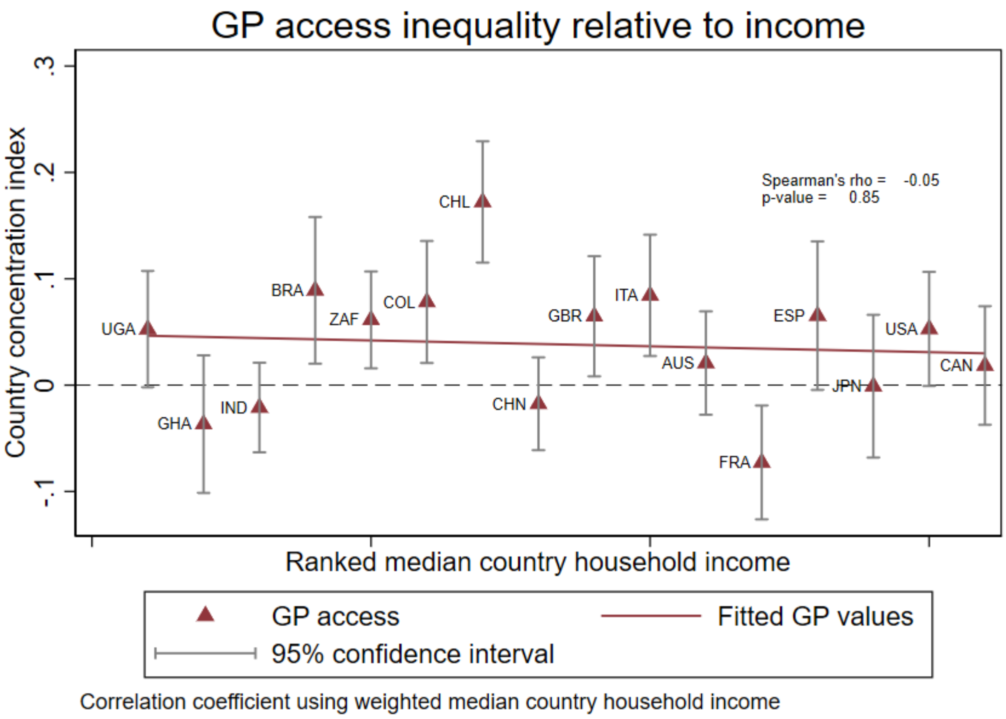
	Group means			
Comparison	**Left**	**Right**	**Difference**	**FH-test**
Africa vs Europe	0.0894	-0.0207	0.1101	2.4847
Africa vs South America	0.0894	0.0661	0.0233	0.492
Africa vs North America	0.0894	-0.2531	0.3425	6.4635***
Africa vs Australasia	0.0894	-0.0066	0.096	2.1658
Europe vs South America	-0.0207	0.0661	-0.0868	1.9588
Europe vs North America	-0.0207	-0.2531	0.2324	4.6218**
Europe vs Australasia	-0.0207	-0.0066	-0.0141	0.3455
South America vs North America	0.0661	-0.2531	0.3192	6.0235***
South America vs Australasia	0.0661	-0.0066	0.0727	1.6399
North America vs Australasia	-0.2531	-0.0066	-0.2465	4.9031**

FH value for significance at 10% level = 3.76108; 5% Level = 4.25605 ;1% level = 5.6205

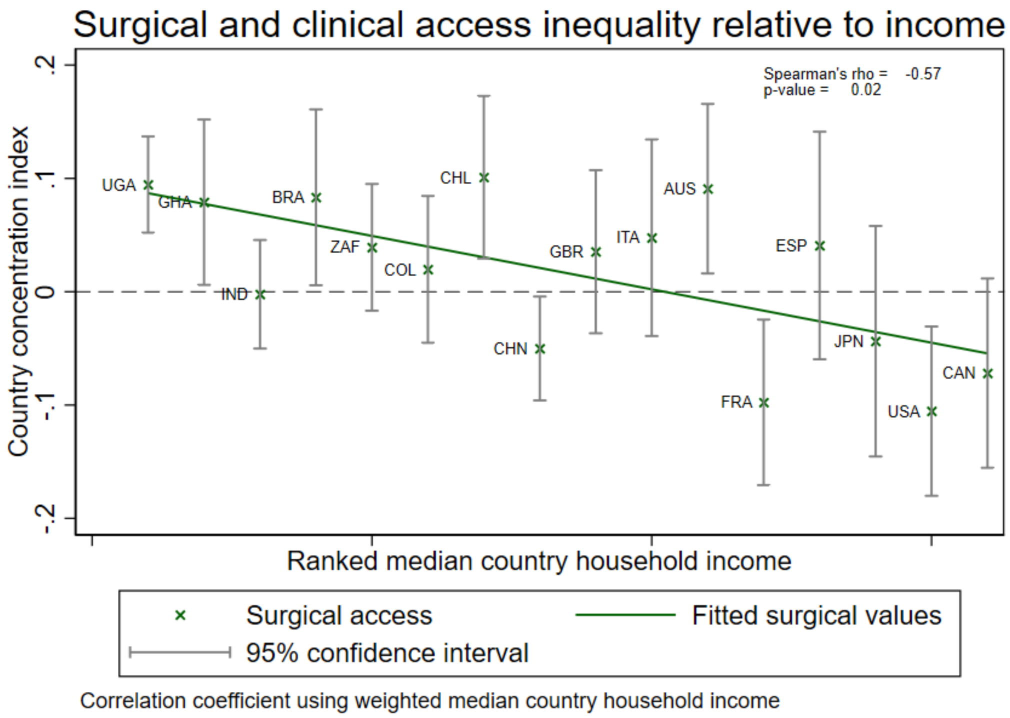
A1 Figure: Proportion of respondents challenged by type of care by country



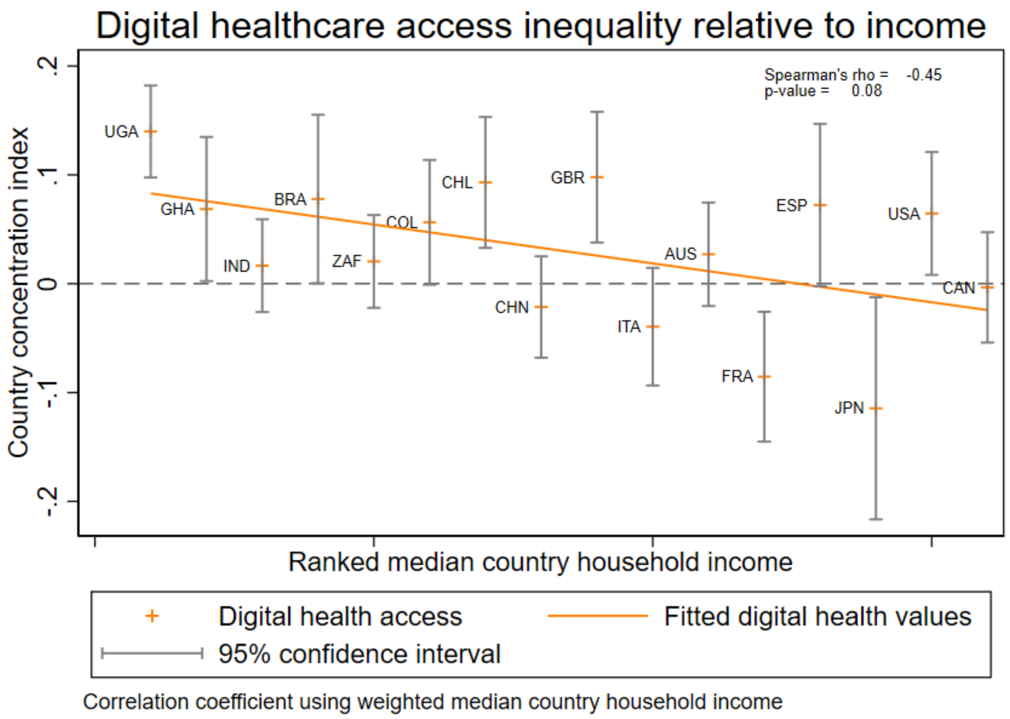
A2 Figure: In-person GP challenge inequality by country ranked median income level using restricted standardization



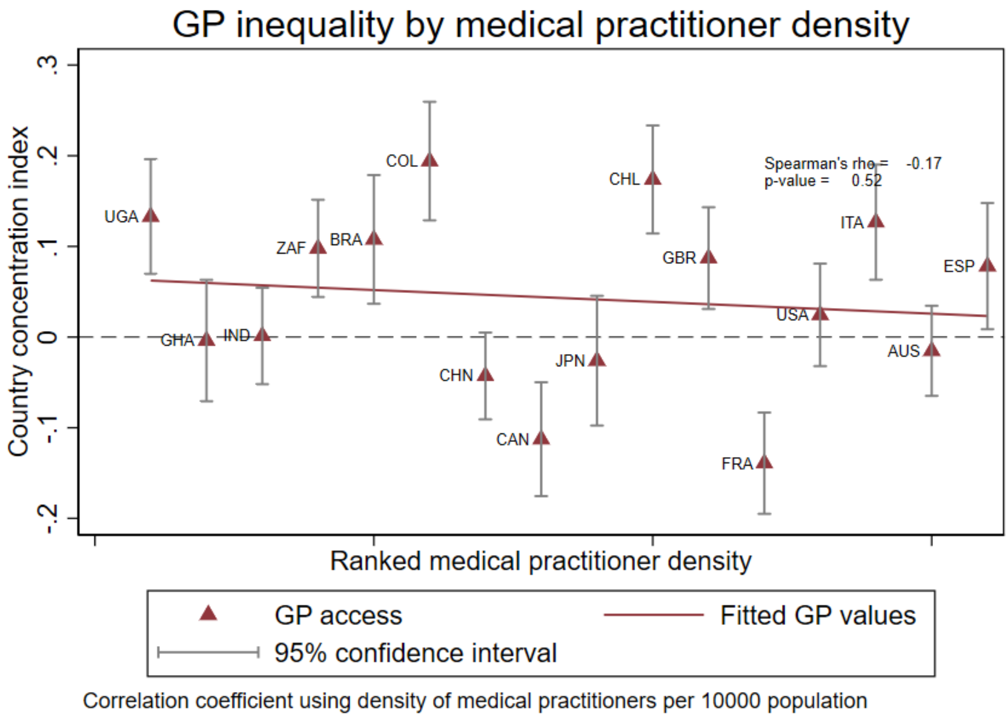
A3 Figure: Surgical/clinical challenge inequality by country ranked median income level using restricted standardization



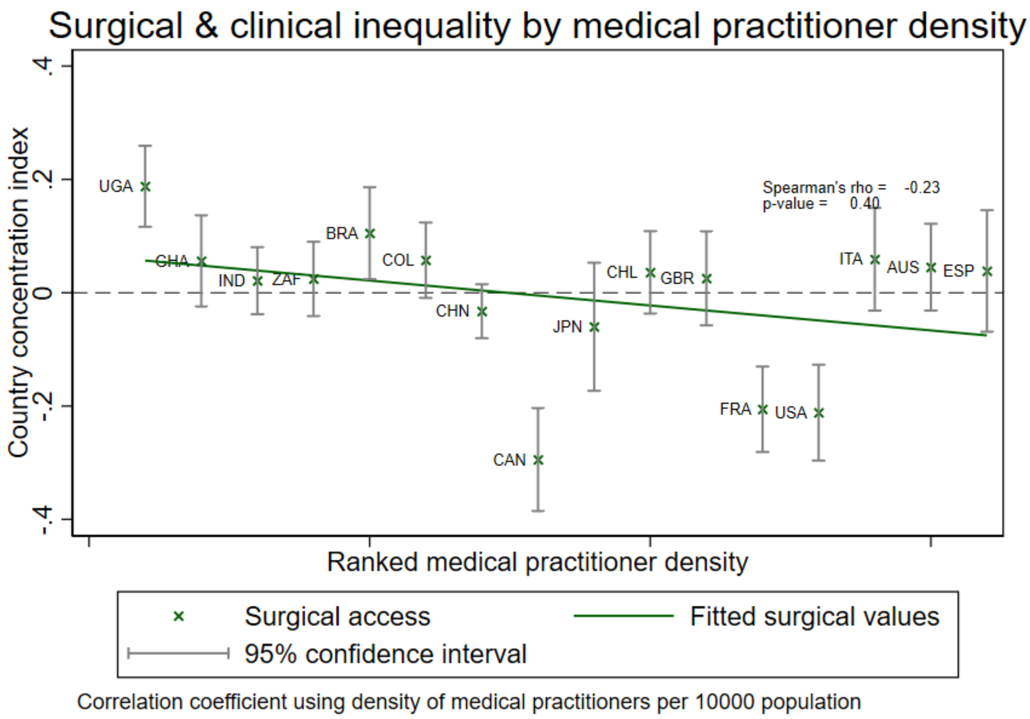
A4 Figure: Digital challenge inequality by country ranked median income level using restricted standardization



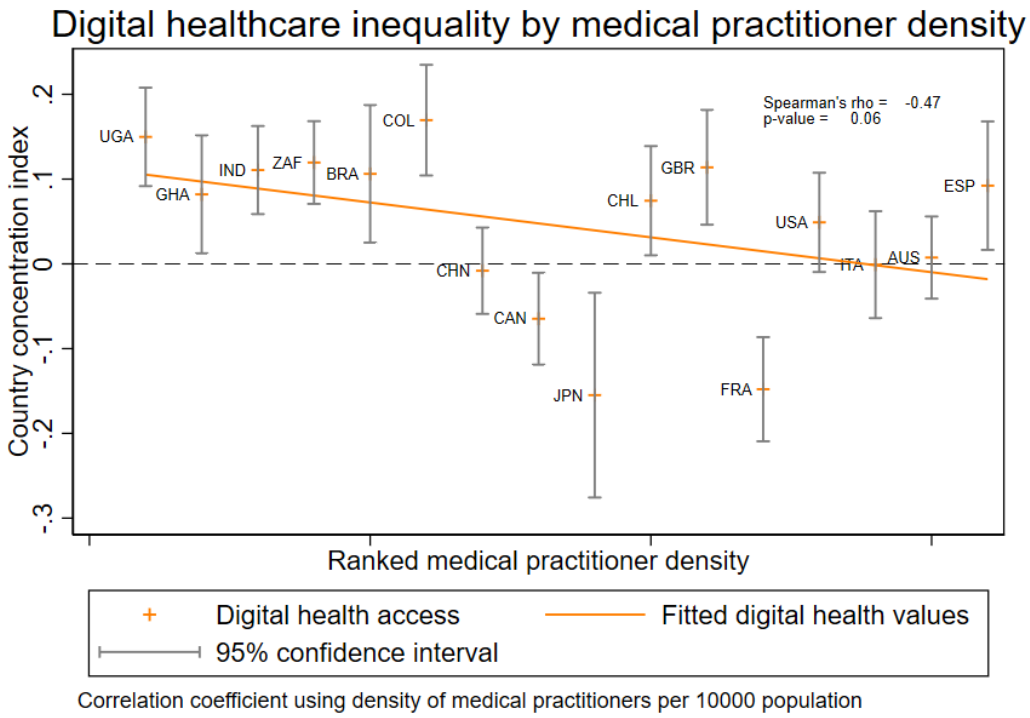
A5 Figure: In-person GP challenge inequality by density of medical practitioners per 10,000 of population



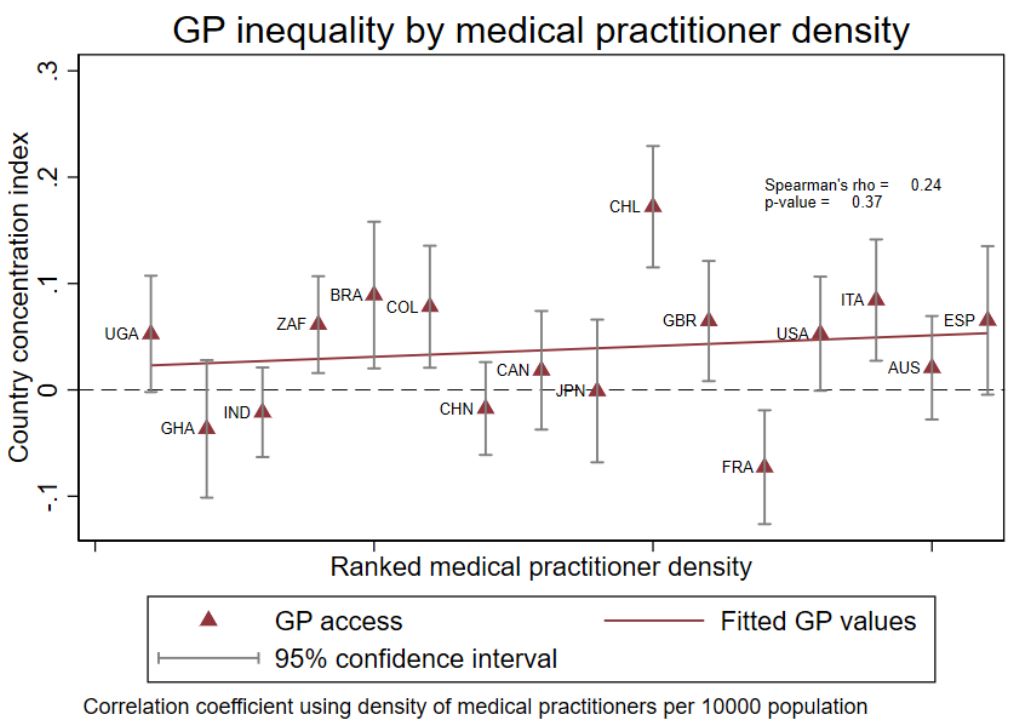
A6 Figure: Surgical/clinical challenge inequality by density of medical practitioners per 10,000 of population



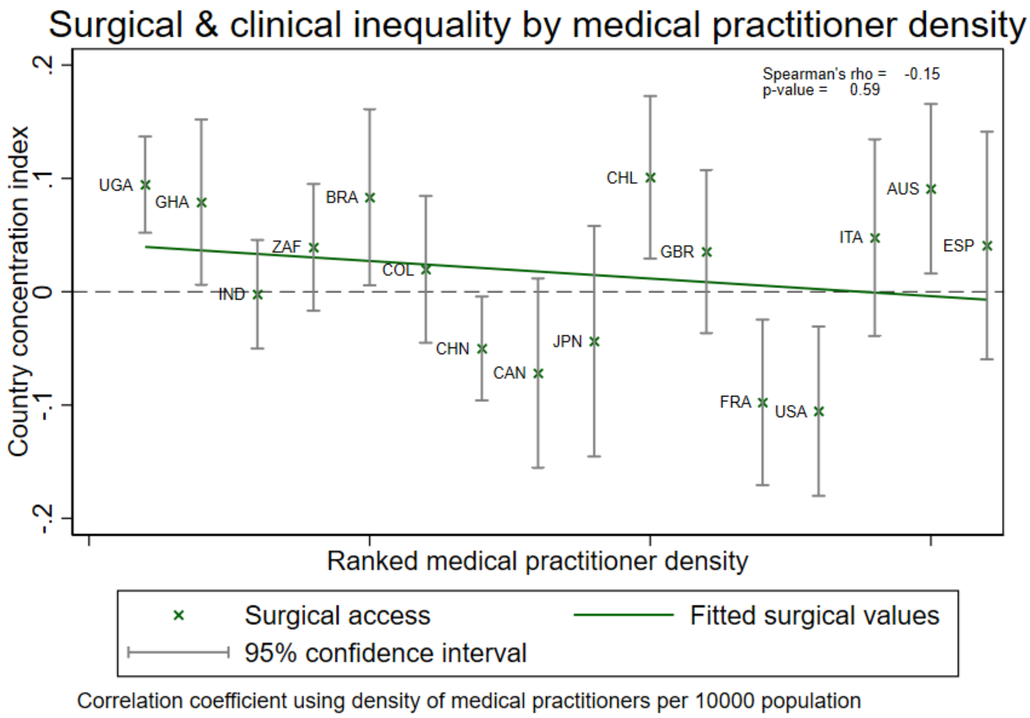
A7 Figure: Digital challenge inequality by density of medical practitioners per 10,000 of population



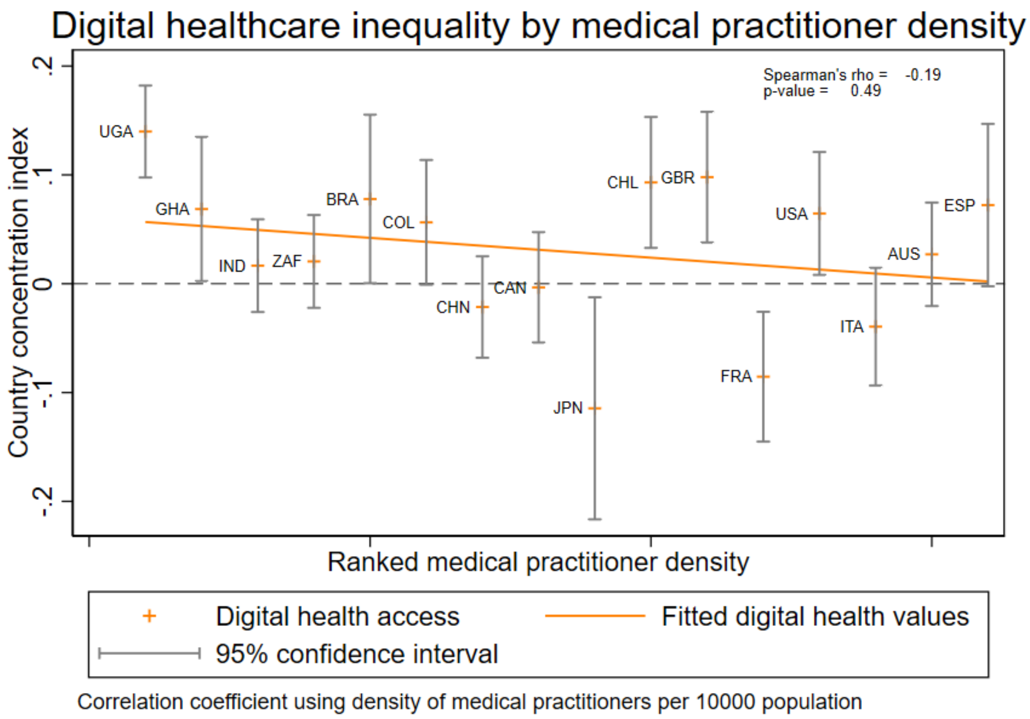
A8 Figure: In-person GP challenge inequality by density of medical practitioners per 10,000 of population using restricted standardization



A9 Figure: Surgical/clinical challenge inequality by density of medical practitioners per 10,000 of population using restricted standardization



A10 Figure: Digital challenge inequality by density of medical practitioners per 10,000 of population using restricted standardization



A11 Note: Concentration Index deviations from the line of equality

The value of a concentration index is taken as twice the area between the y=x equality line and concentration curve. Though the function is weighted (see 3.2.1.) by the relative socioeconomic rank variable, there remains a distinct possibility that two datasets[1] can produce equivalent, or closely equivalent concentration indices while having fairly differently shaped concentration curves. Ordinarily, pairing the concentration index with the corresponding concentration curve – from which the index value is calculated – provides the requisite perspective of the distribution to understand differences, if any such exist, between two indices with equivalent values.

In this study, I have transformed the concentration curves from the originals to deviations from the line of equality to improve perceptibility of the differences in the curves. The magnitude of the concentration index is often small. Discerning the difference between any of the 48 curves could prove challenging. The transformation is stated simply below;

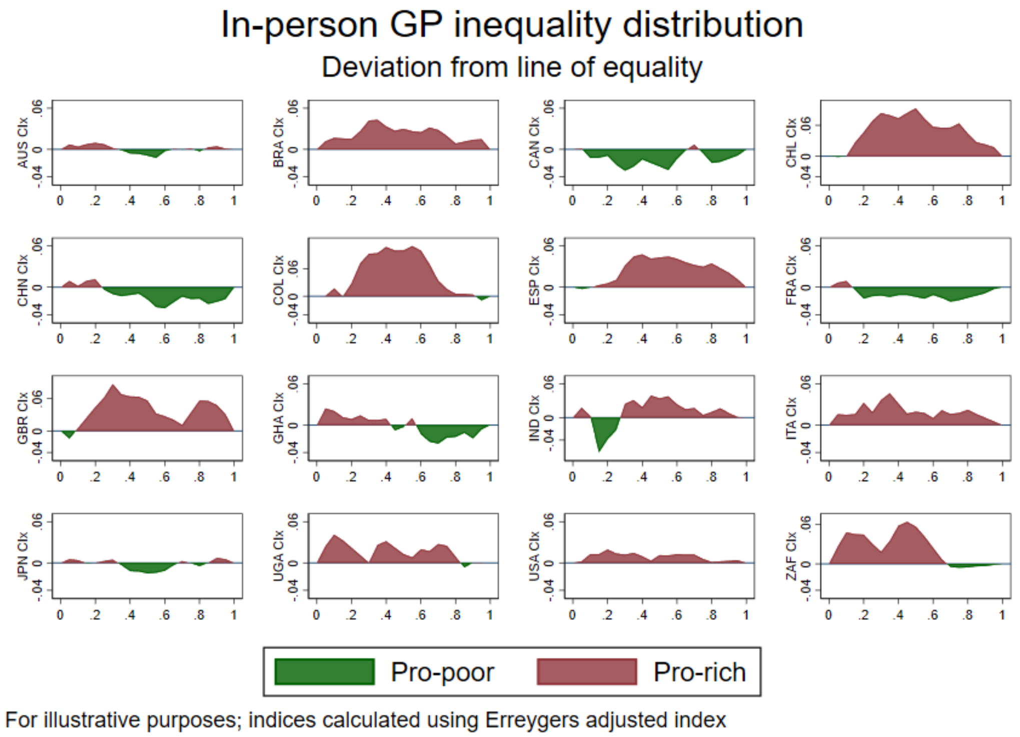
$$f(y) = p_{eq} - E(p)$$

Where the new function is taken as the difference between the percentile of the line of equality (p_{eq}), and the value of the concentration curve at the corresponding percentile E(p). Where the concentration curve lies below the line of equality; the function takes on a positive value; indicating pro-rich results. Where the curve lies above the line of equality, the function is negative, representing pro-poor results at the given percentile of the distribution.

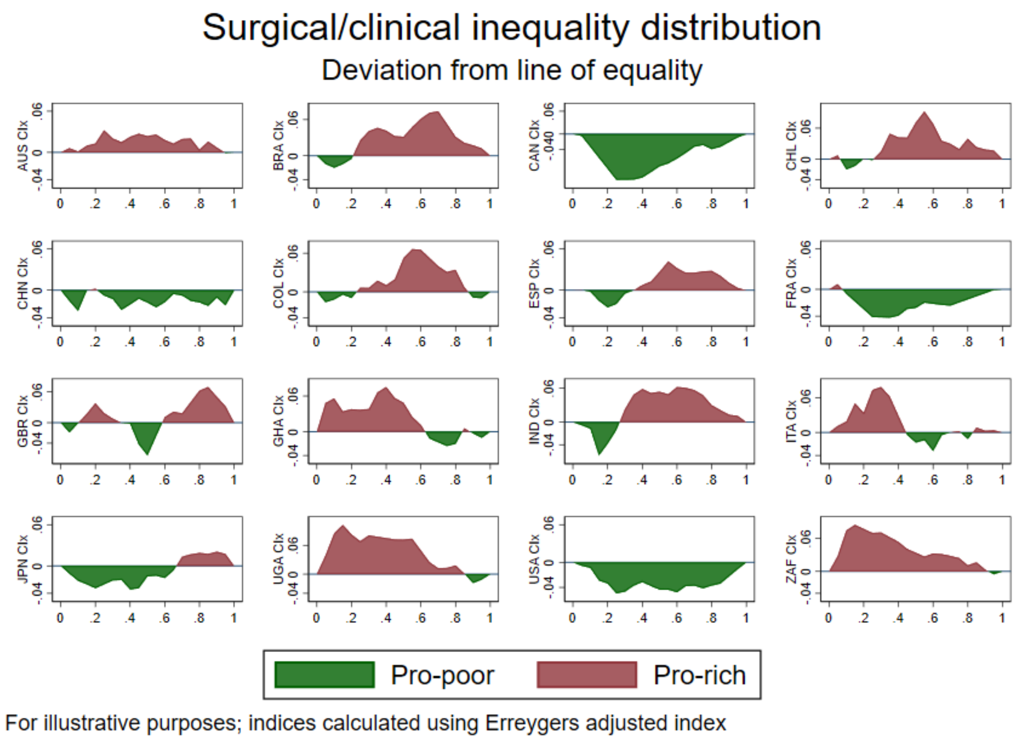
Interrogating the concentration index without an accompanying graphic could lead to erroneous inferences on the distributions of inequality. In most cases, it is possible to simply include a graphic to aid with interpretation. In some cases, however, this may not make sense or be unfeasible, in which case deliberate care is required when viewing the statistics.

[1] Countries, in this context

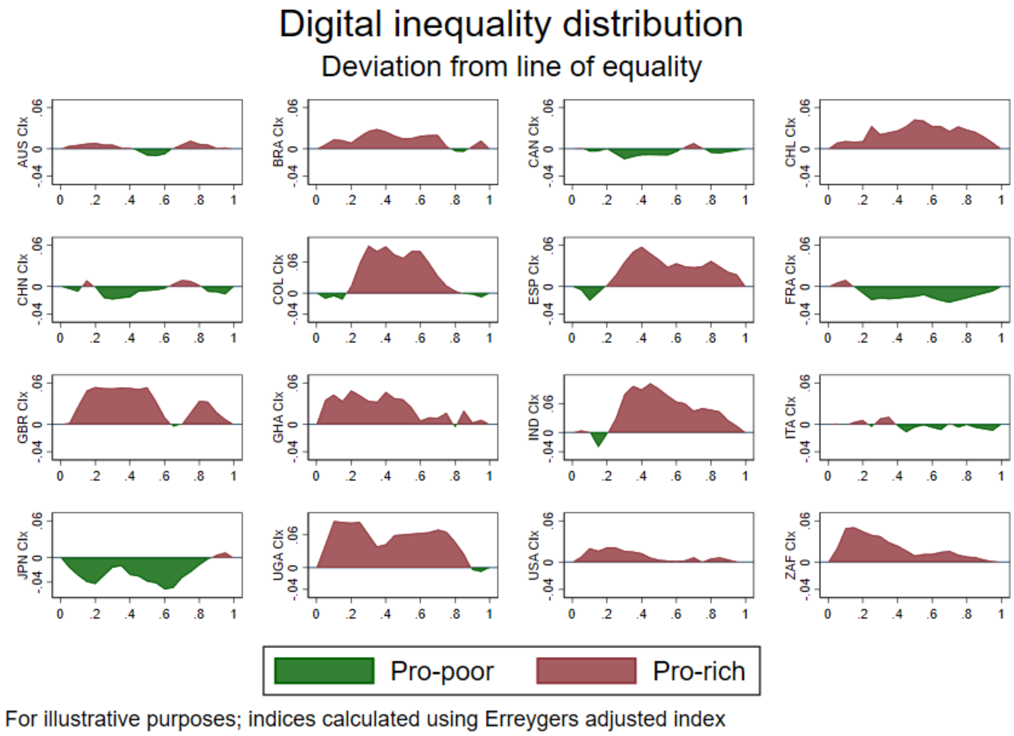
A12 Figure: Concentration Index deviations from the line of equality, In-person GP challenge inequality



A13 Figure: Concentration Index deviations from the line of equality, Surgical/clinical admission inequality



A14 Figure: Concentration Index deviations from the line of equality, Digital inequality



Appendix: B – Chapter 5

TABLES

FIGURES

B1 Table: Reweighting achieved

	Reweighted weight
Australia	99.84
Brazil	93.42
Canada	99.86
Chile	100
China	100
Colombia	99.26
France	99.57
Ghana	99.46
India	99.1
Italy	100
Japan	99.32
South Africa	96.59
Spain	59.59
Uganda	100
UK	99.77
US	99.7

B2 Table: National population weights used in country-population weight method

	2021 Population (thousands)
Australia	25,956
Brazil	209,550
Canada	38,454
Chile	19,456
China	1,426,437
Colombia	51,188
France	66,084
Ghana	32,519
India	1,414,204
Italy	59,729
Japan	125,679
South Africa	61,503
Spain	47,736
Uganda	45,911
UK	67,669
US	340,161

B3 Table: Values of alternative concentration index specifications

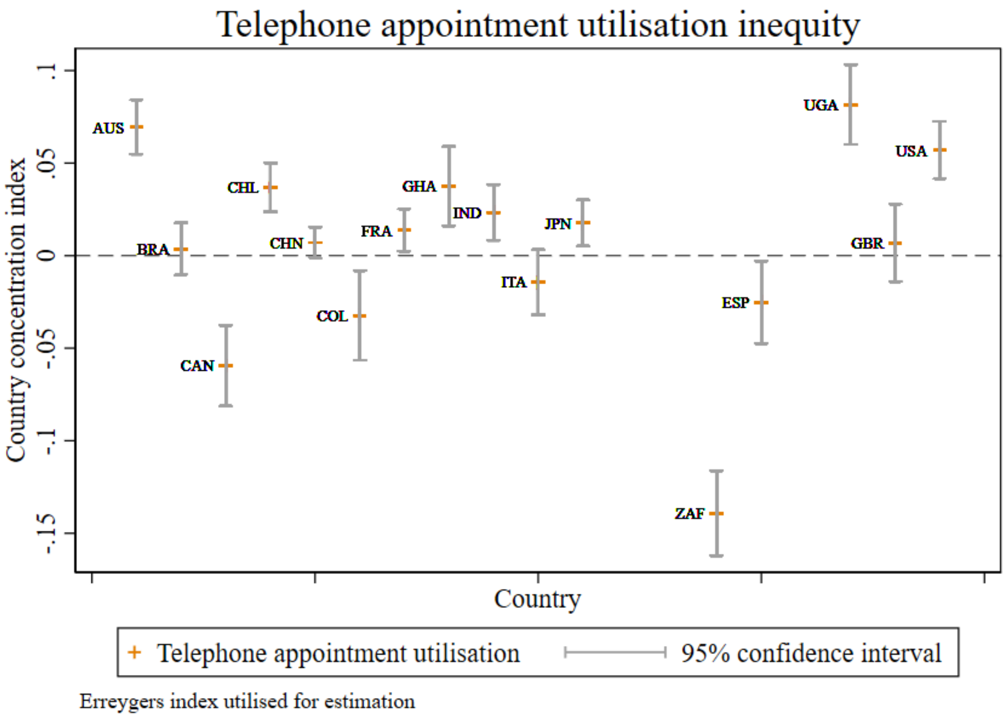
	Telephone contacts				Internet contacts				In person GP contacts				Inpatient overnight hospital stays				Outpatient clinic visits			
	L	E	G	C	L	E	G	C	L	E	G	C	L	E	G	C	L	E	G	C
Australia	0.158	0.069	0.017	0.076	0.264	0.109	0.027	0.21	-0.081	-0.043	-0.011	-0.037	0.082	0.037	0.009	0.081	0.079	0.037	0.009	0.061
Brazil	-0.009	0.004	0.001	0.007	0.029	0.024	0.006	0.055	0.117	0.017	0.004	0.022	-0.221	-0.084	-0.021	-0.184	-0.072	-0.023	-0.006	-0.042
Canada	-0.153	-0.059	-0.015	-0.061	-0.046	-0.011	-0.003	-0.019	-0.069	-0.029	-0.007	-0.03	0.011	0.022	0.005	0.046	-0.282	-0.134	-0.034	-0.172
Chile	0.08	0.037	0.009	0.065	0.209	0.058	0.015	0.162	0.307	0.228	0.057	0.178	0.033	0.007	0.002	0.022	0.164	0.06	0.015	0.157
China	0.026	0.007	0.002	0.022	0.042	0.007	0.002	0.019	0.057	0.031	0.008	0.053	0.015	0.00	0.00	0.001	0.041	0.022	0.006	0.04
Colombia	-0.12	-0.032	-0.008	-0.034	-0.038	-0.006	-0.002	-0.008	-0.027	0.006	0.002	0.006	-0.127	-0.038	-0.009	-0.066	-0.01	-0.005	-0.001	-0.007
France	0.022	0.014	0.003	0.027	0.052	0.029	0.007	0.083	0.097	0.057	0.014	0.061	0.096	0.053	0.013	0.133	0.051	0.029	0.007	0.079
Ghana	0.105	0.037	0.009	0.062	-0.043	0.008	0.002	0.017	0.012	0.035	0.009	0.05	-0.054	-0.004	-0.001	-0.01	-0.042	0.003	0.001	0.005
India	-0.019	0.023	0.006	0.027	0.148	0.065	0.016	0.098	-0.138	-0.023	-0.006	-0.024	-0.039	0.002	0.001	0.003	0.129	0.04	0.01	0.066
Italy	-0.023	-0.014	-0.004	-0.025	-0.053	-0.032	-0.008	-0.086	0.038	0.014	0.004	0.018	-0.004	-0.002	-0.001	-0.006	0.023	0.012	0.003	0.02
Japan	0.056	0.018	0.004	0.048	-0.056	-0.018	-0.005	-0.061	0.209	0.071	0.018	0.09	-0.013	0.00	0.00	0.00	0.18	0.065	0.016	0.089
South Africa	-0.476	-0.139	-0.035	-0.19	-0.516	-0.147	-0.037	-0.206	-0.285	-0.073	-0.018	-0.08	-0.55	-0.133	-0.033	-0.196	-0.481	-0.116	-0.029	-0.15
Spain	-0.038	-0.025	-0.006	-0.028	0.009	0.002	0.001	0.005	0.053	0.032	0.008	0.035	-0.017	-0.011	-0.003	-0.032	0.007	0.003	0.001	0.007
Uganda	0.084	0.082	0.02	0.115	-0.024	0.022	0.006	0.036	-0.056	0.011	0.003	0.014	-0.04	-0.006	-0.002	-0.018	0.068	0.034	0.009	0.058
UK	-0.026	0.007	0.002	0.008	0.096	0.043	0.011	0.093	0.004	0.006	0.001	0.009	-0.002	0.003	0.001	0.008	0.032	0.037	0.009	0.065
US	0.174	0.057	0.014	0.101	0.095	0.02	0.005	0.038	0.21	0.07	0.017	0.093	0.05	0.014	0.003	0.038	0.088	0.029	0.007	0.067

L = Level Index; E = Erreygers adjusted index; G = Generalized concentration index; C = Concentration index

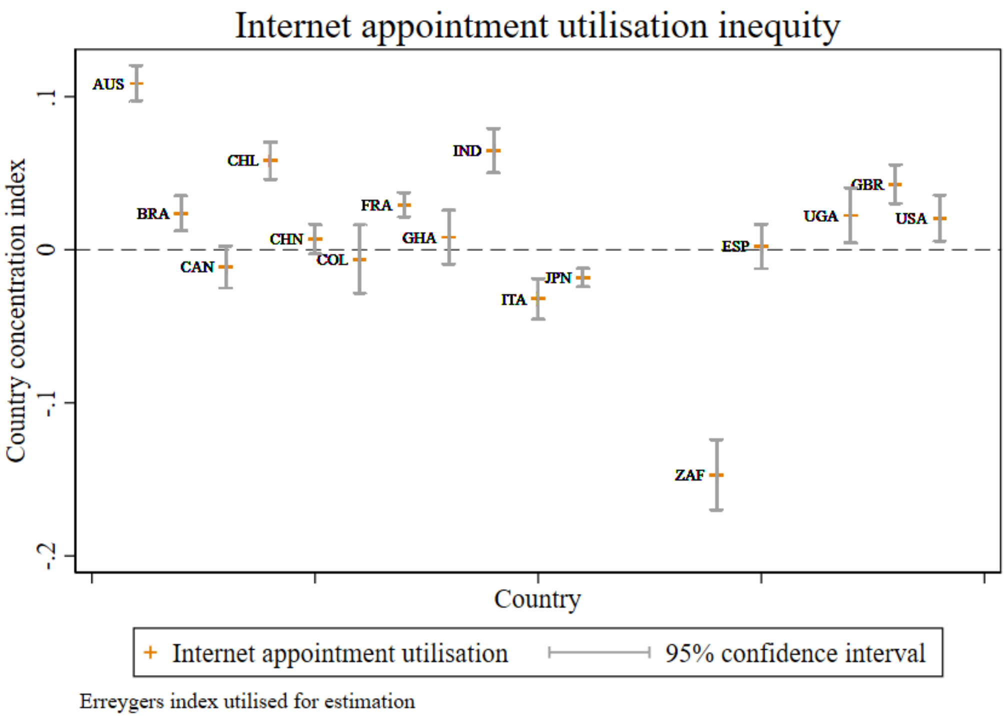
B4 Table: Values of rank similarity indices and Spearman's correlation by type of care

	Telephone contacts	Internet contacts	In person GP contacts	Inpatient overnight hospital stays	Outpatient clinic visits
S_{LE}	43.75%	25%	18.75%	43.75%	50%
S_{LR}	37.5%	37.5%	31.25%	43.75%	25%
S_{ER}	62.5%	62.5%	56.25%	100%	50%
ρ_{LE}	0.935	0.926	0.924	0.921	0.941
ρ_{LR}	0.944	0.959	0.941	0.921	0.935
ρ_{ER}	0.991	0.991	0.985	1	0.924

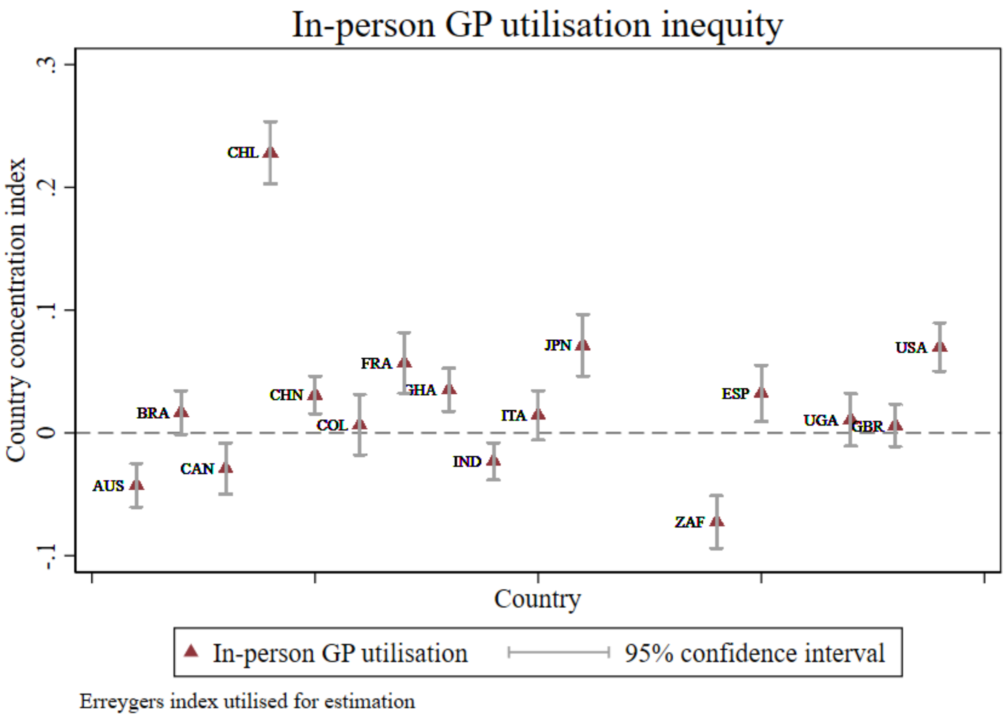
B1 Figure: Telephone contact inequality comparison by country using the Level Index



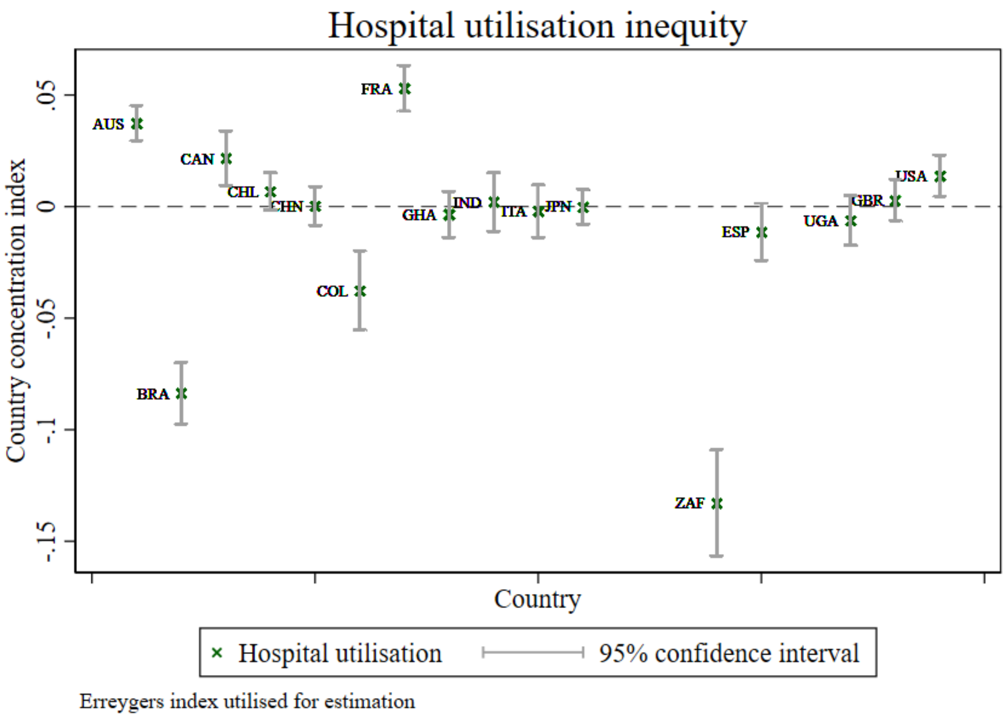
B2 Figure: Internet contact inequality comparison by country using the Level Index



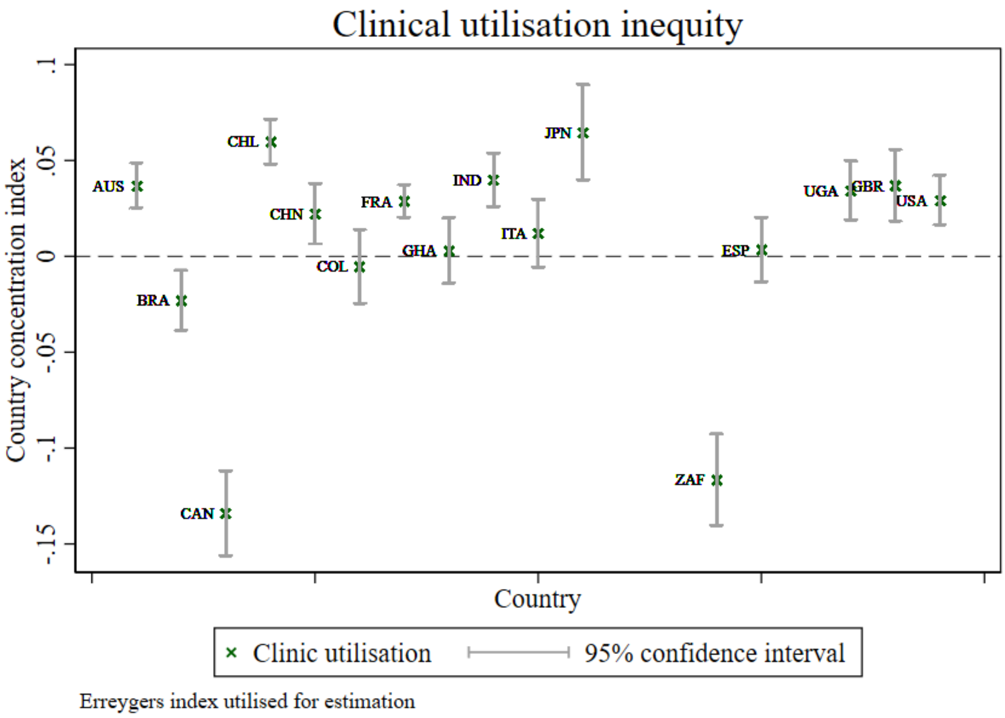
B3 Figure: In person GP contact inequality comparison by country using the Level Index



B4 Figure: Overnight hospital stay inequality comparison by country using the Level Index



B5 Figure: Clinic visit inequality comparison by country using the Level Index



Appendix: C – Chapter 6

TABLES

C1 Table: Representativeness achieved during reweighting

Country	Wave 1 reweighted cumulative weight	Wave 2 reweighted cumulative weight
Australia	99.3	99.8
Brazil	100	93.4
Canada	98.9	99.8
Chile	92.9	100
China	99.9	100
Colombia	98.7	99.3
France	99.1	99.8
India	98.2	98.8
Italy	99.7	100
Spain	99.4	99.7
Uganda	73.2	100*
United Kingdom	99.9	99.8
United States	99.9	100

*Uganda sample weights not representative in wave 2; every response assumed weight of 1.

C2 Table: Concentration index results for acceptance and uptake

	Erreygers						
	Acceptance	95% confidence interval	Rank	Uptake	95% confidence interval	Rank	P-value (Uptake - Acceptance)
Australia	0.084	(0.031 - 0.136)	7	-0.133	(-0.16 - -0.09)	1	<0.001
Brazil	0.009	(-0.03 - 0.050)	2	0.219	(0.177 - 0.260)	16	<0.001
Canada	0.083	(0.022 - 0.142)	6	0.089	(0.047 - 0.131)	10	0.864
Chile	0.025	(-0.02 - 0.074)	3	0.005	(-0.00 - 0.019)	5	0.466
China	0.203	(0.149 - 0.255)	13	0.069	(0.022 - 0.116)	9	<0.001
Colombia	0.028	(-0.01 - 0.075)	4	-0.042	(-0.08 - -0.00)	4	0.025
France	0.184	(0.113 - 0.253)	11	0.157	(0.099 - 0.214)	14	0.569
India	0.12	(0.078 - 0.162)	8	0.023	(-0.01 - 0.058)	6	<0.001
Italy	0.138	(0.067 - 0.208)	10	0.129	(0.085 - 0.172)	13	0.827
Spain	0.121	(0.058 - 0.183)	9	0.093	(0.065 - 0.120)	11	0.422
Uganda	-0.141	(-0.20 - -0.07)	1	-0.127	(-0.16 - -0.09)	2	0.706
United Kingdom	0.069	(0.012 - 0.125)	5	0.056	(0.015 - 0.096)	7	0.713
United States	0.202	(0.138 - 0.264)	12	0.065	(0.005 - 0.123)	8	0.002
Ghana				0.102	(0.045 - 0.159)	12	
Japan				-0.081	(-0.137 - -0.024)	3	
South Africa				0.171	(0.109 - 0.233)	15	

	Wagstaff						
	Acceptance	95% confidence interval	Rank	Uptake	95% confidence interval	Rank	P-value (Uptake - Acceptance)
Australia	0.133	(0.049 - 0.216)	7	-0.32	(-0.40 - -0.23)	2	<0.001
Brazil	0.021	(-0.07 - 0.122)	2	0.515	(0.417 - 0.613)	15	<0.001
Canada	0.113	(0.031 - 0.194)	6	0.205	(0.107 - 0.301)	13	0.156
Chile	0.057	(-0.05 - 0.171)	3	0.104	(-0.17 - 0.379)	7	0.755
China	0.297	(0.219 - 0.374)	12	0.12	(0.038 - 0.201)	8	0.002
Colombia	0.065	(-0.04 - 0.170)	4	-0.111	(-0.21 - -0.00)	4	0.022
France	0.185	(0.114 - 0.255)	10	0.193	(0.122 - 0.263)	12	0.881
India	0.329	(0.215 - 0.443)	13	0.067	(-0.03 - 0.172)	5	0.001
Italy	0.15	(0.073 - 0.226)	8	0.273	(0.179 - 0.365)	14	0.045
Spain	0.178	(0.086 - 0.270)	9	0.565	(0.399 - 0.731)	16	<0.001
Uganda	-0.262	(-0.38 - -0.13)	1	-0.424	(-0.54 - -0.30)	1	0.066
United Kingdom	0.11	(0.019 - 0.199)	5	0.142	(0.038 - 0.245)	9	0.642
United States	0.231	(0.158 - 0.303)	11	0.078	(0.006 - 0.148)	6	0.003
Ghana				0.145	(0.145 - 0.063)	10	
Japan				-0.122	(-0.122 - -0.207)	3	
South Africa				0.178	(0.178 - 0.113)	11	

C3 Table: Decomposition for Ghana, Japan, and South Africa vaccine uptake

	Ghana	Japan	South Africa
Age	-0.0332***	-0.0022	-0.0148***
	(0.0075)	(0.0035)	(0.0049)
Female	-0.0311	-0.1857*	0.0263
	(0.1261)	(0.0989)	(0.1116)
Health level	0.0038	-0.0035	-0.0018
	(0.0033)	(0.0026)	(0.0030)
Marital status	0.1697	0.3316***	0.5281***
	(0.1184)	(0.1118)	(0.1244)
Education (Less than primary)	-	-	-
Education (Primary)	-3.2480	0.9257**	-2.8338
	(2.0873)	(0.4407)	(1.7375)
Education (Secondary)	-4.4630**	0.7217*	-3.3500*
	(2.0182)	(0.3740)	(1.7119)
Education (University)	-4.9527**	0.4857	-4.0769**
	(2.0191)	(0.3727)	(1.7131)
Chronic disease	0.2458	0.0118	-0.0770
	(0.1602)	(0.1050)	(0.1268)
Political ideology	-0.0052	0.0519*	-0.0517**
	(0.0235)	(0.0270)	(0.0230)
Constant	3.1295	-1.2937**	2.0471
	(2.0483)	(0.5053)	(1.7826)
Observations	1092	1044	1239

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix: D – Chapter 7

TABLES

D1 Table: Bootstrapped treatment effects using verified vaccine status on Erreygers adjusted concentration index

D2 Table: Sample characteristics of individuals with verified vaccination status

D3 Table: Frequency statistics of the sample and subgroups

FIGURES

D1 Figure: Covariate balance table

D2 Figure: Estimated inequality uptake trade-off disaggregated by treatment arm using the Level Index and total expenditure as ranking variable

D3 Figure: Estimated inequality uptake trade-off disaggregated by treatment arm using Erreygers adjusted index

D4 Figure: Educational attainment subgroup variation decomposition and inequality estimation

D1 Table: Bootstrapped treatment effects using verified vaccine status on Erreygers adjusted concentration index

	Concentration index	Treatment magnitude[1] [95% CI][2]
Placebo	-0.099	
Treatments		
CDC	0.033	-0.132 [-0.28 - 0.02]
Low cash	0.009	-0.108 [-0.29 - 0.07]
High cash	-0.019	-0.081 [-0.26 - 0.11]

Notes

1. Treatment magnitude refers to the average difference between inequality of treated in treatment villages and inequality of untreated in untreated villages 6 weeks after vaccine availability
2. *** p<0.001, ** p<0.01, * p<0.05

D2 Table: Sample characteristics of individuals with verified vaccination status

		Placebo	CDC	Low cash	High cash
	Sample size	702	488	522	559
Age	Age (mean)	36.2	35.1	36.1	37.5
	Age (SD)	15.5	15.3	15.5	16.8
Gender	Male	327	213	233	217
	Female	375	275	289	341
	Other gender				1
Household	HH size (mean)	6.2	6	6.2	6.4
	HH size (SD)	2.2	3.3	2.8	2.7
	Children in HH (mean)	1.8	1.7	1.9	2.
	Children in HH (SD)	1.6	1.7	1.7	1.8
Education	No Schooling	95	69	85	103
	Pre-school	5	1	8	5
	Primary School	113	83	103	88
	Junior Secondary	359	220	239	285
	Secondary	104	99	75	65
	Tertiary education	26	16	12	13
Employment	Employed full-time	395	274	311	295
	Employed part-time	119	51	60	96
	Retired	16	19	19	20
	Student	49	46	26	37
	Unemployed	100	67	79	68
Living arrangements	Does not live with partner	262	205	206	197
	Live with partner	232	157	164	182
Expenditure	Food spend (mean)	163.4	164.8	164.1	164.6
	Food spend (SD)	99.5	98.2	96.6	103.2
	Non-food spend (mean)	35.1	81.3	41.2	36.6
	Non-food spend (SD)	71.	558.4	57.8	55.8
Vaccination	Unvaccinated at commencement	702	488	522	559
	Vaccine intent	499	350	430	445

	Vaccine hesitant	176	130	81	90
	Not collected / prefer not say	27	8	11	24
	Verified: Vaccinated (6 weeks)	200	117	225	153
	Verified: Not vaccinated (6 weeks)	502	371	297	406
	Reported: Vaccinated	203	155	166	165

		Placebo	CDC	Low cash	High cash
	Sample size	702	488	522	559
Age	Age (mean)	36.2	35.1	36.1	37.5
	Age (SD)	15.5	15.3	15.5	16.8
Gender	Male	327	213	233	217
	Female	375	275	289	341
	Other gender				1
Household	HH size (mean)	6.2	6	6.2	6.4
	HH size (SD)	2.2	3.3	2.8	2.7
	Children in HH (mean)	1.8	1.7	1.9	2.
	Children in HH (SD)	1.6	1.7	1.7	1.8
Education	No Schooling	95	69	85	103
	Pre-school	5	1	8	5
	Primary School	113	83	103	88
	Junior Secondary	359	220	239	285
	Secondary	104	99	75	65
	Tertiary education	26	16	12	13
Employment	Employed full-time	395	274	311	295
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Living arrangements	Does not live with partner	262	205	206	197
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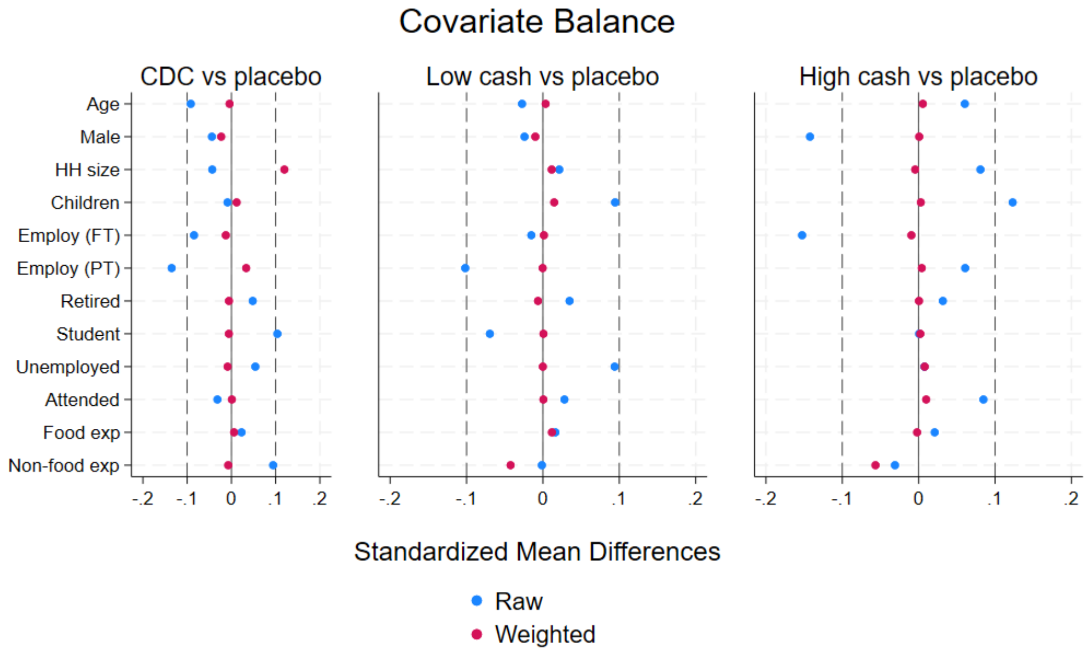
	Food spend (SD)	99.5	98.2	96.6	103.2
	Non-food spend (mean)	35.1	81.3	41.2	36.6
	Non-food spend (SD)	71.	558.4	57.8	55.8
Vaccination	Unvaccinated at commencement	702	488	522	559
	Vaccine intent	499	350	430	445
	Vaccine hesitant	176	130	81	90
	Not collected / prefer not say	27	8	11	24
	Verified: Vaccinated (6 weeks)	200	117	225	153
	Verified: Not vaccinated (6 weeks)	502	371	297	406
	Reported: Vaccinated	203	155	166	165

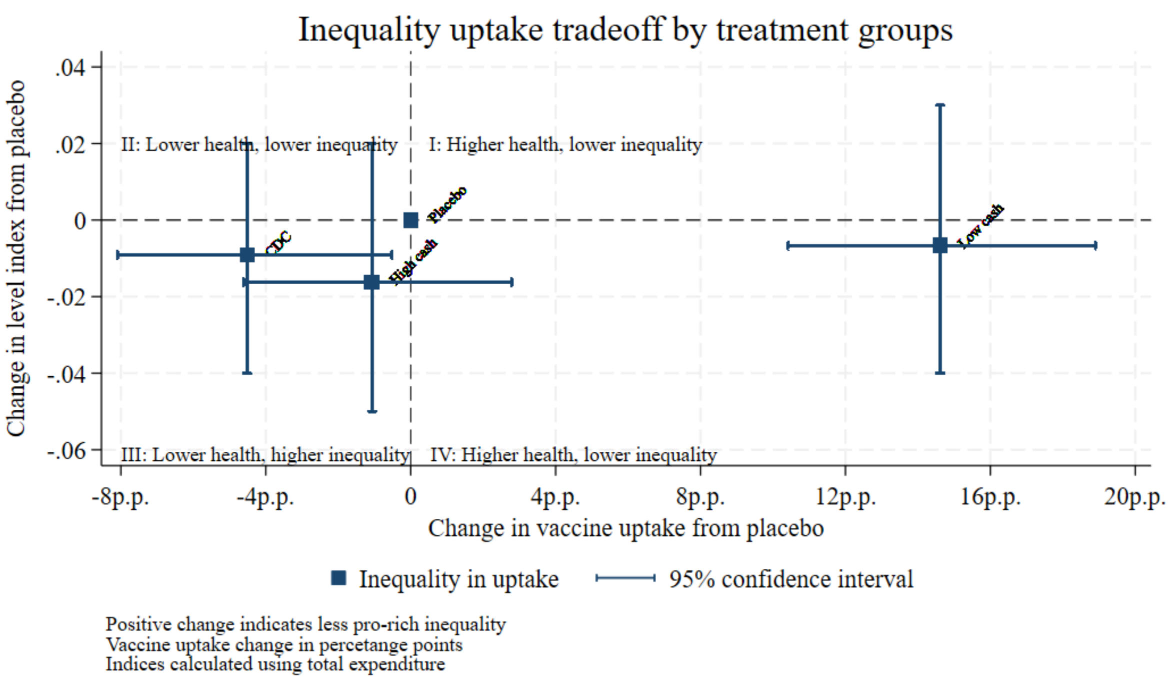
D3 Table: Frequency statistics of the sample and subgroups

	Share (%) of group				
Variable	Total	Placebo	CDC message	Low cash	High cash
Gender					
Female	56.39%	53.42%	56.35%	55.36%	61.11%
Male	43.61%	46.58%	43.65%	44.64%	38.89%
Education Group					
No schooling	15.51%	13.53%	14.14%	16.28%	18.46%
Up to end of primary	17.89%	16.81%	17.21%	21.26%	16.67%
More than primary	66.61%	69.66%	68.65%	62.45%	64.87%

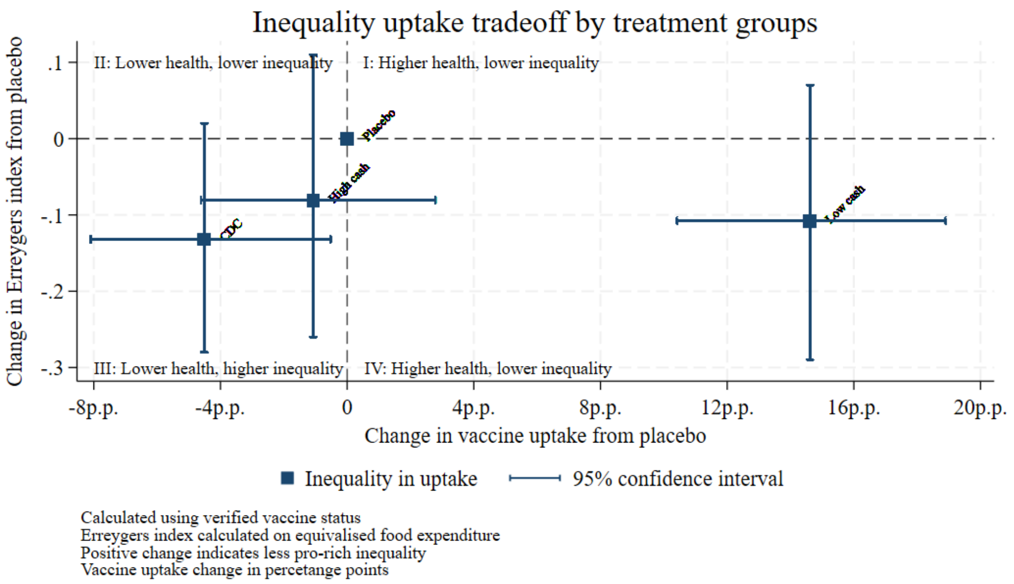
D1 Figure: Covariate balance table



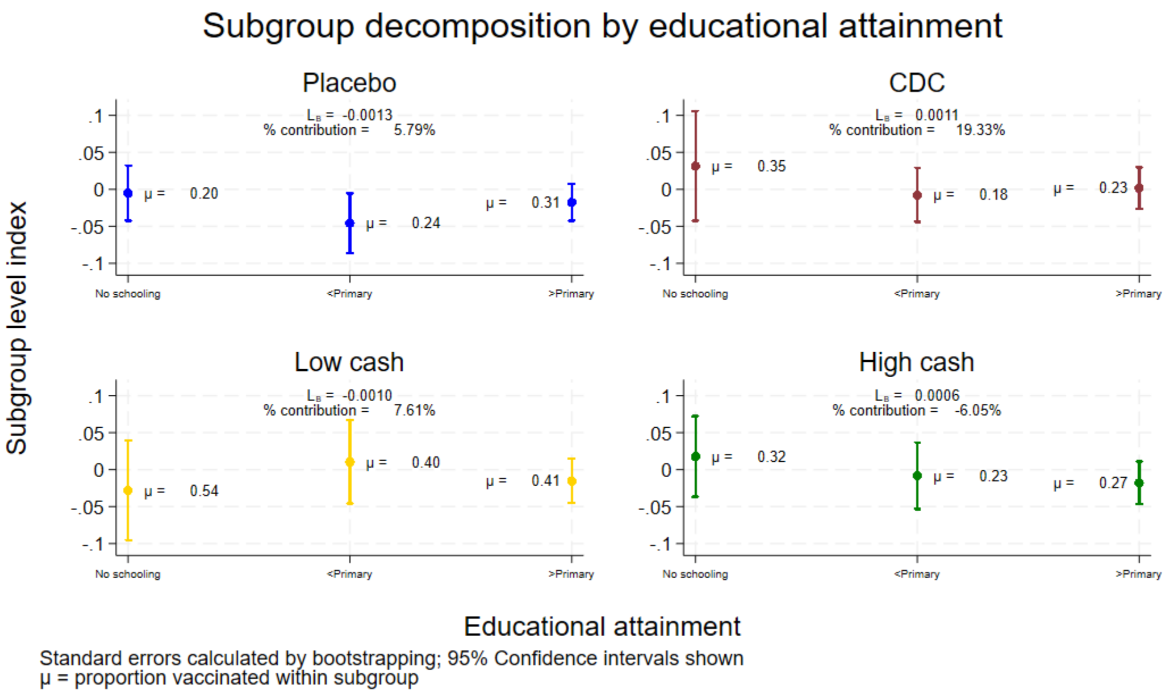
D2 Figure: Estimated inequality uptake trade-off disaggregated by treatment arm using the Level Index and total expenditure as socioeconomic variable



D3 Figure: Estimated inequality uptake trade-off disaggregated by treatment arm using Erreygers adjusted index



D4 Figure: Educational attainment subgroup variation decomposition and inequality estimation



Appendix: E – Chapter 8

Notes

E1 Note: A note on weighting schemes for the synthesis

Tables

E1 Table: Weighting allocations

E1 Note: A note on weighting schemes for the synthesis

Possible schemes include weighting each stage in the healthcare process according to the number of users at each stage, though this would create bias in the direction of the already existing attrition throughout the health process. It has also been shown that simple, mechanical averages often perform better than arbitrarily weighted calculations in works by Kahneman, Sibony, and Sunstein in their book, Noise: A flaw in human judgement.[274] However, in this instance, an unweighted index is itself a weighting scheme that could overweight certain estimates, which I discuss below.

I present 4 different weighting schemes, with weights applied to the equality score, EQZ, where EQZ $\in$ Z and [-1:1] before cumulation across the computed EQZs. Though applying weightings to the estimate scores rather than the estimate values reduces the information and can lead to issues (e.g., a highly pro-rich estimate is offset by a marginally positive estimate), assigning weightings to values in different settings (e.g., given different standardizations) would be problematic.

The first weighting scheme (EQZ1) uses an unweighted sum, where each individual EQZ estimate is weighted evenly. However, given the disparity in the number of estimates produced in each chapter (e.g., two in vaccine intention and uptake; three in access; and five in utilisation), this simple method overweighs utilisation relative to the other stages. In the second scheme (EQZ2) I ascribe an overall weight of 1 to each chapter (e.g., access, utilisation, and vaccination). Each estimate score within these chapters is scaled accordingly (e.g., 1/3rd for each access estimate score, 1/5th for each utilisation estimate score, and ½ for each of the two vaccine estimate scores). This is a viable solution for a perspective of health system equality, but remains slightly out-of-sync with the overall framework of the thesis, which divides the healthcare process into 6 stages, 4 of which I investigate in this dissertation. The third possibility (EQZ3) separates vaccine intention and uptake, assigning weights of 1 to each while holding the weights of the access and utilisation constant from method 2. This method more closely follows the framework of Levesque et al, but heightens the value of vaccination due to its importance during the pandemic.[1] The fourth weighting scheme (EQZ4) aims to mirror the healthcare process as defined by Levesque et al, assigning a weighting of 1 to each stage. To this end, I assign a weighting of 1 to the vaccine intention estimate scores, where they are produced, accounting for the perception of need stage. Where countries are missing estimates (i.e., Ghana, Japan, and South Africa) an EQZ score of 0 is applied so as not to bias the results. I assign a value of 2/3rd to the access estimate scores, as these estimates account for both the seeking and reaching care stages. For the utilisation estimate scores, I assign a value of 1/6th to each of the utilisation chapter estimates. In addition, I assign a value of 1/6th to the vaccination estimate, as a component within broader health services utilisation. This process thus assigns a value of 1 to healthcare utilisation stage, and in so doing, evenly weights each of the four stages I assess in this thesis. I report EQZ4 indices produced using the final method mentioned above in the main body of work. The alternative methods are reproduced in table 8A.

E1 Table: Weighting allocations

	Weighting scheme			
Estimate	EQZ1	EQZ2	EQZ3	EQZ4
Vaccine intention	1	0.5	1	1
Access (x3)	1 x 3	1/3 x 3	1/3 x 3	2/3 x 3
Utilisation (x5)	1 x 5	1/5 x 5	1/5 x 5	1/6 x 5
Vaccine uptake	1	0.5	1	1/6 x 1
Vaccine trial (Ghana)	0	0	0	0
CANDOUR subset	0	0	0	0

Appendix: X – Co-author releases

Philip Clarke

Confirmation of Authorship and Permission to Reuse Published Material in Thesis

I, Prof Philip Clarke, confirm that Zachary Abel, authored and produced the relevant sections of the following publication(/s) and or submissions as lead author:

- Abel ZDV, Roope LSJ, Duch R, Clarke PM. Access to healthcare services during the COVID-19 pandemic: a cross-sectional analysis of income and user-access across 16 economically diverse countries. *BMC Public Health*. 2024;24(1):2678. doi:10.1186/s12889-024-20147-y *(Chapter 4)*
- Abel ZD, Roope LS, Duch R, Cole S, Clarke PM. Inequality in COVID-19 vaccine acceptance and uptake: A repeated cross-sectional analysis of COVID vaccine acceptance and uptake in 13 countries. *Health Policy*. 2025;153:105251. doi:10.1016/j.healthpol.2025.105251 *(Chapter 6)*
- Abel ZD, Roope LS, Erreygers G, Clarke PM. Moving beyond the average: A method to measure health related-inequalities within randomized trials. **First Submitted** February 2025. *(Chapter 7)*
- Abel ZD, Roope LS, Violato M, Clarke PM. Accuracy of online surveys in predicting COVID-19 uptake and demand: A cohort study investigating vaccine sentiments and switching in 13 countries from 2020-2022. **First Submitted** April 2025. *(Chapter 7)*

And that as a co-author, I did not provide more input or advice than would be considered appropriate or acceptable for a thesis.

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Name: Philip Clarke
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- Abel ZDV, Roope LSJ, Duch R, Clarke PM. Access to healthcare services during the COVID-19 pandemic: a cross-sectional analysis of income and user-access across 16 economically diverse countries. *BMC Public Health.* 2024;24(1):2678. doi:10.1186/s12889-024-20147-y *(Chapter 4)*
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- Abel ZD, Roope LS, Erreygers G, Clarke PM. Moving beyond the average: A method to measure health related-inequalities within randomized trials. **First Submitted** February 2025. *(Chapter 7)*
- Abel ZD, Roope LS, Violato M, Clarke PM. Accuracy of online surveys in predicting COVID-19 uptake and demand: A cohort study investigating vaccine sentiments and switching in 13 countries from 2020-2022. **First Submitted** April 2025. *(Chapter 7)*

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Name: ____Laurence Roope________________

Date: ____28/04/2025________________

Raymond Duch

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- Abel ZDV, Roope LSJ, Duch R, Clarke PM. Access to healthcare services during the COVID-19 pandemic: a cross-sectional analysis of income and user-access across 16 economically diverse countries. *BMC Public Health*. 2024;24(1):2678. doi:10.1186/s12889-024-20147-y *(Chapter 4)*
- Abel ZD, Roope LS, Duch R, Cole S, Clarke PM. Inequality in COVID-19 vaccine acceptance and uptake: A repeated cross-sectional analysis of COVID vaccine acceptance and uptake in 13 countries. *Health Policy*. 2025;153:105251. doi:10.1016/j.healthpol.2025.105251 *(Chapter 6)*

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Name: __Raymond Duch_______

Date: ____April 28, 2025______

Guido Erreygers

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- Abel ZD, Roope LS, Erreygers G, Clarke PM. Moving beyond the average: A method to measure health related-inequalities within randomized trials. **First Submitted** February 2025. *(Chapter 7)*

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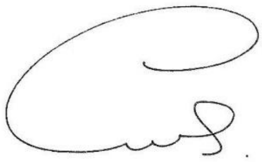

Signed:

Name: Guido Erreygers

Date: 28 April 2025

Mara Violato

Confirmation of Authorship and Permission to Reuse Published Material in Thesis

I, Mara Violato, confirm that Zachary Abel, authored and produced the relevant sections of the following publication(/s) and or submissions as lead author:

- Abel ZD, Roope LS, Violato M, Clarke PM. Accuracy of online surveys in predicting COVID-19 uptake and demand: A cohort study investigating vaccine sentiments and switching in 13 countries from 2020-2022. **First Submitted** April 2025. *(Chapter 7)*

And that as a co-author, I did not provide more input or advice than would be considered appropriate or acceptable for a thesis.

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Signed: Mara Violato

Name: Mara Violato

Date: 28/04/2025

Sophie Cole

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I, Sophie Cole, confirm that Zachary Abel, authored and produced the relevant sections of the following publication(/s) and or submissions as lead author:

- Abel ZD, Roope LS, Duch R, Cole S, Clarke PM. Inequality in COVID-19 vaccine acceptance and uptake: A repeated cross-sectional analysis of COVID vaccine acceptance and uptake in 13 countries. *Health Policy*. 2025;153:105251. doi:10.1016/j.healthpol.2025.105251 *(Chapter 6)*

And that as a co-author, I did not provide more input or advice than would be considered appropriate or acceptable for a thesis.

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Signed:

Name: Sophie Cole

Date: 28.04.2025

Appendix: Y – Survey instruments

CANDOUR wave 1

Link to CANDOUR wave 1 survey instrument, originally cited in https://www.pnas.org/doi/full/10.1073/pnas.2026382118:

https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/PMV0TG

File name: Qualtrics Vaccine Survey – UK – English.pdf

CANDOUR wave 2

Link to CANDOUR wave 2 survey instrument, originally cited in https://www.pnas.org/doi/10.1073/pnas.2405021122:

https://www.pnas.org/doi/10.1073/pnas.2405021122#supplementary-materials

Available in downloadable supporting information

File name: Appendix 01

Pages ixxi to ixxvii

Ghana Financial Incentives Trial

Link to Ghana Financial Incentives Trial survey instruments, originally cited in https://www.nature.com/articles/s41591-023-02670-4:

https://static-content.springer.com/esm/art%3A10.1038%2Fs41591-023-02670-4/MediaObjects/41591_2023_2670_MOESM1_ESM.pdf

Available pages 7-88

Appendix: Z – Data appendix

1.1.1 Sociodemographic variables

The following variables are used in descriptive statistics sections, and in some chapters are employed in the standardization process of the outcome variables, which aims to standardize variables for health need, and enable analysis having stripped out the effects of confounders.

The Dahlgren-Whitehead model of the determinants of health is used as a guideline to indicate factors that determine population health, and is augmented with updated perspectives from the original authors and guidance from the WHO.[275–277] The WHO categorises the determinants of health into three spheres; the social and economic environment, the physical environment, and individual characteristics and behaviours. The variables are captured in alphabetical order.

1.1.1.1 Age

Age plays an important role in the provision of, and need for healthcare services – based on how the human body responds to disease and illness.[278] The population is vulnerable to different diseases at different age groups. For example, the risk of chronic disease increases with age, those over 50 years are more likely to conduct screening checks for diseases, and the prevalence of venereal disease is expected to be highest between the ages of 16-35.[279–282] The needs of a retired individual are of course likely to be different to those of a university student, encompassing different lifestyles as well as different physical needs. Age is thus an important factor to consider. The age squared term is included to account for non-linearity in the demand placed on the health system. Age is self-reported in the CANDOUR survey, and is measured in years. *Used in chapter 4,5,6,7.*

1.1.1.2 Behavioural health risks (self-reported)

Respondents in the CANDOUR survey were asked how willing they were to take risks with their health, and to rate their willingness from 0-10, with 10 being very willing to take risks. Alongside self-reported COVID-19 risk, I use this variable to determine risk behaviours of individuals relating to health, and their willingness to seek out medical treatment and care. I propose that those more willing to take risks are likely to have a higher barrier for seeking medical care.[283] *Used in chapter 4.*

1.1.1.3 Chronic conditions

Diseases are generally accepted to be chronic if they remain for over a year and require ongoing treatment.[284] In some cases, managing chronic diseases may require additional touchpoints with the health system, increasing the health needs of individuals who suffer from chronic illness. The onset of chronic disease is related to several other social determinants of health,[285] and must therefore be included in the standardization. In the CANDOUR survey, respondents were asked if they had any of the following underlying health conditions; diabetes, hypertension, heart disease, asthma or chronic respiratory issues, allergies, kidney disease, or other chronic illnesses requiring long term care. The number of chronic illnesses selected by the respondent was used as the chronic conditions variable (ranging from 0 to 7). *Used in chapter 4,5,7.*

1.1.1.4 Chronic disease presence

A binary indicator of chronic disease is also employed. The indicator and takes on a value of 1 if a respondent has any chronic diseases (i.e., if the variable above has a value greater than 0). *Used in chapter 6.*

1.1.1.5 Chronic medication recipient

Having already included the number of chronic conditions of respondents as a confounding variable of health need, I include dependence on chronic medications as a control variable. In certain settings, prescription fulfilment may require additional contact with the healthcare system, which I wish to control for in this analysis. Respondents were asked if they regularly took medication for any health conditions in the CANDOUR survey. *Used in chapter 4.*

1.1.1.6 COVID-19 risk (self-reported)

Respondents in the CANDOUR survey were asked how likely they were to catch COVID-19 within the next year, and asked to score the likelihood between 0 and 100. I use this variable as an indicator of respondent's engagement with the health system at large, and their likelihood to seek out medical attention and care. *Used in chapter 4.*

1.1.1.7 Education level

Education is one of the compelling social determinants of health, with established links to a number of other social and economic determinants such as social groupings, income, employment opportunities, and healthy ageing itself.[286] Several studies link higher educational attainment to better health outcomes.[287–289] Given its links to other determinants of health, it is important to include in the analysis. In the CANDOUR survey, education level is self-reported as the highest degree or level of education completed. The options range from no formal education, nursery to 8th grade, high school, and various degree levels (associate to doctoral), with intermediate steps (i.e., some high school). The values are recoded into four ordinal categories - less than primary completed; completed primary; completed secondary; completed university. *Used in chapter 4,5,6,7.*

In the Ghana financial incentives trial, education is recorded differently.

Respondents were asked the highest educational qualification they had achieved. If respondents had never been to school, they were coded as "No schooling." Responses of Nursery and Kindergarten were coded as "Pre-school." Responses of primary were coded as "primary." Responses of JSS, JHS, and Middle were coded as "JSS," referring to junior secondary school in the Ghanaian education system. Responses of SSS and SHS were coded as "Secondary," referring to senior secondary school. Levels above, including vocational / technical / commercial, post middle / secondary certificate, post-secondary diploma, bachelor degree, and post graduate qualifications were coded as "Tertiary education." *Used in chapter 7.*

1.1.1.8 Health level (self-reported)

Self-reported health is used as a measure of general wellbeing, taken from the EQ-5D-5L questionnaire. Health is reported from 0-100, with 100 being perfect health. The EQ-5D-5L question-set was not utilised in full, as many of the countries included in the analysis do not currently have EQ-5D-5L value sets which are required to compute a comprehensive health value from the inputted questions. While an international value set could be used, this may have the effect of artificially smoothing relative health differences across countries and blunting the desired cross-country analysis. *Used in chapter 4,5,6.*

1.1.1.9 Gender

Gender affects health needs through biological, social and economic determinants of health. Biological sex impacts the health needs of an individual. There are differences in the biological determinants of health by sex; including genetic vulnerability, hormonal and reproductive elements, and physiological characteristics during the life cycle. For example, the likelihood of a biological woman requiring reproductive healthcare services greatly exceed that of a biological man. A number of studies show differential nutritional status by gender,[290] which necessarily impacts development and health status later in life. Economic elements include the economic roles genders take on and how this may affect the health-seeking behaviours of genders.[280] Gender was self-reported, with options male, female, other, and prefer not to say included as options in the survey. *Used in chapter 4,5,6,7.*

1.1.1.10 Household size

During the COVID-19 pandemic, household size was shown to be a significant factor in transmission of the infectious disease.[291] It stands to reason that larger households have an increased number of potential vectors for infectious diseases. However, severity of the disease was higher when living alone or with three or more individuals compared to two person dwellings.[292] Those living alone were less likely to experience non-severe COVID than those living in two-person households.[292] Larger households have been associated with lower consumption of medical care,[293] however this may be due to confounding with socioeconomic status and the substitution of medical care with home healthcare. Respondents were asked how many adults lived in their household in the CANDOUR survey. The household size variable was truncated at a maximum of 8, resulting in the truncation of 295 households, representing 1.3% of the dataset. *Used in chapter 4,5,6,7.*

In the financial incentives study in Ghana, household size is taken as the total number of household inhabitants. This is disaggregated into adults and children. *Used in chapter 7.*

1.1.1.11 Labour force participation and economic activity

Health is positively correlated with labour force participation; one needs to be well to work. Labour force participation has been shown to have a negative effect on male health but a positive effect on female health.[294] Given the correlation between labour force participation and socioeconomic status, I control for the variable. I also introduce the variable as quantity of available leisure time is likely to influence subjectivity selecting the degree of challenge faced in accessing care. Respondents were asked if they had worked in the week prior to completing the survey. If they had not worked, respondents were asked why. The labour force is defined as those employed or unemployed and of working age who are working or actively seeking work.[295] Individuals who were in active employment and those who gave the following reasons for not working in the prior week were included in the labour force; ill with COVID-19 symptoms; ill during the past week; recently made redundant; employer closed temporarily; employer closed permanently; could not arrange transport to place of employment. I determined that answering with these options did not make respondents economically inactive, marking them for exclusion from the labour force. Respondents who gave the following reasons for not working in the prior week were marked as economically inactive and excluded from the labour force; did not want to work at present, currently caring for children or the elderly; retired; afraid of the spread of COVID-19; other. The labour force participation variable was dichotomized on the above basis between economically active and economically inactive individuals. *Used in chapter 4,5,6,7.*

In the Ghana financial incentives study, possible occupation responses were full-time employment, part-time employment, home maker, retired, student, or unemployed. *Used in chapter 7.*

1.1.1.12 Marital status and living arrangements

Marital status has been shown to have an impact on health levels in numerous studies.[296] Results have shown that being unmarried generally leads to greater increases in mortality and disease for men than for women,[297] though incidence is greater for both sexes than unmarried counterparts. It is proposed that the decreased incidence associated with marriage is caused by the prevention of certain activities which lead to lifestyle diseases.[298] Further, certain research suggests that those in ill-health have more difficulty finding a partner and marrying; thereby identifying and selecting the married group for good health.[298] Respondents were asked if they were married, in a civil partnership, or living with their partner – all of which are associated with similar health benefits in the literature.[299] *Used in chapter 4,5,6,7.*

1.1.1.13 Political ideology

Research has shown that conservative societies are less likely to report poor health than left-wing counterparts.[300–302] Individually, those who identified more with the right politically were also less likely to report poor health.[300] It is unlikely that it is political ideology itself that determines health outcomes, but more likely that it is a proxy for certain attitudes and latent beliefs which impact health outcomes, or perceived health levels. In the CANDOUR survey, respondents were asked to rate their political ideology from 0 to 10, with 0 being left and 10 being right. In certain countries, this question was excluded from the survey due to the political climate. *Used in chapter 4,5,6,7.*

1.1.2 Variables used for sensitivity analysis and validation

These variables are included either as aggregate measures to be used in analysis, as variables used in sensitivity analyses, or as variables used to validate CANDOUR data using a secondary source.

1.1.2.1 Age (median, external)

At the onset of the COVID-19 pandemic, advanced age was cited as a cause of severe COVID-19.[303] Using the CIA World Factbook data,[304] I propose national median age as an alternative explanatory variable that may be linked to systematic inequality in the sensitivity analysis. Median age is taken simply as the median age within each specified country, with the last reported year 2021. *Used in chapter 4.*

1.1.2.2 Consumption data (external, median)

Median annual consumption is an external measure of a median socioeconomic status. The variable is transformed from median daily consumption/income per country, and annualised. The variable is included to determine the validity of the constructed median household income figure in the data when compared to an external source. The values were produced in 2019, however more recent values were not available at the time of analysis.[305] *Used in chapter 4*

1.1.2.3 Corruption index

Corruption plays a larger role in healthcare provision than many would like to admit.[306] Globally, healthcare sectors have been identified as having high levels of corruption,[307] while 33% of OECD citizens and 45% of citizens worldwide characterise the healthcare sector as corrupt.[308] It is possible that corruption in the health sector impedes access to care, and as such, I include it as a possible alternative measure. I use Transparency International's Corruption Perception Index.[309] The index combines data from several sources to build out the index, which measures elements of bribery, diversion of public funds, state capture, integrity, red tape and bureaucratic burdens, nepotism, criminal prosecution of corrupt officials, use of public office for private gain, financial disclosure laws, protections for whistle-blowers, and access to information. *Used in chapter 4.*

1.1.2.4 COVID-19 response (government)

Government responses to the COVID-19 pandemic included a range of measures to combat the spread of COVID-19. Oxford's Blavatnik School of Government developed a COVID-19 Government Response tracker.[230] The dataset builds four indices encompassing various government response measures and rates the government response across the measures, producing a single index. The produced indices are a containment and health index; an economic support index; a stringency index; and an overall government support index. For the purposes of the sensitivity analysis, I use the mean containment index, which details 14 response measures. The closure and containment measures included are school closure policy; workplace closure policy; public event policy; gathering restrictions policy; public transport policy; stay at home policy; internal movement restrictions; and international travel controls. The health policy measures included are the presence of public information campaigns; access to testing and testing policy; policy on contact tracing; facial covering policy; vaccination policy; and policies on the protection of the elderly. Using this combined index as a measure of Government's COVID-19 response through a health and containment lens, I feel it acts as a viable possibility of an alternative measure which could explain observed inequality between countries in the sensitivity analysis. *Used in chapter 4.*

1.1.2.5 Health expenditure per capita (2019, national)

As an alternative to median household income, I offer national per capita health spending, available as one of the World Bank's World Development indicators.[310] The most recent year available for all included countries is 2019. Previous research has found that health expenditure are linked to inequality and socioeconomic development,[311] validating its inclusion as an alternative explanatory variable for testing in a sensitivity analysis. *Used in chapter 4.*

1.1.2.6 *Income per capita (gross national)*

I use Gross National Income per capita as a secondary measure to test external validity of the income measure. I test both GNI per capita using 2017 constant prices and current prices, both in purchase power parity dollars.[312] However, as GNI per capita is a mean value, it is less of interest than the median figures. Given, however, the age of the median figures, I use GNI per capita as a test against the mean figures in an attempt to triangulate the income based sampling in the sample. *Used in chapter 4.*

1.1.2.7 *Internet access*

Specifically in the digital health channel, however perhaps more broadly, access to the internet is known to be an important marker in accessing care.[313] To measure internet access, I use the International Telecommunications Union's digital dashboard.[314] I use the % of individuals with access to internet within a country as a metric for overall internet access. *Used in chapter 4.*

1.1.2.8 *Medical practitioner density*

The supply of healthcare professionals is necessarily a factor in the availability of appointments, and thus potentially related to the ease with which individuals can access health systems and consume healthcare.[315] I propose the density of medical practitioners as a potential alternative correlate for inequality in access to care. The variable is taken as the total number of medical practitioners per 10,000 people in a country. Data availability limited the disaggregation of medical practitioners into generalists and specialists. The most recent available data for the selected countries were between 2019 and 2021, accessed via the WHO's National Health Workforce Accounts data portal.[316] To reach a common year, 2020 was taken. Countries missing 2020 data, but with 2019 and 2021 data were averaged across the two years. *Used in chapter 4.*

1.1.2.9 Region

Countries are allocated to continental groups for regional and geographic analyses. Groups used are Africa (Ghana, South Africa, Uganda); Australasia (Australia, China, India, Japan); Europe (France, Italy, Spain, United Kingdom); North America (United States of America, Canada); South America (Brazil, Chile, Colombia). *Used in chapter 4.*

1.1.2.10 World Bank country and lending groups

Countries are allocated to World Bank Income groups based on the World Bank Atlas Method.[312] Countries are considered low income if Gross National Income (GNI) per capita is below $1,135; lower middle-income if GNI per capita is between $1,136 – $4,465; upper middle-income if GNI per capita is between $4,466 and $13,845; and higher income if GNI per capita exceeds $13,845. External allocation to groups is used, rather than allocating based on sample metrics. Countries are allocated as follows: Low – Uganda. Lower middle – Ghana, India; upper middle – Brazil, China, Colombia, South Africa; High – Australia, Canada, Chile, France, Italy, Japan, Spain, United Kingdom, United States of America. *Used in chapter 4.*