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Essays on Health-related Disparities

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"*Health equity is most certainly not just about the distribution of health, not to mention the even narrower focus on the distribution of health care. Indeed, health equity as a consideration has an enormously wide reach and relevance.* "

Amartya Sen, 2001

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Abstract

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Doctor of Philosophy

Essays on Health-related Disparities

by Yuxi WANG

As the most critical conditions of human life and a significant contributor to human capability, health is the fundamental unit for a functioning society. As a construct, health is also inherently multi-dimensional, and to understand and to evaluate whether the infrastructure of a society endows fair "health opportunities" to its people can be an enduring task for both researchers and policy-makers. In this dissertation, I explore this complex and ever more relevant issue of health disparity from different angles using administrative data and extensive exploration of the literature. In particular, I analyse the geographic disparity in quality of care and the potential drivers - differential provider behaviour. Looking at health status, I investigate the disparity of health outcomes due to external economic shocks and found that individuals from economically disadvantaged areas exhibit significantly worse mental health conditions. Given the geographic disparity, I further examine how different sources of information on provider quality affect patient choice and decision to travel for care. Moreover, I survey on how the internet has facilitated the disparity in information and diverging opinions on health. Finally, from a systems perspective, I scrutinise structural characteristics in health care system design that create disparities in benefits and access. My inquiry into the complex phenomenon of health disparity presents a humble contribution to the exiting literature at the intersection of health economics, medical sociology and social epidemiology.

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Preface

0.1 Introduction

As the most critical conditions of human life and a significant contributor to human capability, health is the fundamental unit for a functioning society. As a construct, health is also inherently multidimensional, and to understand and to evaluate whether the infrastructure of a society endows fair "health opportunities" to its people can be an enduring task. No discipline alone can understand it fully.

It is perhaps cliché to argue that health has a social dimension, as the literature on social determinants of health is well-established and spans multiple disciplinary interests. Nevertheless, in the discussion of social equity and justice in the contemporary world we live in, there is increasing sentiments of discontent, of hostility and of grievance against the enlarging gaps across populations, be it in income, in political rights, or in health. Equality, as an abstract idea, does not render adequate practical interpretation, while the real question is what exactly needs to be equalised. We can relentlessly describe the differences in health and healthcare across many groups of people, but to measure and evaluate what is potentially unjust is, however, a normative question. As social scientists, we are bestowed the privilege and responsibility to make sense of this question. This dissertation will embark on evaluating the state of health disparity from various angles through extensive analysis of empirical data and of existing literature, with specific sets of value judgments in mind.

0.1.1 Some Fundamental Issues

The Multi-dimensionality of Health Equity and Disparity

Suppose we trace back to the earliest debates regarding equality. In that case, we may find Aristotle, in his verse on *Politics*, contending that "all men think justice to be a sort of equality ... However, there remains a question: equality or inequality of what?" [1]. Indeed, the real challenge lies in the specification on what "should" be equalised. This problem conveniently makes the first conceptual distinction between equity and equality, which are almost always homonyms. I argue that equality is intrinsically a descriptive term of facts, while equity statements carry normative values. To be specific, the measurement of inequality usually involves value judgments, primarily in deciding which sets of information to emphasise. In contrast, the mere fact that there is inequality is not a normative statement. Hence, to have an explicitly egalitarian goal in the context of health requires segregating the notion 'health' into different compartments and observing whether the outcomes are consistent with equity.

The most widely-used definition of health disparity is by Whitehead [2]: "the term 'inequity' has a moral and ethical dimension. It refers to differences which are unnecessary and avoidable but are also considered unfair and unjust." If we consider a series of injustices in the broader health realm, we should first make the distinction between say, health needs and achievements, and the facilities offered to meet these demands, and by which I not only mean the provision of health care. For instance, we can reasonably assume that there is a positive relationship between the supply of health care and the socioeconomic condition. If so, when we observe an unequal distribution of healthcare delivery or financing, how exactly do we attribute these differences?

From the perspective of individuals, we can consider genetic propensities, socioeconomic backgrounds, demographics or even culture to have potential influences on one's health achievements. Braveman [3] argues that "health disparities adversely affect groups of people who have systematically experienced greater social or economic obstacles to health based on their racial or ethnic group, religion, socioeconomic status, gender, mental health, cognitive, sensory, or physical disability, sexual orientation, geographic location, or other characteristics historically linked to discrimination or exclusion". Sociologists have long been interested in the influence of social realities on individual or group behaviours, as well as social structures caused by an awareness of this influence [4]. When we talk about health, wellbeing and longevity, the social context of individuals is crucial in determining the risk of exposure, susceptibility, and the course and outcome of a health abnormality, be it infectious, metabolic, genetic, malignant, degenerative or mental [5]. As Sir Michael Marmot extensively discussed in the literature of the social determinants of health, the debates on health equity and disparity need to extend beyond the delivery and distribution of health care [6]. Historian Roy Porter argued that medicine has to consider the broader perspective that includes one's living conditions, lifestyle, diet, work situations, education and family structure in dealing with the challenges to the health of the "whole" person that is outside the doctor's office in the real world [7]. Moreover, there is a strong preference and behavioural component that rely heavily on the informational intake of the individuals. That said, even the supply of different forms of communication may contribute to the disparity in access and ability to process information. All these elements simultaneously affect the process and procedural fairness of what we claim as health outcomes or status. Health equity, therefore, cannot be concerned only with health, seen in isolation. Instead, it must come to grips with the broader issue of justice in social arrangements, paying appropriate attention to the role of health in human life and opportunity.

The recognition of the linkage between social environment and health led to the burgeoning literature, which focuses on the social causes of health disparities, the social function of health care providers, the social organisation and delivery of health care services, and health policy and its politics [4]. Health care provision is itself a complex of services that centre around the physician, hospital, public health and many other entities in the society. The "norm" that the economist usually uses to analyse the market is the operation of a 'competitive model' – the flow of services that would be offered and purchased and the prices that would be paid for them, with no imposed restrictions on supply or demand [8]. However, as famously noted by Kenneth Arrow, the competitive health care markets tend to generate inefficient allocation of resources and contribute to the emergence of non-market institutions (e.g. trust) that compensate for these market failures [8]. The debates on the roles of market and non-market institutions in health care provision and financing have since dominated the discussions on the design of health care systems. Yet a more relevant empirical question is - when do we deem the health care infrastructure unfair and what are the causes? For instance, why can someone be denied care or received inferior treatment just because of one's geographic location? Why are certain disadvantaged social groups perpetually worse off in their health status? All these complex problems beg answers that I hope to (partially) address in this dissertation.

Health Equity in Welfare Theories

Before diving into the motivation of this thesis, I want to retract and briefly discuss the concept of 'equity' as one of the *desiderata* in health goals.

Within the economic tradition, there has been a strong emphasis on utilitarianism, à la Mill, that is "the greatest happiness for the greatest number of people". If we pursue the definition of equity in utilitarian terms, a distribution that contributes to the greatest utility for the greatest amount of people would be equitable if we maximise the aggregate utility. However, it is easy to illustrate why such distribution is not desirable. If we consider two individuals who derive the same utility from health, but their health states respond differently to a certain level of care due to their socioeconomic backgrounds – the more affluent person will be healed more quickly than the poor [9]. Suppose we follow the logic of the utilitarianism, in the scenario when both individuals are equally ill. In that case, the best redistribution will be to allocate more care to the rich so that the aggregated utility is the highest. Moreover, there is a reasonable upper bound for how healthy a person can be. It comes to no surprise that other theorists have severely criticised the utilitarianism as "supremely unconcerned with the interpersonal distribution of that sum" [10].

Rawls' seminal work on social justice, or more specifically "distributive justice", purports that "social and economic inequalities are to be arranged so that they are both: (a) to the greatest benefit of the least advantaged, . . . , and (b) attached to offices and positions open to all under conditions of fair equality of opportunity [11]". This *maximin* or *difference principle* would then operate in favour of the least advantaged – equitable distribution of health or health care is the maximisation of the welfare of those with the least. Rawls emphasises that primary goods, such as income and wealth, should be allocated so that the 'opportunities' of the worse-off in the society are maximized [11]. Egalitarian distribution of resources for essentials of life can be achieved by navigating under a "veil of ignorance" about whether individuals had been born into privileged or disadvantaged households.

This perspective, therefore, requires that provision of health care to be meeting the health needs, and some of the most critical policy issues in the promotion of health care are deeply dependent upon resource allocation to health. In the literature, equity in the delivery of health care encompasses horizontal equity and vertical equity principles. The horizontal equity demands that the same treatments are provided for the same need, while the vertical equity principle requires that different needs receive appropriate different treatments [12]. Inevitably, the strong value judgment is placed on the question of 'who has a greater need?'. As discussed above, defining 'need' for health care is already a challenging task. If we correspond the need with potential for improved health or capacity to benefit, we go back to the initial utilitarianist argument, while if we equate need with the severity of the disease, we find ourselves dealing with the *maximin* principle by Rawls. Practically, an egalitarian goal for a health care system would ensure that health care to be distributed according to the need and financed according to the ability to pay. If we apply the vertical equity principle also on the financing of the health care system, then we are also implying a higher contribution from those with a greater ability to pay.

Rawls further argued that individuals are autonomous moral agents and should, therefore, be responsible for their preferences for a good life [11]. I share similar values with Rawls in that all individuals should have the same opportunity to achieve their potential health outcomes through equally distributed access to care among those with the same health need. However, this theoretical construct also runs into some flaws. If a person that is among the least well-off happens to be the voluntary perpetrator of such destitute condition, is it more equitable to allocate more resources to the most deprived than those who are slightly better off but strives to improve one's situation? For another, a person who is least well-off in health can be endowed with advantages in almost all other dimensions in terms of primary goods. So the multi-dimensionality of the redistributive issue is necessarily complicating the judgment on health equity. This "preference approach" was consequently criticised by scholars such as Cohen [13] and Roemer [14], who believe that preferences are derived from one's upbringing and social influences, of which is beyond one's control. In other words, individuals do not invest equal levels of efforts in the production of their health [14]. The distinction between health endowments and how they are transformed into health status is not addressed sufficiently in Rawls' preference approach. This issue brings us to the discussion on individual choices and behavioural pathways in health.

Sen [15] and Fleurbaey [16] view that individuals should be put in good conditions of autonomy and freedom so that they can be the master of their lives and participate in social interactions. Sen argues that, in a broader context, human development should be measured not only in economic terms but in terms of human capability to freely pursue a quality of life, with health being one of the best indicators of that capability [15]. Sen's theories of freedom and capabilities are hugely influential among the literature that investigates the pathway of health disparity. The relative lack of control and powerlessness can be the fundamental causes of the socioeconomic inequalities in health that we observe. Sir Marmot, in the book *The Status Syndrome*, contends that "for people above a threshold of material wellbeing, another kind of wellbeing is central – autonomy – how much control you have over your life – and the opportunities you have for full social engagement and participation are crucial for health, wellbeing and longevity. It is inequality in these that plays a big part in producing the social gradient" [17]. However, the question then arises how to achieve equal autonomy and control over life - theoretically, we would have individuals correcting for inter-individual differences in the social environment (e.g. health resources) and also adjusting differences in the choice-making abilities (e.g. cognitive skills). How do we make the cut-off point meaningful without challenging the fundamental idea that individuals are responsible agents and exercise some degrees of free will? I do not have a definite answer to this metaphysical issue, but I believe in an adequate institutional structure that facilitates a minimum level of consciousness and responsibility. Sen [18] and Deaton [19] argue that process equity is about procedural fairness (e.g. health care access, delivery, information availability), which is of equal but separate moral importance than outcome equity. Precisely because health outcomes are considered multidimensional, it would be ideal to guarantee a specific range of 'open opportunity' to all through equitable delivery of care. As far as my thesis is concerned, it is crucial to understand that we are dwelling on not only the distribution of health outcomes and status but also the "history' or pathway through which individuals experienced.

0.2 Motivations and Objectives

Although providing basic value judgments is primarily the job of the philosophers, an assessment on the social arrangement or economic situation is contingent upon empirical observations. The exercise, therefore, requires a more concrete examination on the various dimensions of health disparity.

The empirical literature has examined extensively the measurement of inequality, through concentration index, factor decomposition or other calculations of health-related fairness. Most of the studies in this stream have used survey data and therefore, subjective health measures. There are numerous ways with which we can argue why survey data is constructive in the analysis of individual characteristics and health care need. However, I am more inclined to rely on more objective measures of health and health care utilisation in this dissertation, given the potential problems of reporting error due to cultural differences, expectations, or various distorted incentives.

In this dissertation, I explore the issue of health disparity from two broad angles that are related to the previous theoretical discussion – micro-level demand for care and meso-level provisions of care, represented in diagram 1. From the individuals' point of view, on the one hand, socioeconomic, demographic, cultural and hereditary factors are what we call the determinants that are likely to be beyond one's control, and on the other hand, choices in circumstances that contribute to one's health-related behaviours and perceptions. I depart from Rawls' and Sen's proposals that primary goods and capabilities should be equalised so that any residual inequality is deemed a legitimate result of individual choice or responsibility. The practical problem then

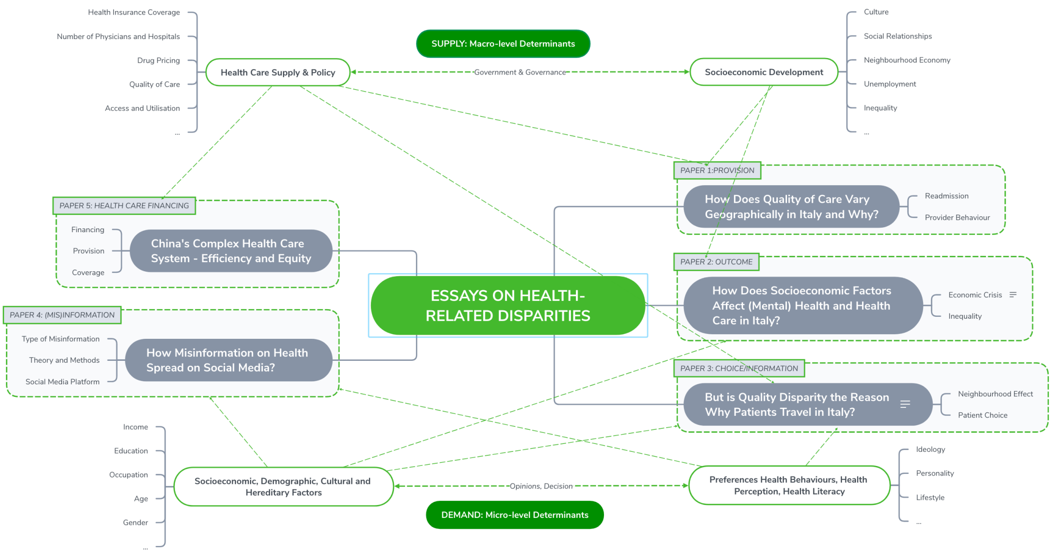


FIGURE 1: Linking the Chapters

becomes how to arrive at a distribution of resources that appropriately compensates individuals for their dissimilar endowments while making them responsible for their preferences and choices [20]. The theoretical, analytical framework would involve a complex structural model that incorporates simultaneously the demand for health, behaviour or lifestyle, and health care, labour supply, and income distribution [21]. Given the complexity and multi-dimensionality of the topic, empirically, it is impossible to have a holistic picture of the issue. Therefore, I look at segments of the overall inter-connected picture. Below I briefly explain the rationales and objectives of each chapter of this thesis.

0.2.1 Objectives

As seen in the diagram 1, the thesis is divided into five broad chapters. Overall, we want to observe, from the provision side, whether there is a spatial disparity in quality of care and what are the drivers (Chapter 1), as well as the structural characteristics in health care system financing that may systematically create a disparity in health care benefits and access (Chapter 5); from the individual or patient side, we want to understand how economic shocks and neighbourhood factors can contribute to the potential disparity in mental health outcomes (Chapter 2), whether the quality disparity or other types of information affect patients' choice of care (Chapter 3), and finally, whether the internet has facilitated the disparity in information and diverging opinions on health (Chapter 4). At first, the different topics seem somewhat non-linear and distant from each other. However, I will demonstrate now that they all relate to the initial discussions on health disparity.

Chapter 1 investigates the geographic disparity in health care quality by focusing on one interesting measurement – unplanned hospital readmission, and for a specific population – the elderly. The issue is related to the horizontal equity in health care delivery that I discussed in the earlier section. Equal care for equal need implies that, if we are looking at one vulnerable segment of the population, and we tease out the factors that are beyond one's control, the provision of care should ensure equal opportunity of being well-treated. In this chapter, I focus on the potential disparity in quality of care through differing provider behaviour in Italy. This chapter is written in collaboration with Simone Ghislandi and Aleksandra Torbica, and the publication can be found here.

Chapter 2 examines the causal effects of the economic crisis on the mental health outcomes of the population. We are particularly drawn to the potential heterogeneous effect across geographic areas characterised by different economic conditions. The issue is closely related to the concept of vertical equity, as an exogenous shock may disproportionately make a particular population worse off and therefore demands a greater need for care. If this is true, the reallocation of health care resources is required to protect those who are more vulnerable. In this chapter, I assess whether there are differential effects of the crisis on severe mental disorder admissions in Italy. This chapter is written in collaboration with Giovanni Fattore, and the publication can be found here

Chapter 3 looks at how individuals respond to the potentially inequitable health care provision – is patient mobility driven by real quality disparity or by word-of-mouth? The issue hinges on the inequality of (perceived) "opportunity" - conditional on that there are quality discrepancies across geographic areas (as discussed in Chapter 1), people react to such disparity by travelling for care given free patient choices. However, the long-term consequence of excessive patient travels may exacerbate the unsustainability of certain regions' health care system. This chapter, therefore, tries to understand whether the hospital choices of the patients are justified by the quality difference or are a mere reflection of the sociality influences in Italy. This chapter is written in collaboration with Anna-Theresa Renner.

Chapter 4 incorporates a new digital dimension and reviews the scope of misinformation spread that could have contributed to the diverging opinions about various health-related topics. The issue is linked to the concept of capability and information intake, where individuals are endowed with the freedom to express or absorb opinions on a platform that is not backed by scientific evidence filtering. If the spread of information about valid health leads to, for example, an increase in life expectancy but at the same time growing opinion disparity due to different cognitive capacities in processing information and misinformation, such trade-off needs to be examined. This chapter, therefore, reviews the literature that examined how misinformation spread on social media. This chapter is written in collaboration with Martin McKee, Aleksandra Torbica and David Stuckler, and the publication can be found here.

Chapter 5 focuses on the equity dimension of one of the most complex and ever-changing health care system's structural design. The focus is on the sub-functions of revenue collection, financing, and purchasing variability across different population groups. The issue of equity in financing, access and efficiency is examined through a systematic analysis (using the WHO framework) of the differential benefit packages, co-payment schemes and infrastructure across types of residence and geographies. This chapter presents a comprehensive and diagrammatical overview of the current state of the health care system design in China. This chapter is written in collaboration with Adriana Castelli, Qi Cao and Dan Liu, and the publication can be found here.

Chapter 1

How Does Quality of Care Vary Across Geography?

Abstract
Unwarranted variation in the quality of care challenges the sustainability of healthcare systems. Especially in decentralised healthcare systems, it is crucial to understand the drivers behind regional differences in hospital qualities such as unplanned readmissions. This paper examines the factors that influence the risk of unplanned hospital readmission and the geographic disparity of readmission rate in Italy. We use hospital discharge data from 2010 to 2015 for patients above 65 years old admitted with Acute Myocardial Infarction. Employing hierarchical models, we identified the patient and hospital-level determinants for unplanned readmission. In line with the literature, the risk of readmission increases with age and being male, while hospitals with higher patient volume and capacity tend to have lower unplanned readmission. In particular, we find that after patient risk-adjustments, there are differential effects of hospitalisation length-of-stay on the probability of readmission across the hospitals that are governed by different payment systems. For hospitals under a prospective payment system, the effect of length-of-stay in reducing the probability of readmission is weaker than hospitals under an ex-post global budget, but the overall readmission rates are the lowest. Moreover, there are substantial geographic variations in readmission rate across Local Health Authority and regions, and these variations of unplanned readmission are explained by differences in hospital length-of-stay and surgical procedures used. Our results demonstrate that differential hospital behaviours can be one of the potential mechanisms that drive geographic quality disparities.

1.1 Introduction

In recent decades, welfare states are increasingly faced with significant challenges of keeping health expenditures under control while increasing the quality of the healthcare system. As a result, several countries have implemented healthcare reforms to increase decentralisation [22–26], to contain cost [27, 28], to favour patient choice and competition [29, 30], and to focus on measuring performance [31–33]. Institutions and health systems at various levels adopted different forms of governance strategies. However, the responsibility endowed at the sub-nation level and the quasi-market mechanism can potentially generate undesirable regional disparities in healthcare quality. As a result, an increasing body of literature has investigated the geographic variation in healthcare reimbursement and utilisation [34], hospital performance [35–37], and various other health outcome indicators [38, 39].

The challenge of quality variation is especially salient in Italy. The country is not only characterised by a persistent regional economic divide between the North and the South, several regions that accumulated a large amount of fiscal deficit during the financial crisis had to adopt strict cost-containing measures to control for their financial problems [40]. The tightened budget imperatives in a decentralised system may, in turn, widen the differences in healthcare access, quality of care and overall health outcomes across regions. This fiscal burden can be further exacerbated by an ageing population, where a rise in healthcare expenditure is imminent. As the welfare state assumes a fundamental role in providing an equitable distribution of healthcare resources [41], considerable variation in the provision and the quality of care can be of grave concern. In this article, we aim to explore the determinants and the geographic variation of one important healthcare quality indicator — unplanned readmission — among the elderly population.

Unplanned readmission rate is considered an intricate quality indicator for hospitals and can be alarming for cost-conscious healthcare systems [42]. Unplanned readmission not only incurs unnecessary opportunity costs for the provider but also generates distress among patients, especially for frail elderly patients. Although there is extensive literature on the marginal effect of certain patient factors on unplanned readmission, very few studies have examined the hospital level factors and how they can explain the geographic disparities in quality of care. As systematic geographic differences in readmission rate can be alarming for the healthcare system, insights into the various determinants of unplanned hospital readmission and its variation are warranted.

The paper is structured as follows. We first justify our motivation by reviewing the related literature and the institutional background of the Italian National Health System. We then explain the method and the data used for the empirical analysis. Finally, the results highlight the geographic disparity of quality of care and potential drivers.

1.1.1 Related Literature

The conception of horizontal equity in health policy concerns the idealised scenario of equal treatment for equal need, or equality of access [43]. Inevitably, health and healthcare are unequally distributed across different segments of the populations, but not all health-related inequalities are *per se* inequitable [44]. Specific determinants such as demographic or hereditary factors may have differential marginal effects on health outcomes, but they do not contribute to inequity of health but instead represent the differential needs for healthcare. Since the provision of healthcare is generally considered to be a resource to meet these needs, the unequal distribution of access and quality of care across patients with the similar morbidity but seek care in different geographic areas militates against the notions of horizontal equity [44]. Factors that contribute to such inequality can be related to macro-level socioeconomic factors, provider behaviour, or lack of information on local needs that inadvertently harm a specific part of the population, causing an overall loss in welfare. As high and equitable quality of care is one of the core goals of most National Health Systems, a close examination of the unwarranted variation is needed when economic constraints become ever more salient.

In evaluating the quality of care and hospital performance, the literature has primarily focused on two main indicators - 30 days mortality and readmission [45, 46]. While findings on mortality tend to be relatively consistent, the results on unplanned readmission, defined as rehospitalisation within 30 days from a previous discharge, and its determinants remain inconclusive. The most widely investigated factors related to unplanned readmission at the patient level include the hospitalisation length-of-stay (LOS) and individual characteristics such as disease profile, age, gender and education [28, 47]. The impact of LOS on the probability of readmission has mixed results, with some studies demonstrating a strong negative effect[48–51] and other findings have shown otherwise [52, 53]. Overall, LOS not only reflects patients' clinical and demographic characteristics but also represents provider behaviour. Therefore, a positive relationship between risk-adjusted LOS and readmission implies that hospitals may have discharged patients prematurely that resulted in readmission, while a negative relationship means initial hospital stays reduced the risk of readmission [52]. The intricate relationship was further investigated by Carey [54], who demonstrated the trade-off effects between longer LOS and the expected cost of readmission for providers. The association between readmission and cost is also explored by various researchers [46, 55, 56]. However, we do not observe systematic patterns, and the differences of results may be attributed to contextual, disease area and timing differences. Research on the associations between hospital-level practices and readmission rate also highlighted the importance of organisational factors such as primary care pathways and surgical procedures used [57, 58].

While understanding the marginal effect of the individual and hospital determinants on readmission is crucial, examining how variations in these factors may explain the geographic inequality in readmission underlines whether such disparity reflects the heterogeneity in the needs of patients, or the provider and general healthcare delivery differences. We, therefore, connect the broader literature that investigates the variation of distinct dimensions of health and healthcare. Inter-regional disparities in resource allocation and efficiency of care are generally considered to be one of the main drivers of variation in the different dimensions of healthcare [59]. Some recent researches have looked at the variation in health and wellbeing indicators [60–62]; others have quantified the inter-regional variation in healthcare delivery and hospital performances [35–39]. The findings stress the importance of both patient and hospital factors variations in explaining the geographic difference in health-related outcomes.

This paper departs from these streams of literature and focuses on both the marginal effects of different determinants of unplanned readmission and the geographic disparity of this quality indicator. To our knowledge, this is the first investigation on how geographic variations of the patient and hospital factors are related the geographic disparities in quality of care in the Italian context. The findings have profound implications for the design of hospital incentive structures and the future resource allocation in the decentralised healthcare system.

1.1.2 Institutional Background

The Italian National Health System, which follows the Beveridge model since 1978, provides universal coverage to every citizen and is mainly funded through national and regional taxation [23, 40]. The Ministry of Health has an executive role over national health planning. At the same time, the organisation and provision of healthcare services are overseen by the 19 regions and 2 autonomous provinces and involves over 150 Local Health Authorities (LHAs or *Azienda Sanitarie Locali, ASLs*). Each Local Health Authority has an average catchment area of 437,000 people and is in charge of providing both primary and secondary care, as well as various independent public hospitals that administer tertiary care [63].

In the early 1990s, the Reform Law introduced decentralisation in the form of devolution in the Italian NHS, where the state gradually ceded its jurisdiction to its 20 regions. This process followed the international New Public Management [64] movement where organisational, political and fiscal devolution were encouraged to make regions more responsible for their health service activities and funding. Such decentralised feature is also present in many other European countries such as Denmark, Germany, Sweden and Spain [22]. In 2001, fiscal decentralisation to the regions was implemented (legislative decree 56/2000), and such constitutional reform in Italy endowed regions with the freedom to choose the type of healthcare model [63]. What was previously known as the Local Health Units (*Unità Sanitarie Locali*) were transformed into the current Local Health Authorities (LHAs), which directly run the public Hospital Units (HUs or *Ospedalia Gestione Diretta*) with their capitated budget and management [65]. Other hospital ownership types included Hospital Trust (*Aziende Ospedaliere*) that are granted the status of trusts with full managerial autonomy, Teaching Hospitals (*Clinici o Policlinici Universitari*), Research Hospitals (*Istituto di Ricovero e Cura a Carattere Scientifico, IRCCS*), Accredited Private Hospitals (*Case di Cura Accreditate*) and other private providers that compete with public hospitals in healthcare deliveries.

Regarding hospital care financing, regions have full autonomy to identify the services to be reimbursed through lump-sum, and to opt for their own diagnosis-related groups (DRGs) tariffs and funding schemes. Regional tariffs may be differentiated by the provider type to reflect the production costs and different responses to price incentives [65]. In general, public Hospital Units directly managed by LHAs are solely financed by global budgets that are based on the consumption of production factors such as personnel, and goods and services. Their budgets are kept separated from the overall budget of LHA's, but their expenses are fully covered within the LHA's financial resources retrospectively [65]. Therefore, Hospital Units do not necessarily have the financial incentives to attract patients and have less pressure to discharge patients early to reduce costs. In contrast, all other types of hospitals are financed primarily by the DRG-based Prospective Payment System (PPS). Under PPS, hospitals are reimbursed a fixed tariff per hospitalisation stay until a certain threshold of LOS, and the unit tariff decreases beyond this threshold to incentivise greater efficiency. For in-patient care provided by the independent public hospitals such as Hospital Trust and Teaching Hospitals, the reimbursements are based on two main components: activity-based payments according to the DRG-classification of discharges and a lump-sum based on average production costs for specific services such as emergencies and management of chronic illness. While for private accredited hospitals, funding is almost entirely dependent on PPS related allocations. Moreover, all regions are free to discriminate tariffs across providers to approximate the price to the actual costs and local specificities.

Following the devolution process in early 2000, some regions capable of executing the reforms experienced improvements in their systems, while others with weaker managerial capacity gradually worsened their financial sustainability [66, 67]. Tighter cost-containment measures further exacerbated the imbalance in light of the recent economic crisis [40]. Between 2001 and 2010, ten regions (Abruzzo, Molise, Apulia, Campania, Calabria, Sicily, Lazio, Piedmont, Sardinia and Liguria) consequently accumulated significant deficits and were expected to reduce the problem of cost overrun [68]. In practice, providers in these regions may reduce the number of beds, the number of staffs or patients' length of hospitalisation.

Consequently, the governance of the NHS is divided into two regional clusters: those with stronger financial capacities retained some health policy autonomy, while the weaker regions were subject to strict central control [63]. For instance, the Lombardy region provides outcome benchmarking and splits purchasers and providers to encourage patient choice and competition [32]. At the same time, many southern regions such as Apulia, Campania, Calabria and Sicily employ a 'command and control' model with an active role of performance management [32]. There is persistent variability of the regional governance models in terms of the managerial structure of hospital care and the extent to which accredited private hospitals are involved in the provision of services [65]. Although there is a significant reduction in the regional deficit and increased stability of the NHS budget to date [63], the consequence on the quality of care remains unclear. Given the high variation in the financing and provision of healthcare services as well as the recent pressure to contain healthcare expenditures, Italy presents an intriguing case study to explore the factors related to geographic disparities in quality of care.

1.1.3 Motivation and Objectives

Our interest in the unplanned readmission indicator has two broad rationales: early hospital readmission represents an economic and social burden for cost-conscious healthcare system; it is subject to opportunistic behaviour [69] where providers discharge patients prematurely to reduce index hospitalisation cost or readmit a patient after a short time to get more reimbursement. The intricate nature of early readmission, therefore, indicate not only the quality of care but also the incentive structures of healthcare providers. Although not all readmissions are avoidable, low readmission rates are commonly regarded as the outcome indicator for good inpatient care [70]. Another widely used hospital performance indicator is the 30 days mortality after discharge. However, we do not have linked registry data and thus do not observe if the patient dies after discharge.

Our objectives are two-fold: i) to explore the marginal effects of factors related to the patient risk of readmission, ii) to examine how hospital behaviour relates the geographic variation of unplanned readmission rate. We pay specific attention to the hospital incentive structure, the discharge decision and the differential use of medical procedures and their role in explaining the geographic differences in readmission rates. The results provide important insights into the incidence and determinants of hospital readmission in Italy and the state of healthcare quality disparity for the observed years.

1.2 Method

1.2.1 Data

Study Population

We analyse the hospital discharge data (Schede di Dimissione Ospedaliera, SDO) from the National Ministry of Health for the years 2010 to 2015. The data is routinely collected by all hospitals in all the regions and include not only administrative information such as diagnosis, treatment, discharge units, admission and discharge dates but also socio-demographic characteristics of the patients. Information about the hospitals in this dataset includes the type of ownership and the Local Health Authorities (LHAs) the institute belongs.

We focus on the elderly population because researches have found that patients over 65 years old are frail and at increased risk for readmission [71, 72], and that the Italian society is characterised by an ageing population suffering from a number of chronic conditions [58]. Moreover, patients were excluded from the analysis if any of the following criteria were met:

1. Patients who died during the hospital stay because they do not experience re-hospitalisation.

2. Patients who are not admitted to acute care units, such as to rehabilitation or long-term-care unit, and therefore have very long length-of-stay.

3. Patients who are admitted through scheduled hospitalisation or transferred from other institutions, and thus readmission is planned.

In cases where patients incurred more than one admission during the first 30 days after discharge, we consider only the first readmission episode.

We select the patients diagnosed with a heart attack - Acute Myocardial Infarction (AMI) given the high volume of emergency admissions and that AMI patient unplanned readmission is commonly used as a healthcare quality indicator. We extract all patients whose main pathology is coded 410.0-410.9 under the 9th International Classification of Disease (ICD-9). Since these patients are often sent to the hospitals nearby, the potential selection bias is ameliorated when investigating the effects of geographic factors [73]. The treatments of AMI patients include Coronary artery bypass graft (CABG) or coronary bypass surgery, cardiac catheters, percutaneous transluminal coronary angioplasty (PTCA) and stent.CABG involves taking a vein or an artery from the patient's body and using it to reroute blood from coronary arteries. A catheter is a thin, flexible tube that is inserted in a vein. PTCA is a minimally invasive procedure that uses an inflated balloon in a vessel to expand the blood vessel to improve blood flow, while the stent is a spring-shaped prosthesis used to complement PTCA. We extract the procedural codes from our dataset and control for the different interventions performed.

We also include organizational factors of the hospitals, such as the type of institution, capacity, and generic quality in the analysis. From the SDO data, we retain the hospital ownership type variable, which includes public Hospital Units (HUs or *Ospedalia a Gestione Diretta*), Hospital Trust (*Aziende Ospedaliere*), Teaching Hospitals (*Clinici o Policlinici Universitari*), Research Hospitals (*Istituto di Ricovero e Cura a Carattere Scientifico, IRCCS*), Accredited Private Hospitals(*Case di Cura Accreditate*) and other private providers. We calculated the volume of AMI patients per year by the provider from the SDO data. The information on the total bed counts of hospitals across the years is obtained from the Italian Ministry of Health (*Ministero della Salute*) website. The rationale for including the capacity information is to proxy the potential size constraints that hospitals face, which can be related to the readmission outcome. We also use the cut-off points of low, medium and high Acute Myocardial Infarction (AMI) mortality rate defined by the National Outcome Programs (Programma Nazionale Esiti) website for the broad quality categorization for the hospitals.

Outcome Measure

The study's primary outcome measure is the risk of readmission within 30 days after discharge for elderly patients diagnosed with Acute Myocardial Infarction (AMI) during the index hospitalisation. The primary outcome measure included readmission with all causes such as infections or complications, not just those that appear related to the initial admission. This measure is in line with the established literature and the readmission measure from the US Centers for Medicare & Medicaid Services and the QualityNet reporting guideline. In addition, because comorbid elderly patients may be more likely to be readmitted to the hospitals due to different pathologies, we also consider a more restricted definition of readmission that includes only readmissions with the same Major Diagnostic Category (MDC). For the analysis on the patient level, we consider these two types of readmission as binary variables to identify the effects of other explanatory variables. In estimating the geographic variations, we treat the readmission rates of each hospital as the outcome variable. The specifications are described in the following section.

Although unplanned readmission is a widely used quality indicator [42, 74] and represents substantial social and economic burdens, we are aware of some of the limitations of this indicator. First, adjustment for patient case-mix and contextual factors need to be carried out correctly in order to infer risk. We used the Ontario AMI prediction rules, a disease-specific instrument, to adjust for the risk scores of the patients. Second, studies show that not all readmissions within 30 days are avoidable [75], which can potentially make the indicator inaccurate. In recognising the potential weakness of the readmission indicator, we believe that the intricate nature of hospital readmission nonetheless offers important insights on the behaviours of the providers.

1.2.2 Econometric Specifications

Geographic disparities in unplanned readmission are linked to factors from various levels. First, differences in the local profile of the patients (case-mix) can be relevant if there is geographic sorting of, for instance, demographic characteristics. Second, at the hospital level, we consider organizational factors such as the type of ownership and capacity. Third, the influence of the Local Health Authority (LHAs) — specific random effects can contribute to the homogeneity within each of the healthcare market structures and the potential inter-LHA disparity in readmission rate. Finally, regional governments have considerable autonomy over their healthcare provision and fiscal policies, so the random effects at the regional level should also give rise to geographic variations. We thus need to account for the hierarchical geographic structure.

Given the multiple sources of variability, we identified two most relevant models in the literature: hierarchical generalized linear model (HGLM) and Cox proportional model with mixed effects. In fact, in a recent systematic review on the influence socioeconomic factors on hospital readmission for heart failure and AMI, most of the studies used either Cox proportional hazard regression or multivariate logistic regression [76]. The HGLM such as multilevel logistic model is commonly used to predict risks or odds ratios for readmission, while the Cox regression model with mixed effects, or sometimes called the frailty model [77], is a flexible model that accounts for the time until the failure event. As the two models are similar by construct and both explicitly model separate random effects at each level [78], we will employ both to understand how patient- and hospital-level variables affect the probability of early readmission.

To quantify the magnitude of the general contextual effect and variances at higher geographical levels, we aggregate the data to hospital level and estimate a linear multilevel mixed-effect model. We also estimate the intra-class correlations at different levels and the explained variance. We now describe each model in more detail.

Unplanned Readmission and Its Determinants

We estimate both the multilevel logistics model for the probability of readmission, and multilevel proportional hazard model for time-to-readmission. As the healthcare path of the patients may depend on the structures of the providers and LHAs, we allow observation within the same hospital and LHA to be correlated to each other. As such, we are accounting for the within-cluster homogeneity.

For the multilevel logistics model, we estimate the following:

$$\begin{aligned} &Logit\ (Pr(Y_{ijk}=1)) = \beta_0 + \beta_{los} LOS_{ijk} + \beta_i LOS_{ijk} \cdot Type_{jk} \\ &+\beta_x X_{ijk} + \beta_z Z_{jk} + \mu_t + \mu_R + \ \beta_R Inc_l + e_{0k} + \eta_{0jk} + v_{0ijk} \end{aligned} \tag{1}$$

Where Y_{ijk} is the binary variable of patient i in hospital j in LHA k, and $Y_{ijk} = 1$ if the patient is being readmitted to the hospital within 30 days of discharge. Here, each LHA cluster k=*1* ... n consists of hospital clusters$j$=*1* ... n_i, and each hospital has i=*1* ... n_{ij} patient observations. X_{ijk} is a row vector containing the patient-level variables including demographics, comorbidities and LOS, and Z_{jk} represents a vector of hospital-level factors such as capacity and patient volume. We allow for a non-linear relationship between age and our outcome variable by including a quadratic term. As discussed in the institutional background section, providers can have different discharge incentive structures due to their payment system. We thus interact the variable LOS_{ijk} with the categorical variable of hospital types, $Type_{jk}$, to allow for the potential heterogeneous effects. We also include a set of year and regional fixed-effects (μ_t and μ_R), as well as a regional average income variable Inc_l to account for the economic disparity across regions. β_x, β_z and β_i are the fixed effects for the explanatory variables. Finally, $e_{0k} \sim N(0,\ \theta_e^2)$, $\eta_{0jk} \sim N(0,\ \theta_\eta^2)$ and $v_{0ijk} \sim N(0,\ \theta_v^2)$ are the random error terms at the LHA, hospital and patient levels, reflecting the cluster-specific random effects. We estimate the marginal effects of the explanatory variables through maximum likelihood. However, we do not report the intra-class coefficient (ICC) in quantifying the contribution of area-level variance to total variance because the computation and interpretation of ICC are often questionable in the context of logistic regression [79, 80].

Similarly, for the multilevel survival analysis, the underlying equation is:

$$\begin{aligned} &h\ (t_{ijk})\ =\ h_0(t)\ \cdot\ exp\ (\beta_{los} LOS_{ijk} + \beta_i LOS_{ijk} \cdot Type_{jk} + \beta_x X_{ijk} \\ &+\beta_z Z_{jk} + \mu_t + \mu_R + \ \beta_R Inc_l + e_{0k} + \eta_{0jk} + v_{0ijk}) \end{aligned} \tag{2}$$

Where t_{ijk} is the observable failure (readmitted) time of the patient i nested in hospital j in LHA k and $h(t_{ijk})$ is the hazard function of the corresponding patient. $h_0(t)$ is the baseline hazard function. β_x, β_z and β_i are the conditional hazard ratios, while the remaining variables are the same from Equation (1). This more flexible model is semiparametric and thus does not have a functional form assumption imposed on the baseline hazard. We estimate the model for the time from discharge to readmission and obtain the influence of the covariates at different levels.

Geographic Variation of Readmission Rates

While it is important to identify the marginal effects of patient and hospital characteristics, we want to understand what drives the geographic variation in readmission. Since we are primarily interested in the unjustified variation generated from the providers, we aggregate the dataset to the hospital level while retaining patient variables as averages. The model consists of three geographic units — hospital, LHA and regions. As our outcome variable (hospital readmission rate) is no longer binary, we consider the multilevel mixed-effect linear model:

$$\begin{aligned} Y_{jkl} \; = \; & \beta_L \overline{LOS}_{jkl} + \beta_i \overline{LOS}_{jkl} \cdot Type_{jkl} + \beta_z Z_{\mathbf{jkl}} + \beta_x \overline{\mathbf{X}}_{\mathbf{jkl}} \\ & + \mu_t + \mu_R + \beta_R Inc_l + \mu_{0l} + u_{0kl} + \varepsilon_{0jkl} \end{aligned} \tag{3}$$

Where Y_{jkl} represents the rate of readmission in hospital j of LHA k in region l, and $\overline{LOS}_{jkl}$ is the average LOS of the patients hospitalized in hospital j. Z_{jkl} represents the hospital ownership types, and the vector $\overline{X}_{jkl}$ is the averaged patient-level information. μ_{0l} is the random intercept at the regional level, u_{0kl} is the random intercept at LHA level, nested within region level, and ε_{0jkl} captures the idiosyncratic hospital factors. We assume that $\mu_{0l} \sim N(0,\ \theta_\mu^2)$, $u_{jk} \sim N(0,\ \theta_u^2)$ and $\varepsilon_{ojkl} \sim N(0,\ \theta_\varepsilon^2)$ and fit the model using restricted maximum likelihood for unbiased estimation of variances. We obtain the intra-class coefficients (ICCs) to assess the total residual variance attributable to both LHA and regional levels.

The total residual variance attributable to the LHA level is:

$$ICC_u = \frac{\theta_\mu + \theta_u}{\theta_\mu + \theta_u + \theta_\varepsilon} \tag{4}$$

And the total residual variance attributable to the regional level is:

$$ICC_\mu = \frac{\theta_\mu}{\theta_\mu + \theta_u + \theta_\varepsilon} \tag{5}$$

Larger values of ICC indicate that a considerable proportion of the residual variance in readmission rate is attributable to these levels. Visually, we compare the plots that rank the LHA and regional residuals for both the empty and the full models to assess the variation explained by the observed variables qualitatively.

We want to understand how much readmission variance is explained by differential hospital behaviours, here proxied by LOS and the different surgical procedures. This can be achieved by comparing the increase in explained variance after including the predictors. In the multilevel analysis, the presence of multiple variance components challenges the reporting of R^2 [81, 82] and we, therefore, calculate the proportional reduction in total variance after incorporating these predictors [83] using the following formula:

$$R^2\ (S\&B)\ =\ 1 - \frac{(\theta_{\varepsilon,full}\ +\ \theta_{u,full} +\ \theta_{\mu,full})}{(\theta_{\varepsilon,null}\ +\ \theta_{u,null} +\ \theta_{\mu,null})} \tag{6}$$

We can argue that while, for instance, ownership-driven variation reflects organizational structural disparities that are beyond the control of hospitals, inequalities that are driven by differential risk-adjusted LOS and the use of surgical procedures are arguably mitigable. If we observe a substantial increase in R^2 after the inclusion of LOS and innovative procedure, this implies the importance of discharge behaviour in driving the regional differences.

1.3 Results

1.3.1 Descriptive Statistics

Since we are examining the disparities across regions, we first compute the average rate of readmission in each region. Figure 1.1 shows the map of the provincial average all-cause readmission rates across all observable years. We can see that descriptively, the readmission rates differ across regions, with the northern regions having on average lower risks than the south. This difference reflects the general picture of the geographic disparity that characterize the economic development of the country.

In Table 1.1, we report all the patient and hospital-level variables of the study population after our exclusion criteria. The patient-level data contains the age, gender, educational level, foreigner, LOS, the different intervention procedures, comorbidities and whether they were discharged to a rehab institution or integrated care home. At the same time, the hospital activity-related information includes volume, capacity, hospital type and AMI in-hospital mortality rate category (low, medium and high mortality) as a proxy for the hospital's overall quality.

1.3.2 Empirical Results

Unplanned Readmission and Its Determinants

Before looking into the marginal effects of patient and hospital factors on readmission risks, we first present a descriptive graph of the readmission Nelson-Aalen cumulative hazard estimates as a function of days after discharge across the selected large regions, as seen in Figure 1.2. We observe that the baseline readmission risk for patients who are admitted to hospitals in the Southern regions of Apulia and Sicily are significantly higher throughout the days after discharge than those admitted in Lombardy and Lazio.

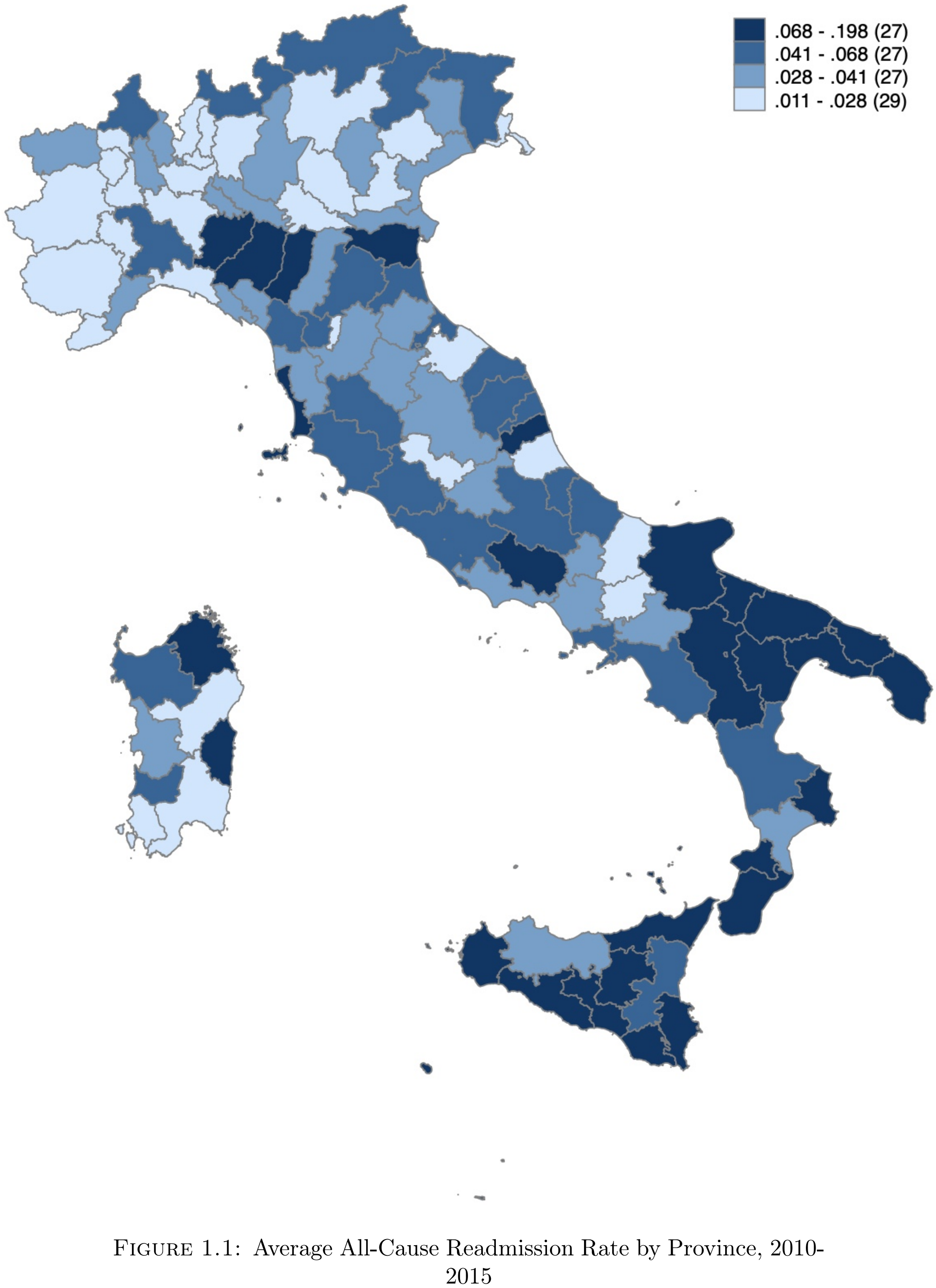


FIGURE 1.1: Average All-Cause Readmission Rate by Province, 2010-2015

TABLE 1.1: Descriptive Statistics

Characteristics of Patients and Hospitals

Variables			**Mean**	**SD**
Patient				
	Age		77.9	7.73
	Male (%)		57,i	
	Education level			
		Elementary School or Lower (%)	24.83	
		Middle School Diploma (%)	53.33	
		High School Diploma (%)	15.02	
		University (%)	6.39	
		Laurea or Above (%)	0.43	
	Foreign (%)		1.1	
	Length of Stay (days)		8.91	7.78
	PTCA and Stent (%)		43.23	
	Catheter(%)		1.04	
	CABG(%)		5.5	
	Ontario AMI Comorbidities	Shock (%)	1.69	
		Diabetes with Complications (%)	3.42	
		Congestive Heart Failure (%)	22.96	
		Cancer (%)	1.73	
		Cerebrovascular Disease (%)	6.11	
		Pulmonary Edema (%)	1.11	
		Acute Renal Failure (%)	2.52	
		Chronic Renal Failure (%)	10.7	
		Cardiac Dysrhythmias (%)	17.7	
	Discharged to Institutions (%)		4.01	
	Readmission within 30 days, All Causes (%)		4.84	
	Readmission within 30 days, Same MDC (%)		0.67	
	Observations	383,162		
Hospital				
	AMI volume		77	101.16
	Capacity		231	269.64
	Types (#)			
		Hospital Trust	109	
		Hospital Unit	412	
		Teaching Hospital	28	
		Research Hospital	33	
		Private Clinic	262	
		Others	39	
	AMI Mortality(#)			
		High	27	
		Medium	794	
		Low	62	
	Observations	883		
Region				
	Annual Income (thousand)		29.64	4.34
	Observations	21		

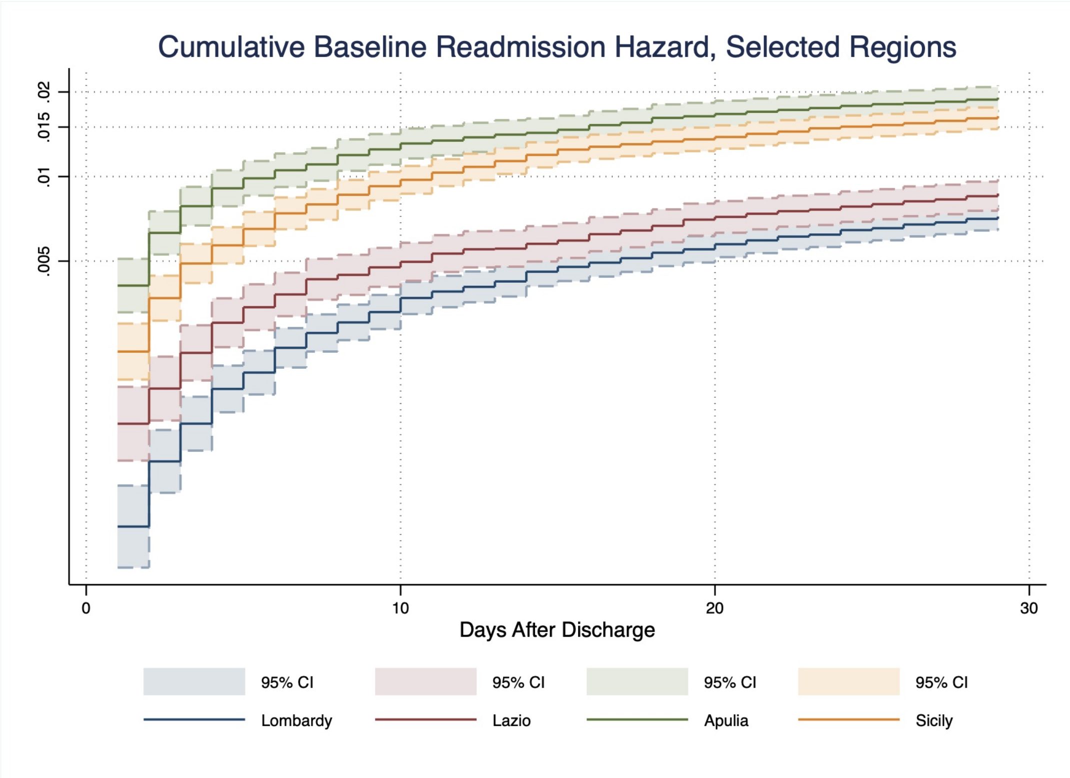


FIGURE 1.2: Cumulative Baseline All-Cause Readmission Hazard by Selected Regions

Table 1.2 reports the coefficients of the patient and hospital-level variables from Equation (1) and (2). We analyse 30 days readmission for all causes as the primary dependent variable, as well as readmission with the same MDC as a secondary indicator. For all-cause readmission, we observe from the coefficients of the interaction term for LOS that, for both the multilevel Logit and hazard models, the probability to be readmitted decreases with LOS for patients admitted to all types of hospitals. The magnitude of this negative effect is higher for patients admitted to Hospital Units and Private Clinics than that of other hospitals. Moreover, the coefficients for hospital types show that independent public hospitals have significantly lower readmission probabilities than the Hospital Units and Private Clinics. This finding is particularly interesting as it partially relates to hospital incentive structures. For hospitals under a global budget as in the case of Hospital Units, there is little incentive to save costs, and thus the index hospitalisation LOS is more effective in preventing future unplanned readmission. Whereas for hospitals under a PPS with some budget allocations such as Hospital Trust, Teaching and Research Hospitals, the LOS is relatively less effective in reducing the probability of all-cause readmission given their incentive to improve efficiency. However, other than the effects of LOS, these independent public hospitals have significantly lower readmission risks than Hospital Units, indicating that other mechanisms other than payment systems are also driving the differences in readmission. Finally, for the profit-making private hospitals that operate solely under PPS, the effect of LOS in reducing the probability of readmission is the strongest, but they have the highest overall hospital readmission. For the more restricted outcome indicator, readmission with the same MDC, we observe a similar effect for LOS in terms of the directions of the coefficients. However, the coefficients are only significant for hospitalisations in Hospital Units and Private Clinics but not for the independent public hospitals.

For the demographic factors, the probability of readmission increases with age, but the effect diminishes with age. Males are more likely to be readmitted than females, and foreigners are less likely to be readmitted. Patients who underwent PTCA and Stent, CABG and Catheter all have less risk of all-cause readmission than patients with no operation performed. However, for readmission with the same MDC, the CABG procedure does not reduce the probability of readmission. The fact that patients were previously discharged to home hospitalisation, rehabilitation institution or other types of integrated home care does not affect the probability to be readmitted.

At the hospital level, we have discussed that the independent public hospitals such as Hospital Trust and Teaching Hospitals have significantly lower risks of all-cause readmission than LHA-managed Hospital Units. However, the same effect is not observed for readmission with the same MDC. The volume of AMI patients reduces the probability of both types of readmission, indicating some degrees of learning effect. Furthermore, hospitals with higher capacity have lower probabilities of readmission. This effect is expected, as bed constraints may contribute to early patient discharges and in turn, result in unplanned readmission. Finally, patients admitted to hospitals with low and medium in-hospital AMI mortality (according to the National Outcome Programs) have lower likelihoods of all-cause readmission. The coefficients for comorbidities, education, years and regional fixed effects can be found in Appendix Table A.1 and A.2. Overall, the probability to be readmitted has decreased with comorbid patients with Shock, cerebrovascular disease and Cardiac Dysrhythmias are less likely to be readmitted, while diabetic patients are more likely to be readmitted. This correlation for the above conditions can be explained by more considerable attention offered by the providers for patients with these severe cardiovascular comorbidities. However, the medical interpretation of the conditions is beyond the scope of this paper. In Appendix Table A.1 and A.2, we also observed that all-cause readmission decreases over the years, but same -MDC readmission increases. Many of the Central and Southern regions have positive and significant coefficients, indicating higher general readmission risks.

Geographic Variation of Readmission Rate

Hospital-level variation in the readmission outcome is estimated in terms of variance and intra-class correlation. We first present the coefficient estimates for the variables collapsed at the hospital level in Table 1.4. Although most coefficients have the same signs as in Table 1.2, some of them cease to be significant. Notably, for all-cause readmission rates, the coefficients for average LOS are significant for all types of hospitals except for Research hospitals, while for the same MDC readmission rate the

Table 1.2: Unplanned Readmission and Its Determinants

Outcome Indicator	**All-Cause Readmission**				**Same MDC Readmission**			
Models	**Logit**		**Hazard**		**Logit**		**Hazard**	
Variables	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Patient-level								
LOS (×Hospital Unit)	-0.0765***	(0.00235)	-0.0519***	(0.00240)	-0.0717***	(0.00701)	-0.0615***	(0.00845)
LOS×Hospital Trust	0.0319***	(0.00459)	0.0266***	(0.00454)	0.0158	(0.0126)	0.0202	(0.0148)
LOS×Teaching Hospital	0.0474***	(0.00530)	0.0338***	(0.00533)	0.00857	(0.0150)	0.00757	(0.0179)
LOS×Research Hospital	0.0475***	(0.0117)	0.0311***	(0.0118)	0.00639	(0.0387)	0.0199	(0.0401)
LOS×Private Clinic	-0.0274***	(0.00988)	-0.0199*	(0.0105)	-0.0608**	(0.0262)	-0.0825**	(0.0378)
LOS×Others	0.0221**	(0.0107)	0.0228**	(0.0109)	0.0793***	(0.0237)	0.0913***	(0.0234)
Age	0.253***	(0.0210)	0.227***	(0.0229)	0.310***	(0.0594)	0.331***	(0.0758)
Age2	-0.00173***	(0.000135)	-0.00153***	(0.000147)	-0.00189***	(0.000375)	(0.0757)	(0.000478)
Male	0.150***	(0.0169)	0.151***	(0.0185)	0.188***	(0.0490)	0.199***	(0.0622)
Foreign	-0.239***	(0.0887)	-0.170*	(0.0973)	-0.808**	(0.357)	-1.205**	(0.558)
PTCA Stent	-0.677***	(0.0226)	-0.617***	(0.0247)	-0.808**	(0.0608)	-0.845***	(0.0786)
CABG	-1.338***	(0.192)	-1.466***	(0.228)	0.227	(0.270)	0.240	(0.340)
Catheter	-0.267***	(0.0546)	-0.270***	(0.0588)	-0.405***	(0.144)	-0.423**	(0.183)
Institutions	0.0401	(0.0613)	-0.293*	(0.153)	-0.242	(0.175)	-0.210	(0.221)
Hospital-Level								
Hospital Type (Reference Hospital Unit)								
Hospital Trust	-0.427***	(0.112)	-0.367***	(0.0997)	-0.113	(0.168)	0.0813	(0.219)
Teaching Hospital	-0.506***	(0.154)	-0.381***	(0.137)	-0.127	(0.196)	0.456	(0.287)
Research Hospital	-0.584***	(0.212)	-0.415**	(0.198)	-0.161	(0.240)	-0.123	(0.505)
Private Clinic	0.178*	(0.100)	0.00852	(0.102)	0.262	(0.172)	0.822***	(0.267)
Others	-0.151	(0.160)	-0.254*	(0.150)	0.254*	(0.150)	-1.098***	(0.391)
AMI Volume	-0.0009***	(0.00025)	-0.0008***	(0.00024)	-0.00104**	(0.00044)	-0.00127**	(0.00059)
Capacity	-0.0006***	(0.00014)	-0.0006***	(0.0001)	-0.0009***	(0.0002)	-0.001***	(0.0004)
AMI Mortality								
Low	-0.295***	(0.107)	-0.0650	(0.100)	-0.140	(0.170)	-0.166	(0.238)
Medium	-0.388***	(0.0929)	-0.175**	(0.0863)	-0.0154	(0.143)	-0.0852	(0.201)
Regional-Level								
Average Income (thousand)	-0.03**	(0.014)	-0.03**	(0.015)	-0.02**	(0.015)	-0.01	(0.052)
Constant	-10.98***	(0.944)	-17.38***	(1.029)	-17.63***	(1.038)	-26.10***	(3.432)
ln_p			0.750***	(0.00872)			0.647***	(0.0265)
Variance LHA Level	0.0702***	(0.0237)	0.0242	(0.0208)	0.0455***	(0.0171)	1.61e-09	(9.79e-05)
Variance Hospital Level	0.368***	(0.0321)	0.251***	(0.0429)	0.232***	(0.0226)	0.561***	(0.155)

Notes: ***, significant at 1%; **, significant at 5%; *, significant at 10%.
Number of observations 383,162. Number of hospitals 883. Number of LHAs 154.
Coefficients for Comorbidities, Education, Regional and Year Fixed Effects can be found in the Appendix Table A.3

TABLE 1.3: Hospital Readmission Rate and its Determinants

Models	**All Readmission**		**Same MDC Readmission**	
Variables	**Coefficient**	**SE**	**Coefficient**	**SE**
LOS (× Hospital Unit)	-0.007***	(0.00123)	-0.0007	(0.0005)
LOS×Hospital Trust	0.00493*	(0.00257)	0.000694	(0.00106)
LOS×Teaching Hospital	0.00916**	(0.00425)	0.000570	(0.00175)
LOS×Research Hospital	0.00380	(0.00291)	-0.000442	(0.00120)
LOS×Private Clinic	-0.00262*	(0.00148)	-0.00163***	(0.000609)
LOS×Others	0.000195	(0.00257)	0.000556	(0.00106)
PTCA Stent (%)	-0.168***	(0.0122)	-0.0174***	(0.00499)
CABG (%)	-0.148***	(0.0484)	-0.0273	(0.0200)
Catheter (%)	-0.00478	(0.0219)	-0.000973	(0.00892)
Hospital Type (Reference Hospital Unit)				
Hospital Trust	-0.0440*	(0.0257)	-0.00220	(0.0129)
Teaching Hospital	-0.0776*	(0.0442)	-0.000545	((0.0182)
Research Hospital	-0.0326	(0.0289)	0.0117	(0.0120)
Private Clinic	0.0504***	(0.0132)	0.0267***	(0.00540)
Others	0.0103	(0.0252)	-0.00393	(0.0104)
AMI Volume	-6.33e-05*	(3.61e-05)	-3.75e-06	(1.48e-05)
Capacity	-5.70e-08	(1.29e-05)	-2.00e-06	(5.35e-06)
AMI Mortality				
Low	-0.00909	(0.0145)	-0.00183	(0.00595)
Medium	-0.00456	(0.0123)	-0.000356	(0.00506)
Average Income (thousand)	-0.0006	(0.002)	0.0002	(0.0004)
Constant	0.464***	(0.0771)	-0.000738	(0.0281)

Notes: ***, significant at 1%; **, significant at 5%; *, significant at 10%.
Number of hospitals 883. Number of LHAs 154. Number of Regions 21.
Coefficients for Patient Characteristics and Fixed-Effects are in Appendix Table A.2

coefficient is only significant for Private Clinics. Moreover, the percentage of patients who underwent PTCA and stent procedures have significantly negative coefficients for both types of readmission rate, while the percentage of CABG procedure only reduces all-cause readmission rate. These variables represent the underlying hospital behaviours and are robust to the aggregation.

We graphically represent the residuals from the empty and the full models at both the LHA and the regional levels. As seen in Figure 1.3 and 1.4, we order the residuals by the unadjusted and adjusted LHA and regional averages of readmission rate and plot the 95% confidence intervals around each residual estimate. The adjusted residuals represent the unexplained variation after accounting for the differences across patient and hospital factors. We observe that, without accounting for the explanatory variables, some LHAs and regions exhibit significantly different levels of variation for both types of readmission rates. The variation is more pronounced for all-cause readmission, as we observe LHA and regions both significantly below or above the average readmission rates. In particular, we see in Figure 1.4 Marche, Piedmont, Veneto and Lombardy have significantly lower-than-average regional all-cause readmission rate, while Emilia Romagna and Sicily has a significantly high readmission rate. After adjusting for patient and hospital characteristics, these variations diminished considerably.

Since we are interested in how hospital behaviours, here represented by LOS and

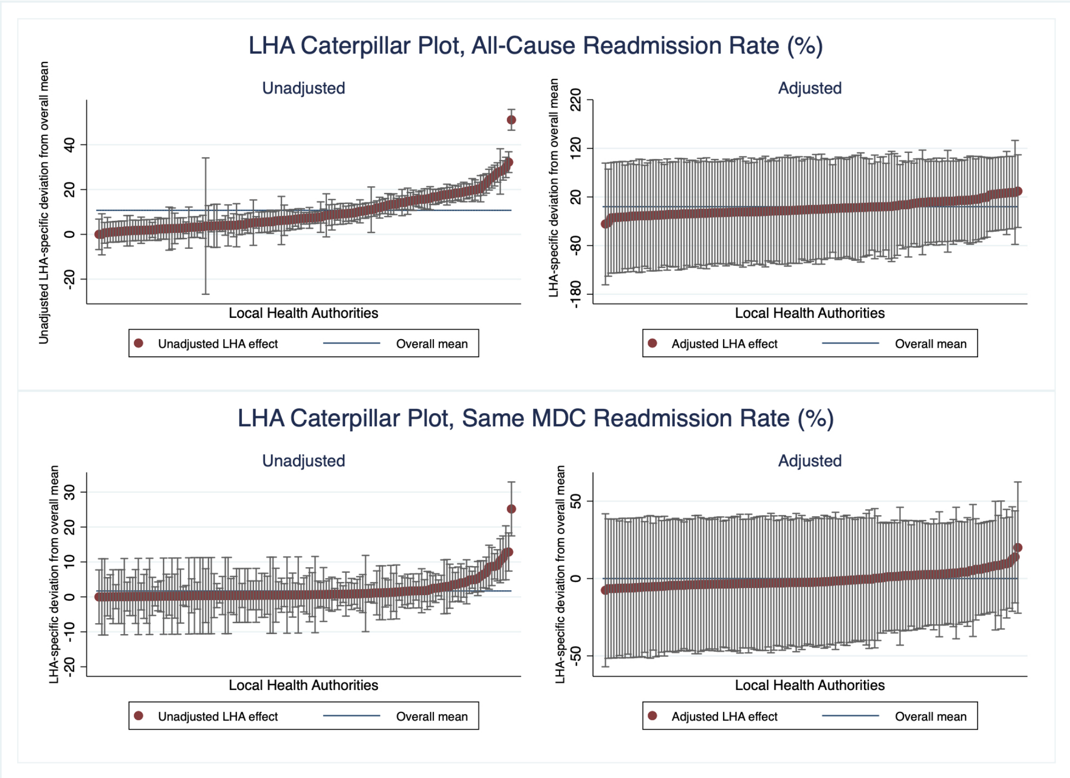


FIGURE 1.3: Local Health Authorities Caterpillar Plot, Readmission Rate

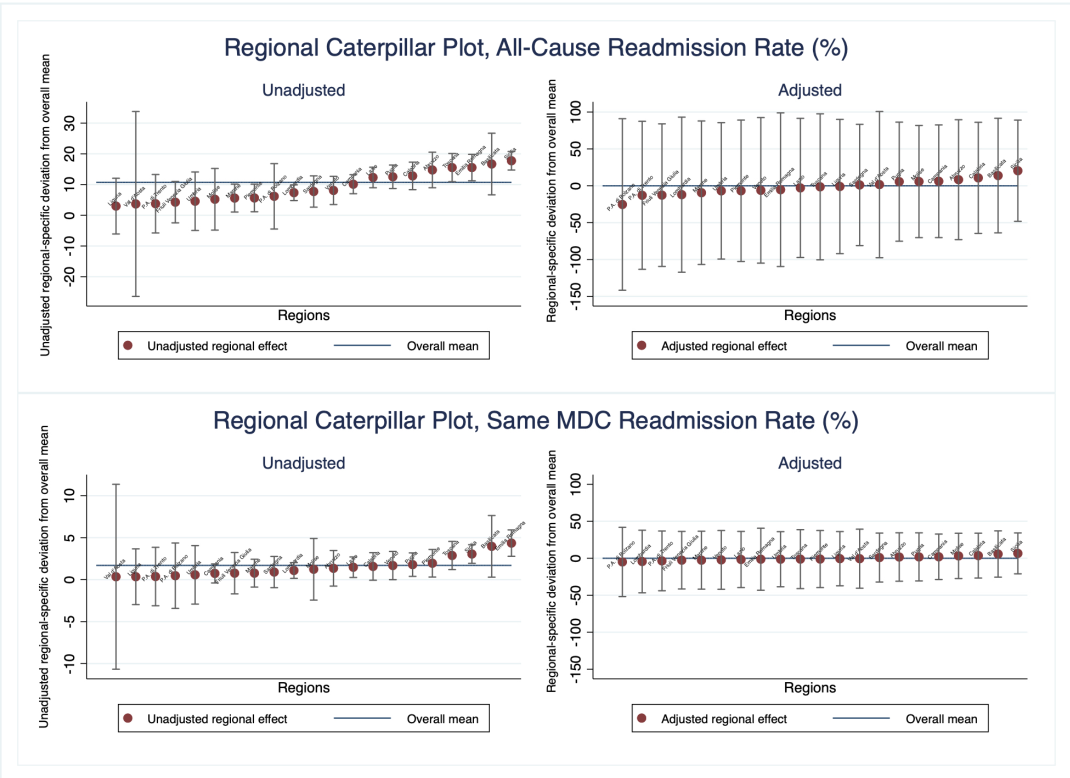


FIGURE 1.4: Regional Caterpillar Plot, Readmission Rate

TABLE 1.4: Variance Analysis

Models	**Variance**	**ICC**	**R-square (S&B)**
All-Cause Readmission			
Full Model (exc. LOS and procedure)			0.1172
Hospital	0.02377		
LHA<Region (154)	0.00106	0.0789	
Region (21)	0.00098	0.0380	
Full Model			0.2175
Hospital	0.02169		
LHA<Region (154)	0.00041	0.0517	
Region (21)	0.00078	0.0340	
Same MDC Readmission			
Full Model (exc. LOS and procedure)			0.04707
Hospital	0.00385		
LHA<Region (154)	0.00003	0.02650	
Region (21)	0.00004	0.01210	
Full Model			0.06567
Hospital	0.00379		
LHA<Region (154)	0.00002	0.01479	
Region (21)	0.00004	0.00932	

different surgical procedures, explain the variation, we investigate the variance components in two separate models for both types of readmission rates. We further compute the intra-class correlation (ICC) and the explained variance as represented by Equation (4),(5), and (6). The intra-class correlations (ICC) estimate the proportion of overall variation in outcomes explained by the variation between geographic units. As seen in table 1.4, for the model excluding LOS and surgical procedures for all-cause readmission, we observe around 11.69% of the total variation is attributed to higher geographic levels, with about 7.89% at the LHA level and 3.8% at the regional level. After incorporating LOS and surgical procedures into the specification, the ICC decreased by 2.72% at the LHA-level and by around 0.4% at the regional level. At the same time the R^2 almost doubled from 0.1172 to 0.2175. This result indicates how LOS and the use of surgical procedures played an indispensable role in driving the geographic variation in all-cause unplanned readmission. Although the scale of results for same-MDC readmission rate is much smaller, we do observe that these hospital factors explained a considerable proportion of the overall variance at the LHA and the regional levels.

1.4 Discussion

In this article, we have investigated the determinants and the geographic variation of elderly hospital unplanned readmission during the period of a high level of decentralisation and cost-containing pressure. We have shown how differences in patient and hospital characteristics can contribute to the probability of readmission with hierarchical models. After accounting for sociodemographic and comorbidity variables, we found that the probability to be readmitted for all causes decreases with longer

LOS for patients admitted to all types of hospitals. The magnitude of this negative effect is lower for independent public hospitals such as Hospital Trusts and Teaching Hospitals than for Hospital Units or Private Clinics. The use of PTCA and stent, CABG and catheter all decreases the probability of all-cause readmission, while the hospital AMI patient volume and capacity are both associated with lower all-cause readmission. Moreover, the effects of LOS, the different medical procedures and hospital types are relatively robust to aggregation to the hospital level. The results for readmission with the same MDC is comparable, while some coefficients lost significance. Our variance analysis further shows that there are strong contextual effects at the LHA and regional levels, while the variation in LOS and the use of different surgical procedures can explain a considerable proportion of the overall readmission variance. Our empirical results broadly reveal the potential pathway through which readmission rates vary across geographic areas — differential provider behaviours.

Our findings on the patient-level determinants of readmission are broadly in line with the previous studies. Specifically, older and male patients are at increased risk of readmission, while longer LOS reduces the probability of readmission [47, 52, 55]. However, we uniquely contribute to the literature by incorporating more hospital-level factors and allowing LOS to have differential effects on readmission across hospital types. The findings reflect the role of hospital discharge incentives, which, to our knowledge, was never explored in previous research. In particular, since public Hospital Units in Italy are financed by global budgets that are reimbursed ex-post, we expect that they have less pressure to discharge patients early for cost-saving purposes. This is confirmed by the significant and negative coefficients of LOS for both of the readmission indicators. On the other hand, since the DRG-based PPS incentivises greater efficiency as reimbursement tariffs decrease beyond a specific hospital LOS, for independent public hospitals such Hospital Trusts, Teaching and Research Hospitals, there is more incentive to discharge the patients before the threshold date in order to avoid tariff abatement. Therefore, LOS may have been less effective in reducing the probability of all-cause readmission than the public Hospital Units. Nevertheless, these independent public hospitals have lower overall readmission than Hospital Units, which highlights the fact that payment incentive systems are not the only drivers of the different readmission rates across hospital types. We believe that future research can incorporate, both theoretically and empirically, the cost dimension of the provider behaviour in the Italian context, as explored in other countries by Kittelsen et al. [84] and Schreyögg and Stargardt [85].

Furthermore, our analysis of the geographic disparity of readmission rate is comparable to the research on the variation of hospital performance indicators such as emergency admission mortality [35, 86], LOS [37] and hospital resource utilisation [38] in other contexts. For instance, similar to our results, Gobillon and Milcent have found that differential use of surgical procedures contributed to the substantial regional disparity in AMI mortality in France [35]. In a multi-country analysis, Lorenzini and Marino have found that hospital size and types explain the cross-country variation in efficiency outcomes such as LOS and costs [37]. These studies highlighted the importance of understanding the disparity in healthcare delivery at different geographic levels. There are, however, two unique and important contributions from our findings. First, the geographic variation of unplanned readmission is primarily explained by not only differential procedures, but also hospital LOS. This result points to the potential geographic clustering of hospital discharge behaviour that can be important for policy-makers to improve equity of care. Second, the hierarchical geographic levels adopted in this paper are important units to consider given the highly decentralised healthcare system in Italy. Since LHAs are responsible for the health of the entire population in a given area, inter-regional differences in sources of funding, healthcare governance model may explain why, even after controlling for patient and hospital factors, we still observe around 10% of the total variance attributable to the LHA and regional level.

Some limitations of this paper need to be recognised. First of all, readmission as an indicator can be tricky to interpret, as there are variations of the percentage of readmission that is considered "preventable", and reasons for early readmission also tend to differ substantially [87]. Secondly, since our dataset does not link to the registry data, we are not able to control or exclude the patients who died after discharge. Finally, we have not fully considered some of the contextual factors at the local health market, such as hospital competition and population density but instead treated them as cluster-specific random effects. This aspect will be essential to consider for future studies on the spatial distribution and patient travelling patterns for elective admissions.

1.5 Conclusion

What we explored in this paper ultimately touches upon the trade-off between quality and efficiency and the potentially divergent trajectories of healthcare quality across regions. For hospitals under PPS, LOS may have been less effective in reducing all-cause readmission than that of hospitals are under a global budget system due to the lack of incentive to keep patients for longer than necessary. However, the overall readmission rates of these independent public hospitals remain significantly lower. Additionally, the negative effect of LOS is the strongest among the Private Clinics, which also have the highest overall readmission rate. These findings indicate that the differences in readmission risks across hospital types are not solely driven by payment incentives. For instance, even though we are analysing emergency admissions, patient selection may still be present in certain regions. The existence of private insurance and payments may also facilitate more extended hospital stay. In general, the geographic variations in unplanned readmission that are driven by differential discharge behaviour, surgical procedures or other unobserved factors had profound implications on the equity dimension of the healthcare system. For health policy-makers, it is admittedly a daunting task to achieve the right balance between endowing more autonomy to regions and maintaining a healthy level of central control over the quality of healthcare delivery. For instance, certain well-governed regions may have achieved both better quality of care and financial performance, while others struggle through the same period and remain at a stagnant stage where the financial constraint is limiting the progress to improve quality. Although after 2015, the cost containment measures have been eased in most regions, the variability across LHA and regions in terms of health governance models and the extent tariffs are used persists. We hope our findings can provide important insights into the potential driver of geographic disparity of quality of care.

Chapter 2

Is there a Socioeconomic Gradient in Health Outcomes?

Abstract
The great economic crisis in 2008 has affected the welfare of the population in countries such as Italy. Although there is abundant literature on the impact of the crisis on physical health, very few studies have focused on the causal implications for mental health and health care. This paper, therefore, investigates the impact of the recent economic crisis on hospital admissions for severe mental disorder at small geographic levels in Italy and assesses whether there are heterogeneous effects across areas with distinct levels of income. We exploit 9-year (2007–2015) panel data on hospital discharges, which is merged with employment and income composition at the geographic units that share similar labour market structures. Linear and dynamic panel analysis are used to identify the causal effect of rising unemployment rate on severe mental illness admissions per 100,000 residents to account for time-invariant heterogeneity. We further create discrete income levels to identify the potential socioeconomic gradients behind this effect across areas with different economic characteristics. The results show a significant impact of higher unemployment rates on admissions for severe mental disorders after controlling for relevant economic factors, and the effects are concentrated on the most economically disadvantaged areas. The results contribute to the literature of spatio-temporal variation in the broader determinants of mental health and health care utilisation and shed light on the populations that are most susceptible to the effects of the economic crisis.

2.1 Introduction

Studies on the social determinants of mental health date back to the early 20th century when Faris and Dunham [88] examined the relationship between Chicago area neighbourhood structural characteristics and mental disorder rates. They found high rates of severe mental disorders in disadvantaged neighbourhoods. These results have spearheaded the sociological research interests in the relationship between socioeconomic factors and mental disorder. In the ensuing years, increasing numbers of studies have investigated the variation of mental disorder incidents across areas with different levels of socioeconomic deprivation [89–93]. These cross-sectional studies have all pointed to the intuitive correlation between a higher mental disorder prevalence or psychiatric admission rate and a higher degree of economic deprivation in the neighbourhood.

The advent of the global financial crisis in 2008 and its economic consequences prompted a revival of this stream of literature, which subsequently assesses the relationship between macroeconomic conditions and mental health outcomes. Conceptually, at the individual level, economic crisis can affect mental health through increased unemployment, perceived insecurity, indebtedness, or decreasing welfare support. Many recent studies have documented the prolonged mental health effects of worsening economic conditions. For instance, in Spain, researchers have shown significant associations between crisis periods and increased frequency of primary care mental disorder diagnosis [94] or self-assessed mental health [95]. Similarly, results are found in relation to different types of affective disorder admission or diagnosis [96–99] and self-reported mental health in various European and US studies [100–104]. However, some Spanish studies have contradictory results, as they found the economic crisis to be associated with a lower number of people demanding mental health services [105, 106].

In Italy, the crisis has had profound implications on the population. The systematic rise in unemployment rates and the worsening labour conditions have given rise to substantial inequalities and social tensions [107]. Also, the generally pessimistic outlook of the economy could have posed additional severe mental health challenges due to the widespread insecurity. Moreover, the governments did not use counter-cycle measures but instead implemented austerity measures, and the health care sector was thereby faced with budget cuts to avoid debt default [108]. These fiscal policies may have unintentionally exacerbated unequal access to care across socioeconomic groups and geographic areas, and the consequences on mental health care utilisation of the population remain under-explored. If highly disadvantaged population not only have a greater need for mental health care due to the crisis, but these needs are not met due to inadequate resources being allocated to the corresponding services, equity concerns arise. This unmet need may even aggravate the burden on the health care system in the long run.

Although the literature on the association between economic crisis and mental health and health care utilisation is plentiful, the research in the Italian context have investigated the issue either using longitudinal survey data with subjective measurement of mental health [109] or looking at the correlation between mental disorder and crisis period at the aggregated level [110]. To our knowledge, no study has, at the Italian national level, proved the causal effect of the economic crisis on mental health care. We aim to contribute to this stream of literature by analysing the potential impact of changing economic conditions on mental disorder admissions throughout the crisis period in Italy. We pay special attention to the differential effect of the crisis on areas characterised by high- and low-income levels. As discussed in the following section, there is a marked paucity of studies that established the causal impact of the crisis on mental health care using administrative data. The results will be informative for policymakers in higher- middle to high- income countries that had experienced rapid socioeconomic changes accompanied by an increasingly cost-conscious health care system.

2.1.1 Related Literature

To establish the socioeconomic determinants of mental health outcomes, we need to look into multi-disciplinary works for deeper understandings of how adverse conditions act as psychological stressors and how such conditions can have implications on the health care system. While the biological or psychological process is beyond the scope of this paper, we intend to invoke social science theories at the micro-social and macro-social levels to explain this link.

The psychological effects of living around neighbourhoods characterised by low social status are explored in the early literature [111, 112]. The emphasis is primarily on the social causes of psychological stress, including the amount of control and autonomy over the environment a person resides [113], the extent to which one feels adequately rewarded for the labour [114–116], or deprivation in its various forms. We recognize the importance of the psycho-social factors, but given our empirical interest, we will only discuss the economic explanation in greater length. Blane [117] identified the materialist explanation for psychological stress as the "experience arising as a consequence of social structure and organization, over which the individual has no control". This illustration is linked to Weber [118] 's concept of "life chances", which depends on one's bargaining power in the labour market [119]. The feeling of little control and of being trapped can evoke frustration and anxiety[120]. This response is likely to happen if individuals from a deprived condition have no means or qualifications to obtain jobs, and the disadvantage is likely to be exacerbated by the neighbourhood where one resides.

At the community level, theories on the sociological process that creates neighbourhood disorders focus on stressors and their implications on residents' health and wellbeing [121–123]. As discussed above, the lack of control and autonomy can contribute to the variation of health across social gradients [124]. Residents who experience concentrated deprivation can generate a widespread sense of powerlessness and mistrust, which can further lead to psychological distress — anxiety, anger and depression [125]. At the macro-societal level, theories on the loss of control during socioeconomic transitions provide insights into the mechanism behind the impact on health. Instability and insecurity in the labour market and unemployment during economic transitions or economic shocks can contribute to the rise in psychological and somatic responses such as chronic stress and anxiety [126]. Lower levels of perceived agency can diminish optimism for the future and ultimately result in poorer population health [125]. These broader adverse conditions can activate the chronic arousal of the stress system in its pathway to influence one's mental health [127]. In the established theoretical literature, area-level socioeconomic factors are indisputably fundamental causes of mental illness.

Social epidemiologists and psychiatric scientists have long investigated the socioeconomic and environmental determinants of mental illnesses empirically. The early study by Faris and Dunham [88] examined the geographic distribution of mental disorders across economic gradients. Their systematic analysis pioneered future studies on the association between social disorganization and mental disorder [89, 128–131]. These studies tested correlations between psychiatric admissions and socioeconomic indicators of the neighbourhood, showing a non-homogenous distribution of admissions to psychiatric care and mental disorders across areas that are differentially deprived.

Interests in this field of research resurfaced with the advent of the great economic crisis, during which rising unemployment and deteriorating working conditions have had implications on the population's mental health. While most research in the economics literature have analysed physical health outcomes and utilisation [104, 132–135], there is much less understanding on the impact of macroeconomic conditions on mental health and health care. Ruhm [136] summarised the previous research and broadly concluded that total mortality is pro-cyclical, that death increases during an economic boom, while for the sub-category of suicides or intentional self-harm the relation can be counter-cyclical. Among other related studies, Belloni et al. [137] have shown that mental health improves upon retirement among 10 European countries, especially for regions that are hit severely by the economic crisis; Drydakis [103] found more devastating effects of unemployment on mental health during the crisis in Greece; McInerney and Mellor [138] have found that sudden wealth loss due to the 2008 market crash caused immediate decline in mental health. Most of the research utilised subjective measures of mental health.

Systematic reviews from inter-disciplinary research provided ample evidence on how economic recessions can be associated with mental health outcome and utilisation [139–141]. Frasquilho et al. [139] found that economic indicators such as rising unemployment and declining income are significantly associated with poor mental wellbeing and increased rates of mental disorders. The majority of the studies investigated countries that are hit the hardest by the economic recession such as Greece [96, 97], Spain [94, 95, 142–144] and Italy [109, 145–147], though primarily using cross-sectional surveys or ecological analysis, thus providing limited evidence of causal inferences [139]. Parmar et al. [140] identified relatively consistent results on the association between deteriorating economic conditions and poor mental health, although risks of bias persist in the studies due to selection and potential confounding effects. A recent systematic review by Silva et al. [141] further summarized the empirical evidence on the association between periods of economic crisis and the use of mental health care, suggesting that periods of economic crisis can be linked to an increase in hospital admissions for mental disorders. For instance, a cohort study by Modrek et al. [98] found a marginally significant increase in the post-recession trend in inpatient utilisation compared with pre-recession trend in the US, while Lee et al. [148], in a time series analysis, found increased hospitalisation rate for affective disorders in Taiwan, especially among the low-income group. We aim to further investigate the causal impact of changing economic conditions on mental health and health care and the social gradient behind in the Italian context, given that the indirect costs in the form of lost mental capital and productivity can pose major challenges for the society.

Another factor related to the economic determinants of mental health is the role of income inequality. The earliest papers on physical health and income inequality showed a cross-sectional association between Gini coefficients of income inequality and various health outcomes [149, 150]. The literature rapidly expanded in early 2000, and a review by Wilkinson and Pickett [151] showed an overwhelming majority of the studies found a positive relationship between income inequality and health. As the gulf between the poor and the rich widens in recent decades, many scholars explicitly looked into the effect of inequality on mental health. A 2017 Lancet Psychiatry meta-analysis collected data from 27 eligible studies and showed that there is a systematic negative effect of income inequality on mental health, with effects that vary widely across countries [152]. Most recently, an in-depth examination illustrated how vast disparities of wealth are associated with elevated levels of stress, anxiety and ultimately, depression and bipolar disorder [153]. We recognize the substantial contribution from these epidemiological studies and intend to incorporate the dimension of income inequality into our study explicitly.

2.1.2 Institutional Background

In Italy, mental health services are offered by the Italian National Health Service (INHS) through a network of community and hospital services. Access is completely free for hospital care, while outpatient specialist services require co-payment. Moreover, broad categories of patients are exempted from such co-payment for economic reasons (low income), age (elderly) or due to specific chronic conditions. With the approval of the Psychiatric Reform in 1978, new admissions to specialised mental institutions were banned (with the exclusion of forensic detention centres), psychiatric hospitals were gradually closed down, and acute hospital care was attributed entirely to general hospitals [154]. As a general rule, psychiatric services are organized around a department in charge of acute hospital care, outpatient services, day-care activities, including psychological treatments, rehabilitation and social services [154]. Although the national legislation requires uniform standards across the country, significant inter- and even intra-regional differences persist after almost 40 years of policies towards geographical equity. In particular, southern regions tend to offer fewer services, mainly community based [155].

The crisis in 2008 hit Italy with some specificities. First, the country's economic performance was stagnating since the early 1990s. The average real GDP growth in the periods of 1993-2008 and 2009-2018 were merely 0.7% and -0.3%, respectively [156].

The great crisis hit an economy that was already strained by weak demand, lack of private investment, high public debt and declining international competitiveness in major industrial sectors. Moreover, government policies in Italy are constrained severely by its high public debt, so any attempt to use Keynesian policies to stimulate the economy with higher public spending is limited by tight budget constraints and the Euro Zone rules.

Unemployment rates have been persistently high since the onset of the crisis, especially among younger adults. In 2018, the employment rate for the population aged between 18 and 64 was 58.5%, almost 10% lower than that the average level registered for EU 28 countries [157]. Given the social structure and the conditions of the labour market, the employment rate is particularly low among the youth — with 43.4%, Italy breaks the EU record for being the country with the lowest employment rate for the age group of 20-29 [157]. Mean values for the leading indicators of economic performance mask significant geographical variations with some areas of the South being one of the poorest and most disadvantaged among all European countries. Southern regions, comprising about one-third of the Italian population, register a GDP per inhabitant that is less than 50% of Lombardy, the wealthiest region of the north [157]. Overall, the impact of the crisis primarily exhibits in the form of rising unemployment.

2.1.3 Objectives

Using a societal perspective, we aim to carry forward the discussion by establishing the causality of deteriorating economic conditions during the economic crisis on mental disorder admissions in the Italian context. The study's objectives are two fold (i) to test and measure the causal impact of the economic crisis on mental disorder admissions in Italy; (ii) to assess the heterogeneous impact of the crisis across areas with distinct levels of income. We wish to not only provide evidence on the socioeconomic determinants of mental health admissions but also potentially connect the research to the policy debates on mental health and health care.

2.2 Methods

2.2.1 Data

We use administrative data from three primary sources and utilise the small geographic level as the unit of analysis to construct a panel data structure. First, we use the hospital discharge dataset collected by the Italian National Ministry of Health on all inpatient admissions during the period 2007-2015. The hospital discharge data provides detailed information about the clinical characteristics of the admitted patients, mainly through indications up to five secondary diagnoses. We requested for the extraction of patients aged between 18 and 65 and diagnosed with affective disorders (ICD-9: 296.0- 296.9), which include severe mental disorders such as bipolar disorder, major depressive disorder and manic disorder. Our choice of age category is informed by our objective to detect the effect among individuals in the labour market, who tend to experience stress due to changing employment status and prospects. In investigating the socio-economic determinants of mental disorders, many studies have focused specifically on affective disorders (or mood disorders), which is a subset of severe mental disorders including bipolar I disorder, major depressive disorder and manic disorder [97]. Patients with affective disorders face substantial morbidity and mortality, as well as social consequences, with life expectancy lower than average [158]. It is estimated that 7.4 % of the global Disability-adjusted Life Years (DALYs) are caused by diseases in the mental and behavioural disorder categories, with major depressive disorder carrying the most onerous burden. Therefore, we focus on this subgroup of affective disorder patients. Even though they represent only a limited fraction of all mental disorder categories, they have the highest admission volume in our dataset and are likely to be more associated with socioeconomic shocks rather than other mental diseases such as schizophrenia, which we consider for the placebo tests.

In the dataset, each patient is geographically located within one of the overall 611 Local Labour Areas – "Sistema Locale del Lavoro" (SLL) – that aggregates the neighbouring municipalities ("comuni") to reflect a common economic structure [135]. The SLLs draw a territorial grid whose boundaries are drawn using the flows of daily work (commuting) detected from the general census of the population and households [159]. This local labour market system represents the ideal geographic unit of analysis, as individuals residing within the area by construction experience similar labour market changes due to the economic crisis. We, therefore, utilise the unemployment rate, labour market and population information at the SLL level obtained from the Italian National Statistical Office (ISTAT). For each SLL, changes in the annual unemployment rates are used as an indicator of crisis intensity in the labour market. Furthermore, since we exploit the variation in the unemployment rate across nine years, we do not specify a restricted definition regarding the timing of economic crisis but rather regard it as a process. To control for the overall resources within the community, we further incorporated the dataset with the distribution of the population income and constructed residents' stated income per person and the Gini coefficients at the SLL level.

Overall, we created a panel dataset of variables regarding patient admission, the unemployment rate, income level and other characteristics at the SLL level. The structure of the nine years panel dataset with 611 areas per year allows us to identify the causal effect of unemployment change on mental disorder admission by eliminating the time-invariant unobserved heterogeneity.

2.2.2 Econometric Model

We exploit the nine years panel dataset and connect variations in admission for affective disorders per 100,000 residents to changes in unemployment rate across time and space. Panel datasets have some appealing characteristics: (1) it allows us to control for individual (for our purpose the SLL area) heterogeneity, (2) it gives more informative data — more variability, less collinearity among the variables, more degrees of freedom and more efficiency. To address the issue of potential omitted variable bias for unemployment rate on admission rate, we considered several identification strategies, and we explain each in turn briefly.

The most commonly used panel data models to eliminate unobserved effects is to apply the within (demeaning) transformation — the one-way fixed-effects (FE) model or to take first differences to exploit variation across periods. We tested the two models against pooled-OLS and random effect models and concluded that the FE estimator is consistent. We, therefore, consider the following equation:

$$adm_{it} = \beta\ Unemployment_{it} + X_{\mathbf{it}}\ \gamma + u_i + \ \varepsilon_{it} \tag{1}$$

Where adm_{it} denotes the number of affective disorder admissions per 100,000 residents for the area i at year t. Variable $unemployment_{it}$ is the unemployment rate for the area i at year t. The coefficient β is of primary interest as it represents the impact of labour market condition on admissions for mental disorders. $\boldsymbol{X}_{it}$ is a vector of control variables that include average income per capita, the Gini coefficient, family size, gender composition and other aggregated patient characteristics at the SLL level. u_i is the unobserved area heterogeneity that is time-invariant such as rurality or general population composition, while ε_{it} is the idiosyncratic error term. We assume the error term ε_{it} to be independent and identically distributed $\varepsilon_{it} \ \sim IID(0, \delta_{\varepsilon}^2)$ and $\boldsymbol{X}\ _{it}$ to be independent of the ε_{it} for all i and t. We estimate equation (1) using fixed-effect panel estimation, where we cluster robust standard errors at the SLL level and include a set of year dummies. We also estimate the same equation using time-lagged explanatory variable $unemployment_{i,t\text{-}1}$ to allow for delayed effects on mental disorder admission. We complement the fixed-effect model with the alternative first-difference estimation, where time-invariant area-specific effects are cancelled over time.

One can argue that the relationship between an increased unemployment rate and mental disorder hospitalisation involves an adjustment process. This dynamic happens when the year's outcome depends not only on the independent variables but also on the outcome of the previous year. Moreover, standard linear panel models, despite their various merits, can suffer from biases due to short time duration. We, therefore, expand our analysis to a dynamic panel model that includes the lagged value of the dependent variable.

$$adm_{it} = \alpha\ adm_{i,t-1} + \beta\ Unemployment_{it} +_{\mathbf{it}}\ \gamma + \ u_i + \ \varepsilon_{it} \tag{2}$$

Where $u_i \ \sim \ IID(0,\ \delta_u^2)$ and $\varepsilon_{ti} \ \sim \ IID(0,\ \delta_{\varepsilon}^2)$ are assumed to be independent of each other and among themselves. The dynamic panel regression has two sources of persistence over time - autocorrelation due to a lagged dependent variable and area heterogeneous effects [160]. Within-group estimators for the above equation can result in bias as elimination of u_i can cause correlations between the transformed error term and the transformed lagged dependent variable. We, therefore, also perform first difference transformation and allow the use of lags of $adm_{i,t\ -1}$ as valid instruments [160–162].

First-difference with lagged adm:

$$\triangle adm_{it} = \alpha\triangle adm_{i,t-1} + \beta\triangle unemployment_{it} + \triangle X_{\mathbf{it}}\gamma + \triangle\ \varepsilon_{it},\ \ t\ =\ 2,\ ...T \qquad (3)$$

Since $\triangle admi_{i,t-2}$ is clearly correlated with $\triangle admi_{i,t-1} = adm_{i,t-1} - adm_{i,t-2}$ but not with the error term $\triangle\varepsilon_{it} = \varepsilon_{it} - \varepsilon_{i,t-1}$, it can be a valid instrument. We estimated the equation using both Anderson and Hsiao estimator [163] and Arellano and Bond estimator [161] based on Generalized Methods of Moments (GMM). For the former, we instrument the lagged dependent variable with twice-lagged level, while for the latter model we combine the first differences with a model using lagged differences as instruments [164]. Lags of $unemployment_{i,t-1}$ are also used as an instrument for unemployment. We include a full set of year dummies.

While we aim to capture the causal impact of changing unemployment on mental disorder admissions, we are also interested in the heterogeneous effects of the crisis across socioeconomic groups. In the last section of the analysis, we create discrete quintile groups according to the area's income level and interact the groups with the unemployment rate for the panel fixed-effect model.

$$\begin{aligned} adm_{it} &= \beta\ unemployment_{it}\ + \delta(unemployment_{it} \cdot Income\_quintile_{it}) \\ &+\eta\ Income\_quintile_{it} + X_{\mathbf{it}}\ \gamma + u_i + \varepsilon_{it} \end{aligned} \qquad (4)$$

The parameter δ identifies the differential effect of the interaction term between the indicator of the area belonging to one of the income level quintiles and the unemployment rate. The coefficients for the different quintile levels represent the crisis effect on admission rate for that income quintile area, and we use both the fixed-effect and dynamic within transformation to estimate the heterogeneous impact.

2.3 Results

2.3.1 Descriptive Statistics

We have a balanced panel of nine years and 611 SLLs. The summary of the variables we constructed can be found in Table 2.1. We observe that overall, the admission rate for all affective disorder hospitalisation is around 77 individuals per 100,000 population on average for the SLLs, with the majority being bipolar disorder admissions. The average age of the patients is around 43 years old, and the average length of stay is around 13 days. The unemployment rate is about 10% but ranges from 1.42% to 38.7%, indicating a considerable variation across areas. Income and inequality measures also differ widely across areas.

Table 2.1: Descriptive Statistics

Variables (Average at SLL level)	**Values**			
	Mean	S.D.	Min	Max
Admissions for All Affective Disorder/100,000	77.164	47.483	0	384.97
Admissions for Bipolar I Disorder/100,000	36.863	28.005	0	259.99
Admissions for Major Depressive Disorder/100,000	21.511	22.539	0	261.51
Admissions for Manic Disorder/100,000	1.073	3.108	0	131.30
Patient Age	43.215	2.278	27.75	57.71
Length-of-stay	12.564	4.577	2	66.87
Unemployment Rate (%)	10.246	5.597	1.42	38.70
Annual Declared Income per Person	11,509	3,084	5,077	20,949
Population of Residents	97,208	257,904	3,156	3,682,555
Gini Coefficient (*100)	14.106	1.821	8.67	24.67
Family Size	2.390	0.220	1.55	3.36
Proportion of Male (%)	48.78	0.77	46.267	53.834
Total Observations	5,499			

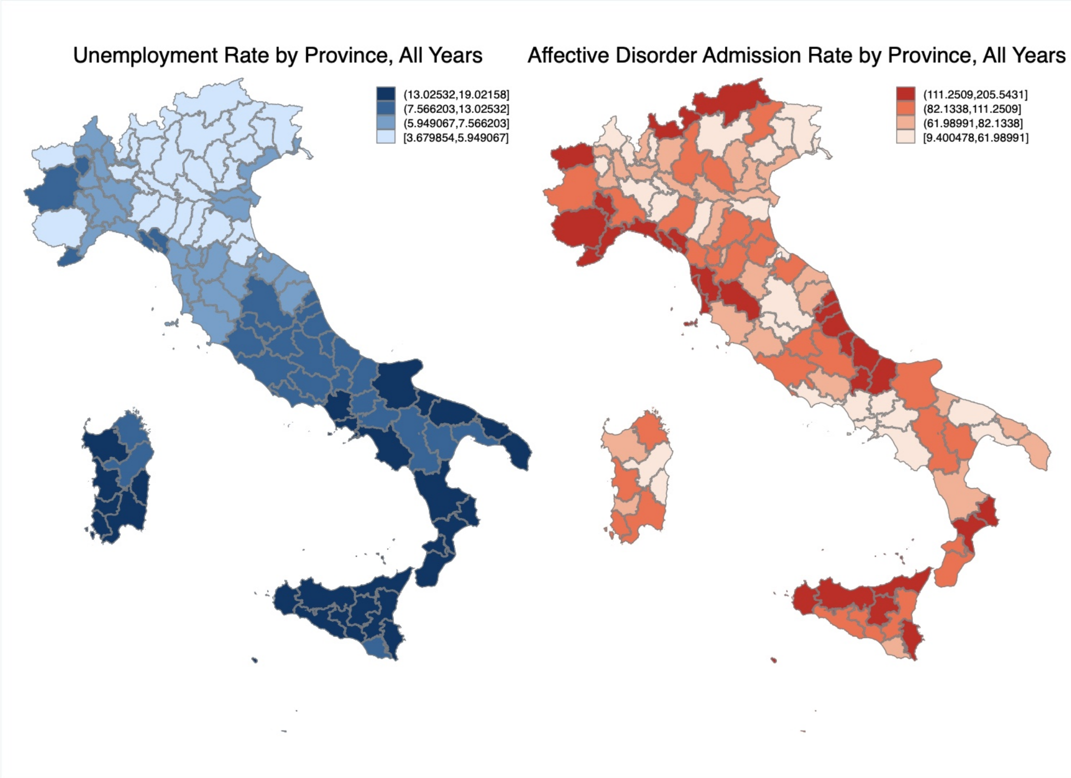


FIGURE 2.1: Geographic Distribution of Unemployment Rate and Affective Disorder Admissions, All years

We further characterize the variation of our variables of interest over geography and time. The spatial variation of the average unemployment rate is found in Figure 2.1 on the left, where we observe a visible gradient between the north and the south. However, affective disorder admissions do not appear to have a clear geographic pattern. Over time, we see in Figure 2.2 that the unemployment rate increases consistently since 2008 and peaked in 2014, with the south having persistently higher levels than the central and northern regions. While total hospitalisation per 100,000 residents initially declined until 2009, it then experienced a drastic increase in the south. Descriptively, it appears that the increase in the unemployment rate over the observed period is accompanied by an increase in the admission for affective disorder patients for the southern regions, while it is ambiguous for the central and northern regions. What we aim to capture is the (heterogeneous) effects of the worsening labour market conditions on admissions for affective disorder.

In understanding the socioeconomic gradient of the correlation, we plotted the two variables of interest across discrete quintile groups according to the average declared income per person (Figure 2.3). The scatterplot shows that in 2007 the correlation is slightly negative with no substantial differences across the quintile groups; but by 2015, there is a positive correlation between unemployment rates and admission rates for the first and the fourth income quintile groups (the dark red and the dark green lines). It means that descriptively, the effect of the crisis on mental disorder admissions differ across areas characterized by distinct economic conditions.

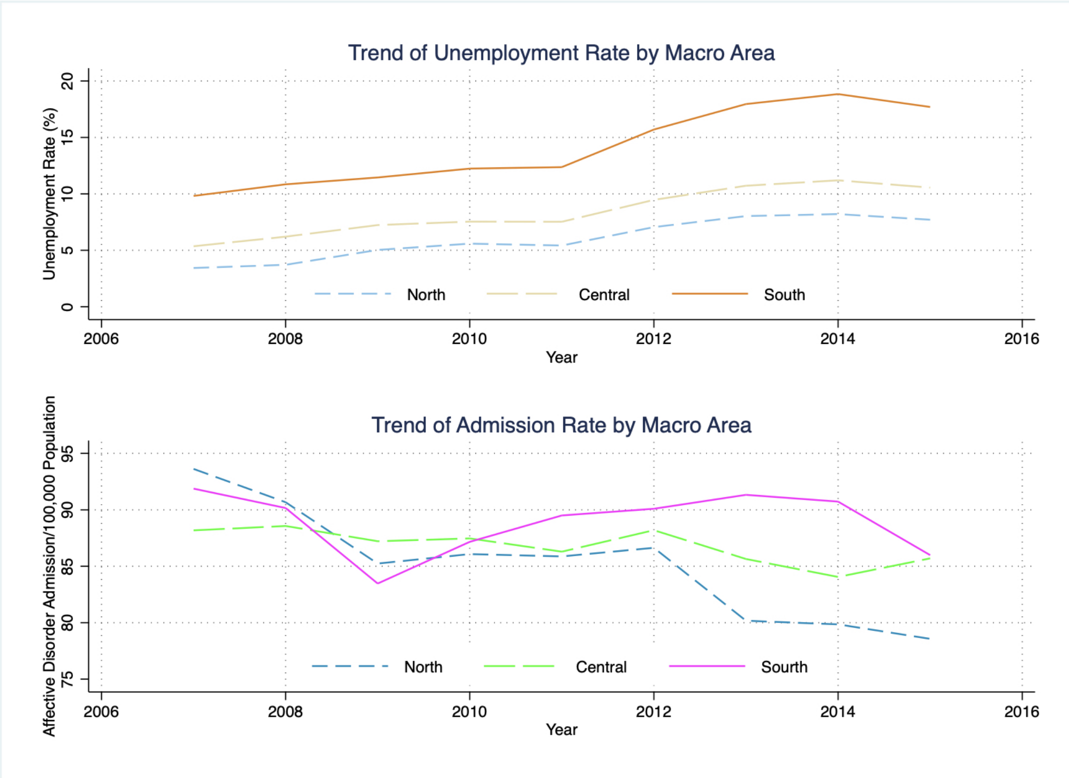


FIGURE 2.2: Time Trends of Unemployment Rate and Affective Disorder Admission Rate, by Macro Area

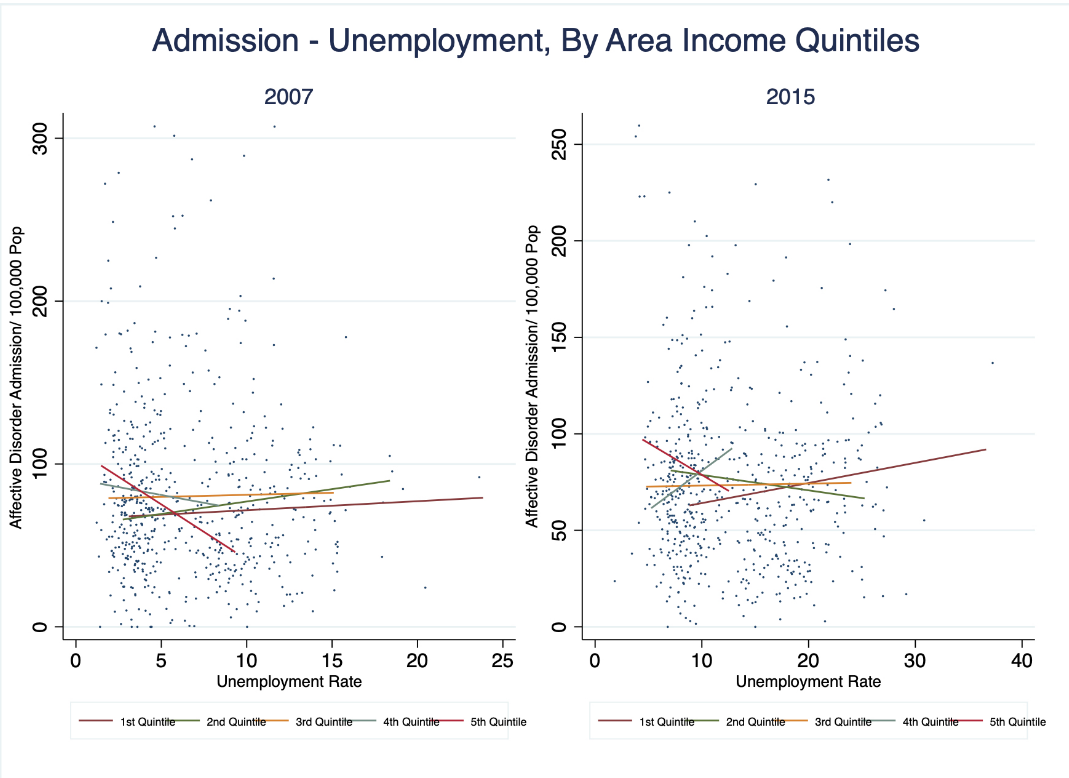


FIGURE 2.3: Scatterplot of Admission Rate Against Unemployment Rate by Area Income Quintiles, 2007 & 2015

2.3.2 Regression Results

Table 2.2 reports the fixed-effect and first difference estimators from Equation (1). For all the models, there are significant and positive effects of unemployment rate on the admission rate for affective disorder — 1 percentage point increase in unemployment gives rise to about 1 out of 100,000 residents being admitted to the hospital due to affective disorder. Although the result is robust for unemployment, most of the control variables are not significant.

For the dynamic panel models, we report in Table 2.3 the fixed effect estimator with lagged dependent variable from Equation (2), the Anderson and Hsiao estimator as well as the Arellano and Bond estimator from Equation (3). Consistently with the linear panel model, all the coefficients for unemployment in the dynamic panel models are positive and significant, with values around 1. The similar results across linear and dynamic panel models show strong evidence for the effect of unemployment on admissions for affective disorder. The specification test for GMM shows that there is 1st order serial correlation (AR1), and no 2nd order serial correlation (AR2). The Hansen test does not reject the over-identifying conditions.

To check the robustness of our findings, we run both the linear and dynamic panel model for the sub-categories of affective disorders — bipolar disorder and major depressive disorder. For each disorder, we first use the fixed-effect estimator with and without the one-year lag of unemployment rate, as well as the Arellano-Bond estimator with a one-year lag. As seen in Table 2.4, the impact of unemployment is significant and robust for major depressive disorder admissions across all models, and similarly for bipolar disorder except for the FE estimator with the lagged unemployment rate.

In identifying the potential gradients of the crisis effect on admission rate, we interact the different income quintiles with the unemployment rate as indicated in Equation (4). We observe in Table 2.5 that for both the linear and dynamic panel models, the impact of unemployment is only significant for areas belonging to the 1st quintile of average income (the coefficient for Unemployment), and, curiously, the marginal effects are negative for areas belonging to the top quintiles of average income. We can reasonably conclude that the adverse impact of rising unemployment admission for affective disorders is concentrated on the most economically disadvantaged areas.

2.3.3 Placebo Test

We further run a placebo test for the hospitalisation rate of schizophrenic patients. There is ample evidence in social psychiatry research that schizophrenia is not associated with sudden labour market changes but with urbanicity and socio-environmental changes, usually with an early onset during teenage years (Silver et al., 2002; van OS, 2004). Although we believe that increasing social fragmentation and income decline may contribute to early onsets of schizophrenic patients, job loss and labour market deterioration should not affect the hospitalisation of these patients. Indeed, in our

TABLE 2.2: Linear Panel Models

Models	**FE**	**FE with Lagged-Unemployment**	**FD**
Variables	Admission	Admission	Admission
Unemp	1.618***		0.849**
	(0.407)		(0.331)
Lagged Unemp		1.052**	
		(0.415)	
Income per Capita	0.000616	0.000303	-0.000338
	(0.00103)	(0.00111)	(0.00101)
Gini (*100)	0.432	-0.107	-0.209
	(1.108)	(1.175)	(0.970)
Patient Age	0.0273	0.235	0.174
	(0.290)	(0.300)	(0.196)
Length-of-stay	0.0342	-0.204	0.158
	(0.234)	(0.242)	(0.151)
Family Size	11.38	15.45	-5.774
	(10.95)	(11.33)	(9.670)
Proportion of Male (%)	-1.302	-1.055	-4.068**
	(1.576)	(1.624)	(1.728)
Constant	89.74	75.69	-1.384**
	(93.81)	(96.17)	(0.584)
Observations	5,499	4,888	4,888
Year Dummy	Included	Included	
F-statistics	2.99***	2.43***	2.35***
Number of small areas	611	611	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.3: Dynamic Panel Mode

Models	**Within Transformation**	**Anderson and Hsiao**	**Arellano and Bond**
Variables	Admission	Admission	Admission
Lagged Adm	0.149***	0.274***	0.0927
	(0.0359)	(0.0517)	(0.0629)
Unemp	1.017***	0.679*	1.460*
	(0.315)	(0.384)	(0.770)
Income per Person	0.000730	-0.000410	-0.00378
	(0.00102)	(0.00122)	(0.0125)
Gini (*100)	-0.196	-0.611	-7.267
	(1.077)	(1.136)	(7.407)
Patient Age	0.240	0.352	3.255
	(0.299)	(0.235)	(5.840)
Length-of-stay	-0.123	0.139	7.936**
	(0.234)	(0.190)	(4.021)
Family Size	5.901	-6.396	-134.2*
	(9.579)	(11.37)	(69.38)
Proportion of Male (%)	-1.995	-4.681**	13.26
	(1.474)	(2.004)	(22.63)
Constant	-1.121***	-1.036	-5.890**
	(0.396)	(0.698)	(2.600)
Year Dummy	Included	Included	Included
Observations	4,888	4,277	4,277
Number of small areas	611		611
Instruments		7	29
Hansen test Chi-square			27.04
AR1 test			-3.91***
AR2 test			2.10**
F-Statistic	5.81***		3.26 ***

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 2.4: Sub-Disorder Admissions

Models	**FE**	**FE**	**FE Lagged**	**FE Lagged**	**Arellano-Bond**	**Arellano-Bond**
	Bipolar I	Depressive	Bipolar I	Depressive	Bipolar I	Depressive
Adm-Lag					0.0557	0.0372
					(0.0355)	(0.0313)
Unemp	0.597***	0.889***			0.734**	0.675**
	(0.215)	(0.257)			(0.308)	(0.282)
Unemp-Lag			0.0875	0.498***		
			(0.177)	(0.144)		
Income per Capita	0.000620	0.000740	0.000799	0.000219	0.000454	-0.00285
	(0.000727)	(0.000619)	(0.000612)	(0.000500)	(0.00493)	(0.00400)
Gini (*100)	0.473	-0.561	-0.364	-0.400	-1.306	-0.669
	(0.755)	(0.690)	(0.611)	(0.499)	(2.910)	(2.408)
Patient Age	0.151	0.339**	0.301**	0.309***	0.200	4.967
	(0.188)	(0.158)	(0.146)	(0.119)	(2.263)	(4.558)
Length-of-stay	-0.0161	0.145	-0.127	0.0531	2.307*	2.618
	(0.129)	(0.116)	(0.107)	(0.0875)	(1.377)	(2.434)
Family Size	10.92	-4.356	1.966	-2.800	-55.04	-43.70
	(6.827)	(6.197)	(5.273)	(4.304)	(35.22)	(34.31)
Male (%)	-0.543	0.0971	-0.990	-0.439	-4.449	7.602
	(0.999)	(0.926)	(0.946)	(0.772)	(12.47)	(10.94)
Constant	11.52	8.771	-478.4	2,539***		
	(56.87)	(52.05)	(487.7)	(398.0)		
Observation	5,499	5,499	4,888	4,888	4,277	4,277
Year Dummy	Included	Included	Included	Included	Included	Included
Instruments					30	30
Hansen test Chi-square					30.31*	22.73
AR1 test					0.049	-7.24***
AR2 test					0.562	-2/09**
F-Statistic	3.33***	5.74***	3.09***	8.55***	5.64***	2.59***

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 2.5: Heterogeneous Effects Across Area Income Quintiles

Models	**Fixed Effect**	**Dynamic Within**
Variables	Admission	Admission
Lagged Adm		0.148***
		(0.0356)
Unemp	0.661**	0.506*
	(0.304)	(0.286)
2 Quintile Inc	-3.305	-2.032
	(7.406)	(7.425)
3 Quintile Inc	14.69*	14.33*
	(8.885)	(8.542)
4 Quintile Inc	10.24	6.813
	(8.885)	(8.678)
5 Quintile Inc	18.51**	14.64
	(9.090)	(9.010)
2 Quintile Inc * Unemp	0.393	0.425
	(0.405)	(0.380)
3 Quintile Inc * Unemp	-0.790*	-0.683
	(0.465)	(0.424)
4 Quintile Inc * Unemp	-0.551	0.116
	(0.634)	(0.605)
5 Quintile Inc * Unemp	-1.768***	-1.082*
	(0.596)	(0.579)
Gini Coefficient (*100)	1.302	0.244
	(1.036)	(1.038)
Patient Age	-0.0126	0.187
	(0.287)	(0.298)
Length-of-stay	-0.00637	-0.177
	(0.238)	(0.238)
Family Size	16.28*	14.56*
	(8.341)	(8.321)
Proportion of Male (%)	-2.815**	-2.843**
	(1.366)	(1.312)
Constant	146.7*	149.8**
	(75.03)	(72.21)
Observations	5,499	4,888

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

placebo regression for admission rates of schizophrenic patients, we observe an insignificant effect of unemployment rate in all specifications (Table 2.6). Whereas for the Gini coefficient, the proxy for income inequality, significantly contributes to the admissions for schizophrenia. Further research is warranted to investigate the mechanism behind rising societal inequality during economic downturns and the likely onset of schizophrenia symptoms.

2.4 Discussion

Our analysis has shown strong evidence for the impact of the economic crisis on admissions for affective disorders for the entire population in Italy. The effect is significant for all the different models that we tested, even though the magnitude is moderate. We argue that since we observe only inpatient admissions, not outpatient interventions, the actual impact could be even more severe. Moreover, it is well-established that affective disorders are associated to cardiovascular diseases [165], and thus the impact of unemployment on wellbeing and health care utilisation is likely to be substantially higher than that measured in this study. We also recognize that our outcome variable is limited in the sense that admission *per se* is a combination of supply and demand factors. While increasing inpatient admissions could reflect a greater need for care, it could be a result of a lack of ambulatory care and consequently use of hospital care when it is not appropriate. If this is the case, it will change partly our interpretations of the result, but we are nonetheless capturing the impact of rising unemployment on mental health care utilisation. Moreover, since the inpatient hospitalisation for affective disorder covers severely ill patients and not patients seeking counselling or outpatient visits, we believe the supply-side influence on admission is minimal. Finally, our results could be subject to migration bias, as individuals may move from more deprived areas to more affluent areas during the crisis. We have qualitatively assessed this possibility and did not observe a systematic change in the resident population over the years. In our dataset, we observe only around 8% of the patients seeking care in a region outside of his/her residence, indicating a low likelihood of patients travelling. Nonetheless, the exact pattern of population mobility is beyond our capacity to investigate given the nature of our data.

Our study uniquely contributes to the stream of literature on the socioeconomic determinants of mental illness by establishing the causal impact of rising unemployment during the economic crisis on severe mental disorder admissions in the context of universal coverage. The linear and dynamic panel models that we tested all point to the same conclusion — higher unemployment increases admission for affective disorder. However, inequality did not play a contributing role. When we analyse the socioeconomic gradient of the impact, we have found that areas with the lowest levels of income per capita are the most affected population. The result shows how people who belong to the more economically vulnerable segment of the society can experience adverse episodes due to their mental distress towards the deteriorating economic

TABLE 2.6: Placebo Regression for Schizophrenia Admission

Models	**FE**	**FE with Lagged Unemployment Rate**	**Arellano-Bond**
Lagged Adm			0.0523
			(0.235)
Unemp	-0.251		0.466
	(0.410)		(0.570)
Lagged Unemp		-0.0231	
		(0.403)	
Income per Capita	-0.000401	-4.97e-05	0.000763
	(0.000784)	(0.000795)	(0.00845)
Gini (*100)	2.672**	2.517**	1.480
	(1.048)	(1.018)	(4.634)
Patient Age	-0.382	-0.302	-1.937
	(0.240)	(0.264)	(2.876)
Length-of-stay	-0.510***	-0.688**	-2.145
	(0.183)	(0.277)	(2.304)
Family Size	-22.31**	-15.05*	-0.532
	(9.903)	(9.028)	(46.23)
Proportion of Male (%)	-1.236	-0.273	1.071
	(1.339)	(1.229)	(14.27)
Constant	168.0**	96.45	
	(78.07)	(72.05)	
Observation	5,499	4,888	4,277
Year Dummy	Included	Included	Included
Instruments			29
Hansen test Chi-square			14.88
AR1 test			-1.35
AR2 test			-0.93
F-Statistic	16.44***	12.49***	12.77***

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

environment. Behind this effect, two mechanisms may be at play: (i) For the unemployed, worsening labour market conditions could have induced the onsets of affective disorders, (ii) For the employed, the social diffusion of job insecurity has raised the anxiety level that potentially led to affective disorder. The findings are in line with the materialist explanation for psychological stress, as adverse economic conditions may have contributed to the chronic arousal of the stress system for those who are either unemployed or live in a neighbourhood that is profoundly affected by unemployment.

The recent COVID-19 outbreak has brought another heavy storm to harm the mental health of the population in Italy. With increased social isolation, the general sense of grief and fear, alongside the grim economic prospects, we can reasonably expect anxiety, stress, and potential mental illness to escalate. Moreover, individuals who have existing mental health conditions may face challenges in their access to care and service continuity due to the interruptions in the health care system. The findings of our research can be critically relevant for the socioeconomic crisis that follows the pandemic disaster. We, therefore, hope to pave the way for more empirical evidence on the ramification of the COVID-19 crisis on the mental health care in various countries.

An estimated 970 million people around the world suffer from mental distress, and the prevalence of, for instance, depression has risen more than 40% over the past 30 years [158]. The overwhelming phenomenon reflects a combination of the rising needs and the increasing awareness to seek treatment. How society perceives mental illness patients and how health care systems allocate resources to treatment and social policies will be a long-lasting debate. We hope that our study can bring to light the importance of adequate policy responses to address the psychological aspects of large-scale socioeconomic shocks in the long term. Specifically, more resources should be invested in social services and mental health specialist, both at the workplace and at the community level, to meet the future surge of needs and to prevent the loss of human capital and consequently labour market opportunities.

Chapter 3

Does Neighbourhood Information on Quality Affect Patient Choice?

Abstract
In an effort to increase competition among providers and, hence, achieve higher quality, many public healthcare systems have introduced free hospital choice. The success of this policy depends on patients' sensitivity towards quality differences, which in turn depends on the availability of information regarding treatment quality. In this paper, we investigate how hospital choice for elective hip replacement surgery is influenced by adverse events experienced by patients residing in the same neighbourhood, compared to the overall quality of a hospital as experienced by all observed patients. We do so by exploiting a dataset of all Italian patients over 65 years who underwent elective hip replacement surgery from 2012 to 2015. Using a patient-level random utility choice model, we find that for patients from Southern rural municipalities, low "local" quality, proxied by in-hospital mortality and readmission rates of patients from the same neighbourhood, significantly reduces the probability of choosing a certain hospital. We do not find evidence that this effect is driven by gender or age. Our results suggest that, in the absence of official quality statistics, patients do not select hospitals with the highest overall treatment quality, but rather avoid those where their neighbours experienced adverse events.

3.1 Introduction

Free healthcare provider choice as an indicator of system responsiveness is not only a policy goal in itself, but can also increase the quality of public healthcare [166]. Under fixed prices, hospitals are incentivised to compete on the quality of services, which, ideally, may lead to an increase in provider quality [167]. This rationale has led many public healthcare systems to introduce free hospital choice for patients, thereby increasing competition among providers, in an effort to improve hospital quality [168], but also to increase accessibility to care [169]. However, this goal will only be achieved if patients' demand is sensitive to perceived hospital quality. In this study, we investigate how free hospital choice is affected by quality indicators derived from different information sources, in particular from past experiences of (non-)neighbours.

Several studies have explored the elasticity of demand over quality following the introduction of hospital report cards or public quality rankings [170–174]. Most of these studies conclude that there is an effect of public quality information on patient choice, albeit a moderate one. Furthermore, a systematic literature review by Aggarwal and colleagues (2017) finds that patients react to a wide range of hospital quality indicators such as in-hospital mortality, readmission rates or other adverse events as well as to official hospital rankings [176].

Following neoclassical economic theory, which assumes that consumers are independent in their tastes and beliefs, most studies on provider quality and hospital choice have omitted a potentially crucial dimension in the decision-making process: information sharing through one's social environment. It is, however, sensible to believe that individuals, before choosing a hospital, seek opinions from friends, relatives and other trusted people, such as their family doctor, to inform their choice [177]. Despite being self-interested, humans are social animals and the failure to account for sociality will not predict well in circumstances where individuals use their social environment to define their beliefs and preferences [178]. The extensive discussion on bounded rationality and behavioural heuristics stresses how individual judgement and decisions are often strongly affected by recent information coming from their immediate social reality [179]. This so-called availability heuristic is a mental shortcut that often leads to systematic bias in decision making. Therefore, the role of information obtained from one's social environment regarding the attributes and desirability of choice alternatives seem of critical importance when analysing patient choice [180, 181].

More recent economics literature seeks to operationalize this insight as neighbourhood effects, geographic proximity and information sharing in the behaviour of individuals. The concept of neighbourhood effect refers to the interdependence among individuals in the same geographic area in which the preferences, beliefs, and constraints faced by one person are affected by (previous) choices of others [182]. McFadden 2010, in his seminal article, has shown how interaction effects play a critical role in the choice of an economic agent [183]. Indeed, a large empirical literature on the economic behaviour of, for instance, family decisions, job search, criminality or consumptions have emphasised the role of social connections. [184–186]. Although widely explored in the job-search literature and to a smaller extent on health behaviours such as smoking [187], the literature on healthcare (utilisation) has, with few exceptions that are detailed below, often failed to recognise the potential neighbourhood effect.

Aizer and Currie (2004) are among the first to examine the neighbourhood effects of healthcare utilisation in the context of California. In trying to understand the nature of the effect, the authors observe that there are strong correlated effects of maternity care utilisation behaviour within groups defined using race/ethnicity and neighbourhood. Moscone, Tosetti, and Vittadini (2012) study the influence of social interaction and demand for healthcare in the Lombardy region in Italy. They find that past experience of health services utilisation in one's neighbourhood explains at least part of a patient's choice of hospital [189]. Similarly, Berta et al. (2016) find a network effect in the choice of a specific hospital ward in the Lombardy region [190]. Aizer and Currie (2004), Moscone, Tosetti, and Vittadini (2012) and Berta et al. all considered neighbourhood effects as the significant impact of the previous year's fraction of patients adopting the same provider in one's neighbourhood, defined as the same zip code area, on the choice of seeking care the provider in the current year. More recently, Grossman and Khalil (2019) have shown how the neighbourhood network effect can contribute to the decision of whether to participate in Medicaid or not among pregnant mothers. Differently from the previous studies, the authors capture the neighbourhood network effect by estimating the influence of living in the same census block on the likelihood of a matched pair of current pregnant mother and recently pregnant mother both enroll in Medicaid [191]. Depending on the specific healthcare system design, these neighbourhood effects can be especially salient where comparative information on quality of care is not easily accessible.

We thus extend the current knowledge on hospital choice by explicitly accounting for a potential neighbourhood effect in the patient's decision-making process. Our analysis differs from recent studies in several crucial ways. Using patient-level administrative data, we propose a novel way to understand the neighbourhood effect of provider quality on patient choice by introducing two different sources of information on quality for each patient - a local and a global one. The former is based on experiences regarding treatment quality of patients from the same municipality, the latter on the overall treatment quality of a hospital. We focus on patients undergoing a specific procedure - elective hip replacement surgery. We restrict our analysis to an intervention that is not time-critical to ensure patients can carefully choose the preferred hospital based on attainable information. The choice of this elective surgery also allows us to differentiate our quality indicator by hip-replacement procedure-specific and overall provider quality, additionally to differentiation between the more subjective local information and the more objective global information dimension. Finally, while other studies use limited samples of patients being treated in hospitals of a specific region (e.g. Lombardy), we observe the full choice set for each patient, consisting of all Italian hospitals. Hence, our analysis cannot suffer from a violation of the independence of irrelevant alternatives [192].

3.2 Background

3.2.1 Institutional context

Our analysis focuses on elderly patients from the South of Italy who underwent elective hip replacement surgery in the Italian National Health Service (INHS). In the INHS, patients are in principle free to choose any hospital across the country for treatment free of charge, usually through a referral pathway from general practitioners (GPs) within a local health district [193]. Given the geographic variation in the regional health care model and quality of care, the phenomenon of high patient mobility is characteristic of the INHS [194, 195]. This patient mobility implies that some of the local health authorities (LHA) are “exporters” of care as they treat patients outside of their own LHA, whereas others are “importers” of care, where patients travel to receive care outside of their own LHA. If an admission occurs outside of the resident’s LHA, hospital reimbursement is regulated by interregional compensation schemes which are based on diagnosis-related groups (DRG) [196]. Specifically, the patient’s LHA has to pay the admitting LHA a fee-for-service based on the prospective national tariff, which creates incentives for LHAs to mitigate outflows and foster inflows [197]. The latter is especially true for treatments in an LHA where the national tariffs are higher than the actual costs of a treatment.

Several studies have empirically demonstrated that high levels of patient mobility from the South to the North persist [194, 196–198], making Northern regions exporters and Southern regions importers of care. While free patient choice might increase efficiency for some specialised treatments, it raises concern about equity and financial sustainability in the South [199]. For elective services such as hip replacements, where patients can carefully select the provider and make substantiated choices, it is highly relevant to know how patients form their decision to bypass their closest provider(s) and incur the private costs of travelling. Moreover, the set of choices for elective patients will not be constrained by geographic factors - all hospitals compete with each other.

3.2.2 Neighbourhood effect

Our assumption on the role of informal social interaction in patient choice is based on several supporting evidence. First, in the Italian healthcare system, there was no official information on the comparative quality of hospitals before 2016. Second, even if there is information available for selected hospitals gathered by independent monitoring agencies, the elderly population in rural municipalities tends to be less familiar with internet technology, it is reasonable to assume that their most relevant source of information is their surrounding social network. Third, hip replacement surgeries are generally performed among the elderly above 60 years old, which represents around 20% of the overall municipality population in the Southern regions (ISTAT). Since most of the Italian population is concentrated in small-to-medium-sized municipalities characterised by strong cultural identity and autonomy, the historical, political, social and religious forces are likely encouraging social interaction [189]. This potentially strong interaction among older residents is supported by empirical studies that have found highly assortative social contacts by age [200, 201].

Finally, we are aware that the choice of hospital, is not necessarily made by the patient alone, but often reflects a joint decision together with the GP.[1] However, there is no reason to assume that physicians are unaffected by local information on hospital quality. GPs might even act as multipliers, as they are likely to advice patients against choosing a certain hospital if one of their other patients recently experienced adverse events there. This is a reasonable assumption because during our study period, like their patients, primary care physicians did not have access to official hospital statistics, and therefore had to rely on information from their own patient pool. Especially in rural areas, this patient pool usually consists of residents from the same geographic area such as a neighbourhood or municipality. Because of the potential joint decision of hospital choice, we refrain from calling the estimated effect a social interaction or network effect, but instead, refer to it more generally as the neighbourhood effect. We hypothesise that this local information-sharing on provider quality significantly affects patient choice for elective treatments.

3.2.3 Theoretical framework

Corresponding to previous studies on patient choice [172, 202, 203], we build our empirical analysis on a patient-level additively separable utility function to obtain the random utility choice model [192]:

$$U_{ij} = V_{ij}(Q_j, t_{ij}) + \varepsilon_{ij} \tag{3.1}$$

The indirect utility equation 3.1 shows that V_{ij}, the representative utility of patient i choosing hospital j from a choice set m, is a function of Q_j, the quality of hospital j, and the transportation costs between patient i and hospital j, t_{ij}. The error term, ε_{ij}, subsumes unobserved hospital characteristics and random utility. This utility function implicitly assumes that patients are rational agents that maximize their utility (or minimize their disutility) subject to the (observable) quality of the hospital and the travel costs. Hence, we expect the patient to choose the hospital where U_{ij} is the highest.

The impact of the quality on U_{ij} crucially depends on whether the quality of and the travel time to the hospital are observable for the patient. As outlined in Section 3.1, in the absence of public report cards or official quality rankings, information might not be observable in the same way for all patients. Furthermore, we know from behavioural economics research that humans are prone to base their decisions on certain heuristics [204]. In our study, the availability heuristic is especially relevant, as it leads people to put a higher weight on events that happen closer by in terms of space and time [179]. We will therefore deviate from most empirical literature on quality and patient choice, and split the quality indicator Q_j into Q^{gb} and Q^{lc}. The former, "global" quality indicator, refers to the overall quality experienced by all elderly patients in Italy, while the latter is the quality experienced by elderly patients

[1] We do not observe who actually takes the decision, and will refer to this joint decision as patient choice in the remainder of this paper.

from the same rural municipality as patient i, and thus reflects the "local" quality. We are particularly interested in whether, all else equal, patients are sensitive to overall hospital quality outcomes, or whether they are primarily reacting to hospital quality based on information from their own neighbourhood.

3.3 Empirical Approach

3.3.1 Model specification

We model patients' hospital choice for hip-replacement surgery by considering each hospital admission as the result of patient i's "choice" over a set of $h = 1, 2, ...j$ mutually exclusive hospitals. We assume that the following linear model represents the individual's underlying utility of the observed hospital choice. As noted in Equation 3.1, we follow the established literature on patient hospital choice to estimate the random utility model using the following model:

$$\begin{aligned} U_{ijt} =& V_{ijt} + \varepsilon_{ijt} \\ =& \beta_1 \log(t_{ijt}) + \beta_2 c_{ijt} + \beta_3' Q^{gb}_{j,t-1} + \beta_4' Q^{lc}_{jk,t-1} + \beta_5' X_{jt} \\ &+ \beta_6 n_{jt} + \beta_7 n_{jkt} + \beta_8 r_{it} + \beta_9 h_{jt} + \varepsilon_{ijt} \end{aligned} \tag{3.2}$$

The variable t_{ijt} refers to the centroid-to-centroid travel time by car between patient i's municipality k and hospital j's municipality, and is a proxy for private travelling costs as a determinant of choice. To calculate travel times, we use a local open-source routing machine based on a street network from *Die Geofabrik* (see https://www.geofabrik.de/ and http://project-osrm.org/ for details). We allow a non-linear effect of travel time by taking the logarithmic form. The variable c_{ijt} is a dummy variable indicating whether the choice of hospital is close by – within 30 minutes by car – and X_{jt} is a vector of hospital attributes.

Our main explanatory variables are vectors $Q^{gb}_{j,t-1}$ and $Q^{lc}_{jk,t-1}$. Once again, the former, global quality indicator, refers to the overall quality of hospital j based on all elderly patients in the prior year. The local quality variable, on the other hand, reflects the quality of hospital j as it was experienced by elderly patients from municipality k. Both $Q^{gb}_{j,t-1}$ and $Q^{lc}_{jk,t-1}$ are composite indicators combining in-hospital mortality and 30-day-readmission rates (see Section B.2 for more detail). The quality vectors are also calculated separately for all-cause and hip replacement-specific procedures to understand the potential patient sensitivity. We assume that the anticipated utility of going to a provider is dependent on the previous period's quality given the informational lag [172, 202]. Therefore, both types of quality variables are lagged by one year. We control for the volume of hip replacement patients at each hospital n_{jt} and the volume of patients from municipality k that seek care at hospital j, n_{jkt}.

We also introduce hospital and regional fixed effects, represented by h_{jt} and r_{it}. As discussed prior, ϵ_{ijt} represents the idiosyncratic part of patient i's consideration of hospital j. Standard errors are clustered at the municipality level. Overall, given the preferences and needs of patient i, he/she will choose hospital j given the entire choice set as choosing any other hospital would have diminished his/her relative utility.

We estimate the random utility model using a highly flexible mixed logit model by allowing random taste variation and unrestricted substitution patterns [192, 205]. In our specification, the hospital characteristics X_{jt} are assumed to be fixed, while the coefficients for travel time and qualities are given independent distributions (lognormal and normal, respectively). In this model, we do not interact the attributes with patient characteristics because (i) mixed logit model already allows the estimated coefficients to vary across individuals, (ii) interactions can only partially account for the taste differences [206], and (iii) our sample only includes elderly patients and is, therefore, relatively homogeneous. We restrict the analysis to patients residing in small, rural municipalities because the assumption of information-sharing and social interaction is more likely to hold there due to the stronger social ties [207]. We follow the criteria given by Eurostat (`https://ec.europa.eu/eurostat/web/rural-development/methodology`) and select the patients from municipalities with less than 300 inhabitants per squared kilometre and maximum population of 5,000. The underlying rationale is that assortative social mechanism is more prominent in rural areas [200, 201].

We also compare the mixed logit model with the more traditional conditional logit model, where the random component ϵ_{ijt} is assumed to by independently and identically distributed (i.i.d.) with type I extreme value distribution [192]. The assumption thus leads to the independence of irrelevant alternatives (IIA) property that allows for potential variations in tastes that are related to patient characteristics by including the interaction terms as follows:

$$
\begin{aligned}
U_{ijt} =& \beta_1 \log(t_{ijt}) + \beta_2(c_{ijt}) + \beta_3 Q^{gb}_{j,t-1} + \beta_4 Q^{lc}_{jk,t-1} + \beta_5' X_{jt} + \theta_1(c_{ijt} \cdot Z_{it}) \\
&+ \theta_2(\log(t_{ijt}) \cdot Z_{it}) + \theta_3(Q^{gb}_{j,t-1} \otimes Z_{it}) + \theta_4(Q^{lc}_{jk,t-1} \otimes Z_{it}) + \theta_{\mathbf{5}}'(Z_{it} \otimes X_{jt}) \\
&+ \beta_6 n_{jt} + \beta_{n3} n_{jkt} + \beta_7 r_{it} + \beta_8 h_{jt} + \varepsilon_{ijt}
\end{aligned}
\tag{3.3}
$$

Where $\otimes$ is the Kronecker product, and Z_{it} is a vector of the individual characteristics that include dummies for age above 80 years and gender. The resulting marginal utilities are obtained from the algebraic sums of the coefficients for the corresponding patient group.

Endogeneity

There are potential reasons for concern about the endogeneity of quality on hospital choice in our model: First, reversed causality might occur as a high number of patients could lead to high quality, especially since hip replacement is a routine surgical intervention. For this reason, we use lagged variables for all quality indicators. We also check whether larger hospitals have better quality by controlling for the overall volume of elderly hip replacement patients in hospital j. Second, some quality indicators might lead hospitals to select low-risk patients ("cherry-picking") in order to perform better, which introduces a potential selection bias. We thus control for the case-mix of hip replacement patients in each hospital using the Charlson Comorbidity Index (CCI). Similarly, the selection from the patient's side can be problematic as more severely-ill patients may choose hospitals with better-observed quality. However, during our study period, no official hospital quality indicators were made publicly available, so we do not expect that our results are biased by risk selection due to widely known quality indicators. Despite this, we do not rule out the possibility that patients systematically choose certain hospitals due to some other inherent quality-related characteristics. We thus adjust all our quality indicators for patient risk profiles (see Appendix B). Third, the error term in our analysis may contain unobserved hospital characteristics that are correlated with our quality indicators, such as more dedicated medical staff, shorter waiting time or better overall amenities in the hospital infrastructure. In this case, using lagged quality variables does not entirely remove the potential bias. We therefore include hospital-specific fixed effects to eliminate any confounding from time-invariant hospital characteristics.

Willingness to travel

Since the estimated coefficients for quality are interpretable as marginal utilities, we can only infer the direction of the effects from the signs. The ratio of estimated marginal utilities, however, is unaffected by linear transformation and can be calculated to compare the impact of different types of quality on demand to the negative effect of travel time. We, therefore, estimate the willingness to travel (WTT), or the marginal rates of substitution, for a one-unit increase in our main quality variables using equations 3.4 and 3.5.

$$\begin{aligned} WTT^{gb} &= \frac{\partial U_{ijt}}{\partial q_{j,t-1}} / \frac{\partial U_{ijt}}{\partial t_{ijt}} \\ &= \frac{-\beta_3}{\beta_1 log(\bar{t})} \end{aligned} \tag{3.4}$$

$$\begin{aligned} WTT^{lc} &= \frac{\partial U_{ijt}}{\partial q_{jk,t-1}} / \frac{\partial U_{ijt}}{\partial t_{ijt}} \\ &= \frac{-\beta_4}{\beta_1 log(\bar{t})} \end{aligned} \tag{3.5}$$

Where t is the average travel time of patient to a hospital for hip replacement surgery. The WTT indicates the extra time (in minutes) that a patient, located in a municipality with an average distance to a provider, is willing to travel for a one-unit change of our quality indicator In other words, we estimate the time a reference patient is willing to spend going to a hospital for better quality. We compare the WTT of different quality indicator to assess the magnitude of patient preference quantitatively. Standard errors are calculated using the delta method [208].

3.4 Results

3.4.1 Summary statistics

Summary statistics of all the sample patients from the Southern regions (mainland) can be found in table 3.1. From 2013 to 2015, we observe 886 patients from rural municipalities in the Southern regions undergoing hip replacement surgery. The mean length-of-stay was around ten days, and the mean Charlson comorbidity index was 0.12. On average, patients in our sample had a estimated travel time of 94 minutes to their chosen hospital. For all the rural patients, we include the choice set of all the hospitals that had at least one elderly hip replacement hospitalisation (N=276), which are primarily LHA-managed hospitals. Hospitals had an average mortality rate of 1.6% and readmission rate of 0.6% for all performed hip replacement surgeries. Among the patients from Southern rural areas, 0.3% died in the hospital and 0.2% experienced 30-day readmission after a hip replacement surgery. The equivalent numbers for all-cause admissions are much larger, with in-hospital mortality rates ranging from 1.3 to 3.5% and readmission rates from 4.7 to 11.1% .

The maps in figure 3.1 show, for each municipality, the average travel time by car in minutes to all hospitals in Italy (panel A) and the volume of elective hip replacement surgeries per population by municipality (panel B). It becomes evident that the Southern regions' residents on average travel longer to seek care. Moreover, more hip replacement surgeries per population are performed on patients from the Northern and Central regions compared to the Southern regions.

Summary statistics of all the sample patients from the Southern regions (mainland) can be found in table 3.1. From 2013 to 2015, we observe 886 patients from rural municipalities in the Southern regions undergoing hip replacement surgery. The mean length-of-stay was around ten days, and the mean Charlson comorbidity index was 0.12. On average, patients in our sample had a estimated travel time of 94 minutes to their chosen hospital. For all the rural patients, we include the choice set of all the hospitals that had at least one elderly hip replacement hospitalisation (N=276), which are primarily LHA-managed hospitals.

One potential issue with including both, the global and the local quality indicator in our model, is that they may be highly correlated. In order to ensure that we can identify the effects of quality separately, we first run a correlation analysis of all four quality variables on patient level in our sample (see table 3.2). We observe that the correlations across all hip replacement-specific local quality indicators are low in magnitude (all below 0.04) and insignificant. While the coefficients between the global hip-replacement and all-cause quality indicators are significant at 5%-level, the magnitudes are very low and should not bias our estimation results [209].

3.4.2 Econometric analysis

We perform our analysis for all patients from small rural municipalities in the Southern regions (excluding the islands) admitted to a hospital from 2013 to 2015, with

Table 3.1: Summary Statistics of Patient Sample, 2013 - 2015
(*Quality* lagged by one year)

Variables	**Mean**	**Std. Dev.**	**Min**	**Max**	**N**
Patient-level variables – *hip replacement patients from rural municipalities in Southern Italy*					
Age	75.37	6.04	65	99	886
Male (%)	36.23	.	.	.	886
Length-of-stay	10.29	6.98	2	149	886
Weighted sum of CCI	0.12	0.34	0	2	886
Travel time by car (in min)	94.47	153.4	0	884.17	886
Closest Hospital (%)	47.5	.	.	.	886
Hospital-level variables – *hospitals conducting at least on hip replacement surgery*					
Hospital capacity	387.18	346.82	22	2248	276
Rehab facility (%)	57.97	.	.	.	276
Hospital types (%)					276
Hospital trust	6.88	.	.	.	19
Teaching or tesearch	9.42	.	.	.	26
Private accredited	10.51	.	.	.	29
LHA-managed	68.84	.	.	.	190
Average length-of-stay	12.4	4.06	1	28.37	276
Average weighted sum of CCI	0.22	0.21	0	1	276
HRS patient volume	96.28	106.56	1	981	276
Quality indicators					
Global quality, $Q^{gb}_{j,t-1}$					
In-hospital mortality - HRS	0.016	0.065	0	0.56	276
30-day-readmission rate - HRS	0.006	0.035	0	0.398	276
Composite quality - HRS	0.022	0.074	0	0.56	276
In-hospital mortality - all-cause	0.035	0.056	0	0.266	276
30-day-readmission rate - all-cause	0.111	0.101	0	0.541	276
Composite quality - all-cause	0.146	0.115	0	0.541	276
Local quality, $Q^{lc}_{j,t-1}$					
In-hospital mortality - HRS	0.003	0.029	0	0.4266	597
30-day-readmission rate - HRS	0.002	0.024	0	0.3983	597
Composite quality - HRS	0.004	0.037	0	0.4266	597
In-hospital mortality - all-cause	0.013	0.038	0	0.3841	4,803
30-day-readmission rate - all-cause	0.047	0.08	0	0.6189	4,803
Composite quality - all-cause	0.060	0.094	0	0.6378	4,803

Notes: CCI – Charlson comorbity index; LHA – Local health authority; HRS –
Hip replacement surgery

FIGURE 3.1: Average travel time and number of hip replacements (municipality level, 2015)

A: Average travel time to a hospital

B: Elective hip replacements per population

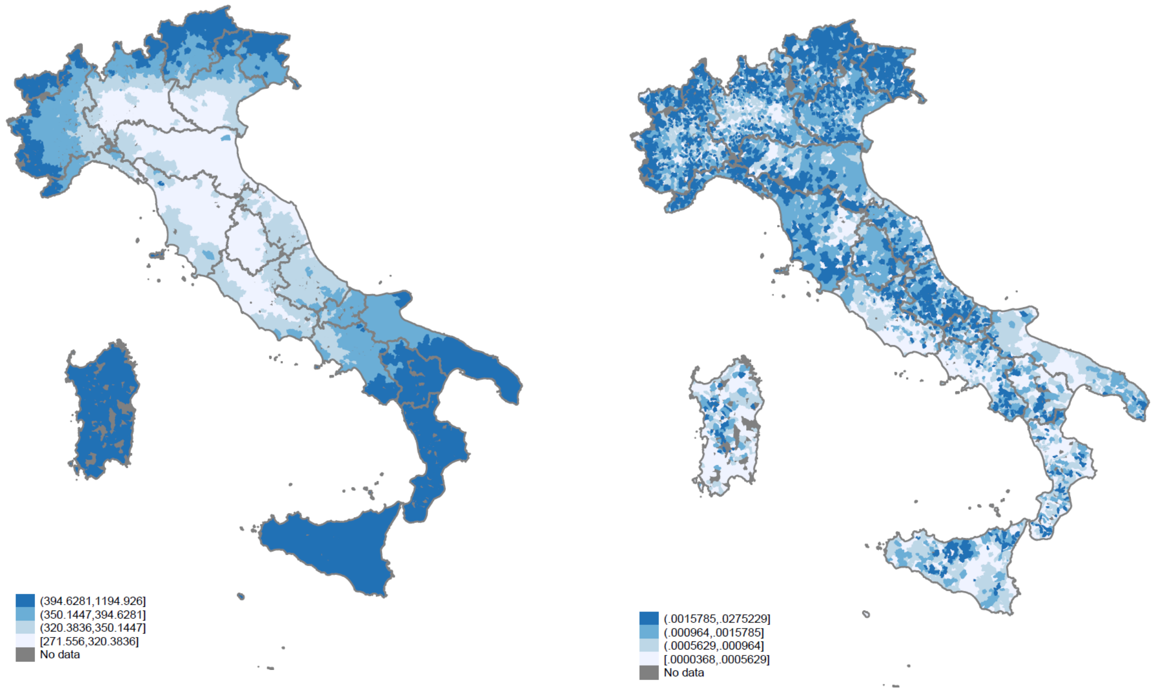


FIGURE 3.2: Average Hip Replacement Quality by Patient Origin Municipality 2013-2015

A: Inhospital mortality rates (%)

B: 30-day readmission rates (%)

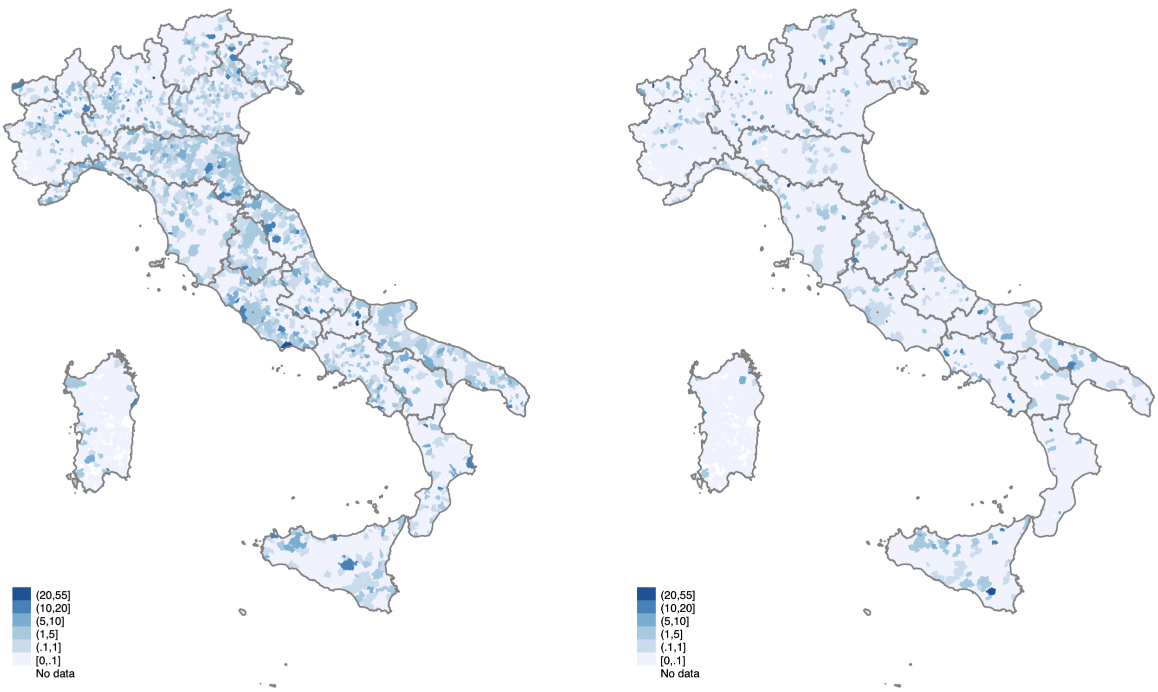


Table 3.2: Correlation of Quality Variables

In-hospital mortality	HRS local	HRS global	All-cause local	All-cause global
HRS local	.			
HRS global	-0.0146	.		
All-cause local	0.0367	0.0136	.	
All-cause global	-0.0122	0.0737*	0.0775	.

30-day Readmission	HRS local	HRS global	All-cause local	All-cause global
HRS local	.			
HRS global	-0.0105	.		
All-cause local	-0.0400	-0.0610	.	
All-cause global	0.0098	-0.1597**	0.1246	.

Composite Quality Index	HRS local	HRS global	All-cause local	All-cause global
HRS local	.			
HRS global	-0.0167	.		
All-cause local	0.0051	-0.0493	.	
All-cause global	0.0068	0.0654*	0.1479**	.

Notes: HRS – Hip replacement surgery; ***p<0.001, **p<0.01, *p<0.05

composite quality variables (mortality or readmission within 30 days) lagged by one year. We run the models separately with and without the local quality variables. The main estimated coefficients from the mixed logit patient choice model with region and hospital fixed effects are presented in table 3.3, and they can, with some adjustments, be interpreted as marginal utilities (or disutilities).

As expected, the disutility from longer travel time is confirmed by the negative and significant coefficient across all models, while the marginal utility of choosing the closest hospitals is not significant - patients are indifferent to bypassing their closest hospital. In Model (1), both coefficients of the global quality indicators are insignificant, suggesting they do not impact patients choice. In Model (2), however, where local quality indicators are included, we observe a significantly negative sign for local hip replacement-specific quality. This indicates that rural patients tend not to choose hospitals where individuals from the same municipality (i.e. theirs neighbours) have experienced increased 30-day readmission or in-hospital mortality after hip replacement surgeries. Hence, for rural regions in Southern Italy, information based on past experiences of their neighbours affects patients' choice of hospital, while the more objective measure of global quality does not. Further, patients tend to choose hospitals where other people from their municipality have been treated before (volume neighbourhood effect). The full list of control variable coefficients can be found in table 3.3.

Mixed Logit models, although highly flexible, require rather restrictive assumptions on the distribution of random coefficients. We thus compare the previous results with the more traditional conditional logit model, where we included interactions with patient age and gender to allow for taste variation. The comparison also allows us to understand differences in patient preferences across specific demographic groups. Table 3.4 shows the results from the specification outlined in euqation 3.3, while the coefficients on the interaction terms express the variation in preference across age group and gender. Similar to the mixed logit results, we see that patients, especially those aged 65-80 and male, tend to bypass the closest hospital, while travel time has consistently negative coefficients across all models. As in the mixed logit model, the global quality indicators are not statistically significant, while the local hip replacement-specific quality indicators are negatively significant. More specifically, there is a distaste for choosing a hospital with more local patients dead or readmitted after a hip replacement surgery, especially among elderly patients under 80, indicating a neighbourhood effect of quality on choice.

TABLE 3.3: Mixed logit estimation of treatment quality on hospital choice

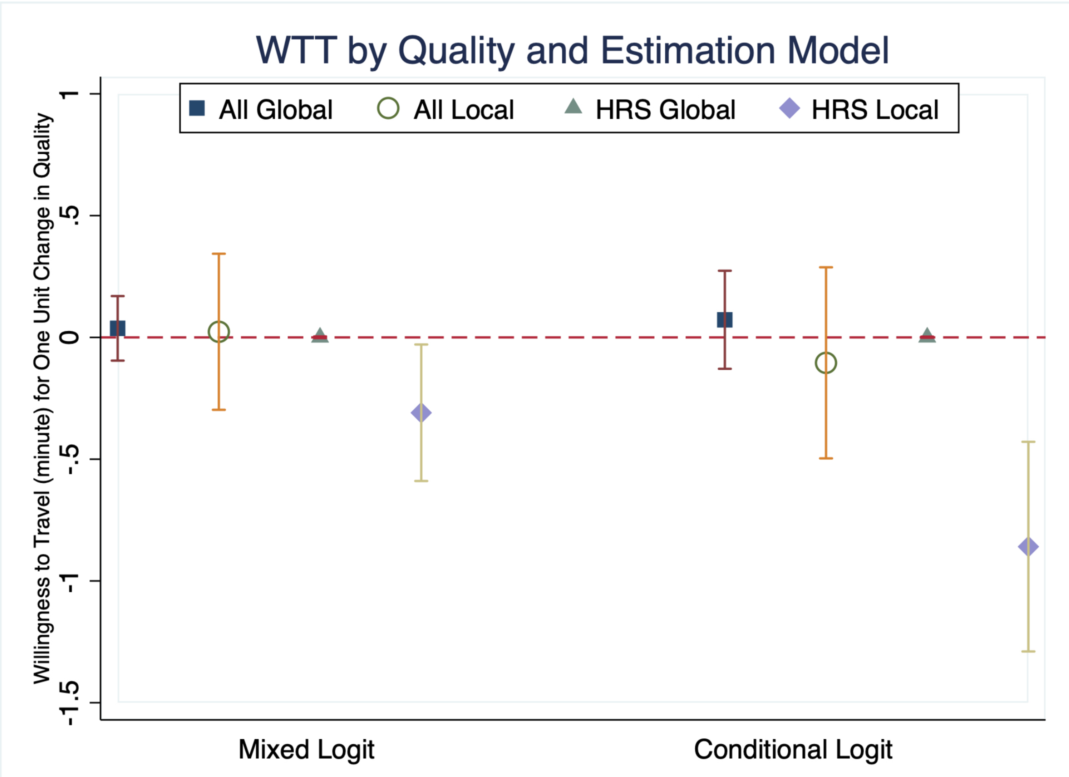
Variables	Without local quality (1)	With local quality (2)
Closest	0.084	0.089
	(0.385)	(1.643)
Travel time (log)	-4.361***	-4.404
	(0.262)	(3.139)
Global quality, $Q^{gb}_{j,t-1}$		
Hip replacement	-0.012	0.010
	(0.027)	(0.028)
All-cause	0.677	0.743
	(0.542)	(0.894)
Local quality, $Q^{lc}_{j,t-1}$		
Hip replacement		-6.198**
		(2.528)
All-cause		0.463
		(3.586)
Hospital volume (global)	0.003***	0.003
	(0.001)	(0.003)
Hospital volume (local)	3.789***	3.873***
	(0.389)	(1.029)
Hospital fixed-effect	yes	yes
Regional fixed-effect	yes	yes
Observations	159,495	159,495
No. patients	886	886
AIC	2521.202	3118.759
BIC	2607.363	3139.787

Notes: Robust standard errors clustered at municipality-level in parenthesis. All models include a range of hospital and regional control variables (full results are displayed in the Appendix in table B.3).
AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion.
***p<0.001, **p<0.01, *p<0.05

Willingness to travel

Table 3.5 and figure 3.3 compare the willingness to travel (WTT) for different quality indicators analysed in the Mixed logit (Table 3.3) and conditional Logit (Table 3.4) models. Overall, a rural reference patient is willing to travel 0.31 more minute for 1% point lower local readmission or mortality rate for hip replacement surgeries. The WTT for better local hip replacement-specific quality is even stronger for female patients below 80 years old at around 0.86 minute per unit improvement of quality. The result is comparable to the findings from Gutacker et al. (2016), who found that WTT to be around 0.07 km for one standard deviation decrease in mortality rate or 0.6 km for readmission rate. The WTT estimates are much lower and not significant for other types of quality. Overall, the results indicate that while choosing a hospital with high local quality yields higher utility, patients are not willing to alter their travel time by much for this improvement.

FIGURE 3.3: Graph of Willingness to Travel (by minute) and 95% Confidence Intervals



3.4.3 Sensitivity analysis

For the sensitivity analysis, we run the mixed logit model individually for readmission and mortality rates. The results presented in Appendix table B.5 show that the local quality effect is mostly driven by the in-hospital mortality rate. The coefficients on the travel time and the hospital volumes are rather similar, underlining the robustness of our results. In addition, we explore the potential impact of other types of hip

TABLE 3.4: Conditional Logit Analysis

Variables	Without local quality (1)	With local quality (2)
Closest	-1.650**	-1.624**
	(0.649)	(0.742)
× male	-2.592***	-2.519***
	(0.824)	(0.883)
× ≥ 81 years	0.855	0.854
	(0.716)	(0.795)
Travel time (log)	-1.637***	-1.660***
	(0.177)	(0.184)
× male	0.110	0.0887
	(0.160)	(0.171)
× ≥ 81 years	-0.385*	-0.373
	(0.211)	(0.230)
Global quality, $Q^{gb}_{j,t-1}$		
Hip replacement	0.0072	0.006
	(0.0083)	(0.0086)
× male	-0.001	-0.001
	(0.012)	(0.012)
× ≥ 81 years	0.017*	0.018*
	(0.010)	(0.010)
All-cause	0.431	0.546
	(0.770)	(0.772)
× male	-0.769	-0.738
	(1.168)	(1.155)
× ≥ 81 years	1.903	1.814
	(1.308)	(1.300)
Local quality, $Q^{lc}_{j,t-1}$		
Hip replacement		-6.486***
		(1.311)
× male		-1.953
		(1.884)
× ≥ 81 years		170.0
		(120.07)
All-cause		-0.789
		(1.524)
× male		-0.925
		(2.437)
× ≥ 81 years		0.0813
		(3.315)
Hospital fixed-effect	yes	yes
Regional fixed-effect	yes	yes
Observations	158,956	158,956
No. patients	886	886
AIC	2462.363	2448.373
BIC	2861.419	2907.286

Notes: Robust standard errors clustered at municipality-level in parenthesis. The reference group for the interaction terms are female patients aged 65-80 years. All models include a range of hospital and regional control variables (full results are displayed in the Appendix in table B.4).
AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion.
***p<0.001, **p<0.01, *p<0.05

Table 3.5: Estimated Willingness to Travel (WTT)

	Mixed logit (1)	Conditional logit (2)
All-cause global	0.0371	0.0724
	(0.0677)	(0.1027)
All-cause local	0.0231	-0.1045
	(0.1635)	(0.2002)
HRS global	0.0005	0.0008
	(0.0017)	(0.0011)
HRS local	-0.3094***	-0.8591***
	(0.143)	(0.2196)

Notes: WTT is the ratio between marginal utility of quality and travel time. Standard errors estimated using delta method in parenthesis. The reference group for the interaction terms are female patients aged 65-80 years. HRS – Hip replacement surgery. ***p<0.001, **p<0.01, *p<0.05

replacement-specific failure indicators - revision rate and surgical complication rates - on patient choice. Table B.7 in the Appendix displays the coefficients for the alternative quality indicators based on a mixed logit model. While, again, the coefficients on travel time and hospital volumes are rather similar to the main model, neither the global nor the local revision or complication rate yield significant coefficients.

3.5 Discussion and Conclusions

Our paper analyses the hospital quality as a determinant of patient choice for hip replacement surgery, with a particular focus on potential neighbourhood effects in rural, Southern Italy. Using individual-level hospital discharge data and a choice model, we observe a negative effect of lower procedure-specific local quality on patient choice. This neighbourhood effect is most pronounced among female patients below 80 years old. Further, we find that patients tend to prefer hospitals where others from the same municipality went before them, similar to the findings from [190]. The preference regarding travel time is consistent across all models, as even though patients tend to bypass their closest hospital, they derive disutility from going to a far-away hospital.

We contribute to the existing literature on hospital quality and patient choice as we measure not only the average effect of previous neighbourhood choices on the probability that a patient chooses a particular hospital (volume effect), but also the effect of treatment quality experienced by those from the same municipality (quality effect). By accounting for the latter we challenge the common assumption of unbiased, rational choices based on perfect information. Indeed, we find robust evidence of a neighbourhood effect which implies that information on hospital quality is shared among residents of the same municipality. However, our study is limited to detecting this overall effect as we cannot infer the precise pathways of information-sharing within the municipalities from our data. Further, we cannot ascertain whether patients are not aware of the objective, global treatment quality provided at a hospital (imperfect information) or whether they choose to ignore it by putting higher weights on local quality indicators (availability bias).

We conclude by drawing relevant policy implications from our findings. Our empirical analysis shows that elderly patients generally choose hospitals with higher "local" quality, proxied by in-hospital mortality and readmission rates of patients from the same neighbourhood. This suggests that, in the absence of official quality statistics, patients do not necessarily select hospitals with the highest treatment quality, but rather avoid those where their neighbours experienced adverse events. This can lead to longer than necessary travel times incurring significant private costs for the patient. The existence of potentially misleading neighbourhood information in hospital choice may be addressed by interventions that increase the visibility of objective hospital quality such as the operating *Programma Nazionale Estiti* by AGENAS. Facilitating access to such official quality indicators will likely lead to better informed choices and, hence, increased sensitivity towards actual quality which can be expected to raise overall hospital quality and therefore improve general patient welfare.

Chapter 4

What About Health-related (Mis)Information on the Internet?

Abstract
Contemporary commentators describe the current period as "an era of fake news" in which misinformation, generated intentionally or unintentionally, spreads rapidly. Although affecting all areas of life, it poses particular problems in the health arena, where it can delay or prevent effective care, in some cases threatening the lives of individuals. While examples of the rapid spread of misinformation date back to the earliest days of scientific medicine, the internet, by allowing instantaneous communication and powerful amplification has brought about a quantum change. In democracies where ideas compete in the marketplace for attention, accurate scientific information, which may be difficult to comprehend and even dull, is easily crowded out by sensationalized news. In order to uncover the current evidence and better understand the mechanism of misinformation spread, we report a systematic review of the nature and potential drivers of health-related misinformation. We searched PubMed, Cochrane, Web of Science, Scopus and Google databases to identify relevant methodological and empirical articles published between 2012 and 2018. A total of 57 articles were included for full-text analysis. Overall, we observe an increasing trend in published articles on health-related misinformation and the role of social media in its propagation. The most extensively studied topics involving misinformation relate to vaccination, Ebola and Zika Virus, although others, such as nutrition, cancer, fluoridation of water and smoking also featured. Studies adopted theoretical frameworks from psychology and network science, while co-citation analysis revealed potential for greater collaboration across fields. Most studies employed content analysis, social network analysis or experiments, drawing on disparate disciplinary paradigms. Future research should examine susceptibility of different sociodemographic groups to misinformation and understand the role of belief systems on the intention to spread misinformation. Further interdisciplinary research is also warranted to identify effective and tailored interventions to counter the spread of health-related misinformation online.

4.1 Introduction

The spread of misinformation is not new, dating back at least to the early days of printing. Even the term "fake news", which has achieved considerable contemporary prominence, was first coined in 1925, when an article in Harper's Magazine, entitled "Fake News and the Public" mourned how newswires were allowing misinformation to disseminate rapidly [210]. The growth of the Internet has, however, initiated a fundamental change. In 2013, the World Economic Forum warned that potential "digital wildfires" could cause the "viral spread" of intentionally or unintentionally misleading information [211]. In the health arena, much concern has focused on the spread of misinformation on immunisation, with social media acting as a powerful catalyst for the 'anti-vaxxer movement'. By encouraging individuals not to vaccinate their children, this movement has been linked to recent measles outbreaks in countries such as the UK, the US, Germany and Italy [212, 213]. The prevalence and persistence of such misinformation justifies a careful and systematic review of published literature on the nature and the mechanisms by which misinformation spreads.

4.1.1 Defining terminology: what is misinformation?

We first review the distinctions between various terms that relate to misinformation. Following the 2016 US presidential election, the term "fake news" attracted substantial media and scholarly attention. The term overlaps with other forms of misleading information, and especially misinformation and disinformation, all conveying messages, stories, theories, or opinions that spread rapidly through social contacts or online media. They differ primarily with respect to intent and mode of spread. Misinformation involves information that is inadvertently false and is shared without intent to cause harm, while disinformation involves false information knowingly being created and shared to cause harm [214]. Although "fake news" is the term that received most popular attention, it is arguably the most problematic one in terms of definitional rigour. Lazer et al. [215] described it as fabricated information that mimics news media content, but this does not capture the complexity of the phenomenon, which can include both satire and information created deliberately to mislead as a means to achieve a political or other goal [216]. A recent report by a parliamentary committee in the UK concluded that "The term 'fake news' is bandied around with no clear idea of what it means, or agreed definition. The term has taken on a variety of meanings, including a description of any statement that is not liked or agreed with by the reader. We recommend that the Government rejects the term 'fake news', and instead puts forward an agreed definition of the words 'misinformation' and 'disinformation'". Since the phrase also has been politicized by powerful figures to discredit certain news media [217], we refrain from using the term "fake news" throughout the paper.

While noting these distinctions, in practice it often seems difficult to differentiate these categories because of the problem in ascertaining intent. For example, anti-vaccine propaganda may be spread by those who have a genuine concern, however misguided, about safety, and by those who are using the issue as a tool to undermine trust in particular governments. Thus, unless the intent is clear, we use the term misinformation as an umbrella term to include all forms of false information related to health, thereby giving those generating it the benefit of the doubt.

4.1.2 Misinformation spread – from micro- to macro-level

Before discussing the macro-phenomenon of misinformation spread, we first conceptualize the potential mechanism following Wardle and Derakhshan [214]. Three major components are involved in the creation, production, distribution and re-production of misinformation – agent, message and interpreter [214]. Our review will look at whether and how existing literature from different disciplines examine the type of actor behind the creation of health-related messages on social media platforms, the descriptive features of the message – the durability and distribution of accurate and misleading information - and most importantly, the interpreter's response and how it contributes to the reproduction of misinformation. At the micro-level, individuals who receive misinformation form judgement about the believability of the message, depending on information source, narrative and context, while the tendency to spread depends on the degree to which receivers suspect such misinformation [218]. At the macro-level, we observe patterns of misinformation cascade and characteristics of networks.

Early literature on spread of rumours (circulating stories or reports of uncertain or doubtful truth) identified the "basic law of rumour" – the amount of rumour in circulation will vary with the importance of the subject to the individuals concerned times the ambiguity of the evidence pertaining to the topic in question [219]. The link between psychological and cultural dimensions generated intriguing questions on what makes misinformation so easy to spread and so hard to debunk.

According to Allport and Postman [219], the ambiguity of the message may be due to the receipt of conflicting stories, with no one more credible than another. The concept of credibility, as investigated extensively in communications research, encompasses message credibility, source credibility, and media credibility [220]. With traditional media, each aspect of information credibility is relatively well understood, although even there some caution is needed. In contrast, with social media, it is particularly challenging to assess the source credibility, as users themselves are the self-publisher, subject to no form of factual verification or accountability. We do know that people regard information from the internet as being as credible as conventional media such as television and radio, but not as that from newspapers [221, 222]. Many studies have thus analysed the credibility of user-generated contents and the cognitive process involved in the decision to spread online information on social and political events [223–226]. This research has highlighted the importance of source credibility and persuasiveness as factors affecting the susceptibility of users to the messages conveyed. Other relevant studies have focused on important concepts such as misperception and confirmation bias, whereby people's views on factual matters are strongly influenced by prior beliefs [227–229]; polarization within networks [230]; and the combined effects of these phenomenon facilitated by social media [231–233]. While much of the existing literature has examined social and political issues, we focus on misinformation related to health and wellbeing.

4.1.3 Misinformation and health: gaps in the evidence base

There is limited understanding of why certain individuals, societies and institutions are more vulnerable to misinformation about health. This is perhaps surprising, as health promotion and public health researchers now pay considerable attention to the potential of the internet as a tool to diffuse health-related information [234–238], employing smart phones and other mobile technologies in preventative interventions [239–242]. Although the internet provides immense opportunities, it also lowers the cost of generating and disseminating information, allowing misinformation and sensationalized stories to propagate. What was once spread locally can rapidly become global, with ideas no longer confined or delayed by geography. This has generated a series of studies of information diffusion [243], rumour spread [244], and consequent behavioural changes [245, 246]. These generally employ sophisticated modelling and simulation techniques to identify the rumour propagation dynamics. However, this is still in its infancy and one recent systematic review of behavioural change models found that most papers investigating spread of health-related information and behavioural changes are theoretical, failing to use real-life social media data [247]. The literature on misinformation spread is growing, but spans disparate disciplines, including communication studies, epidemiology, psychology, and computational science. We contend that it is now necessary to integrate the different perspective and methodologies, to understand the characteristics of susceptible populations and to devise interventions that are most effective in countering this spread.

To address this gap and provide a comprehensive view on the available evidence, we undertake what is, to our knowledge, the first systematic review of studies that investigated the health-related misinformation content on social media and how it spreads online. We include papers stemming from different disciplines and we analyse them on different dimensions.

First, we identify the main health-related topics where misinformation tends to spread and the descriptive features of misinformation. By focusing on the content and the spread of different health-related misinformation, we reveal a broad landscape of issues that attract actors to espouse misleading claims. The findings shed light on the extent to which different topics are identified and investigated in the literature. This approach can inform those working in these areas.

We then explore the existing theories used to explain the phenomenon and undertake a co-citation analysis to ascertain the extent to which ideas spread among disciplinary communities. This seeks to inform social scientists, psychologists, and experts in other fields working to understand this issue, who may otherwise overlook the range of theories that underpin the work of researchers seeking to conceptualize the spread of misinformation. As this is a phenomenon that can be examined from many different perspectives, we have undertaken a co-citation analysis to assess the extent to which different disciplinary paradigms are informing each other, thereby facilitating future interdisciplinary research that can contribute to a more inclusive theoretical framework.

We further discuss the different empirical strategies adopted in the analysis. In doing so, we identify the social media platforms where the authors obtain the empirical data, how they incorporate different statistical models to interpret the data, and the empirical progress in our understanding of the mechanism. We conclude by examining the potential for future interdisciplinary research and practical interventions to counter misinformation spread.

4.2 Methods

4.2.1 Design and Search Strategy

Our reporting strategy follows the PRISMA guidelines [248]. We searched PubMed, Cochrane, Web of Science (WoS) and Scopus for records published between January 2012 and November 2018, using the following search terms in title and abstract:
(i) [misinformation OR fake news OR disinformation OR rumo* OR false OR mislead*]
AND
(ii) online OR social OR media OR news OR twitter OR Facebook OR google]
AND
(iii) [spread OR propagate* OR disseminat* OR circulat* OR communicat* OR diffuse OR broadcast]
AND
(iv) [health OR disease OR infectious OR virus OR vaccin* OR Ebola OR Zika OR measles]

This yielded 206 records from PubMed, 33 records from Cochrane, 341 records from Web of Science, 51 records from Scopus and 62 records from Google Figure 4.1. We identified and removed duplicates, which resulted in 651 records that were first screened based on title, abstract, and keywords and then using full-text where necessary. All eligible references were uploaded into reference management software (Mendeley) for assessment of eligibility.

4.2.2 Screening and Eligibility Assessment

Next, we screened the results of the 651 records based on title and abstract. Articles that were not original, not involving social media, not related to health, not in English and not on human subjects were excluded. At this, and the subsequent stage, we also excluded the very extensive literature on individual cognitive biases, which would be well beyond the scope of a single review. Similarly, we excluded research on static group decision-making, which can create misinformation (e.g. the phenomenon termed groupthink), that subsequently spreads. This left 131 potentially eligible papers, which were subject to full-text analysis, applying the following pre-specified eligibility criteria:

Misinformation. Only records that concern misinformation, disinformation, fake news, rumour or any form of information disorder were included.

Social Media. Misinformation had to be propagated through online media.

Health. Only records related to disease, treatments, public health and wellbeing were included.

Model or Empirical. Modelling (e.g. epidemiological, rumour spread) studies or empirical analysis of the distribution or the dynamic effect of misinformation.

Humans. We are interested in humans and behaviour of humans, and therefore excluded studies about animals and plants.

Original Research. We excluded review articles and editorials.

Language. We excluded articles written in languages other than English.

Finally, we excluded papers that lacked analytic rigour or did not incorporate misinformation as the main component of the analysis, which resulted in 57 articles. The PRISMA (Figure 4.1) shows the results of these exclusions.

4.2.3 Data Extraction

For the 57 included studies, we analysed the following elements in the full-text: (i) health-related issues and findings; (ii) theoretical framework (if any) and disciplines; (iii) study design.

4.2.4 Co-citation analysis

To gain further insights on the disciplines contributing to this increasing area of research, we conducted a co-citation analysis of eligible articles to measure the frequency with which two sources are cited together by other documents. Co-citation analysis yields insight into potential disciplinary siloes and theoretical or methodological gaps in the literature. This was possible with 121 of the papers because 10 articles were not indexed on Scopus, where we extracted citation data from.

4.3 Results

Figure 4.2 shows the number of potentially eligible articles by year. Not surprisingly, the number of studies that investigated health-related misinformation increased over the years, from 7 in 2012 to 41 in 2018 (November) with a sharp rise in 2017. The trend implied the growing scholarly interest in the social phenomenon, potentially amplified by major political events in 2016. We exclude certain articles (n=74) due to their lack of analysis or interpretation of misinformation as mentioned above, and the remainder of this result section relates only to the 57 remaining papers after full-text analysis.

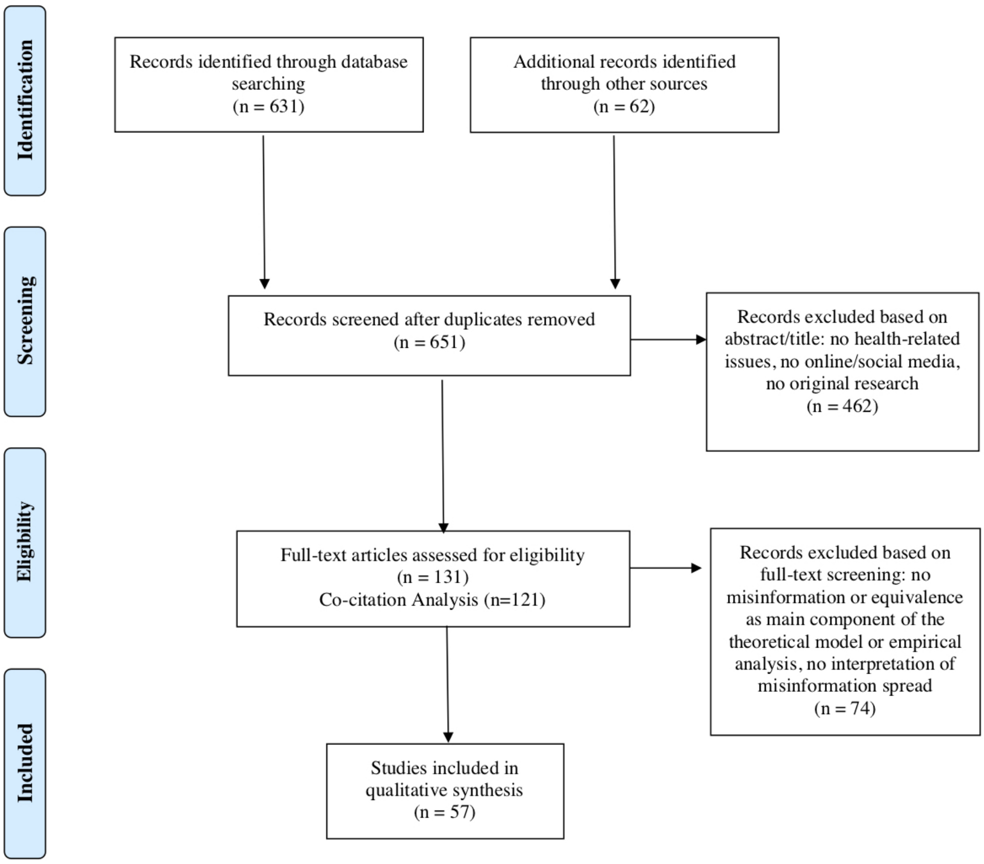


Figure 4.1: PRISMA flow diagram

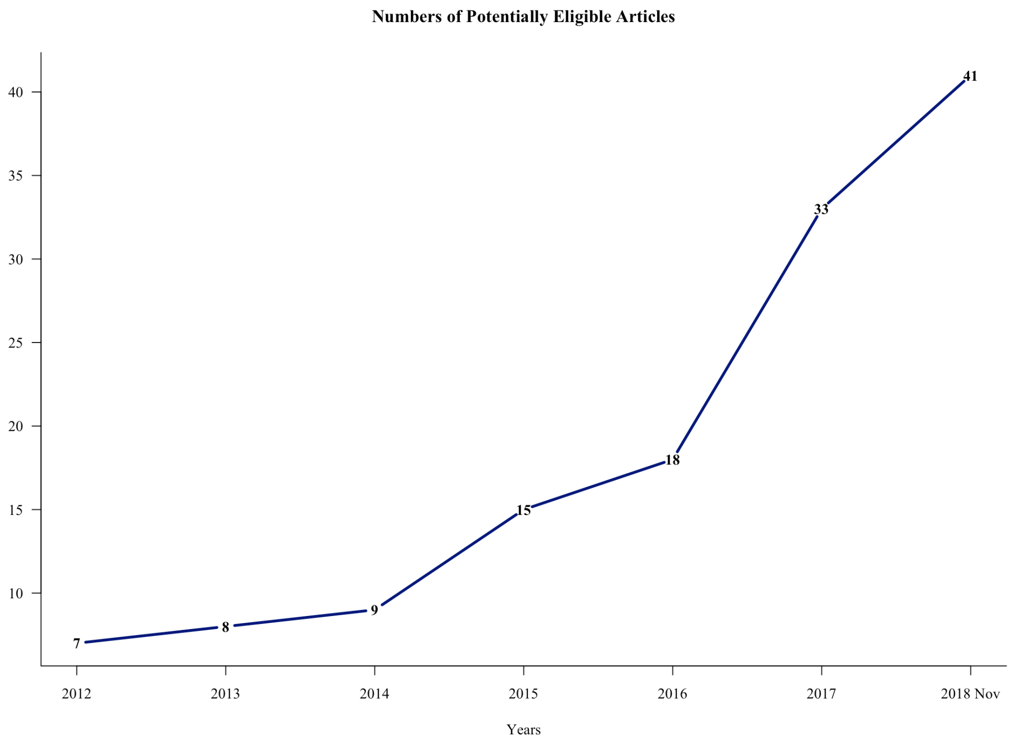


Figure 4.2: Numbers of Potentially Eligible Articles

Key features of the studies included are in the web appendix C. We first investigated what health-related topics have been studied in relation to misinformation. The largest category relates to communicable diseases (n=30), including vaccination in general (8) and specifically against Human Papilloma Virus (HPV), Measles, Mumps and Rubella (MMR) and influenza (3, 2 and 1 respectively), as well as infections with Zika virus (9), Ebola (4), influenza (1), Middle East Respiratory Syndrome (1) and Nile Virus (1). Many articles concern chronic non-communicable diseases such as cancer (3), cardiovascular disease (3), psoriasis (1) and bowel disease (1). Some also address issues of diet and nutrition (3), smoking (3) and water safety or quality (2). Five studies cover a broad range of health-related misinformation or rumour online, while the remaining studies were placed in a miscellaneous category, addressing other specific diseases, health problems or medical interventions (Figure 4.3). We now briefly describe each of these in turn.

4.3.1 Health-related Issues and Findings

Vaccines and Communicable Diseases Vaccine uptake, especially in children, has fluctuated in recent decades in many developed countries, with marked declines during certain periods. In 2012, the journal Vaccine devoted a special issue to "The Role of Internet Use in Vaccination", analysing some of the communication strategies used

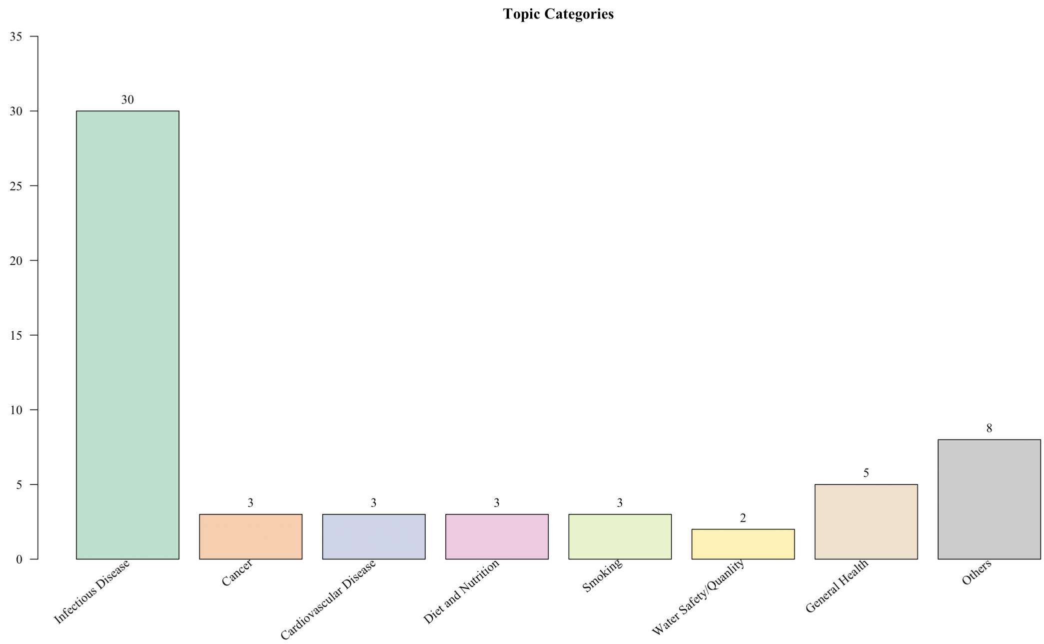


FIGURE 4.3: Topic Categories

by both the anti-vaccination movement and public health professionals. Authors recommended comprehensive, structured, and easily understandable responses to anti-vaccination messages [249–251]. Although refusal of vaccination and movements opposing vaccines date back to the time of Jenner, publication of fraudulent research linking the MMR vaccine to autism and bowel disease [252] was a seminal moment. The concerns raised then, although long since discredited, have been widely disseminated on social media and even now are highly influential among some groups. For instance, Basch et al. [253], Donzelli et al., [254] and Porat et al.,[255] report high online prevalence and popularity of autism-related discussions in fora on vaccination. Tustin et al. [256] and Xu and Guo [257] also reported widespread misinformation about side effects, as well as mistrust in government or pharmaceutical companies in discussions on vaccination. Krishna's [258] study of active propagators of these messages found that those who were knowledge-deficient and vaccine-averse exhibit higher levels of activity than those who are not. Aquino et al. [259] reported a significant inverse correlation between MMR vaccination coverage and online searches and social network activity on "autism and MMR vaccine". Taken as a whole, the research identifies anti-vaxxer and members of online communities favouring conspiracy theories as sources or propagators of misinformation, with discussions tending to revolve around rhetorical and personal arguments that induce negative emotions (fear, anger, sadness). Although there is less misinformation than accurate information, the former has greater popularity among viewers.

The Zika epidemic stimulated considerable activity on Twitter (Wood, 2018) and Facebook [260], as well as spread of news items [261], images [262], and videos [263] on a range of media. Conspiracy theories directed at institutions feature frequently in these discussions. For instance, the Zika virus was portrayed as a bioweapon, while rumours spread that the Zika vaccine had been developed to depopulate the earth [261, 264]. Conspiracist ideation played a crucial role in one's belief in misinformation [265]. However, Bode and Vraga [266] did not find that belief in conspiracies reduced receptiveness to correction of misinformation on Zika virus, although this research generated several important insights for design of interventions to address this issue.

The Ebola outbreak also provided much additional material. For instance, Fung et al. [267] examined the role of Twitter and Sina Weibo (Chinese microblog, equivalent to Twitter) in spreading rumours and speculating on treatments. Pathak et al.[268] found numerous misleading videos online concerning Ebola virus disease. Similar to the studies on vaccination, much of this misinformation comes from individuals who are highly active in influencing opinions, and rumours often garner higher popularity than evidence-based information.

Chronic Non-communicable Diseases Though most research on misinformation has focused on infectious disease, misinformation on chronic illnesses such as cancer and cardiovascular disease are not uncommon on social media. Okuhara et al. [269] looked at online discussions with opposing views on cancer screening in Japan, finding that most propagated anti-cancer screening messages. Staying in Asia, Chen et al. [270] examined the nature and diffusion of misinformation on gynaecologic cancer in China. Chua and Banerjee [271] found that individuals are more likely to trust and share cancer-related rumours if the rumours are dreadful rather than wishful, and if one has had previous personal experience.

Studies on other chronic diseases mostly speculate on or promote alternative treatments, for example on diabetes [272], heart failure [273], hypertension [274] and psoriasis [275]. Again, misleading videos are more influential. In addition, research by Leong et al. [272] in India found that diabetes videos tailored to South Asians were more misleading than those not culturally-targeted.

Others Unsubstantiated messages regarding diets and nutrition can have detrimental effects on susceptible individuals. For instance, Syed-Abdul et al. [276] investigated how anorexia is promoted as fashion and linked to ideas of beauty in YouTube videos, gaining high popularity among young female viewers. Bessi et al. [277], analysing the diffusion of diet, environment and geopolitics-related misinformation, found that active users are more likely to span a range of categories, and that online groups promoting conspiracy theories tend to exhibit polarization. Similar patterns are observed in discussions on water fluoridation, as memorably invoked in the 1964 movie Dr. Strangelove. Seymour et al. [278] analysed the anti-fluoride network online and found that strong ties among the community are obstacles for expert opinions to be accepted. This indicates that social homogeneity may well be the primary driver of content diffusion and clustering. The modelling of rumour spread is therefore informative of the cascades' size and potential intervention designs in countering such spread.

The tobacco industry has a long history of distorting scientific evidence and misleading consumers. Very recently, Albarracin et al. [279] showed how misleading portrayal of tobacco's health consequences introduces positivity towards smoking. The advent of electronic cigarettes prompted Harris et al. [280] to examine content and tweet patterns related to an e-cigarette campaign by a local public health department. The misinformation included arguments that divert attention from the products to messages that sought to discredit authorities.

A few studies have investigated specifically the psychology of individuals who believe and share rumours. Chua and Banerjee [281], in their analysis on epistemic belief and its effect on the decision to share rumour, showed that epistemologically naïve users have higher propensity to share online health rumours. Li and Sakamoto [282] discovered that exposing individuals to measures of collective opinion, through counts of retweets and collective truthfulness ratings could reduce the tendency to share inaccurate health-related messages. Taken as a whole, the evidence indicates that the motivation to believe and share rumours reflects both individual and collective makings, but the consequences are difficult to predict because of the complex psychological factors involved.

Finally, the group of miscellaneous studies mainly examined specific medical interventions or issues such as drugs [283], paediatric disease [284], abortion [285], dialysis [286], suicide [287] and multiple sclerosis [288]. The common sources of misinformation included advertisements or comments related to advertisements [286] and patients' anecdotal experiences [284]. Again, misinformation was more popular than factual messages.

4.3.2 Theoretical Frameworks and Disciplines (Co-citation Analysis)

We next investigated the theoretical foundations in the included studies, but it rapidly became clear that there was no widely agreed approach to this phenomenon, reflecting the broad range of disciplines that have investigated it. The more dominant disciplines and research areas according to the published journals include public health, health policy and epidemiology (n=14), health informatics (n= 8), communications studies (n=5), vaccines (=4), cyberpsychology (n=3) and system sciences (n=3).

Disciplinary approaches adopted to conceptualize the phenomenon are varied, but primarily fall within the fields of psychology (n=8) and communication (n=4), as well as network science (n=7). While theories in psychology focus on individual-level cognitive response to misinformation and its corrections, frameworks in network and data science characterize the (online) societal mechanisms involved. For instance, Chua and Banerjee [271] , in investigating the online behaviour in the face of health rumours, invoked the seminal rumour theory [219], which views personal involvement as a common perception that dictates one's decision to spread rumour. Moreover, rumours that are repeatedly circulated can be reinforced and accepted as credible [289], and the consequent perceived high credibility can in turn increase intention to trust and share rumours [290]. This relates to credibility research, which suggests that perceived credibility and can heighten the persuasive impact, especially for internet users who are not motivated to process information [220, 291]. Similarly, Ozturk et al. [292] explored how different social media settings can reduce rumour spread based on rumour psychology research. Others have referred to psychological studies around conspiracist ideation, inoculation theory and social conformity in understanding the mechanism behind health misperception on social media [263, 266, 282]. Contrastingly, the use of system or network theories are aimed at explaining the patterns of social influence, social learning, social contagion and homophily and polarization processes [264, 277, 293–295]. The framework typically assists the subsequent social network analysis.

Two studies borrowed insights from philosophy – Grant et al. [296] employed the rhetorical framework to examine the persuasive features of pro- and anti- vaccine sites, while Chua and Banerjee [281] used the epistemology framework to explore the role of epistemic belief in affecting rumour-sharing behaviour. Finally, situational theory of publics [297] from public relation studies are adopted to identify vaccine-negative activists (Krishna, 2017). The remaining articles from computational studies and clinical perspectives lack any theoretical underpinning and are purely empirical.

Given that the findings are from disparate disciplines, we conduct the co-citation analysis on all the potentially eligible articles to identify the clusters of disciplinary communities. In co-citation network analysis, the unit of analysis is the cited source, and we include the journals cited at least 5 times within the 121 articles. As seen in Figure 4.4, the distance in the map between any pair of journals reflects their similarity to each other [298], and we use the LinLog/modularity normalization technique to minimize the distance between connected nodes [299]. The size of the nodes represents the number of citations, and the line indicates the presence of citation in either direction. The analysis identified 4 distinct (inter-)disciplinary clusters, which we assigned as follows (with randomly generated colours, from left to right): Social Psychology and Communications (red), General Science and Medicine (blue), Infectious Disease/Vaccine and Public Health (green), Medical Internet and Biomedical Science (purple). Overall, the literature is concentrated in general science and vaccines/infectious diseases. Psychology and communications literature sit on the periphery, with relatively less cross-citation with the science and medicine literature. Interestingly, we also observe a few sociology journals at the bordering regions between clusters, implying their incipient roles in acknowledging different insights across disciplines. There is potential for greater interdisciplinary collaboration.

4.3.3 Study Design

Turning to research design, most studies employed content analysis (n=38) either alone or as a component of the analysis, studying various forms of social media (n=10), YouTube videos (n=12), Twitter or equivalents (n=8), websites (n=5), images (n=1) or mobile messengers (n=2). Authors observe the distribution of useful and misleading

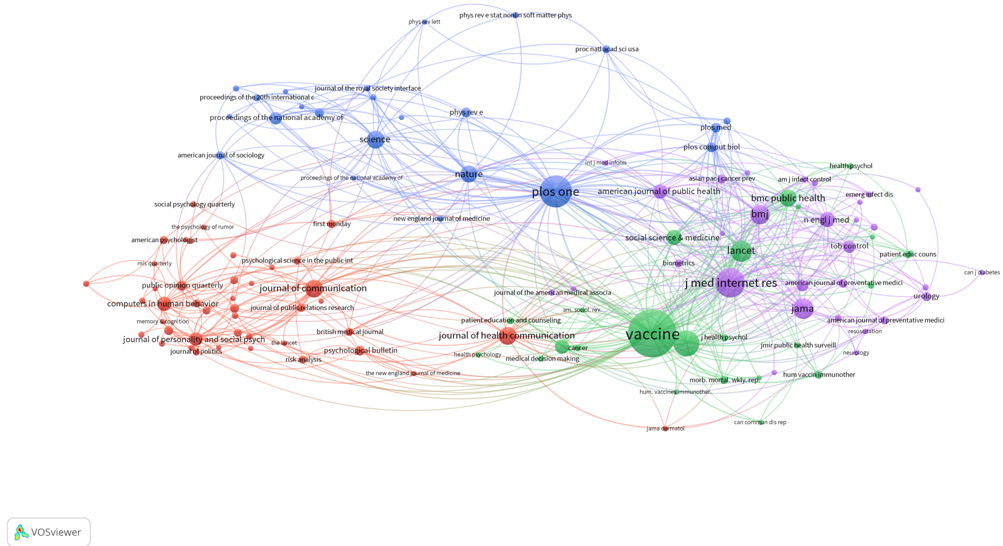


FIGURE 4.4: Co-citation Analysis

information, and the pattern of consumption by different users. Some studies incorporated social network analysis or epidemiological modelling to better explain the dynamics of misinformation spread [264, 277, 280, 293, 300, 301]. Many designs were also complemented by sentiment measures, for instance, the "anti-vaccine" sentiment [257, 302].

Seven studies used experimental designs. Bode and Vraga, in three different papers, manipulated Facebook's "related news" function to confirm or correct (or both) misinformation about the purported link between vaccines and autism, as well as unfounded link between genetically modified organisms (GMO) and health [303, 304]. They also simulated Twitter feeds with false information about Zika virus to evaluate the ability of corrective responses to reduce misperception [304]. Chua and Banerjee [271, 281] undertook web-based experiments with participants exposed to combinations of rumours and counter-rumours. Ozturk et al. [292] explored different ways to reduce rumour spread on Twitter using Amazon's Mechanical Turk, an online crowdsourcing platform. Albarracin et al. [279] used the same platform to evaluate the effects of YouTube videos on viewer attitudes to tobacco products.

A few studies used survey instruments to understand how social media can spread misconceptions about Ebola in West Africa [305] and inflammatory bowel disease in the USA [306], and to explore the relationship between knowledge deficiency and negative attitudes towards vaccines [258]. One case-study adopted an anthropological approach and used thick description to review the rhetorical features of both pro-vaccine and vaccine-sceptical websites [296].

4.4 Discussion

4.4.1 Findings

We found that, while there have been studies of the spread of misinformation on a wide range of topics, the literature is dominated by those of infectious disease, including vaccines. Overall, existing research finds that misinformation is abundant on the internet and is often more popular than accurate information. Several of the studies address areas where state action challenges individual autonomy. The classic example is vaccination, where effective protection of the population requires achievement of levels of uptake sufficient to achieve herd immunity. This review confirms that misconceptions about MMR vaccine and autism, in particular, remain prevalent on social media [259, 270]. Other topics share scientific uncertainty, with the authorities unable to provide confident explanations or advice, as with newly emerging virus infections such as Ebola and Zika viruses [253, 261, 267].

The agents that create misinformation are mostly individuals with no official or institutional affiliations. This relates to our initial discussions on credibility – what makes a source trustworthy for readers? Formal institutions are increasingly challenged by the rise of, for instance, "expert patient", blurring the boundaries between authority and quasi-proficiency [278]. Traditional vertical health communication strategies are eroded by horizontal diffusion of conspiracy-like messages. The narratives of misinformation are dominated by personal, negative and opinionated tones, which often induce fear, anxiety and mistrust in institutions [255, 277, 307]. When people are frightened and doubtful, they can be more susceptible to misinformation. Once false information gains acceptance in such circumstances, it is difficult to correct, and the effectiveness of interventions vary according to each individual's personal involvement, literacy and socio-demographic characteristics, features that tend to be under-explored in existing research.

The included articles adopted disparate theoretical approaches in conceptualizing the phenomenon, with the dominant frameworks from the fields of psychology and network science. Theories employed in psychology aimed to explain individual-level cognitive response of misinformation and rumour online [263, 266, 271, 282, 292], whereas network theories focus on the social mechanism and patterns of misinformation spread [264, 277, 293–295]. Further co-citation analysis on all articles that investigated the phenomenon revealed that the disciplinary landscape concentrates around general science and vaccines/infectious disease, while psychology and communication studies have less cross-citation with the science and medicine literature. The sociology discipline has great potential to bridge the different communities.

Researchers have employed increasingly sophisticated analytic techniques for empirical analysis, such as the use of social media data for sentiment analysis. The majority of the articles included a content analysis of the information on social media, ranging from text, images and videos. Several studies employed complexity and network theories to model the dynamics of rumour spread and opinion polarisation

[301, 308]. Other studies have adopted psychological and linguistic perspectives [267, 287, 309]. While we have excluded research on both individual and group biases, we feel it is important to note how several studies invoked the concept of confirmation bias, concluding that it plays an important role in creating online echo-chambers [254, 277]. This highlights the need for much more research on the socio-psychological characteristics of those who believe and propagate misinformation. In particular, there is a need to understand better the roles of both ideology and belief systems [310] and what might be termed "lazy thinking" [311]. For instance, although the role of literacy and cues to credibility are critical concepts in the design of experiments, they should also be explored in empirical studies, and especially those that use big data from social media platforms.

4.4.2 Gaps and potential for future research

Although sociology and psychology pioneered research to understand rumour [219, 312, 313], psychologists are only beginning to study the implications of the explosion in internet use [314]. While we conclude from the co-citation analysis that studies on misinformation in health cover a wide range of disciplines, there is a marked lack of interdisciplinary research. This could, for example, allow hypotheses to be generated by social scientists using rumour theory and tested using quantitative analysis of social media data.

While most of the studies recommended courses of action based on their results, only a handful of papers proposed specific and tested interventions to reduce misinformation spread. For instance, Ozturk et al. [292] discovered that rumour-countering warnings such as "this tweet may contain misinformation" did decrease participants' likelihood of sharing a rumour, consistent with findings in the psychological literature [315]. Bode and Vagra [266] showed that algorithmic correction (by a platform) and social correction (by peer) are equally effective in correcting misinformation and call for campaigns to encourage users to refuse false or misleading information. The same authors have shown how expert organization can correct misinformation without damaging its credibility, presenting an appealing intervention to reduce misinformation spread [304].

Finally, there is a need to characterise the scale and nature of the phenomenon much better, for example with studies of which socio-demographic characteristics make social media users more susceptible to and therefore likely to share health-related misinformation.

4.4.3 Limitations

Before concluding, we will note several limitations of the systematic review. First, although we have attempted to define the phenomenon we are studying, our search strategy may not capture the terminology used by others. This is not just a problem of language. There are many related phenomena, such as denialism, groupthink, fearmongering, and equivalents in other languages, such as Lügenpresse (lying press) in German and it is possible that these or others may be used, in some circumstances, to describe some elements of what we are studying. Second, even when we agree the terms, such as misinformation and 'fake news', the meanings adopted by authors can vary. Third, as noted at the outset, it is very difficult to ascertain the motives of those spreading particular rumours and myths. leaving us unable to answer the old question "mad or bad?". Fourth, while our focus has been on messages concerning health-related issues, misinformation about other issues can have health consequences. For instance, a man from North Carolina travelled to Washington in 2016 and opened fire at a pizzeria following the spread of what became termed the Pizzagate theory, whereby it was alleged that the pizzeria was the site of a paedophile ring organised by Democratic Party leaders. Even though comprehensively debunked, subsequent polls showed that this allegation was still widely believed. Finally, since we excluded articles that are not published in English, we may have omitted relevant papers published in other languages.

4.5 Conclusion

Social media platforms, although providing immense opportunities for people to engage with each other in ways that are beneficial, also allow misinformation to flourish. Without filtering or fact-checking, these online platforms enable communities of denialists to thrive, for instance by feeding into each other's feelings of persecution by a corrupt elite [316]. The accumulation of individual beliefs in these unfounded stories, conspiracy theories, and pseudoscience can give rise to social movements, such as the anti-vaccination movement, with profound consequences for public health. This is further exacerbated by the fact that it is politically incorrect to question or criticize the belief of others, and the fight for truth is nevertheless against the flow of true believers armed with ignorance and misinformation [317].

We have shown that academic literature on this social phenomenon mainly revolves around vaccination and infectious disease, drawing on various disciplines, frameworks and empirical methods. Among the articles examined, there is broad consensus that misinformation is highly prevalent on social media and tends to be more popular than accurate information, while its narrative often induces fear, anxiety and mistrust in institutions. The severity and the deleterious effects it may pose on the society is hardly quantifiable, but evidence abounds that we need more research on the identification of susceptible populations, and on the understanding of socio-demographic and ideological asymmetries in the intention to spread misinformation.

Finally, since the persistence of misinformation owes both to the psychological responses and to the social contexts under which misinformation spread, potential interventions should target both fronts. At the individual level, although interventions to correct misperceptions are proven effective at times, efforts to retract misinformation need to be carried out with caution in order to prevent backfiring. This requires profound understanding on how epistemic and ideology beliefs act as obstacles to accepting scientific evidence. A more constructive approach may be to cultivate critical thinking and to improve health and media literacy, thereby equipping individuals with the faculty to critically assess the credibility of information. At the system level, how we can amend our information ecosystem to reduce selective exposure and opinion polarization is not a challenge for academics and policy-makers alone to face. We therefore hope that our review can stimulate social scientists, psychologists, computer scientist and medical professionals to not only collaborate with each other, but also engage with industries and internet consumers to understand and counter the effects of this increasingly important social phenomenon.

Chapter 5

Equity and Efficiency Concerns on Health Care System Design

Abstract

Following the global trend of moving towards Universal Health Coverage, China has implemented a new round of health system reform, to achieve universal “safe, effective and affordable basic healthcare services” by 2020. We review the latest reforms using the World Health Organization framework developed by Murray and Frenk. In particular, we diagrammatically describe the structure of the current Chinese health system using the dimensions of Stewardship, Resource Generation, Financing and Provision, and assess the variability of access, levels of benefits, and quality of service across populations. We identified several areas of inequity and inefficiency. First, the fragmented institutional arrangements, with distinct objectives and responsibilities across agencies, create potential nonalignment of incentives. Second, there is a marked scarcity of qualified general practitioners and infrastructures despite the continuing effort to improve the gatekeeping function of primary care providers. Third, as risks are pooled only at the local level within different insurance schemes, the considerable income heterogeneity across geographic territories and resident types can generate significant inequality in access and funding. Fourth, persistent patient preference for higher quality healthcare at hospitals prevents the integration of care across tiers. We believe our comprehensive analysis will be informative for both health policymakers and researchers, in identifying and investigating the inefficiencies of the health system and the potentials for structural integration to achieve healthcare equity.

5.1 Introduction

Following the global trend of moving towards Universal Health Coverage (UHC), China implemented a new round of health system reform in 2009 to achieve universal "safe, effective and affordable basic healthcare services" by 2020 [318]. The primary objectives of the reform included developing primary healthcare services and providing equal access to urban and rural residents. Since 2017, the deepening of the healthcare reforms has been accompanied by a "Healthy China Strategy", where new directives were introduced to provide more well-rounded and full-cycle health services. While

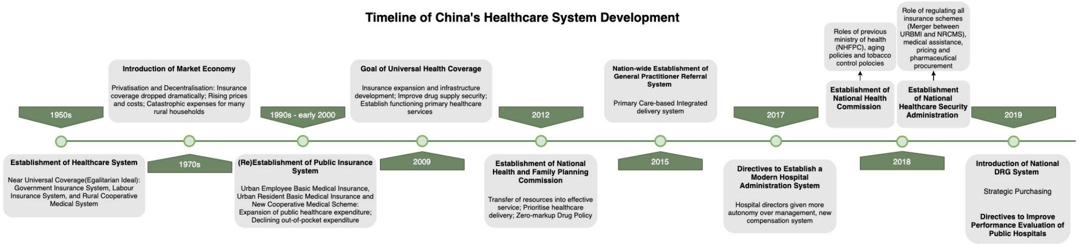


FIGURE 5.1: Timeline of Healthcare Reforms in China

the reform has been rolled out gradually over the years, access to healthcare and the distribution of the benefits have not been straightforward [319]. The process was further complicated by increasing income inequality, an ageing population, low fertility rates, and most recently by the COVID-19 crisis.

As one of the most rapidly changing and comprehensive efforts undertaken by a health system in the world, China's healthcare reforms warrant an extensive examination of the various dimensions of its changing healthcare system. A necessary first step is to unravel and understand the complexities of the Chinese healthcare system; to this end, we undertake the first assessment of China's healthcare system, using the World Health Organization (WHO) framework developed by Murray and Frenk [320]. Our approach is similar to the assessment of the healthcare systems in Ghana and Nigeria when moving towards UHC [321]. In particular, we diagrammatically describe the structure of the current Chinese health system using the four functions of Stewardship, Resource Generation, Financing and Provision, and we analyse the variability of access, levels of benefits, and provision across populations. The strength of our work relies on generating, for the first time to our knowledge, a diagrammatic overview of China's health system, which shows the degree of fragmentation, both horizontal and vertical, of the functions mentioned above. An overview of the potential impact on equity and efficiency of the different dimensions of the healthcare system complements the detailed analysis and descriptions of the four functions.

5.1.1 Background of China's Healthcare Reform

Major reforms have taken place in China to address the persistent challenges due to the inconsistencies in healthcare provision, unequal access, surges in healthcare costs and the burden of chronic illness arisen from previous reforms towards marketisation. A description of key facts about China's healthcare system can be found in the Appendix D. In 2009, the government set objectives to increase universal coverage, develop a functioning primary healthcare service that was previously abolished, ensure equal access for urban and rural residents, and to improve public hospitals' operating environment (1). The timeline of the critical events can be found in Figure 5.1. Among the different objectives, three specific reforms constitute the current focus of the healthcare system design.

Before 2015, the primary care system did not operate under a patient referral network, resulting in extremely overcrowded hospitals in major cities. In 2015, a general practitioner referral system was introduced nationally to improve accessibility and reduce inappropriate use of higher-tier hospital care. To incentive primary healthcare facility use and divert patient from large hospitals, a higher reimbursement rate has been set for the former. However, the uptake of the referral system has been meagre because of the persistent patient preference for hospital-based services, even for minor issues [322, 323]. Further, hospitals are heading medical alliances, in the form of networks, to train lower-level facilities to improve their perceived lower quality of care.

Another policy issue was the multitude of medical insurance schemes as well as the various ministries and agencies involved in the insurance schemes, which have negatively affected the efficiency of the system. As a result, an important reform was introduced in 2018 to merge the New Cooperative Medical Scheme (NCMS) for rural residents and the Urban Resident Basic Medical Insurance (URBMI) for urban residents. Despite elevating the coverage of NCMS to URBMI standards, migrant workers are still not fully protected by the current set-up, as they remain insured in their province of origin. This often translates in lower access to healthcare services, when needed, or in foregoing healthcare altogether. The main reason is that reimbursement for their cross-province medical expenses needs to be sought in the migrants' province of origin, which is hindered by considerable travel distances and associated costs [324].

Since public hospitals are financed through government subsidies, service charges and mark-ups on drug prices, such structure inevitably created distorted incentives to prescribe higher volume and more expensive drugs than necessary to earn additional bonuses. Public hospitals had no incentive to contain cost, thereby dramatically boosted health expenditure. In 2012, alongside the zero-mark-up drug policy, public hospitals had been asked to become more independent in running their daily activities [325]. The most recent approach, called "Modern Hospital Administration System", evaluates hospital directors' performance on clearly defined indicators, such as patient volume and satisfaction, and the level of expenditure, thus realising a more evidence-based approach [326]. The new approach also aims at decreasing out-of-pocket expenditure and hospital length-of-stay [327, 328]. Given the rapidity and the complexity of the various reform waves, one may quickly lose sight of the fundamental building blocks of the system and the roles they play in facilitating or hindering the implementation of the reforms. In what follows, we systematically assess the design of the current healthcare design and its implications on equity and efficiency.

5.2 The Building Blocks of China's Health System

Murray and Frenk [320] recommended that "any systematic attempt to understand the performance of health systems should include a study of factors that potentially

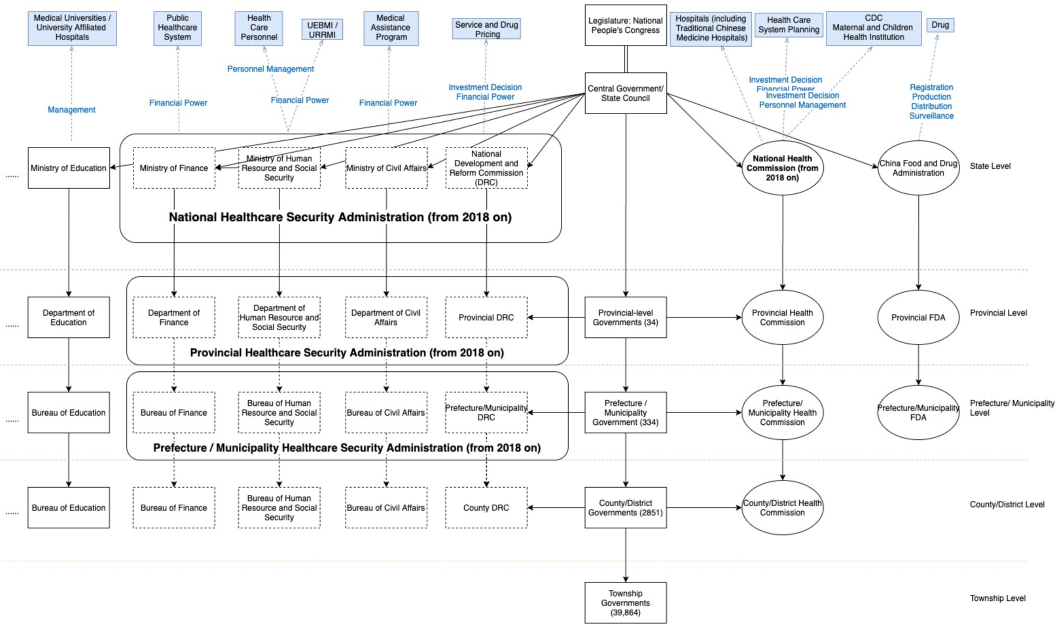


FIGURE 5.2: Stewardship Function

explain it" [320]. They did so by outlining and defining the functions or institutional arrangements that are present in any health system: Stewardship, Resource Generation, Financing and Provision, within a new framework. We chose to employ the WHO framework, developed by Murray and Frenk, because it offered a coherent and consistent approach in identifying a health system's intrinsic goals, its key functions and how these interact and influence the overall performance of a health system. Hereafter, we describe these functions for China's health system and discuss the intermediate outcomes of the current design in terms of efficiency and equity.

5.2.1 Stewardship

The Stewardship function permeates and shapes the entirety of a health system, i.e. financing, provision and resource allocation. Murray and Frenk [320] describe it as comprising three key aspects: (i) setting, implementing and monitoring the rules for the health system; (ii) assuring a level playing field for all actors in the system, i.e. purchasers, providers and patients; and (iii) defining the strategic direction for the health system as a whole. In China, several stakeholders, operating at different government levels, are responsible for various "Stewardship" functions. Figure 5.2 provides a visual aid of the different organisations/institutions at play.

China's health administration has a four-level hierarchical structure. The National Health Commission (NHC, previously the National Health and Family Planning Commission and the Ministry of Health) is at the top, followed by provincial health commissions, responsible for organising and supervising providers. Below these institutions are prefecture/municipal-level health commissions that draft local regulations and coordinate resource allocations; and, at the bottom, are county/district health commissions, which enjoy slight flexibility in implementing provincial health policies. No independent health administration exists at the township level, with providers directly under the county health commission's supervision. The majority of the health legislation are administrative laws issued by the Standing Committee of the National People's Congress; administrative regulations promulgated by the State Council; and local laws and regulations issued by ministries or local governments [329]. The NHC drafts five-year plans that include the budgets and competition policies among healthcare providers [330, 331]. The newly established National Healthcare Security Administration (NHSA) assumes the previous roles of the Ministry of Civil Affairs, the Ministry of Health and the Ministry of Human Resources and Social Security. Specifically, the NHSA manages all the public medical insurance programs and healthcare personnel, sets prices for essential medicines, maintains the safety net (e.g. healthcare access) for the poor in rural areas. The Ministry of Education oversees medical schools, and the Ministry of Finance produces annual budgets and subsidies and monitors the financial performance of central government spending based on the five-year plans. The Food and Drug Administration ensures safety for drugs and medical devices. Finally, the Bureau of Health Politics and Hospital Administration, which operates within the NHC, has the responsibility for assessing and monitoring the quality of healthcare provided [332]. However, there is still limited systematic evidence on process and outcome measures of quality [326]. The sheer number of independent governmental organisations with different remits and strategic designs, each carrying out some form of stewardship function, shows how complex, fragmented and potentially inefficient the health system governance is in China. Different ministries often have conflicting interests and, therefore, do not collaborate proactively. For instance, hospital directors, by design, respond to multiple government agencies with different objectives at the local level. At the same time, hospital directors are rarely monitored for non-compliance and as a result, are not accountable for inefficiencies or low quality service [324]. Although the recent creation of the NHC and NHSA have substantially reduced the organisational fragmentation, it is still challenging to assign clear accountability of the stewardship function, both to the governmental institutions issuing guidance and regulations at the higher government tiers and to those that are tasked with implementing them at the middle and lower levels.

5.2.2 Resource Generation

Resource generation entails all the organisations that govern, produce, and deliver the inputs to health systems. Unlike the financing function, resource generation involves a wide range of institutions that are not strictly or directly related to healthcare delivery. The most critical dimension is human resources, while physical resources such as buildings, equipment and technology, pharmaceuticals, and overall knowledge are also part of this function.

The human capital of China's health sector includes medical staff, nurses and healthcare professionals working in hospitals, primary healthcare institutions and public health agencies. While the number of physicians and medical staff is steadily rising, access to medical professionals was characterised by wide geographic disparities before 2009 [332, 333]. The 2009 reform to achieve universal health coverage has gradually reduced the inequality of resource distribution in recent years, but the gap still exists [334]. By 2018, there were about 2.59 physicians per 1,000 population, ranging from 4.01 to 1.82 physicians, respectively, for urban residents and rural residents [335]. Imbalances in the absolute distribution of healthcare workforce across regions, and between urban and rural areas, represent a crucial barrier for the development of health services, especially in rural areas [336].

The highest level of education attained varies greatly across medical professionals: from postgraduate and undergraduate, to college/technical secondary school/high school and below. By law, a doctor is required to have graduated from a faculty of medicine with a license to practice [337], whereas in rural areas, village doctors have to pass only local exams to obtain a "Village Doctor Certification" [338]. Over the years, the number of medical professionals attaining the highest qualification has risen, with the proportion of bachelor's degree holders increasing from 17.1% in 2005 to 34.6% in 2018 [339]. However, disparity persisted across urban and rural areas, especially in terms of the proportion of personnel that hold a bachelor's degree, or above, in primary healthcare institutions. Although the Ministry of Education oversees medical universities, many of the doctors in rural counties did not have a formal medical education and thus were not subject to the same level of standard medical training outlined by the ministry. For instance, only 6% of health workers in rural areas had a bachelor's degree [324]. The variability of the qualification across geographic areas consequently drove patients to travel to urban areas, in order to seek the best quality of healthcare possible, resulting in extremely overcrowded hospitals in big cities, as well as in long waiting times.

To ensure some basic level of gatekeeping, the 2009 healthcare reform introduced a family doctor and general practitioner (GP) referral system, implemented officially in 2015. However, there was no established education system for family medicine training, as historically universities only train specialists. A policy document suggested a potential change to the education system in order to train undergraduate students to become GPs in three-year programs, rather than the traditional "5+3" program for specialists [318]. Overall, the supply of GP and family doctors are still in their incipient stages, and the roles are quite different from those that exist in European countries. To improve the efficiency of primary healthcare delivery, the government implemented an integrated health information system to connect public hospitals and primary healthcare facilities with more ancillary Internet+ health services [340]. However, the data governance remained fragmented as the NHC hosts the electronic health data and the NHSA hosts the insurance claim records, while each hospital also has a unique medical record system – none of the different sources is interoperable [341]. Therefore, integration of care requires a more effective electronic health system.

A resource unique to the Chinese health system is the Traditional Chinese Medicine (TCM) doctor. Typically, TCM doctor practices either in a TCM specialised hospital or the GP department in local community centres. During the COVID-19 outbreak, TCM played a significant role in effectively treating patients with highly tailored Chinese medicine [342]. Despite the widespread recognition of their importance, the trend to westernise TCM professional education may cause sharp contradictions between the training and the practice of TCM, which historically followed a rigorous apprenticeship tradition [343].

Similar to most countries, the physical resources in China's health system include hospitals of different tiers and specialisations, primary healthcare institutions, specialised public health institutions, and pharmacies. The number of hospitals and their capacity has been unequally distributed across geographic areas - the drastic economic development of the Eastern urban regions of China created a higher concentration of both general and specialised hospitals, for example [340]. This has resulted in the emergence of a peculiar pattern of healthcare use, with residents in more affluent areas overusing hospitals for outpatient care, and residents in more impoverished regions using primary care institutions for inpatient care [328]. The substantial disparity across local governments in terms of financial capability, operating efficiency, quality of care, and continuity of care from primary healthcare centres to tertiary hospitals remains a major challenge [319], despite the recent reforms to facilitate a patient referral network and to elevate insurance coverage of urban residents. This disparity highlights the urgency in accelerating the development of primary care infrastructures in urban regions and the investment of higher-tiered hospitals in the central and western regions. The current fragmentation in the government financing system and insurance arrangements needs to be tackled with urgency in order to (re-)distribute financial resources adequately and to redress horizontal resource disparity.

5.2.3 Financing

Whether it is a collective or a market-based system, the financing function in any health system can be divided into three distinct, but closely interlinked functions: (1) revenue collection, (2) fund pooling and (3) purchasing. In what follows, we discuss the different functions and their potential implications on equity and efficiency, along with the diagrammatic representation of the overall financing structure of the health system.

Revenue Collection and Fund pooling

The Chinese healthcare financing system is a mix of public insurance models. The sources of total health expenditure are composed of government (central and local) taxation, social contributions, and out-of-pocket payments. However, the collection of revenues remains fragmented, as the pooling of funds and government finance does not go beyond the prefecture or municipality level.

Two primary public insurance schemes coexist to collect revenues (see Figure 5.3): a mandatory public insurance for urban employees (cost-sharing with employers) – the

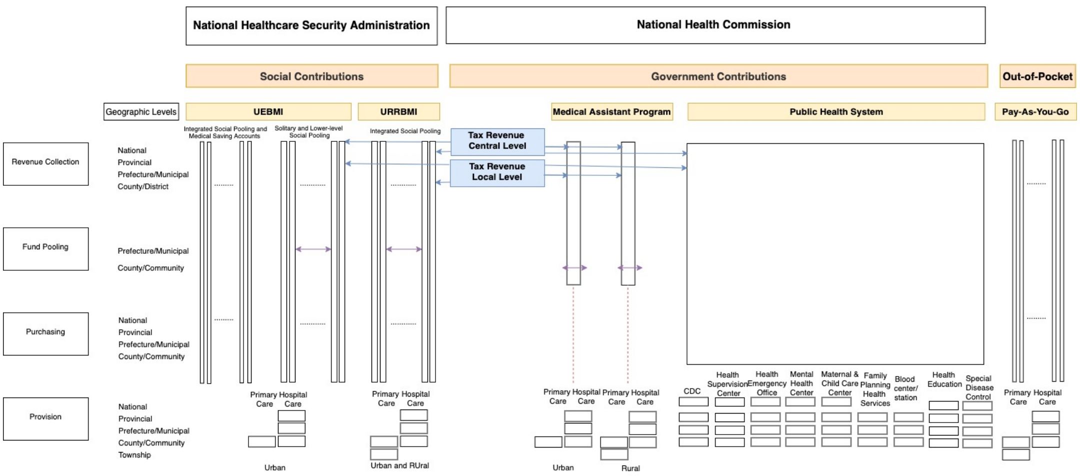


FIGURE 5.3: China's Healthcare System

Urban Employee Basic Medical Insurance (UEBMI), which covers around 300 million workers; and a voluntary public insurance for non-working urban and rural residents including students and children – the Urban-Rural Resident Medical Insurance (URRMI), which is a merger between the URBMI and the NCMS. The URRMI currently covers around 1 billion residents. In addition, there is a Medical Assistant Program (MAP), for those who are not enrolled in the other two schemes. Supplementary private health insurance exists to provide coverage for services not covered by public insurance. The benefits packages usually cover inpatient care and critical outpatient care, while catastrophic insurance schemes exist for specific diseases (e.g. cancer). There is patient cost-sharing, through both deductibles and co-payments, to reduce unnecessary utilisation of healthcare services and reduce the onset of moral hazard. All schemes have their distinct formulas for reimbursing drugs and services.

Within the UEBMI, separate sub-schemes exist to cater for specific types of employees: the "integrated social pooling and individual medical savings accounts (MSAs)" for formally employed full-time workers; the "solitary social pooling" for the 'informally' employed; and the "lower-level social pooling" for retirees. The sub-schemes differ in the way funds are raised and pooled, and in the type and amount of coverage offered. Premiums are collected through both employer and employee contributions (set respectively at 6% and 2% of an employee's salary). In the first sub-scheme, employee contributions are paid directly into their individual MSAs, while employer contributions are split between the integrated social pooling (around 70%) and the MSA (around 30%). Contributions in the "solitary social pooling" schemes are based on the average salary in the local area, while the contribution is even lower for the "lower-level social pooling". In addition to the social pooling, the UEBMI also receives fixed contributions set by the central government. However, fund pooling within UEBMI schemes is horizontally and geographically fragmented, i.e. funds are pooled only within each sub-scheme at the municipality/prefecture level. The fragmentation might generate issues with both vertical and horizontal equity in financing, access to benefits packages, and in terms of co-payments imposed on enrolees. Furthermore, total revenues collected by the UEBMI sub-schemes may vary substantially, affecting both the depth and breadth of benefits packages and the pay-outs that insurance schemes can make. Recent studies have confirmed the imbalance between healthcare costs and choice of hospital types between socioeconomically developed and underdeveloped regions [344].

The newly integrated URRMI is funded primarily by central and local government subsidies, with minimal individual contributions and funds pooled at the prefecture/-municipality level. There is integrated social pooling, but no MSAs. The merger of the previous urban and rural residence schemes has been carried out in a staggered way, with considerable variability in the extent of integration across geographic areas. Eight provinces only enrol resident individuals, while other provinces do not restrict coverage requirements; additionally, in Fujian and Guangdong provinces, there has been full integration across all three medical insurance schemes [345]. Since the revenue of URRMI depends mainly upon the financial capability of the local government, the benefit packages and co-payment schemes tend to differ from UEBMI and can vary substantially across geographic units [346].

Even with the two major insurance schemes, both rural and urban residents, may have been unable to pay for catastrophic healthcare expenses. For this reason, the MAP was in place, with free and voluntary enrolment. Initially only providing subsistence allowance to low-income elderly and disabled residents, the program now extends to fund comprehensive care for the poor. MAP is subsidised by the urban and rural medical assistance system. Differently from other insurance schemes, funds are pooled at the county level.

Purchasing

Purchasing refers to the process by which collected, pooled and possibly risk-adjusted funds are allocated to individual or institutional providers. This process relates to the what, how and from whom healthcare is purchased and whether or not mechanisms are put in place to preclude perverse and often inefficient incentives in healthcare providers. In the case of China, the purchasing authorities are highly fragmented and do not operate under a functioning strategic purchasing mechanism. The various social insurance schemes were previously managed independently by two different ministries, without any strategic interaction. In 2018, the NHSA was established to improve the governance of social insurance programs and change the ways providers were paid. Since its establishment, the NHSA has developed the organisational capacity and improved existing purchasing mechanisms. In the last two years, the NHSA has set in place effective negotiations between purchasers, pharmaceutical companies, and hospitals. However, there is little evidence so far that the new purchasing mechanisms follow the national objectives set out in the "Healthy China Strategy".

The new administration is also in the process of implementing a provider payment reform. Traditionally, China's hospital care has been reimbursed through a fee-for-service reimbursement system. There was, therefore, a need to set appropriate reimbursement rates/mechanisms for providers. Since the late 1990s, various forms of prospective payment methods have been piloted to modify healthcare providers' incentives, while the first version of Diagnosis Related Group (DRG) was established in the 1980s. In 2017, the State Council issued a new policy, which resulted in around 30 cities implementing the DRG system by 2018 [347]. However, the DRG system implemented in China is still rudimental and in an early adoption phase. Many different forms of (prospective) payment systems are still widely used, despite recommendations for uniformed dissemination [348].

Additional to payments received from social insurance schemes, public hospitals also receive direct funding from governments at various tiers. The direct funding is in the form of global budgets, not tied to the needs of the facilities or the populations served, or linked to the performance of the hospitals [349]. They are usually determined by the size of the hospital and the local fiscal capacity, disjoined from incentives set in terms of quality of care or efficiency targets [350].

Despite recent efforts, China is still far from being able to implement strategic value-based purchasing.

5.2.4 Provision

Similar to other sectors of the economy, the provision of healthcare comprises the selection and combination of inputs that, through a production process, leads to the delivery of healthcare goods and services. In China, the NHC is in charge of the national health development planning and management of the healthcare system, while commissioners at the provincial, municipal and county levels are responsible for the delivery of healthcare services. The health delivery system is mixed, comprising both public and private providers. In 2012, there were 912,620 primary health centres (PHC) in China, 52% of which were public facilities, with the rest equally split between private for-profit and private not-for-profit [324]. Secondary and tertiary general hospitals provide most outpatient and inpatient services, and specialised hospitals provide mental, dental and oral health services [329]. In 2012, there were 23,170 hospitals in China, of which just under 58% were public, about 15% were private not-for-profit and just under 28% private for-profit [324]. Although hospitals have been increasingly endowed with more and more autonomy over their daily operations (traditionally operated under a "command and control" model), the government still exerts administrative power over several managerial aspects such as bed numbers and the appointment of key managers. As a result, public hospitals are accountable to the corresponding political authorities and are subject to several public organisations. This distorted version of a semi-autonomous model has been regarded as one of the root causes for the inefficiencies in the delivery of healthcare.

Since 2006, a two-way patient referral regulation has been in place to promote the rational use of health services [329]. In principle, patients in urban areas should first seek medical services at a primary healthcare institution, from which they are then referred to secondary and tertiary hospitals. The ultimate aim is to integrate the three levels of healthcare provision fully. The rapid demographic and epidemiological changes, due to an ageing society and increasing burden of non-communicable diseases, reinforced the need to transform its hospital-centric and volume-driven system into an affordable, high-quality care system around the model of the patient-centred integrated care [324]. However, many of the factors mentioned elsewhere in this paper, such as the fragmented governance arrangement, the lack of qualified healthcare professionals and the variability of financing schemes, all pose significant barriers for the full integration across the different tiers. Finally, the integration process was further complicated by the existence of separate and independently managed organisations, loose definitions of provider function across tiers, as well as ambiguous referral criteria guidelines [324].

The COVID-19 outbreak emphasised the (mis-)functioning of the public health system in China. By design, primary healthcare institutions and specialised public health facilities assume the role of providing public health services, while some community health centres and village clinics offer complementary services such as disease management, rehabilitation, health education and family planning. Other highly-specialised public health institutions such as the Centre for Disease Control and Prevention, health education institutions, maternal and child health institutions and mental health institutions provide different kinds of professional public health services [329, 340]. The NHC and the State Administration of Work Safety are responsible for occupational health, work safety, and launching relevant regulations [351]. Several departments within the NHC are in charge of the administration of public health, including the Disease Control Bureau, Health Supervision Bureau, Emergency Response Office, Primary Healthcare Department, Maternal and Child Health Department, and Food Safety and Supervision Department [329]. Local health bureaux at each level have also set up similar departments which are responsible for local public health management. As there is no single organisation that manages public health, the COVID-19 outbreak has highlighted the need to address current failures and shortcomings as urgency in the near future.

All institutions involved in service provision are shown in Fig. 5.3.

5.3 Discussion

To some extent, the experience of China's healthcare reforms has been unique, given its top-down approach of implementation, and the radical overthrow of existing policies and structure. On the other hand, the cycle of reforms has been driven by ideological changes, due to a change of leadership and the shifting of government's preferences between a government and a market-oriented health system. This process is not too different from many other high- and low-middle-income countries that have experienced various levels of centralisation, decentralisation and liberalisation

[352]. Moreover, in China, reforms were often constrained/limited by the geographical size of the country and variation in terms of socio-economic development. This has led the central government to rely on extensive use of pilot programs, mostly run at the provincial level, to investigate the potential effects of new health policies before national roll-outs. The rationale behind this approach is to allow each province a higher level of discretion within their own jurisdictions when implementing centrally designed policies so that these can be tailored to local health needs and reflect local fiscal capacity. Consequently, the main factors influencing the adoption and implementation of these recent reforms have been local pressures to respond to local governance problems, imitation of innovations adopted by peers, and regional preferences. This decentralised approach has resulted in significant variations at the local level. In more recent years under President Xi's leadership, China has been experiencing an increase re-centralisation of political power, which has meant a renewed expectation for centrally designed policies to be implemented 'as is' at the local level. Nonetheless, local governments can still choose from an array of models when implementing central policies.

What the Chinese lesson offers is a compelling case that involves the largest population experiencing a rapid change from a highly profit-driven and unequal healthcare system to, at least in principle, near-universal coverage [353], but with many of the historical problems still plaguing the system. However, the incredible efforts and momentum exerted by the government, and the firm will for the improvement of the population health, are commendable.

In our effort to systematically describe and assess China's current health system, we have identified several areas of concern. The geographic disparity is profound in terms of healthcare infrastructure and human resources between rural and urban area, and between the more affluent regions along the coast and more impoverished Western inland provinces. Moreover, because the social pooling of insurance funds is only carried out at the prefecture and municipality level, and within each scheme, the marked disparity across geography and individual residence status can generate significant inequality in total funds available as well as in the breadth and depth of benefits packages offered. This inequality is a consequence of considerable variations in the socio-economic development of the country, and which we believe requires concerted efforts by the central government to redistribute the necessary financial resources and healthcare workforce following the principle of both horizontal equity in access and vertical equity in financing. Even within economically advanced areas, a shortage of qualified primary healthcare practitioners and infrastructure contributed to the inexistent gatekeeping function of primary healthcare providers. Since patients persistently exhibited hospital-centric preferences when seeking healthcare, there was an intrinsic tension which prevents the intended integration of care across tiers. These challenges are interconnected and have not been sufficiently addressed by the fast-paced implementation of the reforms. Finally, the existence of multiple insurance schemes and funding pools highlights the inherent inefficiency of the overall system design, with obvious and often non-necessary duplication of cost functions. The absence of a well-developed and structured purchasing function, with reimbursement still often linked to historical expenditure or based on a fee-for-services system, is probably the source of recent escalating healthcare costs. The introduction of a nationally unified DRG-based reimbursement system might improve current inefficiencies, but only if specific financial and quality targets are concurrently introduced.

Our analysis of the four functions of the Chinese health system has brought to the fore a common thread: the enormous complexity of the four functions and the health system as a whole. There is a myriad of institutions, organisations and agencies, operating in a highly fragmented environment, both horizontally - across different ministries and department - and vertically - across the different level of governments. They often have conflicting and ill-defined remits, lacking common objectives and scopes, a clear set of incentives and accountabilities, and more importantly, strategic integration. This finding implies that sustainable and scalable reforms have been compromised, as agencies and ministries often act to defend their own interests, rather than working towards the achievement of the common good. The successful implementation of the health reforms in China may have been historically weakened by flawed decision-making processes which are too often, and sometimes exclusively, reliant on interagency bargaining [324].

Our descriptive analysis of the four functions of a healthcare system provides a valuable overview of the Chinese health system and has highlighted areas of its system design and reforms that warrant future assessments and evaluations. The latter cannot be carried out without a good understanding of the former, as Murray and Frenk originally suggested with their framework.

Concluding Remarks

In my modest journey to undercover some of the intricate issues related to health disparity, I feel compelled to explore even more in-depth the different dimension of this topic in the advent of this COVID-19 pandemic in my future endeavour. This virus' aggressive invasion has posed numerous questions on why our society, even those with the most advanced health care systems and technologies, is ill-equipped for this battle. The challenges are not only thorny for health systems but also for the civil society in a political climate that is highly polarised. I want to, therefore, conclude my dissertation by recognising the complex implications that this crisis may have on our health and health care.

One grim ethical dilemma that many health care systems faced during the worst period of the pandemic is rationing of care for patients. When resources such as ventilators and intensive care units are entirely outstripped by the overflow in of hospitalisations, hospitals almost resemble a battlefield situation where doctors have to pick the patients to save. When there is only one ventilator, with both a 90-year-old and a young person needing to be intubated, does the doctor choose the more vulnerable patient or that with more life years ahead? We are, in fact, re-living war-time scenarios where difficult ethical triage decisions have to be made.

The value judgments that we discussed in the preface have become ever more relevant. In the previous example, utilitarianists would undoubtedly save the young person because, in the ranking of quality of life, he/she would generate the highest total benefit. Egalitarianist a là Rawls would provide for the sickest elderly victim first under the 'rule of rescue". Both moral intuitions have their respective flaws - the former ignores the imperatives of urgency, while the latter lavish extensive resources on a single patient while potentially denying others who may be more likely to survive. In practical term, how we balance horizontal and vertical equity in emergency scenarios requires potentially different sets of principles, and we need to ask ourselves: what makes one life worth saving more than another?

Although I resonate deeply with the egalitarian or prioritarian approach, I also recognise the merits of utilitarianism as being effective in situations of extreme scarcity of medical resources. However, if we consider health benefits as a multi-dimensional concept, we have to incorporate an array of factors that define one's quality of life to rank individuals other than life expectancy or even quality-adjusted life-year (QALY) for that matter - mental health, family size, pain tolerance, compassion personal satisfaction to say the least. Science alone, unfortunately, will not be able to address all the necessary dimensions. So the best way to avoid facing the agonising decision on how to ration care is through collective social action to reduce the case spikes. Scientists and politicians have relentless stressed the importance of self-quarantine and social distancing, which are themselves moral decisions that we, as individuals, can make a meaningful impact on the health care system.

In the long term, we all aim to design our health care systems to ensure the least possible discrimination in resources and quality across geography, race, gender, disability, preferences, income and possibly all traits that can define us (Chapters 1, 3 and 5). We also hope to redistribute more resources and attention to those who have grave needs in the aftermath of the economic, social or epidemiological crisis (2). Moreover, we need to recognise the various complex dynamics of social and political influences on health such as internet misinformation and ideological differences that counter the process of social development (Chapter 5). In our long-lasting battle against health disparity, I hope my observations in this dissertation can offer some meaningful insights into the broader context of humanity's problematic future.

Appendix A

Chapter 1

Table A.1: Appendix, Fixed Effects, All Readmission from Table 1.2

Models	**Logit**		**Hazard**	
Variables	**Coefficient**	**SE**	**Coefficient**	**SE**
Education				
Elementary or Lower	Reference		Reference	
Middle School	-0.0598**	(0.0251)	-0.0463*	(0.0272)
High School	-0.159***	(0.0326)	-0.139***	(0.0359)
University	-0.163***	(0.0434)	-0.176***	(0.0484)
Laurea or Above	0.0725	(0.118)	-0.0270	(0.135)
Comorbidities				
Shock	-0.286***	(0.0717)	-0.358***	(0.0821)
Diabetes with Complications	0.0565	(0.0435)	0.120***	(0.0461)
Congestive Heart Failure	-0.0126	(0.0208)	0.00661	(0.0225)
Cancer	-0.133**	(0.0655)	-0.0852	(0.0697)
Cerebrovascular Disease	-0.217***	(0.0360)	-0.199***	(0.0390)
Plmonary Edema	0.0771	(0.0780)	0.0796	(0.0839)
Acute Renal Failure	0.0502	(0.0573)	0.0558	(0.0612)
Chronic Renal Failure	-0.000708	(0.0272)	0.0291	(0.0292)
Cardiac Dysrhythmias	-0.133***	(0.0223)	-0.109***	(0.0241)
Year Fixed-Effects				
2010	Reference		Reference	
2011	0.0203	(0.0270)	0.0219	(0.0291)
2012	-0.00896	(0.0307)	-0.0366	(0.0334)
2013	-0.0702**	(0.0322)	-0.107***	(0.0352)
2014	-0.0849**	(0.0332)	-0.111***	(0.0361)
2015	-0.180***	(0.0322)	-0.225***	(0.0353)
Regional Fixed-Effects				
Piedmont (10)	Reference		Reference	
Aosta Valley (20)	0.616	(0.702)	0.747	(0.571)
Lombardy (30)	0.338*	(0.195)	0.245	(0.169)
P.A. Bolzano (41)	0.905**	(0.410)	0.709**	(0.354)
P.A. Trento (42)	-0.208	(0.408)	-0.257	(0.350)
Veneto (50)	0.379*	(0.200)	0.305*	(0.170)
Friuli Venezia Giulia (60)	0.101	(0.235)	0.255	(0.200)
Liguria (70)	0.255	(0.296)	0.263	(0.248)
Emilia Romagna (80)	1.189***	(0.198)	1.145***	(0.169)
Tuscany (90)	0.675***	(0.200)	0.577***	(0.168)
Umbria (100)	0.160	(0.250)	0.144	(0.213)
Marche (110)	0.481	(0.327)	0.495*	(0.269)
Lazio (120)	0.806***	(0.188)	0.614***	(0.159)
Abruzzo (130)	0.545**	(0.260)	0.345	(0.228)
Molise (140)	-0.623	(0.485)	-0.674	(0.441)
Campania (150)	0.258	(0.220)	0.0949	(0.197)
Apulia (160)	0.814***	(0.222)	0.635***	(0.194)
Basilicata (170)	1.333***	(0.355)	1.024***	(0.301)
Calabria (180)	0.619**	(0.251)	0.536**	(0.222)
Sicily (190)	0.735***	(0.232)	0.569***	(0.217)
Sardinia (200)	0.229	(0.237)	0.198	(0.206)

Table A.2: Appendix, Fixed Effects, Same MDC Readmission from Table 1.2

Models	**Logit**		**Hazard**	
Variables	**Coefficient**	**SE**	**Coefficient**	**SE**
Education				
Elementary or Lower	Reference		Reference	
Middle School	0.0365	(0.0705)	0.00986	(0.0892)
High School	0.00916	(0.0915)	-0.0196	(0.117)
University	-0.135	(0.127)	-0.215	(0.165)
Laurea or Above	0.475	(0.292)	-0.485	(0.552)
Comorbidities				
Shock	-0.126	(0.203)	-0.306	(0.276)
Diabetes with Complications	0.394***	(0.110)	0.264*	(0.147)
Congestive Heart Failure	0.194***	(0.0558)	0.210***	(0.0700)
Cancer	-0.186	(0.196)	-0.224	(0.249)
Cerebrovascular Disease	-0.350***	(0.112)	-0.418***	(0.144)
Plmonary Edema	-0.0292	(0.234)	-0.134	(0.306)
Acute Renal Failure	-0.113	(0.165)	-0.0325	(0.196)
Chronic Renal Failure	0.468***	(0.0650)	0.540***	(0.0806)
Cardiac Dysrhythmias	-0.286***	(0.0671)	-0.257***	(0.0835)
Year Fixed-Effects				
2010	Reference		Reference	
2011	0.211**	(0.0853)	0.340***	(0.108)
2012	0.301***	(0.0939)	0.365***	(0.120)
2013	0.210**	(0.0970)	0.295**	(0.124)
2014	0.333***	(0.0965)	0.333***	(0.125)
2015	0.321***	(0.0921)	0.414***	(0.118)
Regional Fixed-Effects				
Piedmont (10)	Reference		Reference	
Aosta Valley (20)	-0.547	(1.128)	-0.116	(1.268)
Lombardy (30)	-0.182	(0.242)	-0.200	(0.330)
P.A. Bolzano (41)	0.0502	(0.580)	-0.0670	(0.786)
P.A. Trento (42)	-1.020	(0.648)	-1.632	(0.999)
Veneto (50)	0.447**	(0.225)	0.446	(0.311)
Friuli Venezia Giulia (60)	0.121	(0.272)	0.180	(0.365)
Liguria (70)	0.173	(0.306)	0.283	(0.421)
Emilia Romagna (80)	0.899***	(0.225)	0.848***	(0.309)
Tuscany (90)	0.518***	(0.200)	0.451	(0.280)
Umbria (100)	0.141	(0.293)	0.170	(0.396)
Marche (110)	0.441*	(0.241)	0.583*	(0.310)
Lazio (120)	0.364*	(0.193)	0.0421	(0.275)
Abruzzo (130)	0.218	(0.343)	0.275	(0.457)
Molise (140)	-1.034	(1.091)	-0.650	(1.175)
Campania (150)	-0.0146	(0.336)	0.00196	(0.445)
Apulia (160)	0.712**	(0.292)	0.577	(0.393)
Basilicata (170)	1.031**	(0.404)	1.225**	(0.547)
Calabria (180)	0.317	(0.372)	0.468	(0.489)
Sicily (190)	0.784*	(0.422)	0.701	(0.554)
Sardinia (200)	0.490	0.490	0.524	(0.415)

Table A.3: Appendix, Other Coefficients, Table 1.3

Models	**All Readmission**		**Same MDC Readmission**	
Variables	**Coefficient**	**SE**	**Coefficient**	**SE**
Patient Characteristics (Average)				
Age	-0.00292***	(0.000752)	0.000273	(0.000312)
Male	0.0107	(0.0115)	0.00656	(0.00480)
Education	-0.00174	(0.00305)	-0.00201	(0.00123)
Foreign	-0.0207	(0.0491)	-0.0200	(0.0200)
Sum of Comorbidity	-0.0454***	(0.00636)	-0.0117***	(0.00263)
Institution	-0.0460	(0.0376)	-0.0136	(0.0154)
Year (2010 Reference)				
2011	0.00827	(0.00818)	0.00286	(0.00341)
2012	0.00780	(0.00861)	0.00819**	(0.00357)
2013	0.0164*	(0.00896)	0.00652*	(0.00370)
2014	0.0140	(0.00905)	0.0112***	(0.00374)
2015	0.00703	(0.00893)	0.00437	(0.00370)

Appendix B

Chapter 3

Appendix, Direct Standardisation Method

We standardise our quality indicators in the following steps. We first divide the overall elderly patient population into two age categories (65-80 and 80 +), two gender categories, as well as five categories of Charlson Sum of Comorbidity Index, resulting in 20 subcategories. We further estimate the proportion of each subcategory as a population ratio. Secondly, we calculate the crude rates (number of death or readmission divided by the number of admission) of mortality and readmission under each subcategory for each hospital (global quality) and hospital-municipality combinations (local quality). We then multiply the crude rates by their respective population ratios to obtain the expected number of mortality and readmission for all the subcategories. Finally, we sum all the expected values by hospital and hospital-municipality combinations to get the total expected rates of mortality and readmission.

Table B.1: Appendix, Variable definition and data sources

Variable	**Definition**	**Source**
Explanatory variables		
$Q^{gb}_{j,t-1}$	Composite quality index of hospital j for all patients: – In-hospital mortality – hip replacement – In-hospital mortality – all-causes – 30-day readmission rate – hip replacement – 30-day readmission rate – all-causes	SDO
$Q^{lc}_{jk,t-1}$	Composite quality index of hospital$j$ for patients from k: – In-hospital mortality – hip replacement – In-hospital mortality – all-causes – 30-day readmission rate – hip replacement – 30-day readmission rate – all-causes	SDO
tt_{jk}	Travel time by car between municipality k and hospital j	ISTAT; geofabrik.com
c_{jk}	Indicator for whether hospital j is the closest hospital to the patient's municipality k	ISTAT
Control variables		
X_{jt}	Hospital characteristics including hospital type, average patient stay, average patient sum of comorbidities for hospital j	SDO
	– Total number of beds in hospital j	MoH
	– Adjacent rehabilitation unit at hospital j	MoH
Z_{it}	Patient characteristics including age category (80 and above) and gender	SDO
n_{jt}	Number of hip replacement surgeries in hospital j in year t	SDO
n_{jkt}	Number of hip replacement surgeries in hospital j from municipality k in year t	SDO

Notes: SDO – Hospital Discharge Data; ISTAT – Istituto Nazionale di Statistica (Italian Statistical Office); MoH – Italian Ministry of Health

Table B.2: Appendix, Hospital quality variables

	Intervention in hospital j	
	All procedures	*Hip replacement surgery*
Patients from		
All municipalities (global)	Q^{gb}_{j}	$Q^{gb,hrs}_{j}$
Municipality k (local)	Q^{lc}_{jk}	$Q^{lc,hrs}_{jk}$

TABLE B.3: Appendix, (Continued) result from table 3.3

Variables	Without local quality	With local quality
	(1)	(2)
Rehab unit	0.179	0.166
	(0.165)	(0.457)
Capacity (total bed count)	0.0002	0.0002
	(0.0002)	(0.0008)
(mean) Length-of-stay	-0.0679***	-0.0648***
	(0.0208)	(0.0237)
(mean) Patient sum of comorbidity	-1.950***	-2.011***
	(0.447)	(0.759)
Hospital trust	8.588***	8.646**
	(2.508)	(4.356)
Private accredited	7.992***	8.003***
	(2.451)	(2.916)
Teaching or research	8.358***	8.377**
	(2.515)	(4.160)
LHA-managed	8.553***	8.623***
	(2.530)	(3.075)
Random components		
SD(Travel time), lnormal	0.415	0.303
	(0.343)	(0)
SD(Hip replacement global)	0.0315	0.288
	(0.0194)	(0)
SD(All-cause global)	1.527	1.05e-05
	(0)	(0)
SD(Hip replacement local)		0.301
		(0.851)
SD(All-cause local)		0.342
		(0)

Notes: Robust standard errors clustered at municipality-level in parenthesis.
***p<0.001, **p<0.01, *p<0.05

TABLE B.4: Appendix, (Continued) result from table 3.4

Variables	Without local quality (1)	With local quality (2)
Rehab unit	0.518	0.513
	(0.348)	(0.355)
× male	0.502	0.479
	(0.423)	(0.431)
× old	-0.498	-0.505
	(0.376)	(0.383)
Capacity (total bed count)	8.48e-06	2.24e-05
	(0.0003)	(0.0003)
× male	0.0005	0.0005
	(0.0004)	(0.0004)
× old	8.29e-05	7.25e-05
	(0.0008)	(0.0008)
(mean) Length-of-stay	-0.0210	-0.0213
	(0.0274)	(0.0274)
× male	-0.103**	-0.102**
	(0.0445)	(0.0445)
× old	-0.0429	-0.0422
	(0.0474)	(0.048)
(mean) Patient sum of comorbidity	-2.000***	-2.050***
	(0.631)	(0.648)
× male	0.681	0.676
	(0.850)	(0.879)
× old	-0.374	-0.398
	(1.188)	(1.253)
Hospital Trust	3.684	3.577
	(3.269)	(3.384)
× male	1.232	1.267
	(3.264)	(3.377)
× old	7.783*	7.950*
	(4.584)	(4.758)
Private Accredited	3.150	2.999
	(3.276)	(3.437)
× male	0.0421	0.0293
	(3.315)	(3.397)
× old	8.211*	8.363*
	(4.586)	(4.795)
Teaching or Research	1.927	1.816
	(3.365)	(3.435)
× male	-0.930	-0.906
	(3.273)	(3.411)
× old	9.716**	9.857**
	(4.673)	(4.796)
LHA-managed	3.956	3.838
	(3.312)	(3.420)
× male	1.597	1.623
	(3.115)	(3.230)
× old	7.447	7.591
	(4.658)	(4.820)

Notes: Robust standard errors clustered at municipality-level in parenthesis. The reference group for the interaction terms are female patients aged 65-80 years. ***p<0.001, **p<0.01, *p<0.05

Table B.5: Appendix, Mixed logit analysis with separate quality indicators

Variables	Mortality (1)	Readmission (2)
Closest	0.010	0.246
	(0.358)	(0.295)
Travel time (log)	-4.440***	-4.437***
	(0.188)	(0.186)
Global quality, $Q^{gb}_{j,t-1}$		
Hip replacement	0.012*	0.008
	(0.007)	(0.021)
All-cause	-2.512	-0.328
	(2.606)	(1.019)
Local quality, $Q^{lc}_{j,t-1}$		
Hip replacement	-33.88*	2.158
	(18.13)	(1.661)
All-cause	-9.757	-0.596
	(6.754)	(1.905)
Hospital volume (global)	0.003***	0.003***
	(0.001)	(0.001)
Hospital volume (local)	4.312***	4.227***
	(0.377)	(0.408)
Hospital fixed-effect	yes	yes
Regional fixed-effect	yes	yes
Observations	159,495	159,495
No. patients	886	886
AIC	2312.861	2345.682
BIC	2418.169	2455.776

Notes: Robust standard errors clustered at municipality-level in parenthesis. All models include a range of hospital and regional control variables (full results are displayed in the Appendix in table B.6).
AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion.
***p<0.001, **p<0.01, *p<0.05

Table B.6: Appendix, (Continued) Result from table B.5

Variables	Mortality (1)	Readmission (2)
Rehab unit	0.0841	0.273
	(0.170)	(0.172)
Capacity (total bed count)	0.000	0.000
	(0.000)	(0.000)
(mean) Length-of-stay	-0.0585***	-0.059***
	(0.020)	(0.022)
(mean) Patient sum of comorbidity	-1.781***	-1.937***
	(0.445)	(0.465)
Hospital trust	8.695***	8.708***
	(2.523)	(2.533)
Private accredited	7.868***	8.126***
	(2.519)	(2.559)
Teaching or research	8.310***	8.572***
	(2.533)	(2.533)
LHA-managed	8.513***	8.691***
	(2.573)	(2.588)
Random components		
SD(Travel time), lnormal	1.693***	0.220
	(0.097)	(0.187)
SD(Global hip replacement)	0.013***	0.064***
	(0.004)	(0.015)
SD(Global all-cause)	7.873**	6.524***
	(3.336)	(2.482)
SD(Local hip replacement)	2.333***	0.170***
	(0.000)	(0.041)
SD(Local all-cause)	64.47***	18.17***
	(19.64)	(3.723)

Notes: Robust standard errors clustered at municipality-level in parenthesis.
***p<0.001, **p<0.01, *p<0.05

TABLE B.7: Appendix, Mixed logit analysis with hip replacement revision rate and surgical complications as quality indicators

Variables	Without local quality (1)	With local quality (2)
Closest	-0.265	-0.0312
	(0.382)	(0.321)
Travel time (log)	-4.173***	-4.286***
	(0.166)	(0.177)
Global quality $Q^{gb}_{j,t-1}$		
Revision rate	0.021	0.0099
	(0.060)	(0.012)
Surgical complication rate	-0.015	-0.015
	(0.000)	(0.000)
Local quality $Q^{lc}_{j,t-1}$		
Revision rate		-1.259
		(2.066)
Surgical complication rate		-0.370
		(1.968)
Hospital volume (global)	0.005***	0.004***
	(0.001)	(0.001)
Hospital volume (local)	3.712***	3.751***
	(0.324)	(0.335)
Hospital fixed-effect	yes	yes
Regional fixed-effect	yes	yes
Observations	159,495	159,495
No. patients	886	886
AIC	2498.039	2518.987
BIC	2584.2	2624.295

Notes: Robust standard errors clustered at municipality-level in parenthesis. All models include a range of hospital and regional control variables (full results are displayed in the Appendix in table B.8).
AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion.
***p<0.001, **p<0.01, *p<0.05

TABLE B.8: Appendix, (Continued) result from table B.7

Variables	Without local quality	With local quality
	(1)	(2)
Rehab unit	0.168	0.162
	(0.163)	(0.162)
Capacity (total bed count)	0.000	0.000
	(0.000)	(0.000)
(mean) Length-of-stay	-0.064***	-0.066***
	(0.021)	(0.021)
(mean) Patient sum of comorbidity	-2.015***	-1.933***
	(0.460)	(0.461)
Hospital trust	8.691***	8.693***
	(2.416)	(2.408)
Private accredited	7.918***	7.908***
	(2.362)	(2.349)
Teaching or research	8.489***	8.512***
	(2.415)	(2.405)
LHA-managed	8.405***	8.425***
	(2.402)	(2.390)
Random components		
SD(Travel time), lnormal	0.822***	0.677***
	(0.181)	(0.141)
SD(Global Revision rate)	0.003**	0.019**
	(0.00132)	(0.009)
SD(Global Surgical complication rate)	0.008***	0.00961***
	(0.001)	(0.001)
SD(Local revision rate)		0.040*
		(0.023)
SD(Local Surgical complication rate)		0.0179
		(0.027)

Notes: Robust standard errors clustered at municipality-level in parenthesis.
***p<0.001, **p<0.01, *p<0.05

Appendix C

Chapter 4

TABLE C.1: Appendix, List of Studies

Health Issue (by category)	Setting/Geographic Focus	Theory/Framework	Study Design	Platforms	Authors
Communicable Disease					
Ebola	Nigeria	N/A	Survey	Facebook, Twitter	Abedimpe et al. (2015)
Ebola	Chinese and English-speaking Countries	N/A	Content Analysis (Social Media)	Sina Weibo, Twitter	Fung et al. (2016)
Ebola	US	Epidemiological Models	Content Analysis (Twitter); Epidemiological Modelling	Twitter	Jin et al. (2014)
Ebola	English-speaking Countries	N/A	Content Analysis (Video)	YouTube	Pathak et al. (2015)
Influenza	China	Rumour Theory (Psychology)	Content Analysis (Social Media)	Sina Weibo, Tencent Weibo	Chen et al., (2018)
Middle East Respiratory Syndrome	South Korea	N/A	Social Network Analysis	Twitter, Blogs, Online Community Text, Discussion Board Text, News sites	Song et al. (2017)
Nile Virus Infection	English-speaking Countries	N/A	Content Analysis (Video)	YouTube	Dubey et al. (2014)
Vaccination (general)	English-speaking Countries	N/A	Content Analysis (Video)	YouTube	Basch et al. (2017)
Vaccination (general)	Italy	N/A	Content Analysis (Video)	YouTube	Donzelli et al. (2018)
Vaccination (general)	US	Situational Theory of Publics (Public Relations)	Survey	Websites	Krishna (2018)
Vaccination (general)	Spain	N/A	Content Analysis (Twitter)	Twitter	Porat et al. (2018)
Vaccination (general)	English-speaking Countries	Network Theory	Social Network Analysis	Facebook	Schmidt et al. (2018)
Vaccination (general)	Canada	N/A	Content Analysis (Facebook)	Facebook Instagram Twitter YouTube	Tustin et al. (2018)
Vaccination (general)	English-speaking Countries	N/A	Sentiment Analysis	Google	Xu and Guo (2018)
Vaccination (general) + GMOs	US	Psychological Theory	Experiment	Facebook	Bode and Vraga (2015)
Vaccination (HPV)	US	Theory of Rhetorical Situation (Philosophy)	Qualitative Case Study (Anthropology)	Websites	Grant et al. (2015)
Vaccination (HPV)	US	N/A	Content Analysis (Social Media)	Twitter	Mahoney et al. (2015)
Vaccination (influenza)	Italy	N/A	Content Analysis (Website)	Websites, Blogs	Panatto et al. (2018)
Vaccination (MMR)	Italy	N/A	Content Analysis (Social Media)	Google Trend, Twitter, Facebook; National Institute of Health (Istituto Superiore di Sanità)	Aquino et al. (2017)
Vaccination (MMR)	US	Network Theory	Content Analysis (Twitter); Social Network Analysis	Twitter	Radzikowski et al. (2016)
Vaccination (Polio and HPV)	Pakistan, US	N/A	Sentiment Analysis	Mainstream Media, Twitter, Vaccine Sentimeter	Bahk et al. (2016)
Zika Virus	US	Psychological Theory	Experiment	Facebook, Twitter	Bode and Vraga (2018)
Zika virus	English-speaking Countries	Inoculation Theory (Psychology)	Content Analysis (Video)	YouTube	Bora et al. (2018)
Zika Virus	Global	N/A	Content Analysis (Twitter); Social Network Analysis	Twitter	Ghenai and Mejova (2017)
Zika Virus	Global	N/A	Content Analysis (Image)	Instagram flicker	Seltzer et al. (2017)
Zika Virus	US	N/A	Content Analysis (Social Media)	Facebook	Sharma et al. (2017)
Zika Virus	English-speaking Countries	Network Theory	Social Network Analysis	Twitter	Sicilia et al. (2018)
Zika Virus	English-speaking Countries	N/A	Content Analysis (Weibo)	Facebook, Twitter, LinkedIn, Pinterest, GooglePlus, Web links	Sommariva et al. (2018)
Zika Virus	US	Psychological Theory	Experiment	Twitter	Vraga and Bode (2017)
Zika Virus	English-speaking Countries	Network Theory	Content Analysis (Twitter); Social Network Analysis	Twitter	Wood (2018)
Chronic Non-communicable Disease					
Cancer					
Cancer + Diet and Nutrition	US	Rumour Theory (Psychology)	Experiment	Websites	Chua and Banerjee (2018)
Cancer Screening	Japan	N/A	Content Analysis (Website)	Websites, Blogs, Facebook	Okuhara et al. (2017)
Gynaecologic Cancer	China	N/A	Content Analysis (Social Media)	Sina Weibo Tencent Weibo	Chen et al., (2018)
Cardiovascular Disease					
Diabetes + Diet	India	N/A	Content Analysis (Video)	YouTube	Leong et al. (2017)
Heart Failure	English-speaking Countries	N/A	Content Analysis (Video)	YouTube	Chen et al. (2013)
Hypertension	English-speaking Countries	N/A	Content Analysis (Video)	YouTube	Kumar et al. (2014)
Other Chronic Non-communicable Disease					
Inflammatory Bowel Disease	English-speaking Countries	N/A	Survey	Facebook, Twitter, YouTube, Website	Groshek et al. (2017)
Psoriasis + Diet	English-speaking countries	N/A	Content Analysis (Video)	YouTube	Qi et al. (2016)
Others					
Diet and Nutrition					
Anorexia	English, Spanish, Italian and Portuguese-speaking Countries	N/A	Content Analysis (Video)	YouTube, Vimeo and Voeh	Syed-Abdul et al. (2013)
Diet and Health-related Information	Arabic-speaking Countries	N/A	Content Analysis (Twitter)	Twitter	Alnemer et al. (2015)
Diet and Health-related Rumour	Italy	Network Theory	Content Analysis (Social Media); Social Network Analysis	Facebook, Twitter and YouTube	Bessi et al. (2015)
Smoking					
e-cigarette	US (Chicago)	Network Theory	Content Analysis (Twitter); Social Network Analysis	Twitter	Harris et al. (2014)
Hookah Tobacco Smoking	US	N/A	Content Analysis (Website)	Websites, Facebook, MySpace, Twitter	Primack et al. (2012)
Tobacco	US	N/A	Experiment	YouTube	Albarracin et al. (2018)
Water Safety/Quality					
Water Fluoridation	US	N/A	Content Analysis (Social Media)	Facebook, Twitter, YouTube, Website	Mertz and Allukian (2013)
Water Fluoridation	US	Network Theory	Social Network Analysis; Sentiment Analysis	Facebook, Websites	Seymour et al. (2015)
General Health (Rumour Psychology)					
Health-related Rumours	Southeast Asia	Epistemology (Philosophy)	Experiment	Websites	Chua and Banerjee (2017)
Health-related Rumours	US	Rumour Theory (Psychology)	Experiment	Twitter	Li and Sakamoto (2015)
Health-related Rumours	China	N/A	Content Analysis (Wechat)	Wechat	Li et al. (2017)
Health-related Rumours	US	Psychological Theory	Experiment	Twitter, Websites	Ozturk et al. (2015)
Health-related Rumours	Poland	N/A	Content Analysis (Social Media)	Facebook, Twitter, LinkedIn, Pinterest	Waszak et al. (2018)
Miscellaneous					
Abortion	US	N/A	Content Analysis (Website)	Websites	Bryant et al. (2014)
Dialysis	English-speaking Countries	N/A	Content Analysis (Video)	YouTube	Garg et al. (2015)
Drug	Bahrain	N/A	Content Analysis (WhatsApp)	WhatsApp	Al Khaja et al. (2018)
Multiple Sclerosis	Italy	N/A	Content Analysis (Website)	Websites	Lavorgna et al. (2018)
Paediatric Tonsillectomy + Diet	English-speaking Countries	N/A	Content Analysis (Video)	YouTube	Strychowsky et al. (2013)
Suicide	China	N/A	Content Analysis (Weibo)	Sina Weibo	Li et al. (2018)

Appendix D

Chapter 5

China has a vast territory, with 1.4 billion people, and is the world's second-largest economy by Gross Domestic Product (GDP) [354]. Since early 2000, health expenditure has been on the rise, with per capita expenditure at purchasing power parity reaching almost $1,200 in 2016, compared to about $200 in 2000 [354]. Though health expenditure as a proportion of GDP only increased from 4.5% to around 7% over the years (Fig. 5.1), the volume is considerably high given the drastic growth of the overall GDP. The burden of out-of-pocket expenditure as a proportion of total healthc expenditure declined over the years and flattened out at 29% by 2018. However, this is still relatively high compared to the OECD average of about 21% in the same year [355]. The composition of health expenditure has shifted dramatically, with government and social spending on the rise and out-of-pocket expense shrinking accordingly (Fig. D.1). This trend is the result of the gradual expansion of the basic insurance coverage. Although the infant mortality rate dropped steadily over the same period [354], the challenges of sustaining the healthcare needs of China's population, and the persistent inequality of access, are yet to be resolved. An ageing society and rising chronic non-communicable diseases further hinder these challenges. The recent COVID-19 outbreak has placed the design of the public health system under scrutiny, as the lack of medical supplies, public health specialists and initial information transparency accentuated the issues of China's fragmented healthcare system.

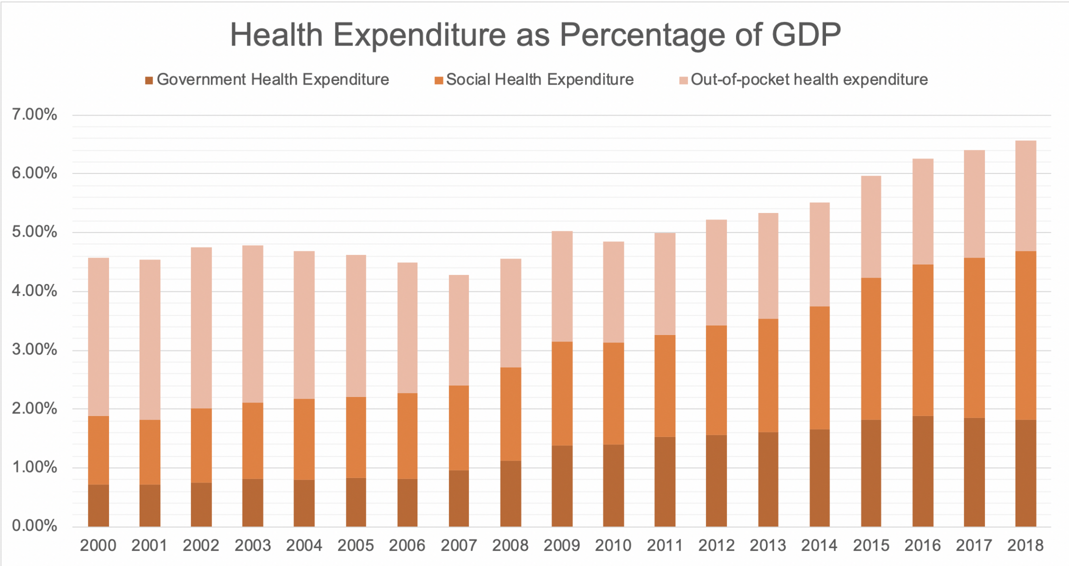


FIGURE D.1: Appendix, Health Expenditure Composition, 2000-2018 (National Bureau of Statistics, China)

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