Essays on the evaluation of health financing and health system policies

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Abstract

This thesis comprises of four independent essays assessing health system policies whose unifying theme is the aim of progressing towards one or more of the universal health coverage (UHC) defining characteristics: Chapter 1 focuses on two different UHC characteristics (service coverage, financial risk protection), Chapter 2 focuses on service coverage, Chapter 3 focuses on financial risk protection, and Chapter 4 focuses on equity. Except Chapter 2, all chapters assess health financing policies, an important pillar of any health system that is aimed at progressing towards UHC.

Chapter 1 explores the effect of health financing system transitions from systems predominantly financed by out-of-pocket (OOP) health expenditures to systems predominantly financed by contributory social health insurance (SHI) or non-contributory government financing. To this end, I conduct a regression analysis across 124 countries, 2000-2017 period. Findings show that transitions to non-contributory government financing, rather than to SHI financing, are more likely to improve health system outcomes. The main reasons include SHI's higher implementation costs and more limited coverage. Policymakers considering SHI reforms to progress towards UHC should interpret these results as a call for caution.

Chapter 2 investigates how Brazil Estrategia da Saude da Familia (ESF) delivered its primary healthcare (PHC) service coverage objectives, assessing via mediation analysis the contribution of different health professionals to the attainment of increased PHC service coverage. We find that a team-based PHC approach has been effective in increasing PHC service coverage, and that increasing community health workers (CHWs) density has provided the most substantial contribution to the increase in PHC services coverage driven by ESF. By implication, maintaining the ESF team-based approach to PHC delivery and expanding the role of CHWs in family health teams may thus be worthwhile policy priorities.

Chapter 3 is divided into two parts. In the first part, I show that the "OOP budget share" (i.e., OOP health expenditures as a percentage of total household expenditures) is a threshold-agnostic measure of financial risk protection. In the second part, I investigate whether there is an association between development assistance for health (DAH) and financial risk protection and, if so, for which households. The main analysis covers 65 countries with above average DAH per capita across the 2000-2016 period, merging 159 household level surveys. The results suggest that, on average, DAH is not associated with financial risk protection outcomes. However, DAH improves financial risk protection for the poorest income quintile sub-group, and when a large percentage of DAH is "on-budget" (i.e., channelled via the recipient government's financial management systems).

Chapter 4 measures to what extent the Sierra Leone public healthcare system redistributes resources from high to low-income groups, assessing the redistribution of resources via benefit, financing and fiscal incidence analysis. The results suggest that the public healthcare system redistributes resources from higher to lower income groups, and therefore reduces income inequality. The redistribution is largely driven by PHC services being markedly pro-poor. Hence, more investments in the public health sector, with a focus on PHC, might further reduce income inequality and improve the redistributive effect of the public healthcare system in Sierra Leone.

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Declaration

I declare that this thesis is a presentation of original work and I am the sole author of this thesis. I am the principal author of all chapters in this thesis. Where individual chapters were co-authored with other researchers, this is indicated with the necessary specifications in this declaration.

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Chapter 1 is co-authored with Dr Sumit Mazumdar (University of York, Centre for Health Economics (UoY-CHE)), and Prof. Marc Suhrcke (UoY-CHE). An earlier version of Chapter 1 is published in *Health Economics*, volume 32, issue 3, pages 574-619. I acknowledge helpful comments from four anonymous reviewers at Health Economics. I am the lead author of the paper. I have developed the initial idea, collected the data, designed the analysis, conducted the analysis, interpreted the results, written the first draft of the paper and completed several revisions. My co-authors contributed at various times with comments on the conceptualization and writing (comments/edits/reviews) of the paper. I have presented earlier versions of this paper at: Health Economics Study Group 2021 Winter Conference at London School of Hygiene and Tropical Medicine, International Health Economics Association (IHEA) Congress in July 2021, and UoY-CHE Global Health Seminar Series. In October 2021, I was invited by World Bank staff to present the paper to the Health, Nutrition and Population Practice as guest speaker during the World Bank Health Financing Global Solutions Group seminar series. In April 2023, I was invited by the Director of Policy, Planning and Health Economics, Ministry of Health and Child Care, Republic of Zimbabwe, to present the paper at the Health Financing Technical Working Group, in the context of discussions about initiation of a National Health Insurance program in the country. In May 2023, I was invited by the Tony Blair Institute for Global Change to be a panellist in a discussion on health financing reforms, which included discussing this paper.

I am the sole author of Chapter 2. I have presented an earlier version of this chapter at the Health, Econometrics and Data Group (HEDG), University of York, seminar series in January 2022.

I am the sole author of Chapter 3 Part I, which has been shared, and received comments from, colleagues at CHE. Chapter 3 Part II is co-authored with Dr Sven Neelsen (World Bank), Dr Patrick Hoang-Vu Eozenou (World Bank), Mr. Marc Francois Smitz (World Bank), and Prof. Marc Suhrcke (UoY-CHE). I have developed the initial idea, collected part of the data, designed the analysis, conducted the analysis, interpreted the results, written the first draft of the paper and completed several revisions. My co-authors contributed with providing part of the data, and at various times with comments on the writing (comments/edits/reviews) of the paper. I have presented earlier versions of this paper at the Health Economics Study Group 2023 Winter Conference at the University of Manchester, and Health Econometrics and Data Group seminar in February 2023.

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Jacopo Gabani

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Preface

This thesis is formed by four independent chapters on health financing and health system policies whose aim is to progress towards universal health coverage (UHC). Three of the four chapters are focused on health financing, a key pillar of health systems wanting to progress towards UHC. The UHC concept states that every individual in a population receives the healthcare needed without suffering undue financial hardship as a result, regardless of their socioeconomic conditions (1). These three dimensions (services coverage, financial risk protection, and equity) have been depicted in the UHC cube (2). As equity is a recognized goal for many health systems (3), and UHC is implying equity in the financing and delivery of health systems (4), UHC has become a national objective for many governments in low- and middle-income countries (5–7) and more recently has been included as part of the United Nations (UN) Sustainable Development Goals (SDG) (8). For these reasons, the way health systems are financed and organized, and the consequences of such decisions on various UHC aspects continue to raise important questions and a lively debate among academics and policy practitioners alike (4,9,10).

The four chapters in this thesis are organized to cover the main dimensions of the UHC cube (2,11): coverage of services, financial risk protection, and equity in financing and healthcare delivery – which together should result in improved health system outcomes. In the first chapter, we take a broad view and analyse the effect of health financing systems on different aspects of UHC (services coverage, financial risk protection and health status). The second chapter focuses on the services coverage aspect of UHC, and in particular primary healthcare services (PHC), a cornerstone for UHC (12,13). The third chapter focuses on the financial risk protection aspect of UHC. Finally, the fourth chapter addresses questions of equity in delivery and financing of healthcare services.

The importance of public health financing in contributing to progress towards UHC is paramount. A health financing transition from health systems primarily financed by out-of-pocket health expenditure (OOP) to health system primarily financed by public health expenditure (14) has been identified as a key condition to achieve health system outcomes (15) of improved health status and financial risk protection. However, while the literature on the impact of public health expenditure on health flourished (16), it has made no differentiation between the two different forms that constitute public health expenditure: contributory social health expenditure (SHI) and non-contributory government health financing. This is particularly important now, because several low- and middle-income countries are considering initiating SHI reforms (17) to accelerate progress towards UHC. Chapter 1 therefore focuses on the impact of health systems financing transitions from being predominantly financed by OOP health expenditures to being predominantly financed by either contributory SHI *or* non-contributory government financing. The analysis is based on fixed effects, random trend and differential trend regressions across 124 countries in the 2000-2017 period. We find that transitions from predominantly OOP to predominantly government-financed systems improved most outcomes more than did transitions to SHI systems. Transitions to government financing increase life expectancy (+1.3

years, p<0.05), reduce under-5 mortality (-8.7%, p<0.05) and reduce catastrophic health expenditure incidence (-3.3 percentage points, p<0.05). Results are robust to several sensitivity tests. Notable reasons include SHI's higher implementation costs and more limited coverage. These results may raise a warning for policymakers considering SHI reforms to reach UHC, and reassure policymakers aiming for expansions of non-contributory government-financed systems.

The second chapter focuses on the service coverage aspect of UHC. The family health strategy (Estrategia da Saude da Familia, ESF) is a team-based program aimed at expanding PHC (18) services coverage in Brazil. This program has been key in supporting Brazil's progress towards UHC (19,20) by increasing substantially the availability of PHC health workers. While the impact of the program has been investigated extensively, finding that ESF has improved PHC services coverage and outcomes (20), it is unclear to what extent the increased density of *each* health professional composing ESF teams has contributed to improved PHC service coverage. For this reason, this chapter objective is to unpack the ESF "black box". I do so via causal mediation analysis (21), which assesses the direct effect of ESF on its intended objectives (i.e., increased service coverage), and the indirect effect of ESF via PHC health professionals (community health workers (CHWs), nurses and physicians) that form ESF teams. The indirect effect is used to measure the contribution of each health professional to ESF impact on PHC services coverage. I find evidence that CHWs contribute substantially to ESF effect for most PHC outcomes considered (proportion mediated for ANC visits, 22.6%, for PNC visits, 8.7%, for diabetes screening, 28.9%, in all cases p<0.01; average across all PHC services: 20.7%). However, the evidence of an indirect effect is very limited for other health professionals (PHC nurses and doctors). I also find a substantial direct effect of ESF on almost all outcomes (average direct effect, proportion of total effect of ESF: >65% with p<0.05, for all outcomes except HIV visits). These results have two main policy implications: first, the ESF team-based organization for the delivery of PHC services is working well and should be maintained. Second, policymakers might consider expanding the role of CHWs within ESF teams.

While the first chapter focused on the impact of transitions from a health financing system predominantly funded by OOP health expenditure to a system predominantly funded by public health expenditure, the third chapter focuses on the impact of increased development assistance for health (DAH) (i.e., health financing from external, non-domestic sources) on financial risk protection outcomes. These outcomes are catastrophic health expenditure defined as OOP health expenditures larger than 10% of total household income (CHE10%), impoverishment below the 1.90US$ poverty line driven by OOP health expenditures (IMP190), and the share of OOP health expenditures over total household expenditure (i.e., the "OOP budget share"). We first start by noting that the "OOP budget share" measure can be interpreted as a threshold agnostic measure of CHE, and we then investigate the association between DAH and financial risk protection outcomes. To the best of our knowledge, this is the first paper that explores whether DAH is associated with financial risk protection outcomes. This is particularly important for at least two reasons. First, as mentioned earlier, financial risk protection outcomes are tracked as part of the UHC indicator in the UN SDG framework (indicator 3.8.2) (8) and, as a consequence, improving financial risk protection is a target for several countries. Second, in several countries DAH is a substantial component of total health expenditure (5). Thanks to a unique dataset merging 159 household survey, across 65 countries, in the 2000-2016 period, we are also able to shed light on which households benefit from DAH. This latter point allows us to investigate whether, for example, the poor are benefiting more from DAH. Using country and year fixed effects regressions, and cohort fixed effects regressions, we find that, on average, in countries with an above average DAH per capita, there is no association between DAH per capita and financial risk protection outcomes. However, DAH per capita improves financial risk protection for households in the poorer population quintiles (IMP190: -0.05 percentage points, $p<0.1$; in pseudo panel models, CHE10%: -0.12 percentage points, $p<0.01$), and it improves financial risk protection when a larger proportion of DAH is "on-budget" (i.e., delivered via recipient government financial management systems) (CHE10%: -0.13 percentage points, $p<0.05$). In sum, DAH investments require careful planning to have an impact on financial risk protection. For example, positive DAH effects for the poorest quintiles of the population might be driven by DAH targeting poorer populations expenditures and doing so effectively. Our results also suggest that channelling more resources via governments financial management systems should be considered to improve DAH impact on financial risk protection.

In the fourth and last chapter, the focus is on the UHC aspect of equity. In this chapter, the research question is to what extent the Sierra Leone public healthcare system is equitable and redistributing resources from the better-off to the worse-off. In order to answer this question, and because PHC is the cornerstone of UHC, we complete a financing, benefit and fiscal incidence analysis (22–24) by health system level. We find that financing of the Sierra Leone public healthcare system is marginally pro-poor, measured as total household expenditure, and that benefits are not distributed according to needs (concentration index (CI) of benefits minus needs: 0.099, $p<0.01$). More specifically, PHC services are markedly pro-poor (CI of outpatient PHC services: -0.220, $p<0.01$) while hospital services are markedly pro-rich (CI of outpatient hospital services: 0.143, $p<0.01$). We also find that the public healthcare system redistributes resources from better-off to worse-off population groups. PHC receives fewer financial resources and delivers a larger improvement in income inequality, than secondary/tertiary care. These results suggest that the Sierra Leone public healthcare system could be more equitable. As the Sierra Leone public healthcare system equity and redistributive effects occur largely thanks to PHC services, policymakers interested in improving Sierra Leone public health system equity, and redistributive effect, should prioritise PHC investments.

Chapter 1: The effect of health financing systems on health system outcomes: a cross-country panel analysis

ABSTRACT

INTRODUCTION. Several low- and middle-income countries are considering health financing system reforms to accelerate progress towards universal health coverage (UHC). However, empirical evidence of the effect of health financing systems on health system outcomes is scarce, partly because it is difficult to quantitatively capture the 'health financing system'.

METHODS. We assign country-year observations to one of three health financing systems (i.e., predominantly out-of-pocket, social health insurance (SHI) or government-financed), using clustering based on out-of-pocket (OOP), contributory SHI and non-contributory government expenditure, as a percentage of total health expenditures. We then estimate the effect of these different systems on health system outcomes, using fixed effects regressions.

RESULTS. We find that transitions from OOP-predominant to government-financed systems improved most outcomes more than did transitions to SHI systems. Transitions to government financing increase life expectancy (+1.3 years, $p<0.05$) and reduces under-5 mortality (-8.7%, $p<0.05$) and catastrophic health expenditure incidence (-3.3 percentage points, $p<0.05$). Results are robust to several sensitivity tests.

DISCUSSION. It is more likely that increases in non-contributory government financing rather than SHI financing improve health system outcomes. Notable reasons include SHI's higher implementation costs and more limited coverage. These results may raise a warning for policymakers considering SHI reforms to reach UHC.

Keywords: health financing, universal health coverage, health system, social health insurance, health expenditure

1.1 Introduction

Universal health coverage (UHC) captures the ambition that the entire population in a given jurisdiction receive the quality health services they need, without suffering financial hardship, regardless of socio-economic conditions (1). Several countries are currently considering health financing system (HFS) reforms to accelerate progress towards UHC (25,26). These reforms may entail the expansion of non-contributory government financing arrangements (e.g., Brazil, Bolivia), or the introduction and/or expansion of contributory social health insurance (SHI) arrangements (e.g., Ghana, Ethiopia). In this paper, SHI financing refers to health expenditures channelled via SHI agencies, implying that a contribution is required to access services, irrespective of whether the contribution is subsidized by the government or not. Government financing refers to any other non-contributory public health expenditure, i.e., where access to services is automatic, not linked to contributions, and usually based on citizenship or residency status. In either case, the aim is to increase pooled public health expenditure and to transition away from out-of-pocket (OOP) private health expenditure (27) towards UHC. HFS reforms entail substantial long-term administrative efforts (e.g., setting up new laws and functional agencies), and may impact financial risk protection and population health for years to come.

Despite the importance of HFS as a major factor for achieving UHC, there is scarce empirical cross-country evidence on the impact of HFSs on health system outcomes. Two important but regionally focused studies (on OECD and Eastern European countries) from more than a decade ago concluded that introducing SHI led to no improvement or even to a deterioration of health outcomes, while having increased costs (28,29). A common issue in these studies is that a country's HFS, depending on existing laws, could only be classified as either "tax-based" or "SHI". By allowing only these two classifications, countries financed predominantly by OOP expenditures were (mis-)classified as either tax-based or SHI. In addition, only the effects of transitioning from tax-based to SHI HFS were examined, thus ignoring the potential effects of transitioning from predominantly OOP to either tax-based or SHI HFSs. Another global study found that (proportional) increases in expenditure in contributory SHI and non-contributory government financing are positively correlated with service coverage indicators, but only non-contributory government financing is correlated with improvements in financial risk protection (30). This study investigated the association of HFS with financial risk protection and service coverage but not health status, controlled only for GDP per capita, and most importantly did not investigate transitions from OOP to either SHI or government financing predominant HFS, which is arguably the decision commonly faced by policymakers when contemplating potential paths towards UHC. Other, broadly related studies have investigated the impact of public health expenditure on health system outcomes, mostly finding a positive effect (16), yet without differentiating public health expenditures into government or SHI financing sources. Finally, a recent systematic review of relevant country case-studies concludes that public health insurance, defined as SHI and community-based health insurance, appears to reduce financial risk protection (31). However, it is not clear whether this effect is applicable to the entire populations of SHI-countries, or to SHI beneficiaries alone.

In this paper, we seek to assess the impact of different HFSs on health system outcomes (i.e., health status, financial risk protection and utilization (32)), and on health expenditures, with a view to informing decisions about potential transitions to either contributory SHI or non-contributory government financing, aimed at accelerating progress towards UHC. We also shed light on potential contextual factors likely to affect the impact of HFSs.

We find that transitions from OOP- to SHI-predominant HFS resulted in increased total health expenditure. However, transitions to government-predominant HFS resulted in greater immunization coverage, and improved health system outcomes (life expectancy, under-5 mortality and incidence of catastrophic health expenditure). As potential reasons, we discuss the role of (higher) costs for implementing SHI, its benefits being contribution-linked, the tendency to favour secondary/tertiary care expenditures, and SHI's limited ability to decrease OOP expenditures. We also detect a role for contextual factors: in particular, increases in informal sector size diminish the effects of HFS on most health system outcomes. Other contextual factors considered (GDP per capita, governance) also act as effect modifiers of HFS, albeit to a lesser extent.

Endogeneity, driven by reverse causality (e.g., countries with low financial risk protection may be more likely to introduce SHI) and omitted variable bias, is a central challenge in all studies investigating the association between HFS, health expenditure and health system outcomes (16), and our study is no exception in this regard. We seek to address endogeneity via fixed effects regressions, exploiting the variation in HFS generated by the health financing transition, which allows controlling for the influence of unobservable or unmeasured time-invariant factors. As our results are robust to most, but not all, different specifications and outcomes, concerns regarding endogeneity driven by reverse causality are not completely resolved. For this reason, we do not claim to provide entirely causal evidence.

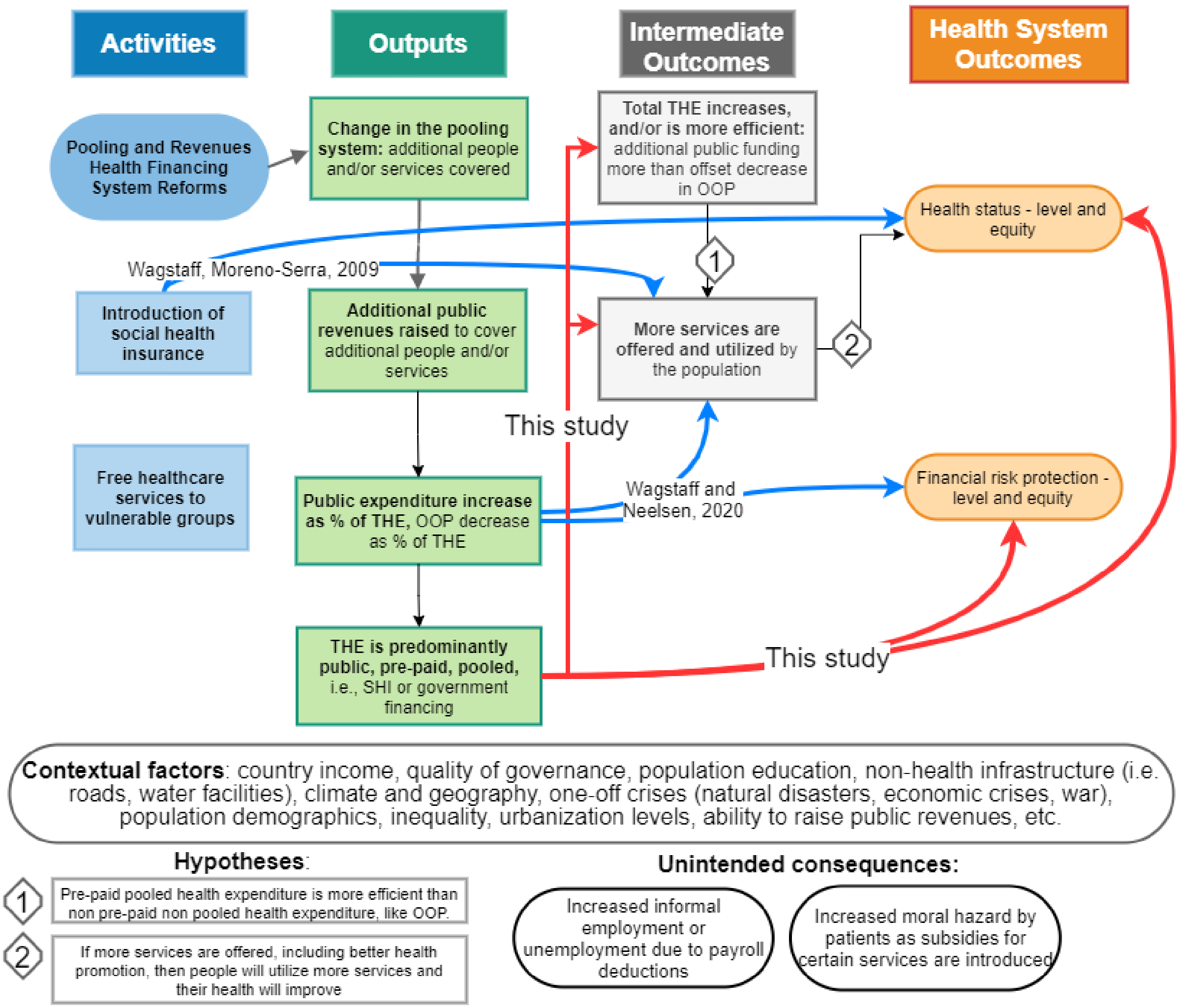
This paper contributes to the literature in several ways. First, we refine the classification of HFS by using a machine-learning, data-driven approach, which allows us to distinguish contributory SHI-, non-contributory government-, and OOP-predominant HFSs. Second, we examine the separate effects of transitions *from* OOP-predominant *to* SHI- *or* government-predominant HFSs. This is an advance on previous studies that commonly considered public health expenditure as a bundled aggregate, irrespectively of its specific financing nature (16,33–35), and on studies that did not model transitions from OOP- to SHI- or government-predominant HFSs (28–30). We also use panel data across more country-years than previous HFS studies, and – in order to reduce omitted variable bias – we take into account the potential role of multiple contextual factors that were used in the public health expenditure literature (16), but were neglected in previous SHI-related studies (28–30). Finally, we provide more depth to the conclusion that “context matters”, by empirically investigating interactions between contextual factors (e.g., informal sector size) and HFS transitions.

While these results should not be taken to imply that non-contributory government-predominant HFSs are *always* ‘better’ than contributory SHI-predominant systems, they may raise a warning to policymakers favouring the path of SHI to accelerate progress towards UHC, while reassuring those aiming for expansions of non-contributory government-financed systems.

1.2 Health financing systems (HFS) and hypothetical effects on health system outcomes

Figure 1.1 illustrates the hypothetical pathways mapping HFS reforms to health system outcomes through intermediate outputs and outcomes. More detailed pathway examples are provided in Appendix A-1. A country with ‘predominant-OOP HFS’ has its total health expenditure (THE) predominantly contributed through OOP, as identified via cluster analysis, and similarly for other classification categories (more on this in section 1.3.1).

Figure 1.1 Conceptual framework



Source: authors' elaboration, expanding frameworks presented in (32).

Notes: the conceptual framework follows a logic model representation. Black lines represent potential causal pathways between HFS and health system outcomes; numbers attached to black lines refer to hypotheses listed in the "Hypotheses" section. The two hypotheses and two unintended consequences noted in the figure are not exhaustive. Red lines represent the pathways investigated by this study. Blue lines represent pathways investigated by existing cross-country regression studies: Wagstaff and Moreno-Serra 2009, and Wagstaff and Neelsen 2020.

As shown in the above framework, governments may reform their HFSs to increase (pooled, pre-paid) public revenues and public health expenditure. These efforts are in line with the recommendation of increasing public health expenditures in order to avoid that OOP expenditures increase impoverishment (36) and decrease utilization of health services (37). For example, assume a country with very high OOP health expenditures decides to subsidize completely all health services to under-5 year old children and pregnant women. The pool of (fully) covered patients increases and more public revenues (payroll contributions and/or general taxes) are then raised to pay for those services. OOP expenditures of pregnant women and families with under-5 year old children will be expected to decrease as services previously paid by OOP are now subsidized by the government via pre-paid taxes: these families are now more protected against financial risk (related to OOP health expenditures). Government non-contributory financing emerges as the largest contributor to THE, exemplifying what we call a transition (14,27) from OOP-predominant to government-predominant HFS. As in the health financing transition described in the literature (14), THE per capita is likely to grow while government financing expenditure becomes predominant and OOP expenditure as percentage of THE decreases. Higher THE, especially via increased government financing and decreased OOP expenditure, would translate into more services offered to the population (37). Assuming there is demand for the services, the population will use more services than before, and, if those services are of sufficient quality, population health will improve (33). Similarly, THE may be spent more efficiently when it is pooled and pre-paid: families paying for services OOP do not pool together their financial resources and pre-pay for complex and efficient services, such as vaccination or public health campaigns, and neither can they share the risks of ill health across life-stages (old-young) or social strata (rich-poor). Pre-paid pooled expenditures in principle allow the government to deliver cost-effective, preventative health services such as vaccinations, community health, and others, as well as to pool the risks of different individuals together (33). In both these cases (i.e., when THE increases and/or when THE is spent more efficiently), if pregnant women and families with children under-5 who utilize public services belong to poorer population groups, health equity may also be positively impacted.

Contextual factors and unintended consequences are included in the conceptual framework. Contextual factors are to a certain extent not directly part of – and to a certain extent may be external to – HFS transitions (e.g., quality of governance, education or income per capita), and may modify the effect of HFSs on health system outcomes (35). One example of an unintended consequence is that the introduction of SHI funded via payroll contributions SHI may drive lower formal employment (26,38,39), which in turn may reduce the amount of revenues generated to fund the system and hence limit SHI coverage.

Figure 1.1 also shows the effects investigated by previous studies (blue lines), and the effects investigated in this paper (red lines), highlighting our contribution to the literature. An important clarification is required: as shown by the red arrow, we do *not* investigate the effect of a SHI reform in the way this has been done in (28,29), which would classify as "SHI" any country with SHI policies, laws and institutions. The effect we investigate is that of *health expenditure transitions*, from being OOP-predominant to being government- or SHI-predominant. Take for example Ghana, which introduced the National Health Insurance Fund (NHIF, a form of SHI) in 2004. By 2017, OOP still accounted for the largest proportion of Ghana's total health expenditures. Hence, Ghana is classified in this paper as an OOP-predominant HFS country, rather than a SHI country, despite the existence of SHI laws and institutions. Therefore, our analysis does not estimate the effect of the introduction of the SHI policy in Ghana. Similarly, Brazil's public health system was instituted by law in 1990, but its HFS transitioned from being OOP-predominant to being government-predominant only in the 2000-2017 period: our study measures the effect of Brazil's (and other countries') health financing transition out of OOP expenditure, rather than the introduction of laws to expand primary healthcare services. As these examples illustrate, our baseline estimates of the effects for SHI- and government financing-predominant HFS should be interpreted as the effects of SHI or government financing policies that are successful in making a HFS transition from OOP predominance to SHI or government financing predominance. SHI or government financing policies that fail to do so would result in HFS being classified as OOP predominant HFS. The effect of increased SHI or government financing expenditure that does not translate into a change in predominant HFS is explored in models where we use SHI and government finance as % of THE as treatment variables (Appendix A-6), instead of using SHI- and government financing-predominant HFS dummies, and in models exploring within-group changes in financing arrangements percentages (Appendix A-4).

1.3 Methods

1.3.1 Health financing system definition

Different health financing arrangements tend to coexist in a country's HFS. The three major health financing arrangements contributing to THE are government financing, social health insurance (SHI) and OOP. These financing arrangements account for 89% of THE on average across all countries, all years (2000-2017); the remainder is largely voluntary health insurance, which includes community-based health insurance (29). Details regarding data sources are in Appendix A-2, while details about health financing arrangements are presented in Appendix A-3.

Government financing is universal in that it provides healthcare coverage to the population automatically based on residency or citizenship status, *without* requiring a direct contribution. Health services are pre-paid, usually by general taxation, and there is usually a common pool for all residents/citizens. Predominantly government-financed countries, whose public health systems are often referred to as "national health service", are e.g., UK, Italy, Spain, Australia, Canada, and Cuba. Publicly funded health insurance schemes that are entirely non-contributory (e.g., Thailand Universal Coverage Scheme (13), or India Ayushman Bharat Pradhan Mantri Jan Aarogya Yojana) are also considered government financing. Due to data limitations, non-contributory government financing arrangements that show features typical of health insurance schemes (e.g., provider and payer split, health insurance premiums or budgets paid by the government) cannot be separated from other non-contributory government financing arrangements. SHI-financing is also pre-paid, but it differentiates itself from government financing by being *contributory*: a contribution has to be paid for a person/household to be able to receive healthcare coverage. Traditionally, the contribution is a deduction from the person's payroll. Individuals or households that do not contribute are not covered. In recent 'extended' forms, population groups that are usually identified as unable or ineligible for payroll or premium contributions are covered through government subsidies out of general tax revenues. In either of these cases, there may be different pools in the same country. Examples of SHI-predominant countries are e.g., Germany, France, Austria, Japan, Poland, and Turkey. Both government financing and SHI financing are heterogeneous and implementation differs by country. OOP financing is generally characterised by private citizens buying or paying for health services when needed, without any pre-payment or risk pooling. Some government financing- and SHI-predominant HFSs may have OOP co-payments made by citizens/members: these fees are included in OOP expenditures. OOP-predominant countries are e.g., Armenia, Bangladesh, Mali, Ecuador, Liberia and India.

Previous studies have classified into the "SHI" group those countries with SHI laws, SHI institutions and/or earmarked payroll deductions (28,29) (i.e., the Bismarck model). All other countries were usually classified as "tax-based" (i.e., the Beveridge model (40)). This approach arguably runs the risk of potentially having misclassified OOP-predominant countries as tax-based HFS (Armenia, Azerbaijan, Ukraine, Uzbekistan, Kyrgyz Republic). As shown in Table 1-1, in all these countries, OOP expenditure is the main contributor to THE. In addition, we provide examples from other countries not included in (28,29).

Table 1-1 Comparison of countries' health financing system (HFS) classification across studies

Country	HFS classification in this paper*	HFS: SHI or tax-based (28,29)*	SHI financing as % of THE	Government financing as % of THE	OOP expenditures as % of THE
Liberia	*OOP*	*Tax-based*	0	31.74	45.51

Armenia	OOP	Tax-based	0	14.18	84.35
Azerbaijan	OOP	Tax-based	0	15.45	83.86
Kyrgyz Republic	OOP	Tax-based	6.760	35.47	56.38
Ukraine	OOP	Tax-based	0	44.64	52.32
Uzbekistan	OOP	Tax-based	0	44.98	53.43
Bolivia	*Government*	*SHI*	30.08	39.92	25.08
Indonesia	*OOP*	*SHI*	22.65	26.46	34.61
Ecuador	*OOP*	*SHI*	24.18	29.37	39.40
El Salvador	*OOP*	*SHI*	24.7	24.65	29.20
Nicaragua	*OOP*	*SHI*	24.12	39.67	32.60
UK	Government	Tax based	0	78.80	15.96
Italy	Government	Tax-based	0	73.71	23.49
France	SHI	SHI	78.05	5.326	9.384
Germany	SHI	SHI	78.05	6.308	12.67
Hungary	SHI	SHI	61.09	8.118	26.89

Source: author elaboration. *possible classifications: OOP-, government- or SHI-predominant, . As an example, we take 2017 data. Countries in italics were not included in (28,29), we classified them based on the rules used in those papers. The sum of OOP, government financing and SHI as % of THE may not equal 100% due to other health financing arrangements (e.g., voluntary private health insurance arrangements, non-resident arrangements).

One option is to use expenditure data to define HFS via arbitrary thresholds. However, arbitrary choices may also misclassify countries with no clearly predominant financing arrangement.

By contrast, a clustering approach provides a classification that has two main benefits: it is largely data-driven and uses as input health expenditures, rather than more arbitrary classification mechanisms based on information, which would be hard to interpret or collect across all world countries. Using k-means clustering (41), each country-year combination is assigned to the HFS that has the closest mean values of government-, SHI- and OOP-expenditure as percentage of THE. More detail regarding the clustering procedure is provided in Appendix A-3. In this approach, the arbitrary choices are limited to the input factors and the number of groups. For the input factors, OOP, SHI and government financing expenditure as % of THE are chosen because, together, they make 89% of total health expenditure in our sample. Other schemes (non-profit institutions serving households (NPISH), voluntary health insurance) are below 5% as a % of THE, and in no country-year observation are found to be the largest scheme. We choose to have three groups because in this way we can better address the research question (i.e., the effect of transitions from OOP to SHI and government financing HFSs), and because clustering optimization analyses (42) suggest that three groups is an optimal choice (see Appendix A-3). The HFS variable generated by the analysis has three possible values: government-, SHI- and OOP-predominant

HFS by country-year. We use the word "predominant" because in all cases HFS are a mix of different health financing arrangements: while one arrangement is predominant, other arrangements coexist. In fact, another benefit of clustering is that it recognizes the mixed nature of HFS by considering data regarding all three major health financing arrangements when assigning country-year observations to HFS groups. In this paper, a health financing transition is defined as a country's "switch" that lasts at least two years from an OOP-predominant HFS to a SHI- or government-predominant HFS.

As the definition of the predominant HFS by country-year may affect our results, we explore the robustness of our main results to different 'predominant HFS' definitions. First, we define the predominant HFS using the highest value between government-, SHI- and OOP-expenditure as percentage of THE. Second, to address concerns that country-year observations may be classified as OOP-predominant while having OOP expenditures as % of THE below 40% (see Table 1-1), we use different thresholds to define OOP-predominant HFS. In other words, we define a country-year observation as OOP-predominant only if OOP expenditures as percentage of THE is larger than a threshold *t*, for example 50%, 45%, 40%, etc. Third, we add other health financing arrangements variables to the clustering procedure so that all health financing arrangements making up 100% of THE (i.e., NPISH as % of THE, voluntary health insurance as % of THE, enterprise schemes as % of THE, and rest of the world schemes as % of THE) are considered.

1.3.2 Empirical strategy: fixed effects and specification tests

1.3.2.1 Empirical strategy

The main specification is as follows:

$$Y_{it} = \alpha + \rho_1 SHI_{it} + \rho_2 GOV_{it} + \gamma \boldsymbol{X}_{it} + T_t + C_i + \varepsilon_{it} \qquad [1]$$

Where Y represents an outcome of interest from Figure 1.1, in country i at time t. SHI and GOV are HFS dummies that take value 1 if the country-year observation respectively belongs to the SHI-predominant or government-predominant HFS group, and 0 otherwise. OOP is the reference HFS. $\boldsymbol{X}$ is a vector of control variables. T represents time fixed effects (FE), and C country FE, which respectively control for cross-country shocks and time-invariant unobservable variables. Coefficients ρ_1 and ρ_2 can be interpreted as the within-country effect on outcome Y of transitioning (i.e., switching) from OOP, the reference category, to SHI- and government-predominant HFS, holding controls (detailed later) constant.

To investigate the question "how does context matter", we augment our model by interacting SHI- and government-predominant HFS dummies with several contextual factors (eq. [2]), detailed later.

$$Y_{it} = \alpha + \beta_1 (SHI_{it} \times CF_{it}) + \beta_2 (GOV_{it} \times CF_{it}) + CF_{it} + SHI_{it} + GOV_{it} + \boldsymbol{X}_{it} + T_t + C_i + \varepsilon_{it} \qquad [2]$$

For the contextual factor analysis, we are interested in the interaction terms coefficients β_1 and β_2, which will be interpreted as CF_{it} modification on the effect of SHI_{it} and GOV_{it} on outcome Y_{it} by computing SHI_{it} and GOV_{it} at different values of CF_{it}.

The main model in eq. [1] is similar to a generalized difference-in-difference (DiD) estimator, with two reversible treatments, one reference group (OOP predominant group), and different treatment timing (i.e., a country can switch from the OOP group to SHI or GOV groups and vice versa at any t). DiD assumes a parallel trend: we therefore subject our results to tests of the DiD parallel trend assumption as done in (28,29).

1.3.2.2 Specification tests

We conduct tests of the parallel trend assumption using random trend and differential trend models. In the random trend model, we relax the parallel trend assumption by adding country-specific linear trends ($c_i t$), as shown in the following equation:

$$Y_{it} = \alpha + \rho_1 SHI_{it} + \rho_2 GOV_{it} + \gamma \boldsymbol{X}_{it} + T_t + C_i + c_i t + \varepsilon_{it} \qquad [3]$$

We estimate equation [3] with and without country-specific linear trends. We then test whether the SHI and GOV effects are different in FE models with country-specific trends (FECS) and FE models without them (FE) (43):

$$Z = \frac{\rho_{1FECS} - \rho_{1FE}}{\sqrt{SE(\rho_{1FECS})^2 + SE(\rho_{1FE})^2}} \qquad [4]$$

This test allows using SEs clustered at country level. Non-rejection of the tests in eq. [4] (2 tests per model, one for ρ_1 and one for ρ_2) would suggest that ρ_{FECS} and ρ_{FE} are not different, that $c_i t$ are not correlated with SHI or GOV, and that the parallel trend assumption (PTA) is consistent with our data. This can be seen intuitively: eq. [3] without $c_i t$ is equal to eq. [1].

The random trend model assumes that each country trend is linear and is not affected by SHI and GOV. These assumptions are likely to not hold in our case, as it is likely that SHI and GOV affect country trends. We therefore relax the parallel trend assumption using a differential trend model (28,29,44). The error term is now:

$$\varepsilon_{it} = \begin{cases} C_i + k_S m_t + \varepsilon_{it} \;\; if\; SHI = 1 \\ C_i + k_G m_t + \varepsilon_{it} \;\; if\; GOV = 1 \\ C_i + k_O m_t + \varepsilon_{it} \;\; if\; SHI = GOV = 0 \end{cases} \qquad [5]$$

Where m_t is an unobserved (differential) trend whose effect on the outcomes is different across SHI-, government- and OOP-predominant countries. This allows each HFS group trend to be non-linear and modified by SHI and GOV, as shown in the following equation:

$$Y_{it} = \alpha + \rho_1 SHI_{it} + (k_S - k_O) SHI_{it} m_t + \rho_2 GOV_{it} + (k_G - k_O) GOV_{it} m_t + \gamma \boldsymbol{X}_{it} + k_O m_t + C_i + \varepsilon_{it} \quad [6]$$

Eq. [6] can be estimated via fixed effects, with interactions between year dummies (first year dummy is excluded and used as reference) and treatment dummies:

$$Y_{it} = \alpha + \rho_1 SHI_{it} + \sum_{t=2}^{T} \rho_{1t} SHI_{it} YEAR_t + \rho_2 GOV_{it} + \sum_{t=2}^{T} \rho_{2t} GOV_{it} YEAR_t + \gamma \boldsymbol{X}_{it} + \beta_t YEAR_t + C_i + \varepsilon_{it} \quad [7]$$

The effect of each transition can be calculated as the average effect of SHI and GOV, respectively:

Mean SHI impact = $\rho_1 + \sum_{t=2}^{T} \rho_{1t}/T - 1$

Mean GOV impact = $\rho_2 + \sum_{t=2}^{T} \rho_{2t}/T - 1$ [8]

As shown in (28,29) the PTA in the differential trend implies that $(k_S - k_O) = (k_G - k_O) = 0$, which can be tested via the following nonlinear restriction, for ρ_{1t} and ρ_{2t}:

$$\frac{(k_S - k_O)\sum_t m_t}{k_O \sum_t m_t} = \frac{\sum_{t=2}^{T} \rho_{1t}}{\sum_{t=2}^{T} \beta_t} = 0 \qquad \frac{(k_G - k_O)\sum_t m_t}{k_O \sum_t m_t} = \frac{\sum_{t=2}^{T} \rho_{2t}}{\sum_{t=2}^{T} \beta_t} = 0 \quad [9]$$

Again, non-rejection of these tests would suggest that the PTA is consistent with our data. This can be seen intuitively: eq. [6] reduces itself to eq. [1] when $(k_S - k_O) = (k_G - k_O) = 0$

Reverse causality does remain a concern, as a country will likely increase SHI and government financing when population health is deteriorating (e.g., a health crisis such as Ebola or COVID-19): we expect that reverse causality will bias the estimated coefficients for SHI and government HFSs downward for life expectancy, and upward for mortality and catastrophic health expenditure incidence. We run a test of reverse causality (in a Granger sense) used in the related literature (28,29,45), noting that the test does not necessarily imply causality (46). We add to eq. [1], [3] and [7] lead HFS variables ($SHI_{i,t+1}$, $GOV_{i,t+1}$) that indicate whether the following year there will be a transition from OOP to SHI or government financing. A non-zero coefficient would suggest that endogeneity is not appropriately addressed, while a zero coefficient would indicate the opposite.

Finally, the recent literature on country and time FE regressions has highlighted the problem ("negative weights") that, in the context of heterogeneous treatment effects, the FE estimator is a weighted average of different effects, including the treatment effect of early vs. late treatment adopter, and vice-versa (47). We therefore decompose ρ_1 and ρ_2 (eq. [1]) to explore whether this issue is affecting our results, for countries for which the transition was staggered (i.e., they remained exposed to the HFS they transitioned to).

Stata 14 (48) has been used. Heteroskedastic- and within-panel serial correlation-robust SEs, clustered at the country level, are reported. A replication package is provided at https://osf.io/snczj/.

1.4 Data

We use annual data for the 2000-2017 period across a global sample of countries from different sources; due to data limitations, our main models include 124 countries. Sample construction details, variables definition, and source datasets are provided in Appendix A-2.

1.4.1 Health financing data

The data on health expenditures (by financing arrangement) as percentages of THE, which is used for the cluster analysis, are from the WHO Global Health Expenditure Database (GHED), for the 2000-2017 period. WHO collects GHED data from countries using the System of Health Accounts (SHA) 2011 methodology (49). We use data under the "Health Care Financing Schemes" section, classification codes HF.1-4. In this paper, we use "arrangement" as a synonym of scheme, to avoid confusion with HFS (health financing system). If tax revenues are used to finance a SHI agency providing contributory SHI coverage, those revenues are "channelled via" SHI and are counted as SHI expenditure. Predominance can be read as "health expenditures channelled predominantly via a" non-contributory government, contributory SHI, or OOP arrangement, based on clustering results. As noted in the literature (50), OOP financing estimates suffer from potential data quality concerns. SHI as a health financing scheme comprises both compulsory public health insurance (96% of total SHI, across all countries, 2000-2017) and compulsory private health insurance (4% of total SHI financing, across all countries, 2000-2017).

1.4.2 Intermediate outcomes and health system outcomes

Intermediate outcomes comprise the immunization coverage index (i.e., the average of measles, DPT and hepatitis immunization rates) from World Bank World Development Indicators (WDI) (51), and (logged) THE per capita in current US$ from WHO GHED. Health status health system outcomes are life expectancy (LE), maternal mortality (MM), and under-5 child mortality (U5M), also from WDI. Mortality outcomes have been logged, as done in the related literature. The World Bank Health Equity and Financial Protection indicators (HEFPI) dataset (52) has been used for the financial risk protection health system outcomes. Since there are many different measures of financial risk protection, the most commonly used (53) has been chosen: catastrophic health expenditure incidence at the 10% level (CAT 10%). Health equity and the UHC index are not used as an outcome due to data limitations. Data for the UHC index was available only for 2010 within the data period of the analysis 2000-2017 from the Global Burden of Disease UHC dataset (54).

1.4.3 Contextual factors: control variables and interaction terms

We select control variables (contextual factors in our conceptual framework, Figure 1.1) that may confound the relationship between public health expenditure and health outcomes (16). The WDI dataset was used for (logged) GDP per capita (PPP, constant 2011 US$), education (primary school enrolment gross %), urbanisation rate, % population with drinking water access, Gini index, and proportion of population above-65 and below-14 (16). The Worldwide Governance Indicators (WGI) dataset (55) was used to extract the control variables government effectiveness and corruption control. We do not control for THE, hospital beds and health workforce, as these factors would be on the causal pathway between HFS and health system outcomes (i.e., "bad controls" (56)).

Contextual factors used as interaction terms in eq. [2] are often cited as "conditions required for" HFS to be successful (26): (logged) GDP per capita, government effectiveness, corruption control, percentage of health revenues from payroll contributions (i.e., labour-tax), informal sector size (informal workers as % of non-agricultural jobs), and general government expenditure (GGE) as % of GDP.

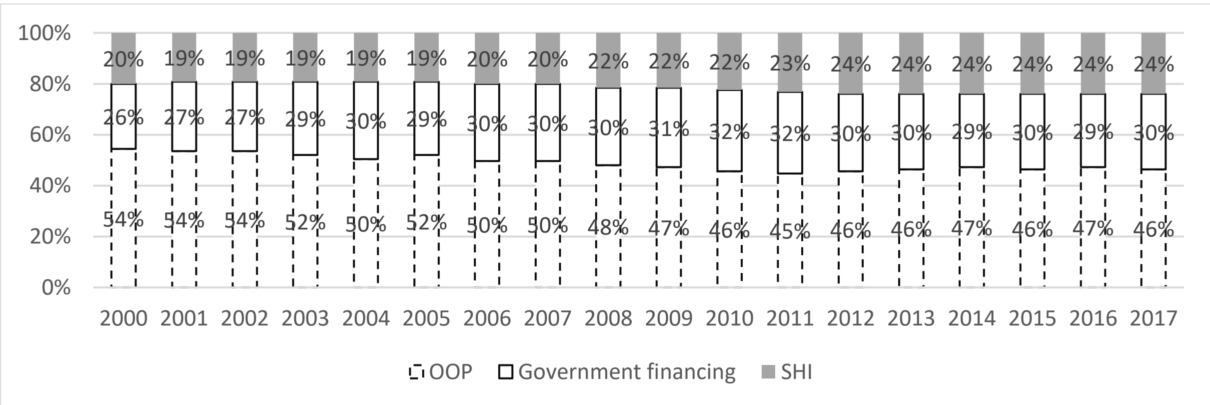
1.5 Results

This section is organized as follows: first, we show clustering results, then we present FE estimates, and, finally, tests and robustness checks including sub-sample analysis (e.g., for LMICs specifically) are shown.

1.5.1 Clustering analysis results

Figure 1.2 shows the results of the k-means clustering analysis. In the 2000-2017 period, the proportion of predominantly-OOP countries decreased (-8%), while SHI-predominant and government predominant increased (+4% each). The clustering analysis confirms the health financing transition from OOP to public health expenditure (14), i.e., government and SHI HFS (27).

Figure 1.2 Proportion of 124 countries by HFS, year 2000 to year 2017

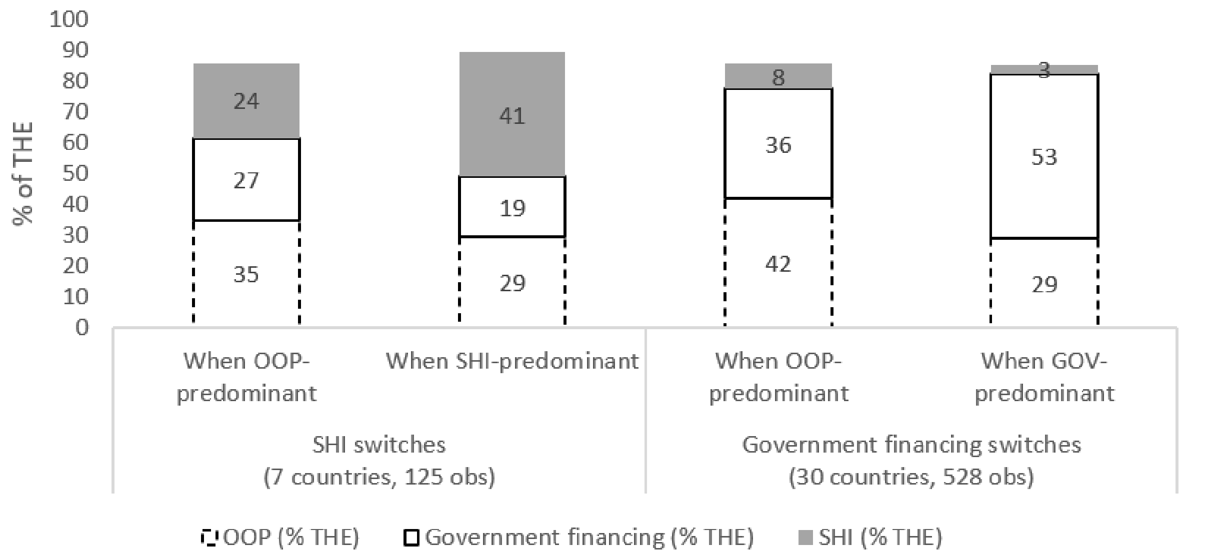


Source: author elaboration. Notes: the graph represents the percentage of countries assigned to each predominant-HFS per year

Table 1-2 provides descriptive statistics for the three HFS groups. In SHI-predominant country-year observations, SHI channelled expenditure does *not* exceed 50% of THE, and there is slightly higher public health expenditure as a proportion of THE (i.e., sum of SHI and government financing as a % of THE) versus predominantly-government financed systems. Table 1-2 suggests that selection into a HFS may not be random: SHI-predominant observations show higher income, better health systems outcomes, higher THE, lower investments in primary health care (PHC) and lower informal sector size, versus other HFS' groups. The OOP-predominant HFS group is characterized, on average, by government financing being almost 30% of THE: in other words, OOP-predominant systems are government financing systems with low public health expenditure.

Figure 1.3 focuses on the countries that switched from OOP to SHI or government financing HFS, or vice versa, in 2000-2017 (full list across 18 years in Appendix A-3). Given that in FE regressions, within-country variation is the focus (see 1.3.2.1), we note that seven countries switched from OOP to SHI, and 30 countries switched from OOP to government financing systems. SHI transitions show a lower decrease in OOP expenditures as % of THE (-6% percentage points), compared to government financing transitions (-13% percentage points). In both cases, the main public health expenditure arrangement increased significantly. In SHI transitions, not only OOP but also government financing did decrease (-8% of THE). For the government financing predominant HFS, the transition from OOP predominant to government financing predominant HFS is driven by growth in GGE as % of GDP (+6%) and growth in domestic health expenditure as % of GGE (+18%), which have finally resulted in a substantial increase in non-contributory government financing as % of THE.

Figure 1.3 Average of OOP, SHI and government financing as % of THE, during health financing transitions



Source: author elaboration. Notes: the figure shows SHI, OOP and government financing as % of THE for countries that switched from OOP- to SHI-predominant and government financing-predominant HFS. The sum of OOP, government financing and SHI as % of THE may not equal 100% due to other health financing arrangements (e.g., voluntary private health insurance, non-resident arrangements).

Table 1-2 Means of main characteristics for full sample and across HFS clusters

Variable	Used as	Full sample	Predominant government HFS	Predominant OOP HFS	Predominant SHI HFS
N (max)		*2646*	*848*	*1282*	*516*
Life expectancy, at birth, years	Outcome	68.8	68.8	65.5	77.0
Under-5 mortality, per 1000 live births	Outcome	44.3	39.4	62.1	8.3
Maternal mortality ratio, per 100000 live births	Outcome	218.3	180.9	324.2	16.8
Catastrophic health expenditure, 10% threshold	Outcome	8.1	4.5	9.2	9.0
Immunization index	Outcome	85.3	89.1	79.7	93.0
Compulsory health insurance (SHI) as % of THE	Used to build HFS variable	16.0	2.7	7.3	59.3
Government financing as % of THE	Used to build HFS variable	36.1	62.6	28.6	11.0
Out-of-pocket (OOP) as % of THE	Used to build HFS variable	36.5	21.4	51.6	23.6
GDP per capita, PPP, current, international US$	Control and interaction term	15394	21662	7771	24185
Corruption index	Control and interaction term	-0.10	0.293	-0.655	0.627
Government effectiveness	Control and interaction term	-0.05	0.242	-0.561	0.753
School enrolment, primary (% gross)	Control	102.0	103.5	100.7	102.6
% population using drinking water services	Control	83.0	83.5	76.6	98.0
% Population above 65 years old	Control	7.7	7.7	5.2	14.1
% Population below 14 years old	Control	29.6	28.8	34.7	18.4
Urbanization (% pop.)	Control	56.2	59.1	48.6	70.3
Gini index	Control	38.0	36.4	41.8	35.7

Health revenues from payroll contributions (%)	Interaction term	12.0	2.1	6.3	42.7
Informal sector size (% of non-agricultural jobs)	Interaction term	57.38	48.40	65.95	32.68
GGE (% GDP)	Interaction term	30.31	34.47	23.90	39.38
GGHE (% GGE)	Intermediate Outcome	9.7	10.4	7.6	13.7
THE (% GDP)	Intermediate Outcome	6.1	6.0	5.5	7.9
THE per capita, PPP, current international US$	Intermediate Outcome	1006	416	2046	1274
Primary health care expenditure, as a % of THE	Intermediate Outcome	51.6	53.0	57.5	43.6

Source: author elaboration, data: see section 1.4

1.5.2 Regression results

Table 1-3 shows estimates from eq. [1]. HFS coefficients in Table 1-3 represent the decrease/increase in the dependent variable ("outcome") as a result of switching to a government- or SHI-predominant HFS, from the reference OOP-predominant system. HFS coefficients ρ for logged outcomes (THE per capita, U5M and MM) are interpreted as $\Delta y\% = (e^{\rho} - 1)$.

Table 1-3 FE estimates for intermediate outcomes, health system outcomes

	INTERMEDIATE OUTCOMES		HEALTH SYSTEM OUTCOMES			
	(1)	(2)	(3)	(4)	(5)	(6)
	Log THE per capita	Imm. Coverage	LE	Log U5M	Log MM	CAT 10%
	FE	FE	FE	FE	FE	FE
Government-predominant	0.043	3.804	1.341**	-0.083**	-0.040	-3.256***
	(0.041)	(2.921)	(0.579)	(0.036)	(0.040)	(0.931)
SHI-predominant	0.117***	-1.486	-0.128	0.051	0.034	6.467***
	(0.035)	(1.606)	(0.395)	(0.037)	(0.067)	(1.129)
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.869	0.177	0.752	0.879	0.646	0.224
Observations	950	970	970	970	970	407
Number of Countries	124	124	124	124	124	111

Source: author elaboration. Notes: FE estimates are the result of eq. [1]. Robust SEs, clustered at country-level, in parentheses. Details on HFS switches are detailed in Appendix A-3. Full regression results including control variables are presented in Appendix A-4. All models control for all variables listed as "control" in Table 1-2. P-values for two-sided t-tests are reported as: ***p<0.01, ** p<0.05, * p<0.1.

In terms of intermediate outcomes (as depicted in Figure 1.1), SHI transitions increase THE (column 1, +12.4%), while no such effect is visible for government financing transitions. FE estimates in column (2) show that transitioning from a predominantly OOP to government- or SHI-predominant HFS have effects that are not statistically different from zero on immunization coverage.

As for health system outcomes, transitioning from OOP- to government-predominant HFS shows – for LE, U5M and CAT10%, respectively – rather strong evidence of an improvement (LE: +1.3 years, U5M: -8.7%, CAT10%: -3.3 percentage points). Government-predominant HFS transitions improve LE, U5M, and CAT10% (three out of four health system outcomes) significantly (p<0.05) more so than SHI-predominant HFS transitions. However, for CAT10%, the SHI lead tests – results not shown, see section 1.3.2.2 – suggest that SHI reverse causality may be a concern: since the SHI HFS lead is statistically different from zero, it appears that SHI transitions occur when CAT10% is high, and high CAT10% "anticipates" SHI transitions. No significant SHI transitions effects are found for maternal or under-5 mortality.

One concern is that health financing mix heterogeneity *within* HFS groups may affect our results. For example, an increase in SHI-financing as % of THE within the OOP predominant group may affect outcomes. To scrutinise this, we run FE regressions of government, SHI, and OOP expenditures as a percentage of THE on all outcomes within the government-, SHI- and OOP-predominant sub-groups: in only six models out of 36, within-group changes in financing arrangements show effects on outcomes different from zero (at 10% level) (see Appendix A-4). In other words, within-group heterogeneity in the percentage of expenditure channelled via different health financing arrangements has limited impact on outcomes.

1.5.3 How does context matter?

Estimates of eq. [2] using all six outcomes and six contextual factors (GDP per capita, informal sector size, proportion of health revenues from labour taxes, government expenditure as percentage of GDP, control of corruption, government effectiveness) are presented in Appendix A-5. In seven of the 36 models estimated, at least one interaction term is significant (5% level), confirming empirically a non-trivial role of contextual factors. We report on those significant estimates only.

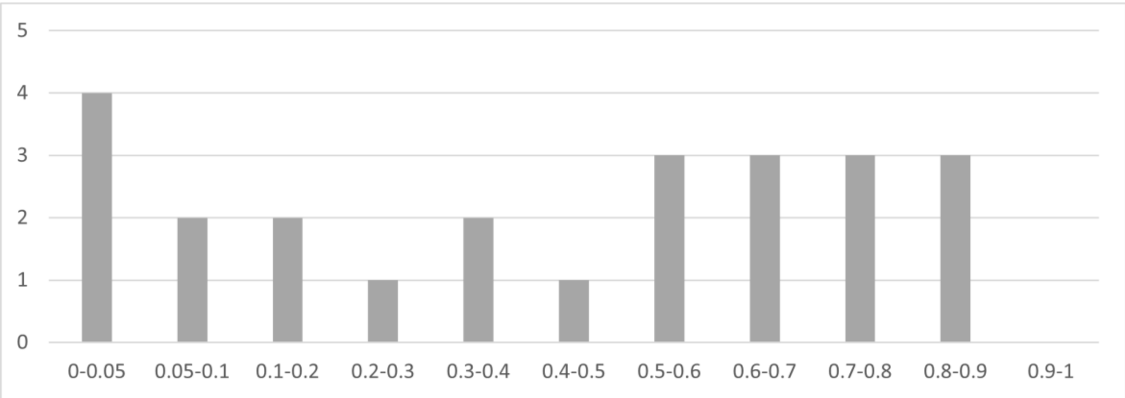
The informal sector size is the contextual factor modifying the effect of HFS transitions in most cases: a one percentage point increase in informal sector size together with a transition to SHI-predominant HFS increases U5M by 0.6%, and decreases immunization coverage by 0.2 percentage points (the latter, when informal sector is beyond 65%). The same increase in informal sector size together with government financing HFS has a very similar effect on immunization coverage, but no effect on U5M. An increase in the log of GDP per capita improves the negative effect of SHI transitions on immunization coverage (+4.8 percentage points), while better corruption control together with SHI-predominant HFS transition delivered higher general government health expenditure as % of general government expenditure (+0.9 percentage points in general government health expenditure per 1 point increase in the control of corruption index).

A percentage point increase in general government expenditure (as % of GDP) together with government-predominant HFS transitions *decreases* general government health expenditure (% of general government expenditure), but the effect is very small (-0.08 percentage points): possibly ministries of finance having large budgets tend to prioritize health sector funding slightly less as a proportion of total budget, when high absolute funding levels are considered sufficient. A one percentage point increase in health revenues coming from labour taxes together with SHI-predominant transitions also *decreases* general government health expenditure (% of general government expenditure) (-0.12 percentage points).

1.5.4 Specification tests and robustness checks

We present first the results of parallel trend assumption specification tests (eq. [4] and [9]) which suggest that the parallel trend assumption is consistent with our data in the large majority of cases (~75%), justifying the use of eq. [1] as our main specification. In the cases interested by potential parallel trend assumption rejections, we present random trend and differential trend model estimates (see Table A-9 in Appendix A-6). These results do not change our conclusion.

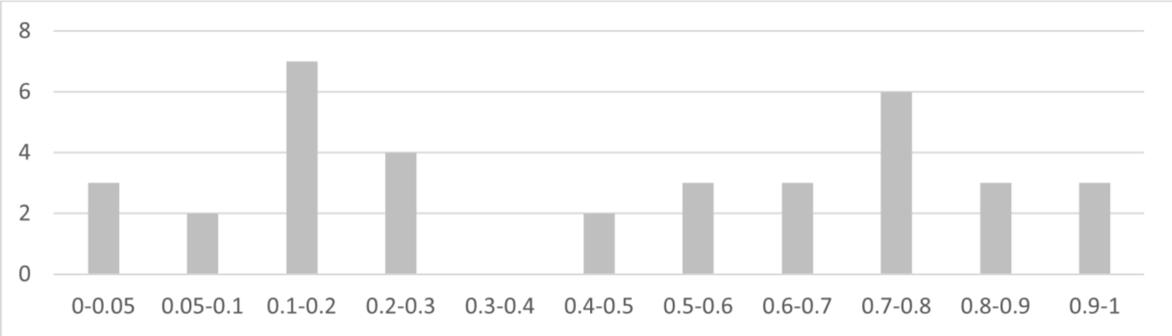
Figure 1.4 Histogram of parallel trend assumption specification tests p-values



Source: author elaboration. Histogram of p-values resulting from PTA tests of the (2) GOV and SHI dummy variables, across 2 specifications, random trend model PTA test (equation [4]) and differential trend model PTA test (equation [9]), all 6 outcomes (total of 24 tests).

Second, we present in Figure 1.5 the results of the reverse causality tests (p-values of GOV and SHI 1-year leads in eq. [1], [3], and [7]): the vast majority of lead HFS (~85%) are not significantly different from zero, suggesting that reverse causality is a rather limited issue across the vast majority of outcomes. However, the reverse causality (in a Granger sense) tests suggest that SHI transition occur when CAT 10% is particularly high, therefore the SHI coefficient for CAT 10% is likely affected by reverse causality.

Figure 1.5 Histogram of reverse causality test p-values



Source: author elaboration. Histogram of p-values of leads of GOV and SHI dummy variables regressed on 6 outcomes across 3 specifications: main DID specification, random trend model (equation [3]), and differential trend model PTA test (equation [7]) (total of 36 tests).

Beyond specification tests, we subject our estimates to a series of robustness checks (see Appendix A-6). First, based on potentially very different contextual patterns in LMICs as compared to high-income countries, we restrict the sample to LMICs. We also run sub-group analyses restricting the sample to the high- and middle-income countries, and to middle-income countries only. Second, given concerns about public health data quality (16,33), we remove outliers (approx. 1% of the sample) using a non-arbitrary methodology (57). Third, we use one-year lagged HFS independent variables as HFS effects on health system outcomes may not be contemporaneous. To explore the robustness of our main results to potentially lagged effects and reverse causality (in a Granger sense), we also implement visual event studies. Fourth, since general government expenditure as a percentage of GDP may limit the impact of HFS, we add it as a control variable. Fifth, we estimate eq. [1] using government and SHI as % of THE instead of HFS dummy variables (removing OOP expenditures as % of THE from the model due to collinearity issues, since the sum of all health financing arrangements is 100%). Sixth, we provide estimates of random trend and differential trend models in cases where the parallel trend assumption is rejected. Seventh, in the related literature, mortality outcomes have been either log-transformed (34,35,58) or un-transformed (28,29,33): to accommodate this alternative practice, in Panel H we use the natural units version of previously logged outcomes. Eighth, since the use of one of our control variables (Gini index) results in a loss of approximately half of total observations, we remove it to check for potential selection bias induced by missing observations. In addition, we remove other controls so that all countries in the dataset are included in the regression. Ninth, we add development assistance for health (as % of THE) to the list of control variables. Finally, we apply adjustments to all time-varying controls that are related to the HFS treatment variable, as per equation 7 in Zeldow and Hatfield 2021 (59).

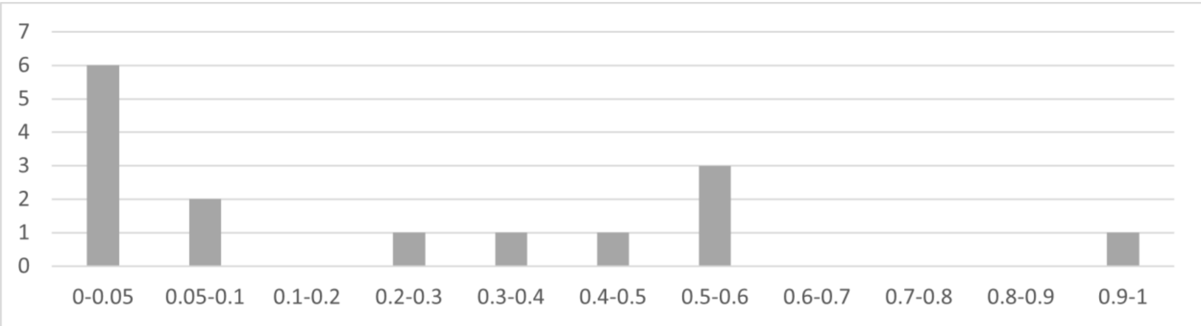
Our baseline results are largely robust to the vast majority of the above-mentioned specifications changes. Using random trend and differential models that relax the parallel trend assumption, the estimated coefficients on LE and CAT10% lose significance but show the same sign as the baseline coefficients. Adding unit-specific linear trends (i.e., random trend model) would increase the importance of countries treated at the beginning and end of the panel (47). For all other outcomes, baseline results are unaffected by relaxing the parallel trend assumption. In one specification (HFS percentages), the government HFS effect on LE loses significance. In the same specification, government financing improves CAT10% and U5M significantly more than SHI (not shown). Our results are particularly sensitive to this robustness check: while our clustering-based HFS definition captures changes in the predominant HFS, HFS percentages capture changes in THE composition regardless of the predominant HFS. In other words, these results suggest that increasing SHI or government financing as a percentage of THE may not have a sizable impact on health outcomes, if the predominant HFS does not change.

Event studies confirm that government financing improves LE and U5M, in particular after 4-5 years, while SHI does not show improvements for any outcome. Using different definitions of HFS (i.e., using the highest value between government financing, SHI and OOP expenditures as a percentage of THE, and using OOP thresholds, as described in Section 1.3.1) does not substantially affect the main results either. In the "highest HFS value" specification, the coefficient for SHI effect on THE loses significance and the coefficient for SHI effect on logged MM shows a worsening, significant effect (+12.1 percentage points, $p<0.01$), suggesting possible health system outcomes worsening due to SHI transitions. The main results are also confirmed when adding all health financing arrangements variables in WHO GHED (i.e., NPISH as % of THE, enterprise schemes as % of THE, voluntary health insurance as % of THE), and when we add all health financing arrangement variables plus THE per capita as input variables to the clustering procedure: in either case, government financing HFS performs better than SHI HFS for all outcomes. Setting the number of clusters to four also shows that government financing predominant HFS perform better than predominant SHI HFS for U5M and CHE 10%, and never shows government financing being worse than SHI. Using additional health system outcomes (CHE 25%, impoverishment driven by OOP expenditures at the 1.90US$ and 3.20US$ poverty line, male and female adult mortality), and health system outcomes from different data sources (i.e., World Bank WDI "Maternal Mortality Ratio, National Estimates"; infant mortality and U5M from Demographic and Health Surveys), confirms that in most cases government financing predominant HFSs show better outcomes than SHI-predominant HFSs.

Our baseline results are not affected by comparisons of late and early switchers ("negative weights"): the weight of ρ_1 and ρ_2 (eq. [1]) driven by comparing late and early switchers outcomes is marginal for countries switching from OOP-predominant to government financing HFS (weight 3-5%) and to SHI-predominant HFS (weight 1-2%).

Across our three main specifications (DiD FE, random trend, and differential trend models), government financing transitions improve (at the 10% level) outcomes more than SHI transitions in most cases (53% of the time, Figure 1.6). The effects of SHI transitions on health outcomes do not exceed that of government financing transitions for any of the outcomes. Estimates from robustness checks largely confirm these conclusions.

Figure 1.6 P-values for difference between government financing and SHI coefficients



Source: author elaboration. Notes: The Figure shows the histogram of p-values for difference between government financing and SHI coefficients ($\rho_1 - \rho_2 = 0$ in [1], [3], [7]). Whenever the p-value is below 10%, there is at least suggestive evidence that government financing HFS transitions show better results than SHI HFS transitions. The p-values are 15, resulting from three models (FE model, random trend model and differential trend model) times five health system outcomes (LE, U5M, MM, CAT 10%, immunization coverage). THE is not considered as an outcome because a larger health expenditure is desirable only if it translates into more services coverage.

1.6 Discussion

Achieving UHC is a widely shared health policy objective, and several countries are considering health financing systems (HFS) reforms (26) to accelerate progress towards UHC. These HFS reforms seek to accelerate the health financing transition (14,27) from OOP-predominant to public health expenditure (i.e., SHI- or government-predominant expenditure as % of THE) predominant HFS. As policymakers face alternative health financing paths, it is important to understand what (if any) differences to health system outcomes they make.

Our main research objective has been to investigate the effect of transitions from OOP-predominant to government- or SHI-predominant HFSs on health system outcomes (i.e., health status, financial risk protection and utilization). Based on a conceptual framework for HFS transitions, we model HFS transitions from OOP-predominant to SHI- and government-predominant HFSs, assigning each country-year observation to a predominant HFS using clustering – a machine learning approach. We estimate the effect of HFS transitions on intermediate and health system outcomes via FE regressions, controlling for time-invariant as well as several contextual factors, while excluding potential "bad controls" (56) on the causal pathway.

Transitions from OOP- to both government-predominant and SHI-predominant HFSs are both expected to deliver health system outcomes improvements via increased public health expenditure (see Section 1.2). However, we find that the effects of government-predominant HFS transitions was more favourable than SHI-predominant HFS transitions, for most outcomes. For the few outcomes where this was not the case, SHI and government-predominant HFSs showed similar results. Hence, there is no outcome for which SHI transitions showed significantly better outcomes than government financing. These results are robust to most checks and tests.

Why do transitions to government financing appear to be superior to those to SHI? While we do not conduct a formal mediation analysis, we discuss several hypotheses on channels of influence, commenting on how the data may or may not support each possible channel.

The main difference between government and SHI financing is that SHI requires contributions made by or on behalf of the person accessing healthcare services. Despite recent cases of general taxation funding SHI expenditure (27), SHI remains mostly financed by regular, typically wage-related contributions (i.e., labour taxes, see Table 1-2): for many LMIC countries, this means that while formal workers are covered via compulsory contributions, for large parts of the population (i.e., informal workers) insurance coverage is voluntary (60). SHI arrangements to cover the uninsured vary considerably across countries, and may generate pool fragmentation and pro-rich bias (60) (e.g.., a pool with comprehensive benefit package for well-off formal workers, and another one with a limited benefit package for the poor, the elderly, or an otherwise defined population group). Even when the non-contributing poor or vulnerable are covered by subsidies, the informal non-poor may be left out of affordable and quality options (61). In our findings, informal sector size turns out indeed as the contextual factor with the biggest negative impact on the effects of HFS transitions.

SHI expansions may also come at higher costs and take longer time, compared to expansions of existing government financing mechanisms (see column (1), Table 1-3). SHI requires institutional, technical and managerial capacity, and substantial investment to collect revenues and manage the provider-payment system (61). Limited regulatory capacity of purchasing institutions has been noted as a key issue (61), and the time to develop capacity is not negligible: several countries in Western Europe took more than 70 years to reach UHC via SHI (62,63). Expanding existing government financing arrangements would likely require less costs and time. The non-healthcare-related costs of SHI introductions or expansions may increase public health expenditure vs. an OOP-predominant-system, with little improvements to healthcare coverage and finally health outcomes. SHI HFS have also traditionally focused more on secondary/tertiary healthcare (61) (suggested by Table 1-2, PHC expenditure descriptive statistics), which may be less efficient than PHC (64). A full assessment of the relative performance of different types of HFS reforms would of course require a comparison of both the incremental costs and benefits of either HFS-type – a challenge that is beyond the scope of this paper, and one that has hitherto not been met in the existing research (65).

SHI transitions appear to not have succeeded in decreasing OOP expenditures as % of THE by as much as government financing transitions. SHI transitions decreased the reliance of THE on OOP expenditures, but they did so partially at the expense of non-contributory government financing (see Figure 1.3). By contrast, government financing transitions did not result in a significant decrease in SHI financing (as % of THE), as illustrated by the experience of Moldova and Russia (see Appendix A-7): increases in SHI expenditure (as % of THE) were accompanied by substantial decreases in government financing (as % of THE), less so in OOP (as % of THE), and a flattening of the U5M curve. At the same time, THE in both countries continued to grow.

Estimates using SHI and government financing as a % of THE (rather than predominant financing dummy variables) do not support the idea of SHI as a complementary arrangement either (Table A-9, Panel F). Increases in SHI expenditure (% of THE) increased THE, but did not improve outcomes. This is compatible with the hypothesis that SHI for formal workers may result in pool fragmentation and pro-rich health expenditure (61), and that implementation costs are a reason for SHI's limited effects. Both these issues arise regardless of SHI being a complementary or a predominant HFS. Rather than introducing SHI as a complementary arrangement, favourable SHI features (e.g., provider-purchaser split, explicit benefit packages entitlement, beneficiaries included in governance bodies, covering vulnerable groups via ad-hoc interventions (28,29,61)) could be included in existing government financing systems, and vice-versa (e.g., via removing SHI link between contributions and services' access, making it de-facto government financing).

Government-financed systems may have undesirable features, too. While automatic universal coverage is a positive feature, benefit packages are often too ambitious, so that the "depth" of this coverage and the actual package of services delivered is often limited in LMICs (9). Often, the purchaser-provider split is missing, and when it is present, there is no joint decision-making body, which includes purchaser(s), covered populations and providers. These arrangements can be implemented in government-predominant HFS, but they are more typical of SHI-predominant HFS. SHI-predominant HFS could see a positive healthcare coverage effect from efficient purchaser-provider systems: however, for such effect to materialize, a well-functioning provider network is required. Assuming that a higher GDP per capita may mean better provider networks, the fact that SHI transitions have a more beneficial effect on immunization coverage when GDP per capita is higher (see Appendix A-5 and section 1.5.3) seem to support this idea. Similarly, a realistic and explicit benefit package, and the idea of entitlement provided by SHI, are seen as the main advantages of SHI (26), and could be considered for inclusion in government financing systems.

Other contextual factors play a role, too. Perhaps counter-intuitively, higher labour-tax financing resulted in *decreases* in government health expenditure (in % of general government expenditure), for SHI-predominant HFS transitions (see Table A-8, column 36). Ministries of Finance may respond to higher SHI labour-tax revenues by decreasing transfers from general tax revenues to health. While we find no evidence that a (proportional) increase in labour-tax revenues modifies HFS effects on health, labour-tax increases may increase informal sector size (38,61), which we find worsen SHI effects on health (Table A-8, columns 31-36). Since we do not investigate the HFS impact on labour outcomes, and research in LMICs on this topic is limited (66), this is an area for further research.

Many countries are contemplating SHI reforms for different reasons (25,26): increasing financial autonomy and increased budgets for health via earmarked-to-health labour taxes, the political attraction of providing entitlements (usually to formal sector workers, which include civil servants), and considering SHI enrolment as the UHC coverage measure. With government financing, all citizens/residents are covered, and the issue is the depth of such coverage, which is difficult to measure, while with SHI there is the SHI coverage measure to report on as "progress towards UHC". Further research could focus on other reasons driving a resurgence in SHI reforms (e.g., donor influence).

Since concerns about reverse causality and the parallel trends assumption could not be entirely resolved, and our results were robust to most – but not all – different specifications and outcomes, we do not claim to have presented fully causal impact estimates. The limitations that are to be borne in mind when interpreting the findings include: first, we do not take into consideration more extensive HFS and health system heterogeneity due to data limitations. Other health system features (e.g., gatekeeping, different provider-payment systems, pooling fragmentation, private-public providers, provider networks, governance structures, etc.) may also affect health system outcomes, but data on a global scale does not exist to capture those. Second, we note that the sample comprises only seven largely middle-income countries that transitioned from OOP to SHI predominant systems (as mentioned in Section 1.5.1). However, interactions of the HFS treatment variable with log GDP per capita show limited heterogeneity in the effect of HFSs due to changes in log GDP per capita (Table A-8), suggesting that this might not be a major issue. Finally, we have not addressed formally "how" (e.g., via mediation analysis) or "for whom" different HFSs work (e.g., health equity), due to data limitations.

While bearing these caveats in mind, the policy implication of these findings is that policymakers considering SHI transitions to accelerate progress towards UHC should take these results as a call for caution. For LMIC policymakers facing the challenge of large informal sectors, higher poverty rates, and often not-well-functioning provider networks, the odds of accelerating progress towards UHC via introduction or expansion of contributory SHI appear more contained, as noted in the recent literature (60). Pursuing the road towards non-contributory financing expansions to accelerate progress towards UHC would appear as the more promising avenue, based on our findings. But then again, one cannot exclude the possibility that SHI can be made to work well for health system outcomes, and we cannot present non-contributory government financing as being unambiguously superior to contributory SHI in every situation (26,39,61). For both expansions, our contextual factors analysis findings suggest that SHI performs better when informal sector is smaller, GDP per capita is higher, and, to a lesser extent, when control of corruption is higher and labour tax financing is lower. Other contextual factors that may improve the effects of SHI transitions comprise higher wages, functioning provider networks, higher government technical, regulatory and financial capacity, and lower average household size (67). Information regarding these contextual factors, and their expected trend, can further strengthen decision-making confidence regarding HFSs reforms. These policy implications and findings are also relevant for governmental and non-governmental development partners supporting governments in moving towards UHC via technical and financial assistance.

Chapter 2: Unpacking the impact of team-based primary healthcare policies: the case of the Brazil family health strategy

ABSTRACT

INTRODUCTION. The Brazil family health strategy (Estrategia da saude da familia, ESF) increased the provision of primary healthcare (PHC) services via a team-based approach. Under ESF, family health teams, composed of (at least) a doctor, a nurse, a nurse technician and several community health workers (CHWs), deliver PHC services – an approach being considered in other countries. Assessing the contribution of different health professionals could improve ESF, potentially enhancing its (cost-) effectiveness.

METHODS. ESF coverage is the main treatment variable, which may increase the densities of PHC health professionals (i.e., PHC physicians, nurses, nurse technicians and CHWs per 1000 people). These increased densities may drive an increase in PHC services per 1000 people (antenatal/postnatal care (ANC/PNC), diabetes, hypertension and HIV visits). Via mediation analysis, I estimate the proportion of the effect of ESF on PHC services coverage that is mediated by each health professional. The average direct effect of ESF on PHC services coverage is also assessed.

RESULTS. I find evidence of an indirect effect of ESF via CHWs on most outcomes considered (all cases $p<0.01$; average proportion of indirect effect over total ESF effect, all outcomes: 20.7%). The indirect effect of other ESF professionals appears limited. I also find an average direct effect of ESF for most outcomes (average proportion of direct effect over total ESF effect, all outcomes: >65%, $p<0.05$ for all outcomes except HIV visits). Several robustness checks confirm these conclusions.

DISCUSSION. these results suggest that increasing CHWs density has made the most substantial contribution to the increase in PHC services coverage induced by the ESF. The average direct effect of ESF on PHC services coverage suggests that a team-based PHC approach has been more effective than increasing health workers' density alone. The policy implication of these results is that ESF team-based organization of PHC delivery should be maintained and expanding the role of CHWs in family health teams should be considered.

Keywords: policy evaluation, primary health care, mediation analysis, health systems strengthening, human resources, community health

2.1 Background

2.1.1 Introduction

Universal health coverage (UHC) is recognized as an important health policy objective, and primary healthcare (PHC) is a cornerstone of UHC (64). In Brazil, the family health strategy (Estrategia da Saude da Familia, ESF), a team-based PHC program focussed on PHC (18) services expansion, has been instrumental to the country's progress towards UHC (19,20). Brazil is an ideal setting for studying publicly financed PHC health system policies, since Brazil Unified Health System (SUS) is the largest public health system in the world, with 153 million people (73% of total population) having been covered by its free PHC services (68) in 2018.

While the evidence regarding the positive impact of ESF on health outcomes and utilization is rich (68–71), it is unclear how different health professionals which constitute the Family Health Teams (FHTs) contribute to the positive effect of ESF, an information which may be helpful in making the program more effective and/or more cost-effective (72). This paper aims to unpack the ESF "black box" (see Figure 2.1), by investigating the causal mechanisms contributing to the impact of ESF on its intended objectives (i.e., increased service coverage), and by assessing their contribution to the impact of the ESF. I focus in particular on the indirect, mediated effect of ESF via PHC health professionals (community health workers (CHWs), nurses, nurse technicians and physicians) that form FHTs, i.e., the backbone of ESF. In addition, I also assess the direct effect of ESF on service coverage, and the indirect effects via PHC infrastructure and equipment. These direct and indirect effects are measured using mediation analysis (72).

The effect of ESF on service coverage and health outcomes has been studied extensively: a systematic review found 31 studies evaluating the effect of ESF on coverage and health outcomes. While the review found that the evidence available is of limited quality (i.e., all observational quasi-experimental studies), it also found that increased ESF coverage is consistently associated with improvements in health outcomes (20). Team-based healthcare, a pillar of the ESF, is being promoted as a successful way to reform PHC (73) also thanks to learning from Brazil and other countries (74,75). Systematic reviews on the impact of increased density of health professionals also found that increasing density of physicians and nurses improves health services utilization (76,77), and that CHWs programs are cost-effective in delivering primary health services (78,79). While these studies are related to ESF and the impact of health professionals' density on service delivery, they do not explore the contribution of different health professionals, or other factors (i.e., PHC infrastructure and equipment), to the effect of ESF.

In this study, I find that the proportion of the total effect of the ESF attributable to the direct pathway from ESF to service coverage outcomes is very large: always above 65% ($p<0.05$ for all outcomes except HIV visits). I also find that a substantial proportion of the total effect of ESF on service coverage is indirect and mediated via CHWs density (20.7% average proportion mediated across five different service coverage outcomes, $p<0.05$ for all outcomes, in analyses considering all health professionals). The indirect effect of ESF via PHC physicians, PHC nurses, PHC infrastructure, and equipment is more limited.

The direct effect results suggest that a team-based PHC approach is more effective in increasing PHC services coverage, compared to focusing on expanding the density of health workers alone, thus providing a strong justification for the use of team-based organizational arrangements. Given that CHWs contribute the most to the overall impact of ESF, an increased number of CHWs per team, or a higher minimum number of CHWs per team, may be considered in future expansions of the ESF program in Brazil. Therefore, the indirect effect results justify considering an increased focus on CHWs, and an increased number of CHWs would likely make ESF more effective (72). These findings also enrich impact evaluations of ESF (68) by testing ESF causal mechanisms and may be relevant for policymakers in other countries considering team-based PHC approaches.

These findings are particularly relevant for at least three reasons. First, team-based PHC approaches like ESF and reforms in the PHC healthcare workforce have recently been identified as key issues for the future of PHC (73): understanding the contribution of different health professionals to team-based PHC policies should be important for countries considering team-based PHC approaches. Second, as the PHC system in Brazil is currently undergoing financing and delivery reforms (80,81), these findings on the contribution of health professionals to the overall effect of the ESF may be relevant for national and regional policymakers in the country. Third, PHC plays a substantial role in epidemics control strategies (i.e., prevention, preparedness) (82), an increasingly important concern globally.

This paper contributes to the limited literature on quantitative process evaluation using mediation analysis in the context of health systems interventions. It also shows the potential of using mediation analysis to unpack the effect of a complex health system intervention and recover policy-relevant insights. To the best of my knowledge, there have hitherto been only two other process evaluations using mediation for health system policy interventions (83,84). Both these studies implemented single-mediator analyses and were not focused on PHC policies: this is the first study to use multiple mediator causal mediation analysis (21) and regression-based mediation in a health system and PHC policy context.

2.1.2 Estratégia da Saúde da Familia, and its effect on health

The ESF program's main feature is the use of family health teams (FHTs), composed by a physician, a nurse, a nurse technician, and usually four to twelve CHWs, to deliver PHC services to a population of 3450 people (85,86). This ratio of people per team is used to measure ESF coverage, which is number of FHTs in a municipality times 3450 divided by the municipality population (85,86). Via increases in the number of FHTs, ESF coverage moved from 7% of the population in 1998 to 73% in 2018 (i.e., 143 million people). These populations receive PHC services and health promotion activities, and they are referred to secondary and tertiary care providers as needed. The Brazil federal government[1] provides incentives to municipalities that increase ESF coverage. ESF expansions have therefore driven an expansion of public health financing (via federal incentives and municipal prioritization), health workers density and services coverage. At the same time, the number of clinics and health posts has more than doubled between 1990-2015, while tertiary health facilities have remained rather stable (87). It should also be noted that ESF expansion almost coincided with the expansion of Bolsa Familia, a conditional cash transfer program incentivizing the use of healthcare services, and with Mais Medicos ("more physicians"), a program aimed at increasing physician density in deprived areas, which started in 2013. Finally, beyond GDP per capita at the municipality level, the adoption of the ESF across municipalities has largely been influenced by municipalities' political positions (69), thus making the staggered expansion of the ESF across Brazilian municipalities a highly suitable setting for quasi-experimental evaluations of the program.

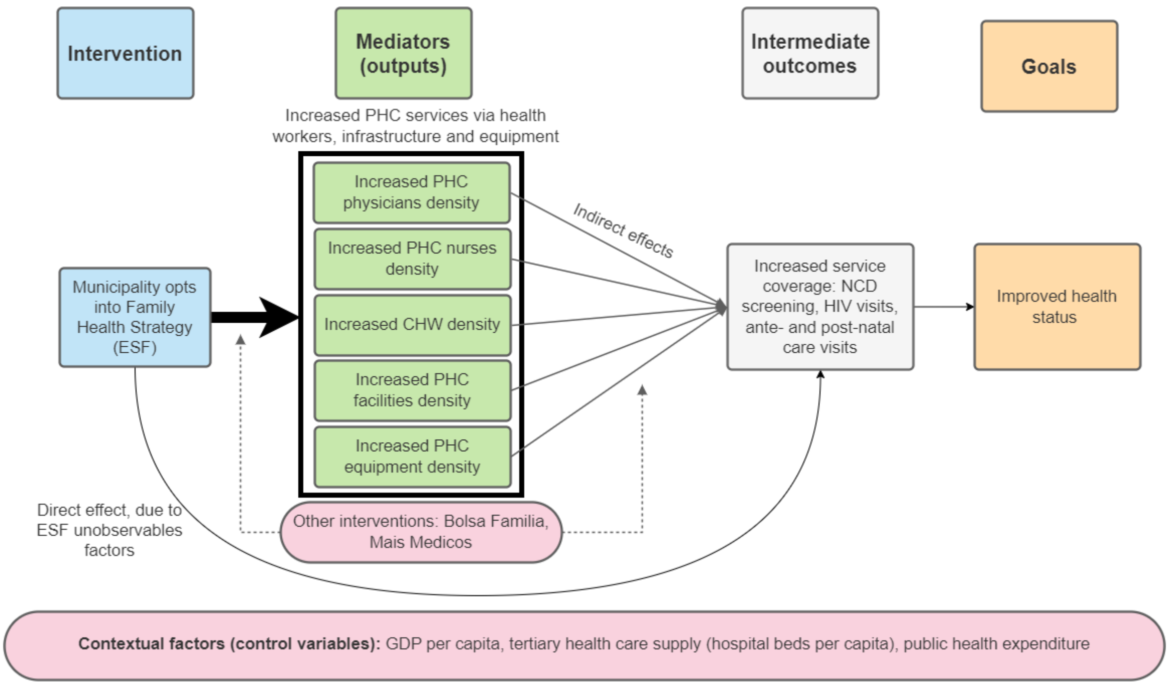
What might be the causal mechanisms through which the ESF delivers increased coverage? (See Figure 2.1 for a graphical illustration of the potential pathways). The ESF mainly operates by increasing PHC services population coverage via FHTs, which may result in increased density of physicians, nurses, nurse technicians and CHWs at the PHC level: these health workers would be expected to increase the supply of health services available to the population, resulting in better population health. CHWs do not directly provide curative healthcare services, can provide some preventive care services (e.g., measuring blood pressure) and are mostly engaged in health promotion activities. CHWs provide health promotion and address low-level health issues (e.g., making sure chronic patients are on track with their drugs and checks, health education, sexual health advice, and so on), and also provide administrative help (i.e., help families navigating the health system, register families). CHWs would normally live in the community, visit registered households, and spend time at the facility sharing information and data collected with other FHT members. Nurses are responsible both for patient care and for organizational tasks (i.e., coordinating CHWs), and doctors are responsible for more complex patients. It is useful to briefly note the role of different health professionals in delivering the PHC services that are used as dependent variables. First, for all outcomes used in the analysis, the number of visits and consultations refer specifically to either medical or nursing visits, conducted by the PHC doctor or nursing staff (88). Second, while CHWs main role is to conduct health promotion activities, it is important to note that they deliver some basic services (e.g., measuring blood pressure). Third, it is likely that, in absence of CHWs, some of the activities that would be carried out by CHWs are actually carried out by nursing or nurse technicians staff. Because of this last point, increased CHWs' density might free up nursing staff time via task shifting, and ultimately affect PHC service coverage via that channel. The focus of the

[1] The Brazilian administrative levels are: federal level (whole country), state level, and municipality level. The health system is decentralized, with the municipality level taking most of the decisions.

program is on PHC, prevention, health promotion, and coordination within the broader health system. FHTs facilitate demand for PHC services, by connecting the community to PHC facilities where those PHC services are offered. These services (e.g., antenatal care (ANC) visits, screening for non-communicable diseases (NCD), and other PHC services) should in principle improve the health status of people covered by the ESF program. It is important to note that FHTs do not provide secondary and tertiary care services. However, FHTs can refer patients to secondary or tertiary care when relevant, e.g., after ANC visits or NCD screening. Opting into ESF may also motivate municipalities to invest in PHC infrastructure (i.e., facilities) and equipment, which are critical factors for the production of PHC services. For this reason these factors are included in the conceptual framework. Finally, the ESF may create synergies with other programs such as Bolsa Familia and Mais Medicos mentioned above. The combination of the Bolsa Familia program – increasing the demand for services – and the ESF program – increasing the supply of PHC services and facilitating patients introductions to secondary and tertiary care – has been found to have improved health outcomes (89). Sharing the information across programs at the municipality level may also improve efficiency in delivering additional services. These channels of impact are at least partially observed as Brazilian public entities provide data of ESF presence, human resources, Bolsa Familia subsidies and Mais Medicos human resources at the municipality level.

Regarding unobservable mechanisms, one is ESF's team-based approach to PHC delivery, which is not captured by the simple increase in density of health professionals at the PHC level. There are other factors that may also positively impact ESF-covered populations' health: additional medicine and drugs brought by the ESF program, and improved information systems and epidemiological information gathered by CHWs.

Figure 2.1. Conceptual framework: causal mechanisms of ESF on health system goals



Source: author elaboration. From now on, and because the econometric strategy is based on mediation analysis, outputs may be referred to "as mediators" in the paper and when mentioning the mediation framework. I recognize that using the term mediator may be confusing for some readers, and the term output may be confusing for others. The conceptual framework should clarify the theoretical basis of the analysis, regardless of the nomenclature.

2.2 Methods

2.2.1 The data

Data on intermediate service coverage outcomes, ESF coverage, health worker densities, and hospital beds, are available from the Brazil government DATASUS website, aggregated at municipality level. The Brazilian Institute of Statistics and Geography (IBGE) website provides data regarding GDP per capita at the municipality level. The Ministry of Social Development website provides data on Bolsa Familia investments by municipality. Data for the Mais Medicos program was provided by the Ministry of Health through an Information Access Law request. Data on public health expenditures comes from Sistema de Informações sobre Orçamentos Públicos em Saúde. The analysis covers years 2007-2015 (9 years). While data regarding ESF coverage is available since 1998, data for outputs is available only for the period since 2007, and data for service coverage is available from 2007 to 2015. Because the ESF started in 1998, and the data on health professionals is available from 2007, it is not possible to assess the impact of the ESF from its first year of implementation. However, this may prove useful in limiting bias to self-selection of municipalities into the program.

2.2.2 Dependent variables and ESF coverage

In the main specification, the dependent variables are intermediate PHC service coverage outcomes, chosen to cover a variety of health areas: HIV consultations for infectious diseases, antenatal care (ANC) and postnatal care (PNC) visits for maternal health, and diabetes and hypertension screening for non-communicable diseases (NCD). Intermediate PHC service coverage outcomes variables are selected from "ESF service provision" indicators available on DATASUS.The ESF treatment variable is ESF population coverage, measured as FHT times 3450 divided by population, following Brazil Ministry of Health guidelines (86). In the literature (70,90), ESF presence has also been modelled as "presence for 1 year, 2 years, … 14 years": for this reason, in a different specification, I use presence of ESF for 3 or more years instead of ESF population coverage.

2.2.3 Density of PHC health professionals and control variables

ESF may or may not increase the density of PHC nurses, PHC doctors, PHC nurse technicians and CHWs. For example, a municipality may adopt ESF, install one FHT, which includes (at least) one PHC doctor, and then decrease the number of non-ESF PHC doctors: in this case, the municipality would be adopting ESF, but would not increase its density of PHC doctors. For clarity, I define PHC health professionals as all nurses (both ESF-specialized and general), doctors (medicos clinicos, ESF- and community health-specialized doctors), and nurse technicians located in PHC facilities (i.e., unidades basicas de saude, centro de saude, unidade de saude da familia, unidade movel fluvial, undidade de atencao a saude indigena), and all CHWs.

I also present an analysis using the density of equipment at the PHC level (any type of equipment, number of pieces, at PHC facilities, per 1000 people) and the density of PHC infrastructure (PHC facilities per 1000 people) as outputs.

Control variables at the municipality level used in previous research evaluating the impact of the ESF included GDP per capita, coverage of Bolsa Familia and Mais Medicos programmes, hospital beds per capita, municipality fixed effects, and time fixed effects (69,70) – all of which are included in the main specification, too. I add public health expenditure in order to address the potential issue that health budget and prioritization of health at the municipal level may limit the ability of municipalities to hire additional health professionals.

2.2.4 Descriptive statistics

Population coverage and FHTs have grown steadily in the years covered by the analysis (Figure 2.2), with a more pronounced increase in 2014, possibly related to the election and economic crisis in that year (and less so by health or service coverage considerations). Table 2-1 provides the descriptive statistics, showing that the average municipality has an ESF coverage above 100%. Because coverage is calculated as "number of FHTs times 3450 divided by population", municipalities with small populations (e.g., below 3450 people, or below 7900 people) and one or two FHTs might have ESF coverage above 100%. The average CHWs quantity per FHT is within ESF staffing norms (i.e., 4-12 CHWs per team (91)).

In Appendix B-1 I compare municipalities with high (larger than 50%) and low (lower or equal to 50%) ESF coverage at baseline (i.e., in year 2007). The difference in means across the control variables suggest the possibility of non-random selection, and justifies the inclusion of these control variables in my models, also following the literature. However, it is important to note that municipalities that have low ESF coverage also show larger GDP per capita, PHC infrastructure density, and equipment density, which would usually facilitate larger PHC service coverage, rather than lower PHC service coverage."

Figure 2.2. Population covered by ESF, from 2007 to 2019

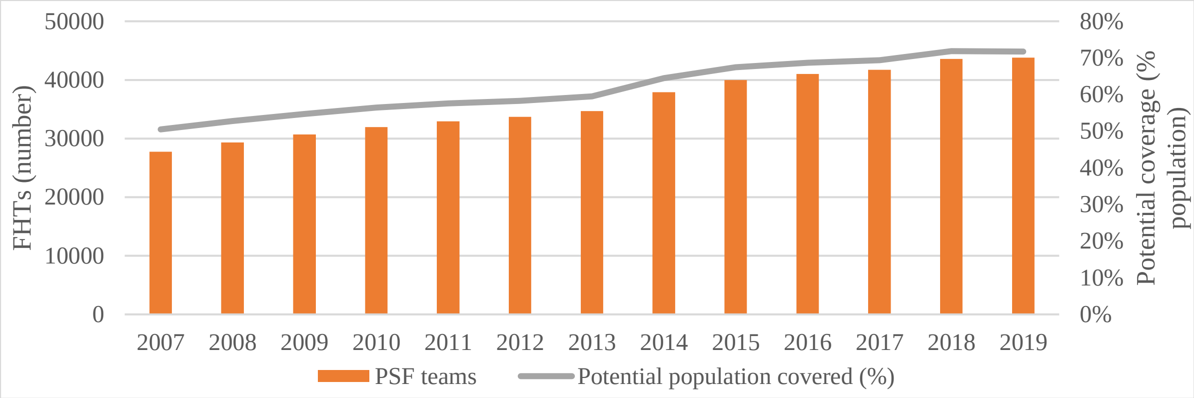


Table 2-1. Descriptive statistics, N=48949, approximately 5600 municipalities over the study period (2007-2015)

Variable	Mean	SD
ANC visits, per 1000 people	70	199
PNC visits, per 1000 people	34	48
Diabetes visits, per 1000 people	100	331
Hypertension visits, per 1000 people	397	1978
HIV visits, per 1000 people	15	322
ESF coverage, % of municipality	107	48
CHWs, per 1000 people	2.3	0.8
CHWs per FHT	8.4	9.9
PHC nurses, per 1000 people	0.27	0.29
PHC physicians, per 1000 people	0.18	0.20
PHC nurse technicians, per 1000 people	0.33	0.49
GDP, per person, Brazilian Real	16286	18859
Bolsa Familia financing, Real, per 1000 people	160098	135173
Mais Medicos physicians, per 10000 people	0.54	1.05
Hospital beds, per 10000 people	17	21

Source: author elaboration based on dataset discussed in the methodology section.

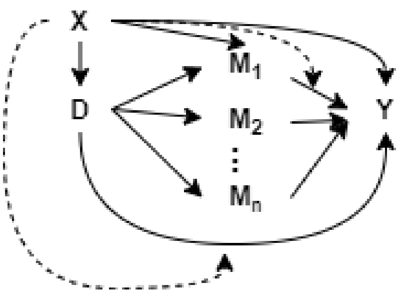
2.2.5 Econometric strategy

A systematic review of studies focusing on the effect of ESF on service coverage and health outcomes found that the vast majority (more than 70%) of studies employed fixed effects analyses, and more than 60% used linear regressions. Poisson, logistic and negative binomial regressions (20) were used less often, and also employed fixed effects. More recently one study employed propensity score matching (92). The methodology in this paper follows the bulk of the literature as it employs regression-based and causal mediation analyses, based on fixed-effects linear regressions.

The econometric strategy is based on a causal mediation framework, often utilized to analyse causal pathways from policies to their intended effects (93,94). Let $\boldsymbol{D}$ be the treatment, a continuous variable, the coverage of ESF in a municipality-year. Let $\boldsymbol{M}$ be a vector of four ESF outputs (PHC physicians per

1000 people, PHC nurses per 1000 people, PHC nurse technicians per 1000 people, and community health workers (CHWs) per 1000 people – called mediators in the mediation analysis framework), $\boldsymbol{X}$ a vector of time-varying confounders (GDP per capita, hospital beds per 10000 people, Bolsa Familia cash transfers in Brazilian real per 1000 people, number of physicians of Mais Medicos program per 10000 people, and public health expenditure per capita) and $\boldsymbol{Y}(d, m)$ is a PHC service coverage outcome (diabetes and hypertension screening, postnatal and antenatal care visits, HIV visits, all per 1000 people). This is the main specification and is described in Figure 2.3, which is a directed graph version of Figure 2.1, with X representing contextual factors and other exogenous interventions. The direct effect is represented by the arrow from D to Y and the indirect effects are represented by arrows going from D to Y passing via $M_{1,2\ldots n}$. The dotted arrows from X indicate possible moderated mediation due to other interventions happening at the same time, i.e., the Mais Medicos and Bolsa Familia programs. While interaction with the former is largely unaddressed in the literature, the latter has been found to be a significant moderator of the effect of ESF (68,89).

Figure 2.3. Study setting



In this situation I can employ causal mediation analysis (95) to quantify the impact along the D→M→Y pathway. Applying the potential outcomes framework, $M_i(d)$ is the potential value of an output given ESF coverage d, for municipality i, and $Y_i(d, m)$ is the potential outcome for municipality i given ESF coverage $D = d$ and output (e.g., CHWs density) $M = m$. Only one outcome is observed, and it is denoted by $Y_i(D_i, M_i(D_i))$, where D_i and $M_i(D_i)$ are the observed values of ESF coverage and CHWs density. Note that the effect would be averaged across time periods t, which is removed from the notation for simplicity. The total effect for a municipality i:

$$\tau_i = Y_i(d_1, M_i(d_1)) - Y_i(d_0, M_i(d_0)) \quad [10]$$

Where d_1 is the treatment ESF population coverage (%), which is equivalent to d_0 (control value) plus 1 percentage point. As shown in the causal mediation literature (95), the total effect can be decomposed in the average causal mediation effect and the average direct effect.

The average causal mediation effect (ACME) across municipalities represents the indirect effect of ESF coverage on PHC service coverage outcomes Y via health professionals, i.e., the arrow going from D to M to Y in Figure 2.3.

$$\delta_i(d) = Y_i(d, M_i(d_1)) - Y_i(d, M_i(d_0)) \quad [11]$$

All other causal mechanisms are represented by the direct effect. The average direct effect (ADE) across municipalities represents the direct effect of ESF coverage on the PHC service coverage outcomes, i.e., the arrow going from D to Y in Figure 2.1.

$$\zeta_i(d) = Y_i(d_1, M_i(d)) - Y_i(d_0, M_i(d)) \quad [12]$$

The sum of ACME and ADE is the total effect (95). While the full algorithm used to compute ACMEs and ADEs is given in Appendix B-2, I show here the models utilized to complete step 1 of the algorithm.

$$M_{i,t} = \beta_1 D_{i,t} + \gamma_1 \boldsymbol{X}_{i,t} + \mu_i + T_t + \varepsilon_{i1} \quad [13]$$

$$Y_{i,t} = \beta_2 D_{i,t} + \gamma_2 \boldsymbol{X}_{i,t} + \beta_3 M_{i,t} + \mu_i + T_t + \varepsilon_{i2} \quad [14]$$

Following common practice in similar studies (84), I perform single mediator analyses, using the R package 'mediate' (96). In addition, I run multiple mediators models too, using R package 'multimediate' (94)). Mediator-mediator interaction may play a role when there are multiple outputs. When the sum of the proportion of the total effect driven by each output (in single output analysis) is similar to the proportion mediated jointly by all outputs in the multiple outputs analysis, I can infer that output-output interaction is minimal (97): this point is explored as part of the analysis.

Since there is evidence of interaction between ESF and other interventions (e.g., Bolsa Familia (98)), I augment the econometric model by interacting ESF treatment $\boldsymbol{D}$ and mediators $\boldsymbol{M}$ with Bolsa Familia and Mais Medicos, originally included in the vector $\boldsymbol{X}$ in the non-interacted main specification.

For the interacted models, the procedure to compute indirect effect (i.e., ACMEs) and ADEs is similar, and is implemented via the same R packages (96). However, the use of (continuous) moderators requires choosing the levels of each moderator to calculate ESF ADEs and ESF indirect effects via health professionals. For both moderators (i.e., Bolsa Familia and Mais Medicos), I select the 25^{th} percentile and 75^{th} percentile values of municipal-level coverage, in order to assess how the indirect effects and ADEs are moderated by low- and high-supply of Bolsa Familia benefits and Mais Medicos physicians. The indirect effects and ADEs are measured for all outputs (a single output at a time), all service coverage outcomes, at both the low- and high-supply level of Bolsa Familia and Mais Medicos. I then test whether the difference between ACMEs and ADEs with "low supply" and ACMEs and ADEs with "high supply" of Bolsa Familia and Mais Medicos is statistically different from zero: a difference that is significantly different from zero would suggest moderation by other interventions. It should be noted that the linear models at step 1 change as follows:

$$M_{i,t} = \beta_1 D_{i,t} + OI_{i,t} + \beta_{2int} D_{i,t} \times OI_{i,t} + \gamma_1 \boldsymbol{X}_{i,t} + \mu_i + T_t + \varepsilon_{i1} \quad [15]$$

$$Y_{i,t} = \beta_2 D_{i,t} + OI_{i,t} + \beta_{2int} D_{i,t} \times OI_{i,t} + \gamma_2 \boldsymbol{X}_{i,t} + \beta_3 M_{i,t} + \beta_{3int} M_{i,t} \times OI_{i,t} + \mu_i + T_t + \varepsilon_{i2} \quad [16]$$

where $OI_{i,t}$ stands for "other intervention" (i.e., Bolsa Familia cash transfer per 1000 people or Mais Medicos physicians' density per 10000 people) evaluated at the 25th percentile, and at the 75th percentile (separately).

Finally, I note that all variables have been demeaned to complete fixed effects regressions. As an example, in eq. [17] I show the demeaning transformation applied to eq. [14].

$$y_{i,t} - \overline{y_\iota} - \overline{y_t} = \beta_2(D_{i,t} - \overline{D_\iota} - \overline{D_t}) + \gamma_2(\boldsymbol{X}_{i,t} - \overline{\boldsymbol{X}_\iota} - \overline{\boldsymbol{X}_t}) + \beta_3(M_{i,t} - \overline{M_\iota} - \overline{M_t}) - (\overline{\mu_\iota} - \overline{T_t}) + (\varepsilon_{i,t} - \overline{\varepsilon_\iota} - \overline{\varepsilon_t}) \quad [17]$$

All of the equations used have been appropriately demeaned to reflect time and municipality fixed effects, and are not shown for simplicity. In robustness checks, I add state-year linear trends, again based on precedents in previous ESF evaluations (69).

Since mediators and outcomes are continuous, and their relationship has been considered linear in several related studies (see online supplement S2 in (68)), causal mediation analysis is equivalent to estimating mediation effects (95,96) following regression-based methods (99). The second main specification is therefore a regression-based, linear structural equation model (SEM) (84,99,100), which estimates ACME as the product of coefficients β_1 and β_3 from eq. [13] and eq. [14], respectively, and ADE as β_2 in eq. [14]. In regression-based methods, to verify that the product of coefficients is different from zero, I calculated bootstrapped standard errors with 500 replications.

Robust standard errors, clustered at the municipality level and accounting for the degrees of freedom resulting from demeaning, are used for inferences. Direct (ADEs) and indirect effects (ACMEs) are simulated 500 times. Stata 14 and R have been used for all analyses, and reproduction materials are available upon request to the author.

2.2.6 Econometric strategy: assumptions

Sequential ignorability, a set of two assumptions, is required in the causal mediation framework to identify ACMEs and ADE (95). The ESF should be independent of potential outcome and outputs (i.e., mediators) conditional on controls, and the outputs should be independent of potential service coverage outcomes conditional on controls and ESF. Formally:

$$Y_i(d,m), M_i(d') \perp D_i \mid X_i = x \quad [18]$$

$$Y_i(d',m) \perp M_i \mid D_i = d, X_i = x \quad [19]$$

The first assumption is valid if municipality selection into ESF treatment (the choice to have an additional team, which increases ESF coverage) is independent from potential outcomes and outputs, conditional on covariates. A violation of this assumption would occur if, for example, municipalities with the lowest service coverage outcomes, or the lowest levels of health professionals' density, are the most prone to adopt ESF. There are a few points suggesting that this assumption would hold in this case. These points were also made in the related literature which, in the vast majority of cases, used a similar fixed effects econometric strategy (see supplementary attachment S2 in (20)). First, I control for several factors (time and municipality fixed effects, hospital beds per capita, Bolsa Familia program funding, Mais Medicos program physicians' density, public health expenditure, and GDP per capita, all at the municipality level) that were used in the literature to ensure identification of the impact of ESF on health (20,69). Second, it has been found that the political party of the municipality government is a major determinant of ESF adoption (i.e., left-leaning municipality government adopt ESF more likely) (20,69). Third, the data starts in 2007, when already 75% of all municipalities had at least one FHT: in other words, if municipalities who needed ESF the most (because of low service coverage outcomes or low health professionals' density) were the first ones to adopt ESF, this would not affect the results.

After opting into ESF, municipalities choose how many health professionals they want to hire, thus determining PHC health worker density as the result. The second assumption states that PHC density selection is independent from potential outcomes, conditional on ESF coverage and covariates. A violation of the assumption in eq. [19] would occur if more PHC physicians, nurses, nurse technicians and CHWs are hired, when service coverage outcomes are particularly low, generating reverse causality bias in the M to Y association, or there are unmeasured confounders. In the case of reverse causality, the expected bias would be a downward bias on the effect of human resources for health on service coverage outcomes. There are several points to consider. First, increases in density of PHC health workers should be largely driven by ESF FHTs, which is largely driven by political considerations (69), once I include the already mentioned controls. In other words, conditional on the ESF coverage and controls, health worker density should be largely independent of the outcomes. A second concern is that municipalities who want to hire more PHC health workers via ESF may be limited by either general or healthcare budget constraints. The general budget constraints of Municipalities should be highly correlated with GDP per capita, which I control for. Healthcare budget constraints, which may be indicative of lower political priority assigned to health, would likely affect service coverage outcomes. To address this issue, public health expenditure (at the municipality level) is included in the list of covariates.

As I have multiple mediators, the sequential ignorability assumption is extended to consider the existence of other outputs (i.e., pieces of equipment per 1000 people, and PHC infrastructure per 10000 people) (94,101). These extensions are presented in Appendix B-2.

While sequential ignorability cannot be tested, robustness checks can be implemented to assess its plausibility (21,93,102). First, the sign of the estimated ACME is the same as the sign of the "true" ACME when $\tilde{\rho} > \rho$, where $\rho = corr(\varepsilon_{i1}, \varepsilon_{i2})$ from eq. [13] and [14], and $\tilde{\rho} = corr(\varepsilon_{i1}, \varepsilon_{i3})$, where ε_{i3} is the error term of equation: $Y_{i,t} = \beta_2 D_{i,t} + \gamma_2 \boldsymbol{X}_{i,t} + \mu_i + T_t + \varepsilon_{i3}$ (93). Second, the sequential ignorability assumption is likely to hold when $\rho = corr(\varepsilon_{i1}, \varepsilon_{i2})$ is close to zero (102). These robustness checks can be performed only in the case of a single mediator (97), and hence no sensitivity analysis is performed for the analysis with multiple mediators.

Given the issues of bias arising in case of heterogeneous effects in a time and municipality (so-called two-way) fixed-effects framework, a Bacon decomposition is implemented (47). First, the continuous treatment ESF coverage is substituted with the binary treatment "presence of ESF for at least 3 years". Second, treatment coefficients resulting from eq. [13] and eq. [14] are then decomposed using a Bacon decomposition (47) to explore whether the results are driven by comparisons between late and early groups, or vice versa.

2.3 Results

2.3.1 Effect of ESF on outputs, and single output analyses

I first show the effect of ESF coverage with each output. I find that, with one single exception (nurse technicians), ESF has an effect on all outputs included in the analysis: PHC physicians, PHC nurses, CHWs, equipment and PHC infrastructure (per 1000 people). A one percentage point increase in ESF coverage is associated with an increased health worker density of, on average, one more doctor, less than one nurse, and six more CHWs, per 1 million people, holding control variables constant. ESF coverage did not affect PHC nurse technician density. For this reason, PHC nurse technicians are henceforth not included in the analysis. In *Appendix B-3*, I present results of the effect of ESF on PHC services coverage.

Table 2-2. ESF coverage effect on outputs: PHC physicians, PHC nurses, PHC nurse technicians, CHWs, equipment and PHC infrastructure per 1000 people, 2007-2015

Outputs → ESF Effect ↓	Physicians	Nurses	Nurse technicians	CHWs	Equipment	PHC infrastructure
ESF coverage (β_2)	0.001***	0.0002***	0.0000	0.006***	0.003***	0.0001***
Municipality FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
N (municipalities)	5562	5562	5562	5562	5562	5562
Observations	66283	66283	66283	66283	66283	66283

Source: data source as described in the methods section. Notes: the table provide results of coefficient β_2 in eq.[13] across different outputs (all outputs per 1000 people), as noted in the columns. Robust standard errors, clustered at the municipality level, are used for inferences. P-value below: 0.1 *; 0.05 **; 0.01 ***

Table 2-3 shows, for three FHT health professionals' densities (outputs) across five service coverage outcomes, the ADE and the indirect effect of ESF via each health professional. The indirect effect of the ESF via CHWs ranged from 7% (in the case of PNC and hypertension visits) to 38% (in the case of HIV visits), averaging 19% over five service coverage outcomes. In all cases, there was at least weak evidence ($p<0.10$) of a positive ACME on PHC services coverage for CHWs. In the case of HIV visits, the ADE of the ESF lost significance, suggesting that a substantial part of the effect of ESF on HIV visits is mediated by CHWs. The sensitivity analysis confirms that the sign of the "true" CHWs ACMEs is the same as the estimated CHWs ACMEs, and that the sequential ignorability assumption is likely to hold (Appendix B-4, Table B-4).

There is little evidence supporting the indirect effect of ESF via PHC physicians for all service coverage measures. For PNC visits, I find evidence of mediation via PHC nurses. However, the proportion mediated was very low in magnitude (proportion mediated: -2.2%). In addition, the sensitivity analysis suggests that the "true" PHC nurses ACME for PNC visits is positive, therefore different from the estimated ACME. Finally, I consistently find evidence ($p<0.05$) of a large ADE of the ESF, with one exception (effect of ESF on HIV visits).

2.3.2 Multiple mediators analysis

Table 2-4 presents the results of causal mediation models with all health professionals outputs as mediators. Table 2-5 present the results of causal mediation with all outputs (health professionals, equipment, and infrastructure), as well as controlling for state linear trends. Figure 2.4 presents the results of the same multiple outputs analysis, using regression-based SEM (see eq. [13] and eq. [14])

I find evidence of a CHWs indirect effect for most service coverage outcomes and in both specifications (proportion mediated for ANC visits, 22.6%, for PNC visits, 8.7%, for diabetes screening, 28.9%, in all cases $p<0.01$; average across all outcomes: 20.7%, results are similar in regression-based models). The limited exceptions are hypertension screening, and HIV visits in the causal mediation analysis only. In all cases except hypertension screening in the causal mediation analysis, CHWs shows the largest indirect effect, and the largest proportion mediated (average CHWs proportion mediated: 20.7%, $p<0.05$ in most cases). I find very limited evidence of an indirect effect of PHC nurses in all cases except PNC visits; for PNC visits, the indirect effect of PHC nurses is negative and low in magnitude (-0.001, $p<0.01$, proportion mediated -2.5%). This result is not stable to robustness checks (see 2.3.3). Evidence of the indirect effect of ESF via PHC physicians is very limited, too. In one single case, hypertension screening, the indirect effect of ESF via PHC physicians is statistically different from zero and with a substantial effect (+0.123, $p<0.01$, proportion mediated: 9.8%). However, when using regression-based models, I find no evidence of an indirect effect of ESF via PHC physicians on hypertension screening.

Beyond increasing PHC services coverage through FHTs, opting into the ESF program may result in increased equipment and PHC infrastructure required by the FHTs to deliver PHC services and health promotion, and the effect of additional equipment or infrastructure may be captured by health professionals' mediators. I therefore add equipment pieces (any equipment piece per 1000 people) and PHC infrastructure (per 10,000 people) to the list of mediators. These results are presented in Table 2.5. The results of Table 2-4 are largely unaffected by these additional mediators. I find evidence of a CHWs indirect effect for most service coverage outcomes, as well as limited evidence for an indirect effect of

PHC nurses and PHC physicians. In addition, I do not find evidence of an indirect effect via equipment or infrastructure. Therefore the indirect effects of health professionals' mediators are not capturing the effects of other possible mediators, i.e., equipment or PHC infrastructure improvements. The multiple mediators results for ANC visits, PNC visits, and diabetes screening are very similar to the single mediator results. For HIV visits, the proportion mediated by each mediator differs between the single and multiple mediators model. However, I still find evidence of an indirect effect of ESF via CHWs (+0.035, $p<0.05$) in the regression-based analysis. The difference between the total proportion mediated by all health professionals in the multiple outputs analyses and the sum of the proportions mediated by each health professional in the single output models (Table 2-3) is larger than 1% in one case only (HIV visits), thus suggesting limited output-output interaction (97).

Results of the tests for a moderating effect of Bolsa Familia and Mais Medicos programs on the indirect effects via health professionals and on ADEs are shown in Appendix B-4, for the causal mediation analysis framework. In none of the cases I find evidence (all tests: $p>0.1$) that indirect effects and ADEs are different when there is a high or low supply of either Bolsa Familia or Mais Medicos programs. In the regression-based analysis, results are largely the same.

Taken together, the results of the mediation analysis with multiple outputs in Table 2-4 and Table 2-5 confirm the single output mediation analysis results (Table 2-3), which consistently found a substantial ESF indirect effect via CHWs, and a substantial ADE. In addition, the multiple outputs analysis suggests that there is limited output-output interaction.

Table 2-3. ACMEs and ADEs in models with a single mediator

Dependent variable →	ANC Visits			PNC Visits			Diabetes screening			Hypertension screening			HIV visits		
Outputs →	PHC	PHC	CHWs	PHC	PHC	CHWs	PHC	PHC	CHWs	PHC	PHC	CHWs	PHC	PHC	CHWs
Effect ↓	Physician	Nurses		Physician	Nurses		Physician	Nurses		Physician	Nurses		Physician	Nurses	
ACME	0.001	-0.004	0.057**	0.006*	-0.004***	0.017***	0.022	0.009*	0.131***	0.238	-0.047	0.216*	-0.008	0.006	0.037***
ADE	0.259***	0.259***	0.202**	0.195***	0.205***	0.183***	0.405***	0.427***	0.300***	2.327***	2.595***	2.321***	0.089***	0.075***	0.043
Prop. mediated	0.4%	-1.5%	21.7%**	2.8%*	-2.2%***	8.8%***	5.2%	1.9%*	31.3%***	9.5%	-1.8%	8.6%*	-9.8%	7.3%	46.1%**
N (municipalities)	5564	5564	5564	5564	5564	5564	5564	5564	5564	5564	5564	5564	5564	5564	5564
Observations	49147	49147	49147	49147	49147	49147	49147	49147	49147	49147	49147	49147	49147	49147	49147

Source: data source as described in the methods section. Notes: the table provide results of single output causal mediation analysis for the effect of ESF coverage on PHC service coverage outcomes, controlling for hospital beds per 10000 people, GDP per capita (in Brazilian real), Bolsa Familia subsidies per 1000 people in Brazilian real, number of Mais Medicos programs doctor per 10000 people, municipality fixed effects, year fixed effects. Each model has one output, as noted in each column (all outputs "per 1000 people"). All dependent variables are per 1000 people. ADE and ACME robust standard errors are estimated via 500 simulations. ADE and ACME procedure is detailed in the econometric strategy section. Robust standard errors, clustered at the municipality level, are used for inferences. P-value below: 0.1 *; 0.05 **; 0.01 ***

Table 2-4. ACMEs and ADEs in models with multiple outputs (PHC physicians, PHC nurses, and CHWs) as mediators

Dependent variable →	ANC Visits			PNC Visits			Diabetes screening			Hypertension screening			HIV visits		
Outputs →	PHC	PHC	CHWs	PHC	PHC	CHWs	PHC	PHC	CHWs	PHC	PHC	CHWs	PHC	PHC	CHWs
Effect ↓	Physician	Nurses		Physician	Nurses		Physician	Nurses		Physician	Nurses		Physician	Nurses	
ACME	-0.001	-0.001	0.060***	0.003**	-0.001***	0.018***	0.001	0.002	0.133***	0.123**	-0.061	0.195	-0.011	0.006	0.041
ADE		0.203*** (79.8%)***			0.180*** (91.2%)***			0.295*** (65.4%)***			2.28*** (84.5%)***			0.047 (72.6%)	
Prop. mediated	-0.4%	-2.0%	22.6%***	2.6%	-2.5%	8.7%***	4.1%	1.6%	28.9%***	9.8%**	-2.4%	8.1%	-13.5%	5.6%	35.3%
N (municipalities)		5564			5564			5564			5564			5564	
Observations		49147			49147			49147			49147			49147	

Source: data source as described in the methods section. Notes: the table provide results of multiple outputs causal mediation analysis for the effect of ESF coverage on PHC service coverage outcomes, controlling for hospital beds per 10000 people, GDP per capita (in Brazilian real), Bolsa Familia subsidies per 1000 people in Brazilian real, number of Mais Medicos programs doctor per 10000 people, municipality fixed effects, year fixed effects. Each model has three outputs, as noted in each column (all outputs "per 1000 people"). All dependent variables are per 1000 people. ADE and ACME robust standard errors are estimated via 500 simulations. ADE and ACME procedure is detailed in the econometric strategy section. As every model include all outputs, there is a single ADE for each model. Robust standard errors, clustered at the municipality level, are used for inferences. P-value below: 0.1 *; 0.05 **; 0.01 ***

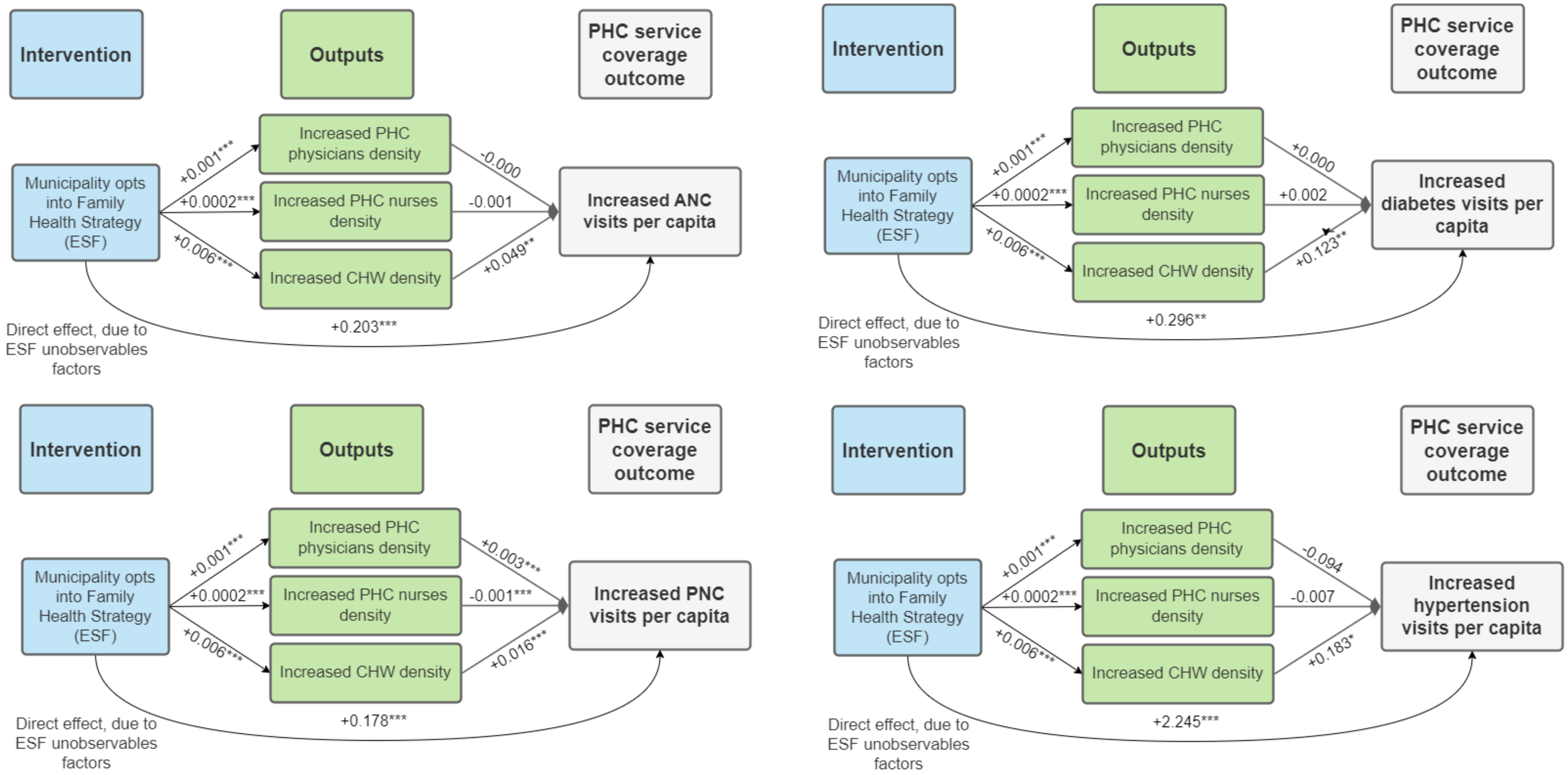
Table 2-5. ACMEs and ADEs in models with <u>*multiple*</u> *outputs (PHC physicians, PHC nurses, CHWs, equipment and infrastructure) as mediators*

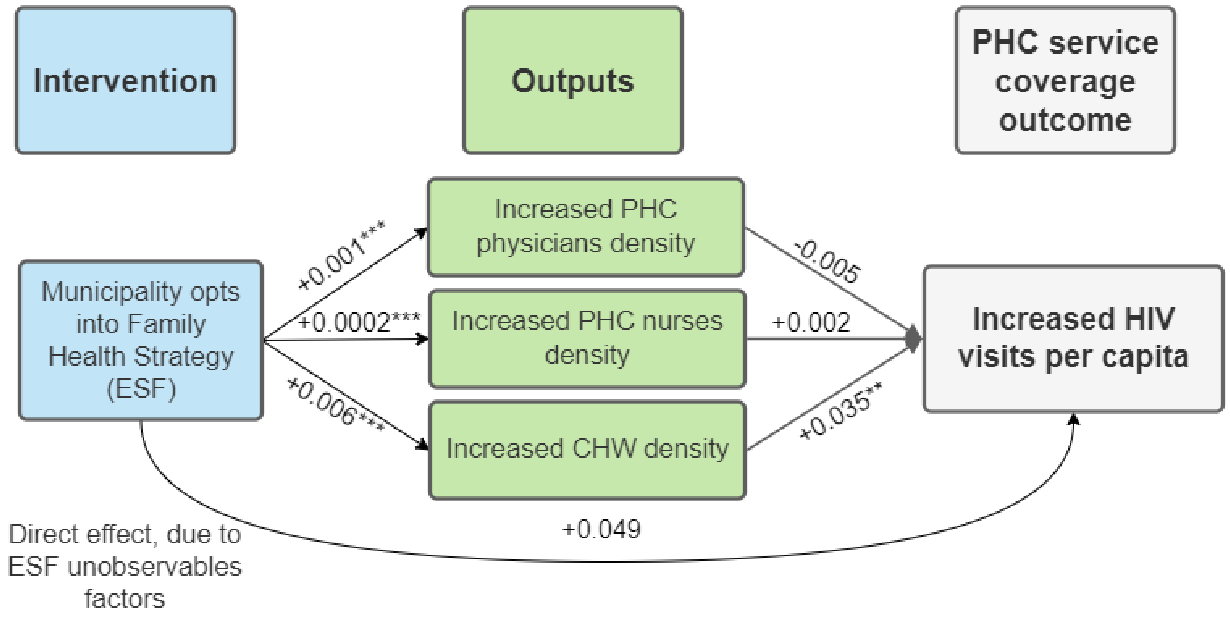
Dependent variable →	ANC Visits					PNC Visits					Diabetes screening				
Outputs → Effect ↓	PHC Physician	PHC Nurses	CHWs	Equipment	Infra-structure	PHC Physician	PHC Nurses	CHWs	Equipment	Infra-structure	PHC Physician	PHC Nurses	CHWs	Equipment	Infra-structure
ACME	-0.001	-0.001	0.054**	0.002	-0.000	0.003***	-0.001***	0.018***	0.001	0.000	-0.001	0.003	0.133***	0.004	0.000
ADE	0.206 (79.4%)***					0.198 (90.6%)***					0.446 (77.8%)***				
Prop. mediated	-0.5%	-0.3%	21.4%	0.6%	-0.1%	1.6%	-0.5%	8.8%	0.4%	0.2%	-0.2%	0.6%	30.7%	0.8%	0.0%
N (municipalities)	5564					5564					5564				
Observations	49147					49147					49147				

Dependent variable →	Hypertension					HIV Visits				
Outputs → Effect ↓	PHC Physician	PHC Nurses	CHWs	Equipment	Infra-structure	PHC Physician	PHC Nurses	CHWs	Equipment	Infra-structure
ACME	0.120**	0.006	0.200	0.032	-0.018	-0.007	0.002	0.039	0.000	-0.000
ADE	2.204 (87%)***					0.0427 (55%)				
Prop. mediated	5.0%	0.2%	8.2%	1.3%	-0.6%	-0.4%	0.2%	39%	0.0%	0.0%
N (municipalities)	5564					5564				
Observations	49147					49147				

Source: data source as described in the methods section. Notes: the table provide results of multiple outputs causal mediation analysis for the effect of ESF coverage on PHC service coverage outcomes, controlling for hospital beds per 10000 people, GDP per capita (in Brazilian real), Bolsa Familia subsidies per 1000 people in Brazilian real, number of Mais Medicos programs doctor per 10000 people, municipality fixed effects, year fixed effects, state linear trend, public health expenditure per capita. Each model has five outputs, as noted in each column (all outputs "per 1000 people"). All dependent variables are per 1000 people. ADE and ACME robust standard errors are estimated via 500 simulations. ADE and ACME procedure is detailed in the econometric strategy section. As every model include all outputs, there is a single ADE for each model. Robust standard errors, clustered at the municipality level, are used for inferences. P-value below: 0.1 *; 0.05 **; 0.01 ***

Figure 2.4. Regression based Structural equation model graph, across outcomes





Notes: effects from ESF coverage to outputs are those shown in Table 2-2, and are estimated as coefficient β_1 in eq. [13]. Indirect effects from outputs to PHC service coverage outcomes are estimated as product of coefficients β_1 and β_3 from eq. [13] and eq. [14] (regression-based, product of coefficient, mediation analysis based on structural equation models, multiple mediator analysis, i.e., all mediators are included at once). Direct effects from ESF to PHC service coverage outcomes is coefficient β_2. HIV visits is not shown for simplicity. Results from regression-based SEM mediation and causal mediation analyses are extremely similar, as expected (21).

2.3.3 Additional analyses and robustness checks

I subject the main results to the below additional analyses and robustness checks (see Appendix B-4 for robustness checks).

The presence of the ESF (in number of years) has been used as the treatment variable in the related ESF impact evaluation literature (69). This would account for a lagged effect of ESF: it is possible for example that two or three years are required for health promotion activities to result in populations changing their behaviour in demanding PHC services, and finally drive increased PHC services coverage. I change the treatment variable from ESF coverage to ESF presence for at least three years (i.e., a binary variable equal to 1 if a municipality has had at least one FHT for three years, zero otherwise). I select three years as the cut-off time to dichotomize the ESF presence variable because a previous impact evaluation showed that, in many cases, it took at least three years of presence of ESF to have an effect on outcomes (see Table V and Table VI in Rocha and Soares 2010 (69)). While the magnitude of the average effects changes vs. Table 2-4, the main conclusions related to ESF indirect effect via CHWs, and ESF ADEs are confirmed. I should note that the negative effect of PHC nurses on PNC visits is not robust to this test, suggesting that this result might be influenced by reverse causality, and PHC nurses are not worsening PNC visits coverage.

Political factors might affect the uptake of ESF. For this reason, and as done in Rocha and Soares 2010 (69), I control for the political party of the Mayor of the municipality (source: Brazil Superior Electoral Tribunal, https://international.tse.jus.br/en/elections/statistics) in the multi-mediator causal mediation models, including also infrastructure and equipment mediators. The results are shown in Appendix B-4. The main results are unaffected, as I find evidence of an indirect effect via CHWs, and evidence of a direct effect of ESF, for most outcomes.

To explore potential direct and indirect effect heterogeneity across poorer and richer municipalities, I interact mediators with municipalities GDP per capita, at the 10^{th} and 90^{th} percentile. The results are robust to changes in GDP per capita levels, suggesting that the municipality-level equity effect of ESF resided in the "who" entered the program (i.e., poorer municipalities are more prone to opt in early), rather than the "how" (i.e., I do not find that the effect of increasing ESF coverage in low GDP municipalities is substantially larger, compared to high GDP municipalities). I should note that, due to data limitations, I can only explore effect heterogeneity across poorer and richer *municipalities*, rather than poorer and richer *households*.

It is possible that municipalities were on different service coverage trajectories before they opted into ESF or increased ESF coverage. To examine whether this is a cause of concern, I add state-time trend to all equations in the regression-based analysis; results are robust to adding state-time trend as controls.

It may be argued that the effect of outputs (health professionals' density) depends on the level of the ESF coverage. ACMEs may, for example, be stronger when ESF coverage is lower. However, this is not the case. As regression-based mediation analysis results are very similar to causal mediation analysis results across most outcomes, I can infer that output-treatment interaction is limited (97). The output-treatment interaction is tested formally, by interacting output and treatment: results are largely stable to this change. Results are also stable to controlling for output values at baseline (i.e., in year 2007) (102). Finally, the Bacon decomposition of the effect of ESF on health professionals' densities and service coverage outcomes shows that the weight of "problematic" groups which would generate bias due to heterogeneity of effects (i.e., early vs. late adopters, and vice-versa) is limited to 10% in most cases, and in all cases is below 15%.

2.4 Discussion

Team-based PHC approaches like ESF, and reforms in PHC healthcare workforces, have recently been identified as two key issues for the future of PHC (73): understanding the contribution of different health professionals to team-based PHC policies is therefore crucial to improve their effectiveness, and cost-effectiveness. In addition, the delivery and financing of PHC in Brazil has recently been reformed (80,81), suggesting that an evaluation of health professionals' contribution to the effect of ESF may be informative to policymakers. Finally, this analysis contributes to the limited literature on quantitative process evaluation based on mediation analyses in the context of complex health system policies (84).

For these reasons, I have sought to unpack the causal mechanisms between ESF and PHC services coverage outcomes, with particular attention to the role of different health professionals forming the FHTs – the core element of the ESF team-based approach. To do so, I distinguish between the direct effect of ESF on coverage of selected services, and the indirect effect of ESF on those same services, which is the effect of ESF mediated by the impact of varying density of health professionals (PHC physicians, PHC nurses, and CHWs) forming the FHTs. These effects are evaluated using a causal mediation framework (21) and a SEM mediation framework (99,100). Other interventions (Bolsa Familia and Mais Medicos) happening at the same time and potentially having synergies with ESF (89) are considered in my framework.

Before commenting on the mediation analysis results, it should be noted that ESF has increased the density of PHC physicians, PHC nurses, and CHWs. However, ESF did not increase the density of PHC nurse technicians. This result suggests that, while the PHC physicians, PHC nurses and CHWs brought in by the FHTs were (at least to some extent) incremental to existing PHC health workers, the PHC nurse technicians brought in as part of FHTs have possibly substituted existing PHC nurse technicians. For this reason, I remind that nurse technicians have not been included in the mediation analysis.

I find a strong indirect effect of ESF, mediated by CHWs density, on the coverage of most PHC services included in the analysis (proportion mediated for ANC visits, 22.6%, for PNC visits, 8.7%, for diabetes screening, 28.9%, in all cases $p<0.01$; results are similar in regression-based models). The proportion of effect of ESF that is not explained by the varying densities of PHC health professionals (ESF ADE) is large (ADE proportion above 65% for all outcomes, $p<0.05$ for all outcomes except HIV visits). The CHWs indirect effect and ESF direct effect findings are similar across single and multiple outputs analyses. These results are robust to several checks, including different specifications (change the treatment definition, use both causal mediation and regression-based mediation analysis), the inclusion of state-specific linear trends, and the inclusion of other potential ESF outputs as mediators (i.e., equipment, and PHC infrastructure).

I also find very little evidence of an indirect effect of ESF mediated by PHC physicians and PHC nurses. The effect of ESF is mediated by PHC physicians in the case of hypertension visits in the causal mediation analysis framework with multiple mediators, but I find no such effect in any other model. I find no evidence of an indirect effect of ESF mediated by PHC nurses' density, except for a negative effect on post-natal care. However, the negative effect is not robust to other specifications, nor to the ACME sensitivity analysis. When using ESF presence for at least three years as the main independent variable, the PHC nurses' indirect effect on PNC visits is positive. I find no evidence of an indirect effect of ESF via other mediators (i.e., equipment and infrastructure) as well.

There are two main implications of these findings. First, the findings for the ADE of ESF suggest that the ESF team-based approach to PHC delivery adopted by the ESF is instrumental to delivering PHC services coverage objectives as compared against simply increasing PHC health professionals' density without a team-based approach. Second, the CHWs indirect effect findings suggest that PHC-delivery teams should largely be formed by CHWs rather than by a large number of physicians or nurses, as done in Brazil, and that the number of CHWs per team may be increased. The indirect effects and ADEs results together suggest that the adequate supply of physicians and nurses brought by ESF is necessary but not sufficient to increase service coverage, while increased CHWs density substantially contributed to increased PHC services coverage. The policy implications of these results are that CHWs role in FHTs may be made even more prominent, and that ESF team-based PHC delivery should be maintained.

While there are several reasons why the ESF team-based approach to PHC is highly beneficial to service coverage outcomes (73,75), it is useful to discuss possible reasons why having more CHWs has a larger effect than increasing other health professionals' density. First, I recall that CHWs are responsible for health promotion activities and do not deliver healthcare services themselves, while FHTs physicians and nurses deliver PHC services. In other words, CHWs work is closer to a demand intervention, while PHC nurses and physicians work is closer to a (PHC) supply intervention. In light of that, one reason behind the substantial contribution of CHWs to the overall effects of the ESF may be that health services demand considerations are currently limiting service coverage increases. For example, considerations about health education and trust, may explain the substantial ESF indirect effect via CHWs for ANC visits and diabetes visits (approximately 25%, in both cases). CHWs might also have an effect on the supply of nursing staff time, and ultimately PHC services coverage, as they might complete tasks (e.g., health promotion, measuring blood pressure, and others) that would need to be completed by nursing staff otherwise.

This explanation presumes that PHC services are accessible and supplied adequately, at least to a sufficient extent. First, the supply of PHC services may have been guaranteed by PHC physicians and nurses. Second, other studies noted that geographical access to PHC facilities is acceptable in the poorest North and North-eastern regions (distance to PHC facility <20min for more than 95% of the population (103,104)), suggesting that at least geographical access is likely acceptable. One study also noted that a key issue preventing access to PHC services was the presence of physicians (103), an issue addressed by FHTs.

The potentially adequate supply of facilities may also explain the limited indirect effect of other mediators, especially infrastructure. There are other reasons that might explain the limited indirect effect of equipment and infrastructure. The focus of the program is largely on FHTs. Hence, the impact of the program on equipment and infrastructure might be lower, ultimately limiting their indirect effect. In addition, there are data limitations related to both equipment and infrastructure. The available data related to infrastructure and equipment is rather limited. For equipment, I have data for "any" piece of equipment. For infrastructure, while I have data for the number of facilities, I have no information regarding infrastructure quality. Once better data is available, further research might explore the effect of these mediators on PHC services.

The fact that the proportion mediated by all mediators in multiple mediator models and in single mediator models is similar, suggests that there is limited mediator-mediator interaction. This could be interpreted as a missing "team effect". However, we note that the ADE results actually captures and shows that a team effect exists, in particular when the team of PHC health professionals is organized as a ESF team. The ADE in fact can be interpreted as increasing ESF coverage, while holding density of health professionals constant. In other words, the results suggest that a 'team effect' exists, especially when the team is an ESF team. This suggests that ESF is an organizational technology that increases the productivity of health professionals.

Other interventions have a limited effect on the indirect and direct effects of the ESF on PHC services coverage, with a single exception, which is not robust to changes in model specification (i.e., Bolsa Familia moderating the direct effect of ESF on PNC visits, only in regression-based analyses). Another study reported a significant interaction of Bolsa Familia and ESF for under-5 mortality, but no ESF-Bolsa Familia interaction with service coverage outcomes (105). With regard to the Mais Medicos program, it is possible that the allocation of doctors to non-prioritized areas (106) may have affected its potential moderation of the effect of ESF. Most importantly, this study focuses on the moderating effect of Bolsa Familia and Mais Medicos on ESF indirect effect via health professionals, and ESF ADE, rather than on ESF average treatment effect, which was the focus of previous studies. Data limitations may also affect the interaction with the Mais Medicos program. Because it started in 2013, in our data it overlapped with ESF for only three years (2013, 2014, and 2015).

An important limitation of this study is related to the Requalifica Unidade Basicas de Saude (Improve PHC facilities) and the Brazilian National Program for Improving Primary Care Access and Quality (Brazilian Portuguese acronym: PMAQ), which funded the construction and refurbishments for primary health care facilities. Due to data limitations, these programs have not been considered in my framework. While public health expenditure might partially capture their effect, these programs might moderate the EFS ADE and the ACME of health professionals, equipment and PHC infrastructure in ways that are not captured solely by public health expenditure (e.g., better quality infrastructure, or better information systems). Further research might address this limitation, and explore the interaction between Requalifica Unidades Basica de Saude and PMAQ.Other limitations are noted in this paragraph.

Other limitations not noted earlier are noted in this paragraph. First, the study is of an ecological nature, like the vast majority of ESF impact evaluations (20), which does not allow for causal interpretation of results at the individual level, given that the dataset is at the municipal level. Second, because data regarding human resources is only available from 2007, I could not use data from the years of ESF from 1998 to 2006. This data limitation means that the paper focused on the expansion of an already established ESF, rather than the expansion of ESF as a completely new program. Third, while ESF team-based approach is likely to be the main ADE driver, it should be noted that ADE of the ESF may be due to unobserved mechanisms other than team-based delivery.

While bearing these limitations in mind, the implications of these findings are that policymakers should consider increasing the prominence of CHWs within FHTs, and should continue supporting ESF team-based PHC delivery. Further research could focus on comparing team-based PHC to other models of delivering PHC, and on more robust methods to evaluate ESF (i.e., using individual level data rather than municipal level data) (20), and on the impact that better PHC referral services have on utilization of secondary and tertiary healthcare services.

Chapter 3: Part I. A threshold-agnostic measure of catastrophic health expenditure

ABSTRACT

Universal health coverage (UHC) is a priority for many governments around the world. Catastrophic health expenditure (CHE) incidence is used to monitor progress towards UHC within the United Nations Sustainable Development Goals framework (SDG, 3.8.2). The choice of CHE incidence as the measure for tracking SDG 3.8.2 was controversial and the debate highlighting concerns about CHE is on-going. One critical point in estimating CHE incidence is that a threshold must be chosen to derive it. For example, UN SDG 3.8.2 uses 10% and 25% as thresholds. This raises two issues. First, country rankings and country trends based on CHE are sensitive to threshold changes, affecting the ability to make conclusions regarding progress towards UHC. Second, any threshold chosen reflects an arbitrary, normative choice. Hence, developing a threshold-agnostic CHE measure would be a desirable aspiration. I first define threshold-agnostic CHE as the area under the CHE incidence sensitivity curve. Then, I show that out-of-pocket (OOP) health expenditure budget share (i.e., OOP health expenditures as a percentage of total household expenditures), a commonly used measure, is equivalent to threshold-agnostic CHE. Therefore, the OOP health expenditure budget share could be interpreted as a threshold-agnostic CHE measure, and considered for country-level and global UHC monitoring purposes, in addition to existing financial risk protection measures.

Keywords: financial risk protection, health financing, out-of-pocket health expenditures, catastrophic health expenditures

3.1 Introduction

Universal health coverage (UHC) is a priority for many governments around the world and, within UHC, financial risk protection is a key target included in the United Nations Sustainable Development Goal (UN SDG) 3.8.2. Catastrophic health expenditure (CHE) incidence is the indicator most widely employed to measure financial risk protection (53), and it is used by World Bank and WHO to monitor progress towards the UHC indicator SDG 3.8.2 (6,53). Measuring progress towards UHC is particularly important given that several countries are implementing or considering reforms to accelerate progress towards UHC (26,107). The choice of CHE (most often measured as the percentage of households that incur out-of-pocket health expenditure that are larger than 10% of their total expenditure or income) (53)) to measure UHC has been controversial (108) and the debate continues as to whether existing CHE metrics really capture financial risk protection (108–111). This debate has highlighted several methodological issues (5,6), and several improvements to CHE have recently been suggested (112).

The motivation of this paper stems from two issues related to CHE, and the CHE thresholds commonly used, 10% and 25%. First, CHE country rankings have been found to be sensitive to threshold changes (113), and this study confirms this point. In addition, I show that CHE within-country, over-time trends are also not robust to a threshold change from 10% to 25% (i.e., a country CHE 10% improves over a certain time period, and CHE 25% worsen, for the same country over the same time period). These instabilities in ranking and country trends are likely to be larger if the threshold change is increased further (say, from 10% to 40%). Hence, the standard CHE measure seems ill-suited to robustly assess the relative performance of countries in terms of financial risk performance, which suggests that developing a threshold-agnostic CHE a desirable aspiration.

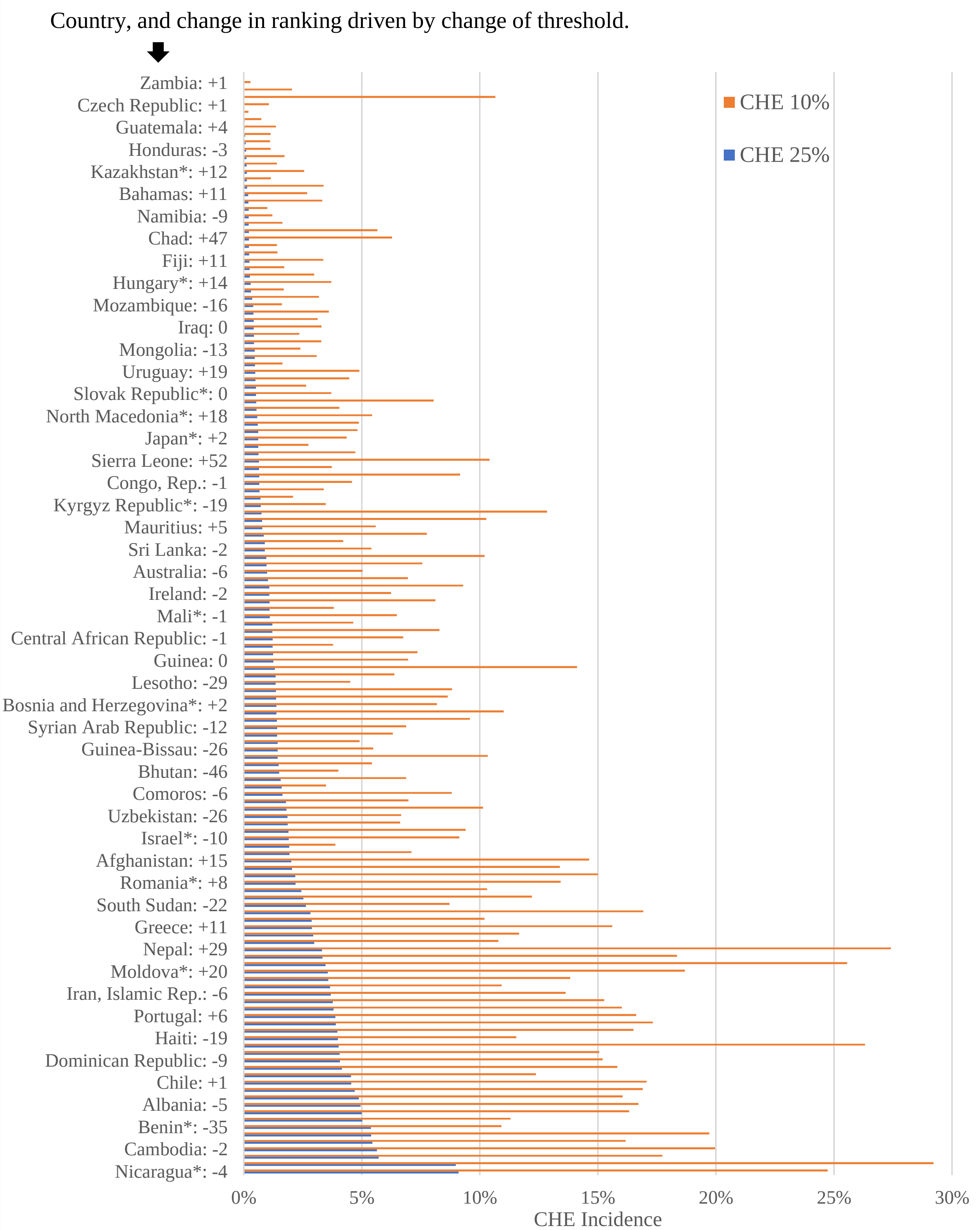
Second, any threshold choice is a normative, arbitrary choice, with no theoretical basis (108). While CHE incidence sensitivity curves (i.e., graphs depicting how CHE incidence changes as its threshold changes (113,114)) would be a solution to this problem, the visual inspection of curves is impractical for comparisons across many countries and/or time periods. In this paper, I propose a measure of CHE that is easily comparable across many countries and/or time periods, and that is agnostic to arbitrary threshold choices. The proposed approach can be applied to CHE computed using any denominator (total consumption, non-food consumption, etc.), to CHE that considers coping mechanisms (115), and to CHE measured across sub-groups, as needed.

Furthermore, by showing that the OOP budget share (i.e., OOP health expenditures as percentage of total household expenditures) is a threshold-agnostic measure of CHE, I provide a new interpretation for the OOP budget share, a widely used measure of financial risk protection (116–119), which could be considered for country-level and global UHC monitoring purposes, in addition to existing financial risk protection measures.

3.2 Limitations of existing CHE measures

An arbitrary choice would not be problematic for global monitoring purposes if comparisons across countries were reasonably threshold-independent. However, the threshold choice in standard measures of CHE does affect country rankings (113), and therefore threshold choices risk compromising unambiguous global financial risk protection monitoring. Country rankings are not robust to threshold changes (from a 5% to a 40% threshold) in at least one case out of two, and in at least three cases out of four when the threshold is allowed to change from 5% to 85% (113). The sensitivity of country rankings to threshold changes is also shown in Figure 3.1.

*Figure 3.1 CHE incidence at 10% and 25% (latest year available), and country ranking changes. *=countries whose CHE time-trend is sensitive to a threshold change*



Source: author, using HEFPI dataset

A lack of robustness in global country rankings to CHE threshold changes would already be a cause of concern. In addition, country-specific trends in CHE are also unstable to threshold changes (see both

Figure 3.1 and Table 3-1). Have Turkey in 2010, Japan in 2013, and Georgia in 2001 improved or worsened in terms of financial risk protection, or have they remained unchanged? Depending on the threshold used, different conclusions may be drawn. In this situation, it is difficult for a researcher to provide robust, unambiguous information to policymakers about country performances in terms of CHE.

Table 3-1. Examples of within-country trend inconsistency

		CHE 10%		CHE 25%	
Country	Year	Value	Trend	Value	Trend
Turkey	2009	3.6%	/	0.7%	/
Turkey	2010	3.9%	Worsen	0.6%	Improve
Japan	2012	4.2%	/	1.0%	/
Japan	2013	3.9%	Improve	1.1%	Worsen
Georgia	2000	12.4%	/	4.7%	/
Georgia	2001	13.9%	Worsen	4.4%	Improve

Source: Health Equity and Financial Protection Indicators dataset (HEFPI), author elaboration. Note: / = not shown

These country-specific incompatible trends are common: country trends are sensitive to a 10%-to-25% threshold changes for 24% of countries (see Figure 3.1), and country trends are likely more sensitive to larger threshold changes.

A CHE incidence sensitivity curve (CHE on X axis, threshold on Y axis (113,114), see also Figure 3.3) is helpful in comparing a limited set of countries, and in discerning at which threshold CHE is increasing or decreasing. However, it is difficult or impossible to use visual inspection of sensitivity curves alone when comparing several countries or even a single country across several time periods. A numerical index has also been proposed (120), but is not threshold-agnostic.

3.3 A threshold-agnostic measure of CHE

I now present the threshold-agnostic measure of CHE (henceforth referred to "threshold-agnostic CHE"), measured as the area-under-the-curve of the CHE sensitivity curve proposed by Hsu et al. (113), originally designed to overcome the issue of arbitrary thresholds, and recently implemented in a study of CHE in Liberia (121).

Let X be a random variable representing the percentage of OOP health expenditure over total expenditure (this could be income, or non-food expenditure, or non-subsistence-food expenditure – from now on I will use "expenditure"). X is by definition $0 \leq X \leq 1$: health expenditure cannot be greater than total expenditure. Let T be a threshold (common ones are 10% or 25%, $0 \leq T \leq 1$).

Following the widely used CHE measurement methodology, let CHE for household j be an indicator variable such that:

$$CHE_j(t) = 1 \; if \; x_j - t > 0, 0 \; otherwise \qquad [20]$$

Then CHE incidence is, for a threshold t and across all households N:

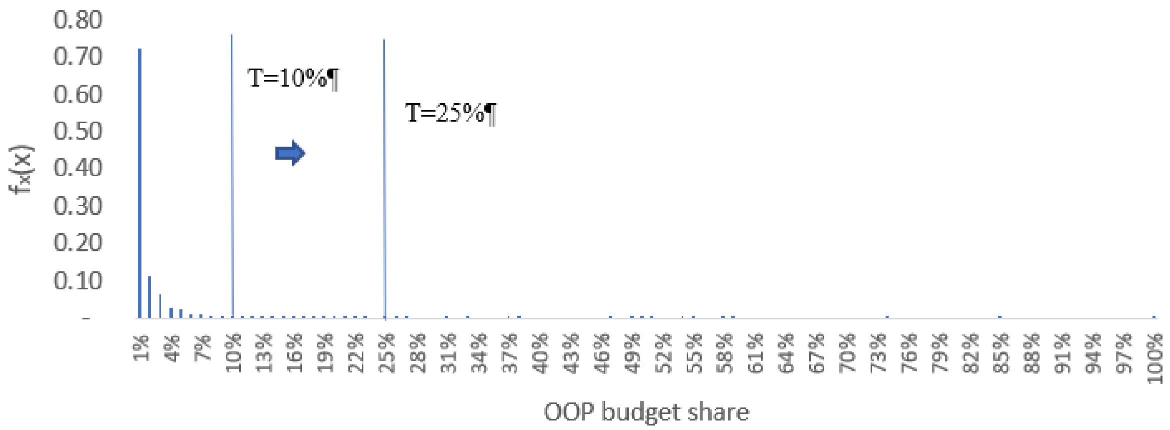
$$\frac{1}{N}\sum_{j=1}^{N} CHE_j(t) = CHE(t) \qquad [21]$$

Let the random variable X have a probability density function $f_X(x)$, which is non-negative and Lebesgue-integrable. Then,

$$CHE(t) = \int_t^1 f_x(x)dx \qquad [22]$$

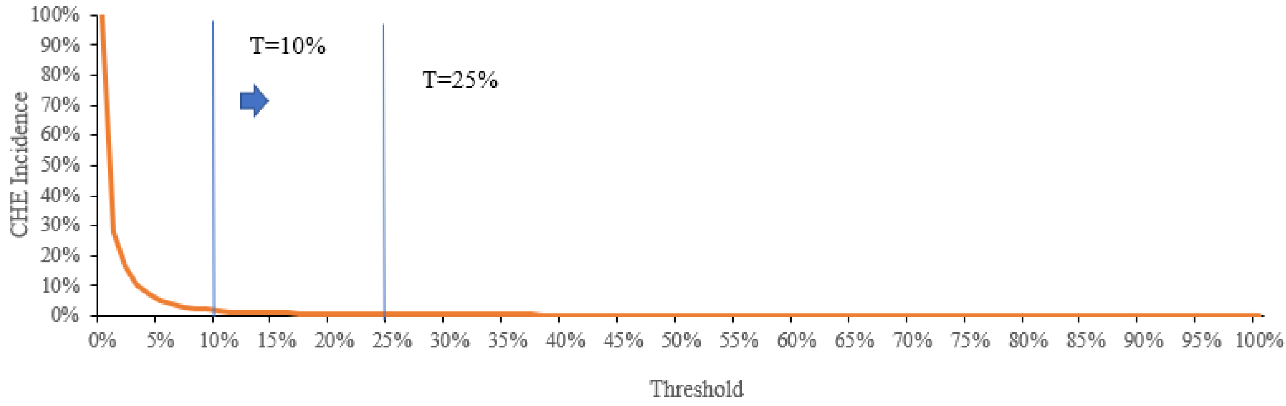
and as the threshold goes up, $CHE(t)$ goes down, as shown in Figure 3.2.

Figure 3.2 OOP budget share (OOP health expenditure divided by expenditure), probability density function



Source: author elaboration using Liberia Household Income and Expenditure Survey (HIES) 2014-2015 (122)

Figure 3.3 CHE sensitivity curve



Source: author elaboration based on (121)

The CHE incidence sensitivity curve (Figure 3.3) plots parametrically $CHE(t)$ against all possible thresholds. The area under the sensitivity curve is a threshold-agnostic (i.e., independent of the threshold) CHE measure (CHE_{TA}):

$$CHE_{TA} = \int_0^1 CHE(t)\, dt \qquad [23]$$

Measuring CHE across all possible thresholds, and then calculating its integral from 0 to 1 may not be trivial. However, the CHE_{TA} in eq. [23] can be easily computed based on its properties, which are described next.

Property 1. *Threshold-agnostic CHE is equivalent to the average CHE(t) across all thresholds in the interval [0,1].* This is shown in the following eq. [24], where the first equivalence is provided by the mean value theorem for integrals.

$$\overline{CHE(t)} = \frac{1}{1-0}\int_0^1 CHE(t)\, dt = \int_0^1 CHE(t)\, dt = CHE_{TA} \qquad [24]$$

This definition still requires that CHE is measured across all possible thresholds, which again may not be trivial. One more property makes the calculation of CHE_{TA} simpler.

Property 2. *Threshold-agnostic CHE is equivalent to the average ratio of OOP health expenditure divided by total expenditure (called OOP budget share in the HEFPI dataset)*

The cumulative distribution function (CDF) of X, which I call $F_X(x)$, is the probability that OOP health expenditure as a proportion of total expenditure takes a value less than or equal to x. The complement of the CDF ($1 - F_x(x) = P[X \geq x]$) is the probability that X takes a value larger than or equal to x, which is in fact equivalent to $CHE(t)$ once a random value of x is substituted with t:

$$1 - F_x(x) = P[X \geq x] = \int_x^1 f_x(x)dx = \int_t^1 f_x(x)dx = CHE(t) \qquad [25]$$

I substitute $CHE(t) = 1 - F_x(x)$ from eq. [25] into eq. [23][2]:

$$CHE_{TA} = \int_0^1 CHE(t)dt = \int_0^1 1 - F_x(x)dx = E[X] \qquad [26]$$

The first equivalence is given by equation [23]. The second equivalence is given by substituting in the complementary CDF based on equation [25]. The third equivalence follows the rule that the cumulative CDF of a non-negative random variable X is equivalent to the expectation of X, the OOP budget share.

The threshold-agnostic CHE proposed is non-negative, from 0 to 1, and is applicable to different measures of CHE, including using different measures for total expenditure (e.g., non-food expenditure), considering coping strategies (115), or measuring threshold-agnostic CHE for population sub-groups (i.e., income quintiles).

A simulation of the above results is provided at the Open Science Framework repository https://osf.io/2z3fg/.

In Table 3-2, I apply the threshold-agnostic CHE to single country trends, using the same countries from Table 3-1, showing that its usage would prevent the inconsistencies that may result from using CHE measures with varying thresholds.

Table 3-2. Threshold-agnostic CHE for countries whose country trend was found to be sensitive to a 10%-to-25% threshold change in Table 3-1

Country	Year	Threshold-agnostic CHE Value	Trend
Turkey	2009	1.8%	/
Turkey	2010	2.0%	Worsen
Japan	2012	2.7%	/
Japan	2013	2.4%	Improve
Georgia	2000	4.7%	/
Georgia	2001	4.9%	Worsen

Source: author, based on HEFPI dataset. / = not shown

[2] The usual form of the rule on the cumulative CDF is $\int_0^\infty 1 - F_x(x)dx = E[X]$. Substituting $+\infty$ with 1 would yield the same result as T and X are defined in [0,1].

To exemplify the issue concerning country rankings robustness to changes in the CHE thresholds, in Appendix C-1 I present country rankings based on CHE threshold at the 10% level, 25% level, and based on threshold-agnostic CHE, measured as the OOP budget share, based on Property 2.

3.4 Discussion

Catastrophic health expenditure (CHE) at the 10% and at the 25% threshold are the official measures used to monitor financial risk protection as part of UHC tracking for the UN SDGs. However, countries' financial risk protection ranking and trends over time are not robust to threshold changes, in at least one case out of five. Moreover, any threshold choice reflects an arbitrary, normative choice. To overcome these issues, I propose a threshold-agnostic measure of CHE. Simply stated, threshold-agnostic CHE is a financial risk protection country-level measure, computed as the area below the CHE incidence sensitivity curve, or equivalently as the OOP budget share.

Threshold-agnostic CHE can be computed as the area under the CHE incidence sensitivity curve (113) or the average CHE across thresholds, but these computations and interpretations are complex, especially for policymakers. I also proved that threshold-agnostic CHE can be computed as the average OOP health expenditure budget share (i.e., OOP health expenditure divided by total expenditure), which is more straightforward to compute and interpret.

The implication of this paper is that the OOP expenditure budget share would be worth considering as an additional measure for global and country financial risk protection monitoring purposes, given its threshold-agnostic characteristic. This should be particularly easy as the OOP health expenditure budget share is available publicly on HEFPI, and has been used widely (116). A second implication is that the OOP health expenditure budget share can now be interpreted as a threshold-agnostic measure of CHE. This is particularly important as the OOP health expenditure budget share has been used widely in the literature (116), perhaps without complete awareness of its threshold-agnostic property.

The OOP health expenditure budget share (i.e., threshold-agnostic CHE) should be complementary to other financial risk protection measures. Sensitivity curves provide insights about how exactly CHE changes depending on the threshold, which is likely useful information for policymakers and is not provided by threshold-agnostic CHE. CHE measures based on specific, arbitrary thresholds are also useful as they provide punctual information on financial risk protection for specific threshold(s), which also is not provided by threshold-agnostic CHE. Because of these limitations, threshold-agnostic CHE should be considered in addition to, rather than instead of, other measures of financial risk protection based on CHE (i.e., CHE sensitivity curves and CHE measures based on arbitrary thresholds).

Finally, threshold-agnostic CHE may improve CHE robustness, avoiding threshold-related sensitivity, and its theory, by avoiding arbitrary threshold choices. However, it does not solve several other CHE-related issues (e.g., CHE does not consider households unmet healthcare needs while services coverage data is limited, CHE may increase as more services are offered, and others (108)).

Despite these limitations, this study contributes to the literature on CHE by providing a threshold-agnostic CHE measure, and by showing an important property of the widely used OOP budget share.

Chapter 3: Part II. Does health aid matter for financial risk protection? An analysis across 159 household surveys, 2000-2016

ABSTRACT

INTRODUCTION: Universal Health Coverage (UHC) is a widely accepted objective among entities providing development assistance for health (DAH) and DAH recipient governments. One key metric to assess progress with UHC is financial risk protection, but evidence on the extent to which DAH promotes financial risk protection (and hence UHC) is scarce.

METHODS: Our sample is comprised of 65 countries whose DAH per capita is above the population -weighted average DAH per capita across all countries. The sample comprises a total of 1.7 million household level observations, for the period 2000-2016. We run country and year fixed effects regressions, and pseudo-panel models, to assess the association between DAH and three financial risk protection measures: catastrophic health expenditure (defined as out-of-pocket health expenditures larger than 10% of total household expenditures ['CHE10%']), out-of-pocket health expenditure as a share of total expenditure ('OOP%'), and impoverishment due to health expenditures, at the 1.90 US$ per day poverty line ('IMP190').

RESULTS: Overall, DAH investment does not appear to be significantly associated with financial risk protection outcomes. However, in both fixed effects and pseudo-panels regressions, a 1 US$ increase in DAH per capita improves at least one financial risk protection outcome for the poorest household quintile within countries (IMP190: -0.05 percentage points, $p<0.1$; in pseudo panel models, CHE10%: -0.12 percentage points, $p<0.01$). DAH also improves most financial risk protection outcomes when it is largely channelled via government systems (i.e., when it is "on-budget") (CHE10%: -0.68 percentage points, $p<0.05$; in pseudo-panel models, CHE10%: -0.14 percentage points, $p<0.01$). Several robustness checks confirm these results.

DISCUSSION: DAH investments require careful planning to improve financial risk protection. For example, positive DAH effects for the poorest quintiles of the population might be driven by DAH targeting poorer populations health expenditures and doing so effectively. Our results also suggest that channelling more resources via governments might be considered as a promising avenue to enhance the positive impact of DAH on financial risk protection.

Keywords: financial risk protection, development assistance for health, equity, universal health coverage, health systems

3.1 Introduction

Universal health coverage (UHC) captures the ambition that the entire population in a given jurisdiction receive the quality health services they need, without suffering financial hardship, regardless of socio-economic conditions (1). Development assistance for health (DAH) – amounting to around 40 billion US$ per year in 2019 (123) – is often disbursed with the stated intent to promote progress towards UHC. In low-income countries (LICs), external DAH contributes to approximately a third of total health expenditure (THE) (124). UHC is a widely recognized objective by several governments in DAH-recipient countries and institutions disbursing DAH (5–7), and it is commonly monitored using financial risk protection indicators within the Sustainable Development Goals (SDGs) framework under SDG 3.8.2 (5–7).

While institutions providing DAH may or may not have an explicit target of improving financial risk protection, it is at least plausible to imagine that DAH *can* improve financial risk protection in DAH-recipient countries. DAH may be easing the budget constraints that many governments in low- and middle-income countries (LMICs) face when delivering health services, by financing public budgets directly or by financing health services delivered by non-governmental for-profit or not-for-profit organizations: by financing health services that would otherwise need to be purchased via out-of-pocket (OOP) health expenditures (e.g., malaria drugs or HIV services), DAH may promote the UHC objective of financial risk protection. DAH may also impact financial risk protection by financing preventative services, which might decrease the chances of incurring health shocks that require large OOP expenditures and would increase the risk of impoverishment (125). While the positive contribution of DAH to financial risk protection may be plausible, such effect is by no means automatic, as donors might also have objectives outside financial risk protection or as there could be "weak links in the chain" (34) from DAH to the intended outcome of financial risk protection. Hence, it is ultimately an empirical question whether, and if so, to what extent DAH improves financial risk protection in DAH-recipient countries.

However, such empirical evidence has thus far been missing. To the best of our knowledge, no study has hitherto investigated the association between DAH and financial risk protection. As DAH may be channelled via non-profit institutions serving households (NPISH, e.g., non-governmental institutions serving households and funded by a donor grant), studies exploring the effect of the share of THE channelled via NPISH on financial risk protection could possibly be "indicative" of the association of DAH with financial risk protection. Three studies have examined the association between the share of THE channelled via NPISH and financial risk protection, using aggregate country-level data (30,53,126), of which two studies found no association (53,126). One study, focusing on UHC indicators (i.e., including both service coverage and financial risk protection), found a significantly negative association between the share of THE channelled via NPISH and financial risk protection (30). In addition, the existing studies did not investigate whether the associations between the share of THE channelled via NPISH and financial risk protection outcomes were modified by country-level contextual factors and/or household-level characteristics. In sum, there appears to be no previous study exploring the association between DAH and financial risk protection, and the few studies that could be "indicative" of that association show ambiguous results.

This study is the first, as far as we are aware, to investigate the association of DAH with progress in financial risk protection, shedding light also on which households (if any) have benefited from DAH investments and under what contextual factors.

The present paper is also innovative with respect to the data and methodology used to systematically analyse the association between DAH and financial risk protection. We use a major, harmonized dataset encompassing 504 household surveys (full list in Appendix C-2), covering the period 1995-2018 and 131 countries, for a total of 9.8 million household observations. For the main analysis, we select countries with a DAH per capita above the DAH per capita population-weighted average from the 504 household surveys, resulting in a sub-sample of 65 countries, 1.7 million household observations, in the 2000-2016 period, across 159 surveys. This is done in order to exclude countries where DAH per capita is arguably too low to be able to impact on financial risk protection. We also undertake robustness checks to explore whether our results are upheld when using all the countries available in the sample.

As in repeated cross-sectional surveys the same individuals are not followed throughout time, we employ pseudo-panel methodologies to control, at least partially, for time-invariant confounding. The paper also considers country-level contextual factors and household characteristics that may modify the impact on the association between DAH and financial risk protection outcomes. In keeping with common practice in the existing literature (116,117), the financial risk protection outcomes considered are catastrophic health expenditures defined as OOP health expenditures above 10% of total household expenditures ('CHE10%'), impoverishment due to household expenditures, using a 1.90US$ poverty line ('IMP190'), and OOP health expenditure as a percentage of total household expenditures ('OOP budget share').

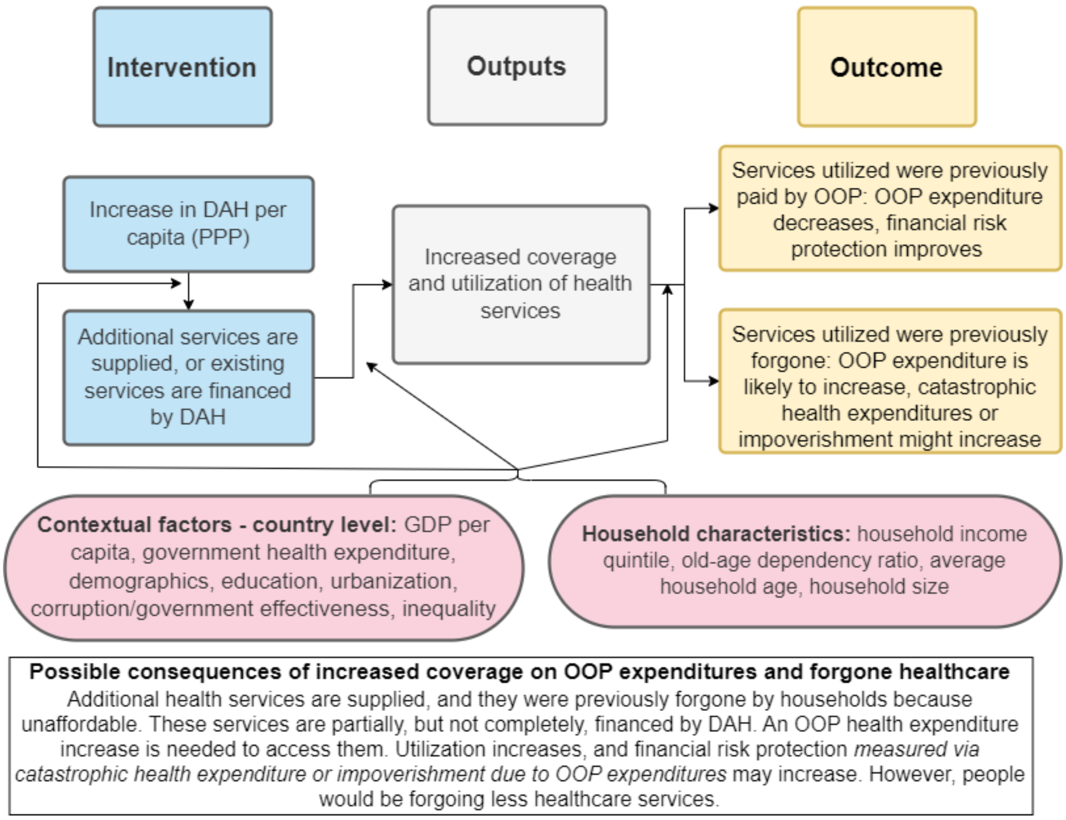
Our results suggest that – on average – DAH investment is not significantly associated with financial risk protection outcomes in the DAH receiving countries in focus here. However, increasing DAH per capita improves financial risk protection outcomes for populations in the poorest quintile (IMP190: -0.05 percentage points, $p<0.1$; in pseudo panel models, CHE10%: -0.12 percentage points, $p<0.01$). DAH per capita also improves financial risk protection outcomes when a higher share of DAH is channelled via government systems (i.e., when it is "on-budget") (CHE10%: -0.68 percentage points, $p<0.05$; in pseudo-panel models, CHE10%: -0.14 percentage points, $p<0.01$). We found mixed results for the association between DAH per capita and financial risk protection outcomes at different levels of other household characteristics, and at different levels of other country contextual factors.

In what follows, we present the conceptual framework underpinning the analysis (Section 3.2), the methods employed in the analysis (Section 3.3), the results of the analysis (Section 3.4) and, finally, a discussion of the results including possible policy implications (Section 3.5).

3.2 Conceptual framework

In Figure 3.4 we present how, in principle, DAH may result in decreasing OOP health expenditures and, as a result, improve financial risk protection.

Figure 3.4. Conceptual framework about how DAH might impact financial risk protection



Source: authors' elaboration

In a situation, where governments fall short of providing adequate services to their population due to limited domestic budgets, and households cannot afford the healthcare services they need, DAH could improve financial risk protection as follows: DAH may finance (private or public) healthcare providers directly (off-budget DAH) or finance governments via their own financial management systems (on-budget DAH). When DAH is on-budget, it may fund services that country governments are unable to provide at a desired coverage or quality level due to budget constraints. In addition, on-budget DAH may fund services delivered by policies or programs specifically intended to address financial risk protection (e.g., the introduction of a public contributory or non-contributory health insurance scheme), which are commonly initiated by national governments. Such policies or programmes offer services that households need and might have purchased in the absence of the policy, though at a higher cost.

As a result, OOP health expenditures might be lower than what they would have been, with beneficial impacts on households' financial risk protection (5).

Underneath this simplified conceptual framework, several assumptions are required for increased DAH to improve financial risk protection – assumptions that may not always be met in reality: contextual factors at the household and country level may impact on the pathway between increased DAH and improved financial risk protection. At the household level, while DAH may be primarily intended to benefit poorer households, these may face barriers to accessing services beyond the direct cost of health services (e.g., physical access and travel costs, health knowledge, stigma for certain health conditions (127)). At the country level, the quality of institutions (both at government and NPISH level, respectively for on- and off-budget DAH), the fragmentation of DAH (128–130), the availability and quality of health services providers (both public and private) may all influence the effectiveness of DAH and public health expenditures in realising the intended objectives (35).

Finally, increased DAH might reduce the probability for people to forgo healthcare due to financial barriers while at the same time *worsening* financial risk protection, as measured via CHE or impoverishment driven by OOP health expenditures. This may occur whenever certain healthcare services (e.g., surgery services) would have been needed by households, but could – prior to DAH support – not be accessed due to financial or other constraints (e.g., surgery services not being supplied at all). DAH could enable those services (e.g., again surgery) to be available *at a cost to households*, so that while forgone healthcare declines and health status might improve (33), OOP health expenditures would nonetheless increase, thus worsening some of the financial risk protection measures (5,108,112,121).

3.3 Data and methods

3.3.1 The data

3.3.1.1 Outcomes and household level data

As detailed in the literature (116,117), we use three financial risk protection measures as our outcome variables. First, we use the *OOP budget share*, which is operationalized as OOP health expenditure divided by the total household budget, commonly proxied by total household expenditures. The OOP budget share is a threshold agnostic measure of catastrophic health expenditure (CHE) that is also equivalent to the average CHE across all thresholds, and the area under the CHE sensitivity curve developed by Hsu et al. (113) (see Chapter 3, Part I). Second, we use CHE incidence i.e., an indicator variable equal to 1 when a household has an OOP budget share larger than a set threshold (131) measured using the most common 10% threshold (30). Finally, we use a measure of impoverishment, i.e., the percentage of people pushed below the 1.90 international US$ poverty line as a result of OOP health expenditures. While these thresholds and poverty lines are in line with conventions, they are ultimately arbitrary. Hence, in our robustness analysis, we use the additional outcomes: CHE at 25%

threshold and impoverishment at the 3.20 international US$ poverty line. These outcome measures are sourced from a microdata dataset which includes 504 surveys (see Appendix C-2 for additional detail), across the 1995-2018 period and 131 countries, for a total of more than 9 million observations. For our main analysis, we focus on countries receiving DAH per capita amounts that are higher than the average (population weighted) DAH per capita in the full sample: these are 65 countries, in the period 2000-2018, for a total of 1.7 million observations. In robustness checks, the full sample of 504 surveys is used.

3.3.1.2 Independent variable of interest and other covariates

The country-level data includes our independent variable of interest, DAH per capita in PPP US$, sourced from the Institute of Health Metrics and Evaluation (IHME) “Development assistance for health database 1990-2020” (132). As data regarding the amount of DAH received by each household is not available, by using this DAH measure at the country level, the implicit assumption is that all households in a country-year benefit from the same amount of DAH. We use as main specification the sub-group of countries receiving more than the average DAH per capita value across the sample (DAH average per capita across the full sample: 6 US$ per capita): this is because many countries receive zero DAH, or less than a few dollars in DAH per capita, which we would not expect to be associated with improvements in financial risk protection. As a robustness check, we re-run our estimates for countries from selected income groups (LMICs), using other thresholds (e.g., an even higher or lower threshold), and using the entire sample.

Other control variables from the same dataset comprise GDP per capita (PPP, constant 2017, US$), total health expenditure per capita, government health expenditure per capita and OOP health expenditure per capita (all PPP US$). Other country level covariates are taken from the World Bank World Development Indicators (WDI) dataset (i.e., percentage of urban population, percentage of population with access to basic drinking water, percentage of population above 65 years old, percentage of population below 14 years old and Gini index) and the World Governance Indicators (WGI) (i.e., corruption control and government effectiveness) (55).

Household level covariates include household expenditure quintiles, old-age dependency ratio (OADR), household size and the average age of the members of the household. OADR is measured by the number of household members above 60 years old, divided by the household members between 18 and 60 years old. Household expenditure quintiles, OADR, the average age of the members of the household, and the presence of elderly family members, have been found to be associated with financial risk protection in the literature (117,133) and are therefore included as controls.

In robustness checks, we source data from the World Health Organization (WHO) Global Health Expenditure Database (GHED) (134) as an alternative to IHME datasets: GHED external health financing and GHED public health financing are used instead of IHME DAH and government health expenditure, respectively.

3.3.2 Methods

Two main specifications are used to investigate the association between DAH and financial risk protection outcomes. In the first specification, we estimate the following country and year fixed effects regression, using linear regression for all three outcomes:

$$Y_{ith} = \alpha + \beta_1 DAH_{it} + \beta_2 \boldsymbol{X}_{it} + \beta_3 \boldsymbol{H}_{ith} + T_t + C_i + \varepsilon_{ith} \qquad [27]$$

where Y_{ith} refers to a financial risk protection outcome, measured in country i, at time t, for household h. DAH_{it} is DAH per capita, in PPP US\$, X is a vector of time-varying country-level controls listed in the previous section, H is a vector of time-varying household-level controls (average household age, size, and country and year-level income quintiles), T are time fixed effects and C are country fixed effects, controlling, respectively, for common shocks and time-invariant unobserved confounding at the country level. The variation being exploited by this model is that of DAH across countries and years, holding constant household characteristics and country contextual factors. For the (continuous) outcome OOP budget share, we employ a linear model, therefore β_1 can be interpreted as the effect driven by a 1US\$ increase in DAH per capita on the Y financial risk protection outcome, controlling for time-invariant country-level unobserved factors, shocks common to all countries, and holding constant X and H covariates. For binary outcomes, i.e., CHE10% and IMP190, we employ linear probability models, so β_1 can be interpreted as the change in probability driven by a 1US\$ increase in DAH per capita on the probability of a household incurring Y financial risk protection outcome, controlling for time-invariant country-level unobserved factors, shocks common to all countries, and holding constant X and H covariates.

A key concern is that DAH may be "crowding out" public health expenditure, which might bias our results. However, as public health expenditure is part of the control variables, the coefficient β_1 is to be interpreted as the association between an increase in DAH per capita of 1 US\$, and financial risk protection outcome Y, holding control variables, including public health expenditure, constant. This means that by controlling for public health expenditure, the issue of DAH "crowding out" public health expenditure is largely controlled for, similar to the approach used in a related study assessing DAH, public health financing and health outcomes (135). In robustness checks, we explore whether conclusions are maintained also when public health expenditure is removed from the list of control variables.

In the second specification, we use a pseudo-panel methodology (136,137). Pseudo-panels are widely used when genuine panel data is not available, but repeated cross-sectional datasets are. The intuition behind pseudo-panels is that cohorts, instead of individuals, are followed over time, presuming that households in the same cohort, with the same time-invariant characteristics (year of birth, and country of residence), have similar behaviours. To operationalize this concept, we group together households that are from the same country, and whose year of birth is within the same 10-year band (year bands: before 1940, 1940-1949, 1950-1959, and so on). Once all observations are grouped into these "country of residence and year of birth" cohorts, we compute cohort means for all variables, resulting in panel data (i.e., the pseudo-panel), where cohorts are followed over time. Instead of having variables by households and a household panel, we have variables by cohorts and a cohort panel dataset (i.e., in a cohort panel dataset, the variable $\bar{X}_{ct}$ is the average of variable X at time t, for households belonging to cohort c). Standard panel methods are then applied to the cohorts.

The resulting model can be written as (136):

$$\bar{Y}_{ct} = \alpha + \beta_1 \overline{DAH}_{ct} + \beta_2 \bar{\boldsymbol{X}}_{ct} + T_t + A_c + \varepsilon_{ct} \qquad [28]$$

Where c are the cohorts, t is time, and averages are taken at cohort-time level. This equation can be estimated using ordinary least squares (OLS). As noted in Verbeek (2008), including a true cohort fixed effect A_c is reasonable when there are enough observations per cohort, as is the case here. The literature suggests a 'rule-of-thumb' minimum of 100-200 subjects per cohort (138,139), and ideally more than 2000 subjects per cohort (136,138). Our dataset allows for cohorts with more than 2000 subjects per cohort.

A strictly linked point is the number of cohort-time observations: an increase in subjects per cohort to reach the suggested threshold may result in a decrease in cohort-time observations, which finally affects the precision of the pseudo-panel estimator. Again, our dataset provides sufficient cohort-time observations: we have a total of 917 cohorts (i.e., 131 countries times seven 10-year bands) and more than 3000 observations in the full sample. In the sub-sample that considers only countries with an above-average DAH, we have 456 cohorts and more than 1000 observations.

It should be noted that binary outcomes (e.g., catastrophic health expenditure at the 10% and 25%, and impoverishment effect) are transformed into continuous variables in the pseudo-panel framework, as they are averaged across households belonging to a cohort.

The cohorts should be defined using characteristics that assign each household to one cohort, and that do not change over time, so that each household remains in the same cohort throughout the study period. In line with previous work (136), we use the year of birth of the household (using a band of 10 years), measured as the difference between the year the survey is taken and the average age of the members of the household. Given the cross-country nature of our dataset, we also use country of residence as a cohort-defining characteristic, again following the literature building pseudo-panels using repeated cross-sectional datasets from the Demographic Health Surveys project (140,141).

In this paragraph, we discuss the implications of using the average age of the members of the household as cohort defining measure, instead of the average age of the head of household, which is the commonly used cohort-defining measure in the literature (136), but is unavailable in our dataset. A cohort defining characteristic should be as time-invariant as possible (in the period considered), and it should create groups of households with similar characteristics. In terms of grouping households with the same characteristics, we assume that most households in a given country would follow a "common lifecycle", composed of, as an example, the following steps: young households with a single element, then young couples with no children, then a couple with children added to the household, and children would finally leave the household forming new young single-element or young couple household(s), leaving the older couple alone. This assumption would not change if we were to use the average age of the members of the household or the age of the head of household to determine the cohort-defining year of birth.

With regards to being time-invariant, the birth year of the head of household can be time-invariant insofar as the head of household does not change household, originate a new household, or stop being the head of household (e.g., death, separation, or change of head of household within the existing members of the household). The average age of the members of the household has similar issues, but in addition, changes in other members of household (e.g., birth, or exit of another member of the household) may also affect it. Noting that in our sample the average household is formed by approximately 4 members, as a robustness check we exclude from the sample households with more than 4 members (we also use different thresholds of 5 and 6 members). This decreases the average household size to approximately 2.5 (when excluding all households beyond 4 members) and decreases the chances that using the average age of the members of the household is substantially more time-variant than the age of the head of household. Intuitively, we do this because the average household age is equal to the age of the head of household, when there is only one household member, and therefore the chances of discrepancy between the two measures is decreased substantially for smaller households.

3.3.3 Who benefits from DAH, and the role of context

DAH often explicitly or implicitly aspires to target the poor who experience limited access to healthcare services due to various barriers (e.g., affordability, geographical challenges), rather than those able to readily afford healthcare services. Household size and old-age dependency ratios (OADR) are other important factors affecting households' financial risk protection (117) (e.g., DAH may specifically target children).

As our dataset includes household-level data across countries, we are in a position to shed light on potential heterogeneity in the impact of DAH per capita, conditional on household-level characteristics, such as income quintile, OADR and household size. Thus, we can provide some detail on who (i.e., which kind of households) might benefit disproportionately from DAH in terms of financial risk protection.

This is operationalized by interacting DAH per capita in eq. [27] and [28] with household income quintile, household OADR and household size. This results in the following equations:

$$Y_{ith} = \alpha + \beta_1 DAH_{it} * H_{ith} + \beta_2 \boldsymbol{X}_{it} + \beta_3 \boldsymbol{H}_{ith} + \beta_4 DAH_{it} + T_t + C_i + \varepsilon_{ith} \quad [29]$$

$$\bar{Y}_{ct} = \alpha + \beta_1 \overline{DAH}_{ct} * \bar{H}_{ct} + \beta_2 \bar{\boldsymbol{X}}_{ct} + \beta_3 \bar{H}_{ct} + \beta_4 \overline{DAH}_{ct} + T_t + A_c + \varepsilon_{ct} \quad [30]$$

Where H is OADR, household size, and household expenditure quintiles, analysed in three separate models. For the cohort fixed effects models, H is averaged at the cohort-time level, as are all other variables. These augmented models would provide an understanding of whether DAH is more beneficial to poorer/wealthier households, to households with a higher/lower OADR, or to large/small households. We compute average marginal effects to assess the association of DAH with financial risk protection outcomes at different levels of household characteristics. For binary financial risk protection outcomes (CHE10%, IMP190) the reported coefficients can be interpreted as the change in probability of a household incurring outcome Y, driven by a marginal increase in DAH per capita at different quintiles of household characteristics H:

$$\left.\frac{\delta \Pr(Y)}{\delta DAH}\right|_{H=H_{1,\dots5}} \quad [31]$$

For the OOP budget share, and pseudo-panel models, the interpretation is that of a change in household or cohort level outcome Y, driven by a marginal increase in DAH per capita at different quintiles of household characteristics H:

$$\left.\frac{\delta Y}{\delta DAH}\right|_{H=H_{1,\dots5}}. \quad [32]$$

Several studies assessing the effect of (mostly public) health expenditures on health outcomes raise the possibility that context might act as an effect modifier (27,142,143). Similarly, factors such as the % of DAH channelled via government systems (i.e., % of DAH that is on-budget), income level (i.e., GDP per capita quintile), and DAH investment composition (i.e., the percentage of DAH devoted to health systems strengthening (HSS) programs, or to AIDS, tuberculosis, and malaria (ATM) programs, or to neonatal, child and maternal health (MNCH)) may act as an effect modifier in the relationship between DAH and financial risk protection outcomes. For example, more on-budget DAH may mean better coordination, and more funding on ATM may increase effect of DAH on financial risk protection in countries where OOP expenditures are mostly due to ATM. To explore this empirically, we interact DAH per capita in eq. [27] and [28] with country level contextual factors:

$$Y_{ith} = \alpha + \beta_1 DAH_{it} * CF_{it} + CF_{it} + DAH_{it} + \beta_2 \boldsymbol{X}_{it} + \beta_3 \boldsymbol{H}_{ith} + T_t + C_i + \varepsilon_{ith} \quad [33]$$

$$\bar{Y}_{ct} = \alpha + \beta_1 \overline{DAH}_{ct} * \overline{CF}_{ct} + \overline{DAH}_{ct} + \overline{CF}_{ct} + \beta_2 \bar{\boldsymbol{X}}_{ct} + T_t + A_c + \varepsilon_{ct} \quad [34]$$

where CF is a country contextual factor, as listed in the previous paragraph. A different model is fitted for each contextual factor, as we do for household characteristics. We note that data on the percentage of DAH devoted to HSS, ATM and MNCH is from the IHME "Development assistance for health database 1990-2020" (132) dataset, while on-budget DAH data is from WHO GHED.

For all the augmented models, Stata's *margins* command is used to show how the DAH per capita association varies at different levels of H and CF. For all analyses, Stata 17, population weights, and robust standard errors clustered at the country level (cohort level for the cohort fixed effects models), are used.

3.4 Results

In this section, we present descriptive statistics, country and year fixed effects regressions results, pseudo-panel models results, and robustness tests. We also comment on the consistency of results across models and tests. Full results and marginal effects plots are presented in Appendix C-4.

3.4.1 Descriptive statistics

Table 3-3 presents descriptive statistics for our outcomes of interest, the main independent variable (DAH per capita), household characteristics (household expenditure, household size, household age and OADR) and contextual factors at the country level (GDP per capita, % of DAH on-budget, and % of DAH devoted to HSS, MNCH or ATM). Countries with DAH per capita above average show a lower GDP per capita, larger household sizes, and lower average household age, compared to all countries in the sample. Further, in countries with DAH per capita above average, DAH per capita is on average at 47% of government health expenditure and at 11% of total health expenditure. After including all control variables, the final sample size is 1.7m observations, across 65 countries (see Appendix C-2 for more details on the sample construction).

Table 3-3. Descriptive statistics (2000-2016 averages)

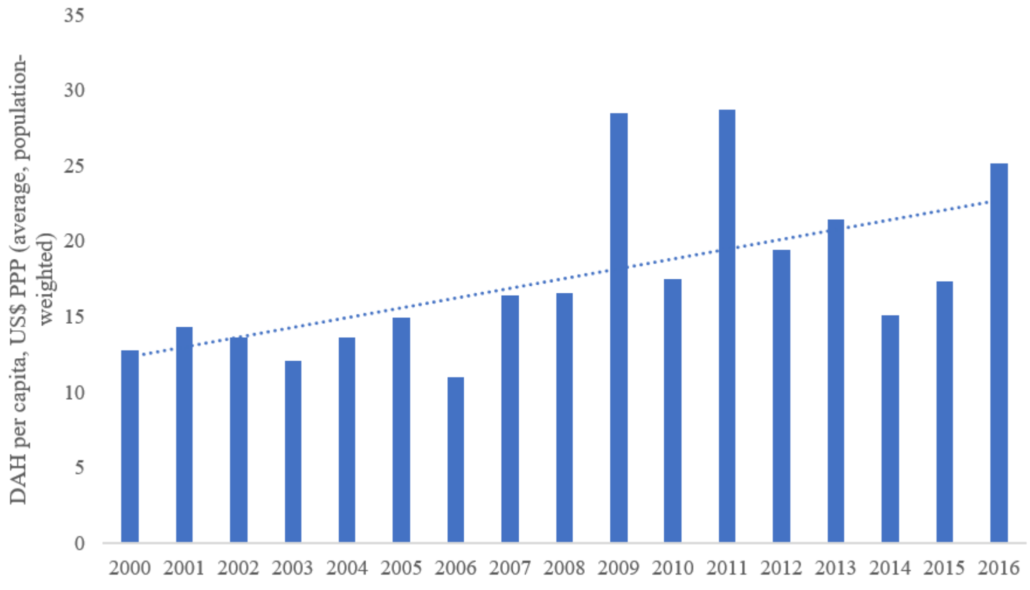
	Level	All countries	Countries with DAH per capita above average
Catastrophic health expenditure, 10% (% of population)	HH	6.9%	7.9%
Impoverishment due to health expenditures, 1.90US$ poverty line (% population pushed into impoverishment)	HH	0.8%	1.0%
OOP health expenditure budget share (% of total expenditure)	HH	2.9%	3.3%
OOP as % of THE	Country	38.7%	44.8%
DAH per capita (PPP, US$)	Country	6.46	17.4
DAH per capita as % of THE	Country	4.3%	11.4%
DAH per capita as % of government health expenditure	Country	20.3%	47.0%
GDP per capita (PPP)	Country	15387	5602
OADR	HH	33%	33.6%
Average household age	HH	31.2	28.1
Household size	HH	4.8	5.6
Household expenditure (US$, per day per capita)	HH	9.7	3.4
% of DAH that is on budget	Country	37.4%	41.6%
% of DAH that is HSS and system-wide approaches (SWAp)	Country	20.0%	17.5%
% of DAH that is maternal, neonatal, child health (MNCH)	Country	25.4%	28.3%
% of DAH that is AIDS, TB, Malaria	Country	28.3%	35.7%
Countries	Country	131	65
Observations	HH	9.7 million	1.7 million

Source: author elaboration based on 504 household surveys, IHME DAH Database (144) and World Bank World Development Indicators (51). Sampling weights used. CHE10%, impoverishment at the 1.90US$ poverty line are binary variables at the household level.

In this paper, we exploit the variation in DAH per capita across countries to measure the association between DAH per capita and financial risk protection outcomes. For this reason, it is important to show how DAH per capita varies over time, for countries that have a DAH per capita that is above the sample average. Figure 3.5 shows that DAH per capita has generally been growing between 2000 and 2016.

In the period 2000-2016 DAH per capita increased quite steadily across all existing country-year observations (see Fig 1, (123)). In our database we do not see the same trend. We observe a general growth with highs and lows because we observe DAH per capita only for country-year observations where a household survey, and therefore financial risk protection data, is available. Hence, the trend seen in Figure 3.5 is driven by DAH trends and missing country-year observations due to missing financial risk protection data. In other words, in years 2009 and 2011 there are more countries which have generally higher DAH per capita. This would be a problem if governments' choice of completing a household survey in a given year was systematically linked to DAH per capita levels and/or financial risk protection levels. We do not believe this is the case, for at least two reasons. Household surveys typically focus on poverty measurements and cover all household consumption categories as well as all sectors (health, education, labour, agriculture, etc.), therefore selection bias induced by financial risk protection *in health* is unlikely. For the same reason, we also believe it is unlikely that completion of a household survey is systematically linked to DAH amounts. In addition, in all our models we include country fixed-effects: averages *across* countries therefore are expected to have only a marginal effects on our results, which are driven by DAH trends *within* each country.(123)

Figure 3.5. DAH per capita, countries with DAH per capita above average, 2000-2016



Source: author elaboration based on IHME DAH Database (144)

3.4.2 Country and year fixed effects

This section shows the results of the main country and year fixed effects regressions without interactions (eq. [27]), regressions interacting DAH per capita with household characteristics (eq. [29]) and regressions interacting DAH per capita with country contextual factors (eq. [33]).

3.4.2.1 Main specification

Table 3-4, columns (1), (2), and (3) present the association of DAH with financial risk protection outcomes estimated via country and year fixed effects regressions (eq. [27]). In the country and year fixed effects models, there is no statistically significant association between DAH per capita and CHE10%, impoverishment using a 1.90US$ poverty line, and OOP budget share, in countries that are above average recipients of DAH per capita.

Table 3-4. Results of the main specification, country and year fixed effects

	(1) CHE10%	(2) IMP190$	(3) OOP budget share
Mean of dep. variable	7.9%	1.0%	3.3%
DAH per capita	0.02	0.01	0.0
	(0.04)	(0.01)	(0.00)
Country FE	YES	YES	YES
Year FE	YES	YES	YES
Cohort FE	NO	NO	NO
Adjusted R^2	0.0497	0.0135	0.0694
Observations	1.7m	1.7m	1.7m
Number of countries	65	65	65

Source: author, based on analyses and datasets described in the methods section, eq. [1] for columns (1), (2), (3). Notes: For columns (1), and (2), the outcome is binary and therefore the coefficient is to be interpreted as the change (in percentage points) in probability of a household incurring CHE10% or IMP190 driven by 1 US$ DAH per capita increase. Linear regressions are used in column (3), the coefficient is therefore interpreted as the change in OOP budget share driven by a 1 US$ DAH per capita increase, keeping constant all control variables mentioned in the methods section. SE are shown in parentheses, clustered at country level for columns (1), (2), and (3)). For columns (1) and (2), pseudo R^2 are reported, while for column (3) adjusted R^2 is reported. p<0.1*, p<0.05**, p<0.001***.

3.4.2.2 Interacting DAH with household characteristics

In the models that interact DAH per capita with household characteristics (results shown in Table 3-5, and Figure 3.6), we find that DAH per capita is negatively associated, at the 10% level, with IMP190 for the poorest income quintile (probability of IMP190: -0.05 percentage points, p<0.1) (see Table 3-5, column 1-3, and Figure 3.6). Here, a “negative” (“positive”) association indicates an improvement (deterioration) – e.g., DAH reduces impoverishment. For CHE10% and OOP budget share, we find no significant association. When DAH per capita is interacted with OADR and household size, there is again no significant association between DAH per capita and financial risk protection outcomes.

3.4.2.3 Interacting DAH with country-level contextual factors

As for the augmented models that interact DAH per capita with country-level contextual factors (Table 3-6 and Figure 3.6), we find that DAH per capita is positively associated with all outcomes, when GDP per capita is high (probability of CHE10% +0.24 percentage points p<0.05, probability of IMP190 +0.04 percentage points, p<0.05, OOP budget share +0.06 percentage points, p<0.01). As a reminder, GDP per capita PPP is around 19,000 US$ in the highest GDP group, comparable with the GDP per capita of upper middle-income countries.

When considering the percentage of DAH per capita that is on-budget, DAH per capita is negatively associated with CHE10% (probability of CHE10%: -0.68 percentage points, p<0.05), and with OOP budget share (-0.17 percentage points, $p<0.05$), when there is a high percentage of DAH that is on budget. When the percentage of DAH that is on budget is low, an increase in DAH is positively associated with IMP190 (probability of IMP190 +0.04 percentage points, $p<0.05$) (see Table 3-5, column 4-6).

Finally, in terms of the composition of DAH, we find that DAH per capita is positively associated with IMP190 (probability of impoverishment +0.03 and +0.05, $p<0.05$), when the percentage of DAH per capita devoted to HSS is in the low and high tercile, respectively. DAH per capita is positively associated with CHE10% and OOP budget share (probability of CHE10%: +0.26 and +0.06 percentage points, $p<0.05$, respectively), when there is a low proportion of DAH devoted to MNCH. A positive association is found between DAH and impoverishment when there is a high proportion of DAH devoted to MNCH (probability of IMP190 +0.02 percentage points, $p<0.05$). We find no significant association between DAH per capita and financial risk protection outcomes at different levels of ATM investments.

Table 3-5. Estimates from country and year fixed effects models interacting DAH per capita with household characteristics

	(1) CHE10%	(2) IMP190	(3) OOP bud. share
Interaction var. →	HH expenditure	HH expenditure	HH expenditure
Mean of dependent variable	7.9%	1.0%	3.3%
Levels of interaction var. ↓			
1 (lowest quintile)	0.02	-0.05*	0.00
2	0.01	0.02	-0.00
3	0.02	0.06	0.00
4	0.02	0.02	0.00
5 (highest quintile)	0.03	0	0.01

	(4) CHE10%	(5) IMP190	(6) OOP bud. share	(7) CHE10%	(8) IMP190	(9) OOP bud. share
Interaction var. →	HH Size	HH Size	HH Size	HH OADR	HH OADR	HH OADR
Mean of dependent variable	7.9%	1.0%	3.3%	7.9%	1.0%	3.3%
Levels of interaction var. ↓						
1 (lowest tercile)	0.01	0.01	0.00	0.03	0.01	0.01
2	0.03	0.01	0.00	-0.00	0.01	-0.00
3 (highest tercile)	0.02	0.00	0.00	-0.06	0.01	-0.01

Source: author elaboration, based on datasets cited in the methods section and eq. [29] for HH expenditure as interacted variable, and eq. [33] for all country-level contextual factors. Notes: for CHE10% and Impoverishment at the 1.90US$ poverty line (IMP190), the numbers in the table represent the percentage point increase (decrease) in probability that a household incurs CHE10% or IMP190, respectively, driven by an increase in 1US$ in DAH per capita at a given quintile or tercile of the interacted variable (shown in columns). For OOP budget share, the numbers represent the percentage point increase (decrease) in household OOP budget share driven by an increase in 1US$ in DAH per capita. Except for HH expenditure, for which quintiles have been used, because they are the traditional household income breakdown, we break interaction variables into terciles, to allow for an easier identification of "high", "medium" and "low" level of the interaction variable. Coefficients interpretation is mentioned in the methods section. Robust standard errors, clustered at the country level, have been used. p<0.1*, p<0.05**, p<0.001***.

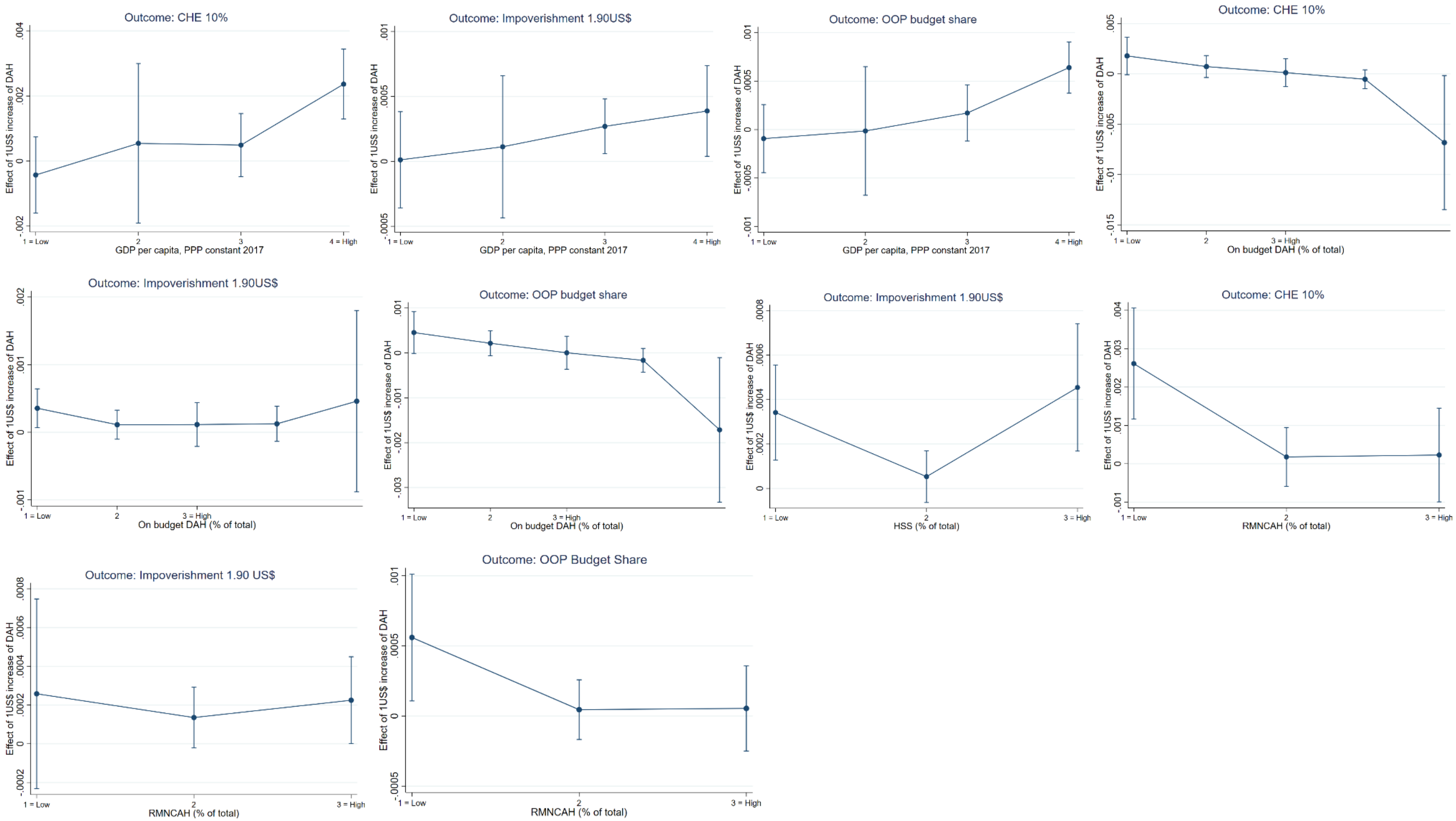
Table 3-6. Estimates from country and year fixed effects models interacting DAH per capita with country level contextual factors

	(1) CHE10%	(2) IMP190	(3) OOP bud. share	(4) CHE10%	(5) IMP190	(6) OOP bud. share
Interaction var. →	GDP per capita	GDP per capita	GDP per capita	DAH % on-budget	DAH % on-budget	DAH % on-budget
Mean of dependent variable	7.9%	1.0%	3.3%	7.9%	1.0%	3.3%
Levels of interaction var. ↓						
1 (lowest quintile)	-0.04	0.00	-0.01	0.18*	0.04**	0.05*
2	0.05	0.01	-0.00	0.07	0.01	0.02
3	0.05	0.03**	0.01	0.01	0.01	0
4	0.24***	0.04**	0.06***	-0.05	0.01	-0.02
5 (highest quintile)	n.e.	n.e.	n.e.	-0.68**	0.05	-0.17**

	(7) CHE10%	(8) IMP190	(9) OOP bud. share	(10) CHE10%	(11) IMP190	(12) OOP bud. share	(13) CHE10%	(14) IMP190	(15) OOP bud. share
Interaction var. →	DAH % HSS	DAH % HSS	DAH % HSS	DAH % ATM	DAH % ATM	DAH % ATM	DAH % MNCH	DAH % MNCH	DAH % MNCH
Mean of dependent variable	7.9%	1.0%	3.3%	7.9%	1.0%	3.3%	7.9%	1.0%	3.3%
Levels of interaction var. ↓									
1 (lowest tercile)	0.13*	0.03***	0.03	0.73	-0.08	0.15	0.26***	0.03	0.06**
2	0.02	0.01	0.00	-0.12*	0.03	-0.03	0.02	0.01*	0.00
3 (highest tercile)	0.06	0.05***	0.02	0.04	0.01	0.01	0.02	0.02**	0.01

Source: author elaboration, based on datasets cited in the methods section and eq. [29] for HH expenditure as interacted variable, and eq. [33] for all country-level contextual factors. Notes: for CHE10% and Impoverishment at the 1.90US$ poverty line (IMP190), the numbers in the table represent the percentage point increase (decrease) in probability that a household incurs CHE10% or IMP190, respectively, driven by an increase in 1US$ in DAH per capita at a given tercile (shown in rows) of the interacted variable (shown in columns). For OOP budget share, the numbers represent the percentage point increase (decrease) in household OOP budget share driven by an increase in 1US$ in DAH per capita. Robust standard errors, clustered at the country level, have been used. $p<0.1$*, $p<0.05$**, $p<0.001$***. For GDP per capita, n.e. stands for 'not estimable': the fifth quintile is empty, as there are no high GDP per capita countries that have also received above average DAH per capita investments.

Figure 3.6. Plots of marginal effects from Table 3-5 and Table 3-6, with at least one marginal effect significant at the p<0.05 level



3.4.3 Pseudo-panel results

This section shows the results of the pseudo-panel regressions (i.e., cohort and year fixed effects regressions) without interactions (eq. [28]), pseudo-panel regressions interacting DAH per capita with household characteristics (eq. [30]) and pseudo-panel regressions interacting DAH per capita with country contextual factors (eq. [34]).

3.4.3.1 Main pseudo-panel specification

In the cohort fixed effects model (Table 3-7, columns (1), (2), and (3)) – with cohorts (i.e., groups of households) as the unit of study – there is no significant association, at the 5% level, between DAH per capita and financial risk protection outcomes in countries that are above average recipients of DAH per capita.

Table 3-7. Results of the main specification, pseudo-panel (cohort and year) fixed effects

Dep. variable	(1) CHE10% Cohort FE	(2) IMP190$ Cohort FE	(3) OOP budget share Cohort FE
Dependent variable mean	8.1%	1.1%	3.3%
DAH per capita	-0.02	0.01*	-0.01
	(0.0003)	(0.0001)	(0.0001)
Country FE	NO	NO	NO
Year FE	YES	YES	YES
Cohort FE	YES	YES	YES
Adjusted- R^2	0.448	0.309	0.629
Observations	1038	1038	1038
Number of countries (cohorts)	65 (436)	65 (436)	65 (436)

Source: author, based on analyses and datasets described in the methods section, eq. [28] for columns (1), (2), (3). Notes: linear regressions are used in all columns, the coefficient is therefore interpreted as the change in dependent variable driven by a 1 US$ DAH per capita increase, keeping constant all control variables mentioned in the methods section, and at cohort level. SE are shown in parentheses, clustered at cohort level. Adjusted R^2 are reported. p<0.1*, p<0.05**, p<0.001***.

3.4.3.2 Interacting DAH with household characteristics

In the augmented models in which we interact DAH per capita with household characteristics (Table 3-8, and full marginal effects results in Appendix C-5), DAH is negatively associated with CHE10% (-0.12 percentage points, p<0.01), and OOP budget share for the lowest income quintile (-0.03 percentage points, p<0.01). Similar negative associations are found between DAH per capita and CHE10% (-0.13 percentage points, p<0.05), OOP budget share (-0.03 percentage points, p<0.01), in the two lowest OADR quintiles. As for household size, DAH per capita is negatively associated with CHE10% for cohorts in the central and higher household size quintiles (-0.09 percentage points, p<0.05, in both cases).

3.4.3.3 Interacting DAH with country level contextual factors

The models interacting DAH per capita with country level contextual factors are presented in Table 3-9. In the case of GDP per capita, DAH per capita is negatively associated with CHE10% (-0.11 percentage points, $p<0.01$) and OOP budget share (-0.03 percentage points, $p<0.01$) when GDP per capita is in the lowest, or second lowest, quintile.

When considering the percentage of DAH per capita that is on budget, DAH per capita is negatively associated with CHE10% (-0.17 percentage points, $p<0.01$), and OOP budget share (-0.04 percentage points, $p<0.01$) when DAH is largely on-budget.

Finally, with regards to the share of DAH devoted to HSS expenditures, DAH is negatively associated with CHE10% (-0.09 percentage points, $p<0.01$) and OOP budget share (-0.02 percentage points, $p<0.01$) when the percentage of DAH devoted to HSS is in the central tercile, while there is no association with IMP190. DAH is also negatively associated with CHE10% (-0.13 percentage points, $p<0.01$) in the central tercile of ATM expenditures as % of DAH, and positively associated with IMP190 (+0.02 percentage points, $p<0.01$) in the top tercile of percentage of DAH devoted to MNCH.

Table 3-8. Estimates from pseudo-panel models interacting DAH per capita with household characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	CHE10%	IMP190	OOP bud. share	CHE10%	IMP190	OOP bud. share	CHE10%	IMP190	OOP bud. share
Interaction var. →	HH expenditure	HH expenditure	HH expenditure	HH OADR	HH OADR	HH OADR	HH Size	HH Size	HH Size
Mean of dependent variable	7.9%	1.0%	3.3%	7.9%	1.0%	3.3%	7.9%	1.0%	3.3%
Levels of interaction var. ↓									
1 (lowest quintile)	-0.12***	-0.01	-0.03**	-0.13**	-0.01	-0.03***	0.05	0.02*	0.02
2	-0.13***	-0.02	-0.03***	-0.09*	0.00	-0.02*	-0.11	-0.01	-0.02
3	-0.06*	0.00	-0.02**	-0.02	0.01	-0.00	-0.09**	-0.01	-0.03**
4	-0.07*	0.00	-0.01	-0.04	0.01	0.00	-0.08*	0.01	-0.02*
5 (highest quintile)	-0.02	0.01	-0.00	-0.00	0.00	0.01	-0.09**	-0.00	-0.02*

Source: author elaboration, based on datasets cited in the methods section, eq. [30]. Notes: for all outcomes, the number in the tables represent the increase (decrease) in cohort-level outcome, driven by an increase in 1US$ in DAH per capita at a given quintile (shown in rows) of the interacted variable (shown in columns). Robust standard errors, clustered at the cohort level, have been used. p<0.1*, p<0.05**, p<0.001***.

Table 3-9. Estimates from pseudo-panel models interacting DAH per capita with country-level contextual factors

Interaction var. →	(1) CHE10% GDP per capita	(2) IMP190 GDP per capita	(3) OOP bud. share GDP per capita	(4) CHE10% DAH % on-budget	(5) IMP190 DAH % on-budget	(6) OOP bud. share DAH % on-budget
Mean of dep. variable	7.9%	1.0%	3.3%	7.9%	1.0%	3.3%
Levels of interaction var. ↓						
1 (lowest quintile)	-0.11***	-0.00	-0.03***	-0.03	-0.01	-0.00
2	-0.14***	-0.01	-0.04***	0.05	0.01	0.02*
3	0.06	0.00	0.02	-0.01	0.00	-0.00
4	-0.14	0.03*	-0.03	-0.17***	-0.00	-0.04***
5 (highest quintile)	n.e.	n.e.	n.e.	-0.17***	-0.00	-0.04***

Interaction var. →	(7) CHE10% DAH % HSS	(8) IMP190 DAH % HSS	(9) OOP bud. share DAH % HSS	(10) CHE10% DAH % ATM	(11) IMP190 DAH % ATM	(12) OOP bud. share DAH % ATM	(13) CHE10% DAH % MNCH	(14) IMP190 DAH % MNCH	(15) OOP bud. share DAH % MNCH
Mean of dependent variable	7.9%	1.0%	3.3%	7.9%	1.0%	3.3%	7.9%	1.0%	3.3%
Levels of interaction var. ↓									
1 (lowest tercile)	-0.01	0.01	0.01	0.17*	0.00	0.03	-0.08	-0.00	-0.03
2	-0.09***	-0.00	-0.02***	-0.13***	0.00	-0.02	-0.04*	0.00	-0.01
3 (highest tercile)	-0.03	0.01	-0.00	-0.03	0.00	-0.00	-0.02	0.02**	-0.01

Source: author elaboration, based on datasets cited in the methods section, eq. [34]. Notes: for all outcomes, the number in the tables represent the increase (decrease) in cohort-level outcome, driven by an increase in 1US$ in DAH per capita at a given quintile (shown in rows) of the interacted variable (shown in columns). Robust standard errors, clustered at the cohort level, have been used. p<0.1*, p<0.05**, p<0.001***. For GDP per capita, n.e. stands for not estimable: the fifth quintile is empty as there are no high GDP per capita countries that have also received above average DAH per capita investments.

3.4.4 Robustness tests

We undertook several robustness tests on the main specification (see Appendix C-3). First, one may argue that DAH per capita should be log-transformed, in line with some other studies that used DAH as the main independent variable (135,145). Second, using countries with DAH per capita higher than average, when the sample average is approximately 6 US$ per capita per year, might be considered insufficient. Therefore, regressions are re-run using DAH per capita higher than 9 US$ per capita per year (corresponding to the 80th percentile of DAH per capita in the full sample). Third, we use WHO GHED instead of IHME data as the source for the DAH per capita data. In theory, the two datasets should provide the same data. However, they are not perfectly identical (146), and therefore it is important to explore possible differences driven by using WHO GHED data. Fourth, it has been argued that when using household income as a control variable, OOP health expenditure must be subtracted from the total household expenditures, to better capture the household's socioeconomic status (147). The measure "household expenditure net of OOP health expenditures" is therefore used as control variable instead of total household expenditures. Fifth, one might expect a lagged effect of DAH per capita onto our outcomes of interest. We therefore lag by one year the DAH per capita independent variable. Sixth, we use a sample of low and lower middle-income countries (5.2 million observations, 64 countries), a sample of low, lower middle and upper middle-income countries (6.2 million observations, 85 countries), and a sample of all countries for which controls are available (7 million observations, 100 countries), instead of "countries with DAH above average". We note that low and lower-middle income countries, in our sample, receive 85% of total DAH financing; upper middle-income countries receive 15% of total DAH financing, therefore low-, lower middle-, and upper middle-income countries cover 100% of total DAH financing. Seventh, we use a logistic regression model instead of a linear probability model for the binary outcomes CHE10% and IMP190. We note that logistic regressions were not used as our main specification due to the incidental parameter problem (148) related to logistic regressions and fixed effects. Eighth, because it has been argued that DAH may crowd out government health expenditure (135,149), we run the same model without controlling for domestic government health expenditure. Finally, we run pseudo-panels using a sample using only smaller household sizes, as described in the methods section.

Because CHE10% and IMP190 are tracked as part of the SDG 3.8.2, using different thresholds and poverty lines (CHE at 10% and 25%, impoverishment at the 1.90US$ and 3.20US$ poverty line), both the country-year fixed effects and the cohort fixed effects regressions are re-run using the higher threshold (CHE 25%) and the higher poverty line (3.20 US$) that were not used as outcomes in our main specification. No substantial changes to our main findings are obtained.

In only two cases (out of ten different robustness checks), our main conclusion is not fully confirmed. In those two cases, DAH per capita is not significantly associated with *most* financial risk protection outcomes. The first case is when we use the log of DAH per capita, where we find no association between CHE10%, OOP budget share and DAH per capita. However, we find that (logged) DAH per capita increases the probability of IMP190 (an increase in 1% in DAH per capita drives an increase in 0.005 percentage points, $p<0.05$). We note tough that in this robustness test, DAH per capita is still not associated with CHE10% and OOP budget share. Moreover, the fact that more DAH per capita worsens IMP190 indicates that this result may be driven by a decrease in forgone healthcare and an increase in OOP health expenditures, as described in Section 3.2. Finally, it is worth emphasising that, although the coefficient is statistically different from zero at the 5% level, its magnitude is particularly low and very close to zero.

The second case of slight departure from our main results is when increasing the sample, i.e., when we consider low, lower middle and upper middle-income countries or all countries, we find that DAH per capita worsens IMP190. First, we note that we find no association between DAH and financial risk protection outcomes in the low and lower middle-income sub-group, which covers 85% of all DAH financing in our sample. An association is found only when upper middle-income countries, representing 15% of total DAH expenditures, are added to the sample: this suggests that a possible association is likely driven by upper middle-income countries, confirming the results of the interaction between DAH per capita and GDP per capita in Table 3-6. Upper middle-income countries are characterised by lower level of DAH per capita (5.2 US$ per capita) vs. other DAH recipient countries, higher incomes, and by higher OOP health expenditures per capita than low- and lower middle-income countries. It is therefore more likely that DAH per capita is not sufficient to improve financial risk protection, and/or it increases services coverage and ultimately increase OOP expenditures, as described in the conceptual framework (Section 3.2). Finally, we recall that even in this case, DAH per capita is not significantly associated with most financial risk protection outcomes (i.e., an association is found for IMP190, but not for CHE10% and OOP budget share).

3.4.5 Consistency of findings across models

As we estimate country and year fixed effects models, pseudo-panel models, and complete several robustness tests, we comment on the three results that are consistent across these different methodologies and tests. First, we consistently find that DAH per capita (i.e., not interacted with any other variable) is, on average, not statistically significantly associated (5% level) with financial risk protection outcomes. Second, DAH per capita is negatively associated with at least one financial risk protection outcome for households in the lowest income quintile. In the country and year fixed effects model, it is IMP190, while in the pseudo-panel models we find an association between DAH per capita and both CHE10% and OOP budget share. Third, DAH per capita is negatively associated with most financial risk protection outcomes when there is a high percentage of DAH per capita that is on-budget.

Other results tend to be more mixed. For household characteristics, in the pseudo-panel models, DAH per capita is negatively associated with financial risk protection outcomes when the old age dependency ratio is low, and when household size is large. However, the same is not true in the country and year fixed effects model.

As for country contextual factors, in the pseudo-panel models, DAH per capita is negatively associated with financial risk protection outcomes at lower levels of GDP per capita, and at an average level of DAH percentage devoted to ATM or to health systems strengthening. However, also in these cases, the results are ambiguous as they are not consistent across pseudo-panel and country and year fixed effects models.

3.5 Discussion

UHC has become a widely recognized policy objective for many governments and international organisations worldwide (5–7). It is measured within the UN SDG framework, using – among others – financial risk protection indicators. Many bilateral and multilateral donors have committed to the same ambition for the countries they are trying to support via DAH, which is a substantial part of total health expenditures in LICs (5) and has been growing substantially in the past 20 years, in both value (145) and number of entities providing it (128). However, empirical evidence on the extent to which DAH has (or has not) been effective in promoting the UHC financial risk protection objective does hitherto not appear to have been presented. This study has sought to begin to fill this gap by exploring the association between DAH and financial risk protection outcomes, as well as to assess in how far household characteristics and contextual factors at the country level may affect this association.

While our main results cannot confirm a significant overall association between DAH and measures of financial risk protection, we do find support for a beneficial ‘effect’ (though an association, and therefore not necessarily in a causal sense) when disaggregating the results by certain within- and between-country factors. For instance, DAH was found to improve financial risk protection for the poorest quintile within countries, and when a higher share of DAH is channelled via government systems (i.e., when it is “on-budget”). Therefore, donors interested in using DAH to promote financial risk protection in target countries might be well-advised to take into account relevant country contextual factors and household characteristics.

Regarding the association between DAH per capita and financial risk protection for the lowest household income quintile, this might be driven by at least two factors. First, while we cannot formally assess whether DAH is targeted towards poorer households due to data limitations, a possible explanation of this result is that DAH is in fact targeting poorer households, and that such targeting is resulting in DAH improving financial risk protection for those households. Equity is a widely accepted goal by governments (3) and global health actors (e.g., WHO (3), Global Fund to fight AIDS, tuberculosis and malaria (150), GAVI (151), and others), hence it may be plausible that DAH has targeted poorer households, and that such households might have benefited more than proportionally from DAH. Second, the amount of OOP health expenditures that needs to be substituted by DAH funding to improve financial risk protection (in absolute terms, i.e., in US$) is lower for households in the lower income quintile than in the highest income quintiles. In other words, if DAH was not targeted but distributed roughly uniformly across the income quintiles, we would expect DAH to improve financial risk protection more among poorer households, rather than among richer households.

As for the seemingly beneficial role of on-budget DAH, this may be due to the associated enhanced recipient country governments ownership, with the countries then better able to coordinate those funds, which in turn might translate into lower transaction costs, lower inefficiencies, and additional resources to deliver services reaching patients (129,152). Governments might also have lower set-up costs than programs delivered by non-profit institutions serving households (NPISH) that have fixed set-up costs to initiate health programs, and possibly more direct accountability towards their citizens via elections, compared to external or foreign entities (153). In addition, it might be argued that off-budget DAH, being less coordinated, is more likely to fund services that would have been forgone, or that are not financed comprehensively, thus resulting in a higher chance of increasing OOP health expenditures to access them. In addition, policies that address financial risk protection directly (e.g., introduction of health insurance schemes) are often government policies that donors can support via on-budget support, rather than initiate or support via off-budget support. Finally, donors might have objectives that differ from government objectives, and outside of financial risk protection (e.g., increasing service coverage). To some extent, this finding is in line with other studies in the literature that confirmed an association between government health expenditure and financial risk protection outcomes but not between the percentage of total health expenditure channelled via NPISH and financial risk protection outcomes (53,126). This may be because NPISH are more likely to be financed by off-budget DAH, except when governments use DAH to purchase services from NPISH. However, in another cross-country panel empirical analysis, Afridi and Ventelou found that channelling more resources via NPISH has a beneficial effect on *health* outcomes as NPISH may face less political constraints and might target the poor better (154). Further quantitative and qualitative research, especially at the country level, might explore the different mechanisms of effect implied by these broad cross-country studies, including the potentially different effects on health and financial risk protection outcomes.

Reliance on on-budget DAH is not without risk. Risks might be related to the quality of PFM systems, government corruption, or government political interests differing from the population best interests. Further research could explore the role of factors like governance, stewardship, corruption, and PFM quality in the relationship between on-budget DAH and financial risk protection outcomes.

To ease the concerns of providers of DAH in terms of country governments misusing DAH funds, providers of DAH could base their DAH allocation choices on the quality of public financial management (PFM) systems of recipient country governments, measured via PFM assessments (e.g., public expenditure and financial accountability (PEFA) assessments). To date, this approach does not appear to have been adopted, as the percentage of DAH channelled via government financial systems is independent from the quality of those same government financial systems (152). We note that PEFA scores data has not been used in our analysis because the number of existing PEFA assessments was far from sufficient to complete such analyses: as more PEFA assessments and household surveys become available, further research may explore the relationship between on-budget DAH, quality of PFM systems, and financial risk protection outcomes.

When we expand our sample to include UMICs, we find that DAH has a positive (i.e., worsening) association with IMP190 only, while no association is found for CHE10 or the OOP budget share. We advance hypotheses on why the association between DAH and CHE10 or OOP budget share might differ from the association between DAH and IMP190. One reason for this might be that IMP190 is considered to be more ‘responsive’ to changes in OOP for populations right above the poverty line. Another reason is that populations closer to the poverty line might be more prone to forgo healthcare due to affordability issues, and therefore might be more affected by the issue of DAH increasing OOP health expenditures by increasing services coverage. Taken together, this would suggest that DAH is providing services that were previously forgone to populations close to the poverty line, and thereby increasing their OOP health expenditures, more than in other groups. The difference in the association across IMP190, CHE10 and OOP budget share appears to be particularly relevant for UMICs, suggesting that the low amount of DAH per capita typical of UMICs could exacerbate this issue. It should also be noted this is not necessarily disproving the association of DAH with financial risk protection with households in the lower income quintile: this is because households in the lower income quintile (defined at the country level) and households below or close to the 1.90 US$ poverty line (defined globally) might be different. Further research might explore better the exact reasons why different measures, which assess the same financial risk protection concept, would yield different results.

Other results are more mixed. Only in our pseudo-panel models, we find evidence that DAH per capita is negatively associated with financial risk protection outcomes when OADR is low, and when household size is large. Assuming that larger household sizes are driven by the presence of more children, this would suggest that DAH is currently focused on younger populations (kids, mothers) and that an extension of DAH efforts towards the need of the elderly population might be considered (117). In pseudo-panel models, DAH per capita was also negatively associated with financial risk protection outcomes at lower levels of GDP per capita, suggesting again successful intentional targeting of DAH efforts towards low-income countries, and at average level of percentage of DAH devoted to ATM. However, these findings are currently less robust, as they are not consistent across the methodologies used in this study.

In interpreting the findings, it is important to be mindful of the limitations of the presented analysis. First, this study analyses the *association* between DAH and financial risk protection. While we control for several observable variables, it is possible that unobservable confounders and reverse causality would affect this association. For example, bias would arise, if countries with a low financial risk protection systematically attracted more DAH. Second, we use total expenditure as the indicator for household living standards and as the denominator for our financial risk protection outcomes measures: CHE10% and OOP budget share. While consumption expenditure is a widely used measure, there is no perfect measure for ability to pay (53), and for other factors (e.g., wealth) that might substantially affect the results. Third, there is no data on DAH broken down to the household level, as the available DAH data is at country level. This means that while we can test – as we did – whether DAH association with financial risk protection is modified by households' characteristics, we cannot test whether DAH was specifically targeting certain households. Fourth, as noted in Section 2, increased service coverage, a key intermediate objective of increased DAH, might result in a worsening of financial risk protection, as measured here. As noted in the literature (5,108), a higher service coverage may result in higher OOP expenditures, if the additional services provided were previously forgone, and may ultimately worsen financial risk protection as measured by CHE10%, impoverishment due to health expenditures, or the OOP budget share. This is beyond the scope of this paper and further research could shed light on how financial risk protection, OOP expenditures and service coverage interact at either the within-country level or across countries. Related to the previous point, forgone healthcare utilization due to limited access or lack of affordability is not addressed in this paper, as such data within and across countries is not available (155): none of the financial risk protection measures used in this paper take into consideration households that have zero (or very low) OOP health expenditures not because they do not need any health service but because of access and/or affordability issues (108,112,121).

While bearing in mind these needs for further research and caveats, our findings underline the importance of planning DAH attentively for it to improve financial risk protection, in particular by considering more on-budget financing and prioritization of lower income households.

Chapter 4: The redistributive effect of the public health system: the case of Sierra Leone

ABSTRACT

INTRODUCTION: Universal health coverage (UHC), equity and reduction of income inequalities are key objectives for the Sierra Leone government. While there is evidence that investing in health systems may drive economic growth, it is less clear whether investing in health systems reduces income inequality. Therefore, a crucial issue is to what extent the Sierra Leone public healthcare system reduces income inequality, and finances and provides healthcare services equitably.

METHODS: We use data from the Sierra Leone Integrated Household Survey 2018 to complete a financing and benefit incidence analysis of the Sierra Leone public healthcare system. We extend these analyses by assessing the redistributive effect of the public healthcare system (i.e., fiscal incidence analysis). We compute the redistributive effect as the change in Gini index induced by the payments for, and provision of, public healthcare services.

RESULTS: the financing incidence of the Sierra Leone public healthcare system is marginally progressive (i.e., Kakwani index: 0.011, $p<0.1$). With regards to public healthcare benefits, while PHC benefits are pro-poor, secondary/tertiary benefits are pro-rich. The result is that overall public healthcare benefits are equally distributed (concentration index (CI) is 0.008 not statistically different from zero). However, needs are concentrated among the poor, so benefits are pro-rich when needs are considered. We find that the public healthcare system redistributes resources from better-off quintiles to worse-off quintiles (Gini coefficient change induced by public healthcare system: -0.5%). PHC receives less financing than secondary/tertiary care but delivers a larger reduction in income inequality.

DISCUSSION: The Sierra Leone public healthcare system redistributes resources and reduces income inequality. However, the redistributive effect occurs largely thanks to PHC services being markedly pro-poor, and the Sierra Leone public health system could be more equitable. Policymakers interested in improving Sierra Leone public health system equity and reducing income inequalities should prioritise PHC investments.

Keywords: fiscal incidence, public health system, inequality, redistribution, health financing

4.1 Introduction

Numerous countries have embarked on health system reforms to accelerate progress towards universal health coverage (UHC) (156,157), the aspiration that their entire populations can access the services they need equitably, without incurring financial hardship (1). Sierra Leone has explicitly stated UHC and equity as goals in the recently approved Ministry of Health and Sanitation (MoHS) National Health Sector Strategic Plan 2021-2025, and improved primary healthcare is a key strategy to reach those objectives (158,159). The MoHS considers primary healthcare (PHC) financing as a critical priority in reaching these goals, recognizing its role as a cornerstone of UHC (12). Moreover, reducing income inequalities is also an explicit target of the Sierra Leone Medium Term National Development Plan 2019-2023 (160).

Although there is some evidence that public health expenditures support economic growth (161–165), the impact of public health expenditure on *inclusive* growth and income inequality is less understood. Policymakers have limited knowledge regarding the extent to which the Sierra Leone public healthcare system is financed progressively or regressively, provides healthcare services (henceforth, benefits) to the population according to their needs, and redistributes resources among different socio-economic groups.

Therefore, the main research question of this paper is whether the Sierra Leone public healthcare system redistributes resources and is equitable in health financing and benefits provision. To answer this question, we adopt the definition of equitable system provided by Ataguba and Akazili (166), which encompasses progressive health financing, and benefits provision based on needs. We run financing (23), benefit (22), and fiscal incidence (167,168) analyses focused on the public healthcare system.

It is important to run financing and benefit incidence analysis together (169–171) because, according to the chosen definition of equitable health system (166), assessing the equity of the Sierra Leone public health system requires an understanding of who bears the health financing burden, and who receives healthcare benefits. For example, if financing for the public healthcare system is progressive (or regressive), but the distribution of benefits is pro-rich (or pro-poor), then we cannot conclude that the public healthcare system is equitable. These insights can also inform political economy implications of health policies aimed at improving equity.

We also examine the redistributive effect of the public healthcare system, defined as the change in income inequality induced by the public healthcare system (24,168,172). We measure the Gini index before and after public health financing and public healthcare benefits are considered, to understand whether the public healthcare system reduces the Gini index of income inequality. The change in Gini index induced by the public health sector is an indicator included in the Sustainable Development Goals (indicator 10.4.2, which refers to the redistributive effect of all government sectors, not only the health sector).

This chapter contributes to the methodological and empirical literature on benefit, financing and fiscal incidence analysis. From a methodological point of view, we merge the benefit and financing incidence analyses methods with fiscal incidence analyses methods, showing how fiscal incidence can be used an extension of financing and benefit incidence analyses. We hope that other researchers will also complete fiscal incidence analyses when completing benefit and financing incidence analyses. From an empirical point of view, we provide financing, benefit and fiscal incidence for the Sierra Leone public healthcare system for the first time, and also show that completing fiscal incidence by health system level is useful to unpack the health sector redistributive effect, and provide policy-relevant recommendations.

This paper primarily focuses on the public healthcare system, including health financing and provision of benefits, so that our findings are more actionable for policymakers. In robustness checks, we complete the analysis including private out-of-pocket (OOP) expenditures and private sector healthcare providers.

The Sierra Leone health system

Before presenting our methods, we provide a brief introduction of the Sierra Leone health system. Sierra Leone is administratively organized in regions, which are divided in districts, and its health system is organized in three levels. The PHC system level is served by peripheral health units (PHUs), encompassing maternal and child health posts (the health facility that is closest to the community) and larger community health centres, which can provide basic emergency obstetric and neonatal care, among other services (18). The secondary level includes regional level and district level hospitals. Finally, the tertiary level includes national referral hospitals such as Connaught Hospital, Ola During Children Hospital and Princess Christian Maternity Hospital (173). This information is important to understand how to use the unit costs provided by National Health Accounts (NHA) 2018 to measure the cost of services utilized by households, as recorded in SLIHS 2018 (further details on this below).

Health expenditures in Sierra Leone are largely financed by households' OOP health expenditures (55% of total health expenditure (THE)), followed by external health expenditure (30% of THE) and government public health expenditure (14% of THE) (51). The remaining 1% is pre-paid private domestic health expenditures. In the ten years before 2018 (i.e., 2007-2017 period), OOP as % THE decreased and government expenditure as % of THE increased, a pattern similar to the so-called "health financing transition" (14,174). Government expenditure is largely financed by taxes, excises, duties, and other domestic revenues, and from external on-budget financing. As the source of external resources are taxpayers of countries providing development assistance for health, these resources have been ignored in our analysis (23). In terms of expenditure allocation, government health expenditure in 2018 was primarily focused on human resources (54% of the government health budget), followed by goods and services, including drugs (35%), and transfers to the PHC level (7%) (175). NHA 2018 also shows that hospital expenditures constituted the largest share (39% of THE), followed by ambulatory and preventive care providers (33%), and health system governance, financing, and administration costs (24%). A more detailed table is provided in Appendix D-1.

4.2 Methods

4.2.1 The data

We use households' total expenditure per adult equivalent as the living standards measure to rank and group households in five socio-economic groups: from the lowest income quintile (#1) to the highest (#5). Official adult equivalences for Sierra Leone are provided by the Sierra Leone Integrated Household Survey (SLIHS) 2018. All analyses use survey household and population weights as relevant and as provided by the SLIHS 2018. Information related to direct and indirect taxes is provided by the Sierra Leone National Revenue Authority. From now on, and although it is recognized that hospitals might provide PHC services, we follow the Sierra Leone definition (176) that the PHC health system level is approximated to be the PHU health system level.

The data source for utilization (i.e., number of visits made by households, at secondary/tertiary hospitals and at PHUs) is the SLIHS 2018 (177), a living standards survey. For costs of services the main source is the Sierra Leone National Health Accounts (NHA) 2018, which had estimated costs for outpatient and inpatient services delivered at different levels of the health system (health centres/primary level, secondary and tertiary level hospitals) (178). Finally, the official "Government of Sierra Leone Budget for Fiscal Year 2020" from the Sierra Leone Ministry of Finance detailing actual revenues collected, health sector budget allocations, and public health expenditures, for the year 2018, was used for adjusting the total value of benefits and financing for health, as detailed in the next sections.

To estimate the redistributive effects of the public healthcare system, we first conduct two primary underpinning analyses: (i) financing incidence analysis and (ii) benefit incidence analysis.

4.2.2 Financing incidence analysis

We estimate direct income taxes, goods and services tax, and fuel excises and duties, paid by each household, using SLIHS 2018. We group goods and services taxes, and fuel excises and duties under "indirect taxes". Each household direct and indirect tax contribution has been computed using the assumptions in Table 4-1, and additional details are provided in Appendix D-1.

Table 4-1. Assumptions and computations for tax used as public health financing sources

Tax	Assumptions and computation
Direct income tax (26% of total domestic government revenues)	First, we measure income earned by all members of households who declared having a formal employment contract. Second, we apply to that income the rates stated by the Sierra Leone National Revenue Authority in the Tax and non-tax revenues guide 2019, to derive income tax revenue.
Goods and services tax (GST) (20% of total domestic government revenues)	We use, for all reported purchased goods, annualised, the standard National revenue Authority rate of 15%. The only exceptions made are local rice and imported rice, as well as other items as per Sierra Leone Revenue authority rules (e.g., printed materials, insurance services), which are GST exempt and for which we compute zero GST.
Excise and duties on petroleum products (8% of total domestic government revenues)	We assume that fuel taxes charged on retail gasoline purchased by households is 9% of the retail value, as reported in a World Bank / Statistics Sierra Leone 2014 report (179). In addition, we assume that 30% of the ticket paid by households when they use taxi, minibuses, motorbikes, and any other transport is fuel.

Source: authors' elaboration

The tax revenues estimates from SLIHS have been compared to the Sierra Leone official Ministry of Finance revenues: in case of discrepancies, the difference was allocated across households following their proportional contribution to each tax estimated via the SLIHS data (23) (e.g., our estimate for all indirect taxes was 13% below the official Ministry of Finance figure, so the indirect tax estimated was increased by that amount, and the increase distributed proportionally to households following the distribution measured via SLIHS 2018). Indirect and direct tax are 79% of total domestic revenues: we note that all other government revenues (e.g., corporate income tax, and mines department revenues) were assumed to have the same households' distribution measured for direct and indirect tax via SLIHS (180). More details on all assumptions made are shown in Appendix D-1. To assess progressivity of public health financing, we present comparisons of contributions to the public healthcare system across income quintiles, concentration curves and indexes, and Kakwani indexes (23,180,181)

For the financing incidence analysis, the concentration curves show the cumulative share of taxes contributed by households ranked by our chosen living standard measure (i.e., total household expenditure per adult equivalent). Concentration indexes (CIs) are computed as twice the area between the concentration curve and the line of equality (i.e., a straight 45 degrees line), which represents the concept of health taxes being exactly equally distributed across different living standards. Formally, the CI (180):

$$CI(T \mid Y) = \frac{2}{\overline{T}} cov(t_i, R_i) \quad [35]$$

Where T represents contributions to financing health by household i, Y represents the living standards measure of household expenditure per adult equivalent, R the fractional rank of household i (which by definition has mean 0.5), ranked by the living standards measure Y (expenditure per adult equivalent). The index is negative if taxes are regressive (concentrated among poorer households) and positive if taxes are progressive (concentrated among richer households). The index was calculated using the conindex Stata command (182).

Finally, the Kakwani index (181) is twice the area between the taxes (or any other) concentration curve, and the living standards concentration curve (i.e., the Lorenz curve). For this reason, when showing health financing concentration curves, we will also show the Lorenz curve. The Kakwani index can be computed as the difference between the CI of interest, in our case total contributions to health, and the Gini index. Finally, it can be computed as the coefficient β in the following convenient regression (180):

$$2\sigma_R^2 \left[\frac{t_i}{\overline{T}} - \frac{y_i}{\overline{Y}}\right] = \alpha + \beta r_i + u_i \quad [36]$$

Where t_i is contributions to financing health made by household i, y_i is the living standards measure of household expenditure per adult equivalent for household i, r_i is the fractional rank of household i in the household expenditure per adult equivalent distribution. This regression method allows us to estimate the Kakwani index standard error (SE) as well, and it is the method used in this paper to compute Kakwani indexes. The Kakwani index for all health financing contributions is measured as the weighted average of the Kakwani indexes (23) of each tax source, with weights (see Appendix D-1) informed by the official budget documents of the Government of Sierra Leone (175,183).

Although the focus of the analysis is the public healthcare system, we extend the financing incidence analysis by including households OOP health expenditures (see Appendix D-2).

4.2.3 Benefit incidence analysis

In order to measure benefit incidence, we implement the following steps (22):

- Estimate households' benefit utilization. SLIHS provides detail of outpatient and inpatient visits at public hospitals, and at PHUs, which are health facilities responsible for primary healthcare service delivery. Many households reported inpatient services at PHUs: it is possible that patients remained overnight at the largest PHUs (community health centres (CHCs)). Outpatient services recall period was 4 weeks, and so the households' utilization was annualized: all outpatient visits were multiplied by 13 to represent a period of one entire year (i.e., 52 weeks). For inpatient services there was no annualization as the recall period was one year.
- Using government total health expenditure for inpatients and outpatients' services at hospitals and PHUs, from NHA 2018, we compute the unit cost per service. For inpatient services, unit cost is measured as total health expenditure for inpatients services divided by "quantity of public healthcare inpatients benefits (nights) utilized" from SLIHS 2018. For outpatient

services, unit cost is measured as total health expenditure for outpatients' services divided by "quantity of public healthcare outpatients' benefits (episodes) utilized", from SLIHS 2018. To compute the government share of total health expenditure for inpatient and outpatient services by hospitals and PHUs, we used the government share of hospital and PHU health expenditure. Unit costs computed in this way are provided in the next section, and more details are provided in Appendix D-1.

- Compute the US$ value of the benefits received by each household as the multiplication of "quantity of public healthcare benefits utilized" from SLIHS 2018 and "public healthcare benefit unit cost" from the previous step. The benefits received by a given income quintile group is the sum of the benefits received by all households in that income quintile group.
- Finally, we compute the public subsidy by subtracting direct user fees paid by each household to the provider to access the services (i.e., consultation fees – which may be informal and used to finance volunteer healthcare workers (184)). As common in other benefit incidence analyses (185), we truncated the public subsidy to zero when subtracting OOP spending resulted in a negative public subsidy[3]. Henceforth, we will refer to public subsidy and public benefits interchangeably.

Formally, we measure public subsidies b per households i as follows (180):

$$b_i = \sum_k \alpha_k (q_{ki} c_k - f_{ki}) \quad [37]$$

Where q_{ki} is the quantity of service k utilized by household i, c_k is the unit cost of service k, f_{ki} are direct user fees paid by household i to access service k, and α_k is an annualization factor, equal to 1 for inpatient services (recall period in SLIHS 2018: one year) and 13 for outpatient services (recall period in SLIHS 2018: 4 weeks).

Because there is no health expenditure for inpatient services at PHUs, but households reported inpatient services at PHUs, the unit cost for inpatient services at PHUs has been assumed to be the average between PHUs outpatient unit costs and hospitals inpatient unit costs.

Benefits values by household are then used to assess pro-richness or pro-poorness of public healthcare benefits (i.e., subsidies) distribution. We compare the total value of benefits received by each income quintile group. As a robustness check, we use WHO CHOICE 2021 data to compute the unit costs and total value of benefits (see Appendix D-2). Concentration curves and indexes[4] are produced for total benefits, outpatient PHU services, inpatient PHU services, outpatient hospital services, and inpatient hospital services, for a total of five curves and five CIs. We note that standard CIs provide a measure of relative inequality (186). For this reason, and in addition to graphs of benefits across quintiles, generalized CIs are provided in Appendix D-2.

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[3] We note here that in the fiscal incidence literature public health services are usually referred to as "in kind transfers"

[4] CIs have been defined in eq. [35] with reference to public healthcare system financing contributions. For benefits, the measurement is exactly the same, except that T contributions with B benefits, yielding: $CI(B \mid Y) = \frac{2}{\bar{B}} cov(b_i, R_i)$

To complete the equity analysis, healthcare needs have to be considered. In absence of a subjective health well-being measure in SLIHS 2018, we compute healthcare need by household in the following way (22): for each household member, the variable "health need" is valued as one (=1) if the household member reported being sick or injured in the past 4 weeks, or if the household member had to consult a healthcare provider for reasons other than being sick or injured. This definition of healthcare need assumes that healthcare need is equal across individuals, regardless of income, age, gender or health conditions. Healthcare need at the household level is computed as the sum of the healthcare need variable for all household members.

First, we compare the distribution of needs across quintiles, and we compare this distribution to the distribution of all public healthcare benefits. Second, we provide a concentration curve for healthcare needs. Finally, we measure the "benefits need index" (also referred to as horizontal inequity (187)), which is the difference between the CI of benefits (for total benefits, and for each level) and the CI of need (187).

$$CI_{BN} = CI_{Benefits} - CI_{Need} \tag{38}$$

Because CIs can go from -1 to +1, CI_{BN} can range from -2 and +2[5], and represents the extent to which public healthcare benefits provision is proportional, pro-poor, or pro-rich when compared to healthcare need.

As CIs can be measured as regressions coefficients via the convenient regression (180), we test the hypothesis that the difference between two CIs is zero via the following formula (43):

$$Z = \frac{CI_1 - CI_2}{\sqrt{SE(CI_1)^2 + SE(CI_2)^2}} \tag{39}$$

Finally, we identify the determinants of the CI of public healthcare benefits using recentred influence functions (RIF) (188–190). Intuitively, each household has a RIF value which represent the household's influence on the CI. Given this premise, the mean of the RIF is equivalent to the CI. This allows for ordinary least squares (OLS) mean regression analyses: RIF values form the dependent variable, and covariates coefficients can be interpreted as the covariates' effect on the CI of a marginal increase in the mean of the covariate if the covariate is continuous, or an increase in proportion of individuals in a certain group if the covariate is a dummy. For a binary variable (e.g., household residing in rural equal one, zero otherwise), the CI percentage contribution (i.e., marginal effect) of an increase of one

[5] In an extreme case where benefits are all concentrated in the poorest (richest) individual, and need is all concentrated in the richest (poorest) individual, then the value of $CI_{benefits}$ and CI_{need} would be respectively -1 (+1) and +1 (-1), and their difference would be -2 (+2).

percentage point in the proportion of households belonging to a particular group (e.g., household residing in a rural area) is calculated as $\frac{\beta}{CI} * 1\%$, where β is the binary variable OLS coefficient.

Two steps are required for this analysis. First, the computation of CI RIF values for each household. Second, covariates of interest (i.e., age of the head of household (HHH), rural/urban residence, education of the HHH, income quintile, employment situation of the HHH, and gender of the HHH) are regressed on CI RIF values. Standard errors (SEs) are bootstrapped as suggested in the relevant RIF-CI-OLS literature (189,190). We present both unweighted and weighted OLS results, in line with the relevant literature on regression weighting (191). We describe in more detail the procedure and its benefits versus other decomposition methods (192) in Appendix D-3.

While the focus of the analysis is the public healthcare system, we extend the benefit incidence analysis by including private healthcare providers (see Appendix D-2).

4.2.4 Measuring the redistributive effect of the public healthcare system

We assess the redistributive effect of the public healthcare system in three steps. First, we compute "net benefits" (168,172) for each household as the difference between the estimated contribution made by the household to public healthcare financing and the public healthcare subsidy received by the household. Net benefits across socio-economic groups show visually whether the public healthcare system is re-distributing resources between better-off and worse-off households.

Second, we measure the Gini index of income inequality before and after public health financing (see eq. [40]), as in O'Donnell et al. 2007, Box 17.1 (180): the change in Gini index measured via eq. [40] represents the redistributive effect of public healthcare financing.

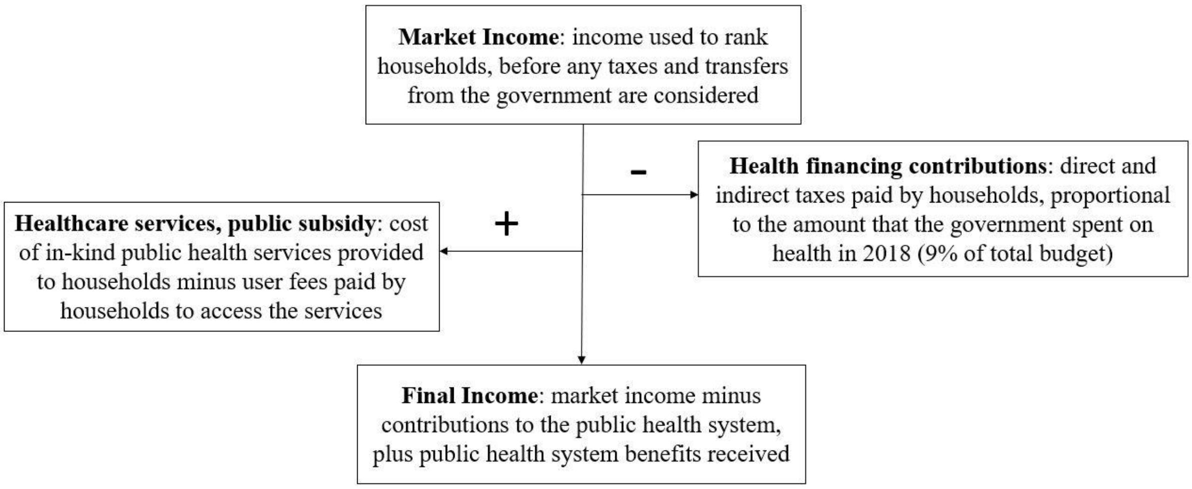
$$RE_{Public\ health financing} = G_{Market\ income} - G_{Market\ income-health\ financing} \qquad [40]$$

Third, we measure the Gini index of income inequality before and after health financing *and* public subsidies, as in Lustig 2015 (168): the change in Gini measured via eq. [41] represents the change in income inequality driven by the public healthcare system ("marginal contribution" in (168,172)).

$$RE_{Public\ health\ system} = G_{Market\ income} - G_{Final\ income=market\ income-health\ financing+public\ subsidies} \qquad [41]$$

Where G stands for Gini index, market income is income before any health financing contributions are collected or health subsidies are provided, and final income is income minus public health financing contributions plus public healthcare subsidies. Via eq. [41], we compute the redistributive effect of the entire public health system, the redistributive effect of the public PHC system, and the redistributive effect of public secondary/tertiary healthcare system.

Figure 4.1. From market income to final income



Source: authors, revising and simplifying from (168,172)

If the public healthcare system is redistributing resources from richer to poorer households, then the final income of poorer households will be larger than their market income.

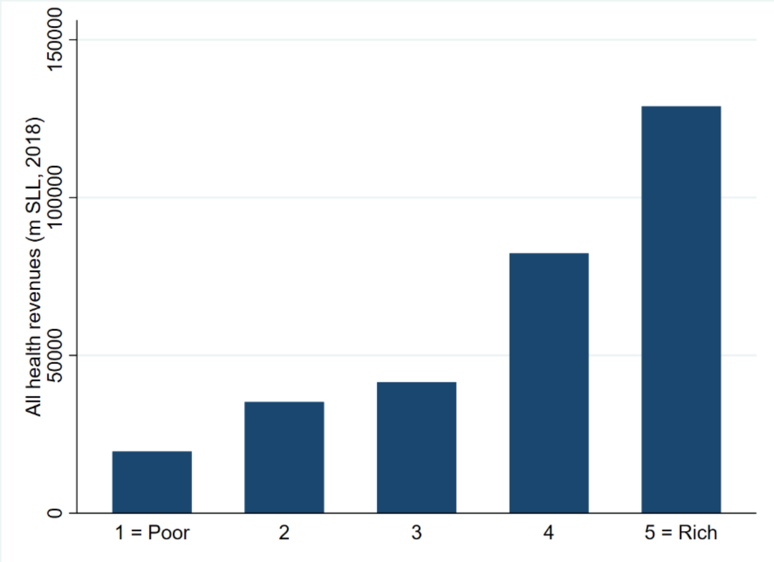
We refer the reader to the numerous online sources explaining how to measure the Gini index, and we measure it using the ‘conindex’ Stata command (182). Stata 17, survey weights, and adult equivalence factors have been used for all analyses. Standard errors (SEs) are robust and clustered. Reproduction materials are available upon request to the author.

4.3 Results

4.3.1 Financing incidence analysis

The Sierra Leone public healthcare system is mostly financed by contributions from the richest quintile (Figure 4.2), as the richest quintile pays for the highest share of public health financing contributions when compared to other socio-economic groups.

Figure 4.2. Public financing incidence analysis



Source: authors' elaboration

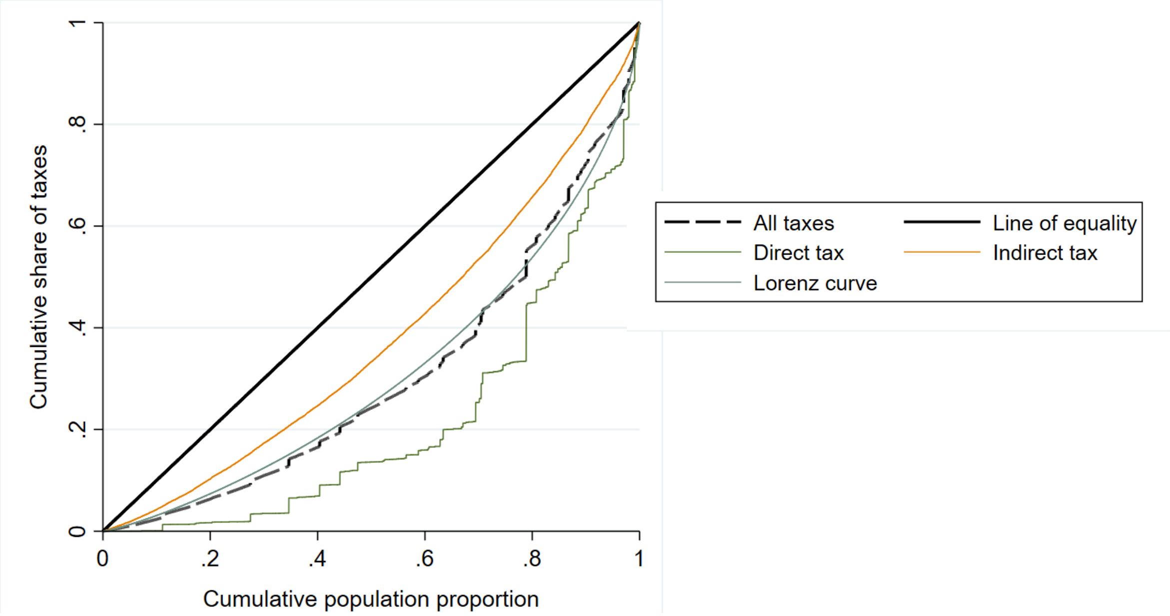
The CIs and curves show that all of the analysed financing sources are concentrated among the richest quintiles, and that this concentration is stronger for direct taxes rather than for indirect taxes. Figure 4.3 also shows that the concentration curve for total public health financing contributions ("all taxes") and the Lorenz curve cross each other multiple times.

The Kakwani index of health financing contributions across all taxes (Table 4-2, 0.011, p<0.1) show that public health financing contributions is marginally progressive. The Kakwani indexes by tax sources (Table 4-2) suggest that this overall result is driven by progressivity of direct taxes and regressivity of indirect taxes.

We note that fuel excises are in fact progressive (0.103***). However, because fuel excise taxes in SLIHS 2018 have a limited weight (over total indirect taxes) compared to GST, and GST are regressive (-0.148***), overall indirect tax revenues are regressive.

In Appendix D-2 we extend the financing incidence analysis including OOP health expenditures. The Kakwani index is the weighted average (23) of the Kakwani indexes for the public healthcare system and OOP health expenditures from NHA 2018. When OOP health expenditures are included, the overall health financing in Sierra Leone becomes regressive.

Figure 4.3. Concentration curves for direct and indirect tax revenues



Source: author calculation, following the concentration curve definition provided in the methods section

Table 4-2. Concentration and Kakwani indexes for sources of public financing for health

	Concentration index	Kakwani index
Total financing	0.393***	0.011*
Direct tax	0.569***	0.188***
Indirect tax	0.242***	-0.139***

Source: authors' calculation. Robust SEs have been used; p<0.1*, p<0.5** and p<0.01***. For completeness, the Gini index is 0.381***

4.3.2 Healthcare benefits incidence analysis

We start by presenting computed services values from NHA 2018 and SLIHS 2018 in Table 4-3.

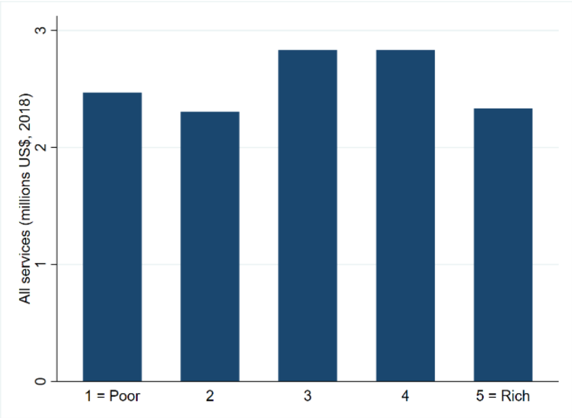
Table 4-3. Unit costs by service and definition/computation in NHA 2018 and SLIHS 2018

NHA health expenditure definition	SLIHS 2018 definition	Computed value (US$) from NHA 2018
Ambulatory care provider, outpatient care	PHUs outpatient	0.34
Not available	PHUs inpatient	2.39
Hospitals, outpatient care	Hospitals outpatient	1.89
Hospitals, inpatient care	Hospitals inpatient	4.45

Source: authors' elaboration. Values from: NHA, 2018, as described in the methods section

The distribution of public healthcare benefits (i.e., subsidies) across quintiles is presented in Figure 4.4. Healthcare benefits were rather equally distributed in 2018, and there is no evident pro-rich or pro-poor bias. In other words, it appears that a similar amount (in value) of public services is delivered across the five income quintiles, except slightly lower benefits for the richest quintile.

Figure 4.4. Benefit incidence across income quintiles, for all services (PHUs and hospitals, inpatient and outpatient)



Source: authors' elaboration

The distribution of public benefits for outpatient and inpatient hospital and PHU services is represented by the concentration indices in Table 4-4 and relative curves in Figure 4.5. The results confirm that the overall public healthcare benefits are distributed equally (CI: 0.012).

The small pro-poor bias of total services is a result of two different patterns: while PHU services are pro-poor (outpatient and inpatient PHU benefits CI: -0.248, $p<0.01$ and -0.220, $p<0.01$, respectively), hospital outpatient services are pro-rich (outpatient hospital benefits CI: +0.143, $p<0.01$), and hospital inpatient services show a non-significant and limited pro-rich bias (inpatient hospital benefits CI: +0.037).

To ensure robustness of our results, we conduct additional checks (see Appendix D-2). We consider additional OOP costs that patients paid to providers, such as drugs and tests. These costs are unlikely to have been remitted to the central level, are not rent extracted by providers, and therefore were not considered in the main analysis given that the objective is to measure public subsidies (180). However, it might be argued that they should be considered. The resulting CIs are consistent with the main analysis results shown in Table 4-4. In a second robustness check, we use unit costs from WHO CHOICE 2021 instead of unit costs computed from NHA 2018. The results are again largely similar to our main results. However, the distribution of overall benefits, is slightly pro-poor rather than being equally distributed. This is driven by a difference in unit costs: the difference between hospital services and PHUs unit costs in WHO CHOICE 2021 is lower than in the NHA. We note that NHA data is collected from government, development partners, and household surveys, while WHO CHOICE unit costs are modelled, therefore NHA data is to be preferred.

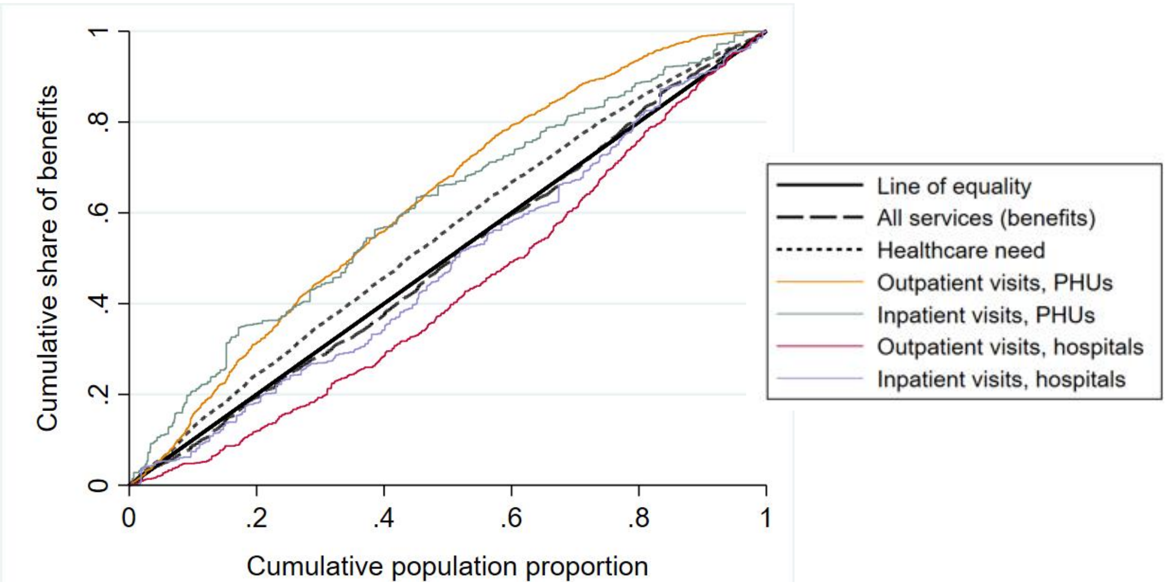
In addition to analysing benefits by income quintile, we explored the distribution of benefits across the 16 districts of Sierra Leone (see Appendix D-2). While public benefits varied across districts, there was no notable concentration of benefits in the most urban district, which encompasses tertiary hospitals and the capital city (Western Area Urban). This reinforces the finding that public benefits are not significantly pro-rich or pro-poor. Notably, the districts of Falaba and Pujehun exhibited the lowest public benefits per capita. The limited public benefits in Falaba may be attributed to the absence of a district hospital, whereas the situation in Pujehun may be due to its low population density and high percentage of rural population, potentially restricting access to hospital services (193).

Table 4-4. Concentration indexes for public healthcare benefits

Public benefits	Concentration index (CI)
All public benefits	0.008
Inpatient hospital	0.037
Outpatient hospital	0.143***
Inpatient PHU	-0.220***
Outpatient PHU	-0.247***

Source: authors' calculation. Robust SEs have been used; p<0.1*, p<0.5** and p<0.01***

Figure 4.5. Concentration curves for healthcare needs, total benefits, PHU inpatient benefits, PHU outpatient benefits, hospital inpatient benefits, and hospital outpatient benefits



Source: authors' calculation, following the concentration curve definition provided in the methods section

Figure 4.6 shows that needs are concentrated among poorer households. The CI of health needs (Table 4-5, -0.091, p<0.01) confirms this finding. However, we note that self-reported healthcare need is likely underestimating the actual need of poorer households (22,194,195).

Figure 4.5 shows that there is a misalignment between the distributions of needs and public healthcare benefits, and this is confirmed by their CIs: the difference between the two CIs is positive and statistically different from zero (+0.099, p<0.01). In other words, total public healthcare benefits are not distributed to the Sierra Leonean population according to their needs (Figure 4.7). This is driven by two different trends: PHU benefits are pro-poor when compared to needs, and hospital benefits are pro-rich when compared to needs. Hospital outpatient benefits remain pro-rich when compared to needs, while inpatient hospital benefits, which showed a non-significant pro-rich bias versus the line of equality, exhibit a significant pro-rich bias compared to needs (Table 4-5, benefits needs index 0.128, p<0.01).

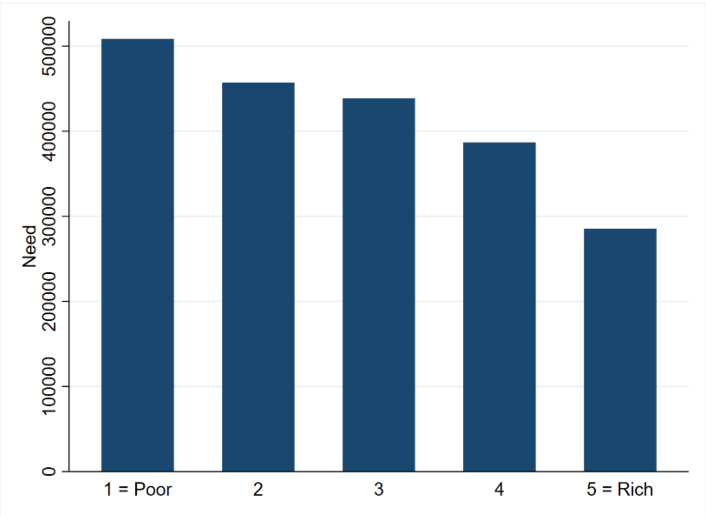
In Appendix D-2 we extend the benefit incidence analysis including private healthcare providers. When private healthcare providers are included, the overall public and private health benefits distribution is markedly pro-rich.

Table 4-5. Concentration indexes and benefits needs index

Public benefits	Benefits (CI)	Needs (CI)	Benefits needs index
All public benefits	0.008	-0.091***	0.099***
Inpatient hospital	0.037	-0.091***	0.128**
Outpatient hospital	0.143***	-0.091***	0.234***
Inpatient PHU	-0.220***	-0.091***	-0.129*
Outpatient PHU	-0.247***	-0.091***	-0.156***

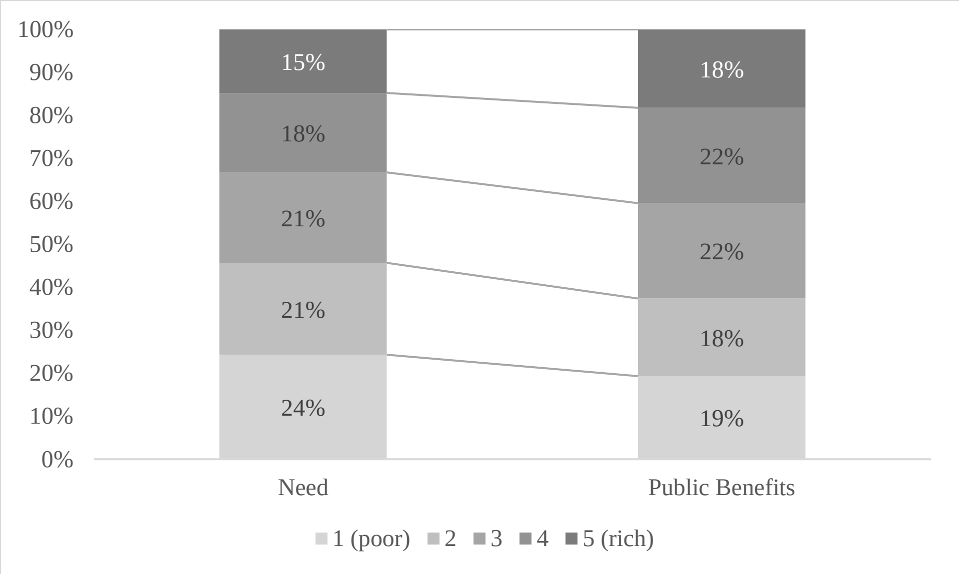
Source: authors' calculation. SEs are robust, clustered and take into consideration SLIHS 2018 survey structure; p<0.1*, p<0.5** and p<0.01***

Figure 4.6. Healthcare need across quintile groups



Source: authors' calculation

Figure 4.7. Comparison of needs and benefits



Source: authors' calculation

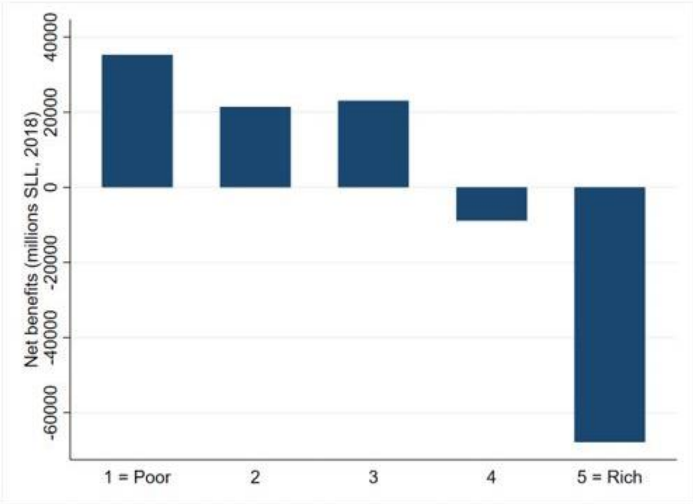
Finally, the result of the RIF-CI-OLS decomposition (see Appendix D-3) shows that an increases in the proportion of households' residence in rural locations (vs. urban) (association with benefits CI: +0.188, p<0.1, effect on CI of an increase in 1% in proportion of rural households: +5%), and household size, for household sizes between 5 and 7 members (association between increase in proportion of households with size 5 and 6-7 members, and CI of public healthcare benefits: 5 members, +0.31, p<0.01, 6-7 members, +0.35, p<0.01, effect on CI of an increase in 1% in proportion of 5 and 6-7 members households, respectively: +8%, +9%), have the largest influence on the CI of public healthcare benefits.

Although the weighted OLS results show larger marginal effects when compared to the unweighted OLS results, the results are otherwise generally consistent with the unweighted OLS results across all covariates in terms of sign, significance and coefficient magnitudes.

4.3.3 Redistributive effect of the public healthcare system

Net public healthcare benefits (i.e., public healthcare subsidies minus public healthcare contributions, Figure 4.8) show that the health system redistributes resources from better off quintiles to worse off quintiles.

Figure 4.8. Net public healthcare benefits incidence across income quintiles



Source: authors' calculation

Figure 4.8 shows that the two richest quintiles contribute more to the public health system than what they receive in benefits, making them net contributors. Conversely, the two poorest quintile and the central quintile receive more benefits compared to their contributions, and are net receivers. This finding indicates that the Sierra Leone public healthcare system redistributes resources from the richest quintiles to the poorest ones.

Table 4-6, row one, shows that the reduction in income inequality induced by public health financing is minimal. This confirms the finding that public health financing is neither progressive nor regressive.

Table 4-6, rows two to four, presents the redistributive effect of the entire public healthcare system (i.e., health financing and benefits provision, all levels considered), further broken down in PHU level and secondary/tertiary level. Both the PHU and secondary/tertiary health system level contribute to redistributing resources and reducing income inequality. In addition, we note that the PHU level delivers a similar reduction in inequality while providing substantially less benefits, than the secondary/tertiary levels.

Table 4-6. Redistributive effects of health financing, and public healthcare system, by level

#	Redistributive effect of: ↓	Gini market income | Gini final income	Reduction in Gini index driven by public health system (%)	Percentage of benefits over total benefits
1	Health financing	0.3810 | 0.3808	-0.0 percentage points (0.0%)	n.a.
2	Public healthcare system	0.3810 | 0.3792	-0.2 percentage points (0.5%)	100%
3	PHU level	0.3810 | 0.3798	-0.1 percentage points (0.2%)	46%

4	Secondary/tertiary level	0.3810 | 0.3800	-0.1 percentage points (0.2%)	54%

Source: authors' calculation.

4.4 Discussion

Achieving UHC, the aspiration that all Sierra Leoneans can access the healthcare they need without suffering financial hardship, is a key target for the Sierra Leone National Health Sector Strategic Plan 2021-2025. Furthermore, reduction of income inequalities is a key objective in the Sierra Leone Medium Term National Development Plan 2019-2023 (160). While some evidence supports the idea that investments in health systems drive economic growth (161–165), it is less clear whether investments in health systems reduce income inequalities. Is the Sierra Leone public healthcare system equitable, and does it redistribute resources from the rich to the poor? To answer this question, we analyse the equity, as defined by Ataguba and Akazili (166), of the Sierra Leone public healthcare system, in both financing and benefit delivery. It is crucial that benefit incidence analysis and financing incidence analysis are conducted together to assess whether a healthcare system is equitable (166). We then extend these analyses by measuring the redistributive effect induced by the public healthcare system (i.e., fiscal incidence analysis).

Our financing and benefit incidence findings are similar to a recent systematic review of benefit and financing incidence analyses in LMICs (14), which also found that direct taxes show a progressive distribution, indirect taxes show a regressive distribution, public PHC benefits incidence is usually pro-poor, and public hospitals benefits incidence is usually pro-rich. However, in the case of Sierra Leone, benefits provision does not align with needs, therefore the public health system could be more equitable.

As it was the case for the benefit incidence analysis, the public healthcare system redistributive effect is driven by PHUs, rather than the secondary/tertiary healthcare system level (see Table 4-6). This is because PHU benefits are pro-poor, while secondary/tertiary benefits are pro-rich. The magnitude of the redistributive effect in Sierra Leone is comparable to that observed in other countries (e.g., Ethiopia (168), Georgia, Armenia, Indonesia and Jordan (172)) and could be enhanced by increasing investments in the public health system, focusing on the PHU level.

In the low-income countries group, it was found that all taxes and subsidies resulted in negative net benefits for the poorest households (196), therefore the Sierra Leone public healthcare system is comparatively more favourable to the poorest quintiles, than other low-income countries. In the same review (196), investments in health were listed as "high value" for reducing inequalities: our results confirm this point.

The first policy implication of this study is to prioritize PHU services within the public health sector budget to improve the equity and redistributive effect of the public healthcare system. Conversely, prioritization of hospital services might result in a less equitable public healthcare system. The second policy implication is that increasing the public health sector budget would contribute to the reduction of income inequality in Sierra Leone.

The government could also consider policies that increase direct tax revenues and reduce indirect tax revenues to enhance equity and redistribution induced by public health financing, given that our findings show that direct taxation is more effective than indirect taxation in improving the equity and redistributive effect of the public health system.

The health sector might not be "best sector buy" for the Government of Sierra Leone to reduce income inequality in Sierra Leone. To determine whether the health sector is the most efficient investment to reduce income inequality we would need to compute the redistributive effect across sectors, which is beyond the scope of this analysis. Expanding this same analysis to other sectors (e.g., education, social protection, and non-social sectors) may be of particular interest to policymakers allocating resources across sectors to reduce income inequality in Sierra Leone. Fiscal incidence for public services delivering public goods (e.g., national defence) is also a largely unexplored research area (167).

An important contribution of this paper is to merge the literature on benefit and financing incidence analysis (22,23) with the fiscal incidence literature on the effect of (public) health systems on income inequality (168,172): to the best of our knowledge, this is the first paper to do that. Moreover, we explore the equity and redistributive effect of the public healthcare system in Sierra Leone, a country for which this knowledge is not available. To the best of our knowledge, this is also the first paper to measure the redistributive effect across health system levels (PHC and secondary/tertiary healthcare): the findings across health system levels might be relevant for other countries advocating for increased PHC financing.

Several limitations should be considered. For this paper, other sectors (e.g., education) are out of scope, and could be considered to compare redistributive effects across sectors. Another limitation is that SLIHS 2018 does not differentiate among different hospitals (e.g., secondary district and regional hospitals, versus tertiary referral hospitals), which might have substantially different unit costs and utilization patterns, nor it does provide detail on PHC services provided by hospitals: such detail would have greatly benefited the usefulness of the findings for policymakers. Measuring healthcare needs in LMICs using self-reported illness consistently under-estimate the needs of lower income households, for various reasons including limited knowledge and the fact that poorer households cannot afford to be sick (5). While we included healthcare needs based on self-reported illness, it is very likely that healthcare need is more concentrated in poorer households than what we have measured. This means that the benefit-needs index (0.099***) is likely affected by a downward bias. Therefore, the public healthcare system is likely less equitable than we measured, if we had a better "healthcare needs" measure.As noted already, we have computed values for "inpatient PHU services" as households declared being in PHUs overnight, despite PHUs are not supposed to provide inpatient services. Importantly, for utilization and costs data, we used SLIHS 2018 and NHA 2018 and we did not use the government Health and Financial Management Information Systems: using these different data sources could change the results. Finally, as in other benefit incidence analyses, quality of care has not been taken into consideration when the monetary values of benefits were computed (197).

Despite these caveats, we believe this research is important for three key reasons. First, it underscores the necessity of sustained investments in PHC to enhance both health equity and income equality. Second, it contributes to the limited literature on financing, benefit, and fiscal incidence analyses in Sierra Leone. Lastly, it demonstrates how benefit (22), financing (23) and fiscal incidence (168) methods can complement each other, providing policy-relevant insights that can inform decision-making processes.

Conclusion

This thesis comprises of four independent chapters on the theme of health system policies aimed at progressing towards universal health coverage (UHC), with particular attention to health financing policies. Universal health coverage (UHC) captures the ambition that the entire population in a given jurisdiction receive the quality health services they need, without suffering financial hardship, regardless of socio-economic conditions (1). While the first chapter used a variety of health system outcomes (health status, service coverage, and financial risk protection), the following three chapters focused on different, specific dimensions of the UHC cube (2): Chapter 2 focused on coverage of PHC services, Chapter 3 focused on financial risk protection, and Chapter 4 focused on equity. The chapters also differed in terms of the research methodologies and datasets used. In Chapter 1, I applied difference-in-difference methods and their variations to a cross-country panel dataset, to assess the effect of health system financing policies on service coverage, health status and financial risk protection outcomes. In Chapter 2, causal mediation analyses and structural equation models were used to assess the contribution of different types of health workers to the service coverage effect of the Family Health Strategy in Brazil. In Chapter 3, we assessed the association between DAH and financial risk protection, applying pseudo-panel methods to a cross-country dataset formed by repeated cross-sectional surveys. Finally, financing, benefit and fiscal incidence analyses were employed in Chapter 4 to assess the redistributive effect of the Sierra Leone public healthcare system, using data from the Sierra Leone Integrated Household Survey 2018 and from Sierra Leone National Health Accounts 2018. In what follows, I elaborate on the contribution, policy implications, and potential future research related to the four chapters of this thesis.

Chapter 1 contributes to the academic and policy debate on the impact of different HFSs on health system outcomes (i.e., health status, financial risk protection and utilization (32)), with a view to informing decisions about potential transitions from OOP-predominant systems to either contributory SHI or non-contributory government financing, aimed at accelerating progress towards UHC. Previous research on this topic focused on comparing SHI systems to "tax-based" systems, while (mis)classifying OOP-predominant HFSs under SHI or "tax-based" systems; neither has there been work on transitions from OOP-predominant systems to either contributory SHI or non-contributory government financing. Beyond these main contributions, Chapter 1 also refines the HFS classification by using machine learning methods (i.e., clustering) and by shedding light on contextual factors affecting HFSs. We find that transitions from OOP-predominant to government financed systems improved most outcomes more than did transitions to SHI systems. From a policy perspective, these results may raise a warning sign for policymakers considering a reform towards contributory SHI in order to reach UHC, while those pursuing a reform towards non-contributory government financing may feel re-assured.

This chapter also highlights possible directions for further research on the topic of health system financing. Being a cross-country study, it offers valuable general insights on health financing reforms and their possible effect on health system outcomes. However, it is not able to examine thoroughly each individual country. Therefore, for a more comprehensive understanding, conducting country-level studies becomes essential as they can delve deeper into the specific context and nuances of each country, allowing for more tailored research questions and recommendations. As noted in the chapter, we have not addressed formally "how" (e.g., via mediation analysis) or "for whom" different HFSs work (e.g., health equity), due to data limitations: country case studies might be able to address these limitations. Once these data limitations are overcome, this would be a promising contribution to the literature, with important policy implications: many countries that are currently considering transitioning from OOP predominant systems to SHI or government financing systems would likely be interested in the effect on equity of such transitions. There are other less obvious limitations that bear implications for further research. For example, the main independent variable of this study is defined based on the characteristics of health expenditure, but it is possible that characteristics of health revenues (i.e., general taxation, labour taxes, or other taxes) may affect health system outcomes, either independently or in conjunction with health expenditures, as shown in Chapter 4. Similarly, health policymakers would likely be interested in the cost-effectiveness of health financing system reforms. This research area remains largely unexplored (65) due to the challenging task of conceptualising and identifying incremental costs and effects of health financing reforms. Further research might also explore more in depth, possibly via country case-studies, "how" to accelerate progress towards UHC via increases in non-contributory financing (198).

Assessing the effect of health financing systems on labour market outcomes is also a very promising, possible extension of Chapter 1. The consequences of SHI systems on labour markets are often discussed in debates over SHI initiation and/or expansion (26,38). In addition, SHI could theoretically both improve (e.g., more people demand – and more employers offer – formal contracts, due to the mandatory health coverage) and worsen (e.g., less people demand – and less employers offer – formal contracts to avoid paying SHI contributions) labour market outcomes, suggesting that empirical evidence would be particularly important. However, to the best of my knowledge, only one cross-country empirical study on the effect of health financing systems on labour outcomes exists, is limited to a specific region (central-eastern Europe, central Asia) (38,66), and suffers from some of the limitations of the literature in classifying health financing systems noted in Chapter 1.

Another area of further research would be to explore formally the contextual political factors affecting health financing system transitions. The health financing literature recognize that political factors play a major role in the development of health financing systems (199,200). However, there appear to be no studies exploring the cross-country association between political parties, their positions (e.g., parties in government, democratic/autocratic political rule, found for example in the Variety of Democracy dataset from the University of Gothenburg (201)) and health financing systems. Starting from the dataset generated in Chapter 1 and using transitions from OOP-predominant to SHI- and government financing-predominant health financing systems as outcomes, one could explore empirically whether certain political parties or political historical factors can explain why countries choose to transition towards SHI or government financing systems.

The literature on the effect of Brazil's Estrategia da Saude da Familia (ESF) has mostly been focused on evaluating the impact of the ESF program. Chapter 2 contributes to the literature by focusing on "how" this impact was achieved. As the main component of the ESF were the "Family Health Teams" (FHT) formed by different health professionals and deployed to increase PHC services coverage, I assessed the contribution of each health professional in the team to the effect of ESF on PHC services coverage. I find that community health workers (CHWs) contributed substantially to the ESF impact on PHC services coverage. The direct effect of ESF was also a substantial contributor to the total (i.e., direct plus indirect) effect of ESF on coverage of PHC services: this was likely due to the different organizational set-up brought by ESF and by the synergies of ESF with other programs. Given these results, there are two implications for policymakers. First, the role of CHWs might be expanded to improve the (cost-)effectiveness of the program. Second, the ESF team-based approach to PHC should be maintained. These considerations might be relevant for other countries considering team-based approaches to PHC, which are being supported by, for example, the World Bank and other international organizations (73).

Further research on the topic of ESF might focus on studying the drivers of ESF's "direct effect" and their relative contributions. I advanced some hypotheses in the chapter (i.e., organizational technologies and structures brought by ESF, and synergies with other programs). However, more detail on which organizational technologies (e.g., care pathways, guidelines for management of communicable and non-communicable diseases, and others) drove the effect would provide evidence to improve the (cost-) effectiveness of the program even further. Another substantial limitation was that the data available (i.e., observational panel data at the municipality level) does not allow for a causal interpretation of results (20): further research providing causal evidence evaluating the processes and impact of team-based approaches to PHC delivery would add value.

Chapter 3 contributes to the literature on the effects of development assistance for health (DAH), by assessing the association between DAH and financial risk protection. DAH accounts for a sizable amount of health expenditure funding in LMICs, amounting to around 40 billion US$ per year in 2019 (123). It is often disbursed to promote progress towards UHC, as a now widely recognized objective shared by several bi- and multi-lateral donors that provide DAH (5–7), and governments in DAH-recipient countries. A key metric – also used here – to measure such progress (as per SDG 3.8.2) is a set of financial risk protection indicators (5–7). While institutions providing DAH may or may not have an explicit target of improving financial risk protection as part of UHC targets (e.g., service coverage), it is at least plausible to expect that DAH may improve financial risk protection in DAH-recipient countries. Our results suggest that DAH investment is – at least on average – not significantly associated with financial risk protection outcomes in countries with what may be considered as a meaningful size of DAH, defined as having a DAH per capita above the cross-country average. However, our results also indicate that increasing DAH per capita does appear to improve financial risk protection outcomes for populations in the poorest quintile. Furthermore, increasing DAH per capita improves financial risk protection outcomes when it is mostly channelled via government financial systems. Concerns about the quality of recipient governments' public financial management (PFM) systems could be eased by providing more funds to countries with good PFM system scores, measured via PEFA assessments. However, this approach does not appear to have yet been adopted (152).

Further research, once PEFA scores and additional household surveys are available, could focus on whether the effect of DAH channelled via country governments' PFM systems is improved when PEFA scores suggest that PFM systems are high quality and well-functioning. More broadly, further research might explore the mechanisms through which DAH might affect financial risk protection, e.g., via mediation analysis.

Moreover, further research could also explore what factors are associated with increased on-budget DAH: if it is not PEFA scores, then what factors could facilitate more DAH on-budget? This question would be particularly interesting for governments who are either providers or recipients of DAH. A related question could explore the factors associated with increased DAH regardless of whether it is on-budget or not: this is particularly important for governments and citizens of LMICs, especially as DAH allocation processes have often been "hidden from view" (202).

In Chapter 4, I focus on the equity and redistribution dimension of UHC. While there is some evidence supporting the idea of a positive effect of (public) health system investments on economic growth (161–165), less is known about the effect of health systems investments on income inequality. Perhaps most importantly for policymakers, in this chapter, we measure the redistributive effect of each level of the public health system: these findings could inform budgetary decisions across different levels of the health system (PHC level, and secondary/tertiary level (SHC/THC)). We find that the public health system in Sierra Leone redistributes resources from the rich to the poor and improves income inequality via the redistribution of resources. We also find that this redistribution is not driven by the contributions to financing the public health system. The redistribution in the Sierra Leone public health system is largely driven by healthcare services (which I called "benefits" in Chapter 4) provision, and within healthcare services provision, by the PHC system level rather than the SHC/THC level, even if the PHC system level receives less funds than the SHC/THC. Hence, investments in PHC can be perceived not only as highly effective but also as the primary driver of the reduction in income inequality induced by the public healthcare system. The implication for policymakers is that PHC investments should be prioritized.

In Chapter 4 we also noted possibilities of policy-relevant further research related to both fiscal and benefit incidence analysis, in Sierra Leone and other countries. The chapter did not assess the redistributive effect of other public sectors (e.g., education, other social and non-social sectors). Comparisons across social sectors have been undertaken to some extent in other countries (172), and their reapplication in Sierra Leone would be of particular interest to policymakers. In other countries, these "cross-sectoral" fiscal incidence analyses very rarely assess fiscal incidence of different health system levels, which is a highly relevant information for health policymakers (i.e., Ministries of Health, National health services, etc.). In addition, from a methodological perspective, it would be interesting to explore how to conduct benefit incidence analysis in non-social sectors delivering non-rivalrous non-excludable (i.e., public) goods (e.g., defence, home security), which are usually not part of fiscal incidence analysis (167,196).

An important limitation is related to all the chapters in this thesis, and more broadly to the evaluation of complex interventions aimed at strengthening health systems. In this thesis, each chapter was based on a conceptual framework. These frameworks, theories, and logic models are routinely used to translate into tractable models the complex realities of the health system reforms analysed. Current methods of quantitative policy evaluation might fail to recognize all the complexities, nuances, and dynamics that are the defining factors of complex system interventions (e.g., health system reforms) (203,204). There are at least two methodological research areas that could address, at least to an extent, this limitation. First, there are methods that evaluate health policies quantitatively and (attempt to) consider their complexities and system dynamics more formally (e.g., agent-based modelling, network analysis, and system dynamic modelling) (203,204). These methods are currently used only occasionally in the population health field (205), and further research could develop and use them for the evaluation of health policies. Second, qualitative methods, including political economy analysis (206,207), might be more apt to answering research questions or clarify nuances that are strictly linked to, but not answerable by, quantitative policy evaluation of complex health policies (208) (e.g., to what extent DAH providers influence "on-budget" DAH financing). Importantly, the different research methodologies mentioned in this paragraph (i.e., both innovative and more standard quantitative methods, and qualitative methods), are not mutually exclusive. The complex nature of health system reforms likely requires mixing and combining these methods to provide a full picture of the effects of complex health policies and interventions.

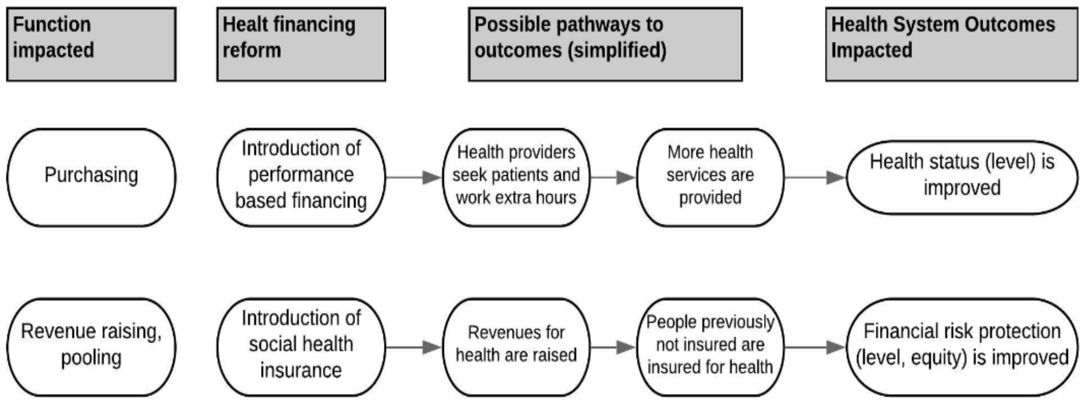
Numerous countries and international organizations are now attempting to accelerate progress towards UHC. Different health system policies, and in particular health financing policies, are being considered by policymakers to accelerate progress towards UHC. These systemic and population-wide policies can play a substantial role in determining to what extent countries manage to progress in terms of the key UHC dimensions of coverage, financial risk protection, and equity, in order to ultimately deliver improved health outcomes for their populations. However, in the instances detailed in this thesis, evidence on the impact of health system policies on key UHC dimensions is rather limited. Therefore, it is crucial to generate evidence that can provide guidance on health system policies whose aim is to accelerate progress towards UHC. The present thesis has evaluated health system policies with the explicit aim of providing policy-relevant evidence to inform health system planning decision making.

Appendix A: appendix for Chapter 1

Appendix A-1 Differentiation across reforms of different health financing functions

The below figure helps clarify the idea that health financing reforms may impact health system outcomes through different pathways depending on the health financing function that is being reformed, as shown below.

Figure A.1 Differentiation across reforms of different health financing functions



Appendix A-2 Detail of variables and data construction

Table A-1 Sample construction

Item	**Number of countries from item**	**Number of countries (cumulative)**
Total number of countries after merging all datasets and deleting countries not present in all datasets	183	183
Countries taken out because not all years present in a dataset	8 (Zimbabwe, Afghanistan, Yemen, Syria, Libya, Iraq, South Sudan, Timor-Leste)	175
Country missing outcome (life expectancy or maternal mortality) for at least 1 year	6 (Andorra, Dominica, Marshall Islands, Palau, San Marino, St. Kitts and Nevis)	169
Countries missing GHED data for at least 1 year	3 (Greece, Saudi Arabia, Albania)	166
Countries taken out because population <500.000 people in at least one period	18 (Bahamas, Barbados, Belize, Cabo Verde, Grenada, Iceland, Kiribati, Luxembourg, Maldives, Malta, Micronesia, Samoa, Sao Tome and Principe, Seychelles, Solomon Islands, St. Lucia, Suriname, Tonga, Vanuatu)	147
Countries missing control variables	23 (United Arab Emirates, Bahrain, Bosnia Herzegovina, Cuba, Djibouti, Eritrea, Gabon, Equatorial Guinea, Guyana, Haiti, Japan,	124

	Cambodia, Kuwait, Lebanon, Myanmar, Namibia, New Zealand, Oman, Papua New Guinea, Qatar, Singapore, Turkmenistan, Trinidad and Tobago)	
Total countries in study		124

We have taken out 18 small and island countries, given that governance, health systems and health financing for those countries present peculiarities when compared to other countries. In small and island countries, changes in predominant HFS are more frequent than other countries (0.72 changes per country for small and island countries, vs. 0.43 in other countries, in the 2000-2017 period), and there are transitions from SHI to government financing system (and vice-versa) that are not seen in other countries, raising concerns about data quality and relevance in the context of a cross-country analysis.

Baseline results change when these countries are included, and when the HFS is defined via clustering. However, the main conclusion that the effect of government financing on health system outcomes is more or as favourable as that of SHI transitions is maintained. We also include all countries and define the predominant HFS using the highest value among government financing, SHI and OOP expenditures as % of THE, showing that estimates are similar to our baseline results and that, again, the conclusion that government financing effect on health system outcomes is better or as good as SHI is confirmed. These checks are presented with other robustness checks in Appendix 6, Table 6.3, panels E and F.

Table A-2 Variable definitions and source

Variable	**Definition**	**Source**
Government financing as % of THE	"Participation is automatic: for all citizens/ residents; or a specific group of the population (e.g., the poor) defined by law/government regulation."	WHO GHED (134), based on OECD SHA. Definition is quoted from OECD SHA (49).
SHI as % of THE	"Participation is mandatory: for all citizens/residents; or a specific group of the population defined by law/government regulation. In some cases, however, the enrolment requires actions to be taken by the eligible persons."	
OOP expenditures as % of THE	"Participation is voluntary: willingness to pay of the household."	
Immunization coverage	Average of immunization coverage for measles, DPT and hepatitis	World Bank WDI
Life expectancy	Life expectancy at birth	World Bank WDI
Maternal mortality	Maternal mortality ratio, modelled estimate, per 100000 live births	World Bank WDI

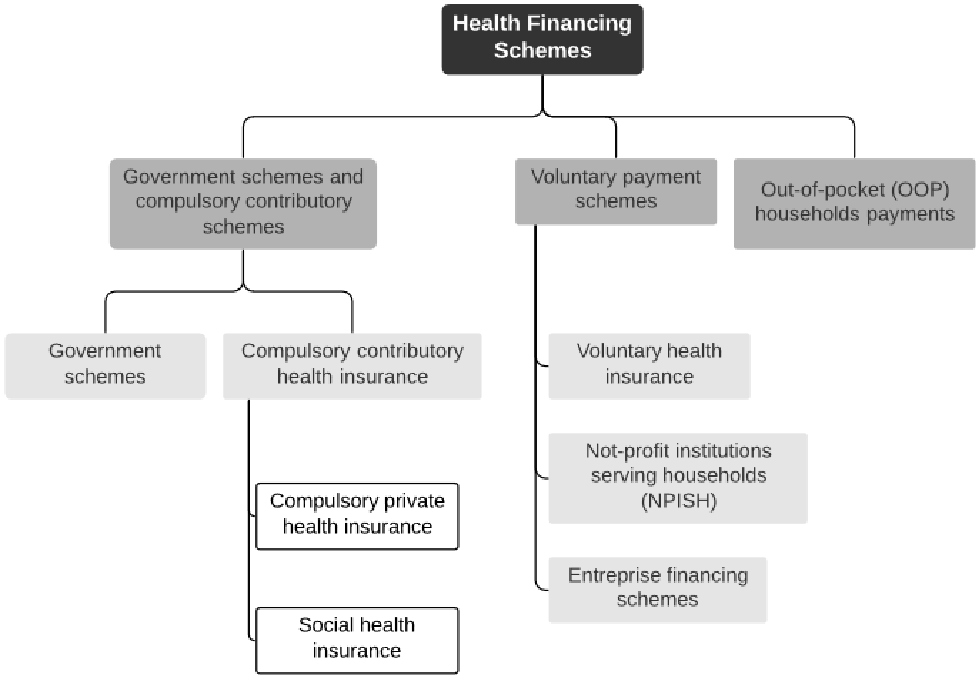
Under-5 Mortality	Under-five mortality rate (death per 1000 live births)	World Bank WDI
Catastrophic health expenditure	Catastrophic health expenditure incidence (% population), at the 10% threshold	World Bank HEFPI
GDP per capita	GDP per capita, current, international US$, PPP	World Bank WDI
Primary school enrolment (gross, %)	Primary school enrolment (gross, % of population)	World Bank WDI
Urbanisation rate	% Population in urban areas	World Bank WDI
Drinking water access	% Population with drinking water access	World Bank WDI
Demographics: population below 14	% population below 14	World Bank WDI
Demographics: population above 65	% population above 65	World Bank WDI
Government effectiveness	"Government effectiveness captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies"	World Bank WGI, definition quoted from https://info.worldbank.org/governance/wgi/Home/downLoadFile?fileName=ge.pdf
Corruption control	"Control of corruption captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests."	World Bank WGI, definition quoted from: https://info.worldbank.org/governance/wgi/Home/downLoadFile?fileName=cc.pdf

Appendix A-3 Health financing arrangement details, and k-means clustering

The health financing arrangement classifications (government financing, SHI and OOP) are not decided by the authors: they are defined by the System of Health Accounts (SHA), Health Financing Scheme (Chapter 7) standards, which form the basis for the WHO GHED. The reader is referred to the SHA manual for a detailed description of the health financing schemes mentioned and used in the paper.

Table A-2 clarifies the meaning of government-financed, SHI-financed and OOP-financed. Government financing refers to "Government schemes". SHI-financing refers to Compulsory contributory health insurance schemes, which includes both SHI-proper and private compulsory health insurance. We call it SHI-financing to avoid confusion, since this is the usual name in the literature. Community based health insurance (not shown in the figure) is included under voluntary payment schemes. We also emphasize that in WHO GHED, what matters is the health financing scheme through which the monies are *spent*: if tax revenues are used to finance the country SHI agency providing contributory SHI, then such monies will be recorded under SHI (see p. 170 of the SHA 2011 manual (29)). However, if government pays premiums or finance the budget of an agency providing non-contributory health insurance or services, those monies count as government financing. To avoid confusion, THE in this paper refers to "current health expenditure" in the GHED dataset. Finally, we note that external financing (i.e., development assistance for health) will be considered part of any given country's public financing scheme (i.e., SHI or government financing) if on-budget. When off-budget, external financing will largely be considered as financing via not-for-profit institutions serving households.

Figure A.2 Health financing schemes definitions



Source: author elaboration based on OECD, Eurostat, WHO, 2017, Chapter 7

K-means clustering (209) is an unsupervised machine learning technique described in many books. The k-means cluster algorithm assigns each country-year combination (i.e., each observation) to the cluster with the least squared Euclidean distance (other distances can be used), which is the cluster with the closest mean.

In this study, we choose to have three clusters as we expect to have country-year combinations that belong to one of the following three groups: predominantly government-financed, SHI-financed or OOP financed. We choose that the variables used for clustering are government-, SHI-, and OOP-financing as a % of THE. The algorithm starts by assigning random cluster "centroids" (a vector of three values, government schemes, SHI, and OOP, as a % of THE) and assigning each country-year combination to the nearest cluster (i.e., the cluster with the least Euclidean distance). At this point, a new cluster centroid is calculated: it is a vector of the mean of the country-year combinations assigned to the cluster. The process is repeated until the cluster centroids position does not change. Via this process, k-means minimizes intra-cluster variance: in other words, the sum of squared distances between each country-year combination and the centroid of the assigned cluster is minimized.

K-means clustering therefore considers, for each country-year combination, the vector of government schemes, SHI, and OOP, each as a % of THE, and that k-means is non-arbitrary, except in the choice of the number of clusters, which we do based on theoretical reasoning about having 3 groups (government schemes, SHI, and OOP) and the variables used for clustering (government schemes, SHI, and OOP, each as a % of THE). One problem with this approach is that countries may move repeatedly and in short period of times in-and-out a certain group, therefore switches lasting only one year have been removed. We note that inclusion in a group is reversible: countries can go from SHI to OOP or OOP to government financing, and vice versa.

It might occur that a country-year observation is classified, for example, in the government financing HFS group, even if OOP as % of THE is higher than government financing as % of THE. This is because each country-year observation is a vector of three values: government financing as % of THE, OOP as % of THE, and SHI as % of THE. Each cluster can also be thought of as a vector of government financing, OOP, and SHI, as % of THE (called centroids), which are measured as the means of all the country-year observations within that same cluster.

The k-means clustering algorithm does not formally consider which one of the three values forming the country-year observation vector (government financing as % of THE, OOP as % of THE, and SHI as % of THE) is the highest. Country-year observations are classified into each group (government financing, OOP, SHI) based on the country-year observation vector Euclidean squared distance to the cluster centroids vector. Therefore, a country-year observation with a very high OOP as % of THE might be classified as "government-financing" when its distance to the government financing cluster is shorter than the distance to the OOP cluster. However, the OOP, government-financing, and SHI cluster will show, respectively, OOP, government financing, and SHI as % of THE as the highest value of the three. This is because the k-means clustering algorithm minimizes distance within clusters' observations and maximizes distance across clusters.

The centroids of the final clusters are the average OOP as % of THE, SHI as % of THE, and government financing as % of THE for each cluster, which are shown in Table 2, section 5.1

These clustering concerns are substantially less relevant when we run the following robustness checks:

1) We classify country-year into HFS groups/clusters using the largest value between OOP, SHI and government financing as % of THE. In 229 country-year observations (8% of total

observations) the predominant HFS defined via clustering is different from the predominant HFS defined by the “largest % of THE” method. An example of this is shown below, for all countries, Year 2017.

2) We use a minimum threshold of OOP as % of THE to classify country-year observations in the OOP-predominant group i.e., a country-year can only be classified as OOP-predominant if the cluster procedure identifies it as OOP predominant *and* its OOP as % of THE is higher than a certain threshold (50%, 45%, 40%, etc.)

We note that data is usually standardized when variables used for clustering are on different scales (e.g., age and income). In our case, all clustering variables are percentage of THE, therefore no standardization is required.

Table A-3 Number of switches resulting from cluster analysis, with countries in brackets

Switch	**Full sample (in italic, countries with missing controls data)**
OOP ↔ SHI	8 switches, 7 countries (Argentina 2, Bulgaria 1, China 1, Moldova 1, Russia 1, Uruguay 1, USA 1) 7 switches from OOP to SHI, 1 switch from SHI to OOP
OOP ↔ GOV	46 switches, 30 countries (Angola 2, Burundi 3, Bulgaria, 1 Bolivia 1, Brazil 1, DRC 2, Rep of Congo 2, *Djibouti 1*, Ethiopia 3, Gambia 1, *Gabon 3*, Guinea-Bissau 1, *Guyana 2*, Jordan 2, Kazakhstan 1, Kenya 1, Sri Lanka 1, Latvia 1, Madagascar 1, Mongolia 1, Mauritius 1, Malaysia 1, Panama 1, Rwanda 1, Tanzania 3, *Trinidad & Tobago 1*, Ukraine 2, Venezuela 2, Zambia 2) 28 switches from OOP to GOV 18 switches from GOV to OOP
SHI ↔ GFA	0

There are 26 cases (1% of all country-year observations), for which the clustering analysis resulted in a one-year long HFS switch. In such cases, the previous year predominant HFS was used: Bolivia,2001; Central African Republic,2015; Republic of Congo,2009; Djibouti,2003; Ethiopia,2004; Gambia,2002; Guinea-Bissau,2002; Guyana,2010; Jamaica,2001; Kazakhstan,2002; Kyrgyzstan,2009; Laos,2009; Lebanon,2012; Madagascar,2002; Madagascar,2009; Madagascar,2013; Moldova,2005; Moldova,2009; Mauritius,2003; Mongolia,2005; Panama,2016; Trinidad and Tobago,2014; Tunisia,2013; Ukraine,2011; Uzbekistan,2014; Vietnam,2001.

Regarding the choice of the number of clusters, we measure the within-sum-of-squares (WSS), the ln (WSS), η^2 defined as $\eta^2 = 1 - \frac{WSS(k)}{WSS(1)}$ and the proportional reduction of error coefficient (PRE), defined as $PRE(k) = \frac{WSS(k-1)-WSS(k)}{WSS(k-1)}$. While for WSS, ln (WSS), and η^2 the optimal cluster number is seen where there is a kink in the curve, or when the decrease becomes smaller versus previous decreases, in the PRE methodology the optimal cluster number is identified when the $PRE(k)$ value is large (versus other $PRE(k)$ values). The graphs suggest that the optimal number of clusters is three, in line with the number of clustering input variables (OOP, SHI and government financing as % of THE, making 89% of THE on average). This is also in line with the literature on HFS, which often suggested using SHI and government financing predominant HFS systems (Wagstaff & Moreno-Serra, 2009), to which we have added OOP predominant HFSs. We also run a robustness check using four clusters instead of three, and find that the overall conclusion is not changed.

Figure A.3 Clustering within-sum-of-squares analyses

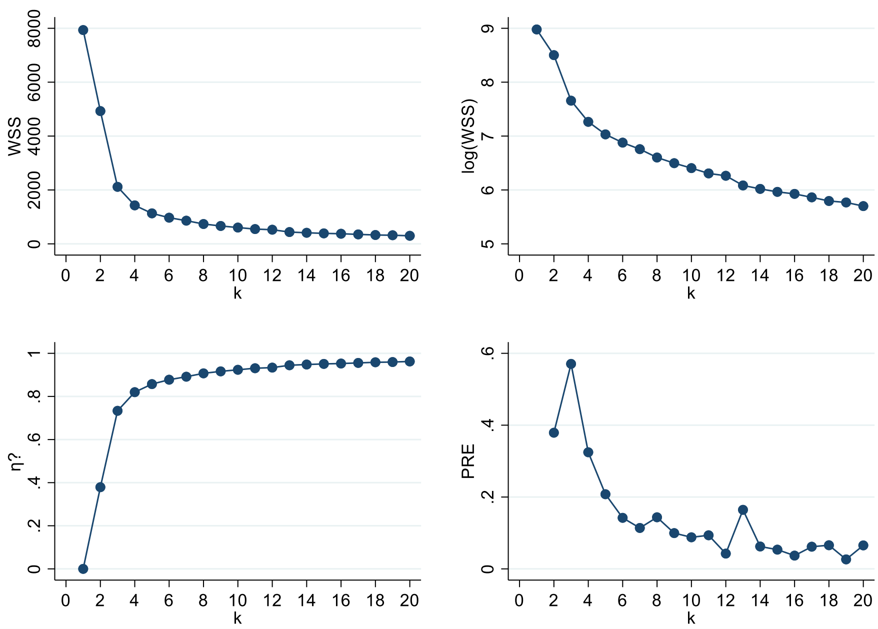


Table A-4 Switches across countries and years

Country	Code	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Algeria	DZA	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	OOP	OOP
Angola	AGO	GOV	OOP	OOP	OOP	OOP	OOP	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Argentina	ARG	SHI	SHI	SHI	SHI	OOP	OOP	OOP	OOP	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
Armenia	ARM	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Australia	AUS	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Austria	AUT	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
Azerbaijan	AZE	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Bahrain	BHR	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Bangladesh	BGD	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Belarus	BLR	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Belgium	BEL	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
Benin	BEN	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Bhutan	BTN	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Bolivia	BOL	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	GOV
Bosnia and Herzegovina	BIH	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
Botswana	BWA	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Brazil	BRA	OOP	OOP	OOP	OOP	OOP	OOP	OOP	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Bulgaria	BGR	GOV	OOP	OOP	OOP	OOP	OOP	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
Burkina Faso	BFA	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Burundi	BDI	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	GOV	GOV	GOV	GOV	OOP	OOP	GOV	GOV
Cambodia	KHM	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Cameroon	CMR	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Canada	CAN	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Central African Republic	CAF	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Chad	TCD	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Chile	CHL	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
China	CHN	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	SHI	SHI	SHI	SHI	SHI	SHI
Colombia	COL	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
Comoros	COM	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Congo, Dem. Rep.	COD	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	GOV	GOV	OOP	OOP	OOP	OOP	OOP	OOP
Congo, Rep.	COG	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	OOP	OOP
Costa Rica	CRI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
Cote d'Ivoire	CIV	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Croatia	HRV	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
Cuba	CUB	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV

Cyprus	CYP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Czech Republic	CZE	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
Denmark	DNK	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Djibouti	DJI	OOP	OOP	OOP	OOP	OOP	OOP	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Dominican Republic	DOM	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Ecuador	ECU	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Egypt, Arab Rep.	EGY	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
El Salvador	SLV	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Equatorial Guinea	GNQ	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Eritrea	ERI	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Estonia	EST	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
Eswatini	SWZ	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Ethiopia	ETH	OOP	GOV	GOV	GOV	GOV	GOV	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	GOV
Fiji	FJI	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Finland	FIN	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
France	FRA	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
Gabon	GAB	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	GOV	GOV	GOV	GOV	OOP	OOP	GOV	GOV
Gambia, The	GMB	OOP	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Georgia	GEO	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Germany	DEU	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
Ghana	GHA	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Guatemala	GTM	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Guinea	GIN	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Guinea-Bissau	GNB	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	OOP	OOP	OOP	OOP	OOP	OOP
Guyana	GUY	GOV	GOV	GOV	GOV	GOV	GOV	OOP	OOP	OOP	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Haiti	HTI	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Honduras	HND	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Hungary	HUN	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
India	IND	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Indonesia	IDN	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Iran, Islamic Rep.	IRN	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Ireland	IRL	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Israel	ISR	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
Italy	ITA	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Jamaica	JAM	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Japan	JPN	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI

Jordan	JOR	OOP	OOP	OOP	OOP	OOP	OOP	OOP	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	OOP
Kazakhstan	KAZ	OOP	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Kenya	KEN	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	GOV	GOV	GOV
Korea, Rep.	KOR	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
Kuwait	KWT	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Kyrgyz Republic	KGZ	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Lao PDR	LAO	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Latvia	LVA	OOP	OOP	OOP	OOP	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Lebanon	LBN	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Lesotho	LSO	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Liberia	LBR	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Lithuania	LTU	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
Madagascar	MDG	OOP	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Malawi	MWI	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Malaysia	MYS	OOP	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Mali	MLI	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Mauritania	MRT	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Mauritius	MUS	GOV	GOV	GOV	GOV	GOV	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Mexico	MEX	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Moldova	MDA	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
Mongolia	MNG	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	OOP	OOP	OOP	OOP	OOP
Morocco	MAR	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Mozambique	MOZ	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Myanmar	MMR	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Namibia	NAM	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Nepal	NPL	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Netherlands	NLD	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
New Zealand	NZL	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Nicaragua	NIC	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Niger	NER	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Nigeria	NGA	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
North Macedonia	MKD	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
Norway	NOR	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Oman	OMN	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Pakistan	PAK	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Panama	PAN	GOV	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP

Papua New Guinea	PNG	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Paraguay	PRY	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Peru	PER	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Philippines	PHL	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Poland	POL	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
Portugal	PRT	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Qatar	QAT	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Romania	ROU	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
Russian Federation	RUS	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	SHI	SHI	SHI
Rwanda	RWA	OOP	OOP	OOP	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Senegal	SEN	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Serbia	SRB	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
Sierra Leone	SLE	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Singapore	SGP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Slovak Republic	SVK	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
Slovenia	SVN	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
South Africa	ZAF	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Spain	ESP	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Sri Lanka	LKA	GOV	GOV	GOV	GOV	GOV	GOV	GOV	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Sudan	SDN	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Sweden	SWE	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Switzerland	CHE	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
Tajikistan	TJK	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Tanzania	TZA	OOP	OOP	OOP	OOP	GOV	GOV	GOV	GOV	GOV	GOV	OOP	OOP	OOP	GOV	GOV	GOV	GOV	GOV
Thailand	THA	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
Togo	TGO	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Trinidad and Tobago	TTO	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	GOV	GOV	GOV	GOV	GOV
Tunisia	TUN	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Turkey	TUR	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
Turkmenistan	TKM	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Uganda	UGA	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Ukraine	UKR	OOP	OOP	OOP	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	OOP	OOP	OOP	OOP	OOP
United Arab Emirates	ARE	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
United Kingdom	GBR	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV
United States	USA	OOP	OOP	OOP	OOP	OOP	OOP	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI	SHI
Uruguay	URY	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	SHI	SHI	SHI	SHI	SHI	SHI	SHI

Uzbekistan	UZB	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Venezuela, RB	VEN	OOP	OOP	OOP	OOP	OOP	OOP	GOV	GOV	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Vietnam	VNM	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP	OOP
Zambia	ZMB	GOV	GOV	GOV	GOV	GOV	OOP	OOP	OOP	OOP	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV	GOV

In the below Table we present, for Year 2017 and all countries, SHI as % of THE, OOP as % of THE, government financing as % of THE, and voluntary health insurance as % of THE, the predominant HFS defined using clustering, and the predominant HFS defined as the HFS with the largest % of THE. Countries in which there is a difference between the two HFS definitions are noted in italic (9 cases, 6% of total country observations in 2017)

Table A-5 Year 2017, classification of countries using different methods

Country	Country Code	Year	SHI as % THE	Government financing as % of THE	OOP as % of THE	VHI as % of THE	Predominance defined by clustering	Predominance as "largest as % of THE"
Angola	AGO	2017	0	47	34	6	Government financing predominant	Government financing predominant
United Arab Emirates	ARE	2017	0	72	19	8	Government financing predominant	Government financing predominant
Argentina	ARG	2017	43	30	15	9	SHI predominant	SHI predominant
Armenia	ARM	2017	0	14	84	1	OOP predominant	OOP predominant
Australia	AUS	2017	0	65	18	10	Government financing predominant	Government financing predominant
Austria	AUT	2017	44	30	19	5	SHI predominant	SHI predominant
Azerbaijan	AZE	2017	0	15	84	1	OOP predominant	OOP predominant
Burundi	BDI	2017	1	47	25	1	Government financing predominant	Government financing predominant
Belgium	BEL	2017	56	21	18	5	SHI predominant	SHI predominant
Benin	BEN	2017	2	39	45	6	OOP predominant	OOP predominant
Burkina Faso	BFA	2017	0	61	32	1	Government financing predominant	Government financing predominant
Bangladesh	BGD	2017	0	19	74	0	OOP predominant	OOP predominant
Bulgaria	*BGR*	*2017*	*43*	*9*	*47*	*1*	*SHI predominant*	*OOP predominant*

Bahrain	BHR	2017	0	58	31	11	Government financing predominant	Government financing predominant
Bosnia and Herzegovina	BIH	2017	68	2	29	0	SHI predominant	SHI predominant
Belarus	BLR	2017	0	70	28	1	Government financing predominant	Government financing predominant
Bolivia	BOL	2017	30	40	25	3	Government financing predominant	Government financing predominant
Brazil	BRA	2017	0	42	27	29	Government financing predominant	Government financing predominant
Bhutan	BTN	2017	0	79	13	0	Government financing predominant	Government financing predominant
Botswana	BWA	2017	0	78	3	9	Government financing predominant	Government financing predominant
Central African Republic	CAF	2017	0	19	31	0	OOP predominant	OOP predominant
Canada	CAN	2017	1	69	14	10	Government financing predominant	Government financing predominant
Switzerland	CHE	2017	42	22	29	7	SHI predominant	SHI predominant
Chile	CHL	2017	58	2	34	6	SHI predominant	SHI predominant
China	CHN	2017	38	18	36	5	SHI predominant	SHI predominant
Cote d'Ivoire	CIV	2017	2	35	39	8	OOP predominant	OOP predominant
Cameroon	CMR	2017	0	18	71	6	OOP predominant	OOP predominant
Congo, Dem. Rep.	COD	2017	1	30	40	3	OOP predominant	OOP predominant
Congo, Rep.	COG	2017	0	36	48	1	OOP predominant	OOP predominant
Colombia	COL	2017	68	6	16	10	SHI predominant	SHI predominant
Comoros	COM	2017	3	16	75	1	OOP predominant	OOP predominant
Costa Rica	CRI	2017	72	3	21	3	SHI predominant	SHI predominant
Cuba	CUB	2017	0	89	10	0	Government financing predominant	Government financing predominant
Cyprus	CYP	2017	0	42	45	12	OOP predominant	OOP predominant
Czech Republic	CZE	2017	69	13	15	0	SHI predominant	SHI predominant
Germany	DEU	2017	78	6	13	1	SHI predominant	SHI predominant
Djibouti	DJI	2017	11	43	27	0	Government financing predominant	Government financing predominant

Denmark	DNK	2017	0	84	14	2	Government financing predominant	Government financing predominant
Dominican Republic	DOM	2017	25	21	45	8	OOP predominant	OOP predominant
Algeria	*DZA*	*2017*	*26*	*40*	*33*	*1*	*OOP predominant*	*Government financing predominant*
Ecuador	ECU	2017	24	29	39	6	OOP predominant	OOP predominant
Egypt, Arab Rep.	EGY	2017	4	29	60	1	OOP predominant	OOP predominant
Eritrea	ERI	2017	0	38	59	0	OOP predominant	OOP predominant
Spain	ESP	2017	4	66	24	5	Government financing predominant	Government financing predominant
Estonia	EST	2017	64	10	24	0	SHI predominant	SHI predominant
Ethiopia	ETH	2017	0	45	34	1	Government financing predominant	Government financing predominant
Finland	FIN	2017	14	62	20	2	Government financing predominant	Government financing predominant
Fiji	FJI	2017	0	67	16	13	Government financing predominant	Government financing predominant
France	FRA	2017	78	5	9	7	SHI predominant	SHI predominant
Gabon	GAB	2017	24	39	25	9	Government financing predominant	Government financing predominant
United Kingdom	GBR	2017	0	79	16	3	Government financing predominant	Government financing predominant
Georgia	GEO	2017	0	37	55	6	OOP predominant	OOP predominant
Ghana	GHA	2017	10	30	40	2	OOP predominant	OOP predominant
Guinea	GIN	2017	2	29	57	1	OOP predominant	OOP predominant
Gambia, The	GMB	2017	0	41	22	4	Government financing predominant	Government financing predominant
Guinea-Bissau	GNB	2017	1	14	72	0	OOP predominant	OOP predominant
Equatorial Guinea	GNQ	2017	1	19	77	0	OOP predominant	OOP predominant
Guatemala	GTM	2017	17	18	54	4	OOP predominant	OOP predominant
Guyana	GUY	2017	2	61	32	2	Government financing predominant	Government financing predominant
Honduras	HND	2017	12	33	49	5	OOP predominant	OOP predominant

Croatia	HRV	2017	76	6	11	4	SHI predominant	SHI predominant
Haiti	HTI	2017	2	12	40	5	OOP predominant	OOP predominant
Hungary	HUN	2017	61	8	27	2	SHI predominant	SHI predominant
Indonesia	IDN	2017	23	26	35	4	OOP predominant	OOP predominant
India	IND	2017	5	23	62	5	OOP predominant	OOP predominant
Ireland	IRL	2017	0	73	12	13	Government financing predominant	Government financing predominant
Iran, Islamic Rep.	IRN	2017	32	14	42	7	OOP predominant	OOP predominant
Israel	ISR	2017	48	16	22	11	SHI predominant	SHI predominant
Italy	ITA	2017	0	74	23	2	Government financing predominant	Government financing predominant
Jamaica	JAM	2017	6	61	17	16	Government financing predominant	Government financing predominant
Jordan	*JOR*	*2017*	*16*	*34*	*30*	*15*	*OOP predominant*	*Government financing predominant*
Japan	JPN	2017	76	9	13	2	SHI predominant	SHI predominant
Kazakhstan	KAZ	2017	0	62	33	1	Government financing predominant	Government financing predominant
Kenya	KEN	2017	8	42	24	10	Government financing predominant	Government financing predominant
Kyrgyz Republic	KGZ	2017	7	35	56	0	OOP predominant	OOP predominant
Cambodia	KHM	2017	0	23	60	1	OOP predominant	OOP predominant
Korea, Rep.	KOR	2017	49	10	34	7	SHI predominant	SHI predominant
Kuwait	KWT	2017	0	87	13	0	Government financing predominant	Government financing predominant
Lao PDR	LAO	2017	2	36	46	0	OOP predominant	OOP predominant
Lebanon	LBN	2017	24	25	33	16	OOP predominant	OOP predominant
Liberia	LBR	2017	0	32	46	7	OOP predominant	OOP predominant
Sri Lanka	LKA	2017	0	44	50	2	OOP predominant	OOP predominant
Lesotho	LSO	2017	0	68	17	0	Government financing predominant	Government financing predominant
Lithuania	LTU	2017	58	9	32	1	SHI predominant	SHI predominant

Latvia	LVA	2017	0	57	42	1	Government financing predominant	Government financing predominant
Morocco	MAR	2017	20	25	54	1	OOP predominant	OOP predominant
Moldova	MDA	2017	50	2	44	0	SHI predominant	SHI predominant
Madagascar	MDG	2017	0	54	25	3	Government financing predominant	Government financing predominant
Mexico	MEX	2017	28	24	41	6	OOP predominant	OOP predominant
North Macedonia	MKD	2017	63	5	32	0	SHI predominant	SHI predominant
Mali	MLI	2017	10	34	35	1	OOP predominant	OOP predominant
Myanmar	MMR	2017	1	17	76	0	OOP predominant	OOP predominant
Mongolia	*MNG*	*2017*	*23*	*41*	*32*	*0*	*OOP predominant*	*Government financing predominant*
Mozambique	MOZ	2017	2	52	7	2	Government financing predominant	Government financing predominant
Mauritania	MRT	2017	10	34	50	2	OOP predominant	OOP predominant
Mauritius	MUS	2017	0	43	49	6	OOP predominant	OOP predominant
Malawi	MWI	2017	0	50	11	3	Government financing predominant	Government financing predominant
Malaysia	MYS	2017	1	50	38	10	Government financing predominant	Government financing predominant
Namibia	NAM	2017	0	48	8	38	Government financing predominant	Government financing predominant
Niger	NER	2017	1	44	48	1	OOP predominant	OOP predominant
Nigeria	NGA	2017	1	14	77	0	OOP predominant	OOP predominant
Nicaragua	*NIC*	*2017*	*24*	*40*	*33*	*1*	*OOP predominant*	*Government financing predominant*
Netherlands	NLD	2017	75	6	11	6	SHI predominant	SHI predominant
Norway	NOR	2017	0	85	14	0	Government financing predominant	Government financing predominant
Nepal	NPL	2017	0	25	58	1	OOP predominant	OOP predominant
New Zealand	NZL	2017	9	69	14	5	Government financing predominant	Government financing predominant
Oman	OMN	2017	0	88	7	3	Government financing predominant	Government financing predominant
Pakistan	PAK	2017	1	29	60	1	OOP predominant	OOP predominant

Panama	PAN	2017	28	33	33	6	OOP predominant	OOP predominant
Peru	*PER*	*2017*	*30*	*33*	*28*	*7*	*OOP predominant*	*Government financing predominant*
Philippines	PHL	2017	12	23	53	11	OOP predominant	OOP predominant
Papua New Guinea	PNG	2017	0	76	9	0	Government financing predominant	Government financing predominant
Poland	POL	2017	59	10	23	6	SHI predominant	SHI predominant
Portugal	PRT	2017	1	65	28	4	Government financing predominant	Government financing predominant
Paraguay	PRY	2017	17	28	44	10	OOP predominant	OOP predominant
Qatar	QAT	2017	0	81	9	9	Government financing predominant	Government financing predominant
Romania	ROU	2017	63	15	20	1	SHI predominant	SHI predominant
Russian Federation	*RUS*	*2017*	*36*	*21*	*40*	*2*	*SHI predominant*	*OOP predominant*
Rwanda	RWA	2017	17	52	6	2	Government financing predominant	Government financing predominant
Sudan	SDN	2017	11	8	72	1	OOP predominant	OOP predominant
Senegal	SEN	2017	4	34	52	8	OOP predominant	OOP predominant
Singapore	*SGP*	*2017*	*8*	*40*	*32*	*3*	*OOP predominant*	*Government financing predominant*
Sierra Leone	SLE	2017	0	27	50	0	OOP predominant	OOP predominant
El Salvador	*SLV*	*2017*	*29*	*35*	*29*	*6*	*OOP predominant*	*Government financing predominant*
Serbia	SRB	2017	54	3	42	0	SHI predominant	SHI predominant
Slovak Republic	SVK	2017	78	2	19	0	SHI predominant	SHI predominant
Slovenia	SVN	2017	69	3	12	14	SHI predominant	SHI predominant
Sweden	SWE	2017	0	84	15	1	Government financing predominant	Government financing predominant
Eswatini	SWZ	2017	0	49	10	11	Government financing predominant	Government financing predominant
Chad	TCD	2017	0	21	58	4	OOP predominant	OOP predominant
Togo	TGO	2017	3	25	58	7	OOP predominant	OOP predominant
Thailand	THA	2017	11	68	11	7	Government financing predominant	Government financing predominant

Tajikistan	TJK	2017	0	33	63	0	OOP predominant	OOP predominant
Turkmenistan	TKM	2017	0	22	73	5	OOP predominant	OOP predominant
Trinidad and Tobago	TTO	2017	0	53	40	7	Government financing predominant	Government financing predominant
Tunisia	TUN	2017	31	27	39	3	OOP predominant	OOP predominant
Turkey	TUR	2017	56	22	17	2	SHI predominant	SHI predominant
Tanzania	TZA	2017	8	62	24	1	Government financing predominant	Government financing predominant
Uganda	UGA	2017	0	20	39	2	OOP predominant	OOP predominant
Ukraine	UKR	2017	0	45	52	1	OOP predominant	OOP predominant
Uruguay	URY	2017	50	17	18	11	SHI predominant	SHI predominant
United States	USA	2017	58	26	11	0	SHI predominant	SHI predominant
Uzbekistan	UZB	2017	0	45	53	0	OOP predominant	OOP predominant
Venezuela, RB	VEN	2017	6	10	63	21	OOP predominant	OOP predominant
Vietnam	VNM	2017	23	27	45	1	OOP predominant	OOP predominant
South Africa	ZAF	2017	0	43	8	36	Government financing predominant	Government financing predominant
Zambia	ZMB	2017	0	56	12	1	Government financing predominant	Government financing predominant

Appendix A-4 Full baseline results, and heterogeneity within HFS groups

Table A-6 Full baseline results, and heterogeneity within HFS groups

VARIABLES	(1) Log THE per capita FE	(2) Imm, index FE	(3) LE FE	(4) Log U5M FE	(5) Log MM FE	(6) CHE10 FE
Predominant government financing	0.043	3.804	1.341**	-0.083**	-0.040	-3.256***
	(0.041)	(2.921)	(0.579)	(0.036)	(0.040)	(0.931)
Predominant SHI	0.117***	-1.486	-0.128	0.051	0.034	6.467***
	(0.035)	(1.606)	(0.395)	(0.037)	(0.067)	(1.129)
Log GDP per Capita (PPP)	0.698***	3.591	1.038	-0.315***	-0.515***	1.230
	(0.093)	(3.776)	(0.643)	(0.097)	(0.178)	(2.073)
Corruption control	0.099**	3.783*	-0.087	-0.058	0.029	2.662**
	(0.041)	(2.225)	(0.577)	(0.043)	(0.079)	(1.140)
Government effectiveness	0.030	-1.636	0.125	-0.088**	-0.041	1.968
	(0.044)	(1.874)	(0.350)	(0.038)	(0.068)	(2.521)
% of population above 65	0.000	-0.389	-0.263*	0.022*	0.049	-0.020
	(0.019)	(0.954)	(0.156)	(0.013)	(0.035)	(0.453)
% population below 14	-0.017*	0.645**	0.335***	-0.029***	-0.035**	0.224
	(0.009)	(0.321)	(0.074)	(0.008)	(0.016)	(0.235)
Urbanization (%)	-0.009	0.364**	0.073	0.003	0.005	0.175
	(0.006)	(0.164)	(0.055)	(0.006)	(0.013)	(0.176)
Access to drinking water (% population)	-0.003	0.474	0.150***	-0.007	0.002	0.074
	(0.005)	(0.298)	(0.042)	(0.004)	(0.012)	(0.080)
Enrollment to primary school (gross, % population	-0.002	0.035	0.019	0.002	-0.001	-0.080*
	(0.002)	(0.075)	(0.017)	(0.001)	(0.002)	(0.040)
Gini index	0.005	0.259*	-0.009	0.004	0.006	0.018
	(0.004)	(0.152)	(0.035)	(0.003)	(0.004)	(0.099)
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.869	0.177	0.752	0.879	0.646	0.224
Observations	950	970	970	970	970	407
Number of Countries	124	124	124	124	124	111

Source: author elaboration. Notes: FE estimates are the result of eq. [1]. Robust SEs, clustered at country-level, in parentheses. Details on HFS switches are detailed in Appendix A-3. All models control for all variables listed as "control" in Table 1-2. P-values for two-sided t-tests are reported as: ***p<0.01, ** p<0.05, * p<0.1.

The results below are for the following equation: $Y_{it} = \alpha + \rho_1 SHI\%THE_{it} + \rho_2 GOV\%THE_{it} + \rho_3 OOP\%THE_{it} + \gamma \boldsymbol{X}_{it} + T_t + C_i + \varepsilon_{it}$, for the subsample of country-year observations that belong to the HFS-predominant group noted in the column of each model, for column 1 to 18. For column 19 to 36, only SHI as percentage of THE is used for the SHI-predominant HFS group, OOP expenditures as percentage of THE is used for the OOP-predominant HFS group, and government financing as % of THE is used for the government financing predominant HFS group.

	(1) Ln THE	(2) Imm Idx	(3) LE	(4) ln U5M	(5) ln MM	(6) CAT 10%	(7) Ln THE	(8) Imm Idx	(9) LE	(10) ln U5M	(11) ln MM	(12) CAT 10%	(13) Ln THE	(14) Imm Idx	(15) LE	(16) ln U5M	(17) ln MM	(18) CAT 10%
	FE	FE	FE	FE	FE	FE	FE	FE	FE	FE	FE	FE	FE	FE	FE	FE	FE	FE
HFS GROUP → VARIABLES ↓	GOV group	GOV group	GOV group	GOV group	GOV group	GOV group	OOP group	OOP group	OOP group	OOP group	OOP group	OOP group	SHI group	SHI group	SHI group	SHI group	SHI group	SHI group
Government financing %	-0.002	0.000	0.049	-0.000	0.002	0.001*	-0.001	0.001	-0.018	0.003	-0.004	-0.003*	0.003	0.001	-0.034**	0.001	0.005	-0.001
	(0.006)	(0.001)	(0.051)	(0.003)	(0.005)	(0.001)	(0.004)	(0.002)	(0.025)	(0.003)	(0.003)	(0.002)	(0.003)	(0.001)	(0.013)	(0.003)	(0.005)	(0.002)
SHI financing %	-0.005	0.004	0.151	0.009	0.019*	-0.000	0.012***	-0.001	-0.007	0.005	-0.004	-0.001	-0.002	-0.001	-0.014	0.000	0.004	0.000
	(0.013)	(0.002)	(0.093)	(0.007)	(0.011)	(0.002)	(0.004)	(0.002)	(0.026)	(0.003)	(0.004)	(0.001)	(0.002)	(0.001)	(0.011)	(0.002)	(0.005)	(0.000)
OOP financing %	-0.003	0.001	0.030	-0.001	-0.006	0.002***	-0.000	0.001	0.010	0.005*	-0.003	-0.002	0.002	-0.000	0.021	-0.001	0.011	0.001
	(0.006)	(0.002)	(0.051)	(0.003)	(0.008)	(0.001)	(0.004)	(0.002)	(0.022)	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.015)	(0.003)	(0.007)	(0.001)
Observations	265	271	271	271	271	116	398	407	407	407	407	193	287	292	292	292	292	98
R-squared	0.875	0.145	0.811	0.940	0.842	0.528	0.875	0.359	0.816	0.922	0.733	0.404	0.959	0.281	0.925	0.873	0.745	0.400
Number of ID	45	46	46	46	46	39	69	69	69	69	69	60	31	31	31	31	31	23
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.861	0.0417	0.788	0.933	0.823	0.376	0.865	0.310	0.802	0.916	0.713	0.302	0.954	0.202	0.917	0.859	0.716	0.168

Table A-7 Heterogeneity within HFS groups

VARIABLES	(19) Ln THE FE GOV group	(20) Imm Idx FE GOV group	(21) LE FE GOV group	(22) ln U5M FE GOV group	(23 ln MM FE GOV group	(24) CAT 10% FE GOV group	(25) Ln THE FE OOP group	(26) Imm Idx FE OOP group	(27) LE FE OOP group	(28) ln U5M FE OOP group	(29) ln MM FE OOP group	(30) CAT 10% FE OOP group	(31) Ln THE FE CHI group	(32) Imm Idx FE CHI group	(33) LE FE CHI group	(34) ln U5M FE CHI group	(35) ln MM FE CHI group	(36) CAT 10% FE CHI group
Government financing %	0.000	-0.001	0.020	0.000	0.004	0.000												
	(0.003)	(0.001)	(0.035)	(0.002)	(0.004)	(0.000)												
SHI financing %							-0.003	-0.001	-0.008	-0.000	-0.001	0.000						
							(0.002)	(0.001)	(0.009)	(0.002)	(0.003)	(0.000)						
OOP financing %													-0.003	0.001	0.022	0.002	0.000	-0.000
													(0.003)	(0.001)	(0.016)	(0.001)	(0.002)	(0.001)
Observations	265	271	271	271	271	116	287	292	292	292	292	98	398	407	407	407	407	193
R-squared	0.875	0.142	0.808	0.939	0.835	0.418	0.958	0.280	0.918	0.873	0.733	0.379	0.858	0.353	0.815	0.920	0.730	0.337
Number of ID	45	46	46	46	46	39	31	31	31	31	31	23	69	69	69	69	69	60
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.861	0.0463	0.787	0.932	0.817	0.248	0.954	0.207	0.910	0.860	0.705	0.163	0.848	0.307	0.802	0.914	0.710	0.233

SOURCE: author elaboration. Datasets discussed in Section 1.4. NOTES: this table present the results of the fixed effects (FE) equation [1], restricting the sample to the sub-group of "countries within the government-, SHI- or OOP-predominant group". All the controls variables and FE (time and country FE) used in the main models are also used here. The independent variable of interest is the percentage of THE channelled via government schemes, SHI schemes and OOP schemes. In the first table, all three percentages have been used. In the second table, only the percentage of THE channelled via OOP schemes has been used for the OOP-predominant group, the percentage of THE channelled via SHI schemes for the SHI-predominant group, and the percentage of THE channelled via government schemes for the government-predominant group.

Appendix A-5 FE estimates of augmented model with interaction terms (eq. [4]), section 1.5.3. Results in italic when observations are not enough

Table A-8 FE estimates of augmented model with interaction terms (eq. [4]), section 1.5.3. Results in italic when observations are not enough

Interaction terms ↓ // Dependent variables →	(1) Imm. Index	(2) LE	(3) ln U5M	(4) ln MM	(5) CAT 10%	(6) GGHE % GGE	(7) Imm Index	(8) LE	(9) ln U5M	(10) ln MM	(11) CAT 10%	(12) GGHE % GGE
Government-predominant & Informal Sector Size	-0.198*	-0.009	0.000	0.002	*1.585****	0.034						
	(0.098)	(0.021)	(0.002)	(0.002)	*(0.005)*	(0.047)						
SHI-predominant & Informal Sector Size	-0.221**	-0.001	0.006***	-0.002		-0.021						
	(0.088)	(0.014)	(0.002)	(0.002)		(0.048)						
Government-predominant & logged GDP per capita (PPP)							-0.470	0.372	-0.090*	-0.174	1.341	-0.693
							(2.491)	(0.559)	(0.046)	(0.119)	(0.820)	(0.478)
SHI-predominant & logged GDP per capita (PPP)							5.847**	-0.260	-0.006	-0.007	-2.469	0.220
							(2.367)	(0.454)	(0.058)	(0.081)	(2.045)	(0.604)
Observations	184	184	184	184	*50*	184	970	970	970	970	407	970
Number of ID	34	34	34	34	*26*	34	124	124	124	124	111	124
Country FE	YES	YES	YES	YES	*YES*	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	*YES*	YES	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.216	0.851	0.952	0.844	*1*	0.474	0.199	0.754	0.880	0.648	0.189	0.172

Interaction terms ↓ // Dependent variables →	(13) Imm. Index	(14) LE	(15) ln U5M	(16) ln MM	(17) CAT 10%	(18) GGHE % GGE	(19) Imm Index	(20) LE	(21) ln U5M	(22) ln MM	(23) CAT 10%	(24) GGHE % GGE
Government-predominant & Government Effectiveness	1.662	1.391*	-0.113*	-0.167	-0.132	0.412						
	(3.198)	(0.714)	(0.063)	(0.127)	(2.943)	(0.752)						
SHI-predominant & Government Effectiveness	-1.362	-0.229	-0.073	0.006	-2.920	0.309						
	(3.867)	(0.540)	(0.052)	(0.112)	(4.440)	(0.816)						
Government-predominant & Control of Corruption							-2.015	1.659	-0.038	-0.174	-1.612	0.785
							(2.575)	(1.119)	(0.062)	(0.116)	(2.124)	(0.666)
SHI-predominant & Control of Corruption							-0.215	-0.277	-0.038	0.038	-4.538	1.00***
							(2.330)	(0.319)	(0.033)	(0.069)	(3.359)	(0.328)
Observations	970	970	970	970	407	970	970	970	970	970	407	970
Number of ID	124	124	124	124	111	124	124	124	124	124	111	124
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.189	0.753	0.879	0.645	0.178	0.166	0.188	0.753	0.880	0.646	0.195	0.171

Interaction terms ↓ // Dependent variables →	(25) Imm Idx	(26) LE	(27) ln U5M	(28) ln MM	(29) CAT 10%	(30) GGHE % GGE	(31) Imm Idx	(32) LE	(33) ln U5M	(34) ln MM	(35) CAT 10%	(36) GGHE % GGE
Government-predominant & GGE as % of GDP	-0.036	0.012	0.001	-0.003	-0.055	-0.085**						
	(0.163)	(0.030)	(0.002)	(0.004)	(0.090)	(0.038)						
SHI-predominant & GGE as % of GDP	0.084	0.013	0.005	-0.005	-0.172	-0.055						
	(0.230)	(0.041)	(0.004)	(0.005)	(0.202)	(0.047)						
Government-predominant & Labour-tax as % of health revenues							-0.015	0.035	-0.000	-0.002	-0.218	0.057**
							(0.21)	(0.036)	(0.003)	(0.003)	(0.240)	(0.024)
SHI-predominant & Labour-tax as % of health revenues							0.174	-0.021	-0.005	-0.002	-0.019	-0.114***
							(0.12)	(0.027)	(0.003)	(0.005)	(0.106)	(0.042)
Observations	970	970	970	970	407	970	970	970	970	970	407	970
Number of ID	124	124	124	124	111	124	124	124	124	124	111	124
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.191	0.756	0.881	0.649	0.179	0.244	0.192	0.755	0.881	0.646	0.184	0.213

SOURCE: author elaboration. Datasets discussed in Section 1.4. NOTES: this table present the results of the fixed effects (FE) with interaction terms, equation [2]. The interaction terms coefficient and p-values are shown in the table.

Appendix A-6 Robustness checks

Table A-9 Robustness checks

	INTERMEDIATE OUTCOMES		HEALTH SYSTEM OUTCOMES			
	(1)	(2)	(3)	(4)	(5)	(6)
	Log THE per capita	Imm. coverage	LE	Log U5M	Log MM	CAT 10%
	FE	FE	FE	FE	FE	FE
PANEL A: BASELINE ESTIMATES						
Predominant government	0.043	3.804	1.341**	-0.083**	-0.040	-3.256***
	(0.041)	(2.921)	(0.579)	(0.036)	(0.040)	(0.931)
Predominant SHI	0.117***	-1.486	-0.128	0.051	0.034	6.467***
	(0.035)	(1.606)	(0.395)	(0.037)	(0.067)	(1.129)
PANEL B: LMICs ONLY						
Predominant government	0.040	3.416	1.366**	-0.073*	-0.042	-3.305***
	(0.043)	(3.133)	(0.608)	(0.037)	(0.038)	(0.923)
Predominant SHI	0.127***	-1.195	-0.220	0.093**	0.019	6.273***
	(0.038)	(2.337)	(0.497)	(0.039)	(0.051)	(1.297)
PANEL C: REMOVED OUTLIERS						
Predominant government	0.018	2.894	1.062***	-0.066*	-0.010	-2.764***
	(0.041)	(1.780)	(0.323)	(0.035)	(0.032)	(0.954)
Predominant SHI	0.119***	-1.766	-0.079	0.049	0.032	6.312***
	(0.036)	(1.552)	(0.398)	(0.037)	(0.067)	(1.094)
PANEL D: LAGGED HFS						
Predominant government	-0.0104	3.210	0.785*	-0.075**	-0.0148	-3.016***
	(-0.27)	(-0.99)	(-1.94)	(-2.07)	(-0.36)	(-3.35)
Predominant SHI	0.105***	-1.183	-0.170	0.062	0.0446	5.917***
	(-2.84)	(-0.63)	(-0.41)	(-1.24)	(-0.65)	(-6.04)
PANEL E: GENERAL GOVERNMENT EXPENDITURE (%GDP) ADDED AS CONTROL						
Predominant government	0.038	3.790	1.359**	-0.082**	-0.042	-3.312***
	(0.043)	(2.917)	(0.570)	(0.038)	(0.042)	(0.944)
Predominant SHI	0.099***	-1.537	-0.066	0.056	0.025	6.512***
	(0.037)	(1.596)	(0.374)	(0.036)	(0.066)	(1.123)
PANEL F: USE PERCENTAGES						
% government	-0.000	0.022	-0.004	-0.001	0.001	-0.130***
	(0.002)	(0.084)	(0.018)	(0.001)	(0.003)	(0.045)
% SHI	0.006**	-0.033	-0.014	0.002	0.002	0.036
	(0.003)	(0.091)	(0.020)	(0.002)	(0.004)	(0.043)
PANEL G: DIFFERENTIAL (THE, U5M) AND RANDOM TREND (LE, CAT 10%) MODELS						
Predominant government	*0.051*		*0.129*	-0.077**		-1.102
	(0.036)		*(0.134)*	(0.032)		(1.092)
Predominant SHI	*0.142****		-0.114	*0.040*		*0.121*
	(0.033)		(0.112)	*(0.039)*		*(0.585)*
PANEL H: NOT LOGGED MORTALITY OUTCOMES						
Predominant government				-9.496**	-52.003	
				(4.066)	(33.701)	
Predominant SHI				2.335	8.218	
				(1.425)	(7.773)	
PANEL I: REMOVE GINI INDEX CONTROL VARIABLE TO MAXIMIZE NUMBER OF OBSERVATIONS						
Predominant government	0.014	0.984	0.979***	-0.065**	-0.048	-1.814
	(0.037)	(1.556)	(0.350)	(0.029)	(0.037)	(1.226)
Predominant SHI	0.095**	-2.759*	-0.540*	-0.016	-0.025	4.583***
	(0.047)	(1.665)	(0.307)	(0.040)	(0.056)	(0.996)
PANEL J: REMOVE CONTROLS TO HAVE ALL 147 COUTNRIES IN SAMPLE						
Predominant government	0.010	1.861	0.840**	-0.041	-0.032	-1.566
	(0.034)	(1.938)	(0.337)	(0.025)	(0.032)	(1.237)
Predominant SHI	0.086*	-4.079**	-1.205***	0.001	0.049	3.523***

	(0.046)	(1.718)	(0.325)	(0.044)	(0.076)	(1.210)
PANEL K: ADD CONFOUNDERS ADJUSTMENT (ZELDOW AND HATFIELD, 2021)						
Predominant government	0.038	5.416*	1.132***	-0.061*	-0.042	-2.141**
	(0.036)	(2.844)	(0.305)	(0.034)	(0.031)	(1.024)
Predominant SHI	0.049	0.622	-0.299	0.071	0.089	4.167*
	(0.034)	(2.275)	(0.254)	(0.048)	(0.069)	(2.283)
PANEL L: ADD DEVELOPMENT ASSISTANCE FOR HEALTH (% THE) AS A CONTROL						
Predominant government	0.050	3.691	1.254**	-0.082**	-0.038	-3.298***
	(0.041)	(2.936)	(0.510)	(0.036)	(0.039)	(0.944)
Predominant SHI	0.126***	-1.657	-0.260	0.053	0.036	6.427***
	(0.037)	(1.670)	(0.377)	(0.037)	(0.067)	(1.132)
PANEL M: USE LOG GDP DECILES AS CONTROL VARIABLE, INSTEAD OF LOG GDP						
Predominant government	0.024	3.595	1.248**	-0.077**	-0.032	-3.047***
	(0.048)	(3.035)	(0.557)	(0.036)	(0.046)	(0.970)
Predominant SHI	0.155***	-1.247	-0.048	0.035	0.007	6.517***
	(0.041)	(1.650)	(0.369)	(0.038)	(0.063)	(1.071)

SOURCE: author elaboration. Datasets discussed in Section 1.4. NOTES: models detail explained in the robustness checks section. Baseline model controls variable included in all models unless specified. In italic, in panel G, coefficients that are statistically different from the baseline model at the 10% level based on tests in eq. [4] and [9]. Robust standard errors in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A-10 Estimates using different definitions of "predominant HFS"

	INTERMEDIATE OUTCOMES		HEALTH SYSTEM OUTCOMES			
	(1)	(2)	(3)	(4)	(5)	(6)
	Log THE per capita	Imm. coverage	LE	Log U5M	Log MM	CAT 10%
	FE	FE	FE	FE	FE	FE
PANEL A: BASELINE ESTIMATES (HFS DEFINED BY CLUSTERING)						
Predominant government	0.043	3.804	1.341**	-0.083**	-0.040	-3.256***
	(0.041)	(2.921)	(0.579)	(0.036)	(0.040)	(0.931)
Predominant SHI	0.117***	-1.486	-0.128	0.051	0.034	6.467***
	(0.035)	(1.606)	(0.395)	(0.037)	(0.067)	(1.129)
PANEL B: HFS DEFINED BY HIGHEST VALUE						
Government financing (% of THE) highest value	0.009	1.332	0.474	-0.075***	-0.060	-1.700*
	(0.038)	(1.253)	(0.296)	(0.022)	(0.040)	(0.872)
SHI financing (% of THE) highest value	0.041	0.210	-0.467*	0.050	0.114***	3.782***
	(0.042)	(1.306)	(0.250)	(0.057)	(0.041)	(1.133)
PANEL C: OOP PREDOMINANT ONLY IF OOP-%-THE ABOVE 50%						
Predominant government	0.101	14.911*	1.020***	-0.053	-0.094	-1.916
	(0.065)	(8.554)	(0.359)	(0.037)	(0.076)	(1.801)
Predominant SHI	0.373***	-3.737**	0.934**	-0.048	-0.033	4.420**
	(0.056)	(1.805)	(0.418)	(0.039)	(0.065)	(2.092)
PANEL D: OOP PREDOMINANT ONLY IF OOP-%-THE ABOVE 45%						
Predominant government	-0.015	8.722**	0.519	-0.013	-0.032	-2.840***
	(0.049)	(3.799)	(0.341)	(0.025)	(0.043)	(1.082)
Predominant SHI	0.200***	-3.056**	0.424	0.043	-0.038	4.495***
	(0.031)	(1.193)	(0.452)	(0.036)	(0.055)	(1.431)
PANEL E: OOP PREDOMINANT ONLY IF OOP-%-THE ABOVE 40%						
Predominant government	-0.036	8.990**	0.818*	-0.023	-0.051	-2.547***
	(0.045)	(3.522)	(0.489)	(0.024)	(0.034)	(0.938)
Predominant SHI	0.189***	-3.508***	0.290	0.053	-0.022	5.295***
	(0.025)	(1.071)	(0.467)	(0.052)	(0.059)	(1.249)
PANEL F: OOP PREDOMINANT ONLY IF OOP-%-THE ABOVE 35%						
Predominant government	0.032	3.813	0.757*	-0.054	0.011	-2.136**
	(0.036)	(3.615)	(0.430)	(0.039)	(0.034)	(0.883)
Predominant SHI	0.163***	-3.411***	0.244	0.049	0.001	4.996***
	(0.028)	(1.297)	(0.438)	(0.066)	(0.046)	(1.354)
PANEL G: OOP PREDOMINANT ONLY IF OOP-%-THE ABOVE 30%						
Predominant government	0.047	4.360*	0.985***	-0.081***	-0.025	-2.691***
	(0.034)	(2.424)	(0.284)	(0.029)	(0.028)	(0.866)
Predominant SHI	0.139***	-2.883**	0.186	0.065	-0.024	6.548***
	(0.033)	(1.369)	(0.382)	(0.046)	(0.048)	(1.164)
PANEL H: USE ALL HF ARRANGEMENTS AS INPUT VARIABLES FOR CLUSTERING						
Predominant government	0.030	4.922	1.103**	-0.058**	-0.058*	-2.188**
	(0.033)	(3.400)	(0.448)	(0.027)	(0.034)	(0.856)
Predominant SHI	0.091***	-0.541	-0.227	0.060**	0.039	4.590***
	(0.027)	(1.487)	(0.350)	(0.029)	(0.056)	(1.333)
PANEL I: USE ALL HF ARRANGEMENTS *and* LN(THE PER CAPITA) AS INPUT VARIABLES FOR CLUSTERING						
Predominant government	0.030	5.289	1.067**	-0.055**	-0.053	-2.188**
	(0.033)	(3.527)	(0.466)	(0.028)	(0.036)	(0.856)
Predominant SHI	0.091***	-0.763	-0.235	0.057**	0.033	4.590***
	(0.027)	(1.408)	(0.355)	(0.026)	(0.053)	(1.333)
PANEL J: SET THE NUMBER OF CLUSTERS TO FOUR						
Predominant government	-0.005	1.571	0.545	-0.041	-0.101	-3.032*
	(0.067)	(4.615)	(0.810)	(0.043)	(0.103)	(1.604)

Predominant OOP, but less predominant	0.072	-1.390	-0.324	0.028	-0.023	-1.633
	(0.054)	(1.138)	(0.403)	(0.028)	(0.067)	(1.371)
Predominant SHI	0.146**	-1.474	-0.831	0.097**	0.065	3.205**
	(0.072)	(2.268)	(0.679)	(0.042)	(0.098)	(1.534)

SOURCE: author elaboration. Datasets discussed in Section 1.4. NOTES: models detail explained in the robustness checks section. Baseline model controls variable included in all models unless specified. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table A-11 Robustness to different income sub-groups

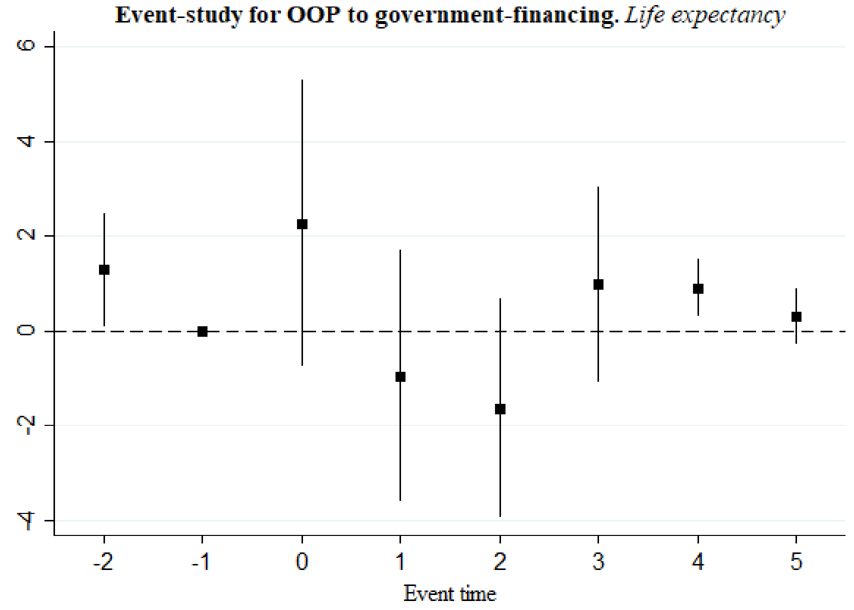
	INTERMEDIATE OUTCOMES		HEALTH SYSTEM OUTCOMES			
	(1)	(2)	(3)	(4)	(5)	(6)
	Log THE per capita	Imm. coverage	LE	Log U5M	Log MM	CAT 10%
	FE	FE	FE	FE	FE	FE
PANEL A: BASELINE ESTIMATES						
Predominant government	0.043	3.804	1.341**	-0.083**	-0.040	-3.256***
	(0.041)	(2.921)	(0.579)	(0.036)	(0.040)	(0.931)
Predominant SHI	0.117***	-1.486	-0.128	0.051	0.034	6.467***
	(0.035)	(1.606)	(0.395)	(0.037)	(0.067)	(1.129)
PANEL B: SUB-GROUP OF HIGH- AND MIDDLE- INCOME COUNTRIES						
Predominant government	0.012	5.657*	0.903**	-0.062	-0.021	-2.657***
	(0.034)	(3.250)	(0.385)	(0.039)	(0.039)	(0.854)
Predominant SHI	0.090**	0.111	-0.246	0.061**	0.074	5.268***
	(0.041)	(1.921)	(0.432)	(0.029)	(0.066)	(1.000)
PANEL C: SUB-GROUP OF LOW- AND MIDDLE-INCOME COUNTRIES						
Predominant government	0.040	3.416	1.366**	-0.073*	-0.042	-3.305***
	(0.043)	(3.133)	(0.608)	(0.037)	(0.038)	(0.923)
Predominant SHI	0.127***	-1.195	-0.220	0.093**	0.019	6.273***
	(0.038)	(2.337)	(0.497)	(0.039)	(0.051)	(1.297)
PANEL D: SUB-GROUP OF MIDDLE-INCOME COUNTRIES						
Predominant government	-0.002	5.587	0.891**	-0.043	-0.018	-3.071***
	(0.035)	(3.554)	(0.404)	(0.039)	(0.042)	(0.891)
Predominant SHI	0.119***	-0.341	-0.062	0.087**	0.018	5.665***
	(0.041)	(2.524)	(0.539)	(0.037)	(0.057)	(1.398)
PANEL E: INCLUDE ALL COUNTRIES						
Predominant government	-0.012	-3.902	-0.787	0.047	0.039	2.120***
	(0.040)	(3.538)	(0.480)	(0.032)	(0.044)	(0.740)
Predominant SHI	0.091*	-4.297	-1.204*	0.126**	0.124	7.728***
	(0.054)	(3.222)	(0.708)	(0.049)	(0.087)	(1.213)
PANEL F: INCLUDE ALL COUNTRIES, USE HIGHEST VALUE FOR HFS DEFINITION						
Government financing (% of THE) highest value	0.009	1.356	0.521*	-0.083***	-0.065	-1.700*
	(0.038)	(1.255)	(0.303)	(0.023)	(0.041)	(0.871)
SHI financing (% of THE) highest value	0.043	0.026	-0.473*	0.048	0.113***	3.782***
	(0.041)	(1.290)	(0.252)	(0.057)	(0.041)	(1.133)

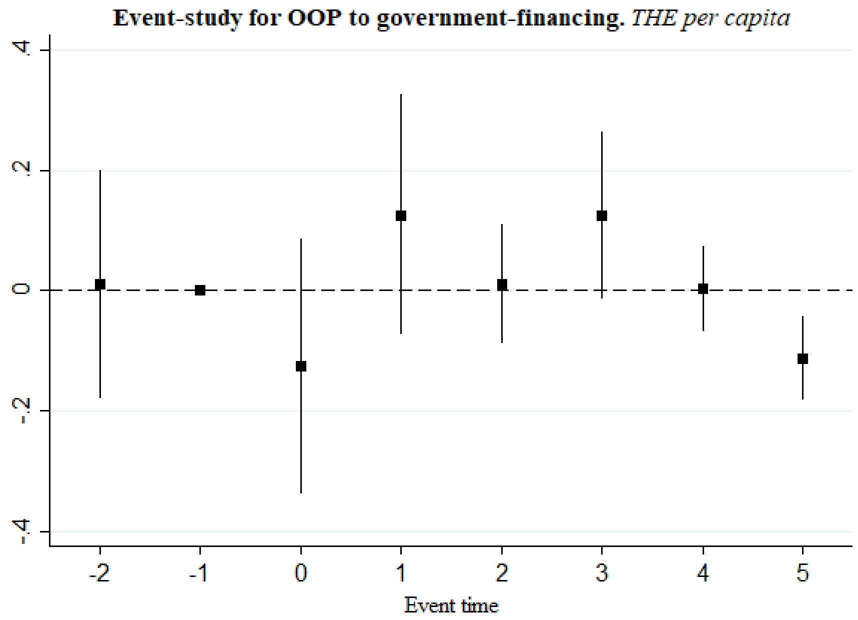
Table A-12 Additional outcomes

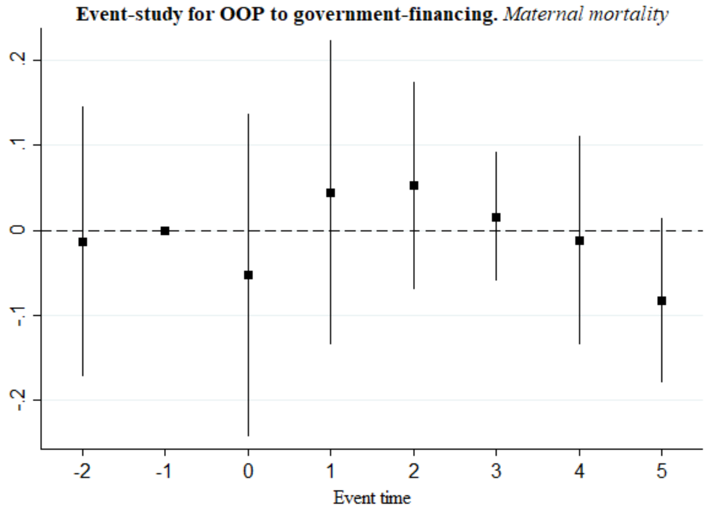
	#	Dep. Variable	Model	Government-predominant HFS		SHI-predominant HFS		Obs.	Coun-tries	Coun. FE	Year FE	Adj. R2
				ρ_2	SE	ρ_1	SE					
HEALTH SYSTEM OUTCOMES	(1)	Ln U5M, DHS	FE	-0.080**	0.036	1.120***	0.119	292	59	YES	YES	0.045
	(2)	Ln IM, DHS	FE	-0.113**	0.042	0.969***	0.114	291	59	YES	YES	0.040
	(3)	AM, Female	FE	-19.3**	(9.417)	-5.898	(8.310)	968	124	YES	YES	0.607
	(4)	AM, Male	FE	-20.1**	(8.485)	-0.909	(10.533)	968	124	YES	YES	0.506
	(5)	MMR, National	FE	-182.28	(119.50)	-10.011	(11.235)	262	124	YES	YES	0.521
	(6)	CAT 25%	FE	-0.877***	(0.264)	0.899**	(0.438)	407	111	YES	YES	0.184
	(7)	Inc. Imp 3.10	FE	-0.380**	(0.163)	-0.735***	(0.231)	407	111	YES	YES	0.140
	(8)	Inc. Imp 1.90	FE	-0.220	(0.183)	-0.084	(0.182)	407	111	YES	YES	0.315
INTERMEDIATE OUTCOMES	(9)	SBA %	FE	1.208	(1.818)	-2.501***	(0.770)	629	94	YES	YES	0.471
	(10)	GGHE % GGE	FE	0.895**	(0.408)	1.047**	(0.472)	970	124	YES	YES	0.167
	(11)	THE % GDP	FE	0.332	(0.298)	0.847**	(0.349)	950	124	YES	YES	0.290

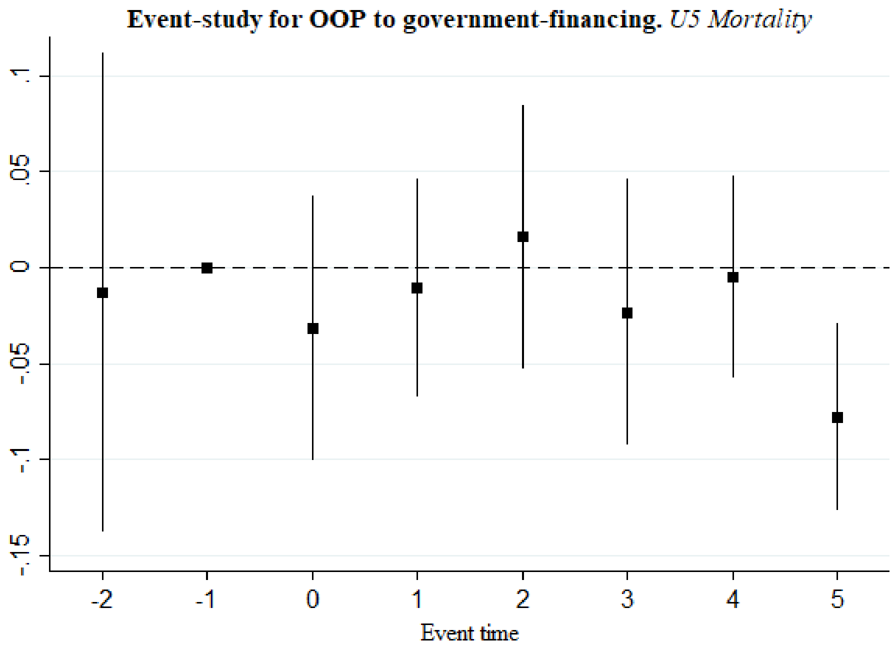
Source: author elaboration. Eq. [1] is estimated using additional outcomes, as detailed in the Results section. Notes: for DHS outcomes, fewer controls were used because otherwise the number of observations would drop below 100. The controls used were: GDP per capita, urbanization, control of corruption, government effectiveness, % population above 65 and % population below 14 years old, in addition to fixed effects. For DHS outcomes, under-5 mortality and infant mortality is provided as “average for the 5 and 10-year period before the survey”: when it was 5-years, the observation year was recorded as “survey year minus three”, when it was 10 years, the year considered was “survey year minus five”. In other words, we attach the “past 5 and 10 year average reading” to the mid-year of that same 5 or 10 year period. Robust standard errors reported, clustered at country-level. p<0.1*, p<0.05**, p<0.01***

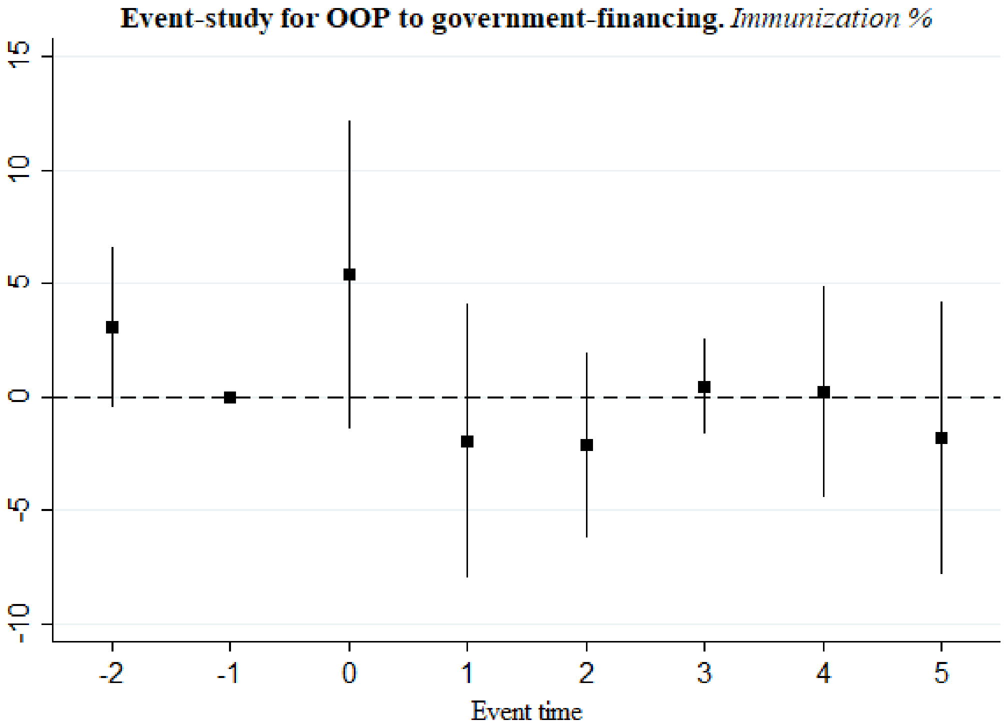
Figure A.4 Event study results: government financing











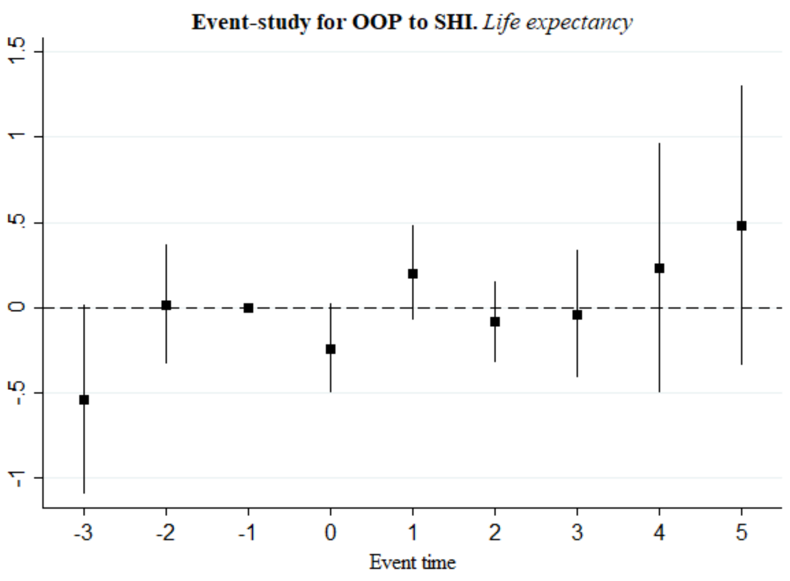
Notes: these are event studies plots, for five outcomes out of six outcomes used for our main results. For CAT 10%, data limitations do not allow an event study. In the case of government financing, there are 30 countries switching between OOP and government financing predomaning HFSs. However, only 17 countries switch only once during the 2000-2018 study period. These 17 countries are included in the event study, while the remaining 13 countries who switch back-and-forth between OOP and government financing are excluded, as the interpretation of their coefficients is not possible.

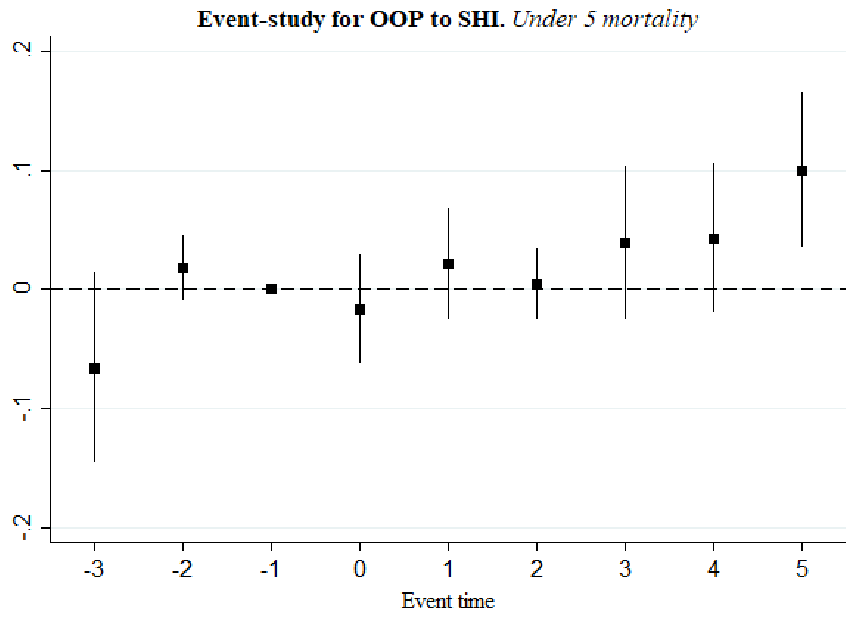
The equation used for the above plots is: $Y_{it} = \alpha + \sum_{j=0}^{5} \rho_j \, GOV_{it-j} + \rho_2 GOV_{it+2} + \gamma \boldsymbol{X}_{it} + T_t + C_i + \varepsilon_{it}$

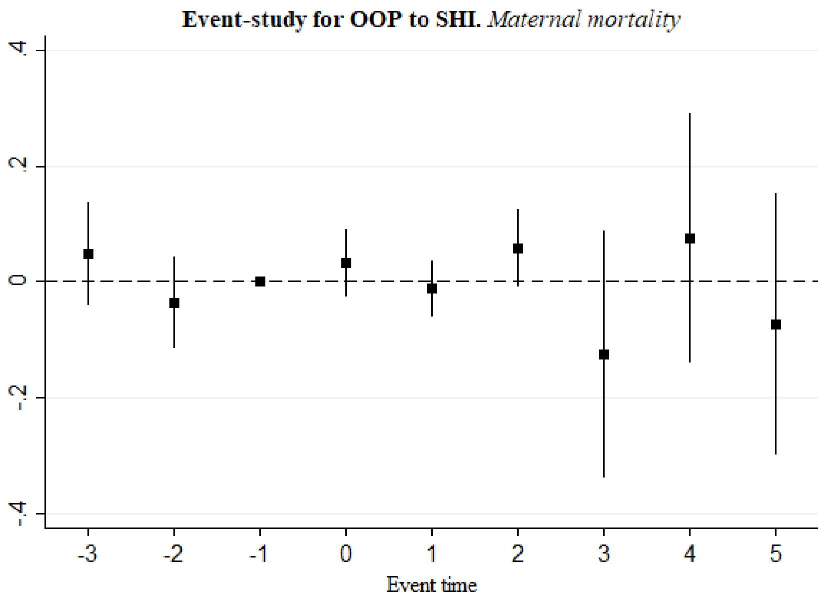
Adding further leads resulted in omitted variables, therefore we limited leads to only two years before the switch from OOP to government financing.

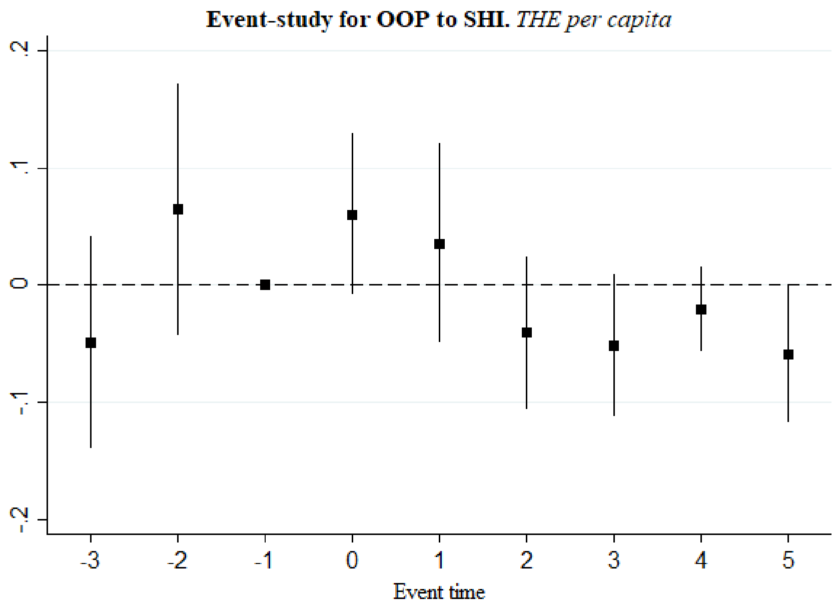
The baseline omitted case is the first lead, where k=1.

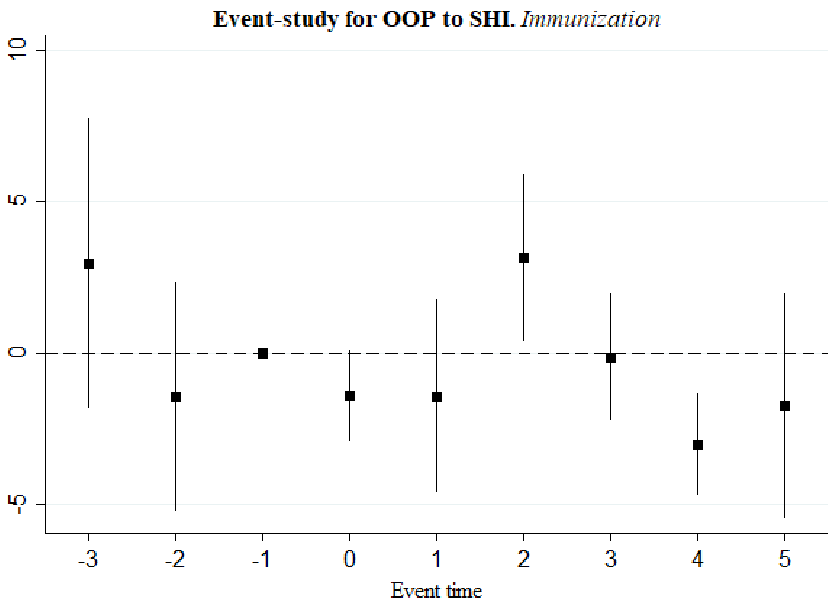
Figure A.5 Event study results: SHI











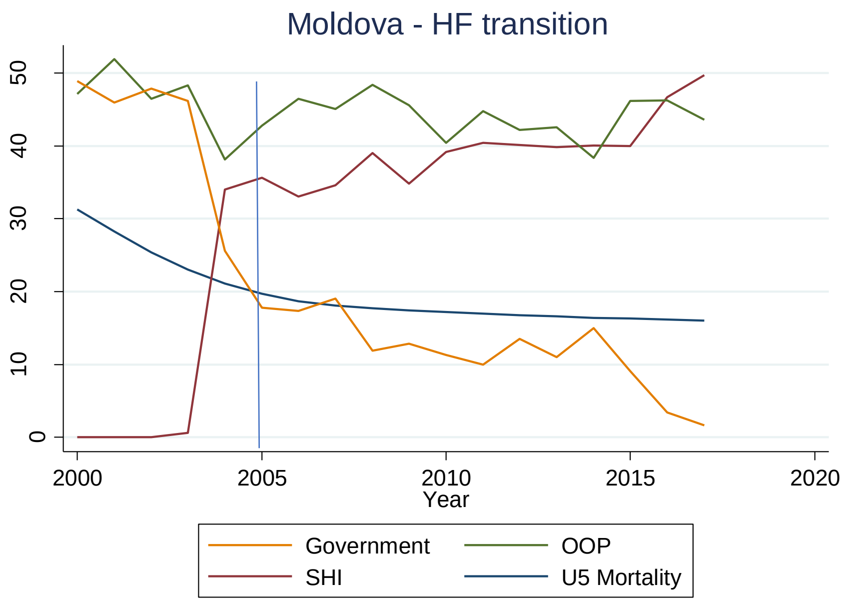
Notes: these are event studies plots, for five outcomes out of six outcomes used for our main results. For CAT 10%, data limitations do not allow an event study. In the case of government financing, there are eight countries switching between OOP and SHI predomaning HFSs. Seven countries switch only once during the 2000-2018 study period. These seven countries are included in the event study, while the remaining 1 countries who switch back-and-forth between OOP and SHI are excluded, as the interpretation of their coefficients is not possible.

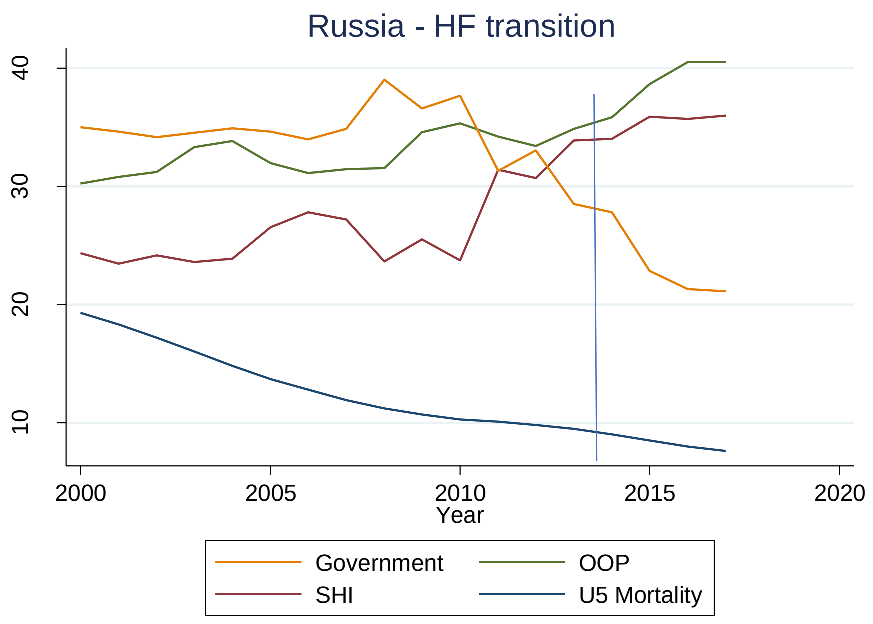
The equation used for the above plots is: $Y_{it} = \alpha + \sum_{j=0}^{5} \rho_j SHI_{it-j} + \sum_{k=2}^{3} \rho_k SHI_{it+k} + \gamma \boldsymbol{X}_{it} + T_t + C_i + \varepsilon_{it}$

The baseline omitted case is the first lead, where k=1

Appendix A-7 Health financing transitions in selected countries mentioned in the discussion section

Figure A.6 Moldova and Russia HF transitions examples





Appendix B: appendix for Chapter 2

Appendix B-1. Descriptive statistics at baseline for high and low ESF coverage municipalities' groups

Table B-1. Comparison of outcome, mediators and control variables at baseline (year 2007) between high and low ESF coverage groups

Variable ↓ Group →	Mean High coverage (ESF coverage>50%)	Mean Low coverage (ESF coverage<50%)	p-value, t test for difference of means
Observations	4356 (78% of all municipalities)	1208 (22% of all municipalities)	
ANC visits per 1000 people	89.3	28.4	<0.000
PNC visits per 1000 people	50.7	15.3	<0.000
Hypertension visits per 1000 people	629.6	143.5	<0.000
Diabetes visits per 1000 people	105.5	32.7	<0.000
HIV visits per 1000 people	17.3	9.7	<0.000
Population	17841	90574	<0.000
ESF coverage (% population)	109.8	21.6	<0.000
Physicians, PHC, per 1000 people	0.22	0.15	<0.000
Nurses, PHC, per 1000 people	0.06	0.12	<0.000
CHWs, per 1000 people	2.4	1.2	<0.000
Equipment (pieces) per 1000 people	1.9	2.4	<0.000
Infrastructure (PHC facilities) per 1000 people	0.09	0.14	<0.000
Bolsa Familia financing (Real) per 1000 people	78246	47899	<0.000
GDP per capita (Real)	8335	12195	<0.000
Hospital beds per 10000 people	19	20	0.2
Public health expenditure per capita	518	484	0.02

Source: author elaboration. Data source is detailed in the methods section. Note: Mais Medicos physician density is not shown because in 2007 the program did not exist. All measures are per 1000 people, unless otherwise stated.

The table above shows the means for outcomes, mediators and control variables across two groups, high and low ESF coverage, where high is defined as ESF coverage of 50% or more, and low equal or less than 50%. Approximately, 20% of municipalities fall into the "low ESF coverage" group. As expected, municipalities with lower ESF coverage have larger GDP per capita, larger populations, have more infrastructure and equipment. However, they also have lower public health expenditures, lower density of (public) PHC health workers, and lower PHC services coverage. Hospital beds per capita are similar across the two groups.

As noted in the methods and discussion sections of Chapter 2, the rather small percentage of municipalities in the “low coverage” group confirms that the study assess the expansion of the existing ESF program. Municipalities with low ESF coverage show lower PHC services coverage and lower density of PHC professionals, except nurses. The difference in means across the control variables suggest the possibility of non-random selection, and justifies the inclusion of these control variables in my models, also following the literature. However, it is important to note that municipalities that have low ESF coverage also show larger GDP per capita, PHC infrastructure density, and equipment density, which would usually facilitate larger PHC service coverage, rather than lower PHC service coverage.

Appendix B-2. Methodology appendix: algorithm and sequential ignorability in case of multiple outputs

The algorithm used to compute ACMEs and ADEs is sketched below, taking ANC visits and CHWs as an example of PHC service coverage outcome and output (mediator), respectively. We refer the reader to appendix D of Imai et al. paper (95) for more details.

1. Step 1: fit linear models for PHC service coverage outcome Y ANC visits and output (mediator) M CHWs density, given all controls mentioned earlier. Service coverage outcome ANC visits (Y) is regressed on the treatment ESF coverage (D), the output (mediator) CHWs density (M), and controls mentioned above, while CHWs density is regressed on ESF coverage and controls, as shown below:

$$M_{i,t} = \beta_1 D_{i,t} + \gamma_1 \boldsymbol{X}_{i,t} + \mu_i + T_t + \varepsilon_{i1} \quad [42]$$

$$Y_{i,t} = \beta_2 D_{i,t} + \gamma_2 \boldsymbol{X}_{i,t} + \beta_3 M_{i,t} + \mu_i + T_t + \varepsilon_{i2} \quad [43]$$

2. Step 2: simulate model parameters 500 times, according to their multivariate sampling distribution and using a multivariate normal approximation, with expected value and covariance equal to estimated parameters and their asymptotic covariance matrix
3. Step 3: for each simulation, repeat the following three steps. Simulate the potential values of CHWs density, simulate the potential values of ANC visits (given the simulated values of CHWs density), and compute causal mediation effects and direct effects
4. Step 4: obtain point estimates for ACMEs of CHWs and ADEs of ESF coverage, on ANC visits, from their distributions, including p-values and confidence intervals.

Regarding the sequential ignorability assumption with multiple outputs (94,101):

$$Y_i(d, m, w), M_i(d'), W_i(d'') \perp D_i \mid X_i = x \quad [44]$$

$$Y_i(d, m, w) \perp M_i(d'), W_i(d'') \mid D_i = d, X_i = x \quad [45]$$

for any x, d, d’,d’’, m, w.

Equation [44] requires ignorability between the treatment and the outcome, and each mediator, conditional on observed confounders. The second hypothesis requires ignorability between the mediators (taken together) and the outcome, as well as no observed or unobserved post-treatment confounding.

Appendix B-3. Estimates of association of ESF with intermediate service coverage outcomes

$$Y_{i,t} = \beta_1 D_{i,t} + \gamma \boldsymbol{X}_{i,t} + \mu_i + T_t + \varepsilon_{i1}$$

Definitions used within equation are the same as in the main text.

Table B-2 Estimates of association of ESF with intermediate service coverage outcomes

Dep. variable (per 1000 people) →	(1) ANC visits	(2) PNC visits	(3) Diabetes screening	(4) Hypertension screening	(5) HIV visits
PSF population coverage	0.293***	0.227***	0.489***	2.901***	0.093***
	(0.067)	(0.018)	(0.072)	(0.630)	(0.025)
Municipalities	5,483	5,477	5,486	5,486	5,472
Municipality fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	49,327	49,273	49,354	49,354	49,228
R-squared	0.002	0.032	0.002	0.002	0.000

Source: data source as described in the methods section. Notes: the table provide results of coefficient β_1 in eq. $Y_{i,t} = \beta_1 D_{i,t} + \gamma \boldsymbol{X}_{i,t} + \mu_i + T_t + \varepsilon_{i1}$ across different PHC service coverage outcomes (all of them are "per 1000 people"), as noted in the columns. Controls listed in the methods section are omitted for simplicity. Robust standard errors, clustered at the municipality level, are used for inferences. P-value below: 0.1 *; 0.05 **; 0.01 ***

Appendix B-4. Robustness checks

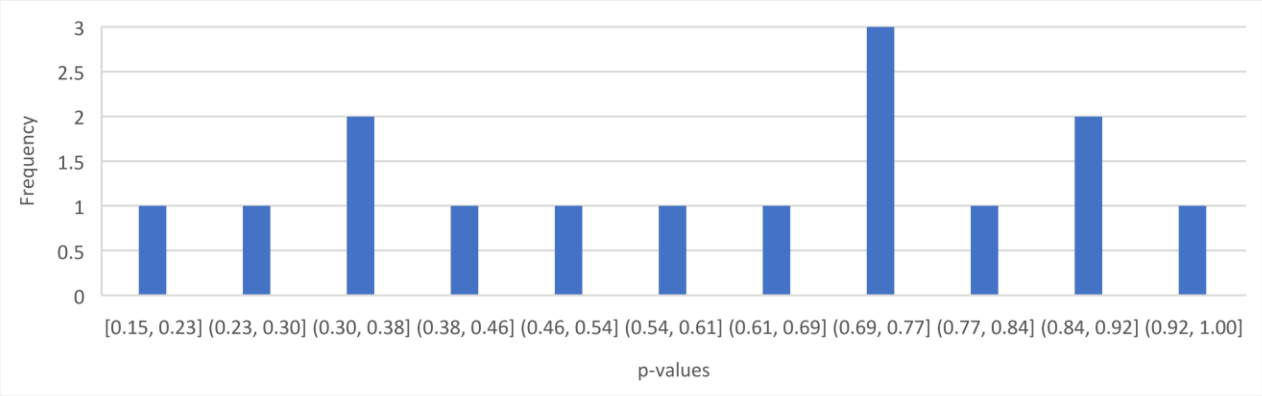
Table B-3 Main robustness checks

	No interaction, all outputs (1)	Change treatment to "be in ESF for 3 or more years" (2)	Regression-based mediation with state-time linear trends (3)	Control for political factors (4)
PANEL A: ANC Visits				
ACME – CHWs	0.057***	3.384***	0.045**	0.055***
ACME – Nurses	-0.001	0.241	-0.006**	-0.001
ACME – Physicians	-0.001	0.026	-0.004	-0.001
ADE	0.206***	8.555***	0.176**	0.210***
PANEL B: PNC Visits				
ACME – CHWs	0.018***	1.583***	0.013***	0.017***
ACME – Nurses	-0.005	0.288***	-0.005***	-0.001***
ACME – Physicians	0.005	0.069***	0.005**	0.003***
ADE	0.184***	3.663***	0.177***	0.185***
PANEL C: Diabetes screening				
ACME – CHWs	0.128***	6.842***	0.112**	0.141***
ACME – Nurses	0.008	-0.886	0.007	0.003
ACME – Physicians	0.019	0.042	0.012	0.002
ADE	0.284***	11.898	0.263**	0.2976***
PANEL D: Hypertension screening				
ACME – CHWs	0.195	19.247***	0.146	0.203
ACME – Nurses	-0.061	-2.475	-0.069	0.007
ACME – Physicians	0.250**	2.047***	0.251	0.120**
ADE	2.210***	43.6397	2.225***	2.320***
PANEL E: HIV visits				
ACME – CHWs	0.041	1.766	0.030**	0.042
ACME – Nurses	0.006	-0.563	0.008	0.003
ACME – Physicians	-0.011	-0.099	-0.011	-0.007
ADE	0.047	-0.897	0.043	0.055

Source and notes: same as table 4 in main text. However, robustness checks are presented instead of interacted models. Detail of each robustness check presented in main text, and also shown in column names.

Figure B.1 P-values of interactions with Bolsa Familia and Mais Medicos

P-values distribution of ACME (75th percentile of other intervention) - ACME (25th percentile of other intervention) =0, when interacting treatment ESF coverage and mediators with other interventions, i.e., Mais medicos and Bolsa Familia

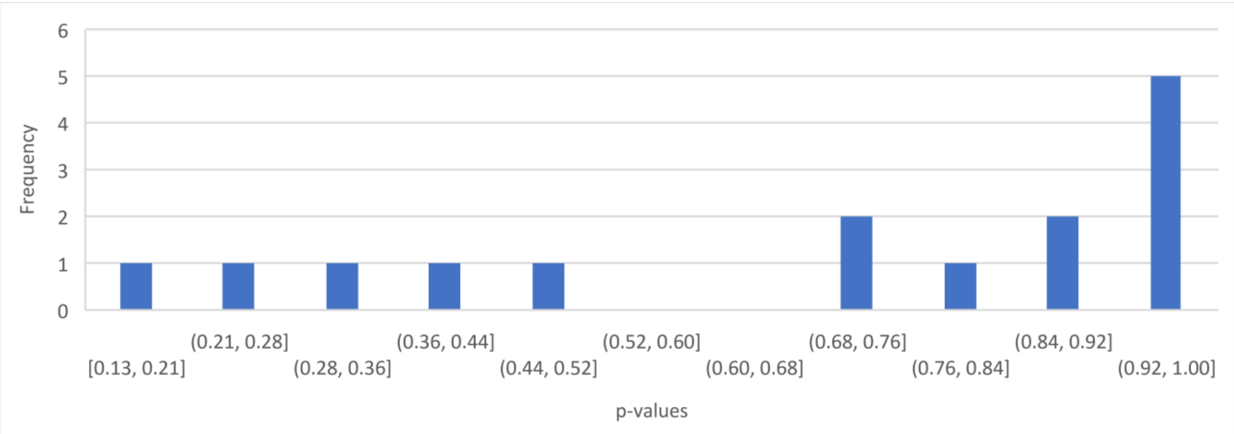


This shows that there is no p-value below 0.15 for the test ACME (75th percentile of other intervention)-ACME (25th percentile of other intervention)=0 for both Bolsa Familia and Mais Medicos. In other words, there is no evidence of a significant interaction between those other interventions and health professionals indirect effects.

For Bolsa Familia and Mais Medicos, the test is performed 15 times, which is equivalent to three FHTs health professionals (CHWs, PHC nurses, and PHC physicians) times five PHC service coverage outcomes (ANC visits, PNC visits, diabetes screening, hypertension screening, and HIV visits). In total, 30 interaction tests with other interventions are performed. In other words, the test is performed for: ANC CHWs, ANC PHC Nurses, ANC PHC physicians, PNC CHWs, PNC PHC nurses, PNC PHC physicians… and so on, for Bolsa Familia, and then repeated for Mais Medicos.

Figure B.2 P-values of interactions with GDP per capita

P-values distribution of ACME (75th percentile of GDP per capita)-ACME (25th percentile of GDP per capita)=0, when interacting treatment ESF coverage and mediators with other interventions



This shows that there is no p-value below 0.13 for the test ACME (75^{th} percentile of GDP per capita)-ACME (25^{th} percentile of GDP per capita)=0. In other words, there is no evidence of a significant interaction between those other interventions and HR ACMEs.

For GDP, the test is performed 15 times, which is equivalent to three FHTs health professionals (CHWs, PHC nurses, and PHC physicians) times five PHC service coverage outcomes (ANC visits, PNC visits, diabetes screening, hypertension screening, and HIV visits). In other words, the test is performed for: ANC CHWs, ANC PHC Nurses, ANC PHC physicians, PNC CHWs, PNC PHC nurses, PNC PHC physicians… and so on.

Table B-4 Regression-based method. ACME and ADE in models with a single output only

Dependent variable →	ANC Visits			PNC Visits			Diabetes screening			Hypertension screening			HIV visits		
Outputs → Effect ↓	PHC Physician	PHC Nurses	CHWs	PHC Physician	PHC Nurses	CHWs	PHC Physician	PHC Nurses	CHWs	PHC Physician	PHC Nurses	CHWs	PHC Physician	PHC Nurses	CHWs
ACME	0.001	-0.005	0.053**	0.006**	-0.006***	0.016***	0.022	0.013***	0.124*	0.250	-0.073	0.202**	-0.008	0.008*	0.035*
ADE	0.257***	0.263***	0.201**	0.196***	0.204***	0.183***	0.419***	0.420***	0.298**	2.374***	2.612***	2.354***	0.090***	0.075***	0.044
Prop. mediated	0%	-2%	18%	3%	-3%	7%	5%	3%	25%	9%	-3%	7%	-9%	9%	38%
Sensitivity	F	F	S	F	F	S	F	S	S	S	F	S	F	F	S
Correlation	-0.0000	+0.0000	-0.0000	-0.0000	+0.0000	+0.0000	+0.0000	+0.0000	-0.0000	-0.0000	-0.0000	+0.0000	-0.0000	+0.0000	-0.0000
N (municipalities)	5445	5511	5549	5445	5511	5549	5445	5511	5549	5445	5511	5549	5445	5511	5549
Observations	65308	66100	66556	65308	66100	66556	65308	66100	66556	65308	66100	66556	65308	66100	66556

Source: data source as described in the methods section. Notes: the table provide results of single output causal mediation analysis for the effect of ESF presence on PHC service coverage outcomes, controlling for hospital beds per 10000 people, GDP per capita (in Brazilian real), Bolsa Familia subsidies per 1000 people in Brazilian real, number of Mais Medicos programs doctor per 10000 people, municipality fixed effects, year fixed effects. Each model has one mediator, as noted in each column (all mediators "per 1000 people"). All dependent variables are per 1000 people. ATE, ADE and ACME robust standard errors are estimated via 500 bootstrapped simulations. ATE, ADE and ACME procedure is detailed in the econometric strategy section. Robust standard errors, clustered at the municipality level, are used for inferences. P-value below: 0.1 *; 0.05 **; 0.01 **. Sensitivity analysis from the causal mediation framework are added to this table: S (success) states that the sensitivity analysis suggests that the "true" ACME coefficient sign is the same as the estimated ACME coefficient sign, while F (fail) states that the sensitivity analysis the opposite, i.e., that the "true" ACME coefficient sign is different from the estimated ACME coefficient sign. Correlation indicates the correlation between the error terms in the mediation and outcome regression: the closer it is to zero, the most likely that the sequential ignorability assumption holds (102).

Table B-5 Results with mediator-treatment interaction models (single mediator analyses, causal mediation framework)

Dependent variable →	ANC Visits			PNC Visits			Diabetes screening			Hypertension screening			HIV visits		
Outputs →	PHC	PHC	CHWs	PHC	PHC	CHWs	PHC	PHC	CHWs	PHC	PHC	CHWs	PHC	PHC	CHWs
Effect ↓	Physician	Nurses		Physician	Nurses		Physician	Nurses		Physician	Nurses		Physician	Nurses	
ACME	0.002	-0.011	0.939**	0.052**	-0.015***	0.311***	0.078	0.005**	2.351**	2.021	0.173	3.965**	-0.096	0.033	0.663**
ADE	4.653***	4.552***	3.619***	3.493***	3.575***	3.250***	7.702	7.61***	5.342**	43.83***	45.27***	41.82***	1.556***	1.422***	0.803
Prop. mediated	0%	-0%	21%	1%	-0%	9%	1%	0%	32%	4%	0%	8%	-7%	2%	46%

Source: data source as described in the methods section. Notes: the table provide results of single output causal mediation analysis for the effect of ESF presence on PHC service coverage outcomes, controlling for hospital beds per 10000 people, GDP per capita (in Brazilian real), Bolsa Familia subsidies per 1000 people in Brazilian real, number of Mais Medicos programs doctor per 10000 people, municipality fixed effects, year fixed effects. Each model has one mediator, as noted in each column (all mediators "per 1000 people"). All dependent variables are per 1000 people. ATE, ADE and ACME robust standard errors are estimated via 500 bootstrapped simulations. ATE, ADE and ACME procedure is detailed in the econometric strategy section. Robust standard errors, clustered at the municipality level, are used for inferences. P-value below: 0.1 *; 0.05 **; 0.01***. Outputs (i.e., mediators) are interacted with treatment at the 25^{th} and 75^{th} percentile, therefore the coefficient reflect an increase in ESF coverage from the 25^{th} to the 75^{th} percentile. The interaction terms (not shown) are never significant at the 5% level, and only once significant at the 10% level, for CHW and HIV visits.

Table B-6 Results controlling for baseline mediator values (single mediator analyses, causal mediation framework)

Dependent variable →	ANC Visits			PNC Visits			Diabetes screening			Hypertension screening			HIV visits		
Outputs → Effect ↓	PHC Physician	PHC Nurses	CHWs	PHC Physician	PHC Nurses	CHWs	PHC Physician	PHC Nurses	CHWs	PHC Physician	PHC Nurses	CHWs	PHC Physician	PHC Nurses	CHWs
ACME	-0.000	-0.001	0.054**	0.003***	-0.001***	0.018***	0.004	0.003	0.136**	0.119	0.001	0.223*	-0.005	0.002	0.038**
ADE	0.254	0.256	0.204***	0.195***	0.199***	0.182***	0.430	0.429	0.297**	2.430***	2.601***	2.388***	0.088***	0.079***	0.044
Prop. mediated	-0%	-0%	21%	2%	-0%	9%	1%	1%	31%	5%	0%	8%	-6%	2%	46%

Source: data source as described in the methods section. Notes: the table provide results of single output causal mediation analysis for the effect of ESF presence on PHC service coverage outcomes, controlling for hospital beds per 10000 people, GDP per capita (in Brazilian real), Bolsa Familia subsidies per 1000 people in Brazilian real, number of Mais Medicos programs doctor per 10000 people, municipality fixed effects, year fixed effects. Each model has one mediator, as noted in each column (all mediators "per 1000 people"), and the value of the output (i.e., mediator) at baseline year (i.e., 2007). All dependent variables are per 1000 people. ATE, ADE and ACME robust standard errors are estimated via 500 bootstrapped simulations. ATE, ADE and ACME procedure is detailed in the econometric strategy section. Robust standard errors, clustered at the municipality level, are used for inferences. P-value below: 0.1 *; 0.05 **; 0.01 ***.

Appendix C: appendix for Chapter 3, Part I and II

Appendix C-1. Comparisons across countries of CHE 10%, CHE 25% and threshold-agnostic CHE, and simulation file

Excel file with simulation showing OOP expenditure budget share/threshold-agnostic CHE properties available at Open Science Framework repository https://osf.io/2z3fg/

Table C-1. Comparisons across countries of CHE 10%, CHE 25% and threshold-agnostic CHE

Country (3 digit ISO)	CHE 10%	Ranking based on CHE 10%	Ranking based on CHE 25% (absolute difference vs. ranking 10%)	Ranking based on threshold-agnostic CHE (absolute difference vs. ranking 10%)
GEO	29%	149	148 (1)	149 (0)
NPL	27%	148	119 (29)	146 (2)
EGY	26%	147	132 (15)	147 (0)
BRA	26%	146	121 (25)	145 (1)
NIC	25%	145	149 (4)	148 (3)
KHM	20%	144	146 (2)	143 (1)
CHN	20%	143	144 (1)	144 (1)
MDA	19%	142	122 (20)	138 (4)
SDN	18%	141	120 (21)	142 (1)
TJK	18%	140	147 (7)	129 (11)
IND	17%	139	129 (10)	139 (0)
CHL	17%	138	137 (1)	141 (3)
COL	17%	137	114 (23)	118 (19)
ARG	17%	136	138 (2)	125 (11)
ALB	17%	135	140 (5)	124 (11)
PRT	17%	134	128 (6)	137 (3)
BRB	17%	133	130 (3)	126 (7)
LVA	16%	132	141 (9)	127 (5)
MDV	16%	131	145 (14)	131 (0)
ARM	16%	130	139 (9)	123 (7)
MLT	16%	129	127 (2)	140 (11)
YEM	16%	128	135 (7)	134 (6)
GRC	16%	127	116 (11)	133 (6)
UGA	15%	126	126 (0)	119 (7)
DOM	15%	125	134 (9)	130 (5)
NGA	15%	124	133 (9)	132 (8)
CYP	15%	123	109 (14)	136 (13)
AFG	15%	122	107 (15)	135 (13)
POL	14%	121	81 (40)	122 (1)
MMR	14%	120	123 (3)	120 (0)
IRN	14%	119	125 (6)	121 (2)
ROU	13%	118	110 (8)	114 (4)
SWZ	13%	117	108 (9)	97 (20)
BGR	13%	116	60 (56)	116 (0)
AGO	12%	115	136 (21)	104 (11)
KOR	12%	114	112 (2)	128 (14)
MRT	12%	113	117 (4)	113 (0)
HTI	12%	112	131 (19)	115 (3)
BOL	11%	111	142 (31)	107 (4)
MAR	11%	110	87 (23)	98 (12)

CHE	11%	109	124 (15)	103 (6)
BEN	11%	108	143 (35)	101 (7)
CMR	11%	107	118 (11)	106 (1)
TGO	11%	106	4 (102)	99 (7)
SLE	10%	105	53 (52)	117 (12)
BGD	10%	104	93 (11)	111 (7)
ECU	10%	103	111 (8)	105 (2)
MNE	10%	102	61 (41)	102 (0)
JAM	10%	101	115 (14)	108 (7)
STP	10%	100	66 (34)	82 (18)
CRI	10%	99	100 (1)	94 (5)
BEL	10%	98	88 (10)	110 (12)
VNM	9%	97	103 (6)	96 (1)
ITA	9%	96	70 (26)	87 (9)
BLR	9%	95	55 (40)	109 (14)
ISR	9%	94	104 (10)	92 (2)
CIV	9%	93	84 (9)	73 (20)
COM	9%	92	98 (6)	100 (8)
SSD	9%	91	113 (22)	77 (14)
LTU	9%	90	85 (5)	88 (2)
PER	8%	89	76 (13)	89 (0)
BIH	8%	88	86 (2)	84 (4)
AZE	8%	87	72 (15)	86 (1)
SRB	8%	86	45 (41)	95 (9)
UKR	8%	85	63 (22)	93 (8)
PSE	8%	84	67 (17)	81 (3)
EST	7%	83	79 (4)	68 (15)
PRY	7%	82	106 (24)	70 (12)
ESP	7%	81	99 (18)	79 (2)
GIN	7%	80	80 (0)	75 (5)
XKX	7%	79	69 (10)	78 (1)
USA	7%	78	96 (18)	83 (5)
SYR	7%	77	89 (12)	90 (13)
CAF	7%	76	77 (1)	61 (15)
UZB	7%	75	101 (26)	46 (29)
NER	7%	74	102 (28)	74 (0)
MLI	6%	73	74 (1)	80 (7)
TWN	6%	72	82 (10)	91 (19)
PHL	6%	71	90 (19)	65 (6)
TCD	6%	70	23 (47)	66 (4)
IRL	6%	69	71 (2)	57 (12)
GAB	6%	68	22 (46)	52 (16)
MUS	6%	67	62 (5)	50 (17)
GNB	5%	66	92 (26)	72 (6)
MKD	5%	65	47 (18)	55 (10)
KEN	5%	64	94 (30)	47 (17)
LKA	5%	63	65 (2)	56 (7)
AUS	5%	62	68 (6)	67 (5)
ETH	5%	61	91 (30)	42 (19)
URY	5%	60	41 (19)	63 (3)
RUS	5%	59	48 (11)	85 (26)
COD	5%	58	49 (9)	59 (1)
FIN	5%	57	52 (5)	71 (14)

SUR	5%	56	75 (19)	37 (19)
COG	5%	55	56 (1)	64 (9)
LSO	5%	54	83 (29)	32 (22)
PAK	4%	53	42 (11)	76 (23)
JPN	4%	52	50 (2)	60 (8)
MWI	4%	51	64 (13)	38 (13)
SVN	4%	50	46 (4)	49 (1)
BTN	4%	49	95 (46)	19 (30)
TTO	4%	48	105 (57)	30 (18)
MEX	4%	47	73 (26)	33 (14)
TZA	4%	46	78 (32)	25 (21)
SWE	4%	45	54 (9)	36 (9)
SVK	4%	44	44 (0)	62 (18)
HUN	4%	43	29 (14)	45 (2)
IDN	4%	42	33 (9)	34 (8)
SYC	3%	41	97 (56)	39 (2)
KGZ	3%	40	59 (19)	22 (18)
THA	3%	39	57 (18)	15 (24)
LUX	3%	38	16 (22)	58 (20)
FJI	3%	37	26 (11)	31 (6)
SEN	3%	36	18 (18)	54 (18)
IRQ	3%	35	35 (0)	51 (16)
BDI	3%	34	37 (3)	44 (10)
TUR	3%	33	31 (2)	29 (4)
BFA	3%	32	34 (2)	69 (37)
HRV	3%	31	39 (8)	48 (17)
LAO	3%	30	28 (2)	24 (6)
GUY	3%	29	51 (22)	28 (1)
BHS	3%	28	17 (11)	35 (7)
CAN	3%	27	43 (16)	41 (14)
KAZ	3%	26	14 (12)	53 (27)
MNG	2%	25	38 (13)	16 (9)
DNK	2%	24	36 (12)	40 (16)
ZWE	2%	23	58 (35)	6 (17)
CPV	2%	22	3 (19)	26 (4)
DEU	2%	21	12 (9)	18 (3)
JOR	2%	20	27 (7)	27 (7)
SLV	2%	19	30 (11)	5 (14)
MDG	2%	18	21 (3)	10 (8)
GBR	2%	17	40 (23)	14 (3)
MOZ	2%	16	32 (16)	7 (9)
FRA	1%	15	25 (10)	21 (6)
PAN	1%	14	24 (10)	112 (98)
ZAF	1%	13	13 (0)	20 (7)
GTM	1%	12	8 (4)	12 (0)
NAM	1%	11	20 (9)	17 (6)
RWA	1%	10	15 (5)	13 (3)
DJI	1%	9	9 (0)	23 (14)
HND	1%	8	11 (3)	9 (1)
GHA	1%	7	10 (3)	11 (4)
CZE	1%	6	5 (1)	43 (37)
BWA	1%	5	19 (14)	4 (1)
MYS	1%	4	7 (3)	8 (4)

ZMB	0%	3	2 (1)	2 (1)
GMB	0%	2	6 (4)	3 (1)
TLS	0%	1	1 (0)	1 (0)
Average diff. vs CHE 10%			15 places	9 places

Appendix C-2. Additional sample details

Table C-2. Sample construction and observations

Sample	Countries	Observations
Full sample	131	9.7m
Keep countries with DAH above sample average	92	2.2m
Keep countries with data for all control variables (household expenditure, age, OADR, size; country GDP per capita, Gini, urban population, people below 15 and people above 65)	65	1.7m

Source: author elaboration

Table C-3. Full list of the 504 surveys in the full sample

ISO-3 Country Code	Year	Name of survey
AFG	2007	Afghanistan - National Risk and Vulnerability Assessment Survey 2007-2008
AFG	2013	Afghanistan Living Conditions Survey 2013
AGO	2008	Angola - Inquérito Integrado sobre o Bem-Estar da População 2008-2009, IDR II e MICS III
ALB	2002	Albania - Living Standards Measurement Survey 2002 (Wave 1 Panel)
ALB	2005	Albania - Living Standards Measurement Survey 2005
ALB	2008	Albania - Household Budget Survey 2008-2009
ALB	2012	Albania - Living Standards Measurement Survey 2012
ARG	1996	Argentina - Encuesta Nacional de Gastos de los Hogares (ENGH) 1996/1997
ARG	2004	Argentina - Encuesta Nacional de Gastos de los Hogares (ENGH) 2004/2005
ARM	1999	Armenia - Integrated Living Conditions Survey 1999
ARM	2001	Armenia- Household Living Standards Survey
ARM	2002	Armenia - Integrated Living Conditions Survey 2002
ARM	2003	Armenia - Integrated Living Conditions Survey 2003
ARM	2004	Armenia - Integrated Living Conditions Survey 2004
ARM	2005	Armenia - Integrated Living Conditions Survey 2005
ARM	2006	Armenia - Integrated Living Conditions Survey 2006
ARM	2007	Armenia - Integrated Living Conditions Survey 2007
ARM	2008	Armenia - Integrated Living Conditions Survey 2008
ARM	2009	Armenia - Integrated Living Conditions Survey 2009
ARM	2010	Armenia - Integrated Living Conditions Survey 2010
ARM	2011	Armenia - Integrated Living Conditions Survey 2011

ARM	2012	Armenia - Integrated Living Conditions Survey 2012
ARM	2013	Armenia - Integrated Living Conditions Survey 2013
AZE	2002	Azerbaijan - Household Budget Survey 2002
AZE	2003	Azerbaijan - Household Budget Survey 2003
AZE	2004	Azerbaijan - Household Budget Survey 2004
AZE	2005	Azerbaijan - Household Budget Survey 2005
BDI	1998	Burundi - Enquête Prioritaire 1998, Etude Nationale sur les Conditions de Vie des Populations
BDI	2013	Enquête sur les conditions de vie des ménages 2013
BEL	2010	Belgium - Household Budget Survey 2010 - Eurostat
BEN	2003	Benin - Questionnaire Unifié sur les Indicateurs de Base du Bien-être 2003
BFA	2003	Burkina Faso - Enquête sur les Conditions de Vie des Ménages 2003, Questionnaire Unifié sur les Indicateurs de Base du Bien-être
BFA	2014	Burkina Faso - Enquête Multisectorielle Continue 2013-2014
BGD	1995	Bangladesh - Household Expenditure Survey 1995-1996
BGD	2000	Bangladesh - Household Income and Expenditure Survey 2000
BGD	2005	Bangladesh - Household Income and Expenditure Survey 2005
BGD	2010	Bangladesh - Household Income and Expenditure Survey 2010
BGD	2016	Bangladesh Household Income and Expenditure Survey 2016
BGR	1995	Europe and Central Asia - Household Expenditure and Income Data for Transitional Economies 1993-1998
BGR	1997	Bulgaria - Integrated Household Survey 1997
BGR	2001	Bulgaria - Integrated Household Survey 2001
BGR	2007	Bulgaria - Multi-Topic Household Survey 2007
BGR	2010	Bulgaria - Household Budget Survey 2010 - Eurostat
BHS	2013	Household Expenditure Survey 2013
BIH	2001	Bosnia and Herzegovina - Living Standards Measurement Survey 2001 (Wave 1 Panel)
BIH	2004	Bosnia and Herzegovina - Household Budget Survey 2004
BIH	2007	Bosnia and Herzegovina - Household Budget Survey 2007
BIH	2011	Bosnia and Herzegovina - Household Budget Survey 2011
BIH	2015	Household Budget Survey 2015
BLR	1998	Belarus - Household Budget Survey 1998
BLR	1999	Belarus - Household Budget Survey 1999
BLR	2000	Belarus - Household Sample Survey 2000
BLR	2001	Belarus - Household Sample Survey 2001
BLR	2002	Belarus - Household Sample Survey 2002
BLR	2003	Belarus - Household Sample Survey 2003
BLR	2004	Belarus - Household Sample Survey 2004
BLR	2005	Belarus - Household Sample Survey 2005
BLR	2006	Belarus - Household Sample Survey 2006
BLR	2007	Belarus - Household Sample Survey 2007
BLR	2008	Belarus - Household Sample Survey 2008
BLR	2009	Belarus - Household Sample Survey 2009
BLR	2010	Belarus - Household Sample Survey 2010
BLR	2011	Belarus - Household Sample Survey 2011
BLR	2012	Belarus - Household Sample Survey 2012
BLR	2013	Household Sample Survey 2013
BLR	2014	Household Sample Survey 2014

BLR	2015	Household Sample Survey 2015
BLR	2016	Household Sample Survey 2016
BOL	1999	Bolivia - Encuesta Continua de Hogars, 1999
BOL	2000	Bolivia - Encuesta Continua de Hogars, 2000
BOL	2012	Encuesta de Hogares, 2012
BRA	2008	Brazil - Pesquisa de Orçamentos Familiares 2008-2009
BRB	2016	Barbados 2016 Survey on Living Conditions
BTN	2003	Bhutan - Living Standards Survey 2003
BTN	2007	Bhutan - Living Standards Survey 2007, Second Round
BTN	2012	Bhutan Living Standard Survey, 2012
CAF	2008	Central African Republic - Enquête Centrafricaine pour le Suivi-Evaluation du Bien-être 2008
CHL	2016	Chile: Encuesta de Presupuestos Familiares 2016
CHN	1995	Chinese Household Income Project, 1995 (ICPSR 3012)
CHN	2002	Chinese Household Income Project, 2002 (ICPSR 21741)
CIV	1998	Côte d'Ivoire - Enquête sur le Niveau de Vie des Ménages 1998
CIV	2002	Côte d'Ivoire - Enquête sur le Niveau de Vie des Ménages de Côte d'Ivoire 2002
CIV	2008	Côte d'Ivoire - Enquête sur le Niveau de Vie des Ménages 2008
CIV	2015	Enquete Niveau de vie des Menages 2014-2015
CMR	1996	Cameroon - Enquête Camerounaise Auprès des Ménages 1996
CMR	2007	Cameroon - Troisième Enquête Camerounaise Auprès des Ménages 2007
CMR	2014	Cameroon - Quatrième Enquête Camerounaise Auprès des Ménages 2014
COD	2004	Congo, Dem. Rep. - Enquête 1-2-3 sur l'Emploi, le Secteur Informel et les Conditions de Vie des Ménages 2004
COD	2012	Congo, Dem. Rep. - Enquête 1-2-3 sur l'Emploi, le Secteur Informel et les Conditions de Vie des Ménages 2012
COG	2005	Congo, Rep. - Enquête Congolaise auprès des Ménages pour l'Evaluation de la Pauvreté 2005
COG	2011	Congo, Rep. - Enquête Congolaise Auprès des Ménages pour le Suivi et l'Evaluation de la Pauvreté 2011
COL	2008	Colombia - Encuesta de Calidad de Vida 2008
COL	2010	Colombia - Encuesta Nacional de Calidad de Vida 2010
COM	2014	Comoros - Household Budget Surveys 2014
CPV	2007	Cape Verde - Questionário Unificado de Indicadores Básicos de Bem-Estar 2007
CRI	2012	Costa Rica - Encuesta Nacional de Ingresos y Gastos de los Hogares 2012-2013
CYP	2010	Cyprus - Household Budget Survey 2010 - Eurostat
CZE	2010	Czech Rep. - Household Budget Survey 2010 - Eurostat
DJI	1996	Djibouti - Enquête Djiboutienne auprès des Ménages - Indicateurs Sociaux 1996
DJI	2002	Djibouti - Enquête Djiboutienne auprès des Ménages II 2002
DNK	2010	Danish Household Budget Survey 2010 - Eurostat
ECU	1998	Ecuador - Encuesta Condiciones de Vida 1998
ECU	2013	Ecuador - Encuesta Condiciones de Vida 2013
EGY	2012	Egypt, Arab Rep. - Household Income, Expenditure and Consumption Survey 2012-2013
ESP	2010	Spain - Household Budget Survey 2010 - Eurostat
EST	1995	Estonia - Household Budget Survey 1995
EST	2001	Estonia - Household Budget Survey 2001
EST	2002	Estonia - Household Budget Survey 2002
EST	2003	Estonia - Household Budget Survey 2003

EST	2004	Estonia - Household Budget Survey 2004
EST	2010	Estonia - Household Budget Survey 2010
ETH	1999	Ethiopia - Household Income, Consumption and Expenditure Survey 1999-2000
ETH	2004	Ethiopia - Household Income, Consumption and Expenditure Survey 2004-2005
ETH	2011	Ethiopia - Socioeconomic Survey 2011-2012
ETH	2015	Ethiopian Socioeconomic Survey 2015
FIN	2010	Finland - Household Budget Survey 2010 - Eurostat
FJI	2002	Fiji - Household Income and Expenditure Survey 2002-2003
FRA	2010	Family Budget Survey / Enquete Budget de Famille 2010 - LIS
GAB	2005	Gabon - Enquête Gabonaise pour l'Evaluation et le Suivi de la Pauvreté 2005
GBR	2010	GBR - Household Budget Survey 2010 - Eurostat
GEO	1997	Georgia - Household Integrated Survey 1997
GEO	1998	Georgia - Household Integrated Survey 1998
GEO	1999	Georgia - Household Integrated Survey 1999
GEO	2000	Georgia - Household Integrated Survey 2000
GEO	2001	Georgia - Household Integrated Survey 2001
GEO	2002	Georgia-Household Budget Survey
GEO	2003	Georgia-Household Budget Survey
GEO	2004	Georgia-Household Budget Survey
GEO	2005	Georgia-Household Budget Survey
GEO	2006	Georgia-Household Budget Survey
GEO	2007	Georgia-Household Budget Survey
GEO	2008	Georgia - Household Budget Survey
GEO	2009	Georgia - Household Integrated Survey 2009
GEO	2010	Georgia - Household Integrated Survey 2010
GEO	2011	Georgia - Household Integrated Survey 2011
GEO	2012	Georgia - Household Integrated Survey 2012
GEO	2013	Georgia - Household Integrated Survey 2013
GHA	1998	Ghana- Ghana Living Standards Survey
GHA	2005	Ghana - Living Standards Survey V 2005-2006
GHA	2012	Ghana - Living Standards Survey VI 2012-2013
GIN	2002	Guinea - Enquête Intégrée de Base pour l'Evaluation de la Pauvreté 2002 - 2003
GIN	2007	Guinea - Enquête Légère pour l'Evaluation de la Pauvreté 2007
GIN	2012	Guinea - Enquête Légère pour l'Evaluation de la Pauvreté 2012
GNB	2002	Guinea-Bissau - Inquérito Ligeiro sobre as Condições de Vida da População 2002
GRC	2010	Greece - Household Budget Survey 2010 - Eurostat
GTM	2011	Guatemala - Encuesta Nacional de Condiciones de Vida 2011
GTM	2014	Guatemala - Encuesta Nacional de Condiciones de Vida 2014
HND	2004	Honduras - Encuesta Nacional de Condiciones de Vida 2004
HRV	1998	Croatia - Household Budget Survey 1998
HRV	2004	Croatia - Household Budget Survey 2004
HRV	2008	Croatia - Household Budget Survey 2008
HRV	2009	Croatia - Household Budget Survey 2009
HRV	2010	Croatia - Household Budget Survey 2010
HTI	2012	Haiti - Enquête sur les Conditions de Vie des Ménages après Séisme 2012
HTI	2013	Haiti - Enquête sur les Conditions de Vie des Ménages après Séisme 2013
HUN	1998	Hungary - Household Budget Survey 1998
HUN	1999	Hungary - Household Budget Survey 1999

HUN	2000	Hungary - Household Budget Survey 2000
HUN	2001	Hungary - Household Budget Survey 2001
HUN	2002	Hungary - Household Budget Survey 2002
HUN	2003	Hungary - Household Budget Survey 2003
HUN	2004	Hungary - Household Budget Survey 2004
HUN	2005	Hungary - Household Budget Survey 2005
HUN	2006	Hungary - Household Budget Survey 2006
HUN	2007	Hungary - Household Budget Survey 2007
HUN	2010	Hungary - Household Budget Survey 2010 - Eurostat
IDN	2001	Indonesia - Survei Sosial Ekonomi Nasional 2001
IDN	2002	Indonesia - Survei Sosial Ekonomi Nasional 2002
IDN	2003	Indonesia - Survei Sosial Ekonomi Nasional 2003
IDN	2004	Indonesia - Survei Sosial Ekonomi Nasional 2004
IDN	2005	Indonesia - Survei Sosial Ekonomi Nasional 2005
IDN	2006	Indonesia - Survei Sosial Ekonomi Nasional 2006
IDN	2007	Indonesia - Survei Sosial Ekonomi Nasional 2007
IDN	2009	Indonesia - Survei Sosial Ekonomi Nasional 2009
IDN	2010	Indonesia - Survei Sosial Ekonomi Nasional 2010
IDN	2011	Indonesia - Survei Sosial Ekonomi Nasional 2011
IDN	2012	Indonesia - Survei Sosial Ekonomi Nasional 2012
IDN	2013	Indonesia - Survei Sosial Ekonomi Nasional 2013
IDN	2014	Indonesia - Survei Sosial Ekonomi Nasional 2014
IDN	2015	Indonesia - Survei Sosial Ekonomi Nasional 2015
IND	2000	India - National Sample Survey 2000-2001 (56th round) - Schedule 1.0 - Consumer Expenditure
IRL	2010	Ireland - Household Budget Survey 2010 - Eurostat
IRN	2009	Iran 2009 Household Expenditures and Income Survey
IRQ	2012	Iraq - Household Socio-Economic Survey 2012, Second Round
ITA	2010	Italia - Household Budget Survey 2010 - Eurostat
JAM	2003	Jamaica - Survey of Living Conditions 2003
KAZ	2001	Kazakhstan - Household Budget Survey 2001
KAZ	2002	Kazakhstan - Household Budget Survey 2002
KAZ	2003	Kazakhstan - Household Budget Survey 2003
KAZ	2004	Kazakhstan - Household Budget Survey 2004
KAZ	2005	Kazakhstan - Household Budget Survey 2005
KAZ	2006	Kazakhstan - Household Budget Survey 2006
KAZ	2007	Kazakhstan - Household Budget Survey 2007
KAZ	2008	Kazakhstan - Household Budget Survey 2008
KAZ	2009	Kazakhstan - Household Budget Survey 2009
KAZ	2010	Kazakhstan - Household Budget Survey 2010
KAZ	2011	Kazakhstan - Household Budget Survey 2011
KAZ	2012	Kazakhstan - Household Budget Survey 2012
KAZ	2013	Kazakhstan - Household Budget Survey 2013
KAZ	2014	Kazakhstan - Household Budget Survey 2014
KAZ	2015	Kazakhstan - Household Budget Survey 2015
KEN	2015	Kenya - Integrated Household Budget Survey 2015-2016
KGZ	2005	Kyrgyz Republic - Kyrgyz Integrated Household Survey 2005
KGZ	2006	Kyrgyz Republic - Kyrgyz Integrated Household Survey 2006

KGZ	2007	Kyrgyz Republic - Kyrgyz Integrated Household Survey 2007
KGZ	2008	Kyrgyz Republic - Kyrgyz Integrated Household Survey 2008
KGZ	2009	Kyrgyz Republic - Kyrgyz Integrated Household Survey 2009
KGZ	2010	Kyrgyz Republic - Kyrgyz Integrated Household Survey 2010
KGZ	2011	Kyrgyz Republic - Kyrgyz Integrated Household Survey 2011
KGZ	2012	Kyrgyz Republic - Kyrgyz Integrated Household Survey 2012
KGZ	2013	Kyrgyzstan Jobs, Skills, and Migration Survey 2013
KGZ	2014	Kyrgyz Republic - Kyrgyz Integrated Household Survey 2014
KGZ	2015	Kyrgyz Republic - Kyrgyz Integrated Household Survey 2015
KGZ	2016	Kyrgyz Republic - Kyrgyz Integrated Household Survey 2016
KHM	2009	Cambodia - Socio-Economic Survey 2009
LAO	2002	Lao People's Democratic Republic-Expenditure and Consumption Survey
LAO	2007	Lao People's Democratic Republic-Expenditure and Consumption Survey
LKA	2006	Sri Lanka - Household Income and Expenditure Survey 2006-2007
LKA	2009	Sri Lanka - Household Income and Expenditure Survey 2009-2010
LKA	2016	Sri Lanka Household Income and Expenditure Survey, 2016
LSO	2002	Lesotho - Household Budget Survey 2002-2003
LSO	2010	Lesotho 2010 Continuous Multi-Purpose Survey / Household Budget Survey
LTU	1998	Lithuania - Household Budget Survey 1998
LTU	1999	Lithuania - Household Budget Survey 1999
LTU	2000	Lithuania - Household Budget Survey 2000
LTU	2001	Lithuania - Household Budget Survey 2001
LTU	2002	Lithuania - Household Budget Survey 2002
LTU	2003	Lithuania - Household Budget Survey 2003
LTU	2004	Lithuania - Household Budget Survey 2004
LTU	2008	Lithuania - Household Budget Survey 2008
LTU	2010	Lithuania - Household Budget Survey 2010 - Eurostat
LUX	2010	Luxemburg - Household Budget Survey 2010 - Eurostat
LVA	2002	Latvia - Household Budget Survey 2002
LVA	2004	Latvia - Household Budget Survey 2004
LVA	2007	Latvia - Household Budget Survey 2007
LVA	2008	Latvia - Household Budget Survey 2008
LVA	2009	Latvia - Household Budget Survey 2009
LVA	2010	Latvia - Household Budget Survey 2010
MAR	2000	Morocco - Enquete Nationale sur la Consommation et les Dépense des Ménages 2000-2001
MAR	2006	Morocco-Enquete Nationale sur les Niveaux de Vie des Menages
MDA	1999	Moldova - Household Budget Survey 1999
MDA	2000	Moldova - Household Budget Survey 2000
MDA	2001	Moldova - Household Budget Survey 2001
MDA	2002	Moldova - Household Budget Survey 2002
MDA	2003	Moldova - Household Budget Survey 2003
MDA	2004	Moldova - Household Budget Survey 2004
MDA	2005	Moldova - Household Budget Survey 2005
MDA	2006	Moldova - Household Budget Survey 2006
MDA	2007	Moldova - Household Budget Survey 2007
MDA	2008	Moldova - Household Budget Survey 2008
MDA	2009	Moldova - Household Budget Survey 2009

MDA	2010	Moldova - Household Budget Survey 2010
MDA	2011	Moldova - Household Budget Survey 2011
MDA	2012	Moldova - Household Budget Survey 2012
MDA	2013	Moldova - Household Budget Survey 2013
MDA	2014	Moldova - Household Budget Survey 2014
MDA	2015	Moldova - Household Budget Survey 2015
MDA	2016	Republic of Moldova 2016 Household Budget Survey
MDG	2001	Madagascar - Enquête Permanente auprès des Ménages 2001
MDG	2005	Madagascar - Enquête Permanente Auprès des Ménages 2005
MDG	2010	Madagascar - Enquête Périodique auprès des Ménages 2010
MDV	2004	Vulnerability and Poverty Assessment Survey II 2004 Maldives
MDV	2009	Maldives - Household Income and Expenditure Survey 2009-2010
MKD	1997	Macedonia, FYR - Household Budget Survey 1997
MKD	1998	Household Budget Survey 1998
MKD	1999	Household Budget Survey 1999
MKD	2000	Macedonia, FYR - Household Budget Survey 2000
MKD	2002	Macedonia, FYR - Household Budget Survey 2002
MKD	2003	Macedonia, FYR - Household Budget Survey 2003
MKD	2005	Macedonia, FYR - Household Budget Survey 2005
MKD	2006	Macedonia, FYR - Household Budget Survey 2006
MKD	2008	Macedonia, FYR - Household Budget Survey 2008
MLI	2000	Mali - Enquete Malienne sur l'Evaluation de la Pauvrete 2000-2001
MLI	2009	Mali - Enquête Légère Intégrée auprès des Ménages 2009
MLI	2011	Enquete Modulaire et Permanente aupres des Menage (EMOP), 2011
MLI	2013	Enquete Modulaire et Permanente aupres des Menage (EMOP), 2013
MLI	2014	Enquete Modulaire et Permanente aupres des Menage (EMOP), 2014
MLI	2015	Enquete Modulaire et Permanente aupres des Menage (EMOP), 2015
MLI	2016	Enquete Modulaire et Permanente aupres des Menage (EMOP), 2016
MLT	2010	Malta - Household Budget Survey 2010 - Eurostat
MMR	2015	Myanmar Poverty Living Condition Survey 2015
MNE	2005	Montenegro - Household Budget Survey 2005
MNE	2006	Montenegro - Household Budget Survey 2006
MNE	2007	Montenegro - Household Budget Survey 2007
MNE	2008	Montenegro - Household Budget Survey 2008
MNE	2009	Montenegro - Household Budget Survey 2009
MNE	2010	Montenegro - Household Budget Survey 2010
MNE	2011	Montenegro - Household Budget Survey 2011
MNE	2012	Montenegro - Household Budget Survey 2012
MNE	2013	Montenegro - Household Budget Survey 2013
MNE	2014	Montenegro - Household Budget Survey 2014
MNE	2015	Household Budget Survey 2015
MNG	2010	Mongolia - Socio-Economic Survey 2010
MNG	2011	Mongolia - Socio-Economic Survey 2011
MNG	2012	Mongolia - Socio-Economic Survey 2012
MOZ	2002	Mozambique - Inquérito aos Agregados Familiares sobre Orçamento Familiar 2002-2003
MOZ	2008	Mozambique - Inquérito sobre Orçamento Familiar 2008-2009
MOZ	2014	Mozambique - Inquérito Sobre Orçamento Familiar 2014

MRT	2004	Mauritania - Enquête Permanente sur les Conditions de Vie des Ménages / Questionnaire Unifié des Indicateurs de Base du Bien-être 2004
MRT	2014	Mauritania - Enquête Permanente sur les Conditions de Vie des ménages 2014
MUS	2006	Mauritius - Continuous Multi-Purpose Household Survey 2006
MUS	2012	Continuous Multi-Purpose Household Survey 2012
MWI	2004	Malawi - Second Integrated Household Survey 2004-2005
MWI	2010	Malawi - Third Integrated Household Survey 2010-2011
MWI	2016	Fourth Integrated Household Survey 2016-2017
NAM	2009	Namibia - National Household Income and Expenditure Survey 2009-2010
NER	2005	Niger - Enquête Nationale sur le Budget et la Consommation des Ménages 2005, Deuxième Enquête
NER	2011	Niger - Enquête Nationale sur les Conditions de Vie des Ménages 2010-2011
NGA	2003	Nigeria - Living Standards Survey 2003, First round
NGA	2010	Nigeria General Household Survey, wave1 2010/2011
NGA	2012	Nigeria General Household Survey, wave2 2012/2013
NIC	1998	Nicaragua - Encuesta Nacional de Hogares sobre Medición de Niveles de Vida 1998-1999 (Panel)
NIC	2001	Nicaragua - Encuesta Nacional de Hogares sobre Medición de Niveles de Vida 2001
NIC	2009	Nicaragua - Encuesta Nacional de Hogares sobre Medición de Niveles de Vida 2009
NIC	2014	Nicaragua - Encuesta de Medición de Nivel de Vida 2014
NPL	2003	Living Standards Survey II 2003-2004 - South Asia Labor Flag Dataset
NPL	2010	Nepal - Living Standards Survey 2010-2011, Third Round
PAK	2001	Pakistan - Integrated Household Survey 2001-2002, Fourth Round
PAK	2004	Pakistan - Social and Living Standards Measurement Survey 2004-2005, Round 1
PAK	2007	Pakistan - Social and Living Standards Measurement Survey 2007-2008
PAK	2010	Pakistan-Household Integrated Economic Survey
PAK	2011	Social and Living Standards Measurement Survey 2011-2012, Round 7
PAK	2013	Social and Living Standards Measurement Survey 2013-2014
PAK	2015	Social and Living Standards Measurement Survey 2015-2016
PAN	1997	Panama - Encuesta de Niveles de Vida 1997
PAN	2003	Panama - Encuesta de Niveles de Vida 2003
PER	2006	Peru - Encuesta Nacional de Hogares sobre Condiciones de Vida y Pobreza 2006
PER	2007	Peru - Encuesta Nacional de Hogares sobre Condiciones de Vida y Pobreza 2007
PER	2008	Peru - Encuesta Nacional de Hogares sobre Condiciones de Vida y Pobreza 2008
PER	2009	Peru - Encuesta Nacional de Hogares sobre Condiciones de Vida y Pobreza 2009
PER	2010	Peru - Encuesta Nacional de Hogares sobre Condiciones de Vida y Pobreza 2010
PER	2011	Peru - Encuesta Nacional de Hogares sobre Condiciones de Vida y Pobreza 2011
PER	2012	Peru - Encuesta Nacional de Hogares sobre Condiciones de Vida y Pobreza 2012
PER	2013	Peru - Encuesta Nacional de Hogares sobre Condiciones de Vida y Pobreza 2013
PER	2014	Peru - Encuesta Nacional de Hogares sobre Condiciones de Vida y Pobreza 2014
PER	2015	Peru - Encuesta Nacional de Hogares sobre Condiciones de Vida y Pobreza 2015
PHL	2003	Philippines - Family Income and Expenditure Survey 2003
PHL	2006	Philippines - Family Income and Expenditure Survey 2006
PHL	2009	Philippines - Family Income and Expenditure Survey 2009
PHL	2012	Philippines - Family Income and Expenditure Survey 2012
PHL	2015	Philippines - Family Income and Expenditure Survey 2015
POL	1998	Poland - Household Budget Survey 1998

POL	1999	Poland - Household Budget Survey 1999
POL	2000	Poland - Household Budget Survey 2000
POL	2001	Poland - Household Budget Survey 2001
POL	2002	Poland - Household Budget Survey 2002
POL	2003	Poland - Household Budget Survey 2003
POL	2004	Poland - Household Budget Survey 2004
POL	2005	Poland - Household Budget Survey 2005
POL	2006	Poland - Household Budget Survey 2006
POL	2007	Poland - Household Budget Survey 2007
POL	2008	Poland - Household Budget Survey 2008
POL	2009	Poland - Household Budget Survey 2009
POL	2011	Poland - Household Budget Survey 2011
POL	2012	Poland - Household Budget Survey 2012
POL	2013	Poland - Household Budget Survey 2013
POL	2014	Poland - Household Budget Survey 2014
POL	2015	Poland - Household Budget Survey 2015
POL	2016	Poland - Household Budget Survey 2016
PRT	2010	Portugal - Household Budget Survey 2010 - Eurostat
PRY	2000	Paraguay - Encuesta Permanente de Hogares 2000
PRY	2014	Paraguay - Encuesta Permanente de Hogares 2014
PSE	2004	Occupied Palestinian Territory-Expenditure and Consumption survey
PSE	2005	West Bank and Gaza - Expenditure and Consumption Survey, 2005
PSE	2006	West Bank and Gaza - Expenditure and Consumption Survey, 2006
PSE	2007	West Bank and Gaza - Expenditure and Consumption Survey, 2007
PSE	2009	West Bank and Gaza - Expenditure and Consumption Survey 2009
PSE	2010	West Bank and Gaza - Expenditure and Consumption Survey, 2010
PSE	2016	Palestinian Expenditure and Consumption survey
ROU	1999	Romania - Integrated Household Survey 1999
ROU	2000	Romania - Integrated Household Survey 2000
ROU	2001	Romania - Household Budget Survey 2001
ROU	2002	Romania - Household Budget Survey 2002
ROU	2003	Romania - Household Budget Survey 2003
ROU	2004	Romania - Household Budget Survey 2004
ROU	2005	Romania - Household Budget Survey 2005
ROU	2006	Romania - Household Budget Survey 2006
ROU	2007	Romania - Household Budget Survey 2007
ROU	2008	Romania - Household Budget Survey 2008
ROU	2009	Romania - Household Budget Survey 2009
ROU	2010	Romania - Household Budget Survey 2010
ROU	2011	Romania - Household Budget Survey 2011
ROU	2012	Romania - Household Budget Survey 2012
ROU	2013	Romania - Household Budget Survey 2013
ROU	2016	Household Budget Survey 2016
RUS	1997	Russian Federation - Household Budget Survey 1997
RUS	1998	Russian Federation - Household Budget Survey 1998
RUS	1999	Russian Federation - Household Budget Survey 1999
RUS	2000	Russian Federation - Household Budget Survey 2000
RUS	2002	Russian Federation - Household Budget Survey 2002

RUS	2003	Russian Federation - Household Budget Survey 2003
RUS	2004	Russian Federation - Household Budget Survey 2004
RUS	2010	Russia Longitudinal Monitoring Survey 2010
RUS	2011	Russian Federation - Household Budget Survey 2011
RUS	2012	Russian Federation - Household Budget Survey 2012
RUS	2013	Russian Federation - Household Budget Survey 2013
RWA	2005	Rwanda - Integrated Household Living Conditions Survey 2005
RWA	2013	Integrated Household Living Conditions Survey 2013 -2014
RWA	2016	Rwanda - Integrated Household Living Conditions Survey 2016-2017
SDN	2009	Sudan (North) - National Baseline Household Survey (NBHS) 2009
SEN	2001	Senegal - Deuxième Enquête Sénégalaise Auprès des Ménages 2001
SEN	2005	Senegal - Enquête de Suivi de la Pauvreté au Sénégal 2005
SEN	2011	Senegal - Enquête de Suivi de la Pauvreté au Sénégal 2011
SLE	2003	Sierra Leone - Integrated Household Survey 2003-2004
SLV	2014	El Salvador - Encuesta de Hogares de Propósitos Múltiples 2014
SRB	2003	Serbia - Household Budget Survey 2003
SRB	2004	Serbia - Household Budget Survey 2004
SRB	2005	Serbia - Household Budget Survey 2005
SRB	2006	Serbia - Household Budget Survey 2006
SRB	2007	Serbia - Household Budget Survey 2007
SRB	2008	Serbia - Household Budget Survey 2008
SRB	2009	Serbia - Household Budget Survey 2009
SRB	2010	Serbia - Household Budget Survey 2010
SRB	2013	Serbia - Household Budget Survey 2013
SRB	2015	Household Budget Survey 2015
SSD	2009	Sudan (south) - National Baseline Household Survey (NBHS) 2009
STP	2000	São Tomé and Principe - Enquête sur les Conditions de Vie des Ménages 2000
SUR	2016	Suriname 2016 Survey on Living Conditions
SVK	2004	Slovak Republic - Household Budget Survey 2004
SVK	2005	Slovakia - Household Budget survey, 2005
SVK	2006	Slovakia - Household Budget survey, 2006
SVK	2007	Slovakia - Household Budget survey, 2007
SVK	2008	Slovakia - Household Budget survey, 2008
SVK	2009	Slovakia - Household Budget survey, 2009
SVK	2010	Slovak Republic - Household Budget Survey 2010 - Eurostat
SWZ	2009	Swaziland - Household Income and Expenditure Survey 2009-2010
SYC	2013	Seychelles - Household Budget Surveys 2013
SYR	2003	Syrian Arab Republic - Household Income and Expenditure Survey 2003
SYR	2007	Syrian Arab Republic - Household Income and Expenditure Survey 2007
TCD	2003	Chad
TGO	2006	Togo - Questionnaire des Indicateurs de Base du Bien-être 2006
THA	2006	Thailand - Household Socio-Economic Survey 2006
THA	2009	Thailand - Household Socio-Economic Survey 2009
TJK	1999	Tajikistan - Household Budget Survey 1999
TJK	2003	Tajikistan - Household Budget Survey 2003
TJK	2007	Tajikistan - Living Standards Measurement Survey 2007 (Wave 1 Panel)
TJK	2009	Tajikistan - Household Budget Survey 2009
TLS	2001	Timor-Leste: Living Standards

TLS	2007	Timor-Leste - Survey of Living Standards 2007 and Extension 2008
TTO	2005	Trinidad and Tobago 2005 Survey on Living Conditions
TTO	2014	Trinidad and Tobago 2014 Survey on Living Conditions
TUR	2002	Turkey - Household Income and Consumption Expenditures Survey 2002
TUR	2003	Turkey-Household Budget Survey
TUR	2004	Turkey-Household Budget Survey
TUR	2005	Turkey-Household Budget Survey
TUR	2006	Turkey - Household Income and Consumption Expenditures Survey 2006
TUR	2007	Turkey-Household Budget Survey
TUR	2008	Turkey-Household Budget Survey
TUR	2009	Turkey - Household Income and Consumption Expenditures Survey 2009
TUR	2010	Turkey - Household Income and Consumption Expenditures Survey 2010
TUR	2011	Turkey - Household Income and Consumption Expenditures Survey 2011
TUR	2012	Turkey - Household Income and Consumption Expenditures Survey 2012
TUR	2013	Household Income and Consumption Expenditures Survey 2013
TUR	2014	Turkey - Household Income and Consumption Expenditures Survey 2014
TUR	2015	Household Income and Consumption Expenditures Survey 2015
TUR	2016	Household Income and Consumption Expenditures Survey 2016
TZA	2000	Tanzania - Household Budget Survey 2000-2001
TZA	2007	Tanzania - Household Budget Survey 2006-2007
TZA	2011	Tanzania - Household Budget Survey 2011-2012
UGA	2002	Uganda - National Household Survey 2002-2003
UGA	2009	Uganda - National Household Survey 2009-2010
UGA	2012	Uganda - National Household Survey 2012-2013
UGA	2016	Uganda National Household Survey 2016
UKR	2002	Ukraine-Household Budget Survey
UKR	2003	Ukraine-Household Budget Survey
UKR	2004	Ukraine-Household Budget Survey
UKR	2005	Ukraine-Household Budget Survey
UKR	2006	Ukraine-Household Budget Survey
UKR	2007	Ukraine- Household Living Conditions Sample Survey 2007
UKR	2008	Ukraine- Household Living Conditions Sample Survey 2008
UKR	2009	Ukraine- Household Living Conditions Sample Survey 2009
UKR	2010	Ukraine- Household Living Conditions Sample Survey 2010
UKR	2011	Ukraine- Household Living Conditions Sample Survey 2011
UKR	2012	Ukraine- Household Living Conditions Sample Survey 2012
UKR	2013	Ukraine- Household Living Conditions Sample Survey 2013
UKR	2014	Ukraine- Household Living Conditions Sample Survey 2014
URY	2005	Encuesta Nacional de Gastos e Ingresos de los Hogares 2005-2006
USA	2012	United States - Consumer Expenditure Survey (Public Use Microdata) 2012
USA	2013	United States - Consumer Expenditure Survey (Public Use Microdata) 2013
USA	2014	United States - Consumer Expenditure Survey (Public Use Microdata) 2014
USA	2015	United States - Consumer Expenditure Survey (Public Use Microdata) 2015
USA	2016	United States - Consumer Expenditure Survey (Public Use Microdata) 2016
USA	2017	Current Population Survey & Annual Social and Economic Supplement, March 2017
USA	2018	Current Population Survey & Annual Social and Economic Supplement, March 2018

UZB	2000	Uzbekistan - Household Budget Survey 2000
UZB	2002	Uzbekistan - Household Budget Survey 2002
UZB	2003	Uzbekistan - Household Budget Survey 2003
VNM	1997	Vietnam- Vietnam Living Standard Survey
VNM	2004	Vietnam - Household Living Standards Survey 2004
VNM	2006	Vietnam - Household Living Standards Survey 2006, 5th round
VNM	2008	Vietnam - Household Living Standards Survey 2008, 6th round
VNM	2010	Vietnam - Household Living Standards Survey 2010, 7th round
VNM	2012	Vietnam - Household Living Standards Survey 2012, 8th round
VNM	2014	Vietnam - Vietnamese Household Living Standard Survey 2014
VNM	2016	Vietnam - Household Living Standards Survey 2016
YEM	2005	Yemen, Rep. - Household Budget Survey 2005-2006
YEM	2014	Yemen - Household Budget Survey 2014
ZAF	1995	South Africa - Income and Expenditure Survey 1995
ZAF	2000	South Africa - Income and Expenditure Survey 2000
ZAF	2005	South Africa - Income and Expenditure Survey 2005-2006
ZAF	2010	South Africa - Income and Expenditure Survey 2010-2011
ZMB	2006	Zambia - Living Conditions Monitoring Survey V 2006
ZMB	2010	Zambia - Living Conditions Monitoring Survey VI 2010
ZWE	2007	Zimbabwe - Income, Consumption and Expenditure Survey 2007-2008

Appendix C-3. Robustness tests results for main specification: effect of an increase in 1 US$ DAH per capita on financial risk protection outcomes, according to different robustness tests

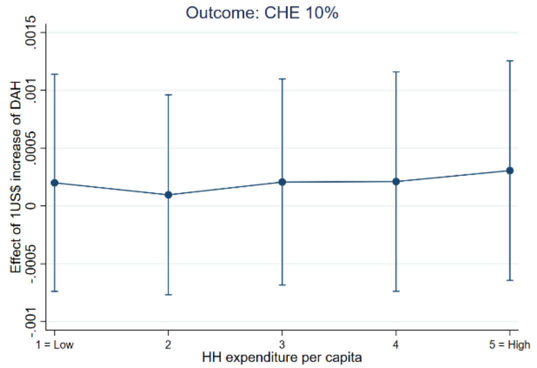
Table C-4. Robustness tests results

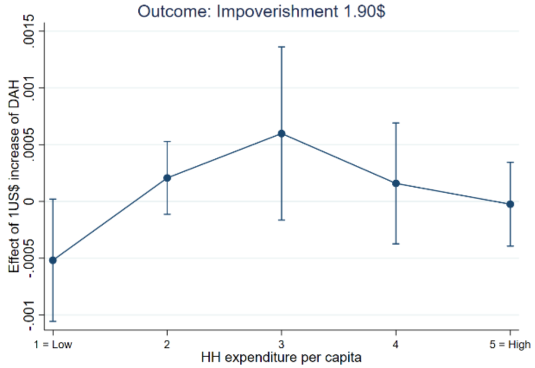
Outcome → Robustness check ↓	Cat 10 (1)	Imp 190 (2)	OOP bud. Share (3)
Panel A: use household expenditure net of OOP health expenditures	0.000	0.000	0.000
Panel B: log DAH per capita	0.012	0.005**	0.003
Panel C: use a 1-year lag of DAH per capita	0.000	0.000	0.000
Panel D: use WHO GHED dataset instead of IHME as source for DAH per capita	-0.000	-0.000	-0.000
Panel E: use only countries with DAH per capita above sample 80th percentile, instead of sample mean	-0.000	0.000*	-0.000
Panel F: remove household expenditure as a control variable	0.0002	0.0001	0.0000
Panel G: use CHE 25% as outcome, instead of CHE10%	0.000		
Panel H: use impoverishment 3.20 US$ poverty line as outcome, instead of 1.90 US$		0.000	
Panel I: remove domestic government health expenditure from the list of control variables	-0.0001	0.000	-0.0000
Panel J: use Low and Lower Middle-Income countries as sample	0.0006	0.0001	0.000
Panel K: use Low-, Lower Middle- and Upper Middle-income countries as sample	0.0003	0.0002***	0.0001
Panel L: use all countries as sample	-0.0000	0.0002***	0.0001

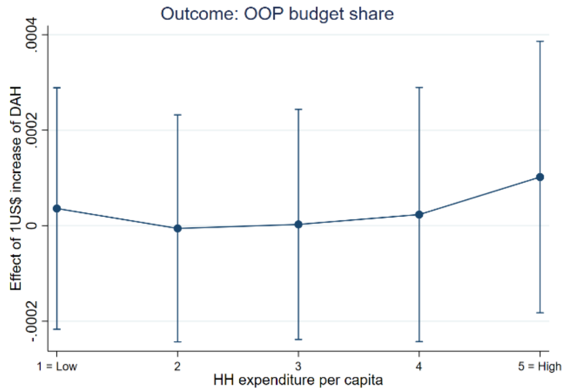
Source: author, based on analyses described in the methods section, eq. [1]. Linear regressions are used in all columns and interpretation is described in the methods section. SE clustered at country level are used to determine p-values. p<0.1*, p<0.05**, p<0.001***.

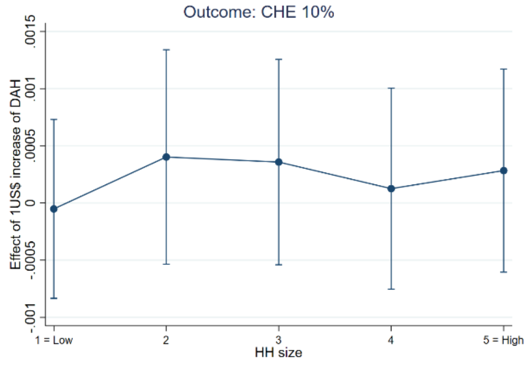
Appendix C-4. Full marginal effects results, and all margins plots: <u>country and year fixed effects models</u>

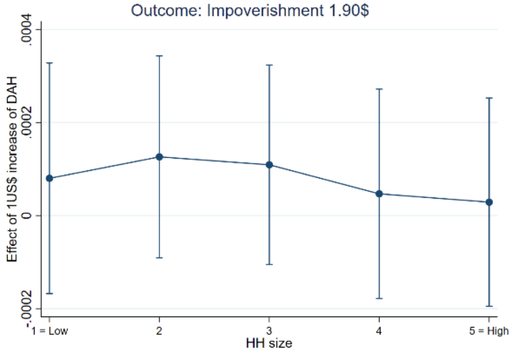
Household characteristics

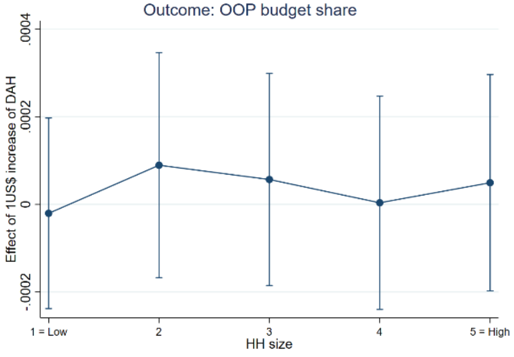






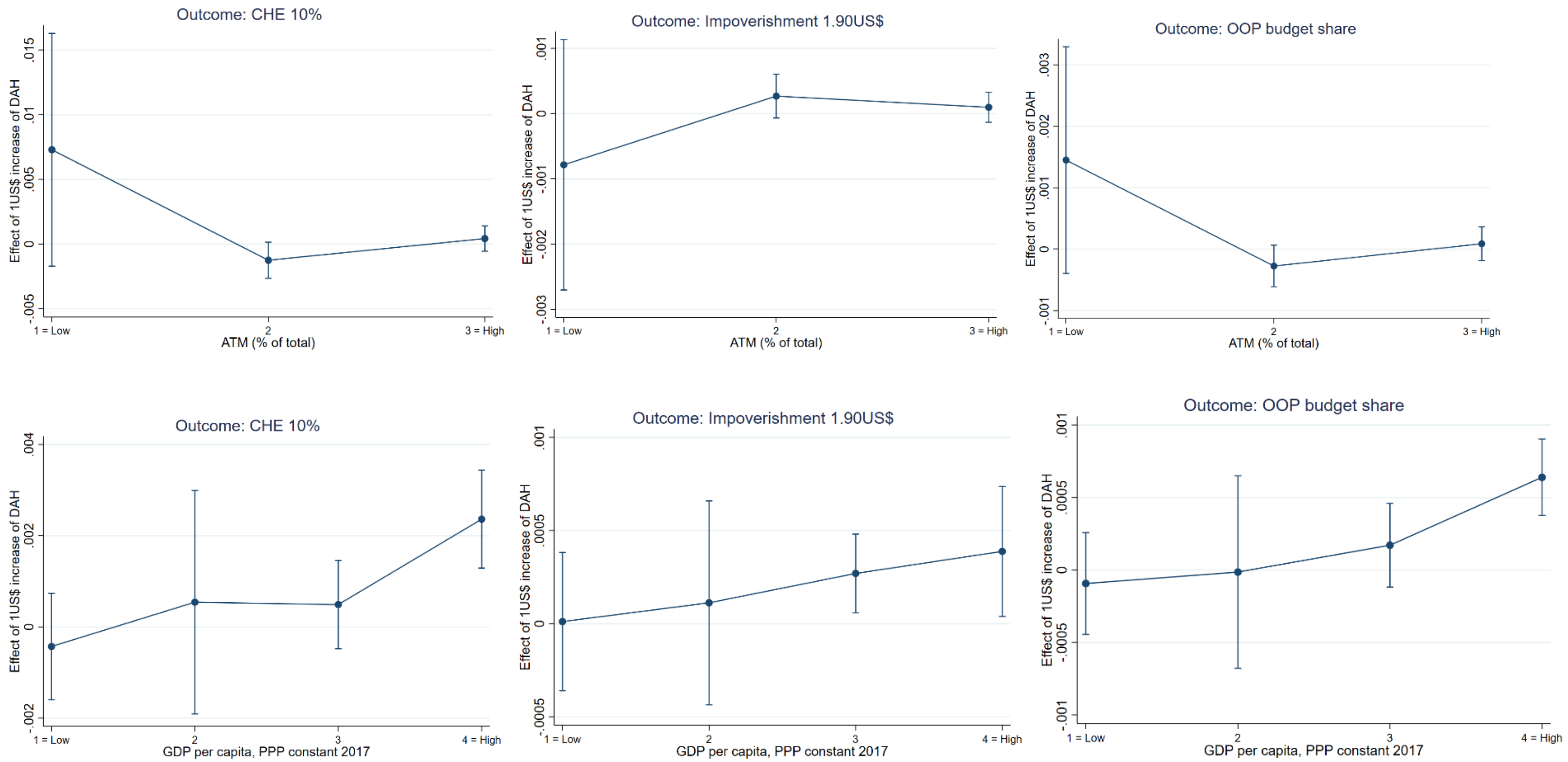


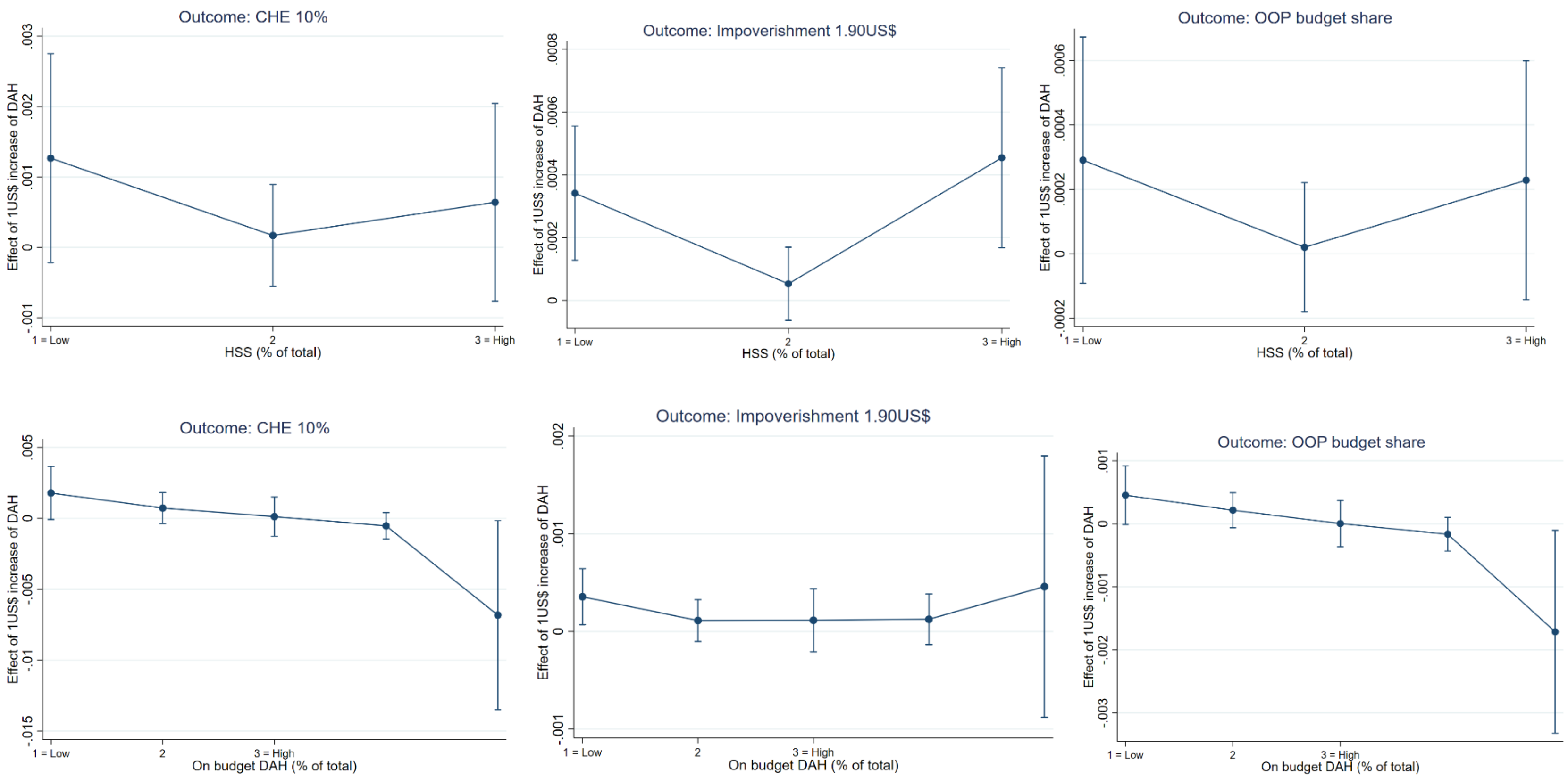


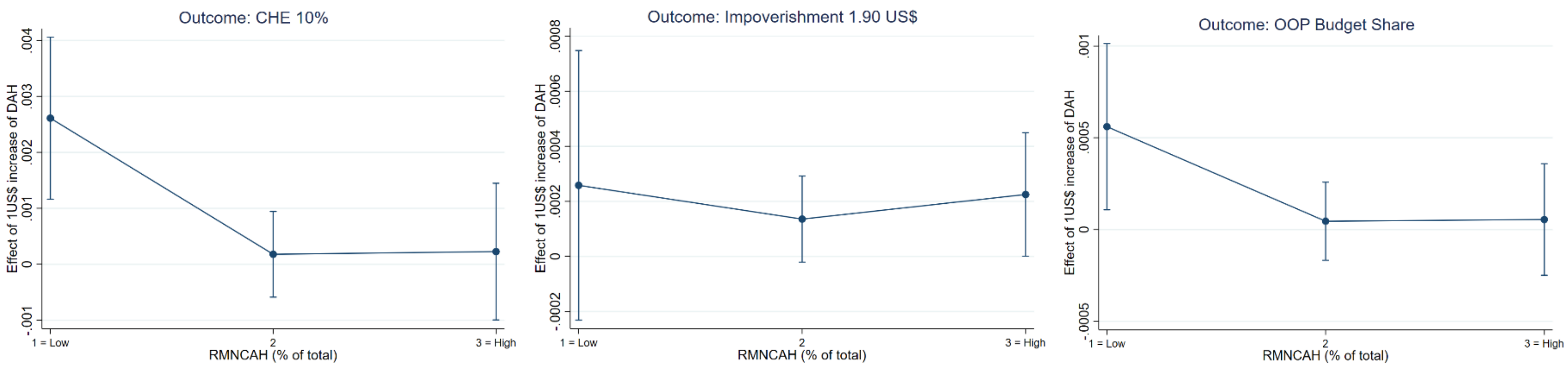


Outcome: CHE 10%
Effect of 1US$ increase of DAH
.001
0
-.001
-.002
1 = Low
2
3 = High
OADR
Outcome: Impoverishment 1.90US$
Effect of 1US$ increase of DAH
.0004
.0002
0
-.0002
1 = Low
2
3 = High
OADR
Outcome: OOP budget share
Effect of 1US$ increase of DAH
.0004
.0002
0
-.0002
-.0004
1 = Low
2
3 = High
OADR

Country contextual factors



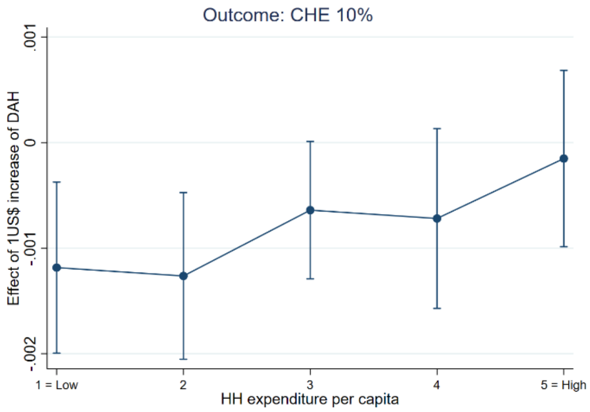

Outcome: CHE 10%
Effect of 1US$ increase of DAH
HSS (% of total)
1 = Low
2
3 = High
Outcome: Impoverishment 1.90US$
Effect of 1US$ increase of DAH
HSS (% of total)
Outcome: OOP budget share
Effect of 1US$ increase of DAH
HSS (% of total)
Outcome: CHE 10%
Effect of 1US$ increase of DAH
On budget DAH (% of total)
Outcome: Impoverishment 1.90US$
Effect of 1US$ increase of DAH
On budget DAH (% of total)
Outcome: OOP budget share
Effect of 1US$ increase of DAH
On budget DAH (% of total)

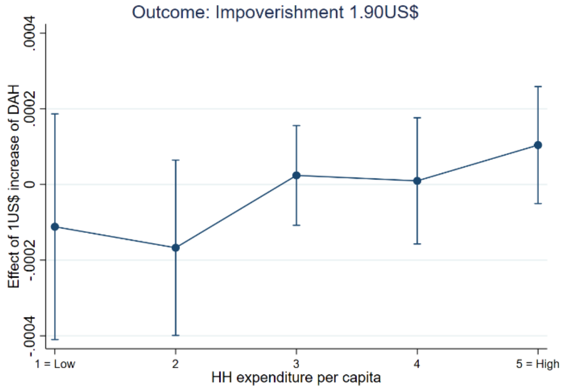


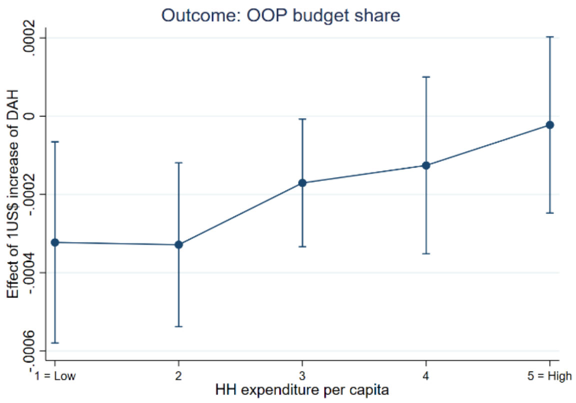
Outcome: CHE 10%
Effect of 1US$ increase of DAH
RMNCAH (% of total)
1 = Low
2
3 = High
Outcome: Impoverishment 1.90 US$
Effect of 1US$ increase of DAH
RMNCAH (% of total)
Outcome: OOP Budget Share
Effect of 1US$ increase of DAH
RMNCAH (% of total)

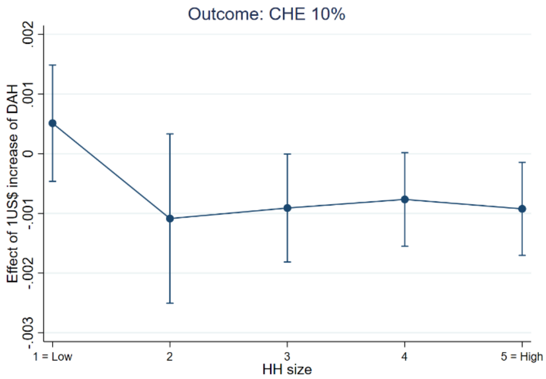
Appendix C-5. Full marginal effects results, and all margins plots: <u>pseudo-panel models</u>

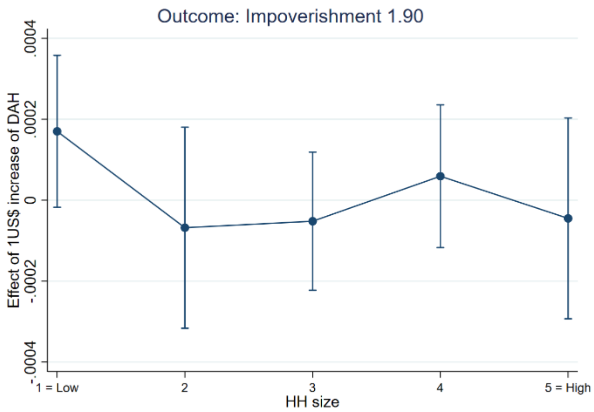
Household characteristics

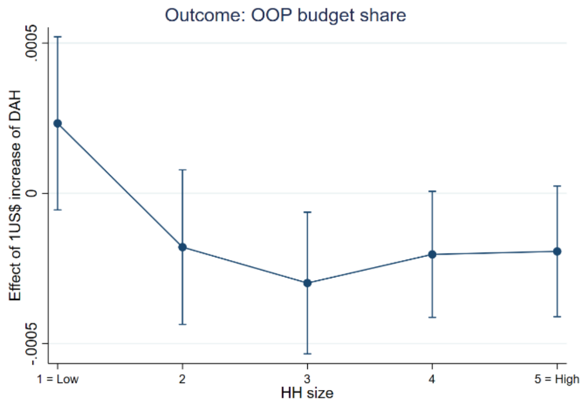


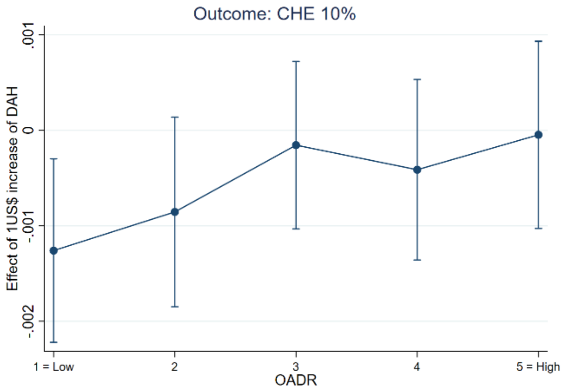


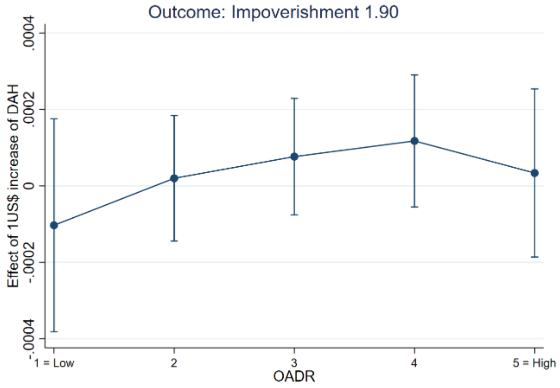


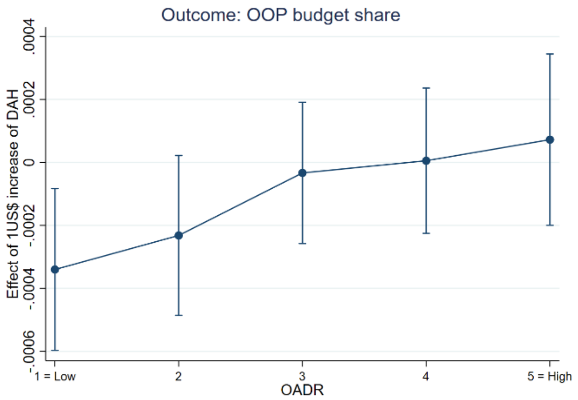




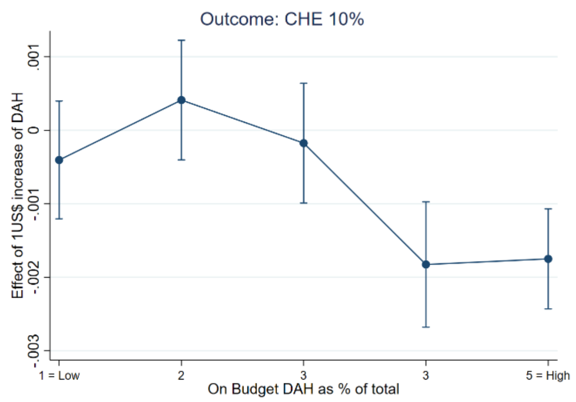


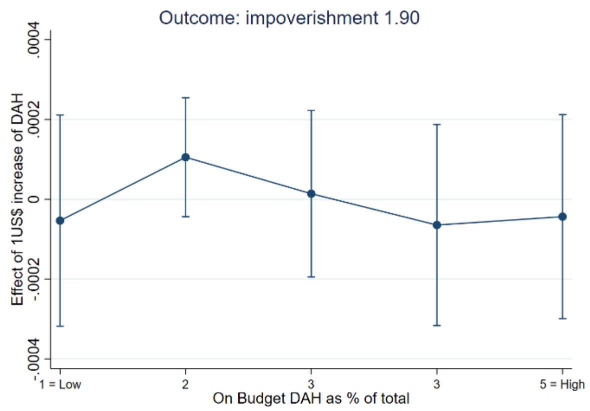

Outcome: CHE 10%
Effect of 1US$ increase of DAH
.001
0
-.001
-.002
1 = Low
2
3
4
5 = High
OADR

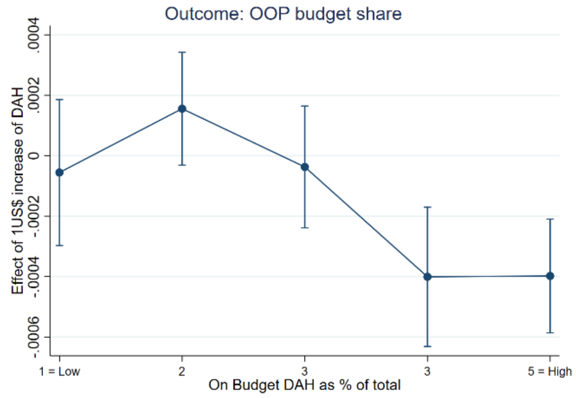

Outcome: Impoverishment 1.90
Effect of 1US$ increase of DAH
.0004
.0002
0
-.0002
-.0004
1 = Low
2
3
4
5 = High
OADR

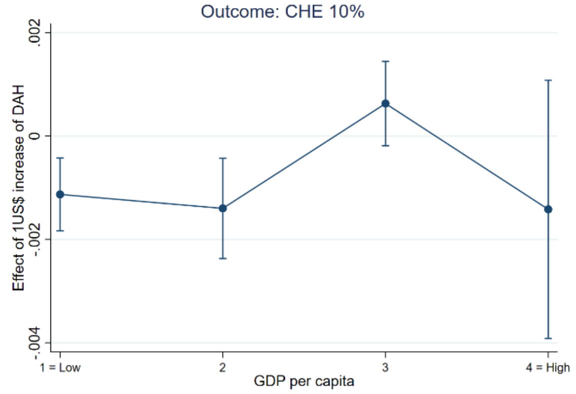

Outcome: OOP budget share
Effect of 1US$ increase of DAH
.0004
.0002
0
-.0002
-.0004
-.0006
1 = Low
2
3
4
5 = High
OADR

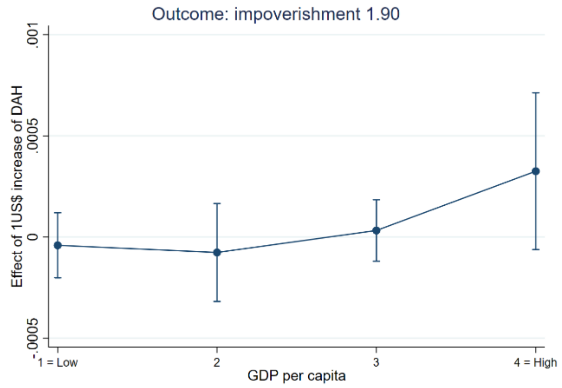
Country contextual factors

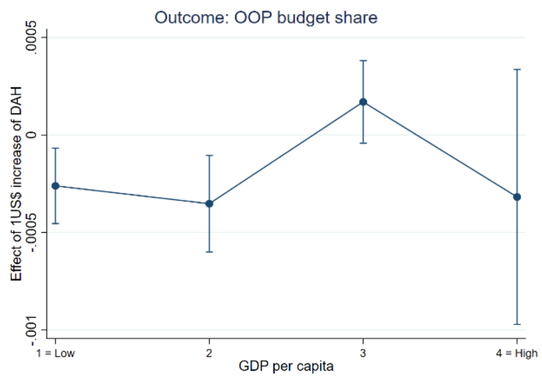


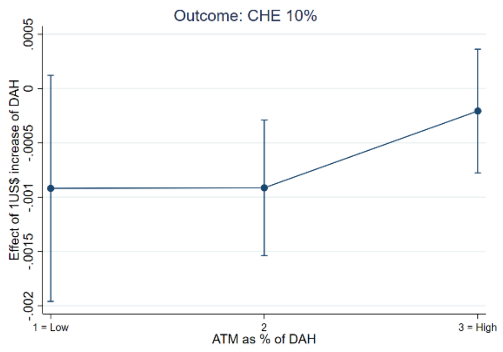


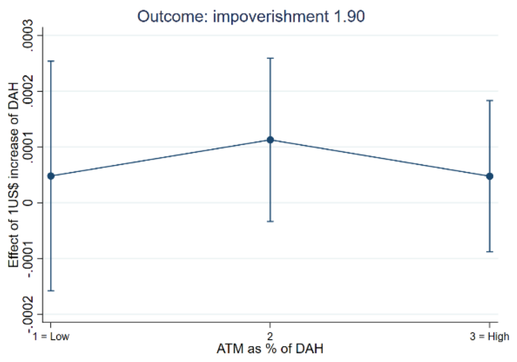


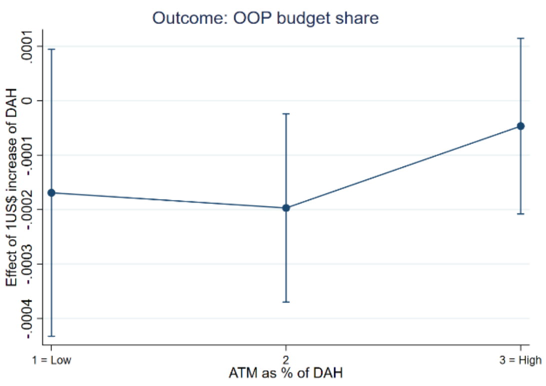


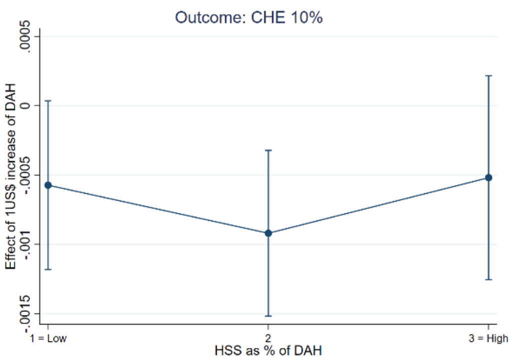


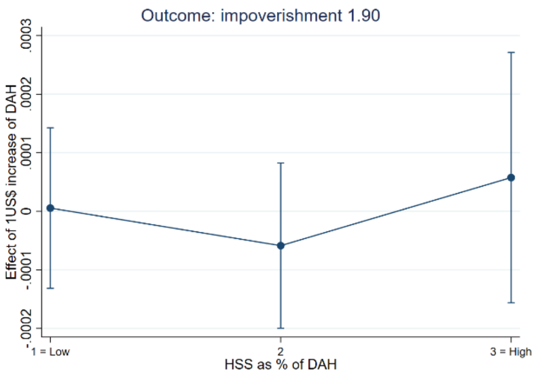


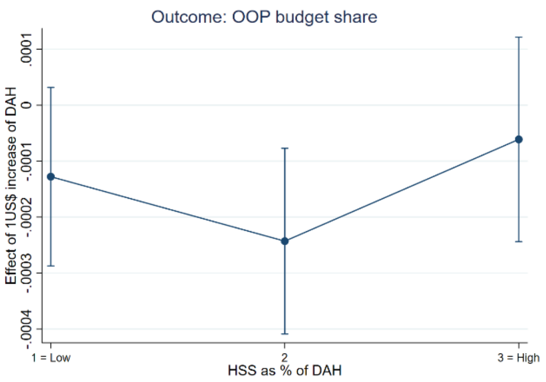


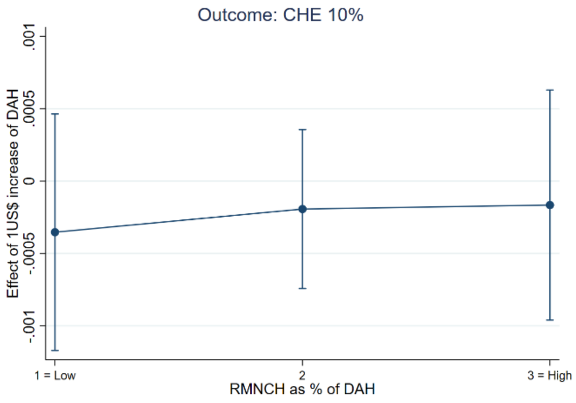


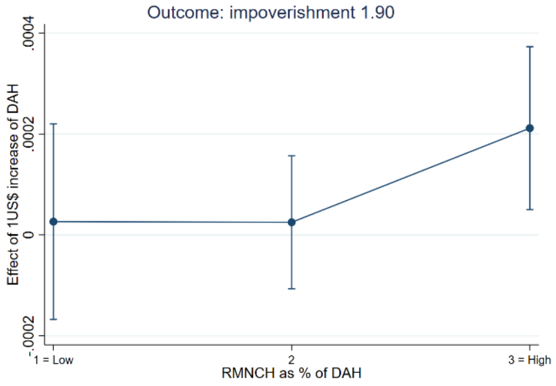

Outcome: OOP budget share
Effect of 1US$ increase of DAH
.0001
0
-.0001
-.0002
-.0003
-.0004
1 = Low
2
3 = High
ATM as % of DAH

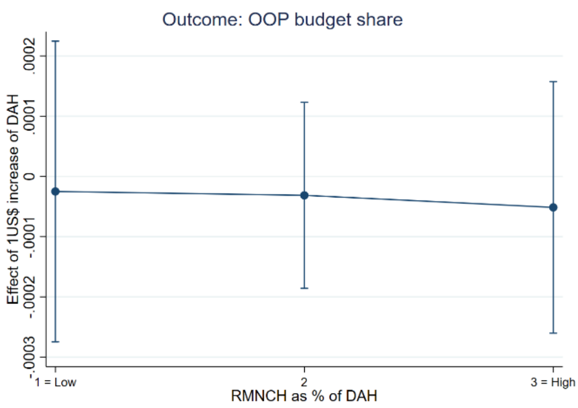

Outcome: CHE 10%
Effect of 1US$ increase of DAH
.0005
0
-.0005
-.001
-.0015
1 = Low
2
3 = High
HSS as % of DAH


Outcome: impoverishment 1.90
Effect of 1US$ increase of DAH
.0003
.0002
.0001
0
-.0001
-.0002
1 = Low
2
3 = High
HSS as % of DAH


Outcome: OOP budget share
Effect of 1US$ increase of DAH
.0001
0
-.0001
-.0002
-.0003
-.0004
1 = Low
2
3 = High
HSS as % of DAH


Outcome: CHE 10%
Effect of 1US$ increase of DAH
.001
.0005
0
-.0005
-.001
1 = Low
2
3 = High
RMNCH as % of DAH


Outcome: impoverishment 1.90
Effect of 1US$ increase of DAH
.0004
.0002
0
-.0002
1 = Low
2
3 = High
RMNCH as % of DAH


Outcome: OOP budget share
Effect of 1US$ increase of DAH
.0002
.0001
0
-.0001
-.0002
-.0003
1 = Low
2
3 = High
RMNCH as % of DAH

Appendix D: appendix for Chapter 4

Appendix D-1. Detailed assumptions on financing and benefit incidence analyses, and health system expenditures

Table D-1.Detailed measurement of cost per units

	NHA 2018, total health expenditure (SLL millions)	**% of hospitals and PHU expenditure paid by government**	**SLL per 1 US$ in 2018 (average)**	**Total cost (US$)**	**Utilization units: inpatient nights, outpatient episodes (source: SLIHS 2018)**	**Cost per unit**
Hospital outpatient	787268.841	5%	7712	5,273,013	2785056	1.89
Hospital inpatient	880233.6184	5%	7712	5,895,677	1324468	4.45
PHU outpatient	143121.9533	14%	7712	2,566,177	7623852	0.34
PHU inpatient (average of hospital inpatient and PHU outpatient)						2.39

Source: authors' calculation

Table D-2. Financing incidence detailed assumptions

Tax	**Tax base**	**Tax applied**	**Explanation**
Indirect tax: goods and services tax	All expenditures except rice, books, fuel, transport	15%	15% is the goods and services tax rate for all goods and services in Sierra Leone
Indirect tax: fuel excise duties	Fuel expenditures	9%	Assumption taken from World Bank / Statistics Sierra Leone 2014 report (179)
Indirect tax: goods and services tax	"Public transport" expenditures	30% of total cost assumed to be fuel, then taxed at 9%, therefore 2.7% of total public transport cost	It is assumed that 30% of total public transport ticket is fuel
Direct tax: income tax	Salary for individuals stating that they have a formal contract. Salary is annualized	According to First Schedule of National Income Tax Act (old Leones): - Below Le 3,600,001.00 per annum: Nil - Le 3,600,001.00 to Le 7,200,000 per annum: 15% - Le 7,200,001.00 to Le 10,800,000 per annum: 20% - Over 10,800,001.00: 30%	None

Below is an overview of all taxes estimated via SLIHS, their weight as % of total taxes, and assumptions for taxes not estimated via SLIHS 2018.

Table D-3. Overview of all assumptions made for financing incidence analysis

Nomenclature used in paper	**Tax**	**2018 (% of GDP) (source: Sierra Leone Budget and Finance Act 2019)**			
	Total	14.3	% of total	% of tax Sierra Leone budget sub-group	
Direct tax	**Income taxes**	5.2	36%	*100%*	
	Of which: Personal	4.1	29%	79%	Estimated using SLIHS*
	Of which: Corporate	1	7%	19%	Assumed distributed as personal income tax
Indirect tax	**Goods and services tax (GST)**	2.7	19%	*100%*	
	Of which: Domestic	1.6	11%	59%	Estimated using SLIHS**
	Of which: Import	1.1	8%	41%	Assumed distributed as indirect tax SLIHS estimate (petroleum and domestic GST). There is no information on SLIHS as to whether goods are imported or not, except for rice.
	Excise taxes	3.4	24%	*100%*	
	Of which: Petroleum products	1.5	10%	44%	Estimated using SLIHS**
	Of which: Import duties	1.8	13%	53%	Assumed distributed as indirect tax SLIHS estimate (petroleum and domestic GST). There is no information on SLIHS as to whether goods are imported or not, except for rice.
Other	**Mines department**	0.7	5%	21%	Assumed to be distributed as all other revenues
	Other departments	2.3	16%	68%	Assumed to be distributed as all other revenues

*Estimated value via SLISH 2018 was 83% of the total amount stated in the Sierra Leone 2019 Budget Act, therefore it was adjusted to reflect the actual Budget Act value. We note that six households with reported income from approximately 250000 USD to 650000 USD have been removed as they are likely reporting mistakes: their jobs are paid monthly (e.g., government job), but they reported being paid hourly instead of monthly, resulting in over-estimation.

**Total indirect taxes estimated via SLIHS were 87% of total indirect taxes as per Sierra Leone 2019 Budget Act, therefore it was adjusted to reflect the actual Budget Act value

Table D-4. Detail of public health expenditures across health providers

Health providers			**Financing schemes: HF.1 Government schemes and compulsory contributory health care financing schemes**	**As% of total**
HP.1		**Hospitals**	86,760.0	39%
	HP.1.1	General hospitals	25,586.3	12%
	HP.1.2	Mental health hospitals	1,734.8	1%
	HP.1.3	Specialised hospitals (Other than mental health hospitals)	2,905.0	1%
	HP.1.nec	Unspecified hospitals (n.e.c.)	56,533.9	26%
HP.3		**Providers of ambulatory health care**	29,463.0	13%
	HP.3.4	Ambulatory health care centres	29,463.0	13%
HP.5		**Retailers and Other providers of medical goods**	509.0	0%
	HP.5.1	Pharmacies	509.0	0%
HP.6		**Providers of preventive care**	44,277.3	20%
HP.7		**Providers of health care system administration and financing**	52,215.5	24%
	HP.7.1	Government health administration agencies	52,215.5	24%
HP.9		**Rest of the world**	7,819.3	4%
All HP			221,044.2	100%

Note: HP (health provider) codes and HF (health financing) codes are used in Sierra Leone NHA 2018, following the SHA 2011 Manual, as per standard NHA practice

Appendix D-2. Robustness checks and extensions of the benefit and financing incidence analyses

Use WHO CHOICE for benefits

We re-do the benefit incidence analysis using WHO CHOICE 2021 data instead of NHA 2018 as the source for outpatient and inpatient visits values in US$. As shown in the table below, the NHA values are different from WHO CHOICE values. For this reason, using WHO CHOICE result in overall benefits being slightly pro-poor and the public healthcare system of Sierra Leone being more equitable. NHA 2018 data, which is collected from development partners, governments and from household surveys, is to be preferred from WHO CHOICE 2021, which is modelled from NHA across countries.

Table D-5. Computed values of benefits from WHO CHOICE and NHA 2018

WHO CHOICE unit cost definition and computation	SLIHS 2018 definition	Computed value (US$) from WHO CHOICE	Computed value (US$) from NHA 2018
Average of health centre outpatient with bed, and without bed	PHUs outpatient	2.325	0.34
Average of primary hospital inpatient and outpatient health centre with bed	PHUs inpatient	5.88	2.39
Average of secondary and tertiary hospital outpatient	Hospitals outpatient	3.13	1.89
Average of secondary and tertiary hospital inpatient	Hospitals inpatient	10.98	4.45

Source: authors' calculations

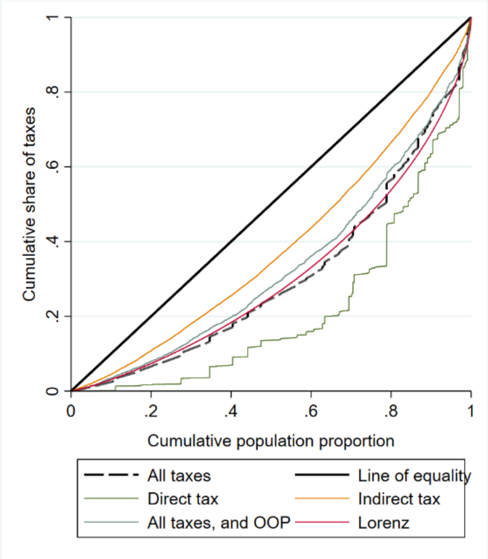
Table D-6. Concentration index using different benefits costs, from WHO CHOICE

Public benefits	Concentration index (CI)	CI – WHO CHOICE
All public benefits	0.008	-0.079***
Inpatient hospital	0.037	0.036
Outpatient hospital	0.143***	0.116***
Inpatient PHU	-0.220***	-0.199***
Outpatient PHU	-0.247***	-0.245***

Source: authors' calculations

Financing and benefit incidence analysis: include OOP health expenditures and private healthcare providers

Figure D.1. Financing incidence, concentration curves including OOP health expenditures

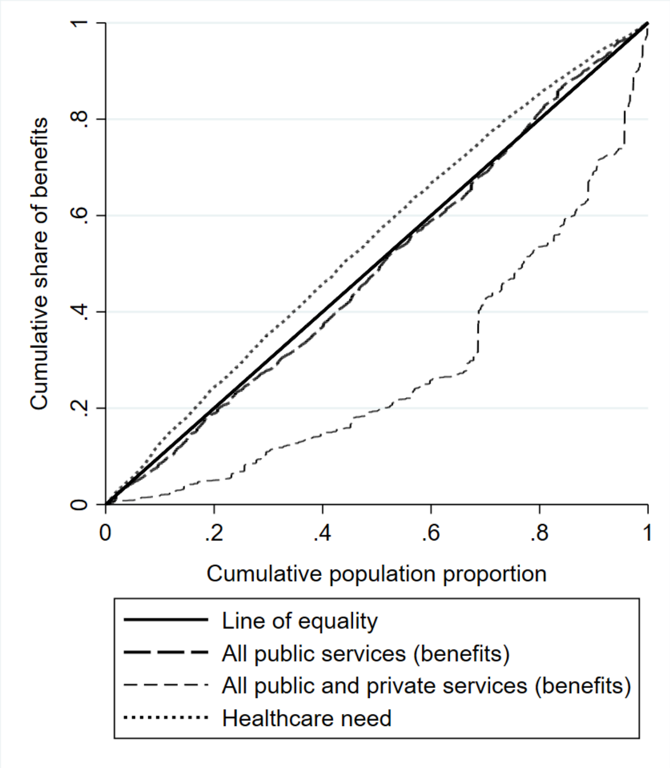


Kakwani index of all taxes and OOP health expenditures: -0.047, p<0.01 => regressive health financing incidence, when including OOP health expenditures

	Kakwani index	SE	NHA 2018	Weights
Government public healthcare expenditure	0.011*	0.006	9%	13%
OOP health expenditures	-0.055	0.002	56%	87%
Weighted average	-0.046	0.005		

Notes: the NHA 2018 do not sum up to 100% because the remaining part (35%) is external expenditures, which have been ignored in this analysis, as done in the literature

Figure D.2. Benefit incidence, concentration curves including private providers



Concentration index of all benefits including from private healthcare providers: 0.44, p<0.01, substantially pro-rich

Using additional OOP costs

User fees collected by health service providers at the PHU level and, to some extent, at the secondary/tertiary level, are possibly informal and expected to fund volunteer health workers (184) (i.e., health workers without a government salary). In our main results, we subtract from public benefits consultations costs, and costs to stay in the hospital (for inpatient services) paid OOP by patients to providers as user fees. In this robustness check, in addition to consultations and costs to stay in the hospital, we subtract from public benefits also drugs and tests costs paid OOP by patients to the providers as user fees. The CIs are largely unchanged.

Table D-7. Concentration index with different definition of user fees

Public benefits	Concentration index (CI)	CI – increased user fees
All public benefits	0.008	-0.01
Inpatient hospital	0.037	0.030
Outpatient hospital	0.143***	0.102***
Inpatient PHU	-0.220***	-0.225***
Outpatient PHU	-0.247***	-0.311***

Source: authors' calculations

Absolute CIs

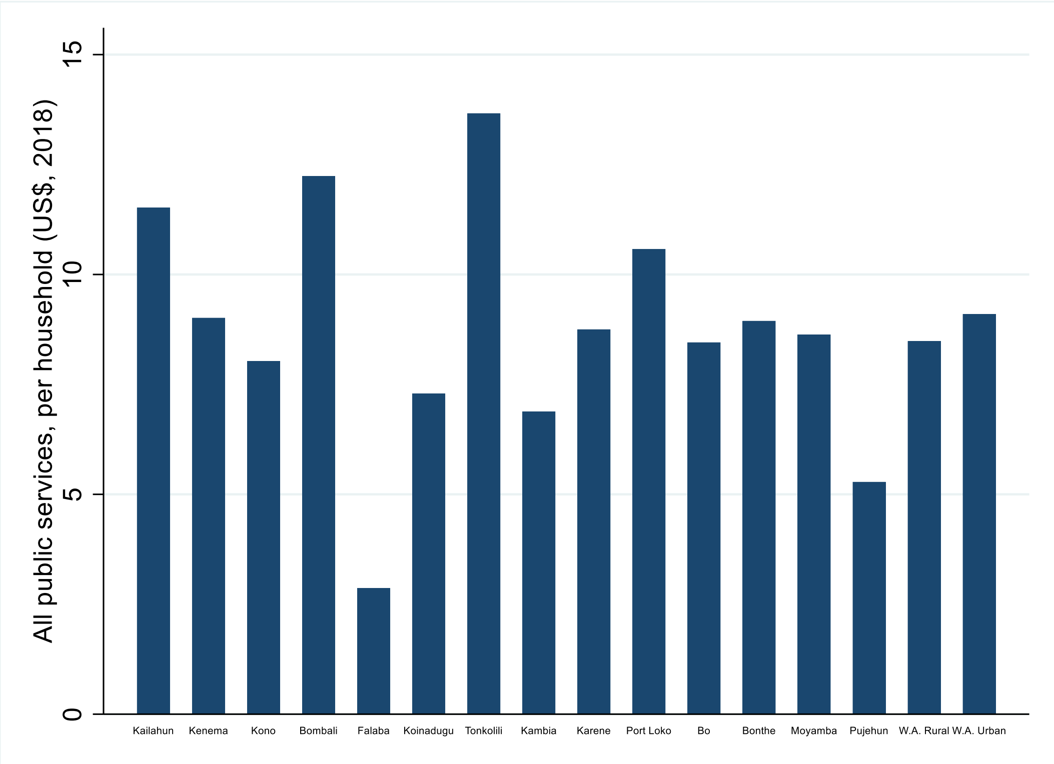
Standard CI is a measure of relative inequality. If benefits are increased by the same percentage to all households, there will be no difference in the standard CI. However, there would be a difference in absolute inequality, which we can measure via the generalized CI (also called absolute CI), computed as the standard CI times the average of the benefits variable. Generalized CIs in SLL are provided in the table below.

Table D-8. Absolute CIs

Public benefits	Standard CI (CI)	Generalized CI (SLL)
All public benefits	0.008	2144
Inpatient hospital	0.037	1491
Outpatient hospital	0.143***	4697
Inpatient PHU	-0.220***	-896
Outpatient PHU	-0.247***	-2891

Source: authors' calculations

Public benefits across districts, US$ per household



Source: author elaboration, notes: W.A. = Western Area

Appendix D-3. Recentred influence function and OLS, detailed methodology and results

Methods described in this section are largely building from Heckley et al. 2016 (188).

We first define a bivariate index I as:

$$I = v^{I}\left(F_{B,R_i}\right) = v^{wI}(F_B)v^{AC}\left(F_{B,R_i}\right) \quad [46]$$

Where B are public healthcare benefits, R_i is the fractional rank of each household based on expenditure per adult equivalent Y (therefore R_i is equivalent to F_Y the cumulative density function (CDF) of Y), $v^{wI}(F_B)$ is a weighting function required to measure a particular version of the CI (standard, Wagstaff or Erreygers), and $v^{AC}\left(F_{B,F_{SES}}\right)$ is the absolute CI AC:

$$v^{AC}\left(F_{B,R_i}\right) = 2cov(B, R_i) \quad [47]$$

The standard, Wagstaff and Erreygers CIs have the same AC but different weights. For the standard CI $v^{wI}(F_B) = 1/\bar{B}$. Substituting $v^{wI}(F_B) = 1/\bar{B}$ and $v^{AC}\left(F_{B,R_i}\right) = 2cov(B, R_i)$ to eq. [46] yields the CI defined in section 4.2.3, footnote 1, defined as $CI = \frac{2}{\bar{B}}cov(B, R_i)$. Because healthcare benefits are not dummy and are not bounded upwards, we prefer the standard CI to the Erreygers and Wagstaff CI which, defining benefits upper bound and lower bounds as B_{ub} and B_{lb} respectively, can be measured by changing the CI weight. For the Erreygers CI, $v^{wI}(F_B) = 4/(B_{ub} - B_{lb})$, and for the Wagstaff CI $v^{wI}(F_B) = \frac{B_{ub}-B_{lb}}{(B_{ub}-\bar{B})(\bar{B}-B_{lb})}$.

Now that we have defined CIs, we can define influence functions (IF). Let G_{b,F_Y} be a distribution function (bivariate) obtained by an infinitesimal contamination of $F_{B,F_Y(y)}$ in both b and $F_Y(y)$:

$$G_{b,F_Y(y)} = (1-\varepsilon)F_{B,F_Y} + \varepsilon\delta_{b,F_Y(y)} \quad [48]$$

G_{b,F_Y} is in fact a distribution that is ε away from the original distribution F_{B,F_Y} in the direction of $\delta_{b,F_Y(y)}$. ε is a weight, or probability, representing the relative change driven by the addition of $\delta_{b,F_Y(y)}$, which is defined as:

$$\delta_{b,F_Y(y)}(l,r) = \begin{cases} 0 \; if \; l < b \; or \; r < F_Y(y) \\ 1 \; if \; l \geq b \; and \; r \geq F_Y(y) \end{cases} \quad [49]$$

Where l is a draw from B and r is a draw from F_Y.

We can now define the bivariate influence function (IF) at point $b, F_Y(y)$ as:

$$IF(b, F_Y(y);\ v^I) = \lim_{\varepsilon\to 0}\frac{v^I\left(G_{b,F_Y(y)}\right) - v^I\left(F_{B,F_Y}\right)}{\varepsilon} \quad [50]$$

The recentred influence function (RIF) can simply be thought of as a minor extension of the IF, obtained by summing the original function to the IF, thus "recentring" it towards the original function.

$$RIF(b, F_Y(y);\ v^I) = v^I\left(F_{B,F_Y}\right) + IF(b, F_Y(y);\ v^I) \quad [51]$$

That is, the contribution of observation $b, F_Y(y)$ to the distribution of v^I, which in our case is the standard CI of public healthcare benefits ranked by household expenditure per adult equivalent.

Following Hackley et al. 2016, and because we defined $v^I(F_{B,F_Y}) = v^{wI}(F_B)v^{AC}(F_{B,F_Y})$, the RIF of CI should take into consideration both index weights and absolute concentration, and is:

$$RIF(b, F_Y(y);\ v^{CI}) = \overbrace{v^{CI}(F_{B,F_Y})}^{CI} + \overbrace{\frac{(\bar{B} - b)}{\bar{B}^2}}^{IF\ of\ weight\ function} v^{AC}(F_{B,F_Y}) + \left(\frac{1}{\bar{B}}\right) IF(b, F_Y(y);\ v^{AC}) \tag{52}$$

Where $IF(b, F_Y(y);\ v^{AC}) = -2v^{AC}(F_{B,F_Y}) + \bar{B} - b - 2bF_Y(y) - 2\int^y \int^{+\infty} b\, F_{B,F_Y} dbdF_Y(y)$

For the proofs of the above equations, , we refer the reader to the appendix of Hackley et al. 2016.

RIF regression decomposition

Following Firpo et al. 2009 (190), and assuming linearity in the relationship between the RIF and covariates, we can use OLS to complete a RIF regression decomposition. RIF values are used as the dependent variable, therefore:

$$RIF(b, F_Y(y);\ v^I) = \boldsymbol{X}\beta + \varepsilon_i \qquad E[\varepsilon_i] = 0 \tag{53}$$

Where $\boldsymbol{X}$ is a vector of covariates. The recentring of the RIF means that $v^I(F_{B,F_Y}) = E[RIF(b, F_Y(y);\ v^I)]$, and therefore:

$$E[RIF(b, F_Y(y);\ v^I)] = E[\boldsymbol{X}\beta] + E[\varepsilon_i] = \bar{\boldsymbol{X}}\beta \tag{54}$$

The unconditional partial effect β on the CI is then:

$$\beta_k = \frac{dv^I(F_{B,F_Y})}{d\bar{\boldsymbol{X}}_{\boldsymbol{k}}} \tag{55}$$

This can be interpreted, for continuous variables, as the effect β_k of an increase in one unit in the unconditional expectation $\bar{\boldsymbol{X}}_{\boldsymbol{k}}$ on the CI ($v^I(F_{B,F_Y})$) of public healthcare benefits B, measured using expenditure per adult equivalent Y as the living standard measure. For dummy variables (for example, “household residing in rural area equal one, zero otherwise), the change from 0 to 1 implied by the OLS regression is equivalent to moving from 0% to 100% of households in rural area, therefore the coefficient need to be interpreted carefully. For a binary variable, the CI percentage contribution of an increase of 1 percentage point in the proportion of households belonging to a particular group (e.g., household residing in a rural area) is calculated as:

$$\frac{\beta_k}{CI} * 1\% \tag{56}$$

We remind that $CI = v^{WI}(F_B)v^{AC}(F_{B,R_i})$ with weight $\frac{1}{B}$.

The benefits of using the RIF-CI-OLS methodology (188) versus the "standard" CI decomposition methodology from Wagstaff, Van Doorslaer, Watanabe (192) are three. First, OLS is a rather familiar methodology and the interpretation of RIF-CI-OLS results is analogous to standard OLS regressions. Second, standard CI decomposition requires more stringent assumptions for identification. More specifically, standard CI decomposition requires that the determinants of health do not determine the rank variable and do not determine the weighting function. Both these assumptions do not appear to be reasonable in our case, as determinants of public health benefits provision (e.g., rural residence, education, employment) are almost certainly determinants of the rank variable (i.e., total household expenditure per adult equivalent), and of the weighting function (i.e., the inverse of average income). While we do not attempt to find causal relationship, we attempt to find associations and therefore the assumptions required are important. The RIF-CI-OLS, for identification of partial unconditional effects require that the CI is differentiable, that the RIF-CI is linear, and that the OLS regression errors have mean zero. Finally, standard CI decomposition results are weighting function agnostic: regardless of the CI weighting function and CI measured (i.e., standard vs. Wagstaff vs. Erreygers), standard CI decomposition would provide the same results. This does not appear to be plausible, and in RIF-CI-OLS decompositions the results change depending on the type of CI and weighting function used. For all these reasons, we believe that RIF-CI-OLS is the preferred methodology for CI decomposition.

To implement the two-step procedure described above, we use the software Stata 17 and the commands egen rifvar and regress (189).

Results

Table D-9. RIF-CI-OLS results

	Covariates	(1) OLS	(2) OLS ME	(3) Weighted OLS	(4) Weighted OLS ME
Residence	Residence (rural=1, urban=0)	0.188*	5%	0.239**	30%
		(0.106)		(0.120)	
Income quintile	Low-income quintile	Reference			
	Mid-low income quintile	0.0589	2%	0.0705	9%
		(0.0847)		(0.104)	
	Mid-income quintile	0.00747	0%	0.0400	5%
		(0.0863)		(0.101)	
	Mid-high income quintile	0.134	4%	0.136	17%
		(0.107)		(0.121)	
	High income quintile	0.0547	1%	0.0574	7%
		(0.170)		(0.176)	
HHH age	HHH age (quartile 1): <36	Reference			
	HHH age (quartile 2): 36-44	0.0432	1%	0.00665	1%
		(0.0443)		(0.0533)	

	HHH age (quartile 3): 45-55	0.0175	0%	-0.00293	0%
		(0.0515)		(0.0554)	
	HHH age (quartile 4): 56 or older	0.0800*	2%	0.0536	7%
		(0.0409)		(0.0425)	
HHH education	HHH education: none	Reference			
	HHH education: primary	-0.110	-3%	-0.110	-14%
		(0.0928)		(0.103)	
	HHH education: secondary or more	-0.0171	0%	0.000424	0%
		(0.0454)		(0.0459)	
HHH employment	HHH: unemployed	Reference			
	HHH: employed, agriculture	-0.0619	-2%	-0.0964	-12%
		(0.105)		(0.122)	
	HHH: employed, all other	-0.0697	-2%	-0.0493	-6%
		(0.0749)		(0.0907)	
HHH gender	HHH gender (female=1, male=0)	0.0189	1%	0.0365	5%
		(0.0514)		(0.0498)	
HH size	HH size (quartile 1): <5	Reference			
	HH size (quartile 2): 5	0.314***	8%	0.289***	36%
		(0.0542)		(0.0496)	
	HH size (quartile 3): 6-7	0.353***	10%	0.340***	43%
		(0.0668)		(0.0697)	
	HH size (quartile 4): 8 or more	0.103	3%	0.0553	7%
		(0.110)		(0.104)	
	Constant	-0.232		-0.272*	
		(0.146)		(0.141)	
	RIF mean (CI):	0.037		0.008	
	Observations	6,810		1,407,531	
	R-squared	0.014		0.015	

Source: authors' elaboration, data sources described in the methods section and methodology in Appendix D-3. Notes: the dependent variable is the RIF of the CI for all public healthcare system benefits. Robust, clustered SEs are used. SEs are bootstrapped using 500 replications. ME stands for marginal effects and are the percentage increase/decrease of the CI driven by an increase in 1% in the relative population sub-group (i.e., rural residents sub-group, mid-low income quintile sub-group, etc.); they are measured as $\frac{\beta}{CI} * 1\%$. The full estimation process is bootstrapped to calculate SEs. *p<0.1, **p<0.05, ***p<0.01

We note that the difference between the RIF mean (i.e., the CI) shown in Table D-9, column 1 and the CI shown in Table 4-4 is driven by SLIHS 2018 weights: this is confirmed by the fact that the CI in Table D-9, column 3 (WOLS) is identical to the CI shown in Table 4-4.

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