# Development Assistance for Health, Resource Allocation and Public Sector Behaviour

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# Declaration

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# Abstract

This thesis comprises three research papers on the allocation of health care resources in resource-poor settings. I first examine the effects of aid conditionality in a theoretical framework where the donor has imperfect information about the local health needs while the central and local governments do not engage in self-interested efforts upon receiving aid. The novelty of the model is to introduce foreign aid in a decentralised health system in order to explore the implications of conditionality of aid on local health expenditures, intergovernmental transfers and social welfare. I analyse the conditions under which aid conditionality increases local health expenditures but reduces at the same time the welfare of the high-need populations; the outcomes of this setting are then compared to the situation where aid is unconditional. I finally discuss these consequences in a health system with two levels of care when the donor restricts aid on Primary Health Care. The findings highlight the potentially detrimental effects of aid conditionality on local health outcomes and underscore the need for establishing close collaboration between donors and all levels of federal governments in the recipient country.

To empirically assess the predictions of the model, I examine the effectiveness of donors in targeting the highest burden of malaria in the Democratic Republic of Congo when the health information structure is fragmented. I exploit local variations in the burden of malaria induced by mining activities as well as financial and epidemiological data from health facilities to estimate how local aid is matching local health needs. Using a regression discontinuity design, I find significant but quantitatively small variations in aid to health facilities located within mining areas.

Comparing local aid with the additional cost of treatment and prevention associated with the increased risk of malaria transmission, I find suggestive evidence that local populations with the highest burden of the disease receive a proportionately lower share of aid compared to neighbouring areas with reduced exposure to malaria infection.

Finally, the last chapter explores to what extent colonial medical missions explain contemporaneous disparities in hospital performance in sub-Saharan Africa. Using archival data from colonial Belgian Congo between 1929 and 1956, this study investigates the effects of colonial health investments on modern health facility performances. I document a strong persistent effect on physical and human capital. Government allocation to colonial hospitals is also substantially higher even when controlling for the medical staff and bed capacity. The ability of the colonial regime to mobilise large health investments and skilled resources appears to be a strong channel of persistence of the colonial effects.

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# Chapter 1

# Introduction

Financing health care is central to population health. Listed by the World Health Organisation (WHO) as one of the six building blocks of health systems, the fundamental aim of a health care financing system is to promote universality and equity in health. Health financing is divided between raising revenue and allocating resources. In resource-poor countries with high disease burdens, the allocation of health resources plays a crucial role in addressing the intertwined challenge of poverty and ill health. Since the government budget constraint of these countries often bind at very low levels of domestic health expenditures, donors are essential actors in financing health care. Discussions surrounding health care resources, therefore, inevitably involve the role and nature of foreign assistance.

During the last three decades, global health actors have mobilised to reduce health inequalities between North and South, with Development Assistance for Health (DAH) increasing from US$ 2.6 billion in 1990 to US$ 37 billion in 2017 (Dieleman, Haakenstad, et al., 2018).[1] In Sub-Sahara Africa, which hosts some of the highest disease burdens, governments finance on average 34% of total health spending, while DAH represents 16%. Nonetheless, large discrepancies exist within this region and the share of DAH in total health care spending can even exceed 40% in countries like Burundi, the Democratic Republic of Congo or Guinea (Dieleman,

[1]The United Nations (UN) Millennium Development Goals set by the UN members states in 2000 explains the dramatic increase of DAH and foreign aid in general.

Haakenstad, et al., 2018). In these settings, understanding the contributing factors through which DAH, and public health spending in general, achieve their objectives of disease burden reduction is primordial in order to make better use of the limited existing resources.

However, the presence of multiple donors with different and sometimes conflicting interests, the fragile fiscal and institutional state of recipient countries and the difficulty to track the dynamics of disease spreading pose serious challenges to the optimal allocation of resources and health system performance as a whole (Gottret and Schieber, 2006). The prominent role of DAH also raises concerns about the sustainability of health care financing and recipient government leadership.

As the United Nations set ambitious health objectives for 2030 with the Sustainable Development Goals (SDGs), building well-functioning health systems with extended coverage requires more effective and efficient use of existing resources.[2] Prioritised interventions and programmes that reach the maximum health benefits and inequity reduction in accessing care are increasingly used to cope with recent stagnation in total health care funding (WHO, 2018b). Donor governments and health aid agencies (such as Global Health Initiatives) are coming under acute pressure to demonstrate evidence of maximised health impacts from the funds disbursed, a term also coined "value for money".[3] Under these considerations, studies on the cost-effectiveness of health interventions or programmes offer insights on the ways to increase health gains through better use of money. Nonetheless, these studies are, by their nature, limited in scope to efficiency considerations and an important question persists: how can DAH be more effective? The related issue of aid effectiveness is addressed in the foreign aid literature, but significant gaps remain when applied to the global health landscape.

[2]Note that funds are effective when they successfully achieve their intended goals, while efficiency refers to the optimal combination of inputs used and outputs produced. Efficiency is further decomposed between allocative efficiency, which consists of maximising the outcome for a given distribution needs, and technical efficiency that either minimises the costs for a given production of output or maximises the production quantity given the resource constraint.

[3]Note that there is no consensus on the definition of value for money among actors in global health. It can refer either to efficiency, effectiveness or both. See Glassman et al. (2013) for a detailed discussion.

The large flows of foreign aid poured into Sub-Sahara African countries have received contrasting interpretations. While some observers expressed hope in the capacity of the international community to mobilise more funds to eradicate poverty and disease burdens (Sachs, 2005), others criticise foreign aid for its limited achievements with respect to money disbursed. Easterly (2006) suggests that lack of accountability of donors, large-scale plans that poorly fit with local needs and political and economic interests are harming recipient countries. Aid would be intrinsically associated with inefficiencies that it cannot depart from. Another strand of research adopts a more nuanced approached and rather advocates for structural reforms accompanying foreign assistance: it puts forward the importance of strategic involvement of the recipient government, the need for capacity building and effective use of resources through targeting the greatest needs (Collier, 2007). To this aim, efforts should be dedicated to funding evidence-based projects that are effective in achieving their goals (Banerjee and Duflo, 2011).

Following this latter line of research, my dissertation attempts to bring new perspectives on the optimal allocation of health funds in resource-poor settings and the conditions under which DAH operates. What I loosely term "conditions" refers to the environmental setting that contributes to shaping the effective use of health resources in the structure of health systems in Sub-Saharan Africa. Although ineffectiveness can have multiple forms and dimensions, this research investigates three determinants that might have wide implications for health care financing: public sector behaviour, decentralisation and colonial legacy. This thesis devotes particular attention to aid effectiveness, which largely contributes to the effectiveness of health care financing in low-income countries.

What causes aid ineffectiveness? Despite the existence of multiple factors hampering the impact of aid, a large strand of the development literature has focused on public sector behaviour and the donor-recipient relationship.[4]

The relationship between the donor and the recipient involves a set of objectives

[4]Other primary causes identified in the literature are aid predictability, aid fragmentation, absorptive capacity and government participation in health funding (Wagstaff and Claeson, 2004; Gottret and Schieber, 2006).

to be reached, the development goals targeted by the donor, and a set of usable resources, the foreign aid. When the preferences between donors and recipient differ, aid resources might simply end up financing items that were not originally intended by the donor if they do not supplement government spending. For instance, the recipient can decrease spending on a programme if a donor finances it, and reallocate resources for other purposes. This phenomenon, called "aid fungibility", is often identified in the literature as the primary cause of aid ineffectiveness (Bauer, 1972). The fungible nature of DAH may mean that the external resources do not have the desired effect on health outcomes. A large body of empirical studies has attempted to identify the phenomenon, which is examined in chapter 2.

The theoretical approach to the fungibility issue emphasises how the existing divergences between the donor and the recipient's objectives can reduce the impact of external funding (Martens et al., 2002; Azam and Laffont, 2003). In cases where donor and recipient's preferences are misaligned and the donor has perfect information about the needs in the country, the implementation of an aid contract enables the donor to incentivise the recipient to act according to the donor's intended objectives and restore the optimality of aid. Importantly, this contract is expected to increase aid effectiveness under the assumption that the donor's allocation decisions achieve the highest health impact in the recipient country. In other words, the donor sets its objective through its presupposed perfect knowledge of the local health needs. In the global health landscape, the widespread use of Performance-based Results (or Performance-based Financing, Pbf) between national governments and multilateral institutions is a direct application of the aid contract. The scheme designs allocation decisions from the highest level and ensure the accountability of the recipient through close monitoring and evaluation of implemented programmes.

What is the validity of this assumption? First, the literature on decentralisation and federalism suggests that high-level decisions tend to ignore local-specific information (Oates, 1972). Second, empirical studies find little evidence to support the view that donors systematically make optimal decisions to maximise health benefits. On the contrary, the findings suggest that donors may disproportionately prioritise some disease-specific programmes (Shiffman, 2007) and that the overall health resource allocation might be weakly aligned with countries' needs (Dieleman, Graves, et al., 2014). A report from the World Health Organisation (WHO, 2018b) on public health spending similarly acknowledges that for some diseases like HIV, external funding does not reflect well the national health needs. Although the burden of non-communicable diseases is gradually growing in low-income countries, the report further states that "donors clearly have less appetite for funding activities specifically earmarked as addressing non-communicable diseases". These facts clearly contradict the predictions of the theoretical model with a perfectly knowledgeable donor that maximises the overall health benefit in the country: changes in disease patterns among local populations should ignite a reallocation of health resources to meet the highest needs.

What mechanisms could explain donors' suboptimal decisions? The effective integration of global health actors into local health care systems can be jeopardised in several ways. Donors may fail to accurately identify the local socio-economic contexts in which their interventions are rolled-out, or may ignore the role of local health practitioners and community leaders in promoting and providing care (Mason et al., 2017). Importantly, these local actors may receive little opportunity to send "feedbacks" on the implemented programmes (Easterly, 2006). These shortcomings may compromise the functioning of local structures and impede the efficient use of health care resources.

Chapter 2 examines the effects of foreign aid on a decentralised health system. The model presents an alternative approach to the conventional donor-recipient modelling, where the donor has imperfect information about the local health needs while the central and local governments do not engage in self-interested efforts upon receiving aid. An important innovative feature of this model is the introduction of a federal system in the recipient country with two-tier governments. While most health systems have now been decentralised in low-income countries, discussions around the aid allocation mechanisms have ignored this feature. The presentation of the model is followed by discussions on the implications of conditionality of aid on local health expenditures, intergovernmental transfers and social welfare. The findings of chapter 2 highlight the potentially detrimental effects of aid conditionality on local health outcomes and underscore the need for establishing close collaboration between donors and all levels of federal governments in the recipient country.

The second part of this thesis comprises empirical studies on the Democratic Republic of Congo (DRC). The country presents distinctive epidemiological, political and socio-economical characteristics of interest in this research. The DRC is the second largest African country with one of the highest child mortality rate in the world; it is also among those with the highest burden of malaria, HIV, tuberculosis and, combined with its low domestic capacity to fund health care, its health system is one of the highest externally funded in Africa. The Congolese health care system is heavily decentralised, with a central government that designs national health policies and national disease programmes and provincial governments which are responsible for their own health budget and allocate health resources among their districts (health zones). Furthermore, the recent troubled history of the country has been marked by regional wars and civil conflicts that are persisting in some resource-rich regions. From a global health perspective, the country presents a challenging situation with political instability and widespread corruption where the rich resources of the country are mostly controlled by an elite that benefits from bad governance (Ntembwa and Van Lerberghe, 2014). Nonetheless, this situation paradoxically provides an interesting opportunity for tracking aid resources and analysing donors' capacity to target population needs. Since donors and aid agencies mostly anticipate misuse of funds in the country, little aid transits through the government budget (The Global Fund, 2016). Consequently, the majority of external funding for health care should not be prone to government's aid diversion.

Chapter 3 uses a spatial regression discontinuity analysis to determine whether donors are able to target local populations with the greatest needs. The purpose of this analysis is to go beyond *ad hoc* assumptions on donor's information about local health needs and test its capacity to maximise health gains and inequity reduction in access to health care. Because DAH is widely controlled by donors and their local partners (who are implementing the interventions in the country), there exists little possibility for the national government to interfere in the allocation of external funding (MSP, 2017). In this specific context, donors become, to some extent, recipients of their own aid since they have to use their funds according to their own preferences. In this case, do we observe that aid is reaching those with the greatest health needs, as intended by the donors? In other words, are donors able to optimally allocate their own health resources? If not, the answer would indicate either that donors are unable to identify those local populations with the greatest health needs or they are unable to reach them (due to logistical difficulties for example). Using a rich set of information at the health facility level, I examine whether donors are locally able to target the population with the greatest health needs. I claim that if donors have perfect information about local needs, the variations in local aid will follow the variations in the local burden of diseases. I exploit the locations of mining activities where the risk of malaria transmission is high and find no evidence to support the assumption that donors are accurately targeting areas with the greatest health needs.

Chapter 4 focus on exploring the root causes of inequalities in health facility performance which may also hamper aid effectiveness. Lack of availability of human resources in rural areas, demotivated medical staff and low-human capital accumulation are major factors that have been identified in the related literature. Another strand of research discusses the effects of drug availability and the influence of challenges related to the provision, storage and supply of health products on service delivery at the facility level. I suggest another channel for understanding inequalities in health facility performance: the historical roots of a health system. In low-income countries that were historically occupied by colonial regimes, the development path of their institutions has often been affected by the manner in which Europeans shaped these institutions (Acemoglu et al., 2001; Banerjee and Iyer, 2005; Nunn, 2014; Jedwab and Moradi, 2016; Michalopoulos and Papaioannou, 2018). Colonial regimes established the primary roots of health systems through investment in health infrastructure and set the first national health policies. Christian missions were closely tied to the colonial expansion and had an important role in health care provision among local populations. These combined factors suggest that colonial legacy could have enduring effects on modern facilities and potentially the observed disparities in hospital efficiency.

I examine in this chapter the long-term effects of colonial health investments on input utilisation and service delivery by modern health facilities. Information is collected from archival data from the Belgian Congo between 1926 and 1956 along with contemporary data on health facilities in the Democratic Republic of Congo (DRC). Starting from a simple theoretical model, I hypothesize that initial investment in health infrastructure construction was higher during the colonial period than after independence, and I provide evidence that supports this assumption. The chapter next introduces several estimation strategies that address potential endogeneity concerns. The results consistently paint a picture where health facilities built during the colonial period receive significantly more subsidies from the central government than post-independence facilities, while demand for health care is found to be unchanged. The findings suggest that colonial hospitals might have established closer connections with the central government to attract a comparatively higher share of subsidies in this resource-constrained setting.

Finally, chapter 5 concludes the thesis by discussing the results outlined in the preceding chapters in light of the current DAH practises in Sub-Sahara Africa and its effect on the financing of health care. The chapter ends with examining the implications of the results for policy and future research.

# Chapter 2

# Aid conditionality in a decentralised health system

## 2.1 Introduction

The debate over foreign aid as an instrument to promote economic growth is controversial. Whilst the foreign aid sector has become larger and more institutionalised, empirical studies have failed to consistently identify a positive effect of aid on growth (Boone, 1994; Burnside and Dollar, 2000). In the health sector, although evidence suggests that Development Assistance for Health (DAH) has substantially reduced global health burdens (Mishra and Newhouse, 2009, Wilson, 2011), it failed to achieve the health improvement objectives set by the Millennium Development Goals.

The causes of aid ineffectiveness have been mostly attributed to the recipient's behavioural response. Whether under the form of poor quality of institutions and governance, lack of political accountability, rent-seeking behaviour or interest group pressures, the failure of foreign aid is often ascribed to the recipient's unreliability to tackle development issues as intended by the donor (Svensson, 2000a; Svensson, 2000b; Burnside and Dollar, 2004). The solution to this moral hazard problem is to incentivise the recipient to commit to the intended development objectives of the donor(Azam and Laffont, 2003).

The underlying assumption of the aid conditionality approach is that the donor has perfect information (or full observability) about the multiple components of the needs in the country, which includes the identification of sub-populations with the highest disease burden, their geographic locations and the severity of the disease. Yet, in low-income countries where local health information is often incomplete and fragmented, identifying and targeting the beneficiaries of a disease specific programme can be a challenging exercise (Niehaus et al., 2013). Furthermore, targeting may exhibit different levels of efficiency depending on whether the decisions are taken by the central government or at the community level (Galasso and Ravallion, 2005, Banerjee, Duflo, et al., 2009).

This chapter intends to address this knowledge gap by exploring the theoretical implications of an alternative assumption: donor's imperfect information about local health needs. In particular, I examine the consequences of this assumption when the donor chooses whether to impose aid conditionality or not to a recipient country with a decentralised health care system. When the donor has the choice to administer health funding at the central or sub-national level while only local governments have perfect information about the local needs, what are the consequences of aid conditionality on the allocation of health care resources across local jurisdictions and the financing of the healthcare system? And how does resource reallocation affects aid effectiveness and health outcomes?

To my knowledge, this is the first attempt to formally examine how DAH affects the distribution of federal transfers in a decentralised health care system. Drawing from the fiscal federalism literature, my theoretical approach explores whether aid diversion is caused by the central government's decision to reduce intergovernmental transfers or by sub-national entities changing their public spending for health.

Starting with a standard model of intergovernmental transfer, I explore the implications of introducing DAH in the model and discuss the effects of aid conditionality on local health expenditures and intergovernmental grants. I find that when the local government is committed to maximise the social welfare of the neediest and the donor has imperfect information about which group in the local community has the highest health need, unconditional aid generates the maximum welfare gain for the neediest health group. I also find that conditional aid increases local health expenditures more than unconditioned aid. This is because when the donor does not successfully target the high-need group, the local government attempts to compensate for the misallocation of resources by increasing domestic health expenditures on the high-need individuals.

I then present a model where the health system is characterised by two levels of health care provision. The results suggests that when the donor primarily chooses to finance primary health care, as commonly observed, the optimal decision of the central government is reallocate health resources to the secondary health care level if the marginal health benefit of the neediest for this level of care is above a minimum threshold.

However, the results also indicate that donor mistargeting and aid conditionality may reduce resources allocated to secondary health care, creating an unbalanced financing in the health system and a possible reduction in social welfare. The exact implications of under-funding the secondary level on aid effectiveness depend on the marginal health benefit of the neediest for this level of health services. While the assumptions of this model purposely excluded the existence of local corruption in some developing countries (Reinikka and Svensson, 2004; Bardhan and Mookherjee, 2005; Bardhan and Mookherjee, 2006), the findings, nonetheless, indicate the potential hazards of aid conditionality. In particular, conditionality with poor targeting may undermine the ability of the recipient country to manage health resources at the different levels of the federal system and exacerbate health inequalities within the country. Furthermore, even if local corruption does exist, through the elite capture for example, the use of unconditional funds might still be more efficient than conditional aid with poor targeting (Basurto et al., 2017).

This work makes several contributions to the literature. First, I introduce a model with a decentralised economy and discuss how DAH can affect the allocation of health resources at the different levels of the federal system. The emphasis on aid conditionality and its consequences on local expenditures reveal that donor's imperfect information can have adverse effects on aid effectiveness. In addition, the introduction of an incentive compatibility constraint, as found in an aid conditionality contract, could divert the recipient's country from targeting the highest needs or even lead the donor to select "bad" government when the needs are not fully observable.

Second, introducing a decentralised health system reveals that different subnational entities in a recipient country may have conflicting targeting decisions when local information does not circulate perfectly. When both the central government and the donor mistarget the need, the local government may not have the financial and structural capacity to reallocate funds to the intended beneficiaries. Furthermore, by adding a second level of health care services, I show that donor's preferences to achieve immediate and measurable results through the primary health level may poorly reflect the need of local communities when their marginal health benefit for second or tertiary health services is higher.

These findings also provide a new theoretical explanation for the empirical evidence of aid fungibility in the health sector (H. Pack and J. R. Pack, 1990; H. Pack and J. R. Pack, 1993; Feyzioglu et al., 1998; Swaroop et al., 2000; McGillivray and Morrissey, 2001; Farag et al., 2009; Van de Sijpe, 2013). Whilst aid fungibility is a factor for reducing aid effectiveness in the traditional approach, my results, on the contrary, reveal that fungibility could have positive health impact when the different levels of the federal government commit to maximising the welfare of the neediest and the donor mistargets its funds. Pettersson (2007) finds no evidence that aid fungibility is associated with a reduction in economic or health outcomes, suggesting that it might not necessarily be detrimental. My findings also closely relate to Wagstaff (2011) who estimates the consequences of fungibility on the productivity of the recipient government's spending. The author shows that spillovers effects might not be limited to aid project areas and that government reallocation to non-project areas might also benefit from productivity gains. My theoretical setting offers an alternative plausibility for the resource reallocation that relies on marginal health gains. In particular, marginal productivity is not a driver of government's spending when the latter commits to maximise the welfare of the neediest. Finally, the results of this model supports the evidence on intrasectoral fungibility (Walle and Mu, 2007, Wagstaff, 2011): when external funding does not reach the intended beneficiaries, local governments reallocate their own resources only within the health sector to achieve higher health impact.

The remainder of the chapter is organised as follows. The next section reviews the related theoretical and empirical literature. In section 2.3, I formulate the resource allocation problem in a decentralised economy and introduce the presence of the donor in primary health care. Section 2.4 contains further theoretical analysis with the introduction of another level of care. The last section contains concluding remarks.

## 2.2 Recipient's public behaviour and fiscal federalism

The impact of foreign aid on the recipient government's behaviour has triggered an intense debate in the related literature. A common theoretical approach relies on agency theory to analyse the incentive problems that may occur in foreign aid delivery leading to aid ineffectiveness. The donor (Principal) is assumed to be fully altruistic: it cares only about the welfare of the poor. On the other hand, the recipient government is assumed to be only partly altruistic and has other incentives than meeting the need of the poor. The recipient may then have incentives to attract a high share of aid disbursement, deviate from the donor decision and follow its own objectives, creating adverse selection and moral hazard (Svensson, 2000a). From the donor's perspective, the solution is therefore to implement an aid contract that incentivises the recipient to comply with its poverty reduction objectives. When the donor is only able to observe the outcomes, the optimal aid contract is the payment conditional on the aid having been spent on the intended outputs, also known as *ex post* conditionality (Martens et al., 2002; Azam and Laffont, 2003). However, when the donor only observes some inputs, conditionality (on inputs) may distort project choice (Cordella and Dell'Ariccia, 2007). In the presence of lobby groups in the recipient country, Lahiri and Raimondos-Møller (2004) show that the optimal strategic behaviour of the donor is to announce its reaction function in order to eliminate the issue of fungibility while maximising the general welfare at the expense of the lobbyists. On the other hand, if the donor behaves as a leader, increased corruption will diminish the amount of aid. In this scenario, conditionality leads simply to no aid to the recipient. But the opposite can also happen as illustrated by the "Samaritan dilemma": the recipient maximises its own utility at the expense of the donor who decides to allocate aid on the basis of poverty criteria. The recipient government has then incentives to exploit the donor's altruism by maintaining a level of poverty qualifying for aid. As the donor cannot commit not to help the poor, aid is counter-productive as long as the recipient can adjust its policy accordingly (Svensson, 2000b). Arguably, the limit of this approach is that repeat offenders will likely discourage donors who will be encouraged ultimately to find alternative solutions. The "Samaritan dilemma" might then exist only for a limited period of time. More globally, this criticism can be extended to the agency theory approach. Repeat offenders tend to reveal their inefficiency in spending aid on the intended items, inciting the donor to target new beneficiaries. Ultimately, "bad" recipients simply drive out of the aid market, removing the moral hazard and adverse selection issues. The examination of aid fungibility relies entirely on the assumption made in these studies of a misbehaving recipient. The derived results from their analytical approaches follow logically the mechanism design of an optimal contract where the recipient is incentivised to maximise the altruistic objectives of the donor.

One way to circumvent these limits is to relax the "bad" government assumption that prevails in this related literature and examine the consequences of asymmetric information on the optimal resource allocations. The source of aid fungibility is consequently not limited to the moral hazard problem of the recipient but can also reflect the lack of adequate information available to the donor who is no longer to fully observe the needs. If the recipient has perfect information about the health needs in its country, diverting aid funds can be optimal. Naturally, the question raises little interest in this simple case if the local government and the donor have aligned preferences. The donor should simply transfer its aid funds to the recipient which uses it to maximise the poverty alleviation objective that it shares with the donor. However examining this approach is more relevant in a federal structure, where the central government does not necessarily have perfect information about the local health needs, contrary to local communities. The latter is supposed to have better information about local needs. This approach, known as the community-driven development, is known as a mechanism already largely adopted among policy makers, which consists of empowering community groups through higher control over planning decisions and investment resources for local projects. Surprisingly, no studies attempted to use it in a theoretical model.

A large literature on foreign aid investigates the impact of donors' funds on government's fiscal policy response. This literature is characterized by two different research approaches: Fiscal Response Models (FRM) and empirical studies on the fungibility of aid. FRM focuses on the role of aid in government expenditures, tax revenues and public borrowing. The theoretical framework introduces a government that maximises its utility by setting the optimal level of these fiscal targets subject to a budget constraint including foreign aid. FRMs are well suited to study the broad coverage of foreign aid influence on a recipient (McGillivray and Morrissey, 2004). However, these models lack of information about the purpose of foreign aid, as they do not offer a comprehensive sectoral disaggregation of foreign aid. Hence FRMs offer a limited interpretation on the inefficiency of aid, as they are not able to describe where the extra funds are diverted.

Empirical studies on fungibility of aid have investigated whether funds allocated to specific projects, services or areas are diverted to other expenditure categories or spent as intended by the donor (McGillivray and Morrissey, 2004)). Empirical evidence shows mixed results on the fungibility of foreign aid, varying according to the level of spending analysis (project, within sector and national or regional levels), the measure of foreign aid (aid disbursement, commitment, on and off-budget) and the variables considered in the empirical work. Most of empirical studies find that foreign aid is fungible, in particular in the health sector (H. Pack and J. R. Pack, 1990; H. Pack and J. R. Pack, 1993; Feyzioglu et al., 1998; Swaroop et al., 2000; McGillivray and Morrissey, 2001; Farag et al., 2009; Harper, 2012). However, Van de Sijpe (2013) points out an important limitation in these studies revolves around their measure of foreign aid: whether considering solely aid disbursement by donors or aid reported by a recipient country, the measure does not fully describe the amount of foreign aid received. In particular, omitting off-budget aid (expenditures that do not pass through the normal budget procedures of the recipient country) may lead to an overestimated degree of fungibility. This bias is all the more important if the ratio off-budget to on-budget is large. More importantly, little information exists to explain how fungibility relates to aid inefficiency. Donors typically expect the recipient countries to demonstrate that the received funds do not create any reallocation of resources that would not have occurred in this absence of aid. Ravallion (2008) argues that the wide implications of this commitment raise serious challenges to estimate the additionality or fungibility of aid. It also implies that donors have perfect knowledge of the "needs" of the recipient or at least superior to the information held locally.

As long as the preferences of donors and recipients are aligned, the reallocation of funds should be limited. But what if donors neither set nor fund priorities in a rational way?

Imperfect information can mislead the donor in determining the recipient's optimal resource allocation. Even if aid is not fungible, the extra funds may yield limited benefit if complementary services are lacking (such as access to water and sanitation, roads and transportation services to hospitals) or if some sub-sectors are favoured by donors at the expenses of others (Wagstaff and Claeson, 2004; Álvarez et al., 2016). For instance, donor prioritization could create discrepancies in the recipient's health care system if it attracts a disproportionate share of global health financing on a specific disease program such as HIV/AIDS (Shiffman, 2007).

Surprisingly, few papers have attempted to investigate the consequences of aid displacement while relaxing the assumptions of "bad" recipient government and donor with perfect information. Using data on 57 countries from 1978 to 2001, Pettersson (2007) compares the impact of aid when it is fungible and non-fungible. He finds no evidence that fungibility is associated with a reduction in economic or health outcomes. More recently, Wagstaff (2011) estimates the consequences of fungibility on the productivity of the recipient government's spending. His analysis focuses on two health projects in Vietnam, and although the author finds evidence of fungibility, he also finds that the reallocated resources are directed to other projects that have been positively affected by spillover effects from the aid-funded health projects (*i.e.* generating gains in productivity).

In the fiscal federalism literature where the fungibility issue stems from, a number of studies have documented that grants lead to crowding-in of states own funding, contradicting the theory. This effect, known as the "flypaper effect", captures the finding that state governments use the grant they receive from the central government to increase their local spending from residents' income taxes. McGillivray and Morrissey (2000) attribute this effect to the "aid illusion" of the median voter. But the crowding-in effect of aid could also happen for other reasons: the external fund on a specific intervention can increase its productivity, or it can be used by the recipient as an opportunity to get around the prohibitive set-up costs. The recipient can then shift its domestic resources to the newly funded intervention and maintain it even when aid stops. Several papers investigate the existence of the "flypaper effect" with foreign aid and found mixed results (H. Pack and J. R. Pack, 1993; Remmer, 2004; Walle and Mu, 2007). Yet the question of whether external fund causes crowding-in of local public spending or leads to substitution effects is primordial, and particularly in the health sector. If external funding to a project or a subsector is reduced or stopped, the recipient may be financially constrained to reallocate accordingly its public spending on the project that used to be financed by aid. If donors' funds target the primary care sector and the recipient reallocates its expenditure to higher-level care, the impact of a reduction in foreign aid mostly hinges on the ability of the recipient to reallocate effectively its expenditure to the primary sector. The existence of asymmetries in budget reallocations (what could be called an "aid elasticity of health care expenditures") could further exacerbate the possible adverse effect of DAH on the recipient's health care system (Gottret and Schieber, 2006), particularly when donors' aid is volatile. When the recipient government is unable to anticipate the future flow of aid, its optimal response may also be to smooth foreign aid over time and/or across sectors given its intertemporal budget constraint (Gottret and Schieber, 2006). In this case, the fungibility of aid is the optimal solution to maximise social welfare and the effectiveness of aid is directly related to the ability of recipient countries to transfer resources in response to the volatility of aid. More generally, a major problem in the donor-recipient relationship stems from donors imposing short term objectives on outcomes for individual interventions, while recipients have to scale up these projects at the national level and ensure the performance of the health care system as a whole. The question of aid fungibility and/or "flypaper effect" is then not a problem *per se*, but the investigation should rather focus on where the resources are reallocated (Swaroop et al., 2000; McGillivray and Morrissey, 2000), and to which extent these reallocations meet the "needs" of the targeted population.

Some of the solutions can be found in the literature on fiscal decentralisation. Decentralised levels of government are arguably in a better position than a central government to ensure the effective provision of public goods within their jurisdictions (Oates, 1972; Bardhan, 2002). In most countries, decentralisation also applies to the health care system on the rationale that as health needs vary within and between districts, local authorities' preferences are supposed to have better alignment with local needs (Faguet, 2004). Therefore, the decentralisation of the health care system has the potential to increase the quality of health inputs and adjust to the needs of the local population. In theory, the devolution of public funds and taxation generates inequalities among sub-national entities (horizontal inequalities). To address this problem, a welfare maximising government uses fiscal transfers to redistribute public revenues among levels of government to attain equity and efficiency in the provision of local public goods such as health care (Buchanan, 1950; Oates, 1972). Yet, empirical evidence on decentralisation in developing countries is inconclusive, particularly because of a wide diversity in the considered outcomes and variations in the quality of the employed methods (Channa and Faguet, 2016). Foremost concerns are political factors that could jeopardize the benefit of decentralisation as they are more prone to dictate resource redistribution than economic considerations. Electoral concerns and political influence may be important determinants in the allocation of grants (Reinikka and Svensson, 2004; Banful, 2011) or local elites can simply divert public resources and undermine decentralisation efforts (Bardhan and Mookherjee, 2006). Notwithstanding this fact, there is also evidence that decentralisation can improve health outcomes such as child mortality under specific conditions (Uchimura and Jütting, 2009; Guanais and Macinko, 2009; Asfaw et al., 2007). The benefits of fiscal decentralisation on health outcomes could be even more important for very poor countries and could play a role in reducing corruption by holding local authorities more accountable (Robalino et al., 2001). However, devolution of health decisions is also likely to have spillover effects on neighbouring regions as well as creating a system of dispersed facilities without ensuring coordination of public goods (Levaggi and P. Smith, 2003). As a consequence, the optimal degree of decentralisation depends on the intended outcome of the public services. As the devolution of resource allocation decisions aims to increase the health system's responsiveness to the population served, strategic health investments should rely on the expertise of all tiers of the federal government to maximise the overall social welfare. Whilst local government should focus on expanding primary health care, central government may be in a better position to provide high-cost tertiary care and to address externalities among sub-national entities (Levaggi and P. Smith, 2003; Mukherjee, 2016). It is therefore up to the central government to achieve equity and efficiency through appropriate health resource allocation strategies across local jurisdictions.

The research agenda on health care provision in developing countries has examined how the devolution of decision-making affects health outcomes. However, these studies do not offer insights into how DAH affects health resource allocations in the federal structure. On the other hand, the agency theory uses a unilateral approach to explain what triggers health aid fungibility, namely "the bad behaviour" assumption. Consequently, the latter approach offers only a partial understanding of the issue of aid diversion, neglecting the effects of aid on health allocation decisions that exist in a federal structure where health care is decentralised. This work attempts to fill this gap by exploring how foreign aid affects health allocation resources devoted by the central government and local health expenditures at subnational level.

## 2.3 The model with primary health care

This section presents a simple model of optimal health resource allocation between the donor, the central government and the local authority. It aims at examining the comparative statics effects of foreign aid and intergovernmental grant on local health expenditures, either when these funds are transferred through budget support to the local government (unconditional aid), or restricted to a specific intervention (for example, funds conditioned to be spent on a specific project, or vertical programmes funded and delivered by international agencies and non-profit organisations).[1] The objective is to shed light on the mechanisms that are driving the effectiveness of foreign aid to the public health sector behaviour.

A federal economy consists of a single representative community which comprises two groups: ill ($P$) and healthy ($R$), with a proportion $\pi$ and $(1-\pi)$ respectively. All members of the community are characterized by a local health need $\theta_k$ ($k \in \{P, R\}$) that is either high or low with $\theta_P > \theta_R$.

All individuals derive utility from the provision of healthcare services. I denote $g_k$ the amount of health services targeted to the group $k$ in the community and individual's valuation of the good is given by $h(\theta_k, g_k)$. The function

[1] Note that vertical programmes such as immunization are usually financed through funds that do not go through the government budget. However, since I assume that the local government allocates the funds in accordance to the donor's decision, I do not need to distinguish this particular case. The funds will be similarly spent on the intended targeted areas whether they are transferred under conditional form to the local government or directly targeted by the donor.

$h(\theta_k, .)$ is assumed to be increasing, smooth and strictly concave in $g$ (for all $\theta_k$ and $g_k$, $h_2(\theta_k, g_k) = \partial h(\theta_k, g_k)/\partial g_k > 0$ and $h_{22}(\theta_k, g_k) = \partial^2 h(\theta_k, g_k)/\partial g_k^2 < 0$). In addition, the marginal benefit of consumption is increasing in individual's type: $h_{12}(\theta_k, g_k) = \partial^2 h(\theta_k, g_k)/\partial g_k \partial \theta_k > 0$.

Individuals differ also in endowed income $y_k$, with $y_R > y_P$. The high-need individuals (who are poor and sick) are not able to pay the user fees to receive primary care services. For simplicity, $y_P$ is set equal to zero among high-need members.[2]

Healthcare provision is decentralised to the local government. The latter is responsive to the welfare of both subgroups in the community, high-need and low-need. Within the community, health services are supplied at a unit cost $q$, such that $q'(.) < 0$ and $q''(.) > 0$: the cost function to produce health services is decreasing and concave. I assume that there is no private market for health care. As it happens in most low-income countries, local governments are not able to collect local taxes but finance the provision of healthcare through fiscal grants and foreign aid (Bardhan, 2002). To part-fund the provision of health services, the local government imposes a user fee $c$ per unit of health services. Since $y_P$ is set equal to zero, only wealthy people are charged the user fee ($y_R > c > y_P$). This financing system is non-coercive and the local government problem of optimal health resource provision has to respect the voluntary participation constraint of the low-need (wealthy) members, $h(\theta_R, g_R) \geq c g_R$. Therefore, the local government faces challenges in raising local revenues to support health expenditures when the share $\pi$ of high-need is high.

The central government is responsible for raising revenues and allocating health resources through a lump-sump grant that pays for a quantity $a$ of health services. In the presence of the donor, I assume that this grant is restricted to the high-need subgroup in each community, as is the quantity of health services $d$ targeted by the donors. Therefore, the central government and the donor have fully aligned objectives. They both have information about the level of total needs among each

[2]The assumption that wealthy people are also healthy is employed to focus on the main interest of the model, foreign aid and the financial constraint of the poor. In as much as wealthy people can afford the health expenditures to be cured, their health status is only temporary and does not motivate for donor funding.

community through information provided by local governments. Therefore, the central government and the donor determine respectively the optimal fiscal grant and aid to transfer based on the need within the community, depending on $\pi$ and $\theta_P$. However, they do not know how needs are distributed within each community, except with a probability $p_1$ for the central government and $p_2$ for the donor, that the need in a local group $k$ is $\theta_k$, with $p_1, p_2 \in [0, 1]$. Hence, if the central government (or the donor) decides to identify a subgroup within the community, its probability of success is $p_1$ (or $p_2$), and with probability $1 - p_1$ (or $1 - p_2$), it identifies the high-need (low-need) subgroup as being the low-need (high-need). Note also that the donor's preferences are always to target the poor and ill community $P$, and never the wealthy. For this reason, there is no need of a community subscript for $d$.

In addition, the central government adapts its fiscal grant transfer to the existing health care resources. The central government transfers a grant $a$ that maximises the local welfare of each subgroup in the community according to the weights given by the central government to the high and low-needs.

On the contrary, the local government has perfect information about the distribution of the needs in the community, but it can have different preferences over high and low-need members. Specifically, the local government assigns a weight $\mu_k$ to each group within the community with $\mu_k \in [0, 1]$. If $\mu_k = 1$, the local government only cares about its high-need members and its preferences are then fully aligned with those of the central government and the donor. However, I will not restrict the following analysis to this specific case and I will rather let $\mu_k \in [0, 1]$. I also assume that the local government seeks to achieve horizontal and vertical equity. That is, individuals with the same needs receive equal amount of health care, and those with higher needs receive higher amount of health care. Therefore, health care resources distribution are based on need and financed by the nonpoors (Wagstaff and Van Doorslaer, 2000).

In this analysis, fungibility is examined under the assumption that neither the local government nor the central government diverts aid for their private benefit. Likewise, there is no form of capture by local elites or group pressure. These conditions posit assumptions that lead *de facto* to fungibility. This study focuses on assessing the extent of diversion of funds (fungibility of aid) when only the local government (fund's recipient) has perfect information about local health needs.

In the following subsection 2.3.1, there is no donor and I examine how conditional grant affects the optimal allocation decision for local health resources. In subsection 2.3.2, I introduce the donor and analyse the effects of conditional grant and aid local health expenditures and social welfare.

### 2.3.1 Determination of local public provision of health care with domestic resources

#### Determination of fiscal grant

I start by assuming that in the absence of the donor, both central and local governments maximize their social welfare function with respect to their own preferences for the sick. However, when the donor will be introduced in the second part, the central government will only care about the sick to fully align its objective function with the donor. The fiscal grants are financed by a national income tax $\tau$. The central government determines the optimal fiscal grant $a$ from the following objective function

$$\underset{a_p,a_R}{Max} \pi\lambda_p h(\theta_p, g_p + a_p) + (1-\pi)[\lambda_R h(\theta_R, g_R + a_R) + y(1-\tau)]$$

where $\lambda_k$ is the weight given by the central government for group $k$. The central government's budget constraint is given by

$$(1-\pi)y\tau \geq qa \tag{2.1}$$

where $a = \pi a_p + (1-\pi)a_R$.

Since the budget constraint (2.1) must bind, the fiscal grant transferred to the community is determined by

$$h_2(\theta_p, g_p + a_p) = \frac{\lambda_R \left(q'(G)a + q(G)\right)}{\lambda_p} \tag{2.2}$$

and

$$h_2(\theta_R, g_R + a_R) = q'(G)a + q(G) \tag{2.3}$$

where the total healthcare expenditures is $G = g + a$, with $g = \pi g_p + (1 - \pi)g_R$. In this setting, the first-order conditions determine the quantity of health care services provided by the central government. The grant received by the high-need subgroup is a function of the local price of health services, local health needs, the share of high-need members, the local health expenditures and the weight assigned by the central government to the low and high-need group. Hence, it follows that the marginal rate of substitution between $a_p$ and $a_R$ is

$$\frac{h_2(\theta_p, g + a_p)}{h_2(\theta_R, g + a_R)} = \frac{\lambda_R}{\lambda_p} \tag{2.4}$$

**Local provision of health resources**

I assume that the local government maximizes its social welfare function with respect to its own preferences for the sick. The central government has the choice to transfer the fiscal grant as unrestricted budget support or to impose the grant to being spent on a specific group within the community. When the fiscal grant is unconditionally transferred to the local government, the central government has no role in the local government problem except to increase the financial resources of the local government. In both cases, the central government allocates resources $aq$ that pay for the price of health care services to reach a given level of health care per capita. For simplicity, I assume that the central government only targets the poor who are also high-need individuals.

**Unconditional fiscal grant**

If the central government decides to transfer an unconditional (without use restrictions) lump sum grant per capita $a$ to the local government, the optimal local expenditures for the provision of health services selected by the local government solve

$$\underset{G^c_P, G^c_R}{Max}\{\pi\mu_P h(\theta_p, G^c_P) + (1-\pi)\mu_R[h(\theta_R, G^c_R) - cg_R]\}$$

subject to the budget constraint:

$$q(G^c)G^c \leq (1-\pi)cg_R + aq(G^c)$$

where the total provision of health services for group $k$ is denoted by $G^c_k = g_k + a$. Note that the budget constraint requires $g_R \leq a$ to hold (which correspond to the case where $\pi = 0$). Then, the total provision of health resources in the community is

$$\begin{aligned} G^c &= \pi G^c_P + (1-\pi)G^c_R \\ &= g + a \\ &= \pi g_P + (1-\pi)g_R + a \end{aligned}$$

The social welfare function of the local government is given by the utility function of the high and low need, as well as the weight that it attributes to each group. The local government's budget constraint is obtained from the funds locally raised on the wealthy and the fiscal grant transfer. Since the budget constraint must bind, the total public provision of health care services is given by:

$$h_2(\theta_P, G^c_P) = \frac{\mu_R}{\mu_P}(q'(G^c)g + q(G^c)) \tag{2.5}$$

$$h_2(\theta_R, G^c_R) = q'(G^c)g + q(G^c) \tag{2.6}$$

The optimal expenditure quantity depends on the relative weight assigned by the local government to the sick and the marginal cost for producing the good. As the preference of the local government for the low-need diminishes in favour of the high-need, the ratio $\mu_R/\mu_P$ decreases and the provision of the health services for the sick increases. As expected, health care expenditures depend positively on the local needs and negatively on the local price.

The slope of the social welfare contour is given by the marginal rate of substitution between the public provision of health care to the high and low-need individuals

$$\frac{h_2(\theta_P, G_p^c)}{h_2(\theta_R, G_R^c)} = \frac{\mu_R}{\mu_P} \tag{2.7}$$

Given the parameters $(\mu_k, \theta_k)$, the optimal public provision of health care to the high-need members is maximal when the low-need members receive no share of the fiscal and the local government gives no weight to the welfare of the low-need members ($\mu_R = 0$). Consequently, the marginal rate of substitution in (2.7) can be interpreted as an "equity weight" related to the two subgroups (P. Dolan and Tsuchiya, 2009). An increase (decrease) in this ratio would decrease (increase) the level of healthcare of the high need relative to the low need group. Note that if the local government has equal preferences between low and high-need members of its community (utilitarian approach), (2.7) leads to $h_2(\theta_R, G_R^c) = h_2(\theta_P, G_P^c)$ which implies that $g_P > g_R$ since the marginal benefit of consumption is increasing in individual's type: $h_{12}(\theta_k, g_k) > 0$ and $\theta_p > \theta_R$. The marginal rate of substitution of the provision of health care between high and low need group is only a function of their relative local needs. Higher marginal health benefit of individuals results in a higher allocation of health services under the utilitarian approach. When the local government only cares about the high-need members (Rawlsian approach) the latter receives the maximum amount $\bar{G}_P^*$ of health care defined by $h_2(\theta_P, \bar{G}_P^*) = q'(G^c)g + q(G^c)$.

There exists a threshold $\theta_k^*(q, G_k, \mu_k)$ that depends on the total provision of health service, the marginal cost, and the weight on group $k$ such that local government is financially constrained when the local need exceeds $\theta_k^*$. Assume from now on that it is the case.

### Conditional grant

Suppose now that the central government decides to restrict the grant to the poor members in the community. That is, the local government has to allocate the fiscal grant according to the central government's decision. This kind of grant is also known as earmarked grant. The central earmarks the fiscal grant on the high-need group of the community with probability $p_1$, but can also incorrectly designate the low-need group as the fiscal grant receiver. As in the previous case, the central government uses the grant $a$. Therefore, the maximization's problem of the local government becomes:

$$\underset{g_P, g_R}{Max}\{\left[\mu_P \pi h(\theta_P, G_p^c) + \mu_R(1-\pi)h(\theta_R, g_R)\right] p_1 \\ + \left[\mu_P \pi h(\theta_P, g_p) + \mu_R(1-\pi)h(\theta_R, G_{pR}^c)\right](1-p_1) - \mu_R(1-\pi)cg_R\}$$

subject to the new budget constraint:

$$q(G^c)g \leq (1-\pi)cg_R \tag{2.8}$$

where $G_{pR}^c = g_R + a$ and $G_p^c = g_p + a$. The first-order conditions for this problem yield:

$$h_2(\theta_P, G_p^c)p_1 + h_2(\theta_P, g_P)(1-p_1) = \frac{\mu_R}{\mu_P}(q'(G^c)g + q(G^c)) \tag{2.9}$$

$$h_2(\theta_R, g_R)p_1 + h_2(\theta_R, G_{pR}^c)(1-p_1) = q'(G^c)g + q(G^c) \tag{2.10}$$

The optimal provision of health benefit packages to the high-need subgroup is then to be compared with the case of the unconditional grant to determine if the conditional grant can benefit the welfare of the sick. Consider now the difference between (2.5) and (4.2). The comparison between the two results can only be done when the local government preferences are aligned with the central government: the local government would only care about the sick. By letting the ratio $\mu_R/\mu_P = 0$ in the two equations, it appears that if $q'(.) < 0$, the expected health care provision transferred to high-need individuals under the conditional grant is lower than the certain provision they receive under the unconditional grant. The conditionality imposed by the central government affects negatively the amount of health services allocated to the high-need subgroup. When the central government does not have perfect information, it gives some probability weight to allocate health resources out of high-need individuals to the low-need members in the community.

Combining (2.9) and (2.10) yields the marginal rate of substitution between the level of health of high and low-need individuals

$$\frac{h_2(\theta_P, G^c_p)}{h_2(\theta_R, g_R)} = \frac{\mu_R}{\mu_P} - \frac{1-p_1}{p_1}\frac{1}{h_2(\theta_R, g_R)}\left(h_2(\theta_P, g_P) - \frac{\mu_R}{\mu_p}h_2(\theta_R, G^c_{pR})\right) \tag{2.11}$$

Assuming that $g_k \leq a$, if $\mu_P > \mu_R$, then the second term on the right-hand side is positive. Comparing (2.11) with the marginal rate of substitution under the unconditional grant (2.7) (and letting $\mu_R/\mu_P = 0$), it results that conditional grant reduces the health resource allocation gap between high and low-need individuals in the community that was prevailing under unconditional grant. The high-need members are then worse off and the low-need better off.

Consider now the effects of fiscal grants on local expenditures. Totally differentiating (2.9) gives the marginal propensity to spend on the sick out of conditional grant

$$\frac{\partial g^*_P}{\partial a} = -\left(1 - \frac{1 - p_1 + \frac{\mu_R}{\mu_P}\frac{\kappa_c(1-\pi) - q'(G^c)}{h_{22}(\theta_P, g_P)}}{p_1\frac{h_{22}(\theta_P, G^c_P)}{h_{22}(\theta_P, g_P)} + 1 - p_1 - \pi\frac{\mu_R}{\mu_P}\frac{\kappa_c}{h_{22}(\theta_P, g_P)}}\right) \tag{2.12}$$

where $\kappa_c = q''(G^c)G^c + 2q'(G^c)$. A straightforward result from (2.12) is that the highest increase in local health expenditures is reached when $p_1 = 0$ as the local government seeks to compensate for the excessive grant allocated to the low-need individuals. On the contrary, an increase in the probability of the central government to successfully determine the local need reduces the only positive term of the equation. As expected, the share of high-need members in the community also negatively affects the propensity of the local government to spend on the ill out of the conditional grant.

### 2.3.2 Public provision of health care resources with foreign aid

I introduce in this section the intervention of a donor which cares only about the high-need members in the community. The donor can decide to give aid as an unconditional fund transfer to the local government, or finance directly a subgroup of its choice within the community. If aid is given to the local government, the latter simply adds the external fund on top of the total amount of public provision. However, if the donor decides to fund directly a local area of its choice (vertical programme), it can only identify the high-need group with a probability $p_2$ that the need $\theta_k$ of the group $P$ is $\theta_P$. That is, $p_2$ is the probability that foreign aid reaches the sick. Because the donor cares only about the sick, both the central and local government align their preferences with the donor to cooperate. Therefore, the fiscal grant $a$ is restricted to benefit the high-need subgroups in each community. Notice an important implication of this theoretical setting. The local government follows the decision of both the donor and the central government when they decide to transfer conditional funds. That is, there is no distinction between the case where the local government receives grants to be spent on a specific group in the community by directly contracting with the donor (this restricted budget support is also known as earmarked aid) and the case where the donor or the central government directly finances the intended group. In both cases, the local government has only a decision-making power over its own resources and funds received as unrestricted budget support. Similarly, whether the donor transfers funds at the central or local level makes no difference on the examination of local health resources. This is because this analysis does not focus on factors related to a misbehaving recipient that would directly explain aid diversion. I rather assume a collaborative partnership between the donor and the recipient at the central and local levels and I examine the implications of imperfectly informed donor and central government and local health expenditures. Therefore, the factor of interest is only the decision of the donor to allocate its funds to a specific group within the community or to provide an unrestricted budget support to the local government.

I also assume that the central government knows about the donor's intervention (whether through unrestricted budget support or conditional aid) and has the possibility to adapt accordingly the intergovernmental grant $a(d)$. A straightforward source of aid diversion appears if the central government decides to reduce its fiscal grant accordingly. In addition to this possibility, I will also examine other conditions under this theoretical setting that could lead to reallocation of health care resources.

There are four cases to consider in this comparative statics analysis that reflect the possibility that both aid $d$ and grant $a$ can be transferred directly or indirectly to the high-need group in the community. In both cases, the donor and the central government have to include the local price of health care services to reach the sick with the intended level of health care resources $d$ and $a$ respectively. In all four cases, the local authority maximises the community aggregate welfare function of high-need and low-need individuals subject to the total health care amount available ($G^P$, $G^R$) to each group and the probability that national government and/or the donor successfully target the high-need group.

Since individuals have the same welfare level within groups, the aggregate welfare function of each group is defined as

$$\begin{aligned} W^P(\theta_P, G^P) &= h(\theta_p, G^P) \\ W^R(\theta_R, G^R) &= h(\theta_R, G^R) - cG^R \end{aligned}$$

In the following four cases, the aggregate welfare functions will differ only with respect to ($G^P$, $G^R$). The benefit of health resource allocation is measured by the variation in welfare for each subgroup.

#### Unconditional grant $a$ and aid $d$

Consider the case where the local government receives unconditional grant and aid. It means that it can use grant and aid on top of its own revenue to determine the per capita level of health care expenditures that it seeks to achieve for the high

$(G_P^d)$ and the low-need individuals $(G_R^d)$. The local government then solves

$$\underset{G_P^d, G_R^d}{Max}\{\pi\mu_P W^P(\theta_P, G_P^d) + (1-\pi)\mu_R W^R(\theta_R, G_R^d)\}$$

subject to the aggregate budget constraint:

$$q(G^d)G^d \leq (1-\pi)cg_R + (a(d)+d)q(G^d)$$

where $G^d$ is the total provision of health resources and each subgroup in the community receives $G_k^d = g_k + a(d) + d$ with $k \in \{P, R\}$. Then it follows that

$$\begin{aligned} G^d &= \pi G_P^d + (1-\pi)G_R^d \\ &= g + a(d) + d \\ &= \pi g_P + (1-\pi)g_R + a(d) + d \end{aligned}$$

Define the price elasticity of health care expenditures is defined as

$$e(G^d) = \frac{q}{G^d}\frac{dG^d}{dq}$$

As in (2.5), if both aid and fiscal grant are transferred to the budget of the local government, the optimal resource allocation is given by the marginal change in social welfare of the high-need with respect to total health care expenditures

$$\frac{\partial W^P(\theta_P, G_p^d)}{\partial G_P^d} = \frac{\mu_R}{\mu_P}\left(q'(G^d)g + q(G^d)\right) = \frac{\mu_R}{\mu_P}q(G^d)\left(1 + \frac{1}{e(G^d)}\frac{g}{G^d}\right) \tag{2.13}$$

and the second-order condition is

$$h_{22}(\theta_P, G_p^d) - \frac{\mu_R}{\mu_P}\kappa_d < 0$$

where $\kappa_d = q''(G^d)G^d + 2q'(G^d)$. The first-order condition indicates that welfare benefits for the high-need individuals depend on the relative preferences of the local government between high-need and low-need subgroups and the price elasticity of health expenditure. The maximum marginal welfare of the high-need is reached when the local government gives no weight to the welfare of the low-need members (Rawlsian case) or when the price elasticity of health care expenditures is equal, in absolute value, to the share of local government health expenditures to the total health expenditures in the community ($\left|e(G^d)\right| = g/G^d$). Because of the limited financial capacity of the local government revenue in low-income countries, it is reasonable to assume that the share of local government health expenditures to the total health expenditures is low as well. Consequently, the marginal welfare of the sick is maximal only if total health care expenditures are highly price-inelastic.

Recall that the threshold $\theta_k^*(q, G_k, \mu_k)$ characterises the maximum local need above which the local government is financially constrained. As this threshold increases with aid and fiscal grant, the local government can reach a larger share of high-need members in the community when aid or grant increases. The concern about aid fungibility requires that $\partial G_P^d/\partial d \geq 1$. If the local government is financially constrained, avoiding fungibility of aid requires that neither local government's spending nor fiscal grant decreases in the presence of aid. However since this condition is only related to total health expenditures $G_P^d$, it is insufficient to inform us about the impact of foreign aid on local health care expenditures nor about the critical role of local government in analysing fungibility of aid. Therefore, I analyse the effects of aid on the optimal local expenditures by totally differentiating (2.13) to obtain the following:

$$\frac{\partial g_P^*}{\partial d} = -(a'(d) + 1)\left(1 - \frac{1 - \pi - \frac{q'(G^d)}{\kappa_d}}{\widetilde{\pi}^d - \pi}\right) \tag{2.14}$$

where $\widetilde{\pi}^d = \frac{h_{22}(\theta_P, G_p^d)}{\kappa_d}\frac{\mu_P}{\mu_R}$ and $\kappa_d = q''(G^d)g + 2q'(G^d)$. The optimal local health expenditures increase with foreign aid, provided that fiscal grant does not decline.

**Proposition 2.1.** *Unconditional foreign aid increases local government spending on the sick when $\kappa_d > 0$ and sufficiently close to 0 and $a'(d) > -1$.*

*Proof.* Assuming $a'(d) \geq -1$, the condition under which $\frac{\partial g_P^*}{\partial d} > 0$ is

$$1 - \frac{1 - \pi - \frac{q'(G^d)}{\kappa_d}}{\widetilde{\pi}^d - \pi} < 0$$
$$1 < \frac{1 - \pi - \frac{q'(G^d)}{\kappa_d}}{\widetilde{\pi}^d - \pi}$$

If $\kappa_d < 0$, the second-order condition implies that

$$h_{22}(\theta_P, G_p^d) - \frac{\mu_R}{\mu_P}\kappa_d < 0$$
$$\widetilde{\pi}^d > 1$$

This yields to the following

$$\widetilde{\pi}^d - \pi < 1 - \pi - \frac{q'(G^d)}{\kappa_d}$$
$$\frac{q'(G^d)}{\kappa_d} < 1 - \widetilde{\pi}^d < 0$$

which is in contradiction with $\frac{q'(G^d)}{\kappa_d} > 0$ since $q'(G^d) < 0$ and $\kappa_d < 0$.
Assume now that $\kappa_d > 0$. The second-order condition then leads to

$$\widetilde{\pi}^d < 1$$

which implies that

$$\widetilde{\pi}^d - \pi > 1 - \pi - \frac{q'(G^d)}{\kappa_d}$$

if $\widetilde{\pi}^d < \pi$. One condition for this last inequality to hold is $\kappa_d$ sufficiently close to 0. Note that

$$\kappa_d = q''(G^d)g + 2q'(G^d)$$
$$= q'(G^d)\left(\frac{q''(G^d)}{q'(G^d)} + 2\right)$$

The term in the parenthesis refers to the convexity (or curvature) of the inverse demand function. Note also that if the need $\theta_P$ of the sick is very high, this last inequality always holds and the marginal propensity to spend aid received on the sick can be positive even if the local government has a higher relative preference for the low-need group. $\square$

The optimal allocations of health resources critically depend on the share of the high-need group in the community: given the preferences of the local government for each subgroup in the community, $\mu_P$ and $\mu_R$, high-need members receive a lower share of health care services as $\pi$ increases. Consider the condition under which $\partial g_P^*/\partial d > 0$, requiring $\widetilde{\pi}^d < 1$. As the share of poor individuals in the community gets closer to $\widetilde{\pi}^d$, the marginal propensity to spend out of aid increases. Nonetheless, when the share of the poor gets too high ($\pi > \widetilde{\pi}^d$), foreign aid has negative effects. This is because $\widetilde{\pi}^d$ is a function of the relative preferences of high-need and low-need individuals as well as the local health needs. Therefore, if the local government's preferences for low-need increase or if the local health needs decrease, $\widetilde{\pi}^d$ will decrease and the additional external fund of the donor becomes an opportunity to reallocate the local government's resources away from the high-need to the low-need group within the community.

However, these considerations are valid only when the local government attributes the weights $\mu_P$ and $\mu_R$ to the high-need and low-need subgroups respectively. In other words, the local government's preferences are misaligned with those of the donor (and the central government) who cares only about the high-need subgroup. Hence, special attention should be devoted to analyse the effects of aid on local health expenditures when the ratio $\mu_R/\mu_P$ tends to zero. Equation (2.14) becomes

$$\left.\frac{\partial g_P^*}{\partial d}\right|_{\frac{\mu_P}{\mu_R}=0} = -(a'(d)+1) \tag{2.15}$$

As a consequence, foreign aid affects negatively local health expenditures unless the central government reduces its fiscal grant by more than one. When the donor, the central and local government's preferences are fully aligned, there is no rationale for the local government to increase its health expenditures following foreign aid.

### Unconditional Grant $a$ and conditional aid $d$

Consider the situation where the donor targets its aid to a specific subgroup in the community while the central government transfers a unconditional grant to the local government. The local government maximises the following objective function

$$\begin{aligned}\underset{G_P^c, G_R^c}{max}\ & \left[\pi\mu_P W^P(\theta_P, G_P^d) + (1-\pi)\mu_R W^R(\theta_R, G_R^c)\right] p_2 \\ & + \left[\pi\mu_P W^P(\theta_P, G_P^c) + (1-\pi)\mu_R W^R(\theta_R, G_{pR}^d)\right](1-p_2)\end{aligned}$$

s.t. $q(G^d)G^c \leq (1-\pi)cg_R + a(d)q(G^d)$

where $G_{pR}^d = G_R^d + d$. The change in the budget constraint reflects the impact of conditional aid on the local government's new budget: the local government is now only able to allocate $G^c$ in the community while the price remains a function of the total health expenditures $G^d$. The local government receives its funding from the user fee collected on the low health-need group as well as from the transfer from the central government. The total marginal welfare of the high-need individuals is given by

$$\frac{\partial W^P(\theta_P, G_p^d)}{\partial G_P^c} p_2 + \frac{\partial W^P(\theta_P, G_P^c)}{\partial G_P^c}(1-p_2) = \frac{\mu_R}{\mu_P} q(G^d)\left(1 + \frac{1}{e(G^d)}\frac{g}{G^d}\right) \tag{2.16}$$

Sufficient conditions for this to be the unique maximum are

$$h_{22}(\theta_P, G_P^d)p_2 + h_{22}(\theta_P, G_P^c)(1-p_2) - \frac{\mu_R}{\mu_P}(q''(G^d)g + q'(G^d)) < 0 \tag{2.17}$$

As expected, if the donor has perfect information about local needs in the community ($p_2 = 1$), the marginal social welfare of the high-need is unchanged whether there is aid is conditional or not. However, if $p_2 < 1$, since $G_P^d > G_P^c$ the social welfare of the high-need individuals is lower under conditional aid. Indeed, the total marginal welfare (right-hand side of the equation) is similar to subsection 2.3.2, while the change in social welfare is now split between a "high" state of welfare where the high-need individuals receive a quantity of health care services equal to $G_p^d$ with a probability $p_2$ and a "low" state of welfare where they receive a quantity $G_P^c$ with probability $1-p_2$ which corresponds to the level of health expenditures where there is no donor.

**Proposition 2.2.** *If the donor has imperfect information about the local health need, conditional aid decreases the social welfare of the high-need individuals.*

How does an exogenous increase in conditional aid affect the local government spending on high-need individuals? Using the Implicit Function Theorem on (2.16), I obtain:

$$\frac{\partial g_P^*}{\partial d} = -(a'(d)+1)\left(1 - \frac{\frac{\widetilde{\pi}^c(1-p_2)}{a'(d)+1} + 1 - \pi - \frac{q'(G^d)}{\kappa_d}}{\widetilde{\pi}^d p_2 + \widetilde{\pi}^c(1-p_2) - \pi}\right) \tag{2.18}$$

where $\widetilde{\pi}^k = \frac{h_{22}(\theta_P, G_p^k)}{\kappa^d}\frac{\mu_P}{\mu_R}$ and $\kappa_d = q''(G^d)g + 2q'(G^d)$.

Consider now the effects of conditional aid with those arising from the situation when both aid and grant are unconditional (2.14).

**Proposition 2.3.** *Conditional aid decreases the marginal propensity to spend on the sick relatively to unconditional aid and increases fungibility when $\pi < \widetilde{\pi}^c$, $a'(d) > -1$ and $p_2$ is close to* 1.

When the donor targets its funding to the high-need group in the community but mistakenly reaches the low-need, high-need individuals get under-allocated compared to the situation where aid is unconditional. As a consequence, the local government increases its spending on health services to the high-need group to compensate for the misallocation of foreign aid.

*Proof.* Subtracting (2.18) to (2.14) gives

$$\left.\frac{\partial g_P^*}{\partial d}\right|_{\text{unconditional-aid}} - \left.\frac{\partial g_P^*}{\partial d}\right|_{\text{conditional-aid}} = \frac{1-\pi-\frac{q'(G^d)}{\kappa_d}}{\widetilde{\pi}^d - \pi} - \frac{\frac{\widetilde{\pi}^c(1-p_2)}{a'(d)+1} + 1 - \pi - \frac{q'(G^d)}{\kappa_d}}{\widetilde{\pi}^d p_2 + \widetilde{\pi}^c(1-p_2) - \pi}$$

Assume that $a'(d) > -1$ and $\kappa_d < 0$. Then $1 - \pi - \frac{q'(G^d)}{\kappa_d} < \frac{\widetilde{\pi}^c(1-p_2)}{a'(d)+1} - \frac{q'(G^d)}{\kappa_d} + 1 - \pi$ under the condition that

$$\frac{\widetilde{\pi}^c(1-p_2)}{a'(d)+1} > 0$$

which holds under the present assumptions ($a'(d) > -1$ and $\kappa_d < 0$).

In addition, since $G_P^d > G_p^c$, $\widetilde{\pi}^d > \widetilde{\pi}^d p_2 + \widetilde{\pi}^c(1-p_2)$. Now if $\pi \leq \widetilde{\pi}^c < 1$, then

$$\frac{1 - \pi - \frac{q'(G^d)}{\kappa_d}}{\widetilde{\pi}^d - \pi} - \frac{\frac{\widetilde{\pi}^c(1-p_2)}{a'(d)+1} + 1 - \pi - \frac{q'(G^d)}{\kappa_d}}{\widetilde{\pi}_d^d p_2 + \widetilde{\pi}^c(1-p_2) - \pi} < 0$$

$$\left.\frac{\partial g_P^*}{\partial d}\right|_{\text{unconditional-aid}} < \left.\frac{\partial g_P^*}{\partial d}\right|_{\text{conditional-aid}}$$

□

In addition, note under the particular case where the donor targets the high-need group with perfect information ($p_2 = 1$), (2.18) becomes

$$\frac{\partial g_P^*}{\partial d} = -(a'(d)+1)\left(1 - \frac{1 - \pi - \frac{q'(G^d)}{\kappa_d}}{\widetilde{\pi}^d - \pi}\right)$$

which is lower than the same partial effect in subsection 2.3.2 where aid and grant are unconditional (2.14). It means that the increase in local government health expenditures on the high-need group is lower when aid is conditional, even if the donor has perfect information about local health needs. On the opposite, the maximum increasing effect of foreign aid on local government's expenditures is reached when $p_2 = 0$.

$$\frac{\partial g_P^*}{\partial d} = -(a'(d)+1)\left(1 - \frac{\frac{\widetilde{\pi}^c}{a'(d)+1} + 1 - \pi - \frac{q'(G^d)}{\kappa_d}}{\widetilde{\pi}^c - \pi}\right)$$

In this case, the partial effects of aid on local health expenditures on the high-need group are higher when aid is conditional. This corresponds to the maximum of health resources the local government can reallocate when the donor targets entirely the low-need group at the expenses of the high-need group and $\pi < \widetilde{\pi}^c$. Consequently, the misallocation of the donor's resources entirely dictates the effects of aid on local health expenditures on high-need individuals.

The case where the governmental grant is conditional while aid is unconditional is examined in the Appendix A. The next and final case will then focus on conditional grant and aid.

### Conditional grant $a$ and aid $d$

Consider now the final case where both the donor and the central government impose a restriction on the funds they transfer to the local government. The donor decides where aid should be allocated within the community. As the donor does not know the need of the local community, it can only make a guess with probability $p_2$ that an identified group in the community correspond to a high-need group.

The level of fungibility is then given by $dG_P^d = (a'(d)p_1 + p_2)dd$. It follows that $dG_P^d/dd \geq 1$ if $a'(d) \geq (1-p_2)/p_1$. In this setting, fungibility is avoided if the central government's response to foreign aid is higher than the right-hand term which depends on the probability of successful targeting of both the donor and the central government. Therefore, imperfect information of the donor and the central government is likely to increase the level of aid fungibility. The maximization's problem of the local government becomes :

$$\begin{aligned}
\underset{g_P,g_R}{max} & \left[\pi\mu_P W^P(\theta_P, G_p^d) + (1-\pi)\mu_R W^R(\theta_R, g_R)\right] p_1 p_2 \\
& + \left[\pi\mu_P W^P(\theta_P, G_P^s) + (1-\pi)\mu_R W^R(\theta_R, G_{pR}^c)\right] (1-p_1)p_2 \\
& + \left[\pi\mu_P W^P(\theta_P, G_P^c) + (1-\pi)\mu_R W^R(\theta_R, G_{pR}^d)\right] p_1(1-p_2) \\
& \quad + \left[\pi\mu_P W^P(\theta_P, g_P) + (1-\pi)\mu_R W^R(\theta_R, G_R^d)\right] (1-p_1)(1-p_2)
\end{aligned}$$

subject to: $q(G^d)g \leq (1-\pi)cg_R$
with $G_R^d = g_R + a(d) + d$. Note how the change in the budget constraint of the local government reflects the conditional aid and fiscal grant: the local government is

left with its own funding raised from the user fee on the low-need group to provide health services $g$ at the price $q(G^d)$ that is determined by the total provision of health services, including conditional aid and grant. The derived optimal allocation to the high-need members is expressed as follows

$$\begin{aligned}\frac{\partial W^P(\theta_P, G^d_P)}{\partial g_P}p_1p_2 + \frac{\partial W^P(\theta_P, G^s_P)}{\partial g_P}(1-p_1)p_2 + \frac{\partial W^P(\theta_P, G^c_P)}{\partial g_P}p_1(1-p_2)\\ + \frac{\partial W^P(\theta_P, g_P)}{\partial g_P}(1-p_1)(1-p_2)\\ = \frac{\mu_R}{\mu_P}q(G^d)\left(1+\frac{1}{e(G^d)}\frac{g}{G^d}\right)\end{aligned} \quad (2.19)$$

Comparing the optimal allocations for high-need individuals with the three other cases, it is straightforward that combining conditional aid and grant reduces the amount of health care services to the high-need group if $p_1$ and $p_2$ are lower than one. The extent of welfare loss is once again related to the welfare difference between $W(\theta_P, G^d_P)$ and $W(\theta_P, g_P)$, provided that the last term corresponds to the lowest social welfare of the high-need. Consequently, the higher the probability weight attributed to the marginal welfare of the high-need group, the higher is the welfare loss of conditional grant and aid compared to unrestricted budget support as in subsection 2.3.2. Whilst the local government cannot prevent the misallocation of conditional aid and grant, it can mitigate the unintended increase in the welfare of the low-need relatively to the high-need by reallocating a higher share of its own health expenditures. However, the local government also faces a higher price $(q(G^d))$ compared to the absence of conditional grant and aid $(q(g))$ while remaining with the same fixed budget. Therefore, the local government's capacity to divert its local funds may be insufficient to compensate for the misallocated resources of the central and the donor.

I now characterize the marginal propensity of local health spending on high-need out of aid and compare it with the previous cases.

**Proposition 2.4.** *Conditional aid causes the marginal propensity of spending on the sick out of aid to increase, provided that $p_2 < 1$ and $a'(d)$ is negative or close to*

*0.*

The misallocation of the donor's fund related to its willingness to target the high-need group forces the local government to increase its own health expenditures to the high-need individuals, under the condition that the fiscal grant remains unchanged. Intuitively, an increase in fiscal grant to the local community would attenuate the increase in local health spending on the sick.

*Proof.* I use the Implicit Function Theorem to derive the marginal effect of foreign aid on the optimal local health expenditures.

$$\frac{dg_P^*}{dd} = -(a'(d)+1)\left(1 - \frac{\frac{a'(d)}{a'(d)+1}p_2(1-p_1)\widetilde{\pi}^s + \frac{1}{a'(d)+1}p_1(1-p_2)\widetilde{\pi}^c + (1-p_1)(1-p_2)\widetilde{\pi}^{g_P} + 1 - \pi - \frac{q'(G^d)}{\kappa_d}}{p_1p_2\widetilde{\pi}^d + p_2(1-p_1)\widetilde{\pi}^s + p_1(1-p_2)\widetilde{\pi}^c + (1-p_1)(1-p_2)\widetilde{\pi}^{g_P} - \pi}\right) \tag{2.20}$$

where $\widetilde{\pi}^k = \frac{h_{22}(\theta_p, G_p^k)}{\kappa_d}\frac{\mu_p}{\mu_R}$. I analyse the marginal propensity to spend on high-need individuals out of foreign aid by comparing the case where aid is conditional (2.20) with unconditional aid and conditional grant (A.2 in the Appendix A). If $p_2 = 1$, the effects are similar to the case where only aid is unconditional (A.2, A). However, if $p_2 < 1$ conditional aid has larger impact on local government expenditures than unconditional aid. Analysing the difference between (2.20) and (A.2) boils down to examining the sign of the following

$$\frac{\frac{a'(d)}{a'(d)+1}\widetilde{\pi}^s(1-p_1) + 1 - \pi - \frac{q'(G^d)}{\kappa_d}}{\widetilde{\pi}^d p_1 + \widetilde{\pi}^s(1-p_1) - \pi} - \frac{\frac{a'(d)}{a'(d)+1}p_2(1-p_1)\widetilde{\pi}^s + \frac{1}{a'(d)+1}p_1(1-p_2)\widetilde{\pi}^c + (1-p_1)(1-p_2)\widetilde{\pi}^{g_P} + 1 - \pi - \frac{q'(G^d)}{\kappa_d}}{p_1p_2\widetilde{\pi}^d + p_2(1-p_1)\widetilde{\pi}^s + p_1(1-p_2)\widetilde{\pi}^c + (1-p_1)(1-p_2)\widetilde{\pi}^{g_P} - \pi}$$

Notice that $\widetilde{\pi}^d p_1 + \widetilde{\pi}^s(1-p_1) - \pi > p_1p_2\widetilde{\pi}^d + p_2(1-p_1)\widetilde{\pi}^s + p_1(1-p_2)\widetilde{\pi}^c + (1-p_1)(1-p_2)\widetilde{\pi}^{g_P} - \pi$ and $\frac{a'(d)}{a'(d)+1}\widetilde{\pi}^s(1-p_1) > \frac{a'(d)}{a'(d)+1}p_2(1-p_1)\widetilde{\pi}^s + \frac{1}{a'(d)+1}p_1(1-p_2)\widetilde{\pi}^c + (1-p_1)(1-p_2)\widetilde{\pi}^{g_P}$, provided that $a'(d)$ is negative or close to 0. As a consequence,

$$\left.\frac{\partial g_P^*}{\partial d}\right|_{\text{case3}} - \left.\frac{\partial g_P^*}{\partial d}\right|_{\text{case4}} < 0$$

$\square$

It should be specified that these results also hold when ($\mu_R/\mu_P = 0$): the local government only seeks to maximise the welfare of the high-need subgroup in the community. This special scenario is an important consideration since the donor and the central government only cares about the sick. Therefore, even when the donor, the central and local government have fully aligned objective, conditional aid increases local health expenditures. These results should be weighed against those obtained under unconditional aid and grant (subsection 2.3.2). When preferences are aligned, conditionality increases local health expenditures at the expenses of the local government's efforts to compensate for the misallocation of aid and grant. However, as the probability of rightly targeting the high-need group get close to one, the increase of local health expenditures to the sick subgroup reduces.

The marginal propensity of health expenditures to sick out of conditional grant is obtained by totally differentiating (2.19)

$$\frac{\partial g_P^*}{\partial a} = -\left(1 - \frac{\widetilde{\pi}^s(1-p_1)p_2 + \widetilde{\pi}^{g_P}(1-p_1)(1-p_2) + 1 - \pi - \frac{q'(G^d)}{\kappa_d}}{p_1 p_2 \widetilde{\pi}^d + p_2(1-p_1)\widetilde{\pi}^s + p_1(1-p_2)\widetilde{\pi}^c + (1-p_1)(1-p_2)\widetilde{\pi}^{g_P} - \pi}\right) \tag{2.21}$$

When the donor does not have perfect information about the distribution of local health needs, fiscal grants transferred to local communities are reduced. The fungibility of foreign aid can then be avoided only at the expenses of an increased burden on local fiscal policy. The examination of (2.21) and (A.6, A) demonstrates that conditional aid and grant reduce the marginal propensity of spending out of conditional grant.

**Proposition 2.5.** *Conditional aid increases the marginal propensity of the local government to spend on the high-need individuals out of the conditional grant when* $0 < p_1 < 1$ *and* $0 < p_2 < 1$.

Proposition 2.5 is proven in the Appendix A.

The final question of interest concerns the varying of $p_1$ and $p_2$. From (2.19) I obtain

$$\frac{\partial g_p}{\partial p_1} = -\frac{p_2(h''(g_p^d)-h''(G_p^s))+(1-p_2)(h''(G_p^c)-h''(g_p)}{h''(G_p^d)p_1p_2+h''(G_p^c)p_1(1-p_2)+h''(G_p^s)(1-p_1)p_2+h''(g_p)(1-p_1)(1-p_2)-\pi\frac{\mu_R}{\mu_p}\kappa_d} < 0$$

$$\frac{\partial g_P}{\partial p_2} = -\frac{p_1(h''(g_P^d)-h''(G_P^c))+(1-p_1)(h''(G_P^s)-h''(g_P)}{h''(G_P^d)p_1p_2+h''(G_P^c)p_1(1-p_2)+h''(G_P^s)(1-p_1)p_2+h''(g_P)(1-p_1)(1-p_2)-\pi\frac{\mu_R}{\mu_P}\kappa_d} < 0$$

As the probabilities of successful targeting decrease, the local government has to increase its health expenditures to avoid a reduction in the welfare of the high-need relative to the low-need members. Therefore, the local government reallocates its health resources to target subgroups characterized by higher marginal health benefits. Nonetheless, the imperfect information setting creates a financial burden on the budget of the local government whose limited capacity may not permit it to reach its desired welfare level of the high-need relative to the low-need individuals.

The role of conditionality of health resources and its associated probability of successful targeting can be described as follows. If either fiscal grant or foreign aid is conditional, the probability weight of misallocating the health resources reduces the welfare of the high-need, as illustrated in figure A.1, A. The welfare loss of the sick, denoted $\triangle W$ is a decreasing function of the probability of successful target and is decreasing with $h(g)$, the minimum health benefit obtained by the sick in the absence of foreign aid and fiscal grant. Notice that when the total health expenditures are conditioned ($G_{condit} = pG^d + (1-p)g$), the level of welfare derived from this health care provision is similar to the welfare level obtained from the unconditional health provision $G_1^d$ which is lower than $G_{condit}$. Consequently, the imperfect information setting generates a loss in external health resources $\triangle G$ that corresponds to the ineffectiveness of grant or foreign aid. In particular, the extent of health expenditure loss is given by $\triangle G = -(p(1-p)/2h''(G_{condit})/h'(G_{condit})$. This inefficiency increases with the concavity of the valuation function $h(.)$ and decreases with the probability of successful target.

These comparative statics results reveal some specific features about the response of the local government expenditures to different modalities of transfer of funds. When the donor (or the central government) has imperfect information about the local needs, conditional aid is only benefiting the low-need group. Reducing aid diversion through targeted programs mostly improves the welfare of high-need individuals if the donor and the central government have perfect information or if the donor has perfect information and the central government transfers an unconditional grant to the local government. Other cases will necessarily lead to higher fungibility of aid.

## 2.4 Introducing two levels of health care

The examination of aid diversion and the effects of aid on local health expenditures and intergovernmental transfers was conducted in the last section in a simple theoretical framework, with only one level of health care services. In this section, I present the comparative statics effects of foreign aid when the health care sector is characterized by two levels of health care, the primary and secondary health care. The motivation behind this introduction is to explore another source of aid fungibility. Indeed, donors tend to prioritize primary care services to respond to high-need individuals that do not have the financial capacity to use these services (such as the poor living in rural areas with limited access to health facilities). But it also refers to the donor's imperfect information about the whole health sector, creating discrepancies between the decision of the donor and the central government to allocate health resources optimally. Consequently, the optimal response of the recipient government could be to divert health resources to higher level of care leading to fungibility of aid.

Suppose that the central government is responsible for financing a higher level of care (e.g. national public hospital). The consumption of this service is valued $v(\theta_k, a_k^h)$ by individuals of type $k$, with $a^g$ the fiscal grant dedicated to this higher level of care. The function $v(\theta_k, .)$ is assumed to be increasing, smooth and strictly concave in its second argument. Denote $m$ the unit cost of providing secondary health care services per capita. I assume that the unit cost of secondary care is higher than the unit cost of primary care, $m > q$.

For simplicity, I assume that the primary and secondary health care services are only used by the poor and ill subgroup in each community[3]. However, the federal government uses an income tax $\tau$ on the rich to finance its health expenditures. As before, local health expenditures $G$ (which are now referred to as primary care) are financed by local governments through user fees, fiscal grant, $a^g$, and possibly foreign aid, $d$. Individuals value the two goods differently depending on each level of consumption. In particular, $h'(0) > v'(0) > h'(\bar{G})$ where $\bar{G}$ represents the minimum amount of primary care services such that $v'(\theta_k, a_k^h) > h'(\theta_k, G)$ for all $G > \bar{G}$. As before, I assume that $d > a$.

### Unconditional aid

Given its preferences for the ill and healthy individuals, the central government solves the following problem

$$\underset{a^g, a^h}{max} \pi \mu_p^c [h(\theta_P, g_P + a^g + d) + v(\theta_P, a^h)]$$

subject to the central government budget constraints

$$qa^g + ma^h \leq (1 - \pi) y \tau \tag{2.22}$$

$$g + d + a^g \leq \bar{G} \tag{2.23}$$

The last constraint denotes the central government's willingness to invest in the higher level of care once the primary health care facilities have reached the investment threshold. Under the assumption that the donor solely focuses on primary health care, the optimal public provision of the federal government is to allocate the minimum health resources to reach this threshold. If the donor's resources, $d$, do not exceed $\bar{G} - g - a^g$, the constraint never binds. Hence, for the sake of interest,

[3]This assumption only simplifies the calculations but does not affect the overall findings detailed below insofar as the donor only cares about the poor.

I assume that $g + d = \bar{G} - \epsilon$. Consequently, the central government only needs to transfer a minimum health resource $a^g$ to reach the primary health care threshold.

At the community level, the optimal provision of health resources between primary care and higher level of care is determined by the following first-order conditions:

$$\pi \mu_P^c h_2(\theta_P, g_P + a_p^g + d) - \alpha_1 \alpha_2 = 0 \tag{2.24}$$

$$\pi \mu_P^c v_2(\theta_P, a_p^h) - \alpha_1 m = 0 \tag{2.25}$$

where
$alpha_1$ and
$alpha_2$ denote the Lagrange multiplier attached to the constraints (2.22) and (2.23) respectively. Combining (2.24) and (2.25), I obtain the marginal rate of substitution between the consumption of the primary care good and the secondary health care good:

$$MRS^{a^g a^h} = \frac{h_2(\theta_P, g_P + a_P^g)}{v_2(\theta_P, a_P^h)} = \frac{1}{m}(q + \frac{\alpha_2}{\alpha_1}) \tag{2.26}$$

The absence of the donor ($d = 0$) implies that the constraint (2.23) is non-binding and $MRS^{a^g a^h} = q/m < 1$. Consequently, the optimal resource transfer from the central government is such that $a^g > a^h$. This inequality reflects the higher investment of the federal government in primary health care in the absence of foreign aid. On the other hand, the presence of the donor ($d > 0$) results in the binding constraint (2.23) and $MRS^{a^g a^h} > 1$, provided that $q + \alpha_2/\alpha_1 > m$. The optimal transfer of health resources from the central government is characterized by a higher allocation of resources to secondary health care services ($a^g < a^h$). Notice that $\alpha_2$ is the marginal utility of total health expenditures when they meet the threshold $\bar{G}$. Hence, a surge in foreign aid generates a reallocation of central government resources from primary to secondary health care if the marginal health benefit of the sick at $\bar{G}$ is large enough.

So far, the optimal allocation analysis within the health sector has been treated only under of the donor's unrestricted budget support to the local government, and

I shall now turn to examine the implication of conditional aid.

### Conditional aid

As before, the donor targets successfully the high-need subgroup with the community with a probability $p_2$. Consequently, the donor's misallocation of funds may reduce the level of primary care services for the high-need individuals while the overall total primary care expenditures in the community are unchanged. The central government solves the following maximisation problem:

$$\underset{a^g,a^h}{max} \pi \mu_p^c [h(\theta_P, g_P + a^g + d)p_2 + h(\theta_P, g_P + a^g)(1-p_2) + v(\theta_P, a^h)]$$

subject to the same constraints of the unconditional problem, (2.22) and (2.23) respectively. From the first-order conditions, the derived optimal health resources are given by:

$$\pi \mu_P^c (h_2(\theta_P, g_P + a_p^g + d)p_2 + +h_2(\theta_P, g_P + a^g)(1-p_2) - \alpha_1 q - \alpha_2 = 0 \tag{2.27}$$

$$\pi \mu_P^c v_2(\theta_P, a_p^h) - \alpha_1 m = 0 \tag{2.28}$$

This yields to the marginal rate of substitution between the consumption of the primary care and the secondary health care good:

$$MRS^{a^g a^h} = \frac{h_2(\theta_P, g_P + a_p^g + d)p_2 + +h_2(\theta_P, g_P + a^g)(1-p_2)}{v_2(\theta_P, a_P^h)} = \frac{1}{m}(q + \frac{\alpha_2}{\alpha_1}) \tag{2.29}$$

In the presence of foreign aid, the constraint (2.23) is binding and $MRS^{a^g a^h} > 1$. However, the comparison of (2.29) with (2.26) indicates that the marginal rate of substitution between the consumption of primary care and secondary care services is lower in the case of conditional aid (because the marginal utility of health care services consumption is lower for the low-need group). This result implies that the conditionality of aid reduces the ability of the central government to transfer health resources from primary care to secondary care services when the probability of the donor to target the low-need group increases.

**Proposition 2.6.** *Conditional aid reduces health resources to secondary health care services transferred from the central government when the probability of the donor to target successfully the high-need group is lower than one.*

Hence, conditional aid limits the reallocation of the central government's funding from primary to secondary health care.

## 2.5 Conclusion

The issue of fungibility of aid has been widely explored in the related theoretical literature through the lens of the Principal-Agent model. Within this approach, the donor can specify a contract where the funds are to be spent based on the observable consequences of the recipient's actions (outcomes produced or inputs used). The objective of the donor is then to restrain the recipient from self-interested efforts. The use of this setting is justified on the basis that the donor has perfect information about the needs in the recipient country but is unable to observe the recipient's actions. However, I show in this work that these results might be sensitive to the information structure.

I develop a model that departs from the analytical approach used in the Principal-Agent setting by assuming (1) that the donor does not have perfect information about the local needs in the recipient country, and (2) that the recipient country does not engage in self-interested efforts upon receiving foreign aid. The novelty of my approach is to examine how foreign aid affects the intergovernmental transfers of health resources in a federal structure system and to assess its implications on local health expenditures. Asymmetric information is characterised by the donor and central government's imperfect observation of the local needs while the local government has full observability. In this theoretical setting, the assumptions of the contract theory no longer hold, and I employ a comparative statics analysis of the effects of foreign aid on local health expenditures and intergovernmental transfers.

I distinguish among several cases characterised by the existence of conditionality of foreign aid and fiscal grants. Intuitively, one might expect that funds transferred as unrestricted budget support to the local government contribute to the fungibility issue and the ineffectiveness of aid, compared to the case where aid is conditional or used to finance directly a specific program. However, when the local government is committed to maximising the social welfare of the ill (and poor) individuals and the donor has limited information about which group in the local community has the highest health need, I find that unconditional aid generates the maximum welfare gain for the high-need group. I also find that conditional aid has more of an increasing effect on the local health expenditures than unrestricted budget support. However, this increase in local government spending on the high-need individuals is the result of the local government's efforts to compensate for the inappropriate allocation of the donor's funding to the low-need group in the community. As the probability of the donor to successfully target the high-need group raises, the expansionary effect of foreign aid on the local government expenditures diminishes. This result suggests that conditionality of aid could have disruptive effects on the recipient's health system when the donor has imperfect information and the local government is committed to reducing the burden of disease of the high-need group. In this setting, the apparent decrease of aid fungibility associated with conditional aid is the result of the local government's attempts to compensate for the donor's misallocation.

When there are two levels of health care provision and the donor earmarks aid to primary care services, the central government is forced to reduce health resources dedicated to the secondary level in order to increase those of the primary health care sector. This situation gives rise to suboptimal health outcomes when the secondary health sector is under-allocated and the marginal health benefit of secondary health services is higher than that of primary health services. This result highlights the potentially disruptive effects of conditionality of aid on the recipient health system.

These findings illuminate the need for the donors to engage with all actors of the decentralised health system in order to make effective health investment decisions

(Collier, 2007). When local communities have perfect information about the distribution of health need, country ownership of foreign aid increases the effectiveness of aid. Priorities should therefore be devoted to increase country ownership of health interventions and collaborative partnership among global health actors. Since health programmes in low-income countries are often supported by many donors, it would be interesting to explore in future research how the externalities generated by various programme interventions from multiple donors are affecting health outcome and aid effectiveness. Empirical research could also test the implications of the model developed in this research by estimating the effects of conditional aid on domestic health expenditures at sub-national levels.

# Chapter 3

# Are donors targeting the greatest health needs? Evidence from mining sites in the D.R.Congo

## 3.1 Introduction

Identifying and reaching the populations who have the most pressing health needs is essential in countries with high disease burden and limited health care resources. Donors prioritise health interventions to achieve the highest reduction in disease burden along with health equity objectives (WHO, 2015a). Targeting the highest health needs requires donors to have complete and accurate information about the distribution and intensity of local needs to make optimal resource allocation decisions in the recipient country. However, barriers to the gathering and sharing of health information are commonplace in low-income countries and may pose a threat to narrow aid targeting.

In this chapter, I explore donors' ability to target the highest health needs at the community level by examining how local variations in the burden of malaria affect the amount of aid allocated locally. Some researchers have already emphasised the importance of aid allocation in maximising donors' intended outcomes along with the challenges related to the identification of the greatest needs.[1] In particular, aid re-allocation to the highest needs could lead to maximum welfare improvements when donors have full observability of the need in the country.

To assess the efficiency of aid targeting, analyses have been done both across and within countries (Esser and Bench, 2011; Dieleman, Graves, et al., 2014; Briggs, 2018). Although these studies provide innovative methodologies to track aid resources, few can relate the findings to the efficiency of aid targeting. First, the efficiency of aid should be determined by analysing how the observed aid allocation differs from the optimal allocation that maximises the objective function of the donors (Collier and Dollar, 2002). Second, aid could potentially improve the welfare of the beneficiaries; simply matching aid resources to the distribution of the local needs could then lead to misleading findings. Third, needs are often defined in general terms that could be measured through multiple potential outcomes (Alatas et al., 2012). Divergences in identifying the key outcomes of interest translate into unclear objectives of aid: the multifaceted relationship between health, education and poverty implies that aid resources can serve many purposes and the estimated outcomes can capture various types of aid (Qian, 2015). Fourth, the existence of various forms of aid support poses a challenge to the identification of donors' funding at the subnational level.[2] Especially, it is practically impossible to distinguish external resources from domestic spending at the local level since a significant part of aid may transit through the government budget. Altogether, these combined factors pose a clear threat to the identification and disaggregation of aid effects.

This chapter addresses these identification issues in several ways. First, I focus the analysis on donor funding for malaria to obtain distinct and measurable outcomes of donors' objectives. The high burden of the disease has attracted important external funding in sub-Saharan Africa and the strategies for malaria elimination are well-known, encompassing effective actions for the prevention, diagnosis and treat-

[1] See for example Ravallion and Chao (1989); Besley and Kanbur (1991); Bigman and Fofack (2000) and Collier and Dollar (2002).

[2] External funding can transit through the government budget (on-budget) or be directed to local interventions (off-budget); see Van de Sijpe (2013).

ment of malaria cases.[3] Thereby, I can link directly health needs related to malaria with aid allocated for the disease. Second, I exploit the presence of multiple mining areas in the eastern part of the Democratic Republic of Congo (DRC) to obtain spatial variations in the burden of malaria. The dramatic increase in the risk of malaria transmission within mining areas has been well documented in the tropical medicine literature (Gallup and Sachs, 2001; Moreno et al., 2007; Vittor et al., 2009; Knoblauch et al., 2014). The spatial variations in the disease pattern prevailing between mining and non-mining areas constitute a natural experiment to analyse the geographical distribution of aid for malaria. The fact that mining sites are characterised by having, locally, the highest risk of malaria transmission essentially means that they should receive comparatively the highest share of aid for malaria. Third, I exploit the unique health financing situation of the DRC to estimate aid for malaria at the community level. The disease is highly endemic in the DRC and several years of civil wars have extensively weakened the health system of the country. The considerable financial support provided by the international community to tackle the humanitarian and health crisis created a disproportionately financed health system. A striking example is found with the National Malaria Control Programme for which external aid accounts for more than 95% of its overall funding (MSP, 2017). Taking advantage of a novel dataset with detailed information on key financial and health indicators at the health facility level, I argue that the stock value of antimalarial commodities can approximate total aid for malaria at the local community level.

To ensure the validity of this assumption, I select health facilities located in a similar geographic area in the Eastern DRC and which should bear similar costs. The varying distances of health facilities to their closest mines form two distinct groups that correspond to the treatment (mining area) and control (non-mining area) groups. The presence of mosquito breeding sites within mines leads to geographical areas with high risk of malaria transmission (Bousema et al., 2012), and the mining threshold corresponds to the maximum travelling distance of miner patients to health

[3] The definition of the population with the highest burden of malaria should not be prone to different interpretations between donors and local governments, as opposed to the concept of poverty.

facilities. The discontinuity in the exposure to intense malaria infection at the mining threshold should translate into a change in the pattern of donor's behaviour if the latter is accurately targeting the highest burden of malaria.

The estimation strategy relies on a regression discontinuity (RD) design to compare the allocation of malaria funding for health facilities in the two groups, and thus, identify the contribution of mining areas on local aid for malaria. To my knowledge, this is the first study to exploit the stock value of antimalarial commodities to obtain direct tracking of donors' funding for malaria to health facilities. Importantly, these estimates can document the precision of donors' targeting of the disease and consequently, provide information about their ability to identify the highest health needs at the local community level.

I find no evidence that donors are targeting areas with the greatest burden of malaria. I first consider whether local aid for malaria increases within mining areas and find a significant but quantitatively small increase in local aid. To assess the magnitude of these estimates, I then explore how the increase in local aid for malaria relates to the associated costs of the additional burden of malaria in mining areas. The results offer a contrasting picture of the initial finding. From the number of reported malaria cases at the facility level, the risk of malaria transmission increases, at least, by 7 percent in mining areas. The estimated costs per capita of providing prevention, diagnosis and treatment for the additional burden of malaria are then compared to the increased aid for malaria in mining areas. I find that more than one third of the costs required to address the additional burden of malaria transmission are not financed by donors, suggesting that local aid is disproportionately distributed among health facilities across mining areas and non-mining areas. The estimates are robust to a number of sensitivity checks, including different RD polynomial orders and various bandwidth selections. These findings provide evidence consistent with studies showing the unequal allocation of donors' funds towards the need at sub-national levels (Odokonyero et al., 2015; Borghi et al., 2017; Kotsadam et al., 2018; Briggs, 2018).

Furthermore, the decomposition of aid allocation between curative treatment, prevention and diagnosis reveals disproportionate funding patterns. A malaria-preventive commodity mostly drives the increase in local aid for malaria within mining areas for pregnant women, whilst aid for other commodities is either small or unchanged. Overall, these findings provide some suggestive evidence that donors have limited capacity to target aid to beneficiaries with the highest health needs.

This analysis contributes foremost to the literature on resource allocation and aid effectiveness. Donors' imperfect observability of local needs is a well-known problem for aid targeting (Besley and Kanbur, 1991) that has been addressed either by using a proxy based on a set of observable household characteristics for the unobservable outcome (proxy-means testing) or by delegating the identification process directly to local community leaders when essential information is missing (Coady et al., 2004; Galasso and Ravallion, 2005; Alatas et al., 2012). My work complements these studies by offering an innovative approach that exploits the geographic location of mines to determine locally the highest health needs and evaluate the precision of aid targeting.

My research also provides a novel contribution to the theoretical literature on aid effectiveness as it offers a unique opportunity to test empirically one of its main assumptions. Specifically, since aid ineffectiveness is widely seen as the consequence of agency problems between the donor and the recipient (Azam and Laffont, 2003), one solution consists of implementing an aid contract that incentivises the recipient to comply with the donor's poverty reduction objectives. This theoretical setting hypothesises that the donor has perfect information about the needs in the country. My results challenge this assumption by arguing that donors might only have limited capacity to collect local health information due to factors hampering the circulation of information from local communities to the central government and donors.[4]

The remainder of the chapter is organised as follows. Section 3.2 provides background on the financial and epidemiological situation in the DRC. Section 3.3 describes the data and the geographical analysis. Section 3.4 presents the empirical

[4]These findings are consistent with the recent experimental literature on the imperfect observability of local needs to donors, which also exploits location-specific data. See BenYishay and Parks (2019) for an excellent review of these studies.

analysis related to the impact of mines on aid for malaria to health facilities and introduces the regression discontinuity setting. Section 3.5 describes the results and section 3.6 discusses policy implications and concludes.

## 3.2 Background

### 3.2.1 Malaria situation and artisanal small-scale mining

**Malaria Situation -** Malaria represents a critical public health challenge in the DRC. Almost the entire country is under high risk of malaria transmission where the disease is among the leading cause of mortality and morbidity (WHO, 2015b). In 2015, the DRC accounts for 7.1% of the global total of estimated malaria deaths, ranking second in the world (WHO, 2015b). Malaria is mostly caused by *Plasmodium falciparum* in the country, a parasite transmitted through the bite of mosquitoes. National strategies to control and reduce the spread of the disease consists of 1) prevention through the use of insecticide-treated mosquito nets (ITNs), Indoor Residual Spraying (IRS) and sulfadoxine-pyrimethamine (SP), a chemoprevention administered to pregnant women and children less than five years old ; 2) identification of malaria cases through light microscopy or rapid diagnostic tests (RDTs)[5]; 3) antimalarial treatment with artemisinin-based combination therapy (ACT), the recommended first-line treatment for uncomplicated malaria cases.[6]

**Mining Sites -** Artisanal and small-scale mining (ASM) refers to informal mining work involving minimum use of mechanical tools (Hentschel et al., 2002). The activity is estimated to be responsible for 90 % of the total mineral production in

[5]The malaria diagnosis relies on two possible tests: a microscopic identification of the malaria parasite and a Rapid Diagnostic Test (RDT). The former test requires extensive expertise and is usually done in clinical centres and hospitals. On the other hand, RDTs exist in kit forms and do not require extensive expertise to perform the test and interpret the results. It is therefore mostly used across health facilities in the DRC.

[6]In 2005, the DRC adopted artesunate and amodiaquine (ASAQ) as the first line treatment for uncomplicated malaria cases, and the combination of artemether and lumefantrine as the second line treatment (MSP, 2011).

the DRC (C. Andrews et al., 2008). Owing to its informal nature, artisanal mining poses significant health and safety hazards. The use of mercury for gold extraction and the presence of dust and fine particles in the air surrounding mines expose miners to unsafe working conditions. Furthermore, mining activities rely on the use of abundant water to filter the extracted minerals, leaving multiple open pits with stagnant water. Consequently, mines provide extensive breeding sites for mosquitoes which could increase the risk of malaria transmission among populations living and working in proximity to mines (Staedke et al., 2003). Multiple evidence of an increased malaria prevalence within mining areas and around mosquito breeding sites, in general, supports this fact (Moreno et al., 2007; Vittor et al., 2009; Knoblauch et al., 2014).

### 3.2.2 Health funding landscape in the DRC

**Health Sector -** The Congolese public health sector is divided in three decentralised levels: a central level for the management of national health programmes and general hospitals; an intermediate level composed of 26 provincial health divisions with provincial level hospitals and laboratories as well as pharmaceutical warehouses; a health district level divided into 516 health zones across the country, where each health zone has at least one hospital. Health zones are then further divided into health areas which include one health centre for about 10,000 inhabitants. Access to health care in the DRC is low in the public health sector, with a utilisation rate of health services of 30% (World Bank, 2015).

**Health Funding Landscape -** Several years of civil wars and continuing lack of government financing have drastically undermined the health system in the DRC. As a result, the country extensively relies on out-of-pocket expenditures and external aid to finance the provision of health care services.[7] The presence of multiple donors affects disproportionately the financing of the health sector, with some dis-

[7] In the DRC, the major source of health financing comes from household funds (45%) followed by external donors (40%) and government expenditures (15%) (MSP, 2017).

ease programmes almost entirely funded by the international community (such as HIV, Tuberculosis or Malaria). This observation is particularly salient with the National Malaria Control Programme where more than 95% of its overall funding comes from external aid (MSP, 2017). The three major donors for malaria control activities in the DRC are the Global Fund to Fight AIDS, Tuberculosis and Malaria, the United States Government (U.S. Agency for International Development, USAID) and the United Kingdom Government (Department for International Development, DFID) which together account for 92% of total aid for the malaria programme in 2017.[8]

According to national guidelines, prevention, diagnosis and malaria treatment in public health facilities is free of charge for patients. But due to low salary and frequent disruptions in salary payments, health workers charge, in practice, small user fees on malaria patients.[9]

### 3.2.3 Evidence of local malaria funding

This section presents the proposed strategy to locally estimate foreign aid allocated to the Malaria Control programme.

Lack of information about donors' funding at the local level is a major barrier to quantify the amount of foreign aid that is allocated to each health facility. One reason behind this data limitation issue is that donors choose either to allocate funds to national disease programmes that transit through the government budget or to directly target health interventions at subnational levels (through the support of local implementing partners). It is, therefore, practically impossible to distinguish external aid from domestic spending at the health facility level. However, the financing of the health system of the DRC offers a unique setting to circumvent this

[8] Other partners for the malaria control programme include the World Bank, the World Health Organisation and UNICEF whose funds correspond to more general support for the health system of the country.

[9] Consultation fees represent about 30% of out-of-pocket expenditures for Congolese patients, whilst the average total medical cost for outpatient care is approximately $7 (Laokri et al., 2018). Patient user fees for diseases funded by external donors (such as malaria) are lowered due to the reduction in the cost of medicine and drug but still include fees to health workers. These fees also tend to increase in urban areas and with the size of health facilities (Bertone et al., 2016).

identification problem. The Malaria Control Programme is almost entirely funded by donors (Figure B.1, Appendix B) which implies that antimalarial commodities in public health facilities are almost exclusively provided by external resources.[10]

The stock value of antimalarial commodities should then be a valid proxy for local external aid if it represents the major source of variations in local funding (whilst all other expenditures related to external aid for malaria remain constant). In general, this assumption would raise concerns as other malaria related costs, namely human resource costs, transportation and storage, are expected to vary significantly across the country.[11]

However, I restrict the data sample to observations that are located within a short distance of the mining threshold and I argue that apart from the provision cost of antimalarial commodities, all other malaria-related costs should remain relatively constant across health facilities in the sample. First, salaries and risk allowances (governmental payment distributed to all health workers) to health workers are provided by the government (mostly through donors' support) based on a salary scale.[12] It is then unlikely that two health facilities, located in a common (rural) area, experience significant disparities in governmental payments for a given qualification of health workers.[13] Second, all health commodities are centrally procured by a

[10]The low contribution of government spending to the malaria control programme (Figure B.1, Appendix B) is mostly dedicated to cover the management operations at the central level (MSP, 2017), and so its contribution to the local provision of commodities should be minimal. The proportionately low government spending also avoids the risk that donors may adapt their aid allocation to specific areas in response to government health investments or *vice versa* (Öhler et al., 2017). Another concern is that no information is available on patients' purchase of antimalarial medicines through retail drug stores. These expenditures may come from antimalarial medicines bought from the illegal pharmaceutical market (Björkman Nyqvist et al., 2012;Cohen et al., 2015). However, I argue that the access to health products on illegal markets should not systematically differ in mining and non-mining areas, so its omission should not systematically bias the results.

[11]According to the 2016 audit report in the DRC, 53% of total malaria funding is for the procurement of antimalarial commodities, 27% for expenditures related to human resources and 11% is attributed to transport and storage of commodities. A remaining 9% is dedicated to the management and organisation of the malaria programme (The Global Fund, 2016).

[12]Note that health workers can also receive top-up payments from donors, and Bertone et al. (2016) find that they represent a relatively small share of total income of health workers in the DRC (an increase of $17 which represents about 10% of the total income of nurses who compose the vast majority of health workers in the sample).

[13]In the estimation results, I control for the number of health workers and their qualification (nurses vs. doctors)

national organisation that manages and coordinates the pool procurement of pharmaceuticals, their distribution and storage in regional warehouses, and their supply to health facilities.[14] The expenditures related to the transport and storage of health commodities are therefore closely tied to the geographic location of the health facility. Since my data sample spans health facilities over a relatively small geographic area compared to the country size (Figures B.2 and B.3, Appendix B), most health facilities are supplied by a common regional warehouse, and should, therefore, share identical costs of storage. Lastly, transportation costs from the regional warehouse to health facilities are likely to differ, depending on the location and accessibility of the health facility. Nonetheless, these transportation costs represent only 7 percent of the overall expenditures related to the malaria programme (The Global Fund, 2016), so these variations should only have a minimal impact on the local allocation of aid.

## 3.3 Data

The data used in this research is drawn from two main sources: the District Health Information System and geographic locations of artisanal mining sites.

**District Health Information System.** Epidemiological and financial data on health facilities were extracted from the District Health Information System (DHIS2), a web-based health information system where health facilities report their routine administrative and clinical data.[15] Reports from health facilities are uploaded monthly to the system and include multiple epidemiological measures on disease burden, consumption and stock level of health commodities as well as financial and human resource information. The DHIS2 contains data on all health

[14] The Congolese organisation that controls the national procurement of drugs (*Federation of Central Procurement in Essential Medicines*) works in close collaboration with the Global Fund to obtain negotiated prices of health commodities with manufacturers (see Annexe B.14).

[15] The DHIS2 database is used by the Ministry of Health to monitor health service delivery, measure achievement and track health progress at the difference levels of health care across the country.

facilities in the DRC regardless of the type of structures (hospital, health centres and health posts) and includes both private and public health facilities, as well as faith-based facilities.[16] However, I restrict the data sample to rural health facilities located in the Eastern DRC, where information on mines is available. In total, there are 1,511 observations located in six provinces: North and South Kivu, Maniema, Ituri, Tshopo and Tanganyika (Figure B.5, Appendix B).

Information on the stock level of commodities is reported at the beginning of each month (and thus before the consumption of commodities) from January to December 2017.[17] Due to inconsistent procurement of commodities to health facilities, I average monthly the stock level of commodities over the entire year of 2017.

Antimalarial commodities correspond to all malaria-related health products that are used for diagnosis (RDT), treatment (ACT) and prevention (SP and ITN). The estimated stock value is then calculated from the stock quantity of each antimalarial commodity at the facility level and their prices. The latter is obtained from the reference pricing list of the Pooled Procurement mechanism established by the Global Fund (see Annexe B.14).[18]

I provide in annexe B an extensive discussion on the data quality of DHIS2 in the DRC and provide evidence of its validity for this analysis.

**Mining areas.** Obtaining precise information on the burden of malaria at the local level is a challenging exercise. The Malaria Atlas Project provides a measure of the risk of malaria transmission based on the suitability of air temperature at national and regional levels (Hay and Snow, 2006). However, this information does not permit to identify the local needs at more granular levels, such as local commu-

[16]Uncomplicated malaria cases, diagnosis and prevention services can be provided in health posts but patients seeking clinical services are referred to health centres or hospitals. At the community level, unpaid health workers may also carry out health promotion activities but there is no information available on the service provided.

[17]The earliest information on health facilities starts in 2015 with the initial implementation of the DHIS2; however, the complete coverage was only reached by the end of 2016.

[18]The Pooled Procurement mechanism set by the Global Fund aims to stabilise prices and ensure market sustainability of health commodities by pooling demand of countries that participate to the programme (The Global Fund, 2018).

nities. The finest source of information comes from the 2013 Demographic Health Survey (DHS) in the DRC, whereas information on local malaria funding is only available from January 2017. Furthermore, the GPS location provided in the DHS are randomised within a 5 km area for confidentiality purposes. This randomisation poses a risk of misidentification of the burden of disease when matched with the precise GPS position of health facilities. I adopt, therefore, a novel strategy that identifies the highest burden of malaria based on the presence of mines.

A comprehensive list of artisanal mining locations in the Eastern DRC was compiled by the International Peace Information Service (IPIS) through multiple data collection campaigns conducted between 2009 and December 2017.[19] The dataset contains information on the geo-location (longitude and latitude) of 3,687 mining sites artisanal mining sites in the entire provinces of North and South Kivu, as well as in the bordering health zones in the provinces of Maniema, Ituri, Tshopo and Tanganyika (Figure B.5, Appendix B).

**Geocoding of health facilities.** The geographic locations of health facilities are only partially provided by the DHIS2. To complete the geocoding of the remaining health facilities in the sample, I triangulate information from the DHIS2 with two other sources of georeferenced data: ReliefWeb maps provided by the United Nations Office for the Coordination of Humanitarian Affairs (OCHA) and OpenStreetMap files. ReliefWeb provides a list of geocoded health facilities in North and South Kivu related to OCHA's humanitarian activities and OpenStreetMap is an open database routinely enriched by field observations, satellite images and integrated datasets. Overall, the data sample comprises 1,511 health facilities (Figure B.2, Appendix B). Distances between health facilities and their closest mines are obtained from the use of geostatistical tools available in Geographic Information

[19]IPIS research teams worked in collaboration with the Congolese Ministry of Mines, the Congolese Public Service for Assistance to Artisanal and Small-scale Mining, the Congolese Mining Register, the Provincial Mining Divisions and representatives from local civil society organisations. See Weyns et al. (2016) for a detailed description of the data and collection process.

System (GIS) software.[20]

Furthermore, data on elevation and terrain features were obtained from NASA's Shuttle Radar Topography Mission (SRTM) satellite images.[21] Elevation information is provided at a high spatial resolution (3 arc-second resolution or approximately 90 metres) which makes it possible to determine the precise geographical features of each observation in the sample. In particular, distances from mines to health facilities are calculated based on the elevation and surface features in order to obtain more realistic distance measures than the straight line Euclidean distance (Figure B.4, Appendix B).[22]

Table B.1, Appendix B, presents summary statistics for key health facility characteristics in mining and non-mining areas and their difference in means with the full sample. Tables B.2 and B.3, Appendix B, restrict the sample to observations that fall respectively within a 8 and 3 km window around the threshold. Columns (1-3) and (4-6) of each table show the number of observations, sample mean and robust standard deviations for non-mining and mining areas respectively. Columns (7-9) indicate the difference in means between non-mining and mining areas, the robust standard errors for the difference and the $p$-value of the test of equality of the mean coefficients between the mining and non-mining samples. Whilst the baseline characteristics present several statistically significant differences using the full sample of observations, these differences tend to disappear as the sample shrinks to smaller areas around the mining threshold. In particular, the difference of an-

[20]ArcGIS 10 and QGIS 2.8 have been used for this exercise.

[21]Terrain's elevation data is produced from radar interferometry technique where a satellite equipped with the instrument collects data to generate a digital elevation map of the Earth (see https://www2.jpl.nasa.gov/srtm/.

[22]Satellite images of light density from the Suomi-NPP Visible Infrared Imaging Radiometer Suite (VIIRS) provides a useful source of information on local economic activity (Henderson et al., 2012; Michalopoulos and Papaioannou, 2013). The location of economic activity in the vicinity of mining areas could potentially correlate with lower disruptions in the provision of health commodities nearby health facilities through better road access or higher consumption of commodities if patients have higher incomes. However the resolution of the satellite images (approximately 1 km) provides a noisy estimate of the location of economic activity compared to the precise data-location of mines and health facilities collected in this study. Furthermore, all mines are located in rural areas where night light density is low, particularly in this region of Africa. Hence, using night light density might not bring a useful sense of the local variations in economic activity around mining sites and health facilities.

timalarial stock value is highly significant with the largest window selection but it becomes insignificant as the sample reduces to closer distance from the mining area threshold. The variations in these differences-in-means with the window selection underline the importance of identifying a clear strategy to determine the causal effects of mining areas on local aid for malaria.

## 3.4 Empirical framework and estimation

### 3.4.1 Setting the RD design

To test whether local aid received by health facilities reflects the burden of malaria among the populations in their catchment areas, I rely on the stock value of antimalarial commodities. However, locally assessing the risk of malaria transmission is a challenging exercise. Despite the fact that health facilities report the monthly number of malaria cases that could be used to determine the location of the highest burden of the disease, the identification of malaria cases relies on the availability of RDTs that are financed by external funding. An increase in the reported number of malaria cases may therefore simply reflect a higher stock of RDTs in the health facility. Furthermore, there could also exist some inconsistencies in the reported number of malaria cases across health facilities that would affect the estimation of the distribution of the burden of malaria. To overcome these issues, I employ an instrument that correlates with the risk of malaria transmission without being caused by external funding or data quality reporting. Following the public health literature on malaria and artisanal scale mining, I propose to use mining areas as the identification strategy.

Since mining areas are located where the exploitation of natural resources is feasible, it constitutes a natural random selection framework where other local characteristics between mining and non-mining areas are unlikely to vary discontinuously at the mining boundary. As a result, the exposure of health facilities to the burden of malaria is a discontinuous function of whether a health facility belongs to a mining area. To test whether the donors are targeting the highest needs, I use a Regression Discontinuity (RD) design that evaluates the effect of mining areas on aid for malaria to health facilities.

The central idea behind the RD design is to compare the treatment outcome of units just above and below a threshold, denoted $c$. This threshold is based on a running variable (or score), $X$, which is, in this case, the distance from a health facility to its closest mine. The treatment group corresponds to health facilities located within a close distance to mines (below the mining threshold) whilst health facilities located above the mining threshold form the control group. The observed outcome is local aid for malaria that is captured by the stock value of antimalarial commodities, and the border of the mining area constitutes a threshold that generates a discontinuous probability of getting infected with malaria. I hypothesise that the mining threshold should also cause a discontinuity in local aid for malaria if donors are responsive to the local needs related to the disease. In this setting, the RD framework requires that all other factors influencing the burden of the disease are smooth across the threshold (Hahn et al., 2001). That is to say, the risk of malaria transmission and aid for malaria on either side of the threshold should only differ across health facilities in the probability of being in a mining area.

### 3.4.2 Estimation framework

The RD design uses the distance from a health facility to its corresponding mining area threshold as the running variable. Specifically, the causal mining effect is estimated using the following specification

$$Y_i = \alpha + \beta_1 mine_i + g(\widetilde{X_i}) + \beta_3 z_i + \epsilon_i \tag{3.1}$$

where $\widetilde{X_i}$ is the centred variable $X_i$ at the cutoff point ($\widetilde{X_i} = X_i - c$) and $mine_i$ is an indicator for mining area ($\widetilde{X_i} \leq 0$). The outcome $Y_i$ corresponds to aid for malaria to health facility $i$, and $g(\widetilde{X_i})$ is the RD polynomial which controls for smooth functions of geographic distance from a mine to its closest health facility

$i$.[23] The key parameter of interest is $\beta_1$, which captures the RD treatment effect. Under the identifying assumption that health facilities in non-mining areas form a valid counterfactual, $\beta_1$ identifies the effects of mines on local aid for malaria. The vector of covariates $z_i$ includes geographic characteristics for facility $i$: elevation, slope, distance to the closest regional distribution centre of health commodities, distance to armed conflicts[24] and the number of mines in the vicinity of the facility.[25] In addition, most health facilities in the data sample are located in a mountainous region where the average altitude is about 1,300 meters (Table B.1, Appendix B); the use of chordal or relative Euclidean distances might then lead to misleading results.[26] I rely instead on a more realistic distance based on slope and surface elevation using information collected from NASA's Shuttle Radar Topography Mission.[27]

The RD approach requires that all relevant factors, besides treatment, vary smoothly across the mining threshold. The underlying assumption is that health facilities within a small bandwidth on either side of the threshold should only differ in their probability of receiving malaria cases for treatment and not in their environmental conditions or inherent capacity to treat patients. I assess the validity of this assumption in section 3.5.

For robustness checks, I also present both parametric and nonparametric estimation of the causal effect of mining area on local aid. The parametric approach assumes a functional form of the regression function. Define the conditional expectation of the outcome given the distance variable on each side of the threshold as follows

[23]The local Linear Regression is used in the baseline results, where $g(\widetilde{X_i}) = \delta_1 \widetilde{X_i} + \delta_2 mine_i \widetilde{X_i}$. The presence of the interaction terms allows for two different regression functions on each side of the threshold. To test the stability of the findings, I also report results with a cubic model that provides a more flexible form of the polynomial.

[24]I use data from Armed Conflict Location and Event Data Project (ACLED) which reports georeferenced information on political violences and protests between January and December 2017.

[25]The purpose of including baseline covariates is only to explore the sensitivity of the results, as they should not affect the estimated discontinuity in a RD setting (D. Lee and Lemieux (2010); Calonico, Cattaneo, Farrell, et al. (2018)).

[26]The chordal distance is the distance between two points on a curve and accounts for the spherical shape of the Earth.

[27]Slope was calculated from this elevation using ArcGIS 10.4.1; the distance based on slope was calculated from the *path distance* function in ArcGIS.

$$\mathbb{E}\left[Y_i(0) \mid X_i = c^+\right] = g(X_i) \tag{3.2}$$

$$\mathbb{E}\left[Y_i(1) \mid X_i = c^-\right] = \beta_1 + g(X_i) \tag{3.3}$$

Under the parametric approach, the functional form of $g(.)$ is assumed to be known and the estimate of the treatment effect is given by the least-square estimates of $\beta_1$. Using the full data sample for the estimation of the RD effect around the threshold is not well-suited to perform an RD analysis, as its internal validity relies on the comparability of observations around the boundary: a global polynomial may produce estimates sensitive to observations far away from the threshold (D. Lee and Lemieux (2010); Gelman and Imbens (2018)). Hence, I restrict the data sample to small neighbourhoods around the threshold to ensure the comparability of units on each side of the threshold.[28]

Controlling parametrically the function form of the regression function may, however, produce biased estimates if the approximating function is insufficiently close to the true function. Thus, most RD studies employ a nonparametric estimation through local modelling that fits at any given point $x_0$ a parametric function fitted only to a fraction of observations in a neighbourhood of $x_0$ (Fan and Gijbels, 1996). The idea behind this approach is to locally approximate the unknown conditional mean function by a local polynomial function of degree $p$, using Taylor's expansion in the neighbourhood of interest (under the continuity assumption of the function $g(.)$).

### Polynomial choice and bandwidth selection

The choice of the polynomial order $p$ and the neighbourhood selection (or bandwidth $h$) around the cutoff are critical in determining the treatment effect. High-order polynomials have the potential to increase the accuracy of the approximated

[28] In the results section, I show that the estimates of the RD effects are robust to various window selections.

function for a given bandwidth, but it comes at the cost of high variability; they could also lead to approximations errors near the cutoff if they over-fit the data (Gelman and Imbens, 2018). Similarly, to ensure that the characteristics of the treatment and the control group are almost identical, the units should be selected as close to the threshold as possible given the data availability. Whilst smaller bandwidths reduce the misspecification bias, they also increase the variability of the estimator. The common practice is then to use a low polynomial order and control the accuracy of the approximation by the bandwidth (Gelman and Imbens, 2018). In particular, Hahn et al. (2001) recommend using local linear regression due to its better boundary bias properties. In the following section, I report the baseline results with the local linear model and test their robustness with a cubic polynomial.

The local linear regression procedure consists of estimating two weighted least squares regressions on each side of the cutoff. To obtain the weights, I use a triangular kernel where weights decay with the distance from the cutoff point.[29] In addition, I follow Calonico, Cattaneo, and Titiunik (2014) who propose a methodology to obtain robust confidence intervals by correcting for the bias introduced by the approximation of the RD local polynomial estimator. The procedure consists of augmenting the confidence intervals centred around the bias-corrected RD estimator and using a standard error that reflects the uncertainty introduced in the biased estimation. In the following section, I report the results of the RD treatment effect using this data-driven methodology, referred to as "CCT".

### 3.4.3 Mining threshold and fuzzy RD design

As described earlier in the text, I cannot rely on the number of reported malaria cases to estimate locally the risk of malaria transmission due to donors' financing of RDTs.

Since mining areas create a conducive environment for malaria proliferation, the risk of malaria transmission in the catchment area of a health facility should be a

[29] Following Imbens and Lemieux (2008), the estimation results should be less sensitive to the choice of the kernel function than to the bandwidth selection.

function of the distance between the facility and its nearest mine. I define a mining area as the maximum distance from a mining site that miners are travelling to seek malaria treatment. This distance is crucial in my empirical strategy as it will be used to determine the mining threshold separating the control and treatment groups.

I first exploit the findings from the literature on patients' utilisation of health services in rural areas. Stock (1983) shows that in Nigeria 89% of patients in rural health centres are coming from a distance that is less than 10 km. In the malaria context, Noor et al. (2003) explore the patient's travelling distance to health facilities in Kenya and find that the median distance is 8 km for patients in rural areas. Likewise, the Demographic Health Survey (DHS) conducted in 2007 and 2013 in the DRC reveals that the patient's travelling to a health facility is less than 2 hours for 75% of the rural population - which would represent a distance ranging from 6 to 8 km at the average human walking speed ranging from 3 to 4 km per hour.[30]

Second, I examine the distance that separates mining sites from the living place of miners to account for the possibility that a health facility and a mining site are situated in opposite directions from the location of a miner's household. Dibwe (2008) examines working conditions in artisanal mining sites in the Katanga province of the DRC and finds that more than 97% of miners are living within 7 km from the mines. More recently, Faber et al. (2017) exploit data on miners from a random sample of 150 mining areas in the DRC and show that that the average traveling distance of miners from their household is 7 km.[31] Based on these findings, I hypothesise that the maximum distance separating a mine to a health facility with a significant share of miner patients should range between 13 and 15 km.

Next, I analyse how this range of mining thresholds fits my data sample. Specifically, the threshold should indicate a discontinuity in the burden of malaria. I define malaria prevalence as the mean share of malaria cases reported by a health facility

[30] Note that the limited paved road network in eastern DRC may further reduce the ability to travel large distances.

[31] Faber et al. (2017) also find that the median travelling distance of miners is 3 km, which suggests the presence of outliers with potentially far greater distances. However, the quasi absence of road network in the Eastern DRC, where my data sample is, should reduce the risk of having large travelling distance among miners.

out of the total population of its catchment area. Figure B.6, Appendix B, presents the malaria prevalence as a function of the distance from a health facility to its closest mining site. Each point plots an average value within a bin that represents a 1 km interval. Figure B.7, Appendix B, shows the non-parametric estimations of malaria prevalence conditional on the distance to the closest mine, using a kernel-weighted local polynomial regression of order 1. In both figures, the malaria prevalence is found to fluctuate within a constant interval that ranges from approximately 12% to 18% with the first ten kilometres from the mining sites. A sharp decrease in the burden of malaria occurs at a distance lying between 14 and 15 km from mines, where the malaria prevalence falls by more than 5%. The fluctuations in the disease prevalence are not recovering from the decrease beyond this point where the 95% confidence interval ranges from about 7% to 14%, which suggests a reduced burden of malaria for all health facilities located beyond 15 km. This visual evidence is remarkably consistent with the findings from the literature.[32] I, therefore, select the midpoint distance between the two sides of the jump as the mining threshold, corresponding to 14.5 km. The selected threshold should ensure that patients are not seeking health services above or below this boundary. In the next section, I also assess the robustness of the results when varying the mining threshold.

An additional concern relates to the potential smooth geographic variations in aid for malaria. As argued above, the discontinuity in the burden of malaria at the boundary of mining areas should induce a change in donors' behaviour if they are accurately targeting the highest needs related to malaria. However, donors might also smoothly respond to the discontinuity in the risk of malaria if the density of health facilities is high at the boundary of mining areas. One explanation is that other factors besides the distance of a health facility from a mine might play a role in the decision making of malaria patients when they select a facility (such as quality of health services). To explore this possibility, I examine the geographic

[32] Although this distance falls within a similar range to the findings from the literature, the concern related to the potential endogeneity issue caused by the use of RDTs remains. In the result section, I further discuss about this concern when presenting the results of the decomposition of the RD effects by commodity.

distribution of health facilities around the mining threshold. Figure B.9, Appendix B, depicts the cumulative distribution function of health facilities conditional on the distance to the nearest facility. The data sample is restricted on health facilities that are located within 4 km from a mining threshold(blue dashed line) and within 10 km from the threshold (red line). The graph reveals the scattered distribution of health facilities in the Eastern DRC. The minimum distance between two health facilities is higher than 5 km for more than 70% of health facilities located within 10 km from the threshold, and almost 50% of health facilities within 4 km from the threshold have the closest facility located beyond 10 km. Only 10% of facilities are separated by less than 3 km. Under such conditions, malaria patients may have very limited possibility to select a health facility on other criteria than distance. Similarly, the probability of occurrence that two health facilities are separated by only a small distance across the mining threshold is very low. This evidence suggests that donors should simply not have the opportunity to smooth aid allocation within small distances across the threshold.

In a sharp RD design, the exposure to the risk of malaria transmission in health facilities should fall abruptly from 1 to 0 at the mining threshold, an assumption that is unlikely to hold since other external factors affecting the risk of malaria transmission also exist in non-mining areas and not everyone is at risk of getting infected with the disease within mining areas (for example, some individuals may naturally acquire immunity to malaria due to long exposure to infectious mosquito bites). Yet, the disproportionate burden of malaria induced by mining areas creates a discontinuity in the share of malaria cases around the threshold, as shown previously. To be more precise, I redefine the problem as follows: let $p$ be the share of malaria cases out the total population in the catchment area of the health facility, and $p_m$ the minimum share of malaria cases that characterises a health facility located in an area with high burden of malaria. I further assume that the probability that a facility receives a minimum share $p_m$ of malaria cases out of the total population that it serves is uniformly distributed within a mining area. The uniform distribution can be a good approximation of the true probability distribution if the latter does not decrease significantly between a mining site and its corresponding threshold. This assumption is supported by the fact that the risk of malaria transmission by mosquito bites is significantly higher in the presence of mosquito breeding sites such as mines, leading to "hotspot" areas where the disease is endemic (Carter et al., 2000).[33] As a result, all neighbouring populations of mining sites that fall under mosquito flight range distances are intensively exposed to mosquito bites; within small geographic distances from the breeding spots, the risk of malaria transmission should be high and spatially homogeneous.

It follows that

$$Pr(p \geq p_m \mid Mine = 1) > Pr(p \geq p_m \mid Mine = 0)$$

where $Mine$ is an indicator for mining area. This setting forms a fuzzy RD design where the jump in the probability $p$ of high exposure to malaria is less than 1 at the mining threshold, but a change in the risk of transmission exists. The mining area is used as an instrument for the risk of malaria transmission to estimate the impact of the latter on local aid for malaria (D. Lee and Lemieux, 2010).

Define $D_i$ a binary variable which equals 1 if a health facility $i$ is exposed to high risk of malaria transmission and 0 otherwise. The estimation of the model for malaria burden on local aid is expressed as

$$Y_i = \alpha_0 + \beta_0 D_i + f(\widetilde{X_i}) + \gamma z_i + \zeta_i \tag{3.4}$$

and the probability of malaria transmission is given by

$$Pr(D_i = 1 \mid X_i) = \alpha_1 + \tau mine_i + h(\widetilde{X_i}) + \gamma_1 z_i + \upsilon_i \tag{3.5}$$

where $f(\widetilde{X_i})$ and $h(\widetilde{X_i})$ are the RD polynomials which control for smooth functions of geographic distance from a mine to its closest health facility $i$. In this setting, the

[33] To be precise, (Carter et al., 2000) show that the distance from the breeding sites where the risk of malaria transmission is the greatest ranges from 2 to 3 km.

discontinuity in local aid (equation 3.1) is simply the reduced-form estimate obtained from the substitution of the two above equations, the discontinuity in the risk of malaria transmission being the first-stage estimate (equation 3.5). In the reduced-form (equation 3.1), $\beta_1$ captures the intent-to-treat effect ($\beta_1 = \beta_0 \tau$), which is the average effect of assignment to treatment. In other words, $\beta_1$ captures the effect on local aid from being exposed to a high risk of malaria, as a consequence of the health facility being located in a mining area, as opposed to not being exposed to a high malaria risk.

The instrumental variable approach relies on two important conditions: 1) that the mining area is a good predictor for the risk of malaria transmission and 2) that mining areas only affect local aid through the increased risk of malaria transmission (exclusion restriction). I provide some supportive evidence for the first condition in the results section, which is in line with the findings from the public health literature. The exclusion restriction is more difficult to demonstrate as unobservable characteristics determining the allocation decisions of donors might exist. However, health donors have clear objectives of reaching the vulnerable populations, irrespective of their locations, and ensure the equality of healthcare access (WHO, 2015a). A preference for targeting mining areas, which tend to be wealthier, would clearly violate the equity objective. Another concern is if mining areas tend to have, in general, better transport conditions, health products may reached the health facilities located in mining areas more easily. In turn, this would translate into a higher stock of health products in mining areas and therefore higher aid for malaria. However, I show in the results section that there does not exist a systematic difference between the transport conditions within mining and non mining areas, as captured by the proximity to conflict events and the distance to the regional centres for the distribution of health products. Based on this evidence and on the theoretical objective of donors, the risk that the exclusion restriction does not hold appears limited.

Finally, I remove hospitals from the sample selection as patients tend to travel more distance to hospitals than to smaller health centres (Stock, 1983). The risk is that they may invalidate the choice of the threshold if patients from mining sites seek treatment in non-mining areas. In addition, the National Malaria Programme indicates that malaria curative treatments in hospitals should primarily relate to severe malaria cases whereas health centres should offer treatment for simple malaria cases (MSP, 2011). This corroborates the fact that all health facilities in the sample have stocks of antimalarial commodities to diagnose and treat simple malaria cases. As a result, I hypothesise that patients should not seek treatment in a hospital when they have symptoms related to simple malaria case.[34]

Lastly, the malaria literature has documented that children are at a higher risk of malaria transmission than adults (D. Smith et al., 2007). This fact could pose a threat to the comparability of the treatment and control groups if mining areas are mostly deprived of children. Although there is imprecise information on child labour in mines, recent evidence suggests that children in the DRC may often engage in mining activities, regardless of international labour standards on child labour (Faber et al., 2017).[35]

## 3.5 Results

Before presenting the estimation results for the effects of mines on local malaria funding, I start by providing evidence of the plausibility of the two main identification assumptions of a valid RD design: continuity around the threshold (no self-selection) and random assignment.

### 3.5.1 Validity

The assumption of the RD design would be violated if health facilities can manipulate the running variable, the geographic distance from the health facility to

[34]A caveat is that the existence of user fees could also play a role in the decision of patients to seek treatment to a health facility. Unfortunately, no information on setting user fees in health facilities in these regions was found; I can, thereby, only assume that user fees should not vary significantly among public health facilities within small geographic distances.

[35]The Multiple Indicator Cluster Survey (MICS) conducted in the DRC in 2010 reveals that more than 60% of children in Eastern DRC are engaged in labour activities including mining. More recently, Faber et al. (2017) use a survey from a random sample of 150 mining areas in the DRC and find that about 13% of miners were aged below 18.

its closest mine. However, this assignment does not leave much room for strategic behaviour as most of artisanal mining activities should be more recent than the presence of health facilities.[36] To investigate the possibility of manipulation of the running variable, McCrary (2008) suggests to examine the distribution of units on both side of the threshold: a systematic manipulating behaviour would be revealed by a peak in the distribution of units on one side of the threshold as health facilities select their preferred group. The objective of the test consists of identifying a discontinuity in the density of health facilities around the threshold that would indicate that units are altering their assignment. Figure B.8, Appendix B, presents a visualisation of the density function of the running variable, which does not reveal obvious discontinuity around the threshold. Note that the running variable is centred at the threshold point, so negative and positive distance correspond respectively to mining and non-mining areas. The smoothness of the density suggests there is little scope for selective sorting of health facilities across the RD threshold.

To formally assess the validity of the continuity assumption, I also perform several density continuity tests of the running variable based on a data-driven procedure proposed by Cattaneo et al. (2017) to explore the possibility of self-selection of units around the threshold. Table B.4, Appendix B, presents the results of the density test, where the null hypothesis corresponds to equal density functions of the treatment and the control group. The first two columns correspond to the choice of the bandwidth (in metres) on each side of the threshold, columns (3) and (4) indicate the number of observations used and the last column gives the $p$-value of the test. I perform the test using two different MSE optimal bandwidth on each side of the threshold (Cattaneo et al., 2017) for which the results are reported in the first row. The second row corresponds to the density test which determines the possibility of equality of the two cumulative distribution functions of the running variable on each side of the threshold. In both cases, the tests fail to reject the null hypothesis of continuity.

[36]Revamping health infrastructures in the DRC is a well-recongized priority, so it is unlikely that the construction of health facilities preceded recent mining exploitations (MSP, 2017).

The falsification (or placebo) test provides further evidence about the plausibility of the identification strategy. Placebo covariates are the pre-intervention (or predetermined) covariates that should not be affected by the mining area under a valid RD design. For each of these covariates, I perform a local polynomial regression where the predetermined covariate is the outcome variable, in order to test the existence of an RD treatment effect. Figure C.13, Appendix B, provides a visual effect of the mining area on the predetermined covariates, where the running variable is the distance to mines centred around the threshold (mining and non-mining areas corresponds respectively to the right and left hand side of the threshold). Importantly, these graphs do not present visual evidence of a discontinuity between mining and non-mining areas for each of the predetermined covariates.

### 3.5.2 Mining effect on local malaria funding

Table B.5, Appendix B, reports the parametric estimates of the effect of mining on the outcome of interest and the placebo outcomes from equation (3.1). Columns (1) and (2) report the OLS estimates of the RD treatment effect on local aid for malaria using a linear model in distance. The corresponding window selection restricts health facilities to be located within 3 km from the mining threshold. Columns (3) and (4) present the OLS estimates when health facilities fall within 8 km from the threshold, and I use a cubic polynomial model to give more flexibility in the approximation of the regression function as the latter spans more observations. For each window selection, I explore the sensitivity of the results to the inclusion of baseline covariates.

As expected in a valid RD design, the coefficient estimates are not affected by the covariates whilst the precision slightly improves. The RD estimates on local aid for malaria indicate a significant positive effect of mining areas that is stable across the window selections. Specifically, the presence of mines induces an increase in local aid per capita between \$0.06 and \$0.07 at the health facility level either when facilities are restricted to be near the threshold (less than 3 km) or further away (within 8 km); these effects are statistically significant, even with the largest window. With an average local population of 10,000 in their catchment areas, health facilities within mining areas receive an additional aid for malaria that ranges between $600 and $700 per month.

The bottom part of the table provides the results of placebo tests which investigate the presence of a mining effect on the outcomes of four pre-determined covariates: total expenditures, total revenue, number of health workers and number of births per health facility. Selecting these covariates enables to test the existence of significant discontinuity across the mining threshold in some of the leading features of health facilities' performance that could relate to local aid absorption capacity. Expenditures and revenue capture the financial dynamic of health facilities whilst the number of births and the number of health workers can capture the ability of health facilities to attract and treat patients respectively. Importantly, these indicators could be causal factors for local aid targeting if donors are able to identify health facilities' characteristics. A systematic difference in these placebo covariates between mining and non-mining areas would then invalidate the RD design. However, the reported $p$-values indicate that mining areas have statistically insignificant effects on these placebo outcomes.

Table B.6, Appendix B, documents the non-parametric estimates. The RD treatment effect corresponds to the difference of the estimates of two locally weighted regressions on each side of the cutoff using a triangular kernel function. Following Calonico, Cattaneo, and Titiunik (2014), the reported results are based on robust confidence intervals and MSE-optimal bandwidth.[37] Column (1) estimates the baseline regression on the sample defined by the MSE-optimal bandwidth and using a local linear polynomial in distance to the threshold. Column (2) adds baseline covariates corresponding to geographic characteristics (elevation and slope) and the number of mines in the surrounding area of the health facility. Columns (3) and (4) replicate the first two columns using a local polynomial of order 3.

[37] The MSE-optimal bandwidth selection and point estimators are specifically chosen to include covariates (see Calonico, Cattaneo, Farrell, et al. (2018) who propose efficient driven methods to incorporate covariates in the RD design).

The estimates of the contribution of mines on local aid for malaria are all statistically significant and consistent with the parametric results, ranging from \$0.06 to \$0.07 per capita. Once again, the bottom part of the table documents the results of the placebo tests on the predetermined covariates and provide evidence of the validity of the RD design.

### 3.5.3 Sensitivity analysis

**Choice of neighbourhood.** Although the estimates of mining areas on local aid for malaria are consistent across both parametric and non-parametric approaches, they might be sensitive to the choice of neighbourhood. In particular, choosing smaller bandwidths has the advantage of reducing the misspecification error related to the approximation of the true function around the threshold, but it comes at the price of greater variability of the RD estimate. The first two graphs in figure B.12, Appendix B, present the sensitivity of the coefficient of aid for malaria to the bandwidth selection and the polynomial order in the non-parametric approach.[38] The bandwidth selection following Calonico, Cattaneo, and Titiunik (2014) is referred to as "CCT" on the $x$-axis of the first graph, and is also used to obtain the RD estimates for varying polynomial orders in the second graph. These graphs reveal that the estimates are remarkably constant across varying neighbourhoods around the threshold and specification models.

**Mining threshold.** The third graph in figure B.12, Appendix B, presents the sensitivity of the RD estimate to the choice of the threshold. This exercise allows to test the validity of the 14.5 km mining threshold described in section 3.4 and enables to estimate an upper bound on the discontinuity effect on antimalarial stock value by varying the threshold distance between mining and non-mining area. As expected, the RD coefficient estimate is sensitive to the location of the threshold as the latter

[38]The sensitivity analysis leads to similar results with the parametric approach.

is a critical element of the RD design. The variations of the coefficient estimate provide suggestive evidence for the validity of the 14.5 km threshold selection. The RD estimates are alternately positive and negative but centred around zero when the threshold is below 14.5 km, that is, supposedly located within the mining area. This finding is consistent with the assumption that the mining border is at least located at a 14.5 km distance from the mine: given the uniform distribution of the burden of malaria within the "true" mining area, there should be little variations in aid for malaria between the health facilities of these areas. Thus, the average difference of aid for malaria between the treatment and the control group conditional on the distance from the mine should not be systematically positive or negative when the threshold of the RD design is located within the "true" mining area. Similarly, for every threshold located beyond the "true" threshold of the mining area, the burden of malaria should decay gradually with distance as the mining effects shade off. The RD estimates should once again be centred around zero, assuming no other external factors would cause a systematic difference in aid for malaria between the treatment and control group. The point estimator of interest is then located at the "true" mining area threshold, for which the RD estimate should reach its maximum value: if the treatment and the control group are correctly identified, the RD strategy based on the "true" threshold is cleared from any unit that would incorrectly be assigned to the treatment or control group, causing a downward bias estimation of the RD effect. The bottom graph in figure B.12, Appendix B, indicates that the upper bound of the RD estimate is obtained with the 14.5 km threshold which has the highest point estimator and is the only estimate whose 95% confidence interval is entirely positive.

Another concern is that some patients might decide to seek healthcare in another health facility for various reasons that constitute the unobserved characteristics of patients. As an additional robustness check, tables B.7 and B.8 present the parametric and non-parametric estimations respectively when I restrict the data sample to health facilities that are separated by at least 3 km. The coefficient estimates are comparable to the main results, providing additional support for the RD strategy.

**Aid targeting within mining areas.** Donors could also perfectly observe the distribution of the needs within a mining area and decide to restrict the allocation of malaria resources to the closest health facilities from mining sites.[39] This donor's strategic decision could have detrimental implication on the availability of care in health facilities away from the mining site, but it could arguably ease the targeting approach if mining sites have better road access within mining areas or if donors choose to strictly targeting miners. Importantly, this assumption would explain the relative small difference that is observed in aid for malaria between health facilities around the mining threshold. I explore this hypothesis in figure B.13, Appendix B, by analysing how aid for malaria at the facility level relates to the distance to its closest mine. The figure shows the non-parametric estimations of local aid conditional on the distance from a health facility, using a kernel-weighted local polynomial regression of order 1. The kernel function is epanechnikov and the the bandwidth corresponds to 700 metres. The $y$-axis represents local aid for malaria per capita at the health facility level and the $x$-axis corresponds to the distance from the health facility to its closest mine in metres. The shaded area denotes the 95% confidence interval of the coefficients. The plot shows a relative constant share of aid for malaria in health facilities located within mining areas, independent of the distance from the mine. This graph, therefore, suggests that there is no evidence that donors choose to target the closest health facilities around mining sites.

### 3.5.4 Decomposition by commodity and additional tests

I now turn to the decomposition of the mining effects by aid allocated to each antimalarial commodity. The baseline results, presented above, focus on all commodities to locally capture the amount of aid for malaria. However, each commodity has a specific role in tackling the disease burden, which can be decomposed in three sub-categories: prevention, identification and curative treatment. The aid decom-

[39] As discussed above, the burden of malaria should be equally distributed within a mining area so this donor's approach would entail inequalities in treatment access among patients within the area.

position enables to examine how the burden of malaria affects the allocation of aid resource to each of these sub-categories.

Figure B.10, Appendix B, provides a visual discontinuity on the stock value of ACT and SP against the distance to the mining threshold in panel A and B respectively. Both plots fit a local cubic polynomial in distance; the jump in outcome at the threshold appears much larger for the stock value of SP than ACT, although in both cases, the effects fade away with distance.

Table B.9, Appendix B, reproduces the table with the parametric regressions presented for the effects on local aid for malaria. Column(1) corresponds to the OLS estimates of the mining area effects on each antimalarial commodity using a 3 km window around the threshold and a linear model in distance. The second column reports the OLS estimates for observations falling in a 8 km window from the threshold and using a cubic model in distance. The mining effect is statistically significant for the stock value of all antimalarial commodities for both window selection except for ITN. The highest mining effects are found to be on aid for SP and ACT for which the stock value increase by \$0.04 and \$0.02 per capita respectively, whilst the effect on the stock value of RDT is marginal (less than \$0.01 per capita).

Table B.10, Appendix B, shows the results with the non-parametric approach, where column (1) and (2) estimate respectively a local linear polynomial and a local cubic polynomial in distance. Compared to the parametric approach, the estimate of aid for ACT and SP are lowered by approximately \$0.005 per capita when using a local linear model; the estimate for RDT remains unchanged. When the specification involves a local cubic model in distance, only the stock value of SP and RDT are statistically significant, and aid to SP reaches almost \$0.05 per capita.

Together, the outcomes from parametric and non-parametric estimations illustrate important findings. First, the effects of mining areas on aid allocated to each antimalarial commodity are relatively constant with respect to the distance from the mining threshold, which attests to the robustness of the results. Second, the mining effect on aid for malaria is largely driven by the effect on aid for SP which accounts for 65% ($0.046/0.072 = 0.64$) of the overall mining effect on local aid for malaria. The remaining part of additional aid in mining areas is mostly devoted to ACTs (about 22 %) and RDTs (11 %).

**Disentangling the mining effects on antimalarial commodities.** A potential concern with the increase in aid for SP commodity relative to ACT is that health facilities within mining areas might be subject to systematically more frequent disruptions in the provision of a specific commodity for reasons inherent to the presence of mines. To assess this eventuality, table B.11, Appendix B, documents the mining effects on the monthly number of stock-out days, consumption and the share of consumption in the stock level for each antimalarial commodity. Column (1) reports the estimates for SP and columns (2)-(5) decompose the mining effects for each age category of ACT treatment that corresponds to age-specific dosage. The last two columns present the estimates of ITN and RDT respectively. The RD estimates of the monthly number of stock-out days are statistically insignificant for all commodities, indicating that mining areas do not disrupt the provision of a specific commodity. Monthly consumption is statistically significant for all commodities except for ACT to children between 6 and 13 and RDT. This result confirms the predominance of the burden of malaria within mining areas through increased demand in antimalarial medicines, in particular among children between 1 and 5 for whom the ACT consumption rose by 4%. The bottom part of the table reveals that the share of consumption in the stock level of each commodity has a negative coefficient estimate which is explained by the higher stock level of antimalarial in mining areas. The estimates are only statistically significant and negative for SP and RDT, indicating that the increase in demand (monthly consumption) within mining areas for these two commodities is lower than their increase in supply. This last result corroborates the previous finding of SP receiving the highest share of aid for malaria.

As a final test, I explore the existence of systematic differences between mining and non-mining areas in the sub-populations targeted by donors. As previously described, ACT treatments are characterised by specific dosages which relate to four different age categories (below 1, between 1 and 5, between 6 and 13 and above 13) whilst SP is a preventive treatment specific to pregnancy. Unfortunately, data limitation prevents from exploring the distribution of age population between mining and non-mining areas. I can therefore only assume that this distribution is similar in the two areas and I rely on the additional burden of malaria caused by the mines as the unique driver for the provision of ACT drugs.[40] Regarding SP preventive treatment, the commodity is given to pregnant women during routine antenatal care (ANC) visits (WHO, 2018a). I examine the presence of a discontinuity in the population of pregnant women by using the reported number of ANC visits.[41] Table B.12, Appendix B, documents the effect of mining areas on the share of ANC visits per capita and malaria prevalence using non-parametric estimations. Columns (1) and (2) denote respectively the local linear and cubic models. Malaria prevalence is defined as the share of malaria cases received in health facility per local population. The RD estimate for the share of ANC visits is statistically insignificant which could reasonably be interpreted as an equal distribution of pregnant women between mining and non-mining areas. This last result, combined with the findings on the similarities in the number of stock-out days for all commodities between the two areas, provides suggestive evidence that malaria prevalence should be the primary causal factor for the determination of local aid for malaria.

**Equity of local aid.** Whilst local aid for malaria increases by \$0.06 per capita in mining areas, the decomposition of the mining effects reveals an unequal distribution of resources allocated to antimalarial commodities. I further document how the distribution of local aid for malaria is matching the needs by examining the vari-

[40]One concern with this assumption is that mining areas could be characterised with lower rate of children due to the health and safety hazards of mines. However, as described in section 3.4, recent studies on child labour suggests that the presence of children should not be significantly lower within mining areas.

[41]For the validity of the test, I hypothesise that antenatal care attendance among pregnant women do not systematically differ in mining areas, an assumption that is not directly testable. Although pregnant women are banned from mining activities, mining work is also more lucrative for them than any other activities surrounding mining areas (Buss et al., 2017). Hence, I suspect that pregnant women in mining areas should have little incentives to move home during their pregnancy and attend a different health facility for antenatal care.

ations in the stock of commodities with respect to the change in burden of malaria between mining and non-mining areas. The bottom part of table B.12, Appendix B, corresponds to the RD estimation of mining effects on malaria prevalence using a local linear polynomial. In mining areas, the number of malaria cases increases between 7 and 8 percent when the nonparametric estimation employs a local linear and a cubic model respectively; both results are statistically significant.[42] In baseline results presented earlier, mining areas were found to have a small but significant effect on aid for malaria. The rise in local aid could underestimate the coefficient of the mining effect on malaria prevalence if aid for malaria contributes (through preventive treatment) to reduce the burden of the disease. The obtained result on malaria prevalence should therefore represents a lower bound estimate.

Next, I quantify the results on local aid for malaria by estimating the theoretical costs that should be borne at the health facility level for the prevention, diagnosis and treatment for an additional unit of risk of malaria transmission. Using the prices of antimalarial commodities from the Pooled Procurement mechanism of the Global Fund (Figure B.14, Appendix B), the total monthly estimated cost for providing malaria treatment and prevention per capita is \$1.25.[43] This result is in line with the finding from WHO (2015a) who estimates that the cost of curative treatment is approximately \$1 in Sub-Saharan African countries. The total cost is decomposed as follows: ACT \$0.7, SP \$0.09, RDT \$0.25 and ITN \$0.21.

The amount of aid required for financing diagnosis, prevention and treatment of malaria relates to the disease burden within a given area. Figure B.15, Appendix B, plots the evolution of malaria-related costs with the additional risk of malaria transmission. The horizontal red dashed line shows the additional aid for malaria

[42]Malaria cases are usually detected at the facility level by RDTs, the latter being provided mostly by donors. This could pose a threat of endogeneity bias but table B.11, Appendix B, reports insignificant effects on the number of stock-out days of RDTs between mining and non-mining areas. This means that the number of detected cases should not be more constrained by the availability of RDT in health facilities located in non-mining area.

[43]To calculate the overall monthly financial costs per capita, I rely on the decomposition of the Congolese population that was taken from the United Nations World Population Prospects: 57 percent of adults (above 14), 25% of children between 6 and 14 and 16% that are less than 5. The share of pregnant women and children who are receiving SP medicines is assumed to be 25% following the estimations in the National Health Accounts in the DRC (MSP, 2017).

that is received in high burden areas according to the nonparametric RD estimation (Table B.6, Appendix B) of the mining effect. The graph indicates that local aid can potentially cover the costs associated to the burden of malaria when the additional risk of malaria transmission does not exceed 4.4%. Beyond this point, health facilities within mining areas do not get their share of aid.

What is the actual risk of malaria transmission? As discussed above, I find that malaria prevalence increases by at least 7 percent in mining areas. At this rate, local aid should increase by a minimum of \$0.09 per capita to fully meet the needs related to malaria. On the other hand, the results of both parametric and nonparametric RD estimations of the mining effects on local aid indicate that the increase in aid for malaria ranges between \$0.05 and \$0.06. Presumably, this result implies that at least more than one third of the additional malaria needs in areas with high burden of the disease is not financed by aid.

Altogether, these results suggest two main conclusions on the patterns of aid targeting. First, the additional risk of malaria transmission is not followed by a proportional increase in local funding for malaria curative treatments. Given the cost of malaria prevention and treatment approximately equals to \$1.25 per patient, a minimum 7 % increase in malaria prevalence would require an additional \$0.09 of aid per capita whilst health facilities are found to receive less than \$0.06 per capita.

Second, aid for preventive commodities for pregnant women (SP) are more responsive to the change in the risk of malaria transmission, although this disproportionate response raises concerns about the effectiveness of aid for this commodity. Whilst the estimated cost of SP represents approximately 7% of the overall costs of providing antimalarial commodities, SP accounts for more than 65% of the additional aid allocated to high risk areas. On the other hand, the share of ACT is 56% in the overall antimalarial cost whilst only 22% of aid is targeting it. There is no evidence that external funding for insecticide-treated bed nets (ITN) is higher for mining areas.

## 3.6 Discussion and conclusion

Targeting of health needs is central in low-income countries with high disease burden and limited resources (Dupas and Miguel, 2017). Important health gains could be achieved through more precise allocation of resources to areas with the greatest health risk.[44] In this study, I exploit the variations in the burden of malaria between mining and non-mining areas to estimate the response of donors to local needs. Aid targeting of population's needs can be assessed through analysing the quantities of health products delivered in existing health facilities, which has been shown to be the most cost-effective distribution method (De Allegri et al., 2009). Using a novel data source to track aid for malaria at the health facility level, I find no evidence to support the assumption that donors are accurately targeting areas with the greatest burden of malaria. Although I document a significant effect of local variations in the burden of malaria on local aid for the disease, the evidence also suggests that local populations with the highest burden of malaria do not receive the highest share of aid for malaria comparatively to those living in neighbouring areas with reduced exposure to malaria infection.

First, the small increase in local aid for malaria does not match the costs incurred for the extra burden of malaria in mining areas. In particular, my findings suggest that local aid is covering at maximum 60 percent of the additional costs induced by the additional risk of malaria transmission. Second, the decomposition of aid by targeted population reveals that resources are unequally distributed with respect to local health needs; this inequality is in turn exacerbated by the overall mistargeting of aid for malaria.

These results pinpoint some limitations in the actual aid allocation and suggests that aid could be more closely tailored to local health needs. Better allocation of aid could generate health efficiency gains and reduce inequities in treatment access for patients across areas with different burdens of malaria (difference in allocated aid)

[44] As a recent example in the DRC, C. Dolan et al. (2019) show that national insecticide-treated bed net campaigns against malaria between 2009 and 2013 achieve significant mortality reduction among children under 5 only in areas with the highest risk of malaria transmission.

and within areas (across population sub-groups). In cases where health information is fragmented and difficult to collect, donors could seek the engagement of local community leaders in aid targeting decisions (Alatas et al., 2012).

My findings resonate with the literature on geographical targeting of aid at subnational levels. Öhler et al. (2017) find no evidence that funding from World Bank to anti-poverty projects is allocated to the poorest areas within countries in Sub-Saharan Africa. Briggs (2018) shows that aid from World Bank and African Development Bank targets comparatively richer geographic areas across African countries. In the health sector, Kotsadam et al. (2018) show that external funding is allocated to subnational areas of Nigeria with lower infant mortality.

More broadly, my findings question the effectiveness of aid in settings with limited information about local needs, and challenge the view that donors possess sufficient knowledge to make optimal decisions of resource allocations (Easterly, 2006). The results best support the assumption that aid mistargeting reflects donors' inaccurate information about local population needs. The fact that the distribution of local funding per commodity does not match the needs of each targeted population could be explained by two factors: the incomplete information of donors about local health needs or ineffective supply chains of health products leading to poor availability of medicines in health facilities (Yadav, 2015). However, the evidence does not support the latter: the number of stock-out days for each antimalarial commodity does not systematically differ among areas with varying risk of malaria transmission. This finding partially rules out the role of the supply chain of health products to explain the difference in the stock of antimalarial commodities between local areas with different burden of malaria.[45] Hence, the results suggest that mistargeting is primarily caused by the decisions of donors.

The results of this research only apply to the malaria programme in Eastern

[45] I cannot completely exclude the possibility that the supply chain of medicines locally affect their provision level to health facilities located in areas with high disease burden without causing systematic stock-outs. However, this eventuality is highly improbable: the quantity of health commodities provided to the facility could hardly remain systematically low without experiencing more frequent stock-outs.

DRC, and it would be speculative to draw general policy implications. Rather, the findings in this chapter underscore important research questions. First, I have shown the critical importance of focusing on a disease-specific programme when documenting the distribution of health resource allocation. Further research on other highly financed diseases (such as HIV/AIDS) could help to uncover the root causes of targeting deficiencies. Second, the fact that funding for some health commodities (ACT, SP) is more sensitive to local variations in the burden of malaria than others (RDT, ITN) suggests that donors have imprecise information about the local variations in disease burden. An alternative explanation is that health workers might be more successful in signalling the need for being provided some specific health commodities than for other health commodities. The signalling efforts of health workers would then induce a partial adjustment in donors' targeting decisions, improving thereby the aid allocation for the specific commodities. Future research on these questions is important to improve health aid targeting.

# Chapter 4

# Colonial origins and hospital performance in the D.R.Congo

## 4.1 Introduction

Persistent inequalities in development and investment in health infrastructures are hampering health system performance in sub-Saharan Africa (Hsia et al., 2011). As health facilities absorb more than half of total health domestic expenditures (WHO, 2014), exploring the root causes of inequalities in hospital performance is crucial to improve the allocation of health resources and achieve their highest impact.

This chapter attempts to bring a new perspective on this issue by investigating the historical legacy of a colonial regime on modern disparities in health system performance. Specifically, the objective is to explore to what extent colonial health investments have a causal effect on contemporary hospital input utilisation and output production.

Previous research on African development has pointed out the role of colonial legacy in shaping institutions and its enduring effects on contemporary economic outcomes (Sokoloff and Engerman, 2000; Acemoglu et al., 2001; Nunn, 2014). They highlight the importance of initial conditions and factor endowments on modern institutional and economic development. In the health sector, colonial powers had a prominent role in the establishment of the health system: they built, financed and organised the structure for the delivery of healthcare in the colonies, set up the earliest national-wide public health policies and provided medical staff and health equipment to the newly created facilities (Schwetz, 1946). One could, therefore, expect that colonial health investment may have had long-lasting effects on health care delivery through better provision of health commodities, financial stability, current investment level, or structural capacity.

On the other hand, the shaping of these institutions could also have been extractive if driven by the economic objective of resource exploitation, producing economic and health inequalities with negative effects on development paths. The Belgian Congo is an illustrative example where labour coercion and constant use of violence for resource extraction disrupted both local communities and the Congolese society (Kivilu, 1984; Lyons, 2002). At the individual level, colonial extractive practices may have had a negative impact on health services demand through mistrust in medicine (Lowes and Montero, 2018). The colonial enterprise also instituted a two-tiered health care system segregating white Europeans, entitled to a high quality of health care, and Congolese black populations for whom health financing mostly served to maintain labour productivity at its desired level (Kivilu, 1984). Altogether, these two opposite approaches point to the same direction: the colonial origin of health facilities may be an important causal factor to explain the large variations in modern health facility indicators (E. Lee et al., 2016). Likewise, the heritage of colonial presence may continue to strongly determine health care demand and utilisation through its intermediate effects on population health (Cage and Rueda, 2017; Lowes and Montero, 2018) or ethnic partitioning (Michalopoulos and Papaioannou, 2016).

I examine the long-term effects of colonial health investments on modern hospital performance by using archival data on the Belgian Congo between 1926 and 1956 along with contemporary data on the Democratic Republic of Congo (DRC). Focusing the analysis on the DRC brings two benefits. First, I obtain refined data from colonial archives on population health, public investments and disease prevalence in this second largest African country. The collected information offers the possibility to accurately estimate the effects of colonial health investments at the subnational level and has the advantage of precisely identifying sources of variation in factors pertaining to colonial settlement decisions. Furthermore, the troubled recent history of the DRC provides a unique setting for examining the persistence of the colonial legacy. From independence in 1960, followed by the Mobutu authoritative regime, to the collapse of the state and the outbreak of civil and regional wars three decades later (Nest et al., 2006), the presence of causal effects on modern facilities would be remarkable. It would suggest a high degree of persistence of initial health investments and the crucial role played by colonial medical missions in determining the performance of modern African hospitals.

Starting from a simple theoretical model, I hypothesize that initial investment in health infrastructure construction was higher during the colonial period than after independence of the Congo, and I document evidence that supports this assumption. I use a simple model of hospital production to derive the effects of a change in initial investment on modern health facility indicators. The model suggests that colonial health settlements may have contributed to building a network of health facilities with comparatively higher physical and human capital than health facilities built at later stages.

To test this model, I construct a dataset of colonial and post-independence health facilities from multiple information sources. First, I exploit historical maps from the Ministry of Colonies of the Belgian Congo that document the location of health infrastructures supported by religious, private and colonial government funds between 1926 and 1956 to build a geocoded dataset of colonial health facilities.[1] I determine their exact location by matching them with the list of modern health facilities obtained from the Ministry of Health of the DRC. In total, the country has about 1,100 hospitals, among which 208 are identified with colonial origins. I

[1]While many recent studies on legacies of religious missions in the past have exploited data from historical atlases, I find that historical archives from the Belgian Congo provide a more accurate and complete source of information. Jedwab, Selhausen, et al. (2018) similarly document that atlases have limited capacity to report mission activities.

augment these data with detailed information extracted from colonial archives on public health data in the Belgian Congo on the geographic distribution of the sleeping sickness, number of health facilities, medical staff and health expenditures at the district level. Second, I use a unique database on epidemiological and financial information on modern health facilities between January 2017 and December 2018 that were collected from the Health Information Management System of the Ministry of Health of the Democratic Republic of Congo. From this database, I examine health facility performance in three areas: financial capacity, input utilisation, and output production.

Next, I identify modern health facilities that originated from colonial settlements and those that were built during the post-independence period. The two samples are subsequently used to estimate the causal effect of colonial investments on modern health facility performance using different strategies. I start with estimating an OLS model that controls for a large set of geographical, epidemiological and demographical covariates at the local level. Drawing upon multiple colonial archival data, I further examine the heterogeneity of effects by hospital ownership, source of colonial funding, targeted population (White or Black) and duration of colonial settlement. I also use the georeferenced locations of colonial missions and health facilities to conduct a matching estimation based on geographic proximity, population covered and health facility ownership. I argue that modern health facilities located within a short distance from a settlement constitute credible counterfactuals to facilities created during the colonisation era. Finally, I address the potential endogeneity of mission settlements (Jedwab, Selhausen, et al., 2018) by using the prevalence of sleeping sickness during the colonial era as an instrument for the settlements of colonial medical missions.

I find that health facilities built during the colonial period receive significantly more subsidies from the central government than post-independence facilities while demand for health care and health service production are similar. This suggests that health facilities originating from colonial settlements established closer ties with the central government than post-independence facilities. The lack of effects of colonial settlements on health demand is in direct opposition to Lowes and Montero (2018) findings of individuals' mistrust in medicine. These contrasting results might be explained by the fact that only specific colonial practises would deteriorate individual trust in medicine. I also find that colonial hospitals are using more capital and labour inputs than hospitals built during the post-independence period. I provide suggestive evidence that differences in initial structural investments are mostly responsible for the contemporaneous disparities in input levels between the two groups. These results are robust across a range of estimation methods, as well as to different assumptions about the spatial clustering structure. Altogether, these findings highlight the importance of examining the historical roots of health facilities to assess their performance. It could help to understand the observed differences in the efficiency of health resources in improving population health at subnational levels.

This research contributes to the literature on the historical roots of economic development.[2] A growing number of studies single out the extractive nature of colonial missions in durably affecting health behaviour and mistrust in medicine. Cage and Rueda (2017) document that Christian missions increase HIV prevalence when they are not combined with health investments. Lowes and Montero (2018) show that colonial medical missions in French Central Africa reduce trust in modern medicine. However, this chapter demonstrates that the presence of colonial settlements could also positively affect the provision of health care through the increased infrastructure capacity of health facilities. The ability of colonial regimes to mobilise large health investments and skilled resources, although driven by resource exploitation, appears to be a strong channel of persistence of the colonial effects. This finding is consistent with Huillery (2009) who documents a positive effect of colonial investments in health, education and infrastructure on the current performance of each of these public goods. It also resonates with Dell and Olken (2019) who show that extractive institutions could result in comparatively higher economic and social outcomes in the long-run. More broadly, the findings in this chapter also add to the

[2] For a thorough review of this literature, see Michalopoulos and Papaioannou (2018).

literature on the persistent effect of investments in infrastructure (Huillery, 2009; Jedwab and Moradi, 2016; Jedwab, Kerby, et al., 2017). The importance of initial factor endowments echoes the results in Jedwab, Kerby, et al. (2017) on the role of colonial sunk investments as a channel of persistence.

However, my analysis differs from these studies in several ways. Previous work has used district-level data to study French and British colonies, which may have specific colonial regime patterns. The focus on Belgian Congo offers an opportunity to examine the effect of a different colonial regime covering a large spatial territory. Furthermore, no studies have, to my knowledge, explored the effects of colonialism on modern hospital performance. With this aim, I construct and analyse a dataset at the health facility level, which allows me to estimate directly the persistence of colonial effects at the granular level and avoid thereby losing information through data aggregation.

The roadmap of the chapter is as follows. Section 4.2 provides an historical background on the DRC and its health system. Section 4.3 describes the data and the geographical analysis. Section 4.4 introduces the conceptual framework. Section 4.5 to 4.7 present the empirical analysis through different identification strategies. Section 4.8 explores some alternative channels for the results and section 4.9 discusses policy implications and concludes.

## 4.2 Historical background

### 4.2.1 Colonial legacy of public health

The colonisation of Congo began in 1885 with the infamous Congo Free State governed by the King Leopold II of Belgium, before becoming the Belgian Congo in 1908 when the Belgian State took over the private colony. The colonial regime primarily aimed at extracting rubber, copal and ivory resources through human exploitation and shaped the Congolese institutions to serve an export-oriented economy (Nest et al., 2006). Private companies that were given large territorial concessions during the

Congo Free State period were the primary beneficiaries of the country's resources exploitation. Using coercive control to mobilise cheap labour force, they grew as important actors of the colonial regime and were at the forefront of an important infrastructure development that took place during the inter-war period. An integrated transport network of railways, roads and waterways served both agricultural and mineral exports.

The first medical campaigns in Congo appeared in the early twentieth century with the outbreak of sleeping sickness, or human trypanosomiasis, a disease transmitted through the bite of a tsetse fly. The initial health policies consisted in the creation of a *cordon sanitaire*, a quarantine aiming to restrict movements of infected people (Schwetz, 1946). However, the Belgian Congo had to wait until the early 1920s for the inception of a health system and the development of medical missions for the Congolese population that were supported by the colonial administration (Lyons, 2002). As colonial powers looked to expand their influence through religion, industry and commerce, the provision of health care was consequently administered by three coexisting actors: the State, Christian missions and private firms. Some independent health organisations partly funded by the Belgian government or private companies also played an important role in the provision of health care.[3] The different and sometimes opposite objectives of the three actors resulted in geographical disparities in the allocation of health resources (Lyons, 2002). All medical care was free of charge. However, priorities of health interventions were given to the European population with the objective of reproducing similar standards of health quality services to what existed in Europe (Figure C.1, Appendix C). On the other hand, the provision of free health care for the Congolese population was primarily geared towards a healthy and productive labour force to support exploitation of natural resources (Hunt, 1999).

After World War II, the colony witnessed rapid economic growth and used its budget surplus and international borrowing to finance the development of the health

[3] Examples of such health organisations are the *Fondation Médicale de l'Université de Louvain au Congo* (FORMULAC), the *Fondation Reine Elisabeth pour l'Assistance Médicale aux Indigènes* (Foreami) or the *Croix-Rouge du Congo*.

care system. This resulted, in 1949, with a massive ten-year health investment plan of 3 billion Belgian Congo francs (known as the Van Hood Duren Plan) aimed to equip all provinces of the Belgian Congo with Medico-Surgical centres (rural hospitals) (Duren, 1953).[4] The total number of health facilities (hospital, dispensaries, maternities, health centres and posts) rose from 568 in 1949 to 2,815 ten years later, and comprised 293 General Referral Hospitals, more than 85,000 hospital beds and 703 physicians (Ministery of the Colonies, 1958). In 1958, two years before independence, the country benefited from one of the most developed medical infrastructure in Africa (Pepin, 2011).

### 4.2.2 Health system and the State

By the time of independence, most of the Congolese population experienced better health and improved socio-economic conditions compared to the previous generations who witnessed the beginning of the colonial enterprise (Kivilu, 1984; Lyons, 2002). The medical workforce entirely relied on white foreign physicians and nurses, while the Congoleses were restricted to medical assistant positions (Kivilu, 1984).

The flourishing economy of European settlers remained until the Congo gained its independence in July 1960. At that time, lack of trained African administrative and technical managers combined with ethnic isolation considerably hampered the social and political development path of the Congolese society (Vanthemsche, 2012). The newly created State immediately entered a period of internal disorders and civilian conflicts until Joseph Mobutu took power in 1965 to begin an authoritarian rule of the Congo (renamed Zaire in 1971) that lasted for the next three decades. While most European skilled workers fled the country following independence and all public services deteriorated, the copper industry resisted the troubling series of events and provided up to 80 percent of Congolese foreign revenue in the 1970s (IBRD, 1973). In the meantime, the quality of the health system sharply declined due to low

[4]These health centres were the focal point of on an integrated network of satellite dispensaries that provided health services to rural peripheries.

investments (Lyons, 2002). The fall in copper prices combined with hyperinflation and a heavy debt burden eventually drove the country to the economic collapse in the early 1990s (Hesselbein, 2007). This disintegration reduced the fiscal space for the public financing of health care and ultimately dragged down government health expenditures (Gardner, 2013). Since then, hospitals have suffered a long decline in their capacity to deliver health services with frequent disruptions in drug supply and health equipment (MSP, 2011).

As the Mobutu regime ended in the late 1990s, wars with Uganda and Rwanda and the fragmentation of Congo into four autonomous regions precipitated the country to a general state-implosion (Nest et al., 2006). The official ceasefire in 2003 and the reunification of the country left a fragile state in economic and political crisis, characterised by inadequate provision of public services, rampant corruption and a dearth of investment. Most of modern health facilities are in dire need of rehabilitation (MSP, 2011).

In this setting, Development Assistance for Health (DAH) grew as a vital source of funding for the current health system. The financing of the health system almost entirely relies on DAH and private out-of-pocket expenditures, which accounts respectively for nearly 40% and 55% of total health financing (MSP, 2017). The evolution of DAH between 1990 and 2017 in the DRC (Figure C.2, Appendix C) reveals the growing share of DAH in the financing of the Congolese health system. The recent surge in Chinese aid and investment in Sub-Saharan Africa has brought large infrastructure projects to the DRC to modernise the country, including the health sector.[5] Yet, the effects of these projects on health system performance remain relatively unknown due to data limitations about Chinese aid.[6]

The modern health system of the DRC has three levels of organisation. At the central level, the Ministry of Health set the national health strategies for each of the

[5]Political considerations may play an important role in the allocation of Chinese's aid to health (Dreher and Fuchs, 2015).

[6]Grépin et al. (2014) find that Chinese health resources in Africa mainly finance health infrastructure and medical staff. Bluhm et al. (2018) show that Chinese investments in transportation infrastructure tend to reduce spatial economic inequalities, but do not find a significant effect on local health projects.

26 provinces of the country, and directly manage all General Referral Hospitals. The provincial health departments are responsible for technical and logistical support of the health system at the intermediate level and the management of provincial hospitals. The third level is composed of 516 health zones, or districts, where each district covers a population of 100,000 to 200,000. The three main types of health facilities at the district level are health posts, health centres and district hospitals (and private clinics). Figure C.3, Appendix C, tracks the evolution of administrative boundaries in Congo from the inception of the colonial period to the most recent change in 2015.

This brief historical overview of events that have shaped the DRC, from independence in 1960 to the present day, highlights the frequent political instability along with economic crises that had far-reaching implications for the performance of the Congolese health system. Exploring the persistence of colonial effects on hospital performance after such a large series of disruptive events could highlight the importance of initial investment in conditioning the development path of health institutions.

## 4.3 Data

**Colonial settlements -** I use two primary data sources. First, I exploit multiple colonial maps on health infrastructures between 1936 and 1953 to georeference the establishment of colonial health investments. These maps, produced by the Belgian Ministry of Colonies, provide information on the geographic distribution of all hospitals and dispensaries that reported health activities to the colonial government. Each map informs about the type of health infrastructure (hospital or dispensary), the population served (Europeans or Congolese) and the ownership (government, religious or private). Figure C.4, Appendix C, provides an example of these maps, which shows the location of all medical infrastructures in 1953. I also use two additional maps that report the health activities of a governmental health organism (the *Fondation Reine Elisabeth pour l'Assistance Médicale aux Indigènes*, Foreami) in the western provinces of Kwango and Bas Congo in 1935. Lastly, a detailed map of all existing Christian missions in 1929 provides additional historical evidence on the colonial presence (Figure C.5, Appendix C). The latter does not allow me to determine whether a Christian mission provided health services or solely focused on religious activities. However, Christian missionaries considered health activities as an important vector for spreading their faith; their presence could then potentially imply the provision of health services during the colonial time.

Equipped with this information, I georeference and geolocalise all historical data: I first construct a geocoded dataset of all colonial medical missions between 1929 and 1953. I then compute the exact location of modern health facilities with colonial origins by matching the colonial health settlements with the list of modern health facilities in the DRC.[7] The geo-location analysis was finally augmented with archival public health data from the Belgian Ministry of Colonies between 1926 and 1955. The archival data offers information on the provision of health services at the provincial level, the number of patients treated, the number of medical staff and the estimated number of beds.

**Modern health facilities -** The list of modern health facilities was obtained from the District Health Information System (DHIS2), a routine web platform managed by the Congolese Ministry of Health that provides financial and epidemiological information on modern health facilities in the DRC. Monthly data was extracted between January 2017 and December 2018. A challenge was that the database provides incomplete information about the geographic coordinates of health facilities. To solve this issue, I triangulate the geographic information of facilities from several sources: ReliefWeb maps for each of the 26 provinces in the DRC; the United Nations Office for the Coordination of Humanitarian Affairs (OCHA) database, OpenStreetMap files and a Red Cross health map.[8] ReliefWeb provides a list of

[7]This step was a challenge as most hospital names with Belgian references changed after Independence, so I had to rely on additional archival documents of the post-Independence period to match all colonial with modern names.

[8]These maps are obtained from the following websites: (ReliefWeb) https://reliefweb.int/; (OCHA) https://data.humdata.org/organization/ocha-dr-congo); (Red Cross) https://www.croixrouge-rdc.org/organisations/ and OpenStreet map (https://www.

geocoded health facilities in the DRC related to OCHA's humanitarian activities and OpenStreetMap is an open database routinely enriched by field observations, satellite images and integrated datasets. The Red Cross health map supplements these data with the location of health facilities supported by the Red Cross in 2018.

The total sample data comprises 17,000 health facilities of which 4,449 have been geolocalised. The sub-sample of geolocalised facilities contains 351 health facilities that were built during the colonial period. Since there exists high heterogeneity among health facilities in terms of size and capacity to deliver health services, I decide to focus the subsequent analysis on hospitals. Restricting the sub-sample of facilities on hospitals leads to 1,099 observations among which 208 have colonial origins. Figure C.6, Appendix C, shows the locations of colonial and post-independence hospitals that are used in the final sample. The share of hospitals that could not be geocoded is 30 percent and only includes post-independence hospitals. To a large extent, these hospitals are located in rural areas where little information exists.[9] This sample selection raises potential concerns: it could lead to underestimation of the colonial effects on health facility performance if the hospitals with unknown locations also have lower performance. However, the sample of geocoded hospitals remarkably contains 98 percent of the 488 General Referral Hospitals (*Hôpital Général de Référence*, HGR) in the country.[10] In the results section, I discuss the implications of the colonial effects on urban and rural hospitals.

**Data description -** Figure C.7, Appendix C, plots the distribution of hospitals by ownership (faith-based, private and public) in the full data sample (dotted bars) and within the facilities with colonial origins (red dashed). The share of colonial hospitals with private ownership out of the total number of private hospitals is very small, which suggests that health facilities have been growing much faster in the private sector since independence than in public or faith-based sectors. The bottom graph of figure C.7, Appendix C, restricts the illustration to public hospitals

openstreetmap.org/).

[9]Although I could not geolocalise all hospitals, I have information on the district they belong to. I, therefore, include all hospitals in the district level analysis.

[10]General referral hospitals (HGRs) are provincial hospitals that provide tertiary care.

(HGR and medium size hospitals composed by district and provincial hospitals) and indicates that public hospitals are essentially HGRs in the data sample.

Table C.1, Appendix C, reports the covariate balance between health facilities built before and after independence of the Congo for financial and structural characteristics, inputs used and output produced. The table shows that a range of these covariates have means that are substantially higher for the hospitals that have colonial origins: monthly days with electricity, beds, medical staff, malaria cases, inpatients and emergency cases. Nonetheless, these discrepancies could be independent of colonial effects: colonial facilities could be located in areas closer to transportation modes for the supply of health products or with better patient access. On the other hand, they could also be exposed to higher burden of disease (such as malaria) than post-independence hospitals if they are systematically located in endemic areas. I develop several empirical strategies to address these concerns.

## 4.4 Conceptual framework

This section provides a simple theoretical model to help shed light on the mechanisms through which colonial health investments may interplay with modern health facility performance. The central objective of the model is to show how the level of initial investment could relate to the optimal choice of input and output involved in the production function of a health facility. One of the fundamental differences in health financing between *pre* and *post* Independence is in the fiscal state capacity to raise revenue and finance social services (Gardner, 2013). There is ample historical evidence that under the colonial regime, the Belgian Congo had higher levels of public financing, skilled workers, quality of institutions, transportation and communication network than after independence (Vanthemsche, 2012). Figure C.8, Appendix C, illustrates the evolution of the share of domestic health expenditures in the total budget between 1927 to 2016. While about 11% of total expenditures were devoted for health during the colonial era, this share significantly declined to 5% during the first decade of Mobutu's regime (in the 1970s), became almost insignificant in the 1990s with the economic collapse of the State, and has fluctuated between 3 and 4% since 2000. Furthermore, the change in the government's participation in health care expenditure cannot not be solely attributed to a fall in public revenue as suggested in figure C.9, Appendix C: the increase in Gross National Income (GNI) in the late seventies and since 2000 has not induced a similar increase in the share of domestic health spending.

**How do initial investment decisions differ between facilities created before and after independence?** - Although extractive, European colonialism also massively invested in infrastructure, roads and mechanised transport. The establishment of a tax system based on custom tariffs, tax on profits and revenues provided important revenues to the colony (Gardner, 2013). After World War II, health care expenditures increased in most African colonies. Colonial regimes were more susceptible to allocate higher resources to public hospitals than after independence: the simultaneous collapse of the state and the economy in Congo after independence and in the early 1970s significantly reduced the government's capacity to finance to health care (Frankema and Buelens, 2013). In addition, the majority of (European) skilled workers fled the Congo following independence to escape the rising political instability, leaving behind indigenous Congoleses with no formal training in business, administration or medicine (Vanthemsche, 2012). The emerging nation also lost its financial and technical support from Belgium. Altogether, independence can be interpreted as a negative external shock on the structural capacity of public investment in all sectors of the economy which should have affected all newly created (post-independence) health facilities.[11] These facts can be modelled as a shift in the efficiency of structural investment from $\theta_C$ to $\theta_P$ in the post-independence period, with $\theta_C >> \theta_P$.[12]

[11]Similar investment patterns occurred across Africa following the fall of colonial regimes (Barnum, Kutzin, et al., 1993).

[12]Note that the significant increase in DAH in the DRC since 2008 (Figure C.2, Appendix C) could affect this assumption: the share of government health expenditure represents approximately 10% of the total budget that includes DAH, which is similar to what is observed during the colonial period. However, only 4 post-independence hospitals in the sample were constructed after 2008, so the recent surge in DAH should not invalidate the assumption.

**Hospital production function** - Hospital, physicians and patients interact to determine the ultimate levels of input used and output produced by health facilities (Hodgkin and McGuire, 1994). For simplicity, I only consider the public hospital decision while keeping the choice of treatment constant among physicians and patients.[13]

Consider three different inputs used in the production function of a hospital: human and physical capital, denoted $L$ and $K$, and infrastructure capital $X$. The latter, also defined as "structural capital", is a long-term determinant of the maximum capacity of output production of a hospital (such as health unit building, power plant, transport access). It differs from physical capital which corresponds to "maintenance capital" and incorporates assets that directly contribute to the delivery of health services; it is characterised by short-term durability (such as drugs, health equipment, beds). The effective stock of public infrastructure capital is therefore defined as $A = \theta X$.

The production function is modelled by a Cobb-Douglas function with constant return to scale (CRTS), and the output is given by the following equation:[14]

$$y_i = A_i k_i^{\alpha} \tag{4.1}$$

where $i$ indicates the type of hospital (Colonial $C$, or post-independence $P$) and $k$ refers to the capital to labour ratio $K/L$. The stock of physical capital equals investment ($I = K$).

**The government's maximisation problem** - Hospitals are financed by the central government which allocates health resources between colonial and post-independence hospitals to maximise the overall output production of health services.[15] The government raises revenue from a tax $\tau$ on hospital's profit to finance

[13] In the empirical analysis section, I control for several factors that could affect patients' decision to seek treatment in a hospital, such as geographical characteristics, access to health facilities and population served by hospitals.

[14] Time subscripts are omitted for simplicity

[15] Hospitals can also be seen as profit maximisers or cost minimisers in competitive environments. For simplicity, I only consider public hospitals where the facilities are provided with publicly funded health care (see Street et al. (2010) for a detailed discussion).

the health grant transferred to colonial and post-independence hospitals. Hospitals use governmental grants to invest in physical capital. The government maximisation problem is

$$\underset{k_C, k_P}{Max} A_C k_C^{\alpha} + A_P k_P^{\alpha}$$

subject to the budget constraint

$$\tau(y_C + y_P) \geq k_C + k_P \tag{4.2}$$

where the subscripts $C$ and $P$ denote the indicators respectively belonging to colonial and post-independence hospitals.

Since the budget constraint (4.2) must bind, the fiscal grants transferred to colonial and post-independence hospitals are determined by

$$A_C(\frac{1}{k_C})^{1-\alpha} = A_P(\frac{1}{k_P})^{1-\alpha} \tag{4.3}$$

The difference in structural investment between colonial and post-independence periods discussed above implies that infrastructure capital is such that $A_C > A_P$. If the effective stock of public infrastructure capital of colonial hospital is at least equal to the efficiency of post-independence infrastructure, then the governmental health grant is the highest for colonial hospitals to maintain equality of equation (4.3). However, the efficiency index $\theta_t$ decreases with time: in modern days, colonial hospitals could then have a significantly reduced efficiency index. Indeed, anecdotal evidence on the advanced deterioration of colonial hospitals tends to indicate that the modern efficiency index might be lower for colonial infrastructures. The long period separating the colonial period from the modern days combined with lack of infrastructure investments in the DRC (Ntembwa and Van Lerberghe, 2014; Brunner et al., 2019) suggest that the infrastructure of colonial hospitals might be more deteriorated than post-independence infrastructures. The effective stock of infrastructure capital might then be more important for post-independence hospitals if the efficiency index of their structure is sufficiently larger than the one of colonial infrastructures to compensate for the difference in initial structural investment. In this case, $A_C$ is lower than $A_P$ to restore equality of equation (4.2) and the optimal response of the government is to allocate a higher grant to post-independence hospitals.

**Proposition 4.1.** *Optimal allocation of health resources implies that the central government transfers a higher health grant to colonial hospitals only when their effective stock of infrastructure capital is the highest.*

See section C.2 in the appendix C for a detailed proof.

The empirical examination of health facility performance should, therefore, consider the initial structural investment of a facility and the efficiency index of the infrastructure. While information on initial structural investment is not available, historical evidence shows that colonial infrastructures should have benefited from a significantly higher initial investment. In section 4.9, I discuss how the efficiency index of modern infrastructures can relate to the results obtained from the empirical analysis and its implications on the persistence of colonial effects.

## 4.5 OLS estimation

I start by estimating the effects of colonial health investments between 1929 and 1956 on contemporary health facility performance using Ordinary Least Square (OLS) estimation. The cross-sectional analysis relies on the following linear regression function

$$Y_f = \alpha_f + \tau Col_f + \delta Access_f + \gamma X_f + \epsilon_f \tag{4.4}$$

where $Y_f$ is a vector of health facility indicators, $Col_f$ is a dummy variable equals to 1 if the facility was created by a colonial settlement, $Access_f$ is the accessibility of health facility $f$ captured by the distance in km to the nearest transportation mode (railway, road or waterways). The coefficient of interest is $\tau$ which captures the effect of historical colonial settlements on current health facility performance. The term $\alpha_f$ captures all administrative and ecclesiastical provincial-specific factors affecting health facility performance. This is important since some provinces might receive more subsidies from the central government or be prone to more specific disease burden than others (such as Ebola).

The vector of controls $X_f$ includes a set of geographic and demographic baseline characteristics at the facility level. The geographic controls are the elevation and slope, obtained from the Shuttle Radar Topography Mission (SRTM), as well as distance to coast, distance to the main provincial city, distance to the nearest Regional Distribution Centre of pharmaceutical products, distance to the nearest hospital and a dummy variable equal to 1 if the facility is located in an urban area.[16] I also control for the presence of armed conflicts that have frequently erupted across the country. The data is obtained from the Armed Conflict Location and Event Data Project (ACLED) that reports georeferenced information on political violence and protests between January 2017 and December 2018. All non-dummy variables are taken in the natural log to remove the skewness of their distribution.

I supplement this set of controls with the distance to the nearest historical transportation mode. To obtain this information, I digitised a 1928 detailed map from the Ministry of Colonies on the communication channels in Belgian Congo (Figure C.10, Appendix C) which comprises railways (black), waterways (blue) and roads (red). Additional information on transport connections from the International Bank for Reconstruction and Development IBRD (1957) supplements the mapping before independence in 1960. Lastly, health facility performance can vary with respect to the geographic distribution of the risk of malaria transmission in the country. I use an indicator of the malaria parasite transmission intensity in 2017 obtained from the Malaria Atlas Project to account for this spatial heterogeneity.[17] I exclude from the data sample Kinshasa General Referral Hospital whose financial and structural

[16] These distance measures are important to control in the DRC since they can be strong determinants of the availability of health care products (MSP, 2011).

[17] The *Plasmodium falciparum* parasite rate (PfPR) is an index of malaria transmission intensity which estimates the proportion of children aged 2 to 10 who carries the parasite (Hay and Snow, 2006). Annual medians of PfPR in 2017 was obtained at approximately 5 km resolution from the Malaria Atlas Project (`https://map.ox.ac.uk`).

capacities outperform the rest of the sample.[18]

In the decentralised Congolese economy, each province is ruled by a local government with its own budget.[19] Provincial public spending might then influence hospital performance. To account for the heterogeneity across provincial budget and the correlation of hospital performance within provinces, standard errors are clustered at this unit level (Abadie, Athey, et al., 2017).

One limitation is that I could not obtain information on the exhaustive list of public investments during the colonial period. Although controlling for the proximity to transportation mode should capture a substantial partial of public investment, colonial investments in education could arguably also be determinant of modern hospital performances. However, Huillery (2009) does not find evidence that, in French West Africa, colonial investments in education impact current health performances, as proxied by the number of medical staff. I hypothesise that similar results should apply to the Belgian Congo.

### 4.5.1 Health facility performance data

The evaluation of hospital performance involves a set of inputs used as a cost minimisation exercise or a set of outputs produced reflecting the maximisation of the health production function (Street et al., 2010).[20] Regardless of the measurement approach, the identification of the set of inputs and outputs involved in the production function is critical to determine hospital performance and, in turn, establish a benchmark comparison between colonial and post-independence hospitals. Following the theoretical model introduced in section 4.4, I use the number of medical staff (nurses) and beds respectively as proxies for human and (short-term) physical capital. Other indicators on medical equipment and machines would have been a

[18]All results are robust to the inclusion of Kinshasa General Hospital.

[19]Note, however, that only 8 % of public domestic health spending is coming from provincial governments, while 80% is from the central government, the remaining share being attributable to other administrative services and mutual funds (MSP, 2017).

[20]The issue of the most appropriate method for modelling hospital costs is subject to debate depending on whether hospitals should be analysed under the perspective of a firm or a non-profit organisation (see Pauly (1987)).

better proxy for physical capital as they can more closely reflect the current level of factors of production of health services than beds. Unfortunately, data on material equipment is incomplete in the DHIS2 and cannot be used for this exercise.

Health production is captured by the number of severe malaria cases treated. Malaria is endemic in the DRC: it is the leading cause of mortality among children below five, and one of the highest disease burdens in the country.[21] Health national policy guidance stipulates that simple malaria cases should be treated exclusively in small health facilities (health posts or health centres) while severe malaria cases should be oriented to clinics and hospitals (MSP, 2011). Consequently, the number of patients treated for severe malaria should be an important indicator of the capacity of a hospital to deliver health services. I will control for the local risk of malaria transmission to ensure that the number of malaria patients reflect the supply of health care. Similarly, the volume of patients seeking care in a hospital can also affect its performance. I use the number of deliveries, outpatient visits and emergency to capture local demand for health care and supply. These indicators could equally reflect both demand and supply and will be interpreted with respect to the number of malaria treated, which should clearly reflects the supply when controlling for the risk of malaria transmission.

Indicators relating to the financial performance of a facility are also considered and include investment and government funding. The former variable is a standard indicator for measuring strategic financial decisions, while the amount of government funding received by a health facility informs about its connection to the central government. However, it is important to distinguish current investment from the initial structural investment presented in the theoretical model. Hospital investment may have strong fluctuations from one year to the other, since the hospital stock produced by the investment can remain for several decades with little depreciation (Barnum, Kutzin, et al., 1993). I, therefore, explore whether the cumulative hospital capital stock produced in the colonial period leads to differences in modern investment

[21]The global health data from IHME provides a detailed ranking of the disease burden in the DRC: http://www.healthdata.org/democratic-republic-congo.

decisions with post-independence hospitals.

Finally, I exploit the average reported number of days per month without electricity to capture the modern efficiency of the infrastructure.[22]

### 4.5.2 Results

The results of the OLS estimation of equation (4.4) are reported in table C.2, Appendix C. The outcome variables are divided into three panels: financial characteristics in panel A with government funding and investment; inputs variables in panel B with the number of beds and nurses; and hospital output in panel C which includes the number of severe malaria cases treated and bed occupancy, defined as the ratio of inpatients by bed. Columns (1) report the effects of colonial settlement without any geographic control; columns (2) control for the access to the facility and columns (3) add all other geographic covariates described above. All regressions include provincial fixed effects. The table reports significant effects of colonial settlements on government support and input utilisation: from the regression that include all control variables, government funding increases by approximately 40% while medical staff and beds raise by 20% and 12% respectively.

Investment and output production are similar between colonial and post-independence hospitals when controlling for the number of inputs used, suggesting that both groups exhibit equal efficiency of resource utilisation. Likewise, health care demand and supply, captured by the number of malaria cases treated, emergency visits, outpatient visits and deliveries, do not significantly differ between the two groups.

Next, I explore whether colonial investments improve the contemporaneous efficiency of input utilisation. To measure efficiency, table C.3, Appendix C, reports the OLS estimates of equation (4.4) when the dependent variables are length of stay and bed occupancy, the latter being defined as the ratio of beds to inpatients and length of stay. A systematic difference in bed occupancy between colonial and post-

[22]Electricity is supplied by a national company in the DRC but with frequent outages. Some hospitals may rely on other sources of electricity (generator, solar, etc.) to maintain the standard functioning of the facility.

independence hospitals would be unanticipated and would suggest possible misuse of resources as health care demand is not significantly affected by colonial health settlements. On the other hand, length of stay can capture the efficiency of treatment provision. The results from table C.3, Appendix C, indicate that bed occupancy and length of stay are not found to differ significantly between colonial and post-independence hospitals, suggesting that the two groups present some comparable efficiency of input utilisation and treatment provision. It also indicates that the increased allocation of health funding to colonial hospitals does not seem to affect their production function when controlling for human and physical capitals.

### 4.5.3 Robustness

Regressions using geographic information can be prone to misleading results when spatial autocorrelation in residuals is not carefully accounted for (Colella et al., 2018; Kelly, 2019). In table C.4, Appendix C, I examine the robustness of the results by varying the cutoff radius for spatial clustering. The standard errors are adjusted following the method of Conley (1999), by clustering observations within circles of varying distances. The covariance matrix in Conley's method is a weighted average of spatial auto-covariances that are equal within some radius distance of observations and with zero covariance beyond the cutoff. The first row reports the coefficient of the colonial settlement from equation (4.4) and the following rows report the standard errors when changing the variance-covariance matrix through a change in the distance cutoff of the spatial clusters. The results are remarkably robust to the radius of Conley correction: the most demanding specification has a 300 km radius of allowed spatial dependence and the standard errors remain very stable for each outcome of interest.

### 4.5.4 Intensity of colonial health investment

The heterogeneity of health investment during the colonial period (Figure C.1, Appendix C) could imply the existence of various and potentially diverging effects on modern hospital performance. I examine the decomposition of colonial health investments effects into several categories: hospital ownership, type of colonial facility and colonial funding source.[23] Regarding the first category, I anticipate that public hospitals should receive more subsidies from the central government, while private hospitals might operate at lower costs (Street et al., 2010). Hospital ownership might also affect the efficiency of input utilisation: length of stay and bed occupancy rate could differ between private and public hospitals due to diverging incentives. I also anticipate some differences across the type of colonial facility (European or Congolese "indigenous"): the initial differences in the quality of health care provision could have persistent effects on modern hospital performance. Lastly, the source of colonial funding may capture varying levels of investment intensities since the State, Christian missions and private firms had their own health budget.

Table C.5, Appendix C, replicates the baseline estimates of table C.2, using additional controls for hospital ownership and two interaction terms: an interaction between colonial settlement and colonial facility, and another interaction between colonial settlement and source of funding. For each of these categories, the colonial effects on government funding remain significant. As expected, private hospitals receive less public health funding than their counterparts, while General Referral hospitals and facilities that served the Congoleses during the colonial period are found to have higher investments. Bed capacity is higher among colonial faith-based hospitals while the number of nurses surprisingly decreases for the same category. Furthermore, hospitals that originated from European health facilities have the number of nurses that increases by almost 20 percentage points but are, nonetheless, treating fewer patients when controlling for medical staff, as indicated by the negative coefficients of malaria patients and emergency cases.

Lastly, the number of nurses increases by almost 30 percentage points in hospitals that were initially funded by the colonial government, while the bed capacity is lower in those same hospitals. This last result could suggest that the colonial gov-

[23] The teaching status of a hospital would have been another important characteristic to explore, but I do not have information on this level.

ernment allocated less funding per health facility for building infrastructure than Christian or private settlers; indeed, historical evidence suggests that the colonial regime primarily aimed to expand the construction of health facilities across the colony (Duren, 1953) while Christian missions and private firms might have been more devoted to local roles around their respective areas of activities (Lyons, 2002). The increase in the number of medical staff is however intriguing and could highlight either some inefficiencies in utilisation of human capital among hospitals with colonial government funding origins or underinvestment in physical capital.[24] In panel D, outpatient visit increases in HGRs which might simply reflect the higher number of referred patients to this category. Lastly, panel E presents the results for input efficiency: bed occupancy is not significantly affected by hospital ownership or the funding source of hospitals with colonial origins; on the other hand, both bed occupancy and length of stay strongly decrease among hospitals which served Europeans during the colonial period. Yet, there are reasons to be cautious with this last result as only 40 hospitals in the data sample were initially constructed for Europeans. This coefficient might, then, capture other underlying effects: for example all hospitals with "European" colonial origins in the sample are located in rural areas and are mostly General Referral Hospitals.[25] Length of stay increases among HGRs and faith-based hospitals; the coefficient is negative but not significant in the private sector.

Next, I examine whether these results hold when restricting the sample to HGRs. Since they are supposed to be entirely subsidised by the central government, we could anticipate the absence of significant difference between the colonial and post-independence HGRs after controlling for all the observable factors that can affect the allocation of health resources. Table C.6, Appendix C, reports the baseline estimates of table C.2 while restricting the sample to HGRs in columns 1, and adding a control for health care demand, captured by the number of outpatient visits. The persistent

[24]Evidence suggests that physician and nurses tend to prefer hospitals in urban areas while deserting rural areas where the need for medical staff is higher (Bertone et al., 2016).

[25]To check this last result, I add an additional control for urban and rural areas and find that length of stay is shorter by 17 percentage points in rural areas.

effects of colonial settlements on government funding, nurses and, to a smaller extent, bed capacity remain significant when the sample is restricted on HGRs. Columns 2 document whether colonial health investments are driven by the surge in health investment during the decade preceding independence. The colonial effects appear to be largely attributed to colonial hospitals built before 1936, which emphasises the importance of initial investments as a channel of persistence.

While these results paint a consistent picture of the effects of colonial health settlements, there are reasons to be cautious in interpreting them. Historical and geographical characteristics might have determined the mission locations of the colonial enterprise in ways that are not accounted for by province fixed effects (Good, 1991; Jedwab, Selhausen, et al., 2018). Likewise, the geographical location might have been an important determinant of the intensity of colonial investment: as an example, private firms operating in mining concessions could have been more inclined to spend comparatively higher on health care services to preserve the health status of their local labour force. These possibilities highlight the concern of endogenous location of medical missions that I shall now address.

## 4.6 Matching estimation

In this section, I explore the effects of colonial health settlements with an alternative estimation strategy: matching on covariates. The rationale for using the matching procedure is to attempt to identify the true causal effect without specifying a functional form for the outcome equation: it only uses colonial hospitals and their nearest post-independence neighbours from a predefined set of matching covariates. The resulted matched sample is then used to obtain the colonial effects by estimating the differences in the outcome of interest between colonial and post-independence hospitals. Importantly, the underlying assumption of this strategy is the comparability of colonial and post-independence hospitals in the matched sample: the outcome of a post-independence hospital is assumed to be as good as the counterfactual colonial outcome - *i.e.* the outcome of a "colonial" hospital if it would not have been funded during the colonial period but after independence.

To implement the procedure, I start with spatial matching and reinforce it with additional matching covariates. Spatial matching should ensure that matched hospitals share similar geographic characteristics and, consequently, addresses the concern that colonial settlements are located in areas with better geographical access or better climatological and epidemiological conditions (or conversely, some hospitals could operate under more adverse environmental factors). The matching procedure offers the possibility to ensure that hospitals in both colonial and post-independence groups operate under similar constraining factors.

Specifically, define a neighbourhood $N(Y_i)$ of colonial hospital $i$ with observable characteristics $Y_i$ and $P$ the set of all neighbour hospitals of $i$. The set of matched sample $M_i$ of colonial hospital $i$, where post-independence hospitals $j$ fall into, is such that

$$M_i = \{j \in P | Y_j \in N(Y_i)\}$$

The overall matching sample only keeps observations for which the observable characteristics are the closest to colonial hospitals.

**Neighbourhood and matching estimator** - Once the sample is obtained, the matching procedure consists of minimising the distance between covariate values of colonial and post-independence hospitals. I use a Mahalanobis distance metric, which is appropriate for multivariate matching and robust to skewed variables. Distance between colonial ($i$) and post-independence ($j$) hospitals is formally defined as

$$(Y_i, Y_j) = \sqrt{(Y_i - Y_j)' S^{-1} (Y_i - Y_j)}$$

where $S$ is the sample covariance matrix of the covariates $Y$ in the Mahalanobis metric.

Following Abadie and Imbens (2006), I conduct a one-to-one nearest neighbour matching estimator. The estimator relies on an algorithm which consists in selecting one treated unit and matching it based on covariate values with its nearest control, the "nearest" term being defined as the smallest distance metric. The matching estimator uses average outcomes for matched units of the opposite group as an estimate of the unobserved potential outcome. Suppose a hospital $i$ has a colonial origin ($Col_i = 1$). Then its potential outcomes are defined as

$$\hat{Y}_i(1) = Y_i$$
$$\hat{Y}_i(0) = Y_j \ , \forall j \text{ such that } Col_j = 0$$

where hospital $j$ is the nearest hospital to $i$, $Y_i$ and $Y_j$ are the outcomes of the colonial and matched post-independence hospitals respectively, while $\hat{Y}_i(1)$ and $\hat{Y}_i(0)$ are the potential outcomes of a hospital when funded by colonial investment or not. I choose to match with replacement, meaning that a matched unit from the set of controls can be used multiple times.[26] I use the biased-corrected matching estimator proposed by Abadie and Imbens (2011) that adjusts for the differences in covariates values within the matched sample when there is more than one continuous matching covariate. The estimation leads to the Sample Average Treatment Effect (SATE), which underlies the fact that the matched sample results from non-random attrition (only matched hospitals are used in the estimation).

The identification and consistency of the estimate rely on two assumptions: i) Unconfoundedness or random assignment of the treatment (meaning that exposure to the treatment is independent of the outcome variable conditional on all relevant characteristics to the probability of treatment being observed) and ii) common support (or overlap) assumption, (defined as $0 < P(Col = 1|X) < 1$) which stipulates that there is a positive probability of being both a colonial or a post-independence hospital given a set of observable covariates $X$.

I argue that both assumptions should be valid in this exercise. Although the location of colonial settlements might be motivated by several factors that include geographic characteristics, the exact location of a medical mission at a sufficiently

[26]Matching with replacement increases the quality of matching and reduces the bias, but it increases the variance of the estimator. I address this issue in the results section.

low level should also bear a randomised component. The favourable conditions that could motivate a settlement decision such as the proximity to a transportation mode, the economic activity of the area or the burden of disease among the local population could be found in various location points within a pre-defined geographic area of interest. The optimal location site for the construction of a hospital is then unlikely to be unique but should rather be delimited within a small distance of points of interest during the colonial time (such as European or Congolese residential areas, proximity to transportation mode, access to water, etc.). Within this geographic area of optimal conditions, the choice of the construction site is likely to have an important random component: at the beginning of the colonial period, few public infrastructures already existed (such as roads, railways, schools) which would have otherwise limited the list of potential places to construct a facility with the desired proximity to public infrastructure or ease of access. On the contrary, the small existing number of public infrastructures during the colonial period might have opened up various possibilities of location for the construction site of a hospital and increased, thereby, the area of its potential construction. The colonial settlement should also not preclude the construction of hospitals in its vicinity if the geographical area of optimal conditions is sufficiently large, or the population density is high enough. In other words, the overlap assumption may become invalid in the case where a colonial hospital is located in an area that presents few geographic comparabilities with bordering areas and its population is sufficiently low to deter the construction of new health facilities. Although these conditions are unlikely to hold in the highly populated DRC, I check this possibility in the following subsection by restricting the data sample to small geographic areas around colonial hospitals.

### 4.6.1 Variables for balancing

**Bias-variance trade-off**: Successful matching requires achieving low imbalance between colonial and post-independence hospitals in order to reduce the estimation bias, while a sufficiently large matched sample size should reduce the variance.

The primary covariates used for the spatial matching are the longitude and latitude of health facilities. Second, I explore which additional covariates to include in the matching procedure that should affect health facility performance. Since there is no pre-treatment controls *per se* (it is not possible to find controls shared by colonial and post-independence hospitals before their creation), the choice of these additional matching covariates is sensitive: they should affect health facility performance without being determined by the colonial presence. Specifically, the empirical distribution of the covariates should be similar between matched colonial and post-independence hospitals. I use three baseline covariates that are likely to be correlated with the outcome of interest: geographic location (longitude and latitude) and the size of population served.[27]

Figure C.11, Appendix C, assesses distributional balancing in the baseline covariates between treated and untreated units in the matched sample. For each matching covariate, the graphs plot the average distance between the empirical quantile distributions of the colonial and post-independence groups calculated over the full sample (left) and the matched sample (right); in the latter, unmatched units are pruned to improve balance. The quantile-quantile (QQ) plots provide suggestive evidence of balance in the covariates for the matched sample, with values of each covariate being almost identical at every quantile.

Figure C.12, Appendix C, explores the validity of the common support assumption by comparing kernel densities of the selected matching covariates over the colonial (dashed blue) and post-independence (red) groups of hospitals. The plots provide visual evidence of the common support assumption for all matching covariates.

### 4.6.2 Results

Table C.7, Appendix C, reports the results of the matching estimations for the three sets of dependent variables: financial characteristics (government funding and

[27]The population served corresponds to the number of inhabitants in the area covered by the hospital. Additional information on the demographic profile was unfortunately not available.

financing), ii) input used (bed occupancy and number of nurses) and iii) output produced (severe malaria cases treated and emergency cases). The latter two dependent variables are divided by the number of medical staff. Columns (1) report the matching estimates when using only longitude and latitude as matching covariates, columns (2) add the matching on population served. The table indicates a significant effect of colonial health settlements on government funding and the number of beds, confirming the OLS results in the previous section. However, there is no more evidence of colonial effects on the number of nurses under the matching method. This difference with the OLS results might come from the sample restriction around matched observations. For government funding and bed capacity, the coefficients on colonial settlements are similar to the OLS estimates when all control variables are included. The increased bed capacity among colonial hospitals supports the proposition made in the theoretical model (section 4.4) that higher initial structural investment has a long-lasting impact on the physical capital of hospitals. The large effects of colonial investments on modern government funding are more puzzling. Why would modern hospitals with colonial origins receive a higher governmental grant than other hospitals?

Table C.8, Appendix C, attempts to elucidate this question by decomposing the colonial effects by hospital ownership: public, private, faith-based and General Referral Hospital (*Hôpital Général de Référence*, HGR). To do this, I perform a similar matching estimation as described in the baseline results, while adding an exact matching on hospital ownership. This procedure reduces heterogeneity and provides information about potential variations in the causal effects by ownership. The colonial effects on government funding are insignificant on all types of hospital ownership except for HGRs.[28] This result is surprising since all HGRs are supposed to be fully subsidised by the central government, according to the national health policies (MSP, 2011). Yet, many observers note that the limited budget allocated to health in the DRC adversely affects the subsidies transferred to hospitals, with

[28]Government funding is divided by the number of medical staff as it is primarily used to finance salaries.

infrequent and low disbursements (Ntembwa and Van Lerberghe, 2014; Bertone et al., 2016). The observed colonial effects on governmental grants could therefore underline the long-run relationship that some HGRs maintained with the central government to secure minimal funding. Because of their establishment during the colonial period, they might have been more successful in signalling their financial needs than newly created hospitals after independence. Unfortunately, the validity of this interpretation is limited by the lack of studies on this particular topic of health financing in the DRC.

Colonial hospitals have higher bed capacity for all types of ownership, with the exception of faith-based hospitals. Among private and faith-based colonial hospitals, the number of nurses per bed increases as well, which could be interpreted as an indicator of higher quality of health services. On the other hand, there is no colonial effect on medical staff among public hospitals.

### 4.6.3 Sensitivity analysis

I test the robustness of the results by restricting the matching sample to post-independence facilities that are located within a maximum geographic distance from colonial hospitals. Figure C.13, Appendix C, reports the sensitivity of the matching estimate to bandwidth selection for each of the outcome of interest introduced earlier. The graphs use bandwidths ranging from 5 to 100 km which correspond to the distance to the nearest hospital and the coefficients are obtained from the biased-corrected matching estimator proposed by Abadie and Imbens (2011). The regressions include all matching covariates presented above and use robust standard errors. Unsurprisingly, the variability in the coefficient estimates within the first 5 km is high in all cases due to the small size of the matched sample. The estimates are relatively constant as the distance to the nearest hospital increases for all cases. When the dependent variable is government funding or bed capacity, the matching estimates are consistently significant and positive. These findings confirm the robustness of the results described earlier. The small variations in the coefficient estimates with respect to bandwidth selection also suggest that proximity to colonial hospitals might have little effect on the outcomes of modern hospitals.

## 4.7 Instrumental variables estimation

### 4.7.1 Sleeping sickness

I explore an additional identification strategy that addresses the potential endogeneity of the colonial presence through an instrumental variable approach to estimate equation 4.4. I instrument colonial settlements by the historical geographic distribution of the sleeping sickness at the district level as reported in the public health archival data of the ministry of colonies.[29] The argument is that medical missions were mostly dedicated to contain and reduce the burden of sleeping sickness (Lyons, 2002). The exposure of districts where the burden of the disease is high should then be a good predictor for the presence of medical campaigns (Lowes and Montero, 2018).[30] Figure C.14, Appendix C, depicts the kernel density of colonial health settlements and the health zones (district level) where the presence of the sleeping sickness was reported between 1910 and 1933. The figure illustrates that the prevalence of sleeping sickness is a good predictor of the colonial presence: it documents a strong spatial correlation between colonial settlements and the prevalence of the sleeping sickness.

Does the instrument satisfy the exclusion restriction? The spread of the disease was primarily caused by movements of local populations and the ecological conditions that prevail during the colonial period (Lyons, 2002). The various socio-economic transformations that took place during the twentieth century in Congo

[29] Specifically, I exploit the reporting of sleeping sickness where the infection rate is at least equal to 1%. This arbitrary threshold aims to consider only geographic areas where the burden of sleeping sickness became significant. The archival maps also report the areas where the infection rate is less than 1%, but without further information about the number of identified cases, I cannot claim that they significantly impacted the location of colonial settlements.

[30] The tsetse fly suitability index (TSI) developed by Alsan (2015) is a useful indicator for the risk of sleeping sickness transmission at the African regional level. However, the data that I collected from the colonial public health archives provide refined information at the district level that is more suitable for this analysis

are likely to have deeply transformed these factors and changed the geographical distribution of the disease (Figure C.15, Appendix C). More importantly, although the sleeping sickness epidemic has had devastating effects among the population of Eastern Africa in the early 20th century (Scott, 1942; Lyons, 2002), its modern burden became negligible compared to other endemic diseases in the region, such as malaria or HIV (Fèvre et al., 2008). In 2017, WHO (2017) indicates that there were 1,000 new sleeping cases in the DRC, while 34,000 HIV positive were reported to be on treatment and 25 million were estimated to be malaria-infected. Unsurprisingly, these latter two diseases have attracted much more economic support from the international community during the last three decades. The implication at the health facility level is that the modern distribution of the sleeping sickness should not significantly affect health facility performance. In turn, the geographic distribution of the disease during the colonial presence should be even less correlated with contemporaneous hospital performance.

I formally examine the presence of colonial health settlements in the following first-stage equation:

$$Col_f = \alpha_f + \beta Sleeping_f + \gamma X_f + \nu_f \tag{4.6}$$

where $Sleeping_f$ is a dummy variable equal to one if sleeping sickness was present among the Congolese population during the colonial period where hospital $f$ is located. Turning to the structural equation, the effects of colonial settlements on hospital performance can be estimated as

$$Y_f = \alpha_f + \tau \hat{Col}_f + \delta Access_f + \gamma X_f + \epsilon_f \tag{4.7}$$

As before, $\alpha_f$ captures the administrative provincial fixed effects and $X_f$ is the set of control covariates described in section 4.5 at the facility level $f$.

### 4.7.2 Effects on hospital indicators

Table C.9, Appendix C, presents the first stage estimates for four dependent variables: government funding, investment, bed capacity and medical staff. The table shows that the presence of sleeping sickness strongly affects the geographical distribution of colonial settlements: the presence of medical missions increases by nearly 50 percentage points within sleeping sickness areas.

Table C.10, Appendix C, presents the local average treatment effect (LATE) estimates using the sleeping sickness instrument. As a comparison, the table also reports the coefficients of the OLS estimation (equation 4.4). Following I. Andrews et al. (2019) recommendations on potentially weak instruments, each IV column also reports the 95% Anderson-Rubin (AR) confidence interval of the coefficient on colonial settlements. The coefficient estimates are remarkably similar to the OLS estimates, except for bed capacity which is found higher with the IV estimates. Notice that because the IV strategy identifies areas with sleeping sickness disease during the colonial period, all hospitals that are located in those areas are treated as colonial. Yet, nothing prevented new hospitals to be constructed in those areas after independence, although, they might have little incentives to be close to existing facilities. Consequently, the instrument may treat some post-independence hospitals as colonials. The high standard errors of the IV estimates reflect this variability, which reduces, in turn, their statistical significance. Nonetheless, they offer further evidence of the robustness of the results.

## 4.8 Additional channel: Does DAH systematically support colonial hospitals

The conceptual framework introduced in section 4.4 gives insights on possible mechanisms through which colonial health investments could have enduring effects on modern health facilities. As such, I claim that it could be a causal nexus for the contemporaneous hospital performance if the difference between colonial and post-independence investment is high enough. I explore in this section an alternative channel of persistence of colonial effects.

The three diseases that attract the highest share of Development Assistance for Health in the DRC are HIV, Tuberculosis and Malaria (MSP, 2017). Since domestic public health expenditures are extremely low in the DRC and insufficient to cover the population health needs, donors finance almost entirely these three disease programmes and are intensively involved in the provision, storage, and distribution of the related health products (MSP, 2011). At the health facility level, donor's support can be directly observable by the availability of health products related to the three diseases. I can, therefore, explore whether donors support differently colonial and post-independence hospitals. Because malaria is endemic in the DRC, almost all health facilities are being provided with antimalarial medicines by donors (Chapter 3); I then exclude antimalarial medicines and focus solely on HIV and Tuberculosis treatment.[31] Using the presence of HIV or tuberculosis treatment in a facility as a proxy for international aid support, I estimate the following specification

$$Aid_f = \alpha_f + \tau Col_f + \delta Physician_f + \epsilon_f \tag{4.8}$$

where the dependent variable $Aid_f$ is an indicator variable that equals 1 if the facility receives aid support and 0 otherwise. The variable $Physican$ controls for the number of physicians in health facility $f$ that could positively affect the probability of aid support. Table C.12, Appendix C, reports the estimates of the regression (4.8) using a linear probability model. The first column reports the estimate without any control and the next three columns add physician, geographic characteristics and population served as controls. The results are similar with a logit model and reveal that donors' support increases by approximately 6 percentage points in hospitals with colonial origins. This quantitatively small effect becomes nonetheless statistically insignificant when the control variables are included. It is therefore not

[31] The treatment cost for an HIV infected person represents a huge financial burden, and in a country with one the highest poverty rate of Africa, the absence of donors' financial support would substantially reduce the possibility to tackle the disease burden.

possible to conclude that donors support could be a major channel of persistence of the observed colonial effects.

## 4.9 Discussion and conclusion

This study documents that colonial health settlements in the Belgian Congo established a network of health infrastructures with high structural capacity that persistently affected the contemporaneous performance of health facilities. I show that public hospitals with colonial origins receive higher funding from the central government than their counterparts which were created after independence. The effect persists even when the number of medical staff is controlled for. I further demonstrate that the persistence of colonial effects depends both on the type of the colonial funding source (State, religious and private firms) that established the health infrastructure and the targeted population during the colonial period (White European or Black Congolese). The long-run impacts of medical missions and their magnitude are remarkable in a country like DRC which suffered from decades of political and economic instability, civil wars and the complete collapse of the health system.

A plausible channel that can account for this persistence is the difference in initial infrastructure investments between colonial and post-independence hospitals. The theoretical model introduced in section 4.4 suggests that higher governmental funding to colonial hospitals is the optimal solution to the central government's problem that maximises the production of health services if the effective stock of infrastructure capital is the highest in colonial hospitals. I have explored whether donors could be a potential channel for the colonial effect without finding any evidence to support it. The results therefore suggest that colonial investment could be a causal nexus for the contemporaneous allocation of public resources.

Furthermore, colonial hospitals might not only have a better structural capacity in the short-term, they might also have established closer connections with the central government in the long-run. The limited budget of the government and the rampant corruption in the country might participate in building a network of favoured facilities lobbying for government participation. The historical connection of colonial hospitals with the central government might play a substantial role in attracting more attention from the political leaders. On the other hand, post-independence facilities, which tend to have lower structural capacity, might be less able to leverage government funding. Colonial investments would, therefore, provide a comparative advantage to colonial hospitals in competing with other health facilities to lay claim to limited public resources. This argument echoes Banerjee, Iyer, and Somanathan (2007) who demonstrate that political considerations can be closely tied to the provision of public goods in resource-constrained settings. The 2015 National Health Accounts of the DRC (MSP, 2017) indicate that more than 80% of the relatively small public health investments are devoted to the construction of health infrastructures. This suggests that recently created health facilities might receive little financial support to invest in medical equipment, information and communications technology, or to expand health services. In the short-term, this may reduce their capacity to treat patients, deliver quality health care and even pay their staff (Fox et al., 2013; Bertone et al., 2016).

The findings also suggest that the funding source of colonial settlements that can be an important vector of persistence of colonial effects on modern hospital performance. Hospitals initially funded by the colonial State tend to have lower bed capacity compared to hospitals funded by private capital or religious organisations during the colonial period. Historical evidence indicates that the primary health policy objective of the State was to expand the coverage of health care services across the country, contrary to Christian missions that aimed to reach local populations and privately funded settlements that focused on their working force (Duren, 1953; Lyons, 2002). Private and faith-based colonial settlements might then have had the opportunity to invest more resources in their own infrastructures, increasing thereby their structural capacity and producing persistent effects on modern facilities.

The results are consistent with previous literature on colonial public investments: Huillery (2009) finds suggestive evidence that modern public investments tend to be located in places historically funded by the colonial regime. Jedwab, Kerby, et al. (2017) investigate the root causes for the persistence of colonial investments in public goods in Kenya and find sunk investments and spatial coordination failures to be the most important channels. My findings resonate with these results: I show that the colonial regime had comparatively higher financial capacity and made higher structural investments in health facilities than the post-independence Congo State.

The findings from this research come from a specific country setting and should be carefully interpreted with regard to their external validity. Nonetheless, the structural investment mechanism emphasised in this chapter underlines the importance of examining the colonial roots of African health systems to understand the disparities in modern health care financing. Although health investments tended to be higher during the colonial period than after independence, colonial regimes may also have favoured unequal distribution of health care services through segregation between European and "Indigenous" populations. They could also have allocated more health resources near their economic interests. As colonial regimes are often at the origin of modern health systems in countries with colonial roots, the initial distribution of health care resources in those countries might have enduring effects on the contemporaneous provision of health care. This present study suggests that a thorough identification of health facilities built during the colonial era, the role they played and their connection with the central government should receive full consideration to understand contemporaneous inequalities in hospital performance. In particular, the observed pattern of persistence of colonial effects on the development of health institutions could offer valuable information to guide the reallocation of health resources in order to reduce inequalities in health care delivery and access to treatment. The current situation may exacerbate inequalities in access to health care if the public domestic resources are unequally distributed among public health facilities. They may give rise to a parallel two tier health system where the quality of health care is conditioned upon political considerations. Donors could play an important role in supporting strategies that address these disparities and set the right financial incentives to health care providers.

# Chapter 5

# Conclusion

Health resource allocation decisions have tremendous consequences on population health. In Low-Income Countries, global health donors play a crucial role in the financing of health systems, but their presence can also turn to be pervasive and harmful when information about population health needs is opaque and leaves unmet needs (Sridhar and Batniji, 2008). As outlined in the introduction, a range of factors have been identified in the literature affecting the effectiveness of health resources and their optimal allocation. Each chapter of this dissertation attempted to explore some of the major root causes of ineffectiveness and inefficiency in the financing of health systems in poor-resource countries. This section now summarises the findings of each chapter, lays out the contributions they bring to the related literature and discusses their overall implications.

## 5.1 Optimal allocation of health resources

Most low-income countries have now embarked on a decentralisation process of their economy. In the health sector, reforms have been adopted in the past decades to decentralise health systems with the objective of empowering local communities and better responding to local needs (Oates, 1972). If local governments have access to better information about local needs than the central government and donors, they may also have an advantage in selecting projects where Development

Assistance for Health (DAH) is the most effective. Within a decentralised economy, the appropriateness of aid conditionality raises concerns and its validity should be questioned.

The analyses in Chapter 2 indicate that a close collaboration between donors and all tiers of government is required to allocate health resources optimally. In settings where information is fragmented and incomplete while institutions are poorly performing, donors face an increased risk of obtaining and basing resource allocation decisions on misleading information. The chapter demonstrates that aid conditionality can drive resources away from their optimal allocations; conditionality might also increase the financial burden of the local government when it is committed to reducing the burden of disease within its communities. In that case, the local government's efforts to compensate for the misallocation of foreign aid reduce both fungibility and aid effectiveness. The model illustrates the potentially misleading effects on health outcomes of policies that would strictly focus on eliminating any possibility of reorienting aid through conditionality.

On the other hand, if aid is fungible within the health sector but unconditional, additional funding for health projects to improve outcomes in a specific area may end up financing health activities elsewhere. If the local government commits to poverty and ill-health reduction, unconditional aid increases both fungibility and aid effectiveness. An alternative situation where fungibility could increase aid effectiveness is when the donor precisely identifies the local needs and local government spending exhibits diminishing returns. In this scenario, the total benefits from DAH will depend on factors such as the initial allocation of domestic health resources among areas, the extent of diminishing returns to government spending, and DAH impacts on the productivity of government spending across areas (Wagstaff, 2011).

A natural way to empirically assess the predictions of chapter 2 would be to exploit observed data on allocations of health resources within the government, through grant transfers and local public spending, and donors' funding. However, the scarcity of data on fiscal transfers within African countries limits the possibility to examine this question. Nonetheless, existing data on local spending and disease burden can still provide information about the geographical distribution of health resources, understand how flows of global funds are determined, and identify overfunded geographic areas. This exercise is carried out in chapter 3 which points to the limitations of geographical aid targeting. The findings suggest that neither aid agencies nor local partners are able to identify or reach populations with the greatest needs. The results also highlight that local aid is disproportionately distributed among populations with respect to their burden of disease. The excess of health aid in some geographic areas could flag concerns about the cost-effectiveness of aid.

What factors could explain these results? At the local level, collecting accurate information in poor resource settings can be challenging when routine data is poorly and infrequently reported, and local institutions lack resources to circulate information to decision-makers. For donors, this poses a clear difficulty to track the dynamics of disease patterns among local populations, particularly in contexts of rapidly evolving burdens of diseases. Donor's mistargeting has two direct consequences: an allocative inefficiency if populations with the worst health outcomes are not receiving their share of health funds, and a technical inefficiency if some geographic areas with low health needs receive aid in excess. At the health facility level, the latter point typically materialises in overstocks of disease-specific medicines with respect to the population needs in the catchment area of the facility. Excess drug stocks increase, in turn, the risk of product expiry, the associated costs of storage, and the irrational use of medicines. The World Health Organization (WHO) estimates that more than half of all medicines consumed in the world were wrongly prescribed or dispensed (WHO, 2004). Regarding malaria treatment, Cohen et al. (2015) demonstrate that large subsidies for health products might favour inappropriate consumption of medicines with respect to patients' symptoms. Altogether, these findings highlight that allocative inefficiency may have far-reaching implications on the overall effectiveness of health resources in achieving significant health gains and minimising the overall intervention costs.

Allocation inefficiency can also stem from the complex supply system of medicines that prevail in most Sub-Sahara African (SSA) countries. Challenges in coordinating the storage and supply management of drugs due to multiple actors involved (such as district and regional warehouses, private wholesalers and distributors), numerous channels of medicine procurements working in parallel (private, public and international procurement agencies) and decoupled from patients' needs, could seriously exacerbate the risk of misallocating health resources (Yadav, 2015). The lack of a coordinated national procurement and distribution framework is a clear impediment to a well-functioning health system.

An additional barrier to improving the efficiency of the supply chain resides in the extent of necessary infrastructure investments in the country. In most of Sub-Saharan Africa, public infrastructure inherited from the colonial period is in dire need of investment. Still, donors often appear reluctant to heavily invest in projects not directly related to health or poverty in general, and the limited public budget of the country obstructs the path for making the required investments in public infrastructure.[1] In many countries, a poor transportation network considerably limits the capacity of improvements in the supply chain structure.

## 5.2 Health facility performance

In 2014, the Ebola outbreak in West Africa tested local health systems and revealed their weakness. In Sierra Leone, Guinea and Liberia, health systems showed low reactivity to the disease outbreak due to limited capacity for public health surveillance, lack of qualified human resources, medical equipment, health products and slow coordination of donors to respond in a timely manner (Chan, 2017). The tragic episode revealed the importance of strengthening health systems and global health security infrastructure to respond to future crises. As health system performance is determined by its responsiveness to changes in population health and its fair distribution of health financing (Murray et al., 1999), disparities in hospital

[1]Some exceptions exist, such as the public-private partnership the Project Last Mile, which was launched in 2010 between The Coca-Cola Company, The Coca-Cola Africa Foundation, The Global Fund, United States Agency for International Development and the Bill and Melinda Gates Foundation. In 2019, they operate in 8 African countries.

efficiency and public funding can contribute to hamper health systems.

Chapter 4 aimed to increase our understanding of inequalities in health facility performance through a historical lens and explored how colonial settlements continue to affect contemporaneous health facilities. The findings highlight that historical factors can be strong determinants of both health facility performance and government financial support. I find evidence of disparities in the allocation of public health resources between colonial and post-independence hospitals which are likely to contribute to regional inequalities in access to health care. Additionally, they could, effectively, create a two-tier provision of a health care system with different quality of health care delivery. Since government funding is primarily used to pay staff, salary payments may be more regular among colonial hospitals and, therefore, attract more qualified health workers. Even though the chapter does not find evidence of significant differences in length of stay or bed occupancy between colonial and post-independence hospitals, further research on this subject should explore how colonial legacy affects the modern quality of health care delivery. More generally, additional evidence across Sub-Saharan Africa is necessary to understand how the colonial heritage influences modern health systems and how heterogeneity in colonial ruling affected the channel of persistence.

## 5.3 Policy implications and future work

One of the 2015 Sustainable Development Goals (SDG) is for health systems of low-income countries to move away from excessive reliance on out-of-pocket expenditures and reduce, thereby, the proportion of households that incur catastrophic spending on health services. The challenge lies in finding and applying solutions to the sustainable financing of the healthcare system while making progress towards Universal Health Coverage (UHC).[2] These solutions entail greater capacity

[2] WHO (2010) defines UHC as the concept of "providing financial protection from the costs of using health services for all people of a country as well as enabling them to obtain the health services that they need, where these services should be of sufficient quality to be effective".

and willingness of governments to mobilise public revenues,[3] increased public domestic spending on health and better allocation of funds (WHO, 2010).

In this regard, donors' involvement with recipient governments is essential. First, aid coordination should be prioritised between donors. Although the presence of multiple donors, with sometimes conflicting objectives, has long been recognised as a threat to aid effectiveness,[4] donors continue to operate with little coordination efforts. Some of the risks they pose are the duplication of projects or the absence of aid funds in hard-to-reach areas, increasing thereby the costs of delivering aid and impairing the targeting of the vulnerable populations (**bourguignon2015**). The State in the recipient country may have neither the capacity nor the necessary information to stimulate aid coordination. Second, donors should provide support in designing fiscal policies that foster a better provision of health services in terms of quality and coverage, and guarantee the smooth transition of the financing of health programmes as governments reallocate resources to health priorities (Resch and Hecht, 2018). In decentralised countries, the reduced role of the central government in local health spending should ignite a change in the relationship between global health donors and recipient countries. Local governments should have better information about local health needs and be more accountable to their local representatives (Oates, 1972). This paradigm shift in donors' approach would induce greater involvement of subnational governments in aid allocation decision-making processes in order to ensure greater accountability.

Additionally, both donors and recipient countries should devote a particular attention to augment the availability of local information. Data on basic indicators such as local disease burdens, the number of patients treated or under treatment and local (and regional) government health spending are often inaccurate or missing. Investment efforts should, therefore, also focus on collecting reliable local information to improve decision-making processes. More extensive use of precise and reliable

[3]In 2001, African leaders met in Abuja and pledged to reach 15% of government expenditure allocated to health sector.

[4]The Paris Declaration on Aid Effectiveness in 2005 recognised aid coordination (or harmonisation) as a core objective for making aid more effective.

information on health needs at the community level is crucial to maximise the impact of health interventions. Once again, health-decision makers should engage with local community representatives to identify the gap in existing information in order to better assess epidemiological and demographic profiles.

Collecting regional and local data on the procurement and supply of medicines is also needed to improve the efficiency of health spending. In some countries, routine measurement of stock availability in health facilities already exists and is essential to capture the regional disparities in the supply of drugs. Furthermore, data on the stock of medicines can be useful indicators of local health resources when reliable health spending data is missing. The empirical studies presented in chapters 3 and 4 rely on this innovative approach. I provided suggestive evidence that stocks of antimalarial medicines in health facilities can be good indicators for the aid funding allocated to the disease when government health spending is minimal. The robustness of this approach could be tested with different context-specific diseases; for instance, the stock of Antiretroviral (ARV) medicines could be a promising candidate to capture HIV related funding at the local level. Another line for future research would be to exploit routine data on the stocks of medicines in central and regional distribution centres. Gathering evidence at these different points of the medicine distribution would offer the possibility to track resources from the entry points of the medicine in the country to its consumption by patients. They would also provide invaluable insight to better understand the source of inefficiencies in the distribution of health products, as well as the overall geographical allocation of resources. Anecdotal evidence from the DRC or Liberia suggests that this type of data already exists within the medicine distribution system, but it is often fragmented and incomplete due to the presence of the numerous actors that poorly exchange their information. Better coordination between donors and central, regional and local medicine suppliers is therefore crucial to meet local health needs.

This dissertation explored several methods to scrutinise the allocation of health care resources in the DRC. Similar research in other national settings is necessary to examine the external validity of my results. Furthermore, I have previously discussed the complexity of the environment in which most African health systems operate. Whilst the analysis in chapter 3 includes a thorough estimation of the costs associated with the procurement, storage and distribution of medicines, as well as the estimated costs involved with human resources, the scarcity of data limits the possibility to expand the analysis to wider areas. Indeed, an analysis based on a large geographic coverage would entail important heterogeneity in the transportation costs of drugs, specially if the area contains far, isolated and hard to reach locations. More research on the "last mile" costs (the costs associated with the final point of delivery) in isolated areas is important to understand the geographical distribution of transportation costs within countries and ultimately, how resources should be allocated to meet the desired health outcomes. Further empirical evidence on geographic aid targeting in different settings should also assist in determining how donors' capacity to reach the greatest needs is affected by accessibility. Do donors allocate more health resources in easy-to-reach areas for a given burden of disease within the local population? How do resource allocation decisions respond to a change in the burden of disease? These questions are important to tackle in order to better understand the capacity of donors to target health needs in a timely manner and strengthen health systems.

Nonetheless, future research would probably be also limited by the availability of data, particularly to capture the dynamics of diseases among the local population. Demographic and Health Surveys (DHS) are useful to obtain epidemiological information, but their infrequency offers limited possibilities to precisely estimate the evolution of diseases among local populations. Alternative techniques that rely on Geographic Information System (GIS) data, such as the one introduced in chapter 3, can provide valuable information to estimate the local burden of diseases. When combined with colonial data, GIS techniques could also prove to be useful to push further the examination of colonial legacy and understand the path dependence of financing of modern health systems.

This dissertation has emphasised policy alternatives to increase health funds' effectiveness and strengthen health systems in poor-resources countries. In this regard, its overall message is hopeful. Reforms in the global health landscape that integrate closer collaboration between donors and recipient countries to increase government and local communities ownership, capacity for financial management and predictability of donors' funding have the potential to increase the overall effectiveness of aid.

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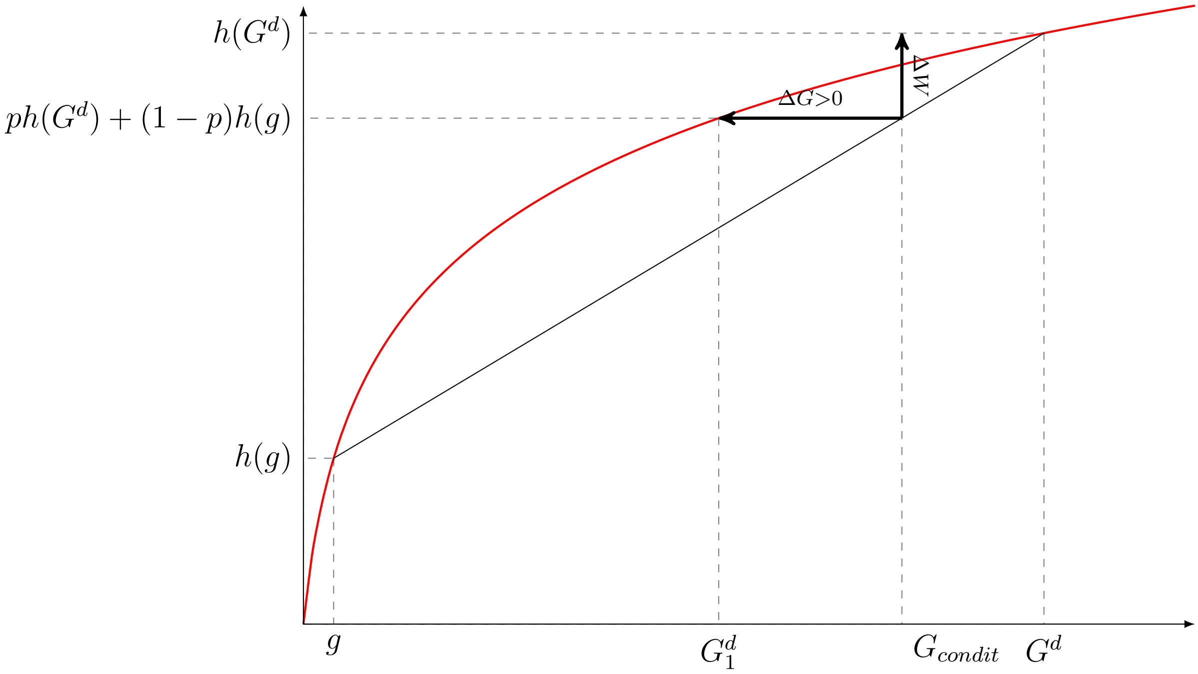
# Appendices

# Appendix A

# Appendix for chapter 2

Figure A.1: Health benefits based on conditional and unconditional health resources




## A.1 Local public provision of health care with domestic resources

**Proofs for the determination of fiscal grant** The central government determines the optimal fiscal grant $a$ from the following objective function

$$\underset{a_p,a_R}{Max}\pi\lambda_p h(\theta_p, g_p + a_p) + (1-\pi)[\lambda_R h(\theta_R, g_R + a_R) + y(1-\tau)]$$

where $\lambda_k$ is the weight given by the central government for group $k$. The central government's budget constraint is given by

$$(1-\pi)y\tau \geq qa$$

where $a = \pi a_p + (1-\pi)a_R$.

The budget constraint binds and I insert it into the objective function of the central government

$$\underset{a_p,a_R}{Max} \pi\lambda_p h(\theta_p, g_p + a_p) + (1-\pi)[\lambda_R h(\theta_R, g_R + a_R) + y - q(\pi a_p + (1-\pi)a_R)]$$

FOC with respect to $a_p$

$$\pi\lambda_p h_2(\theta_p, g_p + a_p) - \pi\lambda_R \left(q'(G)a + q(G)\right) = 0$$

FOC with respect to $a_R$

$$(1-\pi)\lambda_R \left(h_2(\theta_R, g_R + a_R) - \left(q'(G)a + q(G)\right)\right) = 0$$

The FOC with respect to $a_p$ and $a_R$ can then be simplified as

$$h_2(\theta_p, g + a_p) = \frac{\lambda_R \left(q'(G)a + q(G)\right)}{\lambda_p}$$

and

$$h_2(\theta_R, g + a_R) = q'(G)a + q(G)$$

**Proofs of Unconditional fiscal grant**

If the central government decides to transfer an unconditional (without use restrictions) lump sum grant per capita $a$ to the community, the optimal local expenditures for the provision of health services selected by the local government solves

$$\underset{G_P^c,G_R^c}{Max} \{\pi\mu_P h(\theta_P, G_P^c) + (1-\pi)\mu_R[h(\theta_R, G_R^c) - cg_R]\}$$

subject to the budget constraint:

$$q(G^c)G^c \leq (1-\pi)cg_R + aq(G^c)$$

where the total provision of the private good for group $k$ is denoted by $G_k^c = g_k + a$ with $g = \pi g_p + (1-\pi)g_R$.

Note that $G^c = \pi G_P^c + (1-\pi)G_R^c$. Inserting the budget constraint into the objective function of the local government gives:

$$\pi\mu_P h_2(\theta_P, G_P^c) - \mu_R\pi[q'(G^c)G^c + q(G^c)] + \mu_R\pi a q'(G^c) = 0$$

$$\begin{aligned} h_2(\theta_P, G_P^c) &= \frac{\mu_R}{\mu_P} q'(G^c)(G^c - a) + q(G^c) \\ &= \frac{\mu_R}{\mu_P} q'(G^c) g + q(G^c) \end{aligned}$$

since $G^c = g + a$. Likewise, the FOC with respect to the second argument lead to:

$$(1-\pi)\mu_R h_2(\theta_P, G_R^c) - \mu_R(1-\pi)[q'(G^c)G^c + q(G^c)] + \mu_R(1-\pi)a q'(G^c) = 0$$

Hence,

$$\begin{aligned} h_2(\theta_P, G_R^c) &= q'(G^c)(G^c - a) + q(G^c) \\ &= q'(G^c) g + q(G^c) \end{aligned}$$

### Proofs of Conditional fiscal grant

The marginal propensity to spend on the sick out of conditional grant is obtained by applying the implicit function theorem on the first order-condition (4.2) gives:

$$\begin{aligned} \frac{\partial g_P^*}{\partial a^g} &= -\frac{h_{22}(\theta_P, g_P)p_1 - \frac{\mu_R}{\mu_P}(q''(G^c)g + q'(G^c)}{h_{22}(\theta_P, G_P^c)p_1 + h_{22}(\theta_P, g_P)(1-p_1) - \pi\frac{\mu_R}{\mu_P}(q''(G^c)g + 2q'(G^c))} \\ &= -\left(1 - \frac{h_{22}(\theta_P, g_P)(1-p_1) + \frac{\mu_R}{\mu_P}(q''(G^c)g + q'(G^c) - \pi\frac{\mu_R}{\mu_P}(q''(G^c)g + 2q'(G^c)}{h_{22}(\theta_P, G_P^c)p_1 + h_{22}(\theta_P, g_P)(1-p_1) - \pi\frac{\mu_R}{\mu_P}(q''(G^c)g + 2q'(G^c))}\right) \\ &= -\left(1 - \frac{1 - p_1 + \frac{\mu_R}{\mu_P}\frac{q''(G^c)g + 2q'(G^c)(1-\pi) - q'(G^c)}{h_{22}(\theta_P, g_P)}}{p_1\frac{h_{22}(\theta_P, G_P^c)}{h_{22}(\theta_P, g_P)} + 1 - p_1 - \pi\frac{\mu_R}{\mu_P}\frac{q''(G^c)g + 2q'(G^c)}{h_{22}(\theta_P, g_P)}}\right) \\ &= -\left(1 - \frac{1 - p_1 + \frac{\mu_R}{\mu_P}\frac{\kappa_c(1-\pi) - q'(G^c)}{h_{22}(\theta_P, g_P)}}{p_1\frac{h_{22}(\theta_P, G_P^c)}{h_{22}(\theta_P, g_P)} + 1 - p_1 - \pi\frac{\mu_R}{\mu_P}\frac{\kappa_c}{h_{22}(\theta_P, g_P)}}\right) \end{aligned}$$

with $\kappa_c = q''(G^c)g + 2q'(G^c)$.

## A.2 Public provision of health care resources with foreign aid

#### Proof of case 1: Grant $a$ and aid $d$ unconditional

Totally differentiating (2.13) yields the following marginal propensity to spend out of aid:

$$\begin{aligned}
\frac{\partial g_P^*}{\partial d} &= -(a'(d)+1)\frac{h_{22}(\theta_P, G_P^d) - \frac{\mu_R}{\mu_P}(q''(G^d)g + q'(G^d)}{h_{22}(\theta_P, G_P^d) - \pi\frac{\mu_R}{\mu_P}(q''(G^d)g + 2q'(G^d)} \\
&= -(a'(d)+1)\left(1 - \frac{\frac{\mu_R}{\mu_P}(q''(G^d)g + q'(G^d) - \pi\frac{\mu_R}{\mu_P}(q''(G^d)g + 2q'(G^d)}{h_{22}(\theta_P, G_P^d) - \pi\frac{\mu_R}{\mu_P}(q''(G^d)g + 2q'(G^d)}\right) \\
&= -(a'(d)+1)\left(1 - \frac{\frac{\mu_R}{\mu_P}(1-\pi)\kappa_d - \frac{\mu_R}{\mu_P}q'(G^d)}{h_{22}(\theta_P, G_P^d) - \pi\frac{\mu_R}{\mu_P}\kappa_d}\right) \\
&= -(a'(d)+1)\left(1 - \frac{1 - \pi - \frac{q'(G^d)}{\kappa_d}}{\widetilde{\pi}^d - \pi}\right)
\end{aligned}$$

with $\widetilde{\pi}^d = \frac{h_{22}(\theta_P, G_p^d)}{\kappa_d}\frac{\mu_P}{\mu_R}$ and $\kappa_d = q''(G^d)g + 2q'(G^d)$.

#### Conditional grant $a$ and unconditional aid $d$

In this situation, the local government allocates its local resources $g$ and the external funding that it receives from the donor to maximise its objective function. However, it has no control over the allocation of the federal grant $a$. The optimal resource allocations solve the problem:

$$\begin{aligned}
\max_{G_P^{gd}, G_R^{gd}} &\left[\pi\mu_P W^P(\theta_P, G_P^d) + (1-\pi)\mu_R W^R(\theta_R, g_R)\right] p_1 \\
&+ \left[\pi\mu_P W^P(\theta_P, G_P^s) + (1-\pi)\mu_R W^R(\theta_R, G_{pR}^c)\right](1-p_1)
\end{aligned}$$

s.t. $q(G^d)G^s \leq (1-\pi)cg_R + dq(G^d)$

where $G_P^s = g_P + d$ and $G^s = g + d$. The local government's first-order conditions yield to:

$$\frac{\partial W^P(\theta_P, G_p^d)}{\partial G_P^s} p_1 + \frac{\partial W^P(\theta_P, G_P^s)}{\partial G_P^s}(1-p_1) = \frac{\mu_R}{\mu_P} q(G^d) \left(1 + \frac{1}{e(G^d)} \frac{g}{G^d}\right) \tag{A.1}$$

Sufficient conditions for the existence of a unique maximum are

$$h_{22}(\theta_P, G_P^d)p_1 + h_{22}(\theta_P, G_P^s)(1-p_1) - \frac{\mu_R}{\theta_P \mu_P}(q''(G^d)g + q'(G^d)) < 0$$

Unconditional aid transfer to the local government coupled with a conditional grant leads to similar results to the previous case. The welfare loss of conditional grant is given by the probability of the central government to misallocate its funds (targeting the low-need) and the social welfare difference between $W(G_P^d)$ and $W(G_P^s)$. In particular, if the share of foreign aid on total health expenditures is high and close to unity, the welfare loss of conditional grant becomes marginal. Totally differentiating (A.1), the effects of aid on local health expenditures are given by:

$$\frac{\partial g_P^*}{\partial d} = -\frac{(a'(d)+1)h_{22}(\theta_P, G_P^d)p_1 + h_{22}(\theta_P, G_P^s)(1-p_1) - (a'(d)+1)\frac{\mu_R}{\mu_P}(q''(G^d)g + q'(G^d)}{h_{22}(\theta_P, G_P^d)p_1 + h_{22}(\theta_P, G_P^s)(1-p_1) - \pi\frac{\mu_R}{\mu_P}(q''(G^d)g + 2q'(G^d))} \tag{A.2}$$

$$= -(a'(d)+1)\left(1 - \frac{h_{22}(\theta_P, G_P^s)(1-\frac{1}{a'(d)+1})(1-p_1) + \frac{\mu_R}{\mu_P}(\kappa_d - q'(G^d) - \pi\kappa_d)}{h_{22}(\theta_P, G_P^d)p_1 + h_{22}(\theta_P, G_P^s)(1-p_1) - \pi\frac{\mu_R}{\mu_P}\kappa_d}\right) \tag{A.3}$$

$$= -(a'(d)+1)\left(1 - \frac{h_{22}(\theta_P, G_P^s)\frac{a'(d)}{a'(d)+1}(1-p_1) + \frac{\mu_R}{\mu_P}\left(\kappa_d(1-\pi) - q'(G^d)\right)}{\theta_P, G_P^d)p_1 + h_{22}(\theta_P, G_P^s)(1-p_1) - \pi\frac{\mu_R}{\mu_P}\kappa_d}\right) \tag{A.4}$$

$$= -(a'(d)+1)\left(1 - \frac{\frac{a'(d)}{a'(d)+1}\widetilde{\pi}^s(1-p_1) - \frac{q'(G^d)}{\kappa_d} + 1 - \pi}{\widetilde{\pi}^d p_1 + \widetilde{\pi}^s(1-p_1) - \pi}\right) \tag{A.5}$$

where

$$\widetilde{\pi}^k = \frac{h_{22}(\theta_P, G_p^k)}{\kappa^d}\frac{\mu_P}{\mu_R}$$

The effects of foreign aid on local health expenditures critically depend on the sign of $a'(d)$. If the central government decides to tie its fiscal grant to the presence of foreign aid ($a'(d) > 0$), then local expenditures increase.

Comparing (A.2) with the case of unconditional aid and grant (2.14), the impact of an conditional grant on the partial effect of aid on local government spending depends on the sign of $a'(d)/(a'(d)+1)\widetilde{\pi}^s(1-p_1) - q'(G^d)/\kappa_d$ [1]. When this term is positive, a conditional grant increases the effects of aid on local health expenditures to the high-need. However, the positivity condition cannot hold if the central government has almost perfect information about local health needs ($p_1$ close to 1) or if the effect of aid on the fiscal grant is insignificant ($a'(d)$ close to 0). In such cases, conditional grant reduces the effect of aid on the local health expenditures to the high-need group.

In addition, since conditional grant funding increases with foreign aid, the local government can reduce its own health expenditures. Nonetheless, this effect is mitigated by the probability that the central government incorrectly assesses the local needs of each subgroup. Consequently, the maximum effect of external aid on local expenditures is reached when $p_1 = 0$ and decreases with $p_1$ increasing.

The comparison of case 2 (2.18) and case 3 (A.2) leads to more ambiguous results and depends on the probabilities of the donor and the central government to successfully target the high-need group, as well as the central government's response to foreign aid. When both the central government and the donor have perfect information ($p_1 = p_2 = 1$), the case where fiscal grant is conditional (case 2) has lower increasing effect on the local health expenditures propensity to spend out of aid than the case where aid is conditional (case 3), provided that $d > a$. The logic behind this mimics the proof in case 2 (conditional aid and unconditional grant): since the local government increases its health care spending to compensate the misallocation of resources from either the donor or the central government, the

[1]The case where $a'(d) < 0$ is omitted as it constitutes a straightforward source of fungibility of aid. However, this case can be easily included in the reasoning below, and will be mostly the opposite of the results obtained when the marginal effect of aid on fiscal grant is positive.

marginal propensity to spend out of aid depends directly on probability that local needs are correctly assessed and on the quantity of health resources transferred. The effects of a conditional grant on local government spending in the presence of unconditional aid are obtained from totally differentiating the first-order condition:

$$\frac{\partial g_P^*}{\partial a} = -\frac{h_{22}(\theta_P, G_P^d)p_1 - \frac{\mu_R}{\mu_P}(q''(G^d)g + q'(G^d)}{h_{22}(\theta_P, G_P^d)p_1 + h_{22}(\theta_P, G_P^s)(1-p_1) - \pi\frac{\mu_R}{\mu_P}(q''(G^d)g + 2q'(G^d)} \tag{A.6}$$

$$= -\left(1 - \frac{h_{22}(\theta_P, G_P^s)(1-p_1) + \frac{\mu_R}{\mu_P}(q''(G^d)g + q'(G^d) - \pi\frac{\mu_R}{\mu_P}(q''(G^d)g + 2q'(G^d)}{h_{22}(\theta_P, G_P^d)p_1 + h_{22}(\theta_P, G_P^s)(1-p_1) - \pi\frac{\mu_R}{\mu_P}(q''(G^d)g + 2q'(G^d)}\right) \tag{A.7}$$

$$= -\left(1 - \frac{(1-p_1) + \frac{\mu_R}{\mu_P}\frac{\kappa_d(1-\pi) - q'(G^d)}{h_{22}(\theta_P, G_P^s)}}{\frac{h_{22}(\theta_P, G_P^d)}{h_{22}(\theta_P, G_P^s)}p_1 + 1 - p_1 - \pi\frac{\mu_R}{\mu_P}\frac{\kappa_d}{h_{22}(\theta_P, G_P^s)}}\right) \tag{A.8}$$

$$= -\left(1 - \frac{(1-p_1)\widetilde{\pi}^s + 1 - \pi - \frac{q'(G^d)}{\kappa_d}}{p_1\widetilde{\pi}^d + (1-p_1)\widetilde{\pi}^s - \pi}\right) \tag{A.9}$$

with $\widetilde{\pi}^s = \frac{h_{22}(\theta_P, G_p^s)}{\kappa^d}\frac{\mu_P}{\mu_R}$.

Comparing the case where the donor is absent (2.12) with (A.6) reveals ambiguous effects. Assuming $\kappa_j < 0$, the comparative effects of a conditional grant in the presence and the absence of foreign aid depend on the difference in the marginal rate of substitution between conditional grant with unconditional aid and conditional aid alone. It means that the level of local health expenditures critically depends on the effects of aid on the marginal health benefit of high-need individuals.

**Proposition A.1.** *If the donor's intervention has a significantly large effect on the marginal health benefit of the high-need members or when $p_1$ is large enough, the local government's marginal propensity to spend out of conditional grant is higher with foreign aid than without it.*

*Proof.* Compare the effects of conditional grant with (A.6) and without (2.12) foreign aid. The condition under which foreign aid negatively affects the marginal propensity to spend out of conditional grant is

$$\frac{h_{22}(\theta_P, G_P^d)}{h_{22}(\theta_P, G_P^s)}p_1 + 1 - p_1 - \pi\frac{\mu_R}{\mu_P}\frac{\kappa_d}{h_{22}(\theta_P, G_P^s)} > \frac{h_{22}(\theta_P, G_P^c)}{h_{22}(\theta_P, g_P)}p_1 + 1 - p_1 - \pi\frac{\mu_R}{\mu_P}\frac{\kappa_c}{h_{22}(\theta_P, g_P)}$$
$$p_1(\frac{h_{22}(\theta_P, G_P^c)}{h_{22}(\theta_P, g_P)} - \frac{h_{22}(\theta_P, G_P^d)}{h_{22}(\theta_P, G_P^s)}) < \pi\frac{\mu_R}{\mu_P}(\frac{\kappa_c}{h_{22}(\theta_p, g_p)} - \frac{\kappa_d}{h_{22}(\theta_p, G_p^s)})$$

In addition, $\kappa_c > \kappa_d$ (if $\kappa_j < 0$) and $g_P < G_P^s = g_P + d$. Hence one of the condition under which this last inequality is satisfied is when $p_1$ is close enough to 0.

The other condition comes from the comparison of the numerators between (A.6) and (2.12). In particular, foreign aid deteriorates the marginal propensity to spend out of conditional grant if

$$\frac{\kappa_c(1-\pi) - q'(G^c)}{h_{22}(\theta_P, g_P)} > \frac{\kappa_d(1-\pi) - q'(G^d)}{h_{22}(\theta_P, G_P^s)}$$

This last inequality is ambiguous as $\kappa_c > \kappa_d$ and $h_{22}(\theta_P, g_P) < h_{22}(\theta_P, G_P^s)$. Therefore, this inequality holds if the effect of foreign aid on the marginal health benefit of the high-need groups is small enough. $\square$

Provided that foreign aid has a significant impact on the marginal health benefit of the high-need, local government expenditures rise with external funding. However, when the probability of the central government to rightly target the high-need group is low or when the amount of foreign aid $d$ is small enough, this result does not hold and the donor funds exacerbate the reduction in local expenditures. This result holds even if the local government cares only about high-need individuals ($\mu_R = 0$). On the other hand, if the local government only maximizes the welfare of the low-need group, then the presence of foreign aid increases the local government's expenditures for health care services toward the sick when the fiscal grant is conditional.

**Proofs of Case 4. Conditional grant $a$ and aid $d$**

I use the Implicit Function Theorem to derive the marginal effect of foreign aid on the optimal local health expenditures.

$$\frac{dg_P^*}{dd} = \\ -\frac{(a'(d)+1)h_{22}(\theta_P, G_P^d)p_1p_2 + a'(d)h_{22}(\theta_P, G_P^c)p_1(1-p_2)}{h_{22}(\theta_P, G_P^d)p_1p_2 + h_{22}(\theta_P, G_P^c)p_1(1-p_2) + h_{22}(\theta_P, G_P^s)(1-p_1)p_2 + h_{22}(\theta_P, g_P)(1-p_1)(1-p_2) - \pi\frac{\mu_R}{\mu_P}\kappa_d} \\ -\frac{h_{22}(\theta_P, G_P^s)(1-p_1)p_2 - (a'(d)+1)\frac{\mu_R}{\mu_P}(\kappa_d - q'(G^d))}{h_{22}(\theta_P, G_P^d)p_1p_2 + h_{22}(\theta_P, G_P^c)p_1(1-p_2) + h_{22}(\theta_P, G_P^s)(1-p_1)p_2 + h_{22}(\theta_P, g_P)(1-p_1)(1-p_2) - \pi\frac{\mu_R}{\mu_P}\kappa_d}$$

Define $\widetilde{\pi}^k = \frac{h_{22}(\theta_p, G_p^k)}{\kappa_d}\frac{\mu_P}{\mu_R}$. Then,

$$\begin{aligned}\frac{dg_P^*}{dd} &= -\frac{(a'(d)+1)\widetilde{\pi}^d p_1p_2 + a'(d)\widetilde{\pi}^c p_1(1-p_2) + \widetilde{\pi}^s(1-p_1)p_2 - (a'(d)+1)(1-\frac{q'(G^d)}{\kappa_d})}{\widetilde{\pi}^d p_1p_2 + \widetilde{\pi}^c p_1(1-p_2) + \widetilde{\pi}^s(1-p_1)p_2 + \widetilde{\pi}^{g_P}(1-p_1)(1-p_2) - \pi} \\ &= -(a'(d)+1)\left(1 - \frac{\frac{a'(d)}{a'(d)+1}p_2(1-p_1)\widetilde{\pi}^s + \frac{1}{a'(d)+1}p_1(1-p_2)\widetilde{\pi}^c + (1-p_1)(1-p_2)\widetilde{\pi}^{g_P} + 1 - \pi - \frac{q'(G^d)}{\kappa_d}}{p_1p_2\widetilde{\pi}^d + p_2(1-p_1)\widetilde{\pi}^s + p_1(1-p_2)\widetilde{\pi}^c + (1-p_1)(1-p_2)\widetilde{\pi}^{g_P} - \pi}\right)\end{aligned}$$

I should then examine the special case when the local government only cares about the sick ($\mu_R/\mu_P = 0$). In this scenario, equation (2.20) becomes

$$\left.\frac{\partial g_P^*}{\partial d}\right|_{\frac{\mu_P}{\mu_R}=0} = -(a'(d)+1)\left(1 - \frac{\frac{a'(d)}{a'(d)+1}p_2(1-p_1)h_{22}(\theta_P, G_P^s) + \frac{1}{a'(d)+1}p_1(1-p_2)h_{22}(\theta_P, G_P^c) + (1-p_1)(1-p_2)h_{22}(\theta_P, g_P)}{p_1p_2h_{22}(\theta_P, G_P^d) + p_2(1-p_1)h_{22}(\theta_P, G_P^s) + p_1(1-p_2)h_{22}(\theta_P, G_P^c) + (1-p_1)(1-p_2)h_{22}(\theta_P, g_P)}\right)$$

**Proof of Proposition 2.5**:

Consider the difference in equations (A.6) and (2.21). It follows that:

$$\left.\frac{\partial g_P^*}{\partial a}\right|_{\text{case3}} - \left.\frac{\partial g_P^*}{\partial a}\right|_{\text{case4}} = \\ \frac{(1-p_1)\widetilde{\pi}^s + 1 - \pi - \frac{q'(G^d)}{\kappa_d}}{p_1\widetilde{\pi}^d + (1-p_1)\widetilde{\pi}^s - \pi} - \frac{\widetilde{\pi}^s(1-p_1)p_2 + \widetilde{\pi}^{g_P}(1-p_1)(1-p_2) + 1 - \pi - \frac{q'(G^d)}{\kappa_d}}{p_1p_2\widetilde{\pi}^d + p_2(1-p_1)\widetilde{\pi}^s + p_1(1-p_2)\widetilde{\pi}^c + (1-p_1)(1-p_2)\widetilde{\pi}^{g_P} - \pi}$$

Define the difference in the numerator as

$$A = (1-p_1)\widetilde{\pi}^s - (\widetilde{\pi}^s(1-p_1)p_2 + \widetilde{\pi}^{g_P}(1-p_1)(1-p_2)) = (1-p_1)(1-p_2)\left(\widetilde{\pi}^s - \widetilde{\pi}^{g_P}\right) > 0$$

if $0 < p_1 < 1$ and $0 < p_2 < 1$ since $\widetilde{\pi}^s > \widetilde{\pi}^{g_P}$. In addition, define $B$ as the difference in the denominators:

$$
\begin{aligned}
B &= p_1\widetilde{\pi}^d + (1-p_1)\widetilde{\pi}^s - \left(p_1 p_2\widetilde{\pi}^d + p_2(1-p_1)\widetilde{\pi}^s + p_1(1-p_2)\widetilde{\pi}^c + (1-p_1)(1-p_2)\widetilde{\pi}^{g_P}\right)\\
&= p_1(1-p_2)\widetilde{\pi}^d + (1-p_1)(1-p_2)\widetilde{\pi}^s - (p_1(1-p_2)\widetilde{\pi}^c + (1-p_1)(1-p_2)\widetilde{\pi}^{g_P})\\
&= (1-p_1)(1-p_2)\left(\widetilde{\pi}^s - \widetilde{\pi}^{g_P} + \frac{p_1}{1-p_1}(\widetilde{\pi}^d - \widetilde{\pi}^c)\right) > 0
\end{aligned}
$$

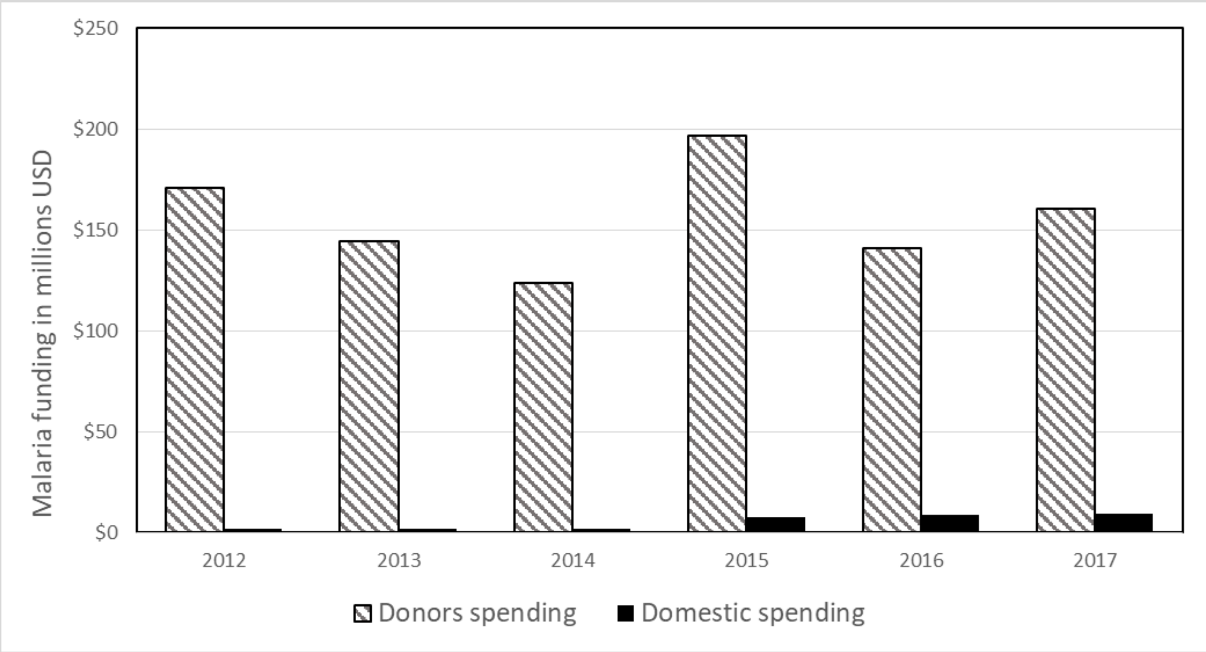
if $0 < p_1 < 1$ and $0 < p_2 < 1$ since $\widetilde{\pi}^d > \widetilde{\pi}^c$ and $\widetilde{\pi}^s > \widetilde{\pi}^{g_P}$. It follows that $B > A$, then

$$
\left.\frac{\partial g_P^*}{\partial a}\right|_{\text{case3}} < \left.\frac{\partial g_P^*}{\partial a}\right|_{\text{case4}}
$$

# Appendix B

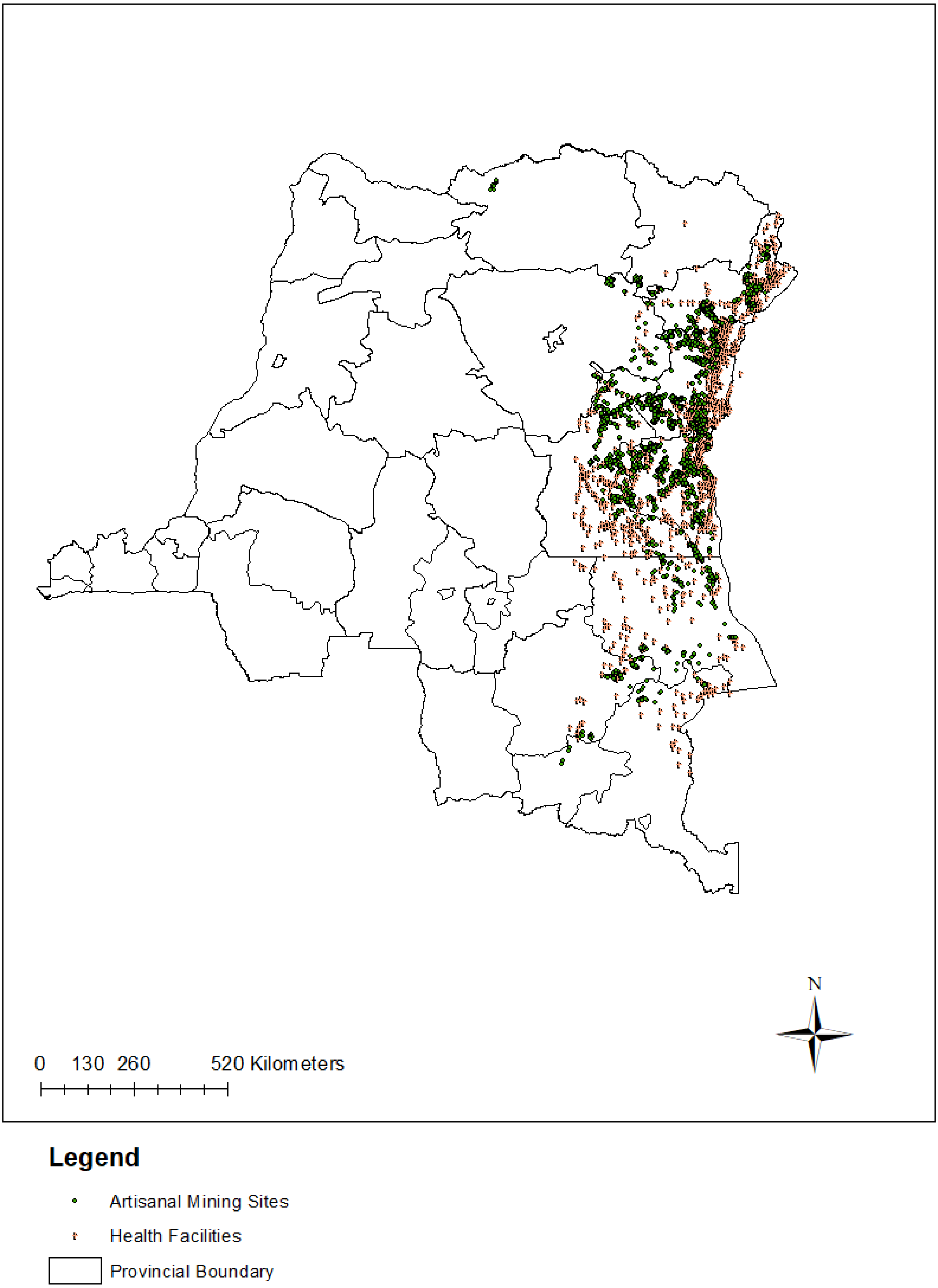
# Appendix for chapter 3

Figure B.1: Share of donors and domestic spending in total malaria investment



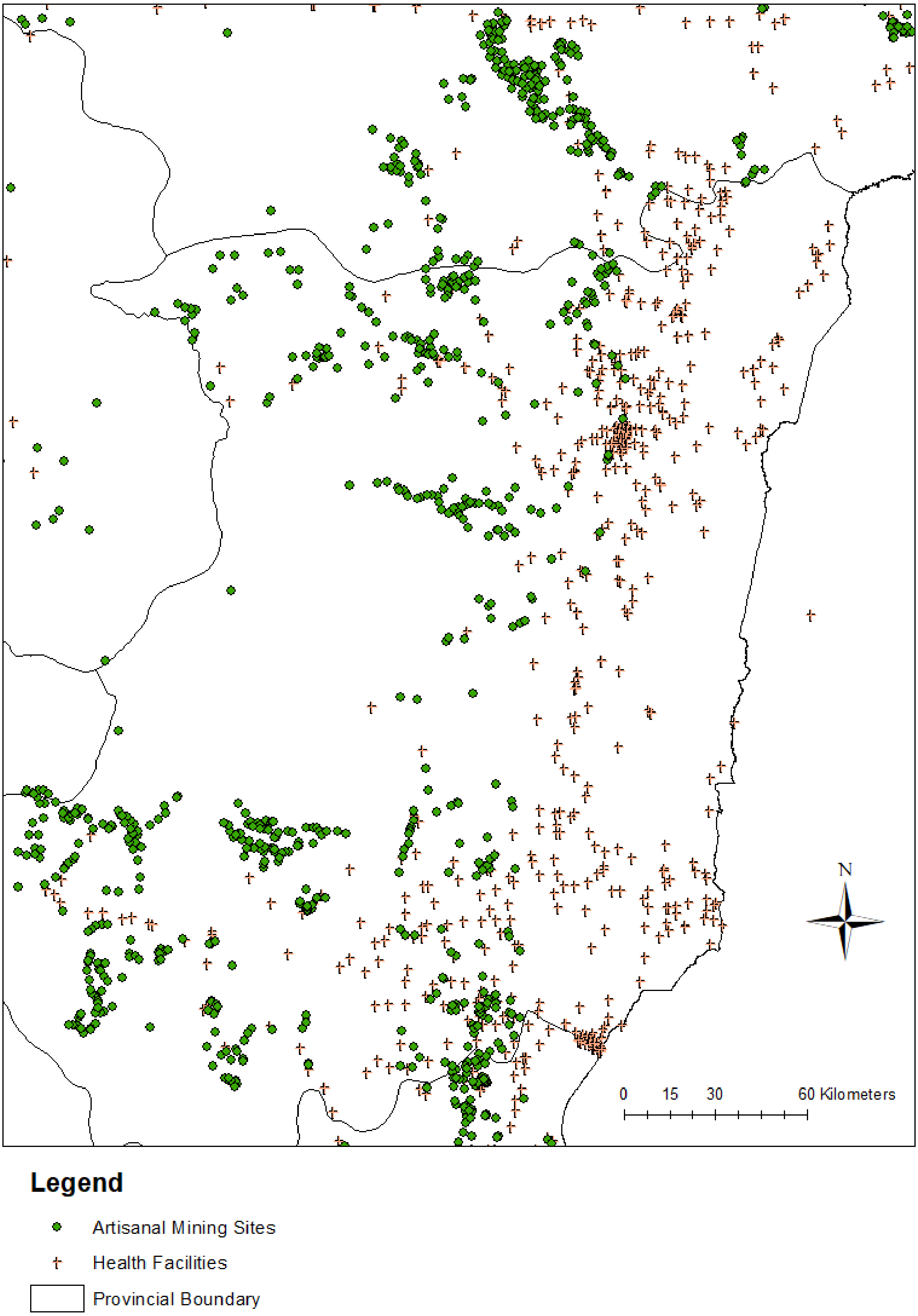

**Notes:** The above figure documents the evolution of the contributions of external aid and government spending to the national malaria programme, which highlights the strong dependence of the health system of the country on donors. This information was extracted from the National Health Accounts of the DRC, MSP (2017). External aid and government spending amount respectively to $160 million and $9 million in 2017.

Figure B.2: Mapping of the full sample of health facilities and mines in the DRC



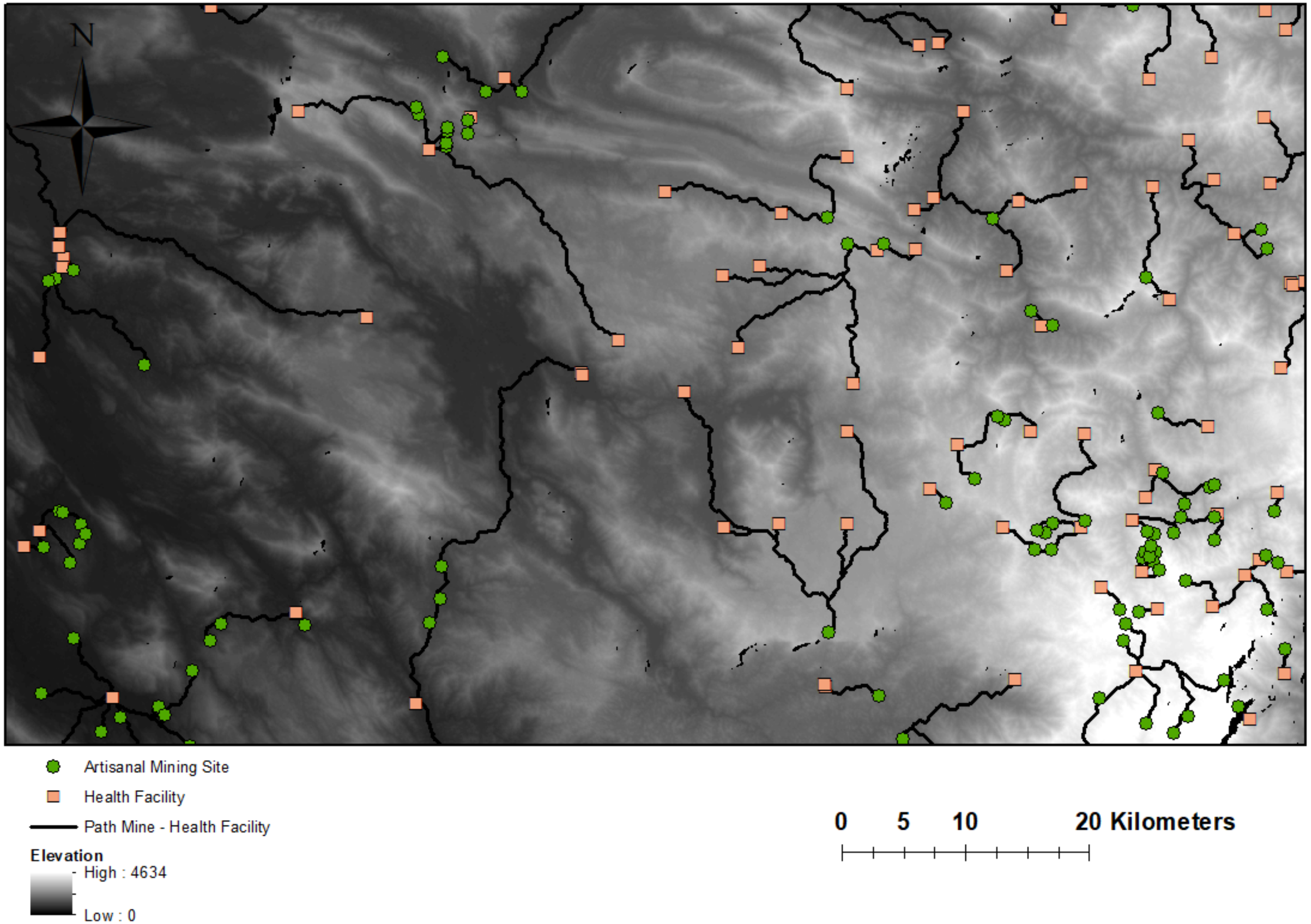

**Notes:** The map shows the geo-location of the mines and the health facilities in the Estern DRC along with provincial level boundaries. The mines and health facilities are located in North and South Kivu, Ituri, Maniema, Tshopo and Tanganyika.

FIGURE B.3: Mapping of health facilities and mines in North Kivu



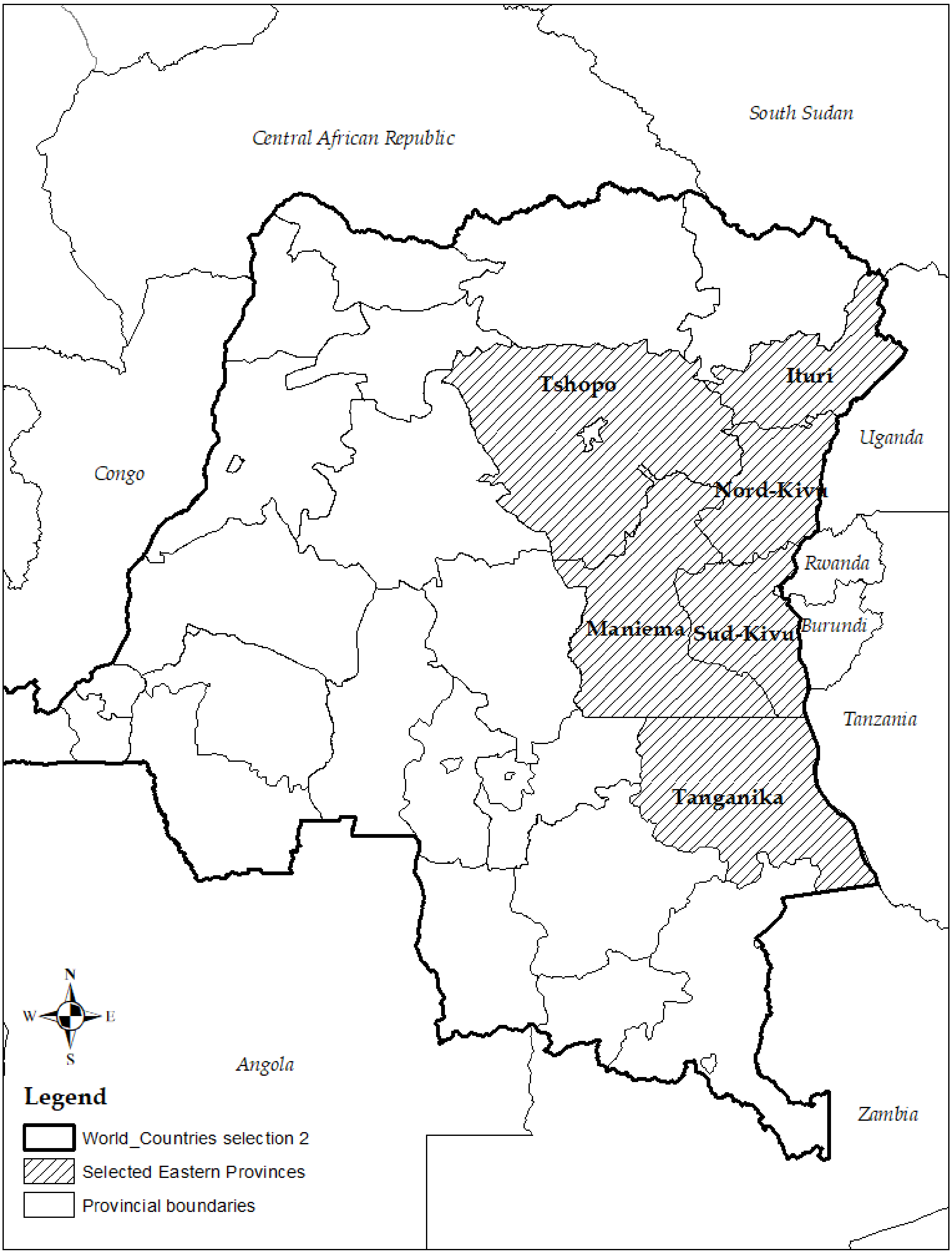

**Notes:** The map shows the exact geo-location of the mines and the health facilities in North Kivu, one of the provinces which contains the most observations in the sample.

Figure B.4: Paths from health facilities to mines with elevation feature



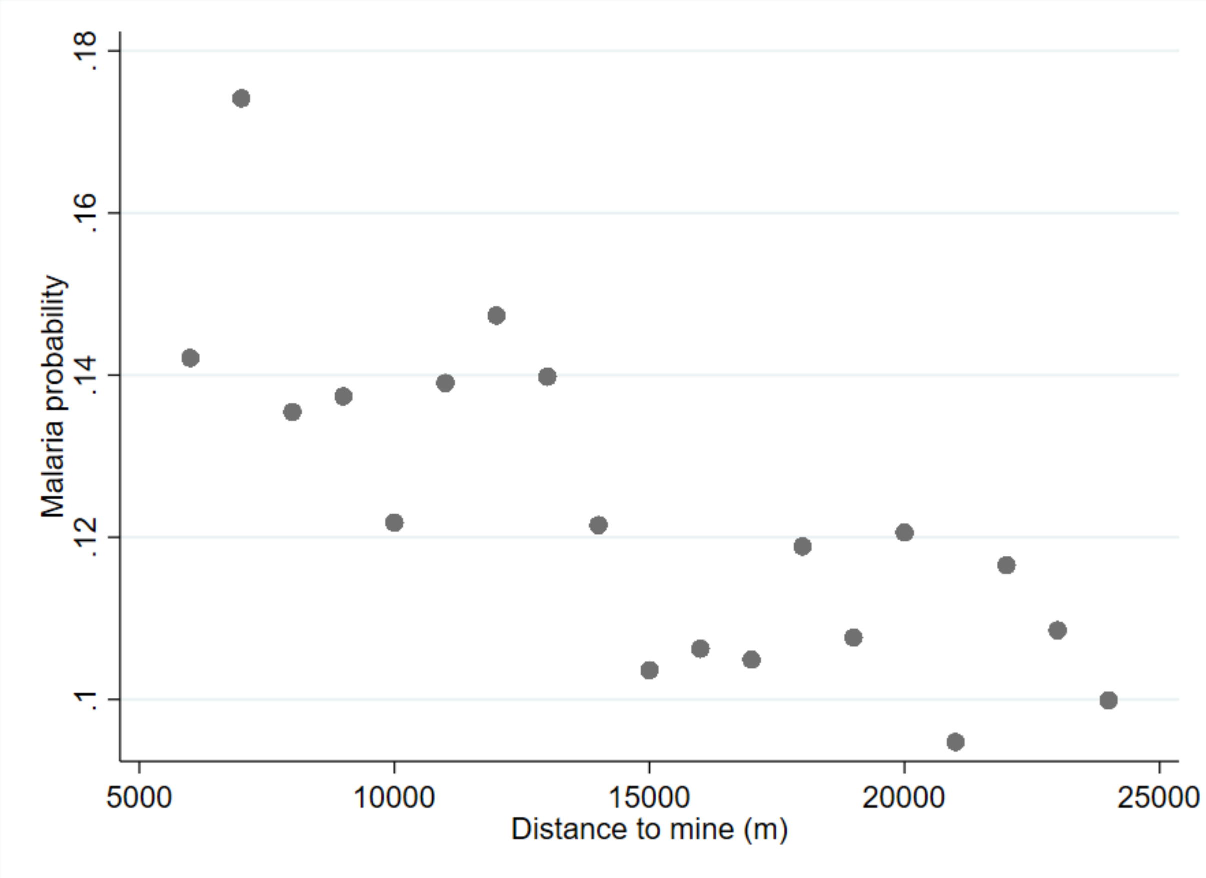

**Notes:** This map plots health facilities and mines along with the algorithm-derived shortest paths based on elevation. The cost path function was used in ArcGIS 10 to estimate the least cost path from each health facility to the closest mine.

Figure B.5: Administrative map of the DRC and the selected provinces



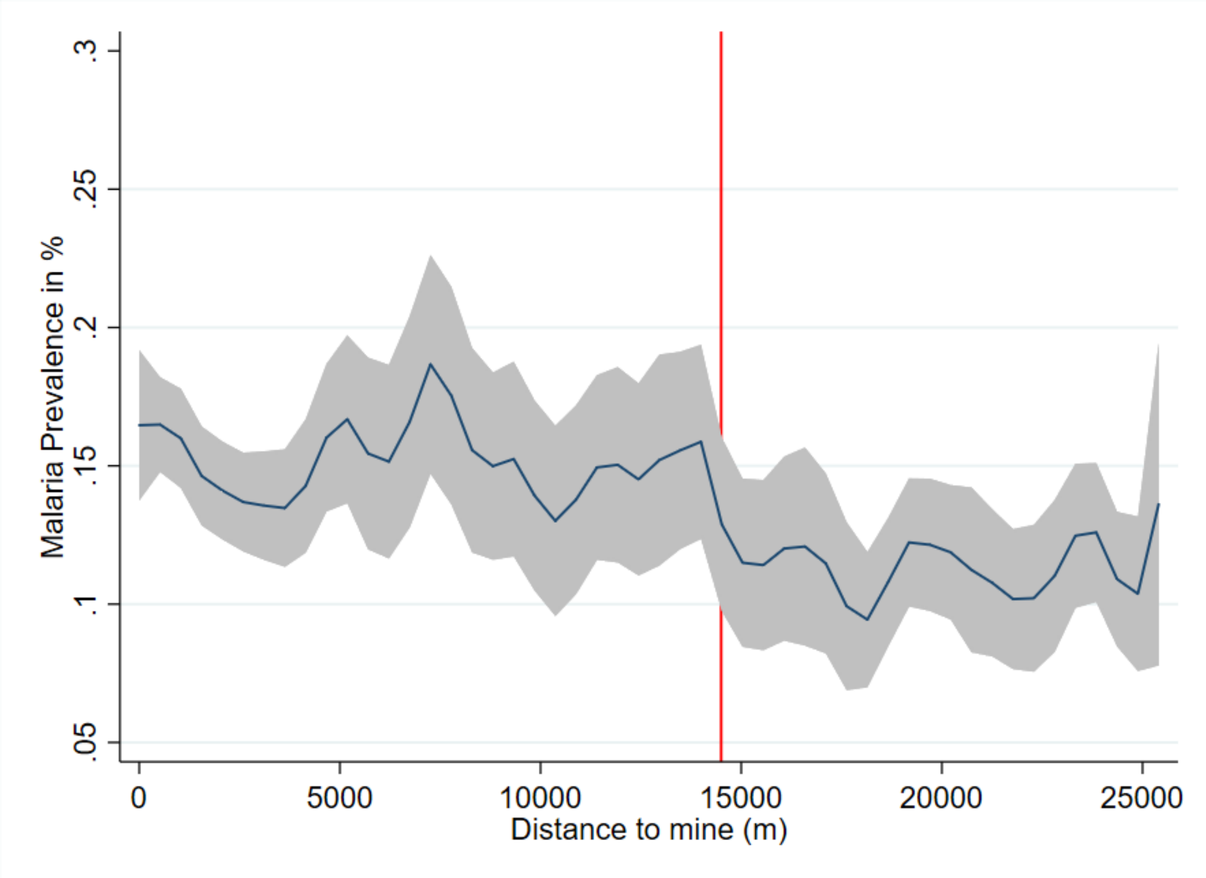

**Notes:** The map shows the provincial boundaries of the DRC and the selection of provinces that contains the location of health facilities and mines from the data sample: North and South Kivu, Ituri, Maniema, Tshopo and Tanganyika.

Figure B.6: Malaria prevalence as a function of the distance to mines



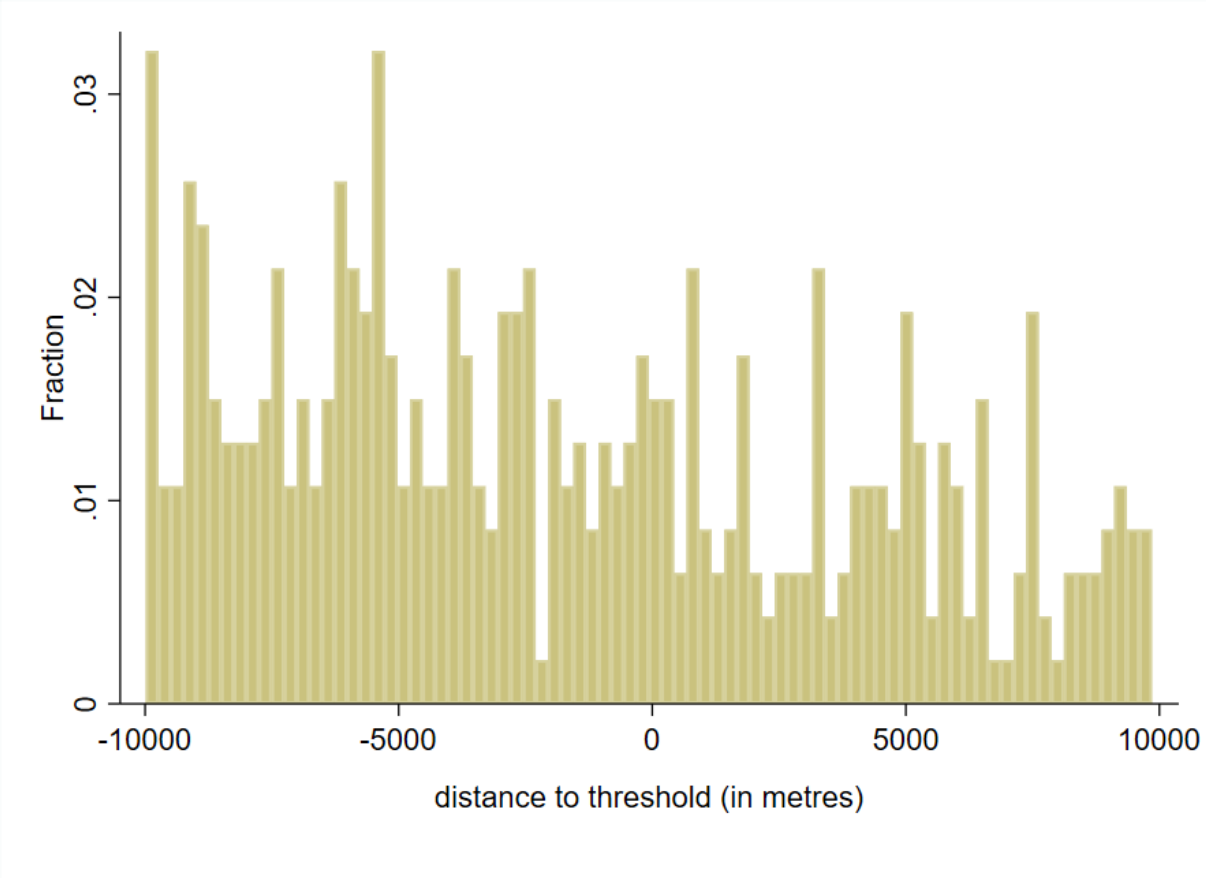

**Notes:** Each point plots an average value within a bin that represents a 1 km interval. The y-axis indicates the malaria probability which is defined as the total number of malaria cases divided by the total population in the catchment area of each health facility.

Figure B.7: Local polynomial estimations of malaria prevalence as a function of the distance to mines



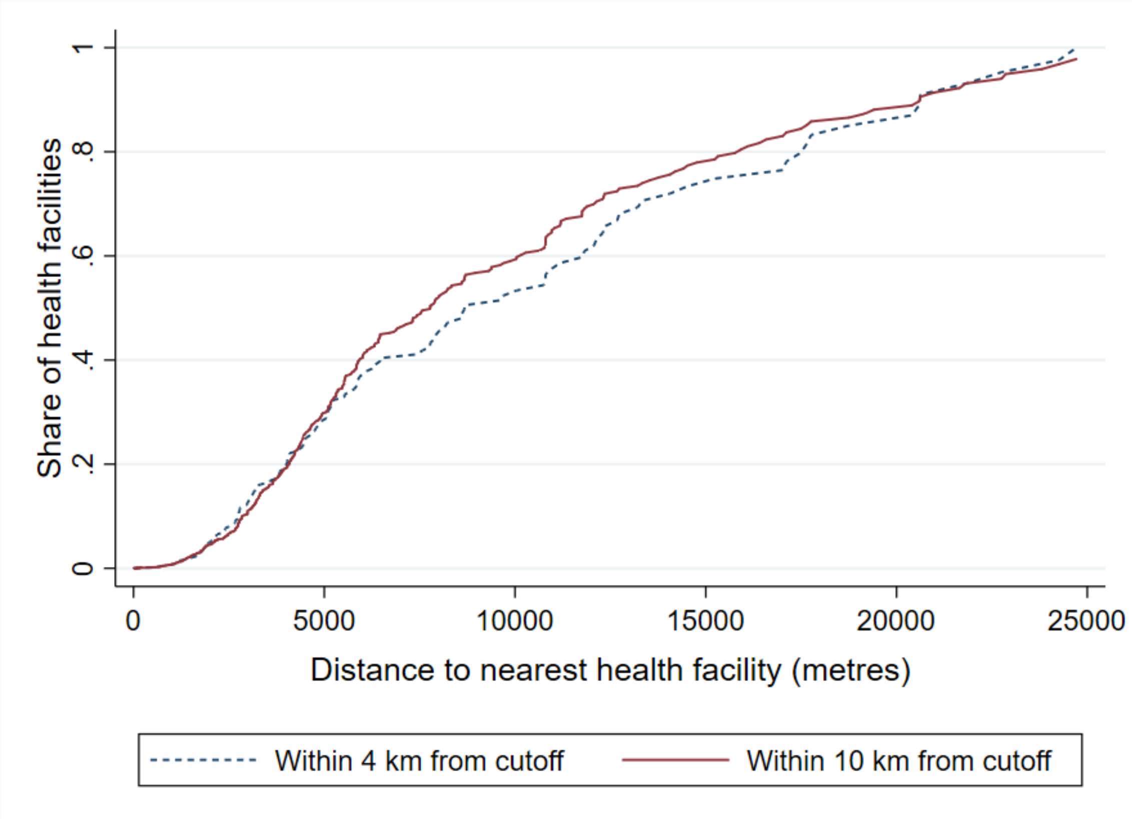

**Notes:** This figure shows the non-parametric estimations of malaria prevalence conditional on the distance from a health facility to its the closest mine, using a kernel-weighted local polynomial regression of order 1. The kernel function is epanechnikov and the the bandwidth corresponds to 700 metres. The y-axis represents the malaria prevalence defined as the share of malaria cases in the population catchment area of the health facility and the x-axis corresponds to the distance from health facility to the closest mine in metres. The shaded area denotes the 95% confidence interval of the coefficients.

FIGURE B.8: Density of the running variable



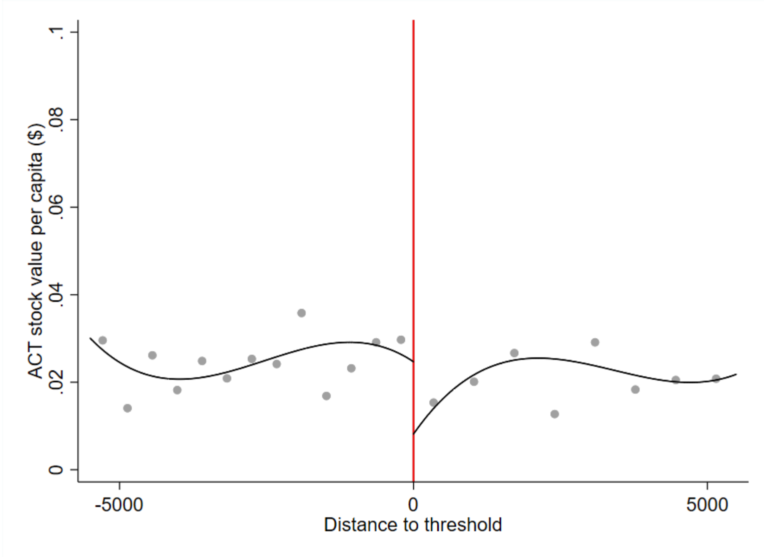

**Notes:** The above figure shows the distribution of the running variable for health facilities in the sample. The running variable is the distance from the health facility to the mining threshold, which is located 14.5 km from a mine. The running variable is centred around the threshold, so distances are negative in the mining areas (left side of the threshold) and positive in non-mining areas (right side of the threshold). The $y$-axis shows the percentage of observations within each bin, where the latter represents a 250 metre-interval.

Figure B.9: Cumulative Distribution Function

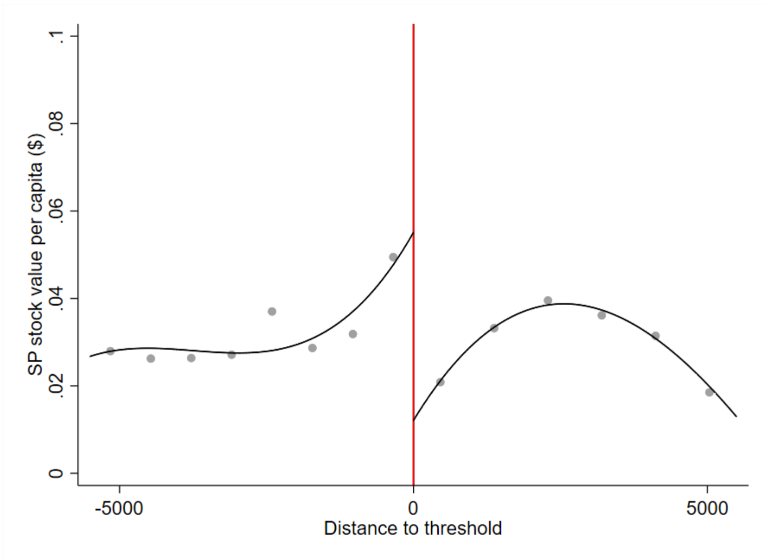



**Notes:** The above figure shows the cumulative distribution function of health facilities conditional on the distance to the nearest health facility. The data sample is restricted on health facilities located within 10 km (red line) and 4 km (blue dashed line) from the threshold. Distances are reported in metres on the $x$-axis. The sample is also restricted to health facilities whose maximum distance to another closest facility is 30 kilometres.

Figure B.10: RD effect on the stock value of artemisinin-based combination therapy and sulfadoxine-pyrimethamine commodities



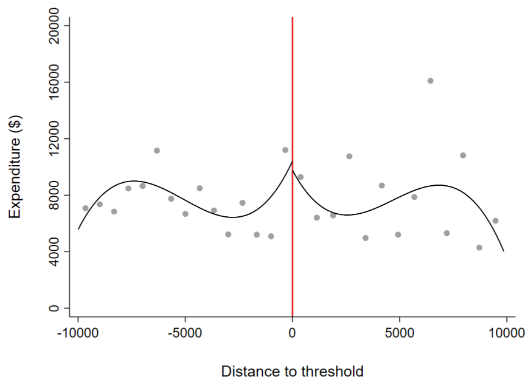

(A) Stock value of ACT



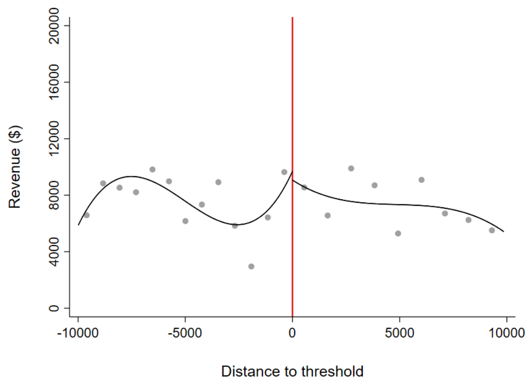

(B) Stock value of SP

**Notes:** Each point plots an average value within a bin conditional on the distance to the mining threshold. The distance is in metres and the solid line plots a local cubic regression.

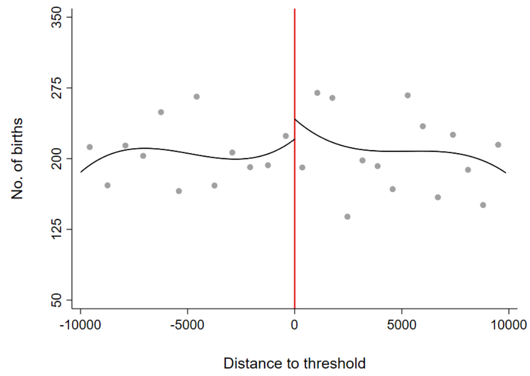
Figure B.11: Evidence on continuity condition



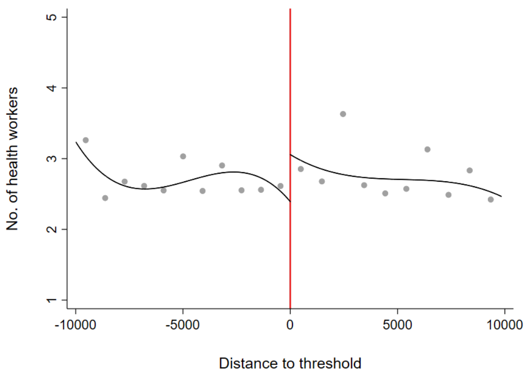

(A) Expenditure



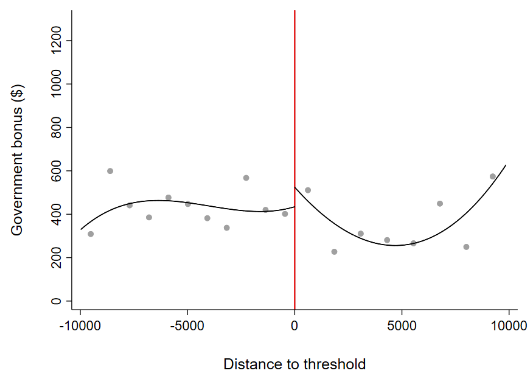

(B) Revenue



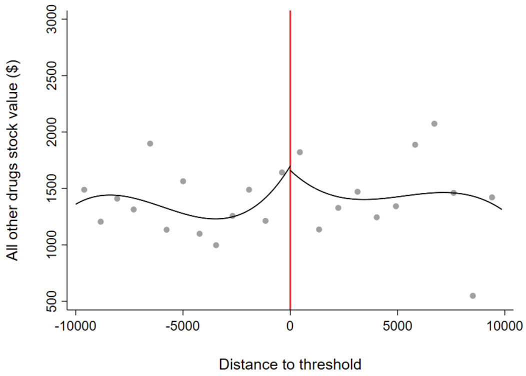

(C) Number of births




(D) Number of health workers



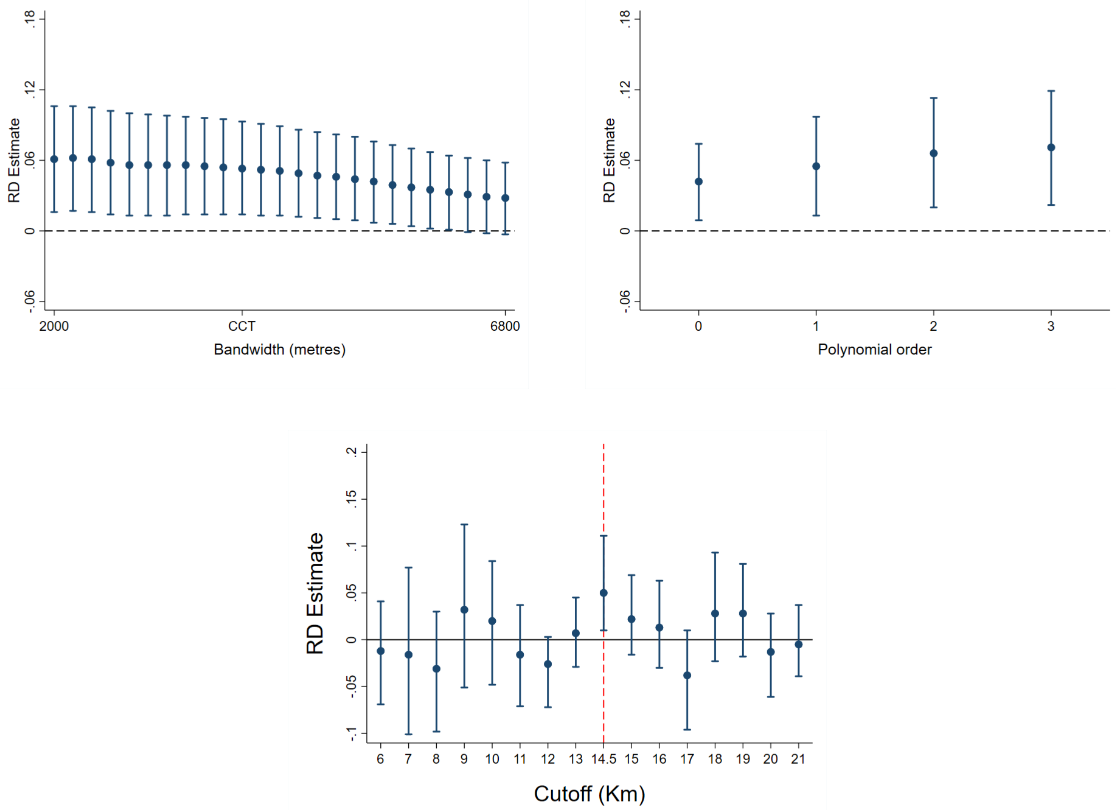

(E) Government bonus




(F) Stock value of total other drugs

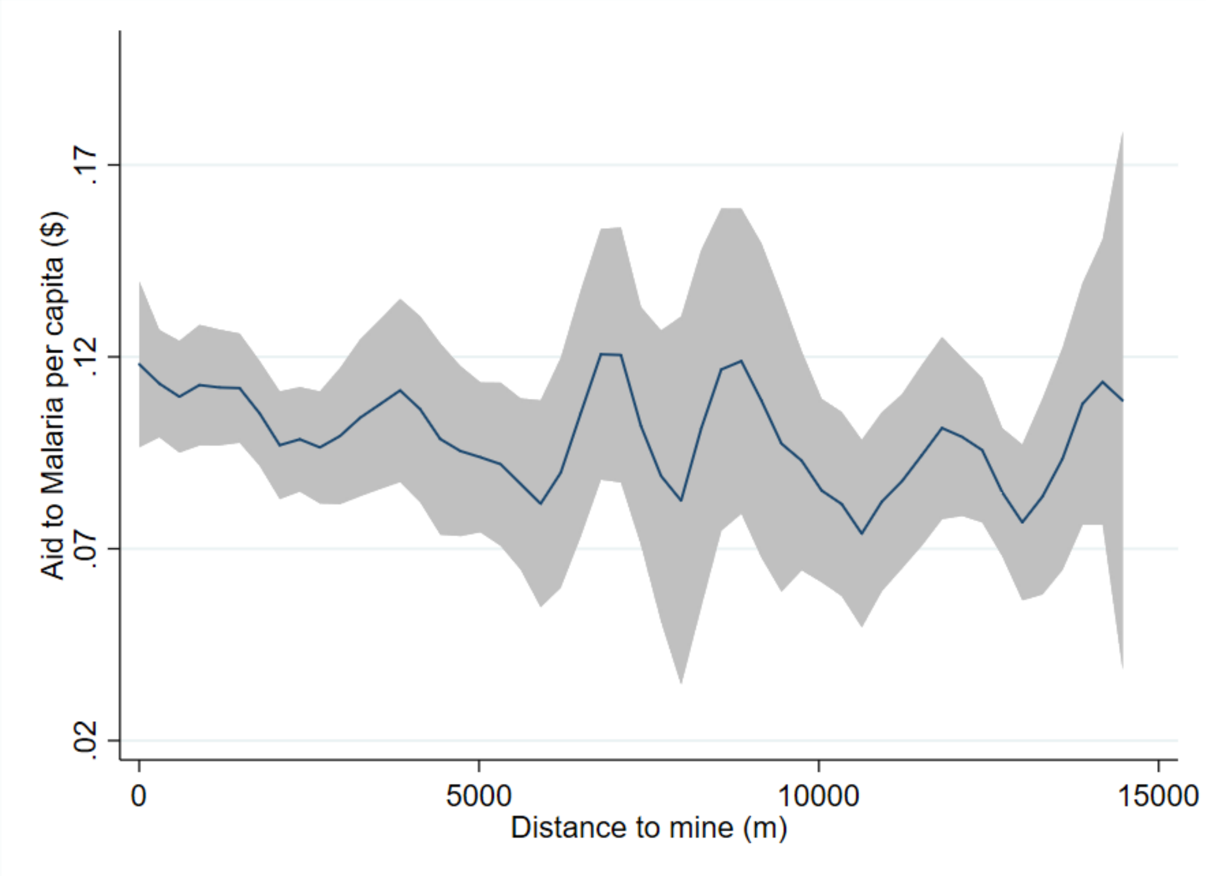
**Notes:** Each point plots an average value within a bin conditional on the distance to the mining threshold. The distance is in metres and the solid line plots a local cubic regression.

FIGURE B.12: Robustness checks




**Notes:** The figures plot estimates from separate RD regressions of the outcome on mining area. The regressions include pre-determined covariates for geographic characteristics and use robust standard-errors. Each graph shows the point estimates and 95% confidence intervals. The bandwidth selection follows the data-driven procedures suggested by Calonico, Cattaneo, and Titiunik (2014) for figures (B) and (C) and is referred to "CCT" in figure (A). The vertical red line in figure (C) plots the 14.5 km cutoff that is used in all baseline results.

Figure B.13: Local polynomial estimations of aid for malaria as a function of the distance to mines within mining areas




**Notes:** This figure shows the non-parametric estimations of aid for malaria conditional on the distance from a health facility to its the closest mine within mining areas, using a kernel-weighted local polynomial regression of order 1. The kernel function is epanechnikov and the the bandwidth corresponds to 700 metres. The y-axis represents the malaria prevalence defined as the share of malaria cases in the population catchment area of the health facility and the x-axis corresponds to the distance from health facility to the closest mine in metres. The shaded area denotes the 95% confidence interval of the coefficients.

Figure B.14: Prices of antimalarial commodities

The Global Fund

21-Sep-18

**Pooled Procurement Mechanism Reference Pricing: Antimalarial medicines** (version: quarter 3 2018)

The Global Fund has established Framework Agreements with manufacturers of antimalarial medicines artemisinin-based combination therapy and other antimalarials medicines with the aim to achieve lower prices sustainable and reliable on-time supply of the full range of the needed antimalarial medicines.

Reference prices for Artemether/Lumefantrine 20/120mg, 6x1 and 6x2 are equal for dispersible and non-dispersible. We encourage to procure the dispersible form as better formulations for children.

The Pooled Procurement Mechanism (PPM) aims to deliver the orders for the following antimalarial medicines at or below reference pricing below. These prices should be used for budgeting purposes and will be us Quotes.

Actual prices achieved for a grant will depend on how early the orders (> 5 months) are placed by Principal Recipients - and additionally the achievement of certain volume thresholds through the pooled volumes tc negotiated prices through the mechanism. Actual prices achieved will be charged to the grant.

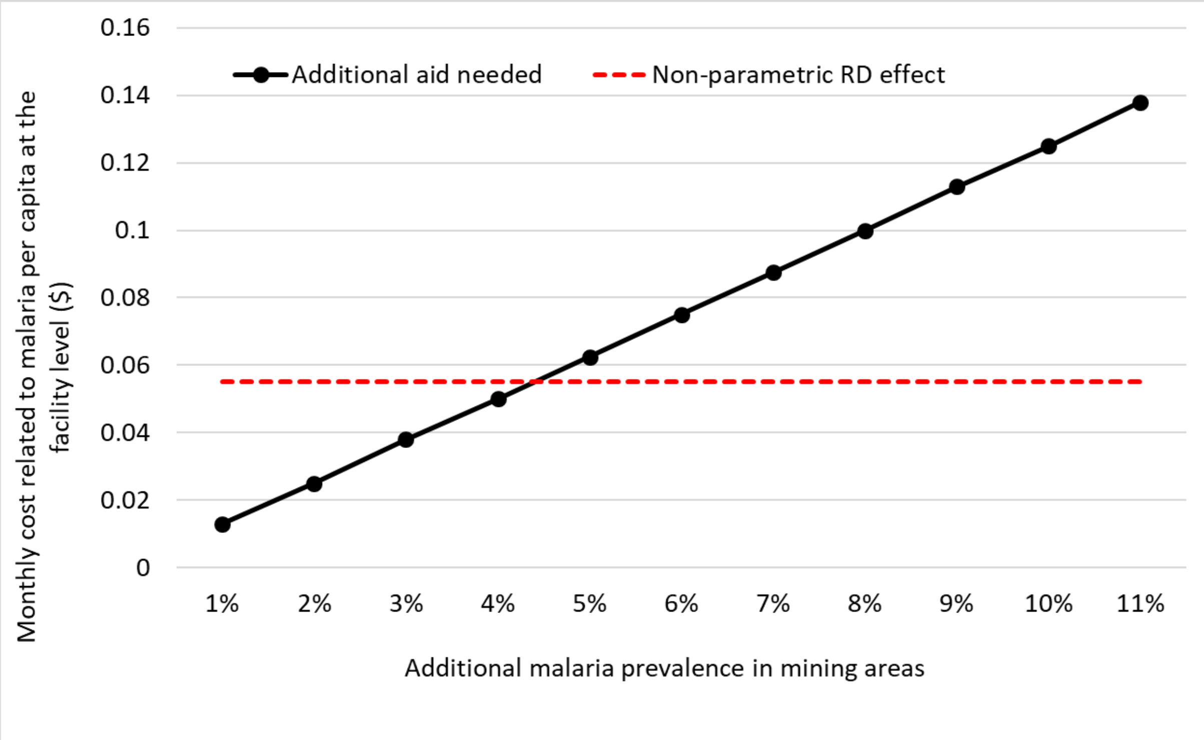
Note that pricing for some items may not be available for some countries due to patent or licensing restrictions.

Some non-optimal products/formulations/pack-sizes have been removed from this version of the reference price list: pricing can be provided on request should the product still be commercially available.

| Product Description | Pack Size | Reference price US$ Per Pack for planned procurement (>5 months) | Maximum price US$ Per Pack for late orders or country registration constraints | Reference price US$ Per Treatment for planned procurement (>5 months) |
|---|---|---|---|---|
| **Antimalarial medicines** | | | | |
| Artemether/Lumefantrine 20/120mg, 6x1, dispersible tablets | 30 blisters | $ 9.00 | $ 11.70 | $ 0.30 |
| Artemether/Lumefantrine 20/120mg, 6x2, dispersible tablets | 30 blisters | $ 14.40 | $ 20.70 | $ 0.48 |
| Artemether/Lumefantrine 20/120mg, 6x1, non dispersible tablets | 30 blisters | $ 9.00 | $ 11.70 | $ 0.30 |
| Artemether/Lumefantrine 20/120mg, 6x2, non dispersible tablets | 30 blisters | $ 14.40 | $ 20.70 | $ 0.48 |
| Artemether/Lumefantrine 20/120mg, 6x3, non dispersible tablets | 30 blisters | $ 16.50 | $ 16.50 | $ 0.55 |
| Artemether/Lumefantrine 20/120mg, 6x4, non dispersible tablets | 30 blisters | $ 20.40 | $ 21.00 | $ 0.68 |
| Artemether/Lumefantrine 40/240mg 6 tablet | 30 blisters | $ 9.90 | - | $ 0.33 |
| Artemether/Lumefantrine 40/240mg 12 tablet | 30 blisters | $ 19.50 | - | $ 0.65 |
| Artemether/Lumefantrine 60/360mg 6 tablet | 30 blisters | $ 15.00 | - | $ 0.50 |
| Artemether/Lumefantrine 80/480mg 6 tablet | 30 blisters | $ 18.00 | - | $ 0.60 |
| Artemether/Lumefantrine 40/240mg 6 tablet | 1 blister | $ 0.45 | - | $ 0.45 |
| Artemether/Lumefantrine 60/360mg 6 tablet | 1 blister | $ 0.55 | - | $ 0.55 |
| Artemether/Lumefantrine 80/480mg 6 tablet | 1 blister | $ 0.65 | $ 1.25 | $ 0.65 |
| Artesunate / Amodiaquine 25/67.5mg, 3x1 | 25 blisters | $ 5.00 | - | $ 0.20 |
| Artesunate / Amodiaquine 50/135mg, 3x1 | 25 blisters | $ 7.25 | - | $ 0.29 |
| Artesunate / Amodiaquine 100/270mg, 3x1 | 25 blisters | $ 11.29 | - | $ 0.45 |
| Artesunate / Amodiaquine 100/270mg, 3x2 | 25 blisters | $ 19.44 | - | $ 0.78 |
| Artesunate 30mg powder for solution for injection | 1 vial | $ 1.45 | - | - |
| Artesunate 60mg powder for solution for injection | 1 vial | $ 1.45 | - | - |
| Artesunate 120mg powder for solution for injection | 1 vial | $ 2.60 | - | - |
| Artesunate suppository 100mg | 2's | $ 0.63 | - | $ 0.63 |
| Amodiaquine (as hydrochloride)+Sulfadoxine/Pyrimethamine 153mg+500/25mg 3+1 tablet dispersible co-blistered | 50 blisters | $ 14.75 | - | $ 0.30 |
| Amodiaquine (as hydrochloride)+Sulfadoxine/Pyrimethamine 76.5mg+250/12.5mg 3+1 tablet dispersible co-blistered | 50 blisters | $ 13.25 | - | $ 0.27 |
| Artesunate+Sulfadoxine/Pyrimethamine 100mg+500/25mg 6+3 tablet co-blistered | 25 blisters | $ 40.00 | - | $ 1.60 |
| Artesunate+Sulfadoxine/Pyrimethamine 50mg+500/25mg 6+2 tablet co-blistered | 25 blisters | $ 23.75 | - | $ 0.95 |
| Artesunate/Pyronaridine 60/180mg tablet 9 | 10 blisters | $ 20.44 | - | $ 2.04 |
| Artesunate/Pyronaridine 20/60mg granule | 90 sachets | $ 12.22 | - | $ 0.14 |
| Artesunate/Mefloquine 25/50mg 3 tablet | 30 blisters | $ 36.60 | - | $ 1.22 |
| Artesunate/Mefloquine 25/50mg 6 tablet | 30 blisters | $ 43.50 | - | $ 1.45 |
| Artesunate/Mefloquine 100/200mg 3 tablet | 30 blisters | $ 57.00 | - | $ 1.90 |
| Artesunate/Mefloquine 100/200mg 6 tablet | 30 blisters | $ 90.00 | - | $ 3.00 |
| Chloroquine (as Phosphate) 250mg as phosphate (155mg as base) tablet 100 | bulk | $ 3.80 | - | - |
| Chloroquine (as Phosphate) 250mg as phosphate (155mg as base) tablet 1000 | bulk | $ 34.00 | - | - |
| Chloroquine (as Phosphate) 250mg as phosphate (155mg as base) 10 tablet 10 blister | 10 blisters | $ 3.70 | - | $ 0.37 |
| Chloroquine (as Phosphate) 250mg as phosphate (155mg as base) 100 tablet 10 blister | 10 blisters | $ 39.00 | - | $ 3.90 |
| Primaquine 7.5mg (as base) (equivalent to 13.2mg Primaquine Phosphate) tablet 1000 | bulk | $ 30.20 | - | - |
| Primaquine 7.5mg (as base) (equivalent to 13.2mg Primaquine Phosphate) 10 tablet 10 blister | 10 blisters | $ 3.80 | - | $ 0.38 |
| Primaquine 7.5mg (as base) (equivalent to 13.2mg Primaquine Phosphate) 10 tablet 100 blister | 100 blisters | $ 48.00 | - | $ 0.48 |
| Sulfadoxine/Pyrimethamine 500/25mg 3 tablet | 10 blisters | $ 3.50 | - | $ 0.35 |
| Sulfadoxine/Pyrimethamine 500/25mg 3 tablet | 100 blisters | $ 33.50 | - | $ 0.34 |
| Sulfadoxine/Pyrimethamine 500/25mg 3 tablet | 10 blisters 5 boxes | $ 14.85 | - | - |
| Sulfadoxine/Pyrimethamine 500/25mg tablet 100 | bulk | $ 11.15 | - | - |
| Sulfadoxine/Pyrimethamine 500/25mg tablet 1000 | bulk | $ 95.90 | - | - |

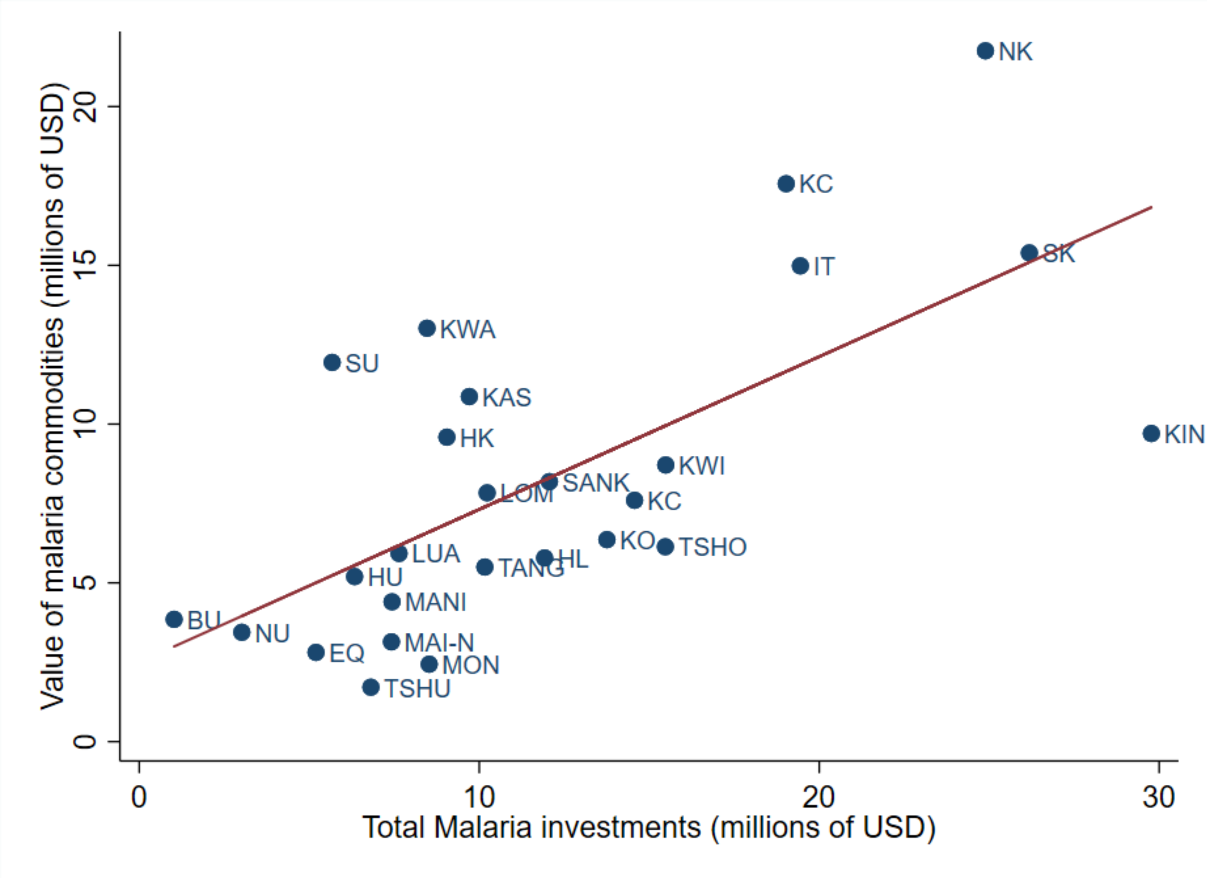
**Notes:** The above document presents the reference pricing of antimalarial medicines negotiated by the Global Fund through the Pooled Procurement mechanism (reference prices for Rapid Diagnostic Tests (RDT) and Insecticide-Treated bed Nets (ITNs) were also extracted from the Global Fund's documents (The Global Fund, 2018) . The Global Fund's objectives are to stabilise prices and ensure market sustainability of health commodities by pooling demand of countries that participate to the programme (The Global Fund, 2018).

Figure B.15: Evolution of aid needed with the additional risk of malaria transmission




**Notes:** The figure plots the evolution of malaria-related costs that are required to cope with the additional risk of malaria transmission. The horizontal red dashed line shows the additional aid for malaria that is received in high burden areas according to the nonparametric RD estimation (table B.6) of the mining effect. The total cost of malaria diagnosis, prevention and treatment is calculated from the price list of antimalarial commodities of the Global Fund (figure B.14).

Figure B.16: Stock value of antimalarial commodities and total malaria investment




**Notes:** Scatter plot of stock value of antimalarial commodities in 2017 for each of the 23 provinces of the Democratic Republic of Congo with fitted line versus total malaria investments in each province.

Table B.1: Summary statistics and difference-in-means, full sample

| | Outside mining area | | | Within mining area | | | Difference-in-means | | |
|---|---|---|---|---|---|---|---|---|---|
| | Obs. | Sample mean | s.d. | Obs. | Sample mean | s.d. | Diff-in-means | s. e. | p-value |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| **Geographic characteristics** | | | | | | | | | |
| Elevation (in metres) | 489 | 1,251.23 | 24.84 | 738 | 1,218.87 | 19.27 | -32.36 | 31.44 | 0.30 |
| Slope | 489 | 5.03 | 0.30 | 738 | 6.34 | 0.31 | 1.31 | 0.43 | 0.00 |
| Distance from closest facility (km) | 489 | 5.56 | 0.28 | 738 | 4.63 | 0.19 | -0.93 | 0.34 | 0.01 |
| Distance from closest hospital (km) | 436 | 20.78 | 0.96 | 700 | 20.22 | 0.68 | -0.56 | 1.18 | 0.63 |
| **Facilities characteristics*** | | | | | | | | | |
| Antimalarial stock value | 446 | 0.08 | 0.00 | 652 | 0.10 | 0.00 | 0.02 | 0.01 | 0.00 |
| Total other drugs stock value | 474 | 0.11 | 0.01 | 724 | 0.13 | 0.01 | 0.02 | 0.01 | 0.01 |
| Revenue | 477 | 0.90 | 0.07 | 709 | 0.88 | 0.07 | -0.02 | 0.10 | 0.85 |
| Investment | 316 | 0.07 | 0.01 | 520 | 0.06 | 0.00 | -0.01 | 0.01 | 0.21 |
| Payroll tax | 394 | 0.03 | 0.00 | 595 | 0.02 | 0.00 | -0.01 | 0.00 | 0.03 |
| Government bonus | 335 | 0.04 | 0.00 | 557 | 0.05 | 0.00 | 0.01 | 0.01 | 0.00 |
| No. nurses | 469 | 0.00 | 0.00 | 705 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| No. births | 451 | 0.02 | 0.00 | 686 | 0.02 | 0.00 | 0.00 | 0.00 | 0.46 |
| Local Population** | 489 | 14.43 | 0.82 | 738 | 12.20 | 0.37 | -2.24 | 0.90 | 0.01 |
| **No. days antimalarial stock outs** | | | | | | | | | |
| Insecticide-Treated bed Nets | 423 | 6.47 | 0.31 | 583 | 5.87 | 0.24 | -0.60 | 0.40 | 0.13 |
| Rapid Diagnostic Tests | 391 | 2.83 | 0.51 | 524 | 2.09 | 0.16 | -0.74 | 0.53 | 0.16 |
| Sulfadoxine-Pyrimethamine | 396 | 3.73 | 0.44 | 532 | 4.26 | 0.57 | 0.52 | 0.72 | 0.47 |
| ACT (ages +14) | 400 | 3.41 | 0.23 | 529 | 3.53 | 0.46 | 0.12 | 0.52 | 0.81 |
| ACT (ages 6-13) | 403 | 3.02 | 0.20 | 512 | 3.39 | 0.53 | 0.37 | 0.57 | 0.52 |
| ACT (ages 1-5) | 407 | 3.08 | 0.24 | 537 | 3.82 | 0.24 | 0.74 | 0.33 | 0.03 |
| ACT (ages -1) | 409 | 3.30 | 0.25 | 560 | 4.44 | 0.26 | 1.14 | 0.36 | 0.00 |

**Notes:** Mining area is defined as the geographic area where the distance from a mine to its closest health facility is less than 14.5 km. The unit of observation is health facility and all financial characteristics as well as commodity stock value are expressed in U.S. Dollars. All indicators correspond to monthly average numbers. The first six columns show the number of observations, sample mean and robust standard errors for non-mining and mining areas respectively. The last three columns indicate the difference in means between non-mining and mining area, the robust standard errors for the difference and the *p*-value of the test of whether the mean coefficients in the mining and non-mining sample are equal.

* Variables are expressed as share in local population.

** Mean and standard deviation of local population are expressed in thousands.

Table B.2: Summary statistics and difference-in-means, 8km window around the border

| | Outside mining area | | | Within mining area | | | Difference-in-means | | |
|---|---|---|---|---|---|---|---|---|---|
| | Obs. | Sample mean | s.d. | Obs. | Sample mean | s.d. | Diff-in-means | s. e. | p-value |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| **Geographic characteristics** | | | | | | | | | |
| Elevation (in metres) | 161 | 1,319.01 | 44.37 | 232 | 1,217.65 | 34.40 | -101.36 | 56.14 | 0.07 |
| Slope | 161 | 5.88 | 0.47 | 232 | 5.91 | 0.48 | 0.03 | 0.67 | 0.97 |
| Distance from closest facility (km) | 161 | 5.72 | 0.47 | 232 | 5.42 | 0.37 | -0.30 | 0.60 | 0.61 |
| Distance from closest hospital (km) | 142 | 21.08 | 1.50 | 214 | 20.89 | 1.15 | -0.19 | 1.89 | 0.92 |
| **Facilities characteristics*** | | | | | | | | | |
| Antimalarial stock value | 145 | 0.08 | 0.01 | 201 | 0.10 | 0.01 | 0.01 | 0.01 | 0.12 |
| Total other drugs stock value | 157 | 0.12 | 0.01 | 226 | 0.12 | 0.01 | 0.01 | 0.01 | 0.55 |
| Revenue | 157 | 0.73 | 0.06 | 217 | 0.73 | 0.05 | -0.00 | 0.08 | 0.98 |
| Investment | 116 | 0.05 | 0.01 | 157 | 0.06 | 0.01 | 0.01 | 0.01 | 0.52 |
| Payroll tax | 128 | 0.02 | 0.00 | 178 | 0.01 | 0.00 | -0.01 | 0.00 | 0.07 |
| Government bonus | 114 | 0.03 | 0.00 | 158 | 0.05 | 0.01 | 0.01 | 0.01 | 0.04 |
| No. nurses | 155 | 0.00 | 0.00 | 219 | 0.00 | 0.00 | 0.00 | 0.00 | 0.51 |
| No. births | 146 | 0.02 | 0.00 | 216 | 0.02 | 0.00 | 0.00 | 0.00 | 0.82 |
| Local Population** | 161 | 12.36 | 0.57 | 232 | 11.44 | 0.50 | -0.93 | 0.76 | 0.22 |
| **No. days antimalarial stock outs** | | | | | | | | | |
| Insecticide-Treated bed Nets | 132 | 6.19 | 0.53 | 179 | 5.96 | 0.45 | -0.22 | 0.70 | 0.75 |
| Rapid Diagnostic Tests | 117 | 2.38 | 0.31 | 159 | 1.80 | 0.30 | -0.58 | 0.43 | 0.18 |
| Sulfadoxine-Pyrimethamine | 119 | 3.83 | 0.56 | 165 | 2.88 | 0.35 | -0.94 | 0.66 | 0.16 |
| ACT (ages +14) | 115 | 3.57 | 0.38 | 165 | 4.49 | 1.41 | 0.92 | 1.46 | 0.53 |
| ACT (ages 6-13) | 116 | 3.19 | 0.35 | 156 | 4.56 | 1.69 | 1.37 | 1.72 | 0.43 |
| ACT (ages 1-5) | 127 | 3.36 | 0.42 | 170 | 3.40 | 0.40 | 0.04 | 0.58 | 0.95 |
| ACT (ages -1) | 124 | 3.86 | 0.51 | 175 | 4.12 | 0.48 | 0.26 | 0.70 | 0.71 |

**Notes:** Mining area is defined as the geographic area where the distance from a mine to its closest health facility is less than 14.5 km. The unit of observation is health facility and all financial characteristics as well as commodity stock value are expressed in U.S. Dollars. All indicators correspond to monthly average numbers. The first six columns show the number of observations, sample mean and robust standard errors for non-mining and mining areas respectively. The last three columns indicate the difference in means between non-mining and mining area, the robust standard errors for the difference and the *p*-value of the test of whether the mean coefficients in the mining and non-mining sample are equal.

* Variables are expressed as share in local population.

** Mean and standard deviation of local population are expressed in thousands.

Table B.3: Summary statistics and difference-in-means, 3km window around the border

| | Outside mining area | | | Within mining area | | | Difference-in-means | | |
|---|---|---|---|---|---|---|---|---|---|
| | Obs. | Sample mean | s.d. | Obs. | Sample mean | s.d. | Diff-in-means | s. e. | p-value |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| **Geographic characteristics** | | | | | | | | | |
| Elevation (in metres) | 68 | 1,302.82 | 71.69 | 81 | 1,278.82 | 61.83 | -24.01 | 94.67 | 0.80 |
| Slope | 68 | 6.81 | 0.79 | 81 | 6.61 | 1.18 | -0.20 | 1.42 | 0.89 |
| Distance from closest facility (km) | 68 | 6.10 | 0.80 | 81 | 5.60 | 0.60 | -0.50 | 1.00 | 0.62 |
| Distance from closest hospital (km) | 58 | 20.98 | 2.35 | 74 | 22.28 | 1.91 | 1.29 | 3.03 | 0.67 |
| **Facilities characteristics*** | | | | | | | | | |
| Antimalarial stock value | 59 | 0.08 | 0.01 | 71 | 0.09 | 0.01 | 0.01 | 0.01 | 0.29 |
| Total other drugs stock value | 67 | 0.11 | 0.01 | 78 | 0.14 | 0.02 | 0.04 | 0.02 | 0.12 |
| Revenue | 66 | 0.76 | 0.10 | 76 | 0.68 | 0.09 | -0.08 | 0.13 | 0.56 |
| Investment | 51 | 0.06 | 0.01 | 51 | 0.06 | 0.01 | 0.00 | 0.02 | 0.87 |
| Payroll tax | 56 | 0.01 | 0.00 | 59 | 0.01 | 0.00 | 0.00 | 0.01 | 0.50 |
| Government bonus | 47 | 0.04 | 0.01 | 52 | 0.05 | 0.01 | 0.01 | 0.01 | 0.22 |
| No. nurses | 66 | 0.00 | 0.00 | 79 | 0.00 | 0.00 | 0.00 | 0.00 | 0.68 |
| No. births | 57 | 0.02 | 0.00 | 80 | 0.02 | 0.00 | -0.00 | 0.00 | 0.63 |
| Local Population** | 68 | 12.72 | 0.94 | 81 | 11.47 | 0.91 | -1.25 | 1.31 | 0.34 |
| **No. days antimalarial stock outs** | | | | | | | | | |
| Insecticide-Treated bed Nets | 59 | 7.02 | 0.86 | 65 | 6.32 | 0.81 | -0.70 | 1.18 | 0.56 |
| Rapid Diagnostic Tests | 50 | 2.18 | 0.37 | 59 | 1.46 | 0.33 | -0.73 | 0.50 | 0.15 |
| Sulfadoxine-Pyrimethamine | 52 | 5.03 | 1.10 | 59 | 2.71 | 0.59 | -2.31 | 1.24 | 0.07 |
| ACT (ages +14) | 51 | 2.90 | 0.44 | 61 | 3.20 | 0.57 | 0.30 | 0.71 | 0.67 |
| ACT (ages 6-13) | 50 | 3.11 | 0.54 | 60 | 7.13 | 4.34 | 4.02 | 4.38 | 0.36 |
| ACT (ages 1-5) | 55 | 3.66 | 0.81 | 65 | 3.17 | 0.68 | -0.48 | 1.05 | 0.65 |
| ACT (ages -1) | 56 | 4.49 | 0.82 | 64 | 4.22 | 0.79 | -0.27 | 1.14 | 0.81 |

**Notes:** Mining area is defined as the geographic area where the distance from a mine to its closest health facility is less than 14.5 km. The unit of observation is health facility and all financial characteristics as well as commodity stock value are expressed in U.S. Dollars per capita (sing local population catchment area of the facility). All indicators correspond to monthly average numbers. The first six columns show the number of observations, sample mean and robust standard errors for non-mining and mining areas respectively. The last three columns indicate the difference in means between non-mining and mining area, the robust standard errors for the difference and the *p*-value of the test of whether the mean coefficients in the mining and non-mining sample are equal.

* Variables are expressed as share in local population.

** Mean and standard deviation of local population are expressed in thousands.

Table B.4: Manipulation Density tests

| Density tests | (1) $h_{mining}$ | (2) $h_{non-mining}$ | (3) $N_{mining}$ | (4) $N_{non-mining}$ | (5) p-value |
|---|---|---|---|---|---|
| Separate MSE Optimal bandwidth | 3,647 | 5,348 | 84 | 105 | 0.84 |
| Restricted C.D.F | 6,723 | 6,723 | 175 | 129 | 0.89 |

**Notes:** The table shows the results of the manipulation test based on the local polynomial density estimation technique (Cattaneo et al., 2017) where the density functions of the mining and non-mining areas are equal under the null hypothesis. The first two columns correspond to the choice of the bandwidth (in metres) on each side of the threshold, columns (3) and (4) indicate the number of observations used and the last column gives the p-value of the test. I perform the test using two different MSE optimal bandwidth on each side of the cutoff for which the results are reported in the first row. The second row corresponds to the density test where the Cumulative Distribution Functions (C.D.F.) of the running variable on each side of the cutoff are assumed to be equal.

Table B.5: Parametric estimation of the effect of mining areas

| | *Linear model (p=1)* | | *Cubic model (p=3)* | |
|---|---|---|---|---|
| Window selection | 3 km | | 8 km | |
| Control variables* | No | Yes | No | Yes |
| | (1) | (2) | (3) | (4) |
| **Aid for malaria per capita** | | | | |
| RD Mining effect | 0.058 | 0.058 | 0.072 | 0.070 |
| s.e. | 0.024 | 0.022 | 0.027 | 0.026 |
| Standard p-value | 0.017 | 0.011 | 0.008 | 0.007 |
| Obs. | 130 | 130 | 346 | 346 |
| **Placebo outcomes, standard p-values** | | | | |
| Expenditures | 0.414 | | 0.614 | |
| Revenue | 0.693 | | 0.767 | |
| No. of health workers | 0.768 | | 0.633 | |
| No. of births | 0.826 | | 0.716 | |

**Notes:** The table reports the results of the weighted least squares estimations based on specification (3.1). In the upper part of the table, the dependent variable is the antimalarial stock value and the bottom part of the table reports the standard p-value of the $\beta_1$ estimates for a list of pre-determined covariates. Each of these covariates is used as the dependent variable in order to test the validity of the RD design, and I report robust standard errors. Columns (1) to (4) report the results obtained using a local linear regression and columns (5) to (8) present results using a local cubic model that provides more flexibility as the $g(.)$ function covers a larger support (7 to 10 km).

* Control variables are the geographic characteristics (elevation and slope) and the number of mines surrounding a health facility.

Table B.6: Non-parametric estimation of the effect of mining areas

| | *Linear model (p=1)* | | *Cubic model (p=3)* | |
|---|---|---|---|---|
| Control variables* | No | Yes | No | Yes |
| | (1) | (2) | (3) | (4) |
| Bandwidth h (in metres)** | 3,997 | 3,945 | 8,093 | 7,755 |
| **Aid for malaria per capita** | | | | |
| RD Mining effect | 0.053 | 0.054 | 0.072 | 0.073 |
| Robust s.e. | 0.024 | 0.022 | 0.029 | 0.026 |
| Robust p-value | 0.011 | 0.006 | 0.009 | 0.004 |
| Obs. | 170 | 165 | 348 | 339 |
| **Placebo outcomes, robust p-values** | | | | |
| Expenditures | 0.539 | | 0.608 | |
| Revenue | 0.857 | | 0.937 | |
| No. of health workers | 0.472 | | 0.466 | |
| No. of births | 0.845 | | 0.795 | |

**Notes:** The table reports the results from nonparametric estimations of specification (3.1) using a local linear and cubic model. In the upper part of the table, the dependent variable is the antimalarial stock value whilst the bottom part of the table presents the robust $p$-values of the estimates of the mining effects on several pre-determined covariates following the procedure described by Calonico, Cattaneo, and Titiunik (2014).

* Control variables are elevation and slope.

** The bandwidth selection follows the MSE-optimal procedure proposed by Calonico, Cattaneo, and Titiunik (2014), as well as the construction of robust standard errors $p$-values. The smoothed distribution function used is the triangular kernel.

Table B.7: Robustness: Parametric estimation of the effect of mining areas with restriction on the distance between health facilities

| | *Linear model (p=1)* | | *Cubic model (p=3)* | |
|---|---|---|---|---|
| Window selection | 3 km | | 8 km | |
| Control variables* | No | Yes | No | Yes |
| | (1) | (2) | (3) | (4) |
| **Aid for malaria per capita** | | | | |
| RD Mining effect | 0.050 | 0.060 | 0.074 | 0.071 |
| s.e. | 0.020 | 0.022 | 0.028 | 0.026 |
| Standard p-value | 0.012 | 0.009 | 0.008 | 0.006 |
| Obs. | 168 | 168 | 344 | 344 |
| **Placebo outcomes, standard p-values** | | | | |
| Expenditures | 0.897 | | 0.610 | |
| Revenue | 0.931 | | 0.793 | |
| No. of health workers | 0.629 | | 0.662 | |
| No. of births | 0.683 | | 0.765 | |

**Notes:** The table reports the results of the weighted least squares estimations based on specification (3.1) and restricting the straight line distance between health facilities to be more than 3 Km. In the upper part of the table, the dependent variable is the antimalarial stock value and the bottom part of the table reports the standard p-value of the $\beta_1$ estimates for a list of pre-determined covariates. Each of these covariates is used as the dependent variable in order to test the validity of the RD design, and I report robust standard errors. Columns (1) to (4) report the results obtained using a local linear regression and columns (5) to (8) present results using a local cubic model that provides more flexibility as the $g(.)$ function covers a larger support (7 to 10 km).

* Control variables are the geographic characteristics (elevation and slope) and the number of mines surrounding a health facility.

Table B.8: Robustness: Non-parametric estimation of the effect of mining areas with restriction on the distance between health facilities

| | *Linear model (p=1)* | | *Cubic model (p=3)* | |
|---|---|---|---|---|
| Control variables* | No<br>(1) | Yes<br>(2) | No<br>(3) | Yes<br>(4) |
| Bandwidth h (in metres)** | 3,947 | 3,869 | 8,202 | 7,486 |
| **Aid for malaria per capita** | | | | |
| RD Mining effect | 0.056 | 0.056 | 0.074 | 0.072 |
| Robust s.e. | 0.025 | 0.023 | 0.029 | 0.027 |
| Robust p-value | 0.009 | 0.005 | 0.008 | 0.007 |
| Obs. | 163 | 160 | 352 | 325 |
| **Placebo outcomes, robust p-values** | | | | |
| Expenditures | 0.522 | | 0.604 | |
| Revenue | 0.794 | | 0.927 | |
| No. of health workers | 0.482 | | 0.479 | |
| No. of births | 0.915 | | 0.737 | |

**Notes:** The table reports the results from nonparametric estimations of specification (3.1) using a local linear and cubic model and restricting the straight line distance between health facilities to be more than 3 Km. In the upper part of the table, the dependent variable is the antimalarial stock value whilst the bottom part of the table presents the robust $p$-values of the estimates of the mining effects on several pre-determined covariates following the procedure described by Calonico, Cattaneo, and Titiunik (2014).

* Control variables are elevation and slope.

** The bandwidth selection follows the MSE-optimal procedure proposed by Calonico, Cattaneo, and Titiunik (2014), as well as the construction of robust standard errors $p$-values. The smoothed distribution function used is the triangular kernel.

TABLE B.9: Parametric estimation of the effect of mining areas by antimalarial commodity

| | *Linear model (p=1)* (1) | *Cubic model (p=3)* (2) |
|---|---|---|
| Window selection (km) | 3 | 8 |
| **ACT - Treatment** | | |
| RD Mining effect | 0.016 | 0.019 |
| s.e. | 0.009 | 0.010 |
| p-value | 0.068 | 0.049 |
| Obs. | 147 | 388 |
| **Sulfadoxine-Pyrimethamine (SP) - Prevention** | | |
| RD Mining effect | 0.039 | 0.046 |
| s.e. | 0.011 | 0.013 |
| p-value | 0.001 | 0.001 |
| Obs. | 134 | 357 |
| **Rapid Diagnostic Test (RDT)** | | |
| RD Mining effect | 0.006 | 0.005 |
| s.e. | 0.002 | 0.003 |
| p-value | 0.022 | 0.077 |
| Obs. | 145 | 380 |
| **Insecticide-Treated bed Net (ITN)** | | |
| RD Mining effect | 0.002 | 0.003 |
| s.e. | 0.006 | 0.009 |
| p-value | 0.771 | 0.700 |
| Obs. | 134 | 347 |

**Notes:** The table reports the results of the weighted least squares estimations based on specification (3.1) for each antimalarial commodity, with robust standard errors. Each commodity's stock value is expressed as a share in the population catchment area of the facility. For each regression, I control for the government bonus and geographic characteristics (distance to the closest health facility, elevation and slope) and the number of mines surrounding a health facility.

Table B.10: Non-parametric estimation of the effect of mining areas by antimalarial commodity

| | *Linear model (p=1)* (1) | *Cubic model (p=3)* (2) |
|---|---|---|
| **ACT - Treatment** | | |
| RD Mining effect | 0.013 | 0.014 |
| s.e. | 0.008 | 0.010 |
| Robust p-value | 0.061 | 0.180 |
| Bandwidth (metres) | 4,178 | 6,516 |
| Obs. | 201 | 329 |
| **Sulfadoxine-pyrimethamine (SP) - Prevention** | | |
| RD Mining effect | 0.036 | 0.046 |
| s.e. | 0.012 | 0.014 |
| Robust p-value | 0.001 | 0.001 |
| Bandwidth (metres) | 3,131 | 7,680 |
| Obs. | 136 | 345 |
| **Rapid Diagnostic Test (RDT)** | | |
| RD Mining effect | 0.005 | 0.008 |
| s.e. | 0.003 | 0.003 |
| Robust p-value | 0.049 | 0.002 |
| Bandwidth (metres) | 4,928 | 8,063 |
| Obs. | 224 | 268 |
| **Insecticide-Treated bed Net (ITN)** | | |
| RD Mining effect | 0.006 | -0.002 |
| s.e. | 0.008 | 0.011 |
| Robust p-value | 0.332 | 0.742 |
| Bandwidth (metres) | 4,324 | 5,656 |
| Obs. | 186 | 252 |

**Notes:** The table reports the results from nonparametric estimations of specification (3.1) using a local linear and cubic model for each antimalarial commodity. The bandwidth selection follows the MSE-optimal procedure proposed by Calonico, Cattaneo, and Titiunik (2014), as well as the construction of robust standard errors $p$-values. The smoothed distribution function used is the triangular kernel. Each commodity's stock value is expressed as a share in the population catchment area of the facility. For each regression, I control for the geographic characteristics (elevation and slope) and the number of mines surrounding a health facility.

Table B.11: Effect of mining areas on stock-outs, consumption and stock

| | SP<br>(1) | ACT<br>< 1<br>(2) | ACT<br>1-5<br>(3) | ACT<br>6-13<br>(4) | ACT<br>< 14<br>(5) | ITN<br>(6) | RDT<br>(7) |
|---|---|---|---|---|---|---|---|
| **No. of stock-out days per month** | | | | | | | |
| RD Mining effect | -0.461 | -1.144 | -1.038 | 7.869 | 0.495 | 1.992 | -0.775 |
| s.e. | 1.656 | 1.895 | 1.686 | 9.326 | 1.121 | 1.731 | 0.792 |
| Robust p-value | 0.977 | 0.545 | 0.498 | 0.317 | 0.746 | 0.143 | 0.290 |
| Obs. | 134 | 221 | 226 | 182 | 122 | 202 | 145 |
| **Monthly consumption** | | | | | | | |
| RD Mining effect | 0.006 | 0.019 | 0.038 | 0.005 | 0.021 | 0.006 | 0.059 |
| s.e. | 0.003 | 0.012 | 0.016 | 0.005 | 0.011 | 0.004 | 0.040 |
| Robust p-value | 0.026 | 0.071 | 0.013 | 0.385 | 0.032 | 0.106 | 0.122 |
| Obs. | 180 | 202 | 187 | 168 | 221 | 273 | 214 |
| **Monthly stock** | | | | | | | |
| RD Mining effect | 0.101 | 0.007 | 0.007 | 0.003 | 0.006 | 0.021 | 0.169 |
| s.e. | 0.036 | 0.005 | 0.005 | 0.003 | 0.005 | 0.037 | 0.108 |
| Robust p-value | 0.002 | 0.142 | 0.124 | 0.189 | 0.144 | 0.520 | 0.090 |
| Obs. | 130 | 180 | 163 | 202 | 264 | 220 | 294 |
| **Monthly share of consumption per stock** | | | | | | | |
| RD Mining effect | -0.165 | -1.083 | -0.418 | -1.396 | -0.359 | -0.171 | -0.839 |
| s.e. | 0.088 | 1.022 | 1.522 | 1.120 | 1.005 | 0.170 | 0.448 |
| Robust p-value | 0.029 | 0.208 | 0.667 | 0.154 | 0.741 | 0.205 | 0.029 |
| Obs. | 164 | 183 | 171 | 178 | 175 | 161 | 193 |

**Notes:** The table reports the results from nonparametric estimations of specification (3.1) using local linear regressions for each outcome. The bandwidth selection follows the MSE-optimal procedure proposed by Calonico, Cattaneo, and Titiunik (2014), as well as the construction of robust standard errors *p*-values. The smoothed distribution function used is the triangular kernel. ACT drugs are decomposed by age category in columns (2) to (5) and correspond to below 1 year old, between 1 and 5, between 6 and 13 and above 14 years old respectively. Each commodity's stock value is expressed as a share in the population catchment area of the facility. For each regression, I control for the geographic characteristics (elevation and slope) and the number of mines surrounding a health facility.

Table B.12: Effect of mining areas on antenatal care and malaria prevalence

| | *Linear model (p=1)* (1) | *Cubic model (p=3)* (2) |
|---|---|---|
| **No. of prenatal visits per capita** | | |
| RD Mining effect | 0.002 | 0.005 |
| Robust s.e. | 0.004 | 0.006 |
| Robust p-value | 0.456 | 0.353 |
| Bandwidth h (in metres)* | 4,943 | 8,049 |
| Obs. | 224 | 378 |
| **Malaria prevalence** | | |
| RD Mining effect | 0.065 | 0.079 |
| Robust s.e. | 0.028 | 0.038 |
| Robust p-value | 0.011 | 0.038 |
| Bandwidth h (in metres)* | 4,212 | 7,273 |
| Obs. | 202 | 352 |

**Notes:** The table reports the results from nonparametric estimations of specification (3.1) using local linear regressions for each outcome. The bandwidth selection follows the MSE-optimal procedure proposed by Calonico, Cattaneo, and Titiunik (2014), as well as the construction of robust standard errors $p$-values. The smoothed distribution function used is the triangular kernel. For each regression, I control for the geographic characteristics (elevation and slope) and the number of mines surrounding a health facility.

* The bandwidth selection follows the MSE-optimal procedure proposed by Calonico, Cattaneo, and Titiunik (2014), as well as the construction of robust standard errors $p$-values. The smoothed distribution function used is the triangular kernel.

# Data Appendix

I detail in this section the variables that are used in the analysis.

## Geographic Characteristics

*Elevation*: Elevation measured in metres above the sea level. Data on elevation and terrain features were obtained from NASA's Shuttle Radar Topography Mission (SRTM) satellite images. Elevation information is provided at a high spatial resolution (3 arc-second resolution or approximately 90 metres). Information is then processed in ArcGIS to obtain elevation data.

*Slope*: Slope is measured in degrees and is obtained from NASA's Shuttle Radar Topography Mission (SRTM) satellite images and processed in ArcGIS.

*Distance from closest facility*: corresponds to the geographic distance from a health facility to the closest facility. Distances are calculated with ArcGIS based on the latitude and longitude of each health facility in the data sample.

*Distance from closest hospital*: corresponds to the geographic distance from a health facility to the closest hospital. Distances are calculated with ArcGIS based on the elevation and surface features, and using the latitude and longitude of each health facility in the data sample. The function *costpath* is used in ArcGIS to calculate the optimal path based on the geographic features; distance information on the estimated path is then extracted for each health facility.

## Facilities Characteristics

*Antimalarial stock value*: Antimalarial commodity corresponds to any commodity that is used as mean of prevention, identification or treatment of malaria. It comprises Insecticide-Treated mosquito Nets (ITNs) and Sulfadoxine-Pyrimethamine (SP), (chemoprevention administered to pregnant women and children less than five) for prevention ; 2) Rapid Diagnostic Test (RDT) for identification and Artemisinin-based Combination Therapy (ACT) for treatment of malaria. Data on the monthly stock of each antimalarial commodity is obtained from the DHIS2. The estimated value is U.S. Dollars and is based on the reference pricing of antimalarial medicines negotiated by the Global Fund through the Pooled Procurement mechanism for 2017.

*Total other drugs stock value*: corresponds to the medicines listed as Essential Medicines from the WHO Model list (https://www.who.int/medicines/publications/essentialmedicines/en/). Data on the monthly stock of these medicines are obtained from the DHIS2, and the stock value is expressed in U.S. Dollars.

*Revenue*: is the monthly revenue reported by health facilities in the DHIS2, and expressed in U.S. Dollars.

*Investment*: is the monthly investment reported by health facilities in the DHIS2, and expressed in U.S. Dollars.

*Payroll tax*: is the monthly payroll tax reported by health facilities in the DHIS2, and expressed in U.S. Dollars.

*Number of nurses*: is the monthly number of nurses who are working in the health facility as reported in the DHIS2. The number includes nurses with two different qualification levels, A1 and A2.

*Number of births*: is the monthly number of birth in the health facility as reported in the DHIS2.

## Stock outs days antimalarial

*Insecticide-Treated mosquito Net*: corresponds to the average monthly number of days the health facility ran out of ITNs in 2017.

*Rapid Diagnostic Test*: corresponds to the average monthly number of days the health facility ran out of RDTs in 2017.

*Sulfadoxine-Pyrimethamine*: corresponds to the average monthly number of days the health facility ran out of SPs in 2017.

*ACT (ages +14)*: corresponds to the average monthly number of days the health facility ran out of Artemisinin-based Combination Therapy (ACT) for patients above

14 in 2017.

*ACT (ages 6-13)*: corresponds to the average monthly number of days the health facility ran out of Artemisinin-based Combination Therapy (ACT) for patients between 6 and 13 in 2017.

*ACT (ages 1-5)*: corresponds to the average monthly number of days the health facility ran out of Artemisinin-based Combination Therapy (ACT) for patients between 1 and 5 in 2017.

*ACT (ages -1)*: corresponds to the average monthly number of days the health facility ran out of Artemisinin-based Combination Therapy (ACT) for patients below 1 in 2017.

## Evidence of Data quality in the DHIS2

DHIS2 is notoriously known for varying data quality performance across African countries where it is implemented. Even within the DRC, there is considerable heterogeneity in the completeness of reported data depending on the type of indicators. In particular, indicators (number of patients, stock and consumption of commodities, number of stock-out days, estimated number of affected population) pertaining to diseases heavily funded by donors (HIV, malaria) exhibit significantly higher quality performance than those related to disease mostly funded by government funding (such as non-communicable diseases). Moreover, two provinces which contain most of health facilities analysed in this study (North and South Kivu) have the highest state of data completeness across provinces in the country.

To ensure the validity of the data, I also cross-validated the epidemiological and financial data with two external sources. For data on malaria prevalence, I compare the obtained numbers from DHIS2 with the most recent Demographic Health Surveys in the DRC that was conducted in 2013/2014 and I do not find significant variations. Furthermore, I estimated the stock value of antimalarial commodities from the reported stock at health facility level and the cost of procurement of each commodity, the latter being obtained from the Pooled Procurement Mechanism

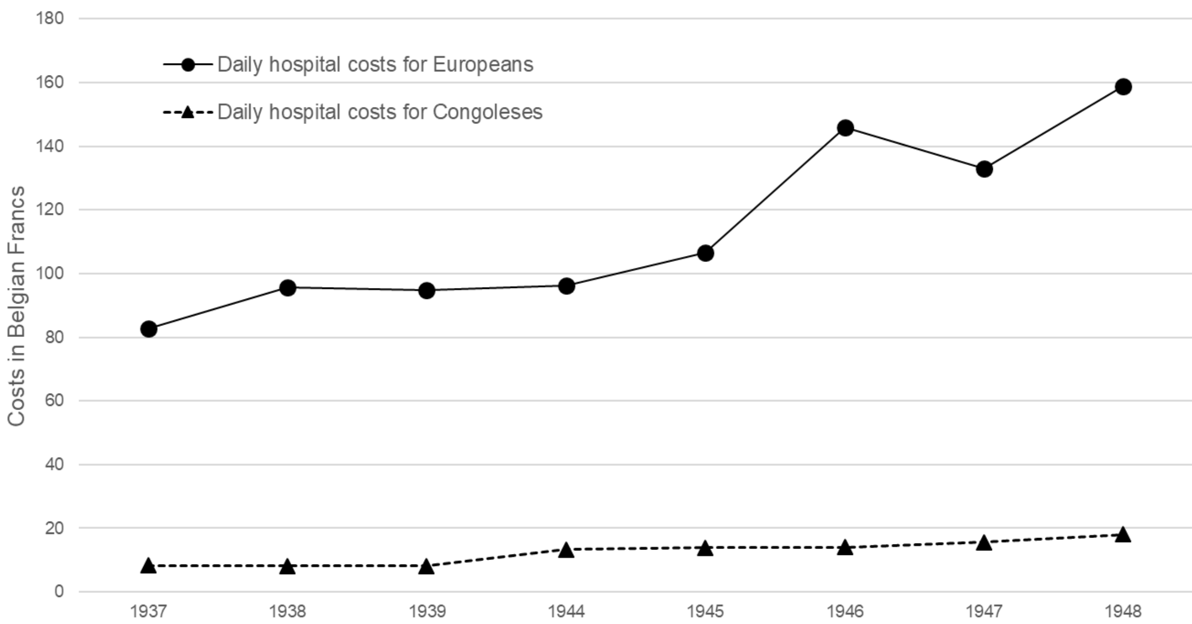
Reference Pricing of the Global Fund (Figure B.14, Appendix B). I then calculated for each province of the DRC the sum of the estimated stock value of antimalarial commodities of each health facility. Furthermore, information on total malaria's funding at the provincial level was obtained from the three most important donors for malaria in the DRC (namely the Global Fund, U.S. Government (USAID) and U.K. Government (DFID)), representing approximately 97% of total donors' funding for malaria in the country (MSP, 2017). Figure B.1 graphs the scatter plot of the estimated stock value of antimalarial commodities at the provincial level on the donors' malaria funding. The estimated coefficient indicates that the stock value of antimalarial commodities represents 48% of total malaria investment (Figure B.16, Appendix B). This information is consistent with the findings from a recent audit report of the Global Fund in the DRC (The Global Fund, 2016) which estimates that 53% of total the Global Fund's investment is dedicated to the procurement of antimalarial commodities[1].

[1]This estimate was obtained from the financial information of the Global Fund's local partners and the estimated annual budget of the malaria control programme.

# Appendix C

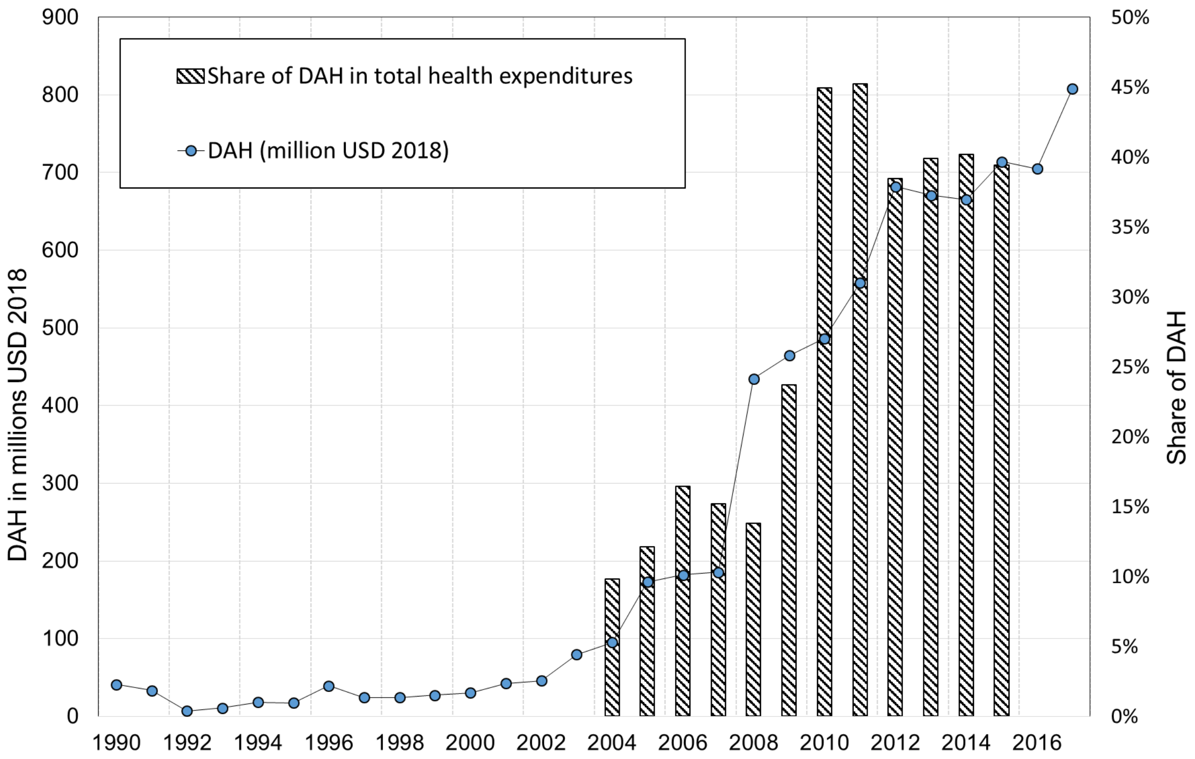
# Appendix for chapter 4

Figure C.1: Daily cost of European and Congolese hospitals




**Notes:** The graph plots the country average daily cost of hospitalisation for European and Congolese (dashed line) hospitals between 1937 and 1948. The estimated cost of hospitalisation includes health treatment costs, salary, provision of drugs and health equipment and general maintenance costs. *Source*: Archival data from annual medical report in Belgian Congo for each year of the covered period.

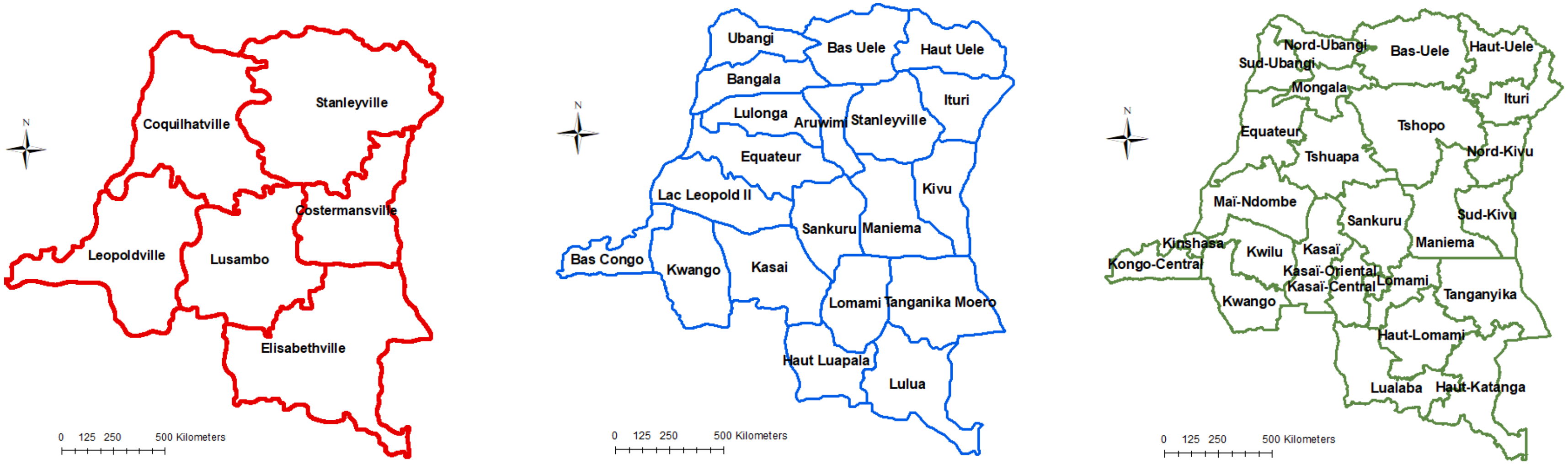
FIGURE C.2: Development Assistance for Health in the DRC, 1990-2017




**Notes:** The graph plots the total Development Assistance for Health between 1990 and 2017 in millions of 2018 USD in the DRC and its share in total health expenditure starting from 2004. *Source:* author's computations using the Development Assistance for Health Database 1990-2018 from IHME Global Health Data Exchange (`http://ghdx.healthdata.org/`) and Global Health Observatory data from WHO (`http://apps.who.int/gho/data/node.home`).

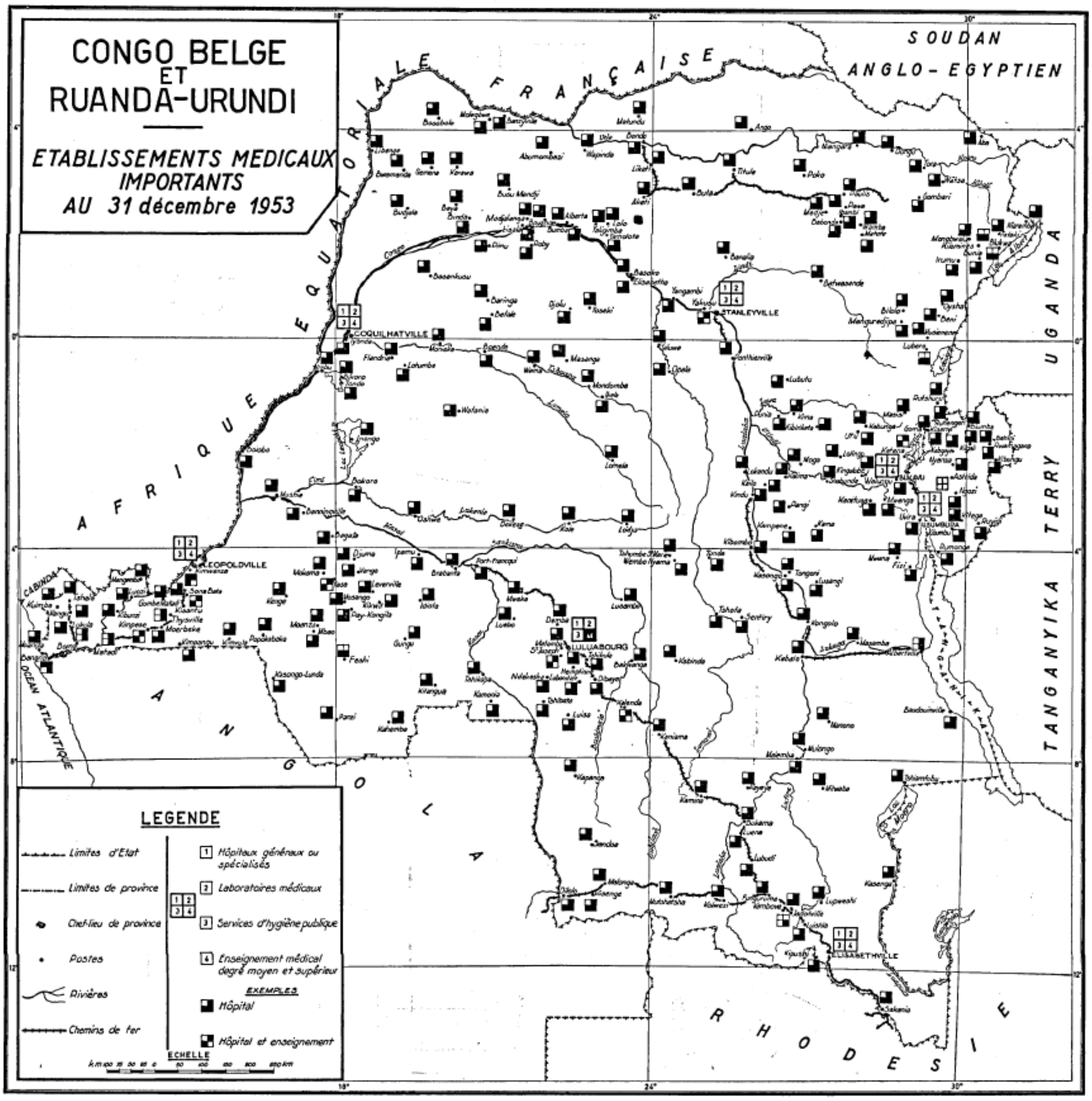
Figure C.3: Administrative boundaries

(a) 1895 boundaries (provinces) (b) 1908 boundaries (districts) (c) 2015 provinces




**Notes:** The figures illustrate the evolution of the administrative boundaries in Congo from the colonial period to the present day (since 2015). The Belgian Congo was divided into 6 provinces and 22 districts. Since 2015, the DRC is composed of 26 provinces that approximately correspond to the colonial districts, while most colonial names have been changed.

Figure C.4: Mapping of colonial medical structures in 1953

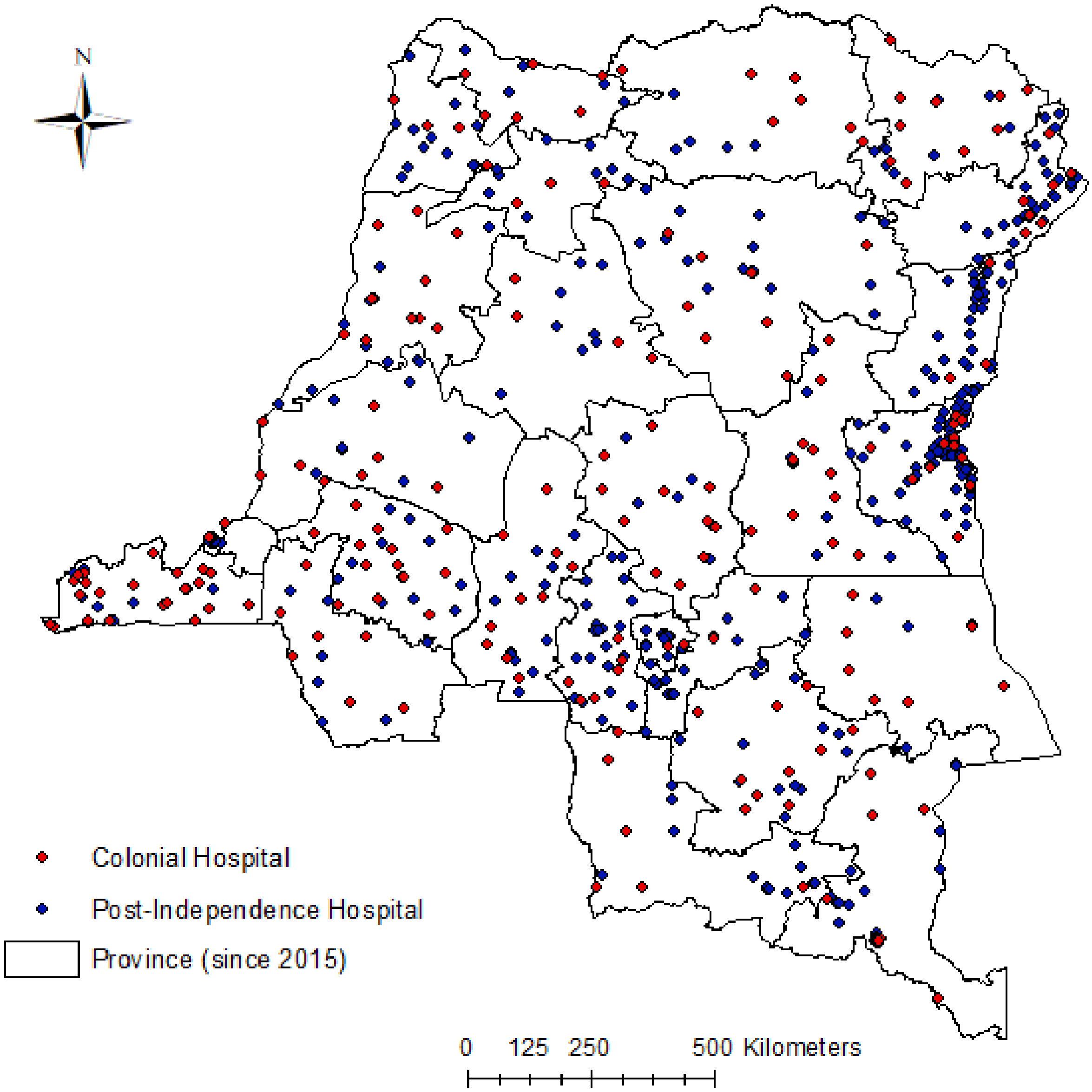



**Notes:** The map depicts the location of all major health infrastructures in 1953. *Source:* Ministry of Colonies.

FIGURE C.5: Mapping of Christian missions in 1929

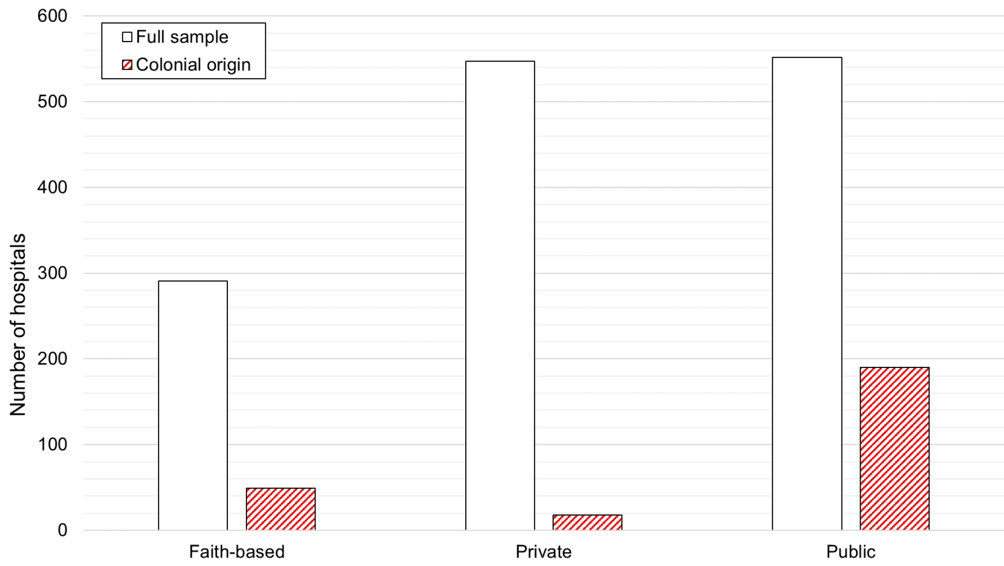

**Notes:** The map depicts the location of Christian missions (Catholics and Protestants) in 1929. *Source:* Ministry of Colonies.

Figure C.6: Mapping of the full sample of colonial and post-independence hospitals

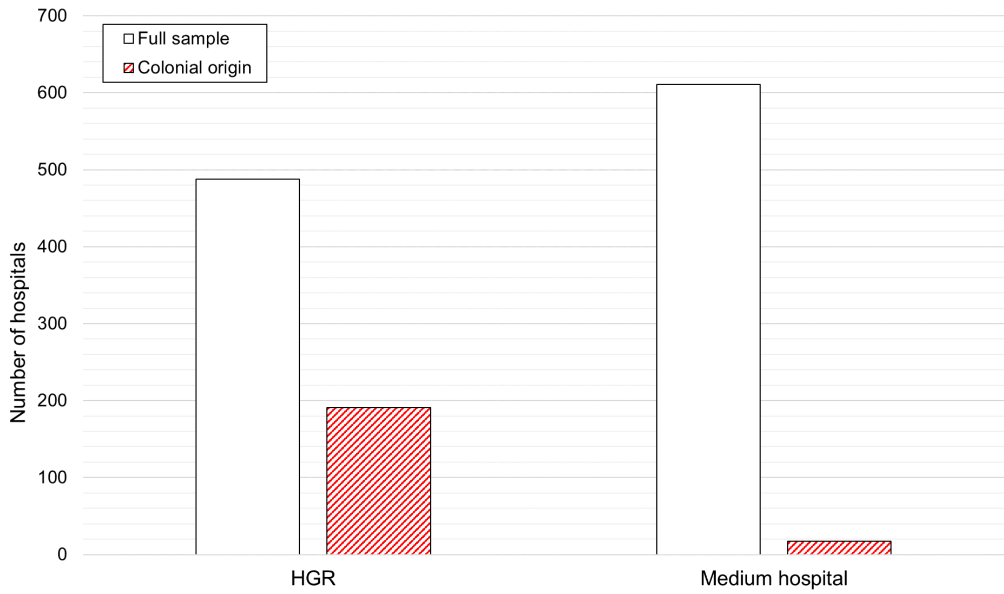



**Notes:** The map shows the geo-location of the hospitals that were built during the colonial period between 1920 and 1956 and those that were built after independence in 1960.

Figure C.7: Distribution of hospitals in the data sample



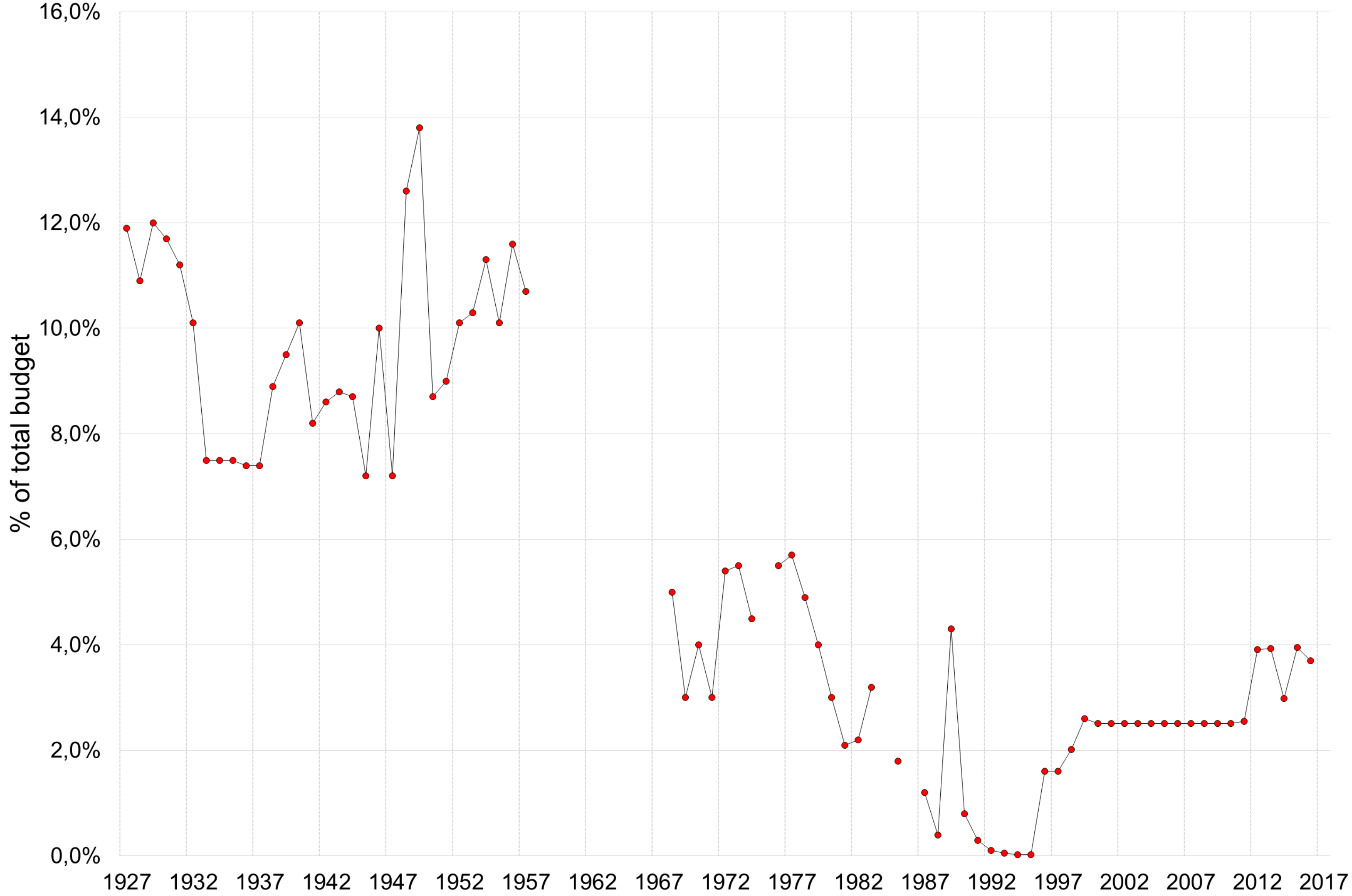

(A) Hospital distribution by ownership




(B) Hospital distribution within the public sector

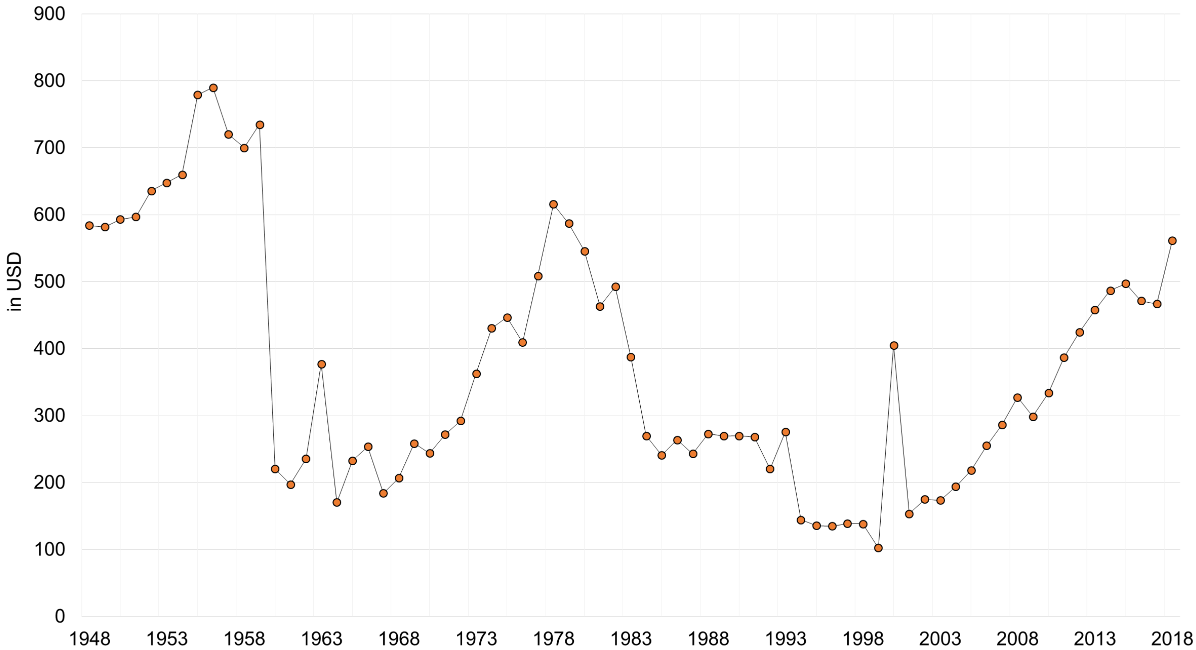
**Notes:** The two graphs plot the distribution of hospital by ownership (A) and by size (B) when restricted to the public sector (the size refers either to General Referral Hospital (HGR) or to all other public hospitals (district or provincial hospitals)). Each graph plots the number of hospitals within the full data sample (green bars) and within the restricted sample of hospitals with colonial origin (red dashed). *Source:* author's computations.

Figure C.8: Share of domestic health spending in total budget, 1927-2016




**Notes:** The graph plots the share of domestic general government health expenditure as a percentage of total budget between 1927 and 2016. Note that no data was found for the period directly following independence in 1960. *Source:* author's computations using *Annuaire statistique de la Belgique et du Congo Belge* and *Rapport annuel, Direction Générale des services médicaux du Congo Belge 1929-58* for the colonial period; World Bank and IMF data for 1970-2000 and Global Health Observatory data from WHO after 2000 (https://www.who.int/gho/health_financing/public_exp_health/en/).

FIGURE C.9: DRC Gross National Income per capita in 2018 USD, 1948-2018

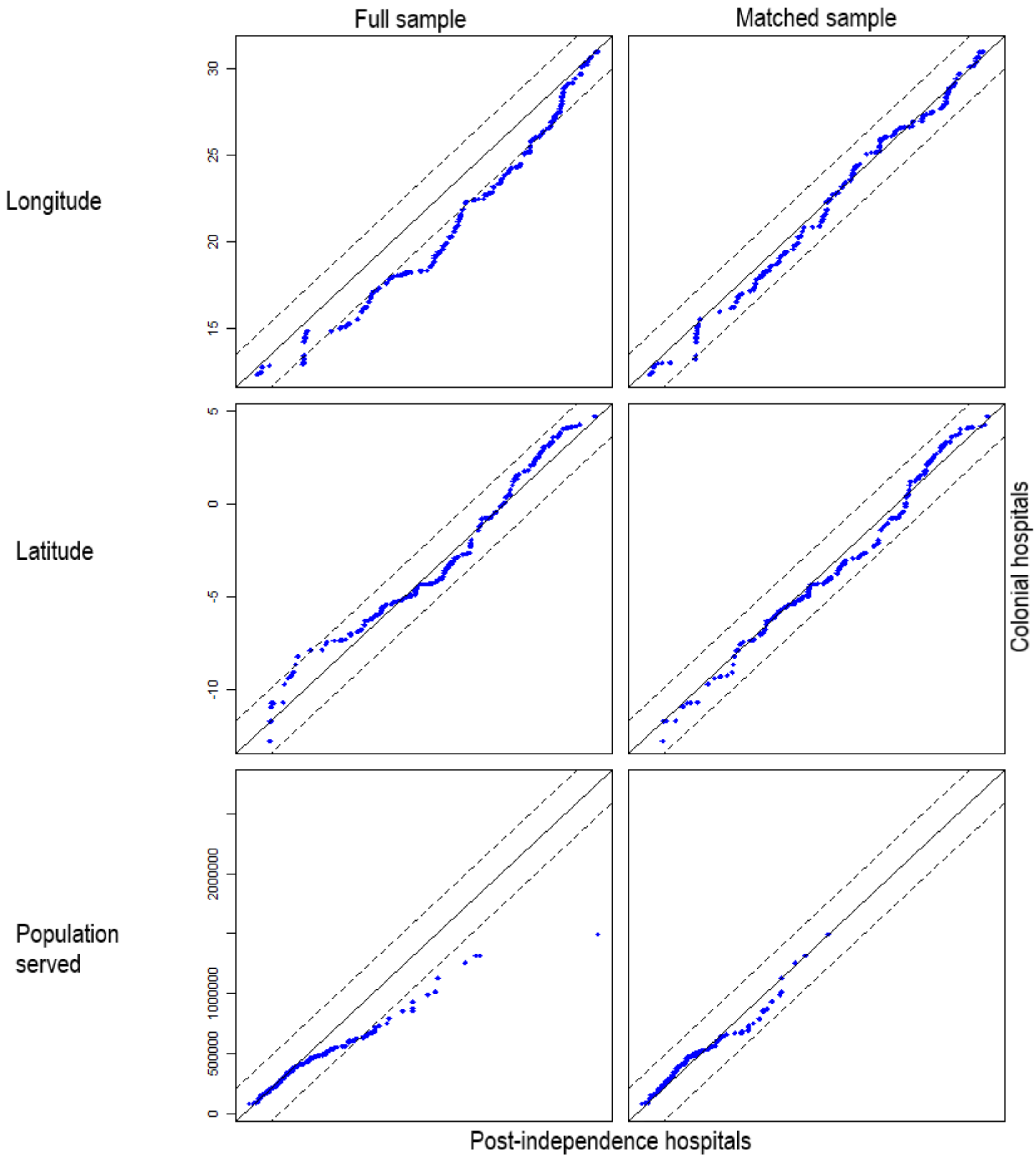



**Notes:** The graph plots the Gross National Income per capita of the DRC in 2018 USD between 1948 and 2018. *Source:* World Bank national account data (https://data.worldbank.org/indicator/NY.GNP.PCAP.CD).

Figure C.10: Communication channels in 1928

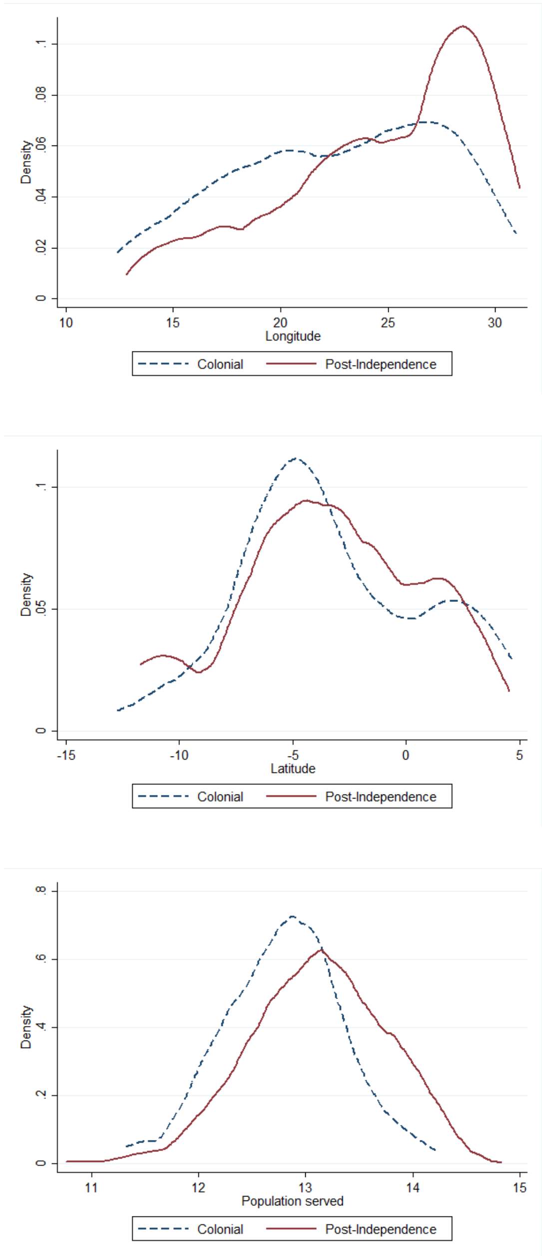

**Notes:** The map shows the communication channels organised in public services in 1928: railways (black), waterways (blue) and roads (red). *Source:* Institut Cartographique militaire Service Cartographique du Ministère des Colonies.

Figure C.11: QQ plots



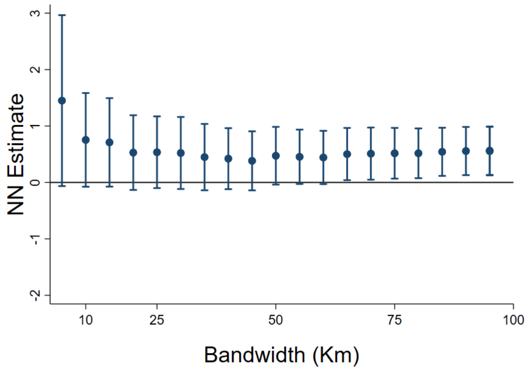

**Notes:** Each graph plots the average distance between the empirical quantile distributions of the colonial and post-independence groups calculated over the full sample (left) and the matched sample (right) for the matching covariates of interest: longitude, latitude and population served. In the matched samples, unmatched units are pruned to improve balance. For a perfect matching of the distributions, the covariate values should lie on the 45 degree line. The quantile-quantile (QQ) plots are produced using the MatchIt package in R (**ho2011**).

Figure C.12: Evidence of common support assumption

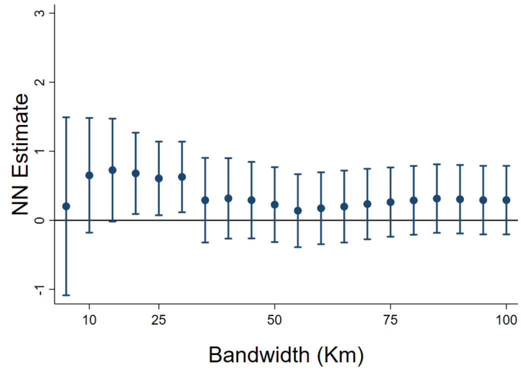



**Notes:** Each graph plots the kernel density estimation using the Epanechnikov kernel for colonial (dashed blue) and post-independence hospitals. The graphs show the density distribution of the three variables of interest: longitude, latitude and population served.

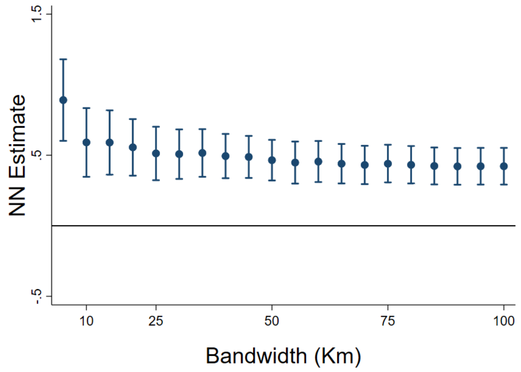
Figure C.13: Matching estimate sensitivity to bandwidth selection



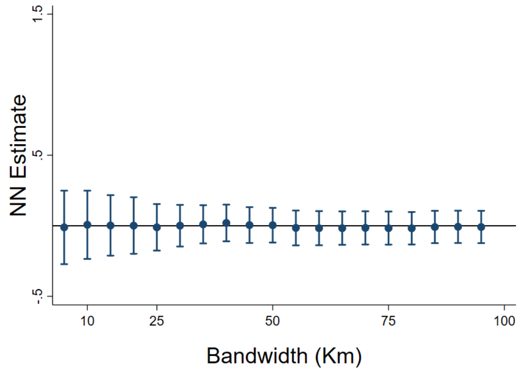

(a) Government funding



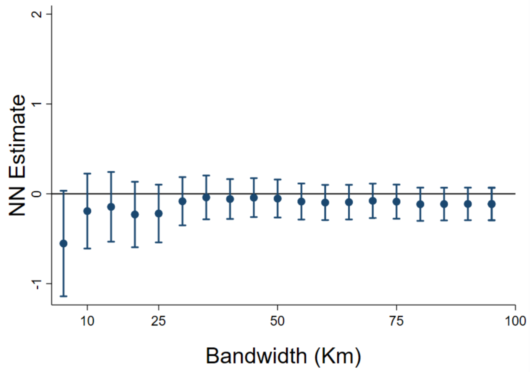

(b) Investments



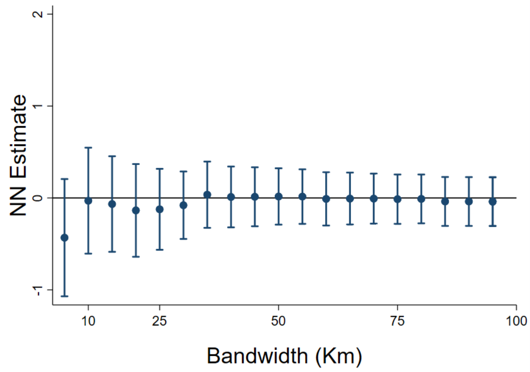

(c) Beds




(d) Medical staff



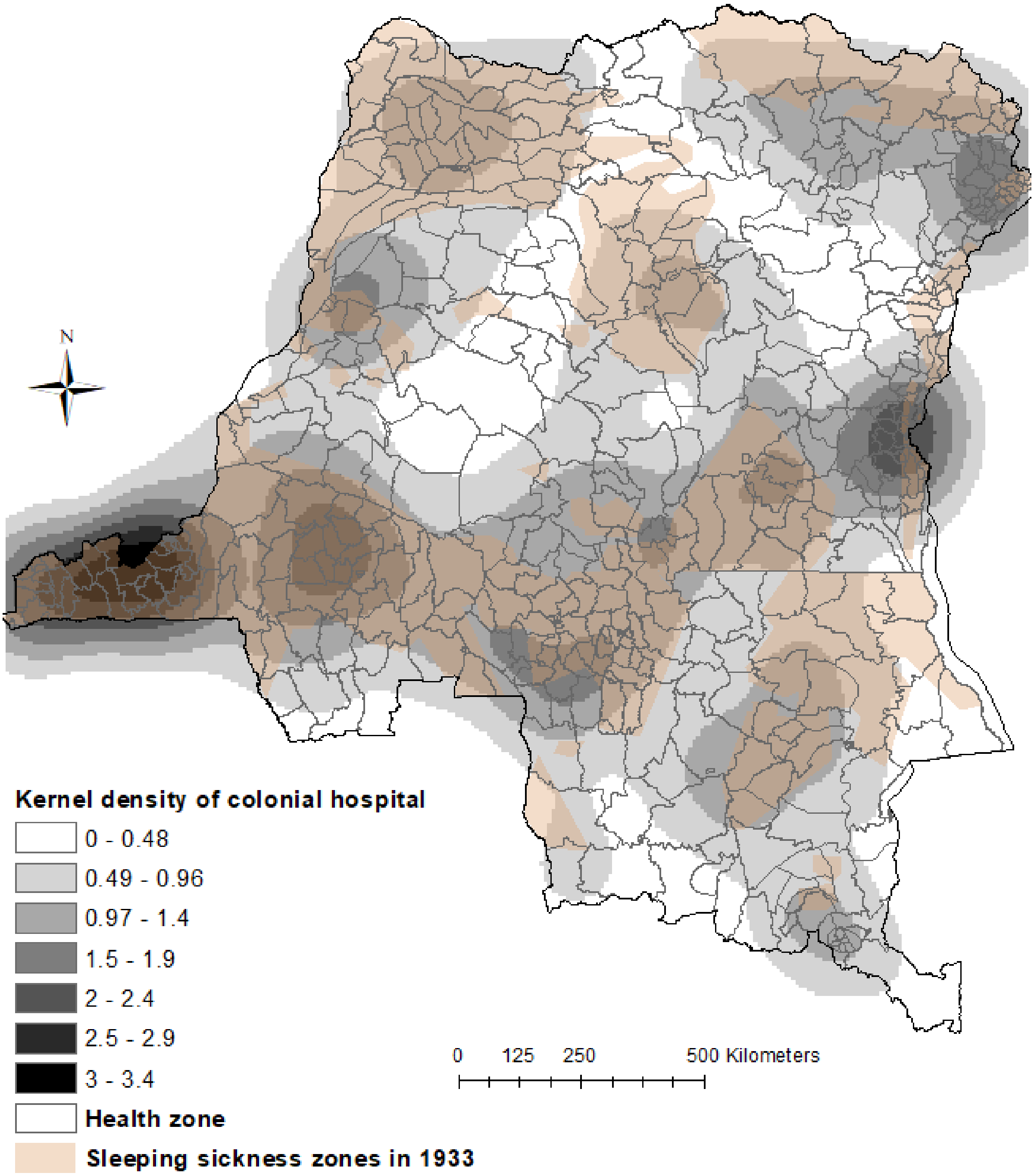

(e) Malaria case treated




(f) Emergency case

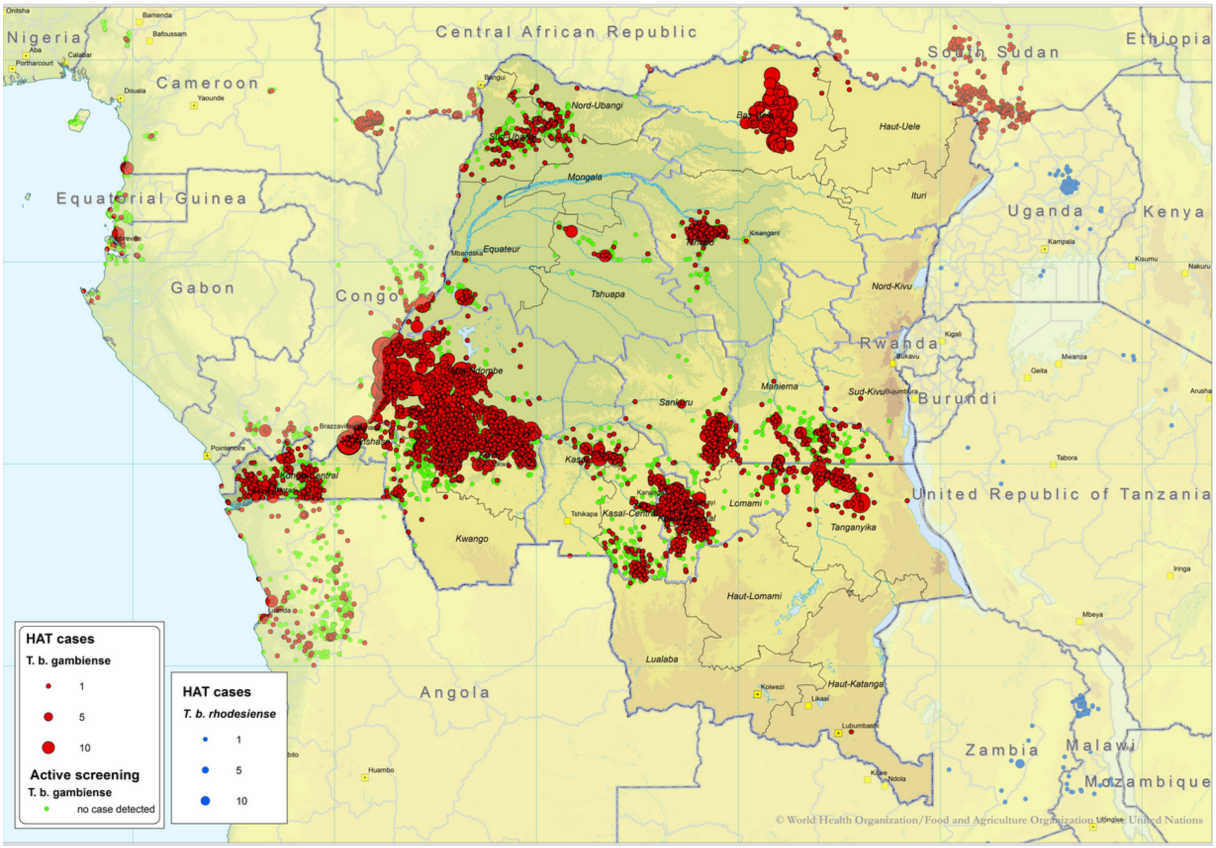
**Notes:** Each graph plots estimates from a one-to-one nearest neighbour matching procedure with replacement, using the biased-corrected matching estimator proposed by Abadie and Imbens (2011). The regressions include all matching covariates presented above and use robust standard errors. Each graph shows the point estimates with the 95% confidence interval. The bandwidth corresponds to the distance to the nearest hospital, ranging from 5 to 100 km.

Figure C.14: Kernel density of colonial settlements and the presence of sleeping sickness in 1933




**Notes:** The map depicts the kernel density of colonial health settlements and the geographic distribution of the sleeping sickness (in brown) by health zones (district level) as reported in the public health data of the Ministry of Colonies between 1928 and 1933 (Lyons, 2002). A health zone is reported with sleeping sickness when the prevalence of the disease is at least equal to 1%.

FIGURE C.15: Distribution of sleeping sickness in the DRC in 2016




**Notes:** The map depicts the geographical distribution of sleeping sickness (human African trypanosomiasis) through the reported number of new cases between 2012 and 2016. *Source:* the map is produced by Franco et al. (2017) and accessed from the WHO website (https://www.who.int/trypanosomiasis_african/country/foci_AFRO/en/).

Table C.1: Summary statistics and difference-in-means

| | Post-Independence | | | Colonial | | | Difference-in-means | | |
|---|---|---|---|---|---|---|---|---|---|
| | Obs. | Sample mean | s.d. | Obs. | Sample mean | s.d. | Diff-in-means | s. e. | p-value |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| **Financial characteristics** | | | | | | | | | |
| Expenditure | 682 | 6,965 | 1,033.56 | 197 | 7,291 | 1,081.92 | 327 | 1,496.26 | 0.83 |
| Revenue | 674 | 6,786 | 652.33 | 197 | 9,800 | 1,437.80 | 3,014 | 1,578.86 | 0.06 |
| Government funding | 441 | 1,168 | 323.02 | 150 | 1,522 | 303.28 | 354 | 443.08 | 0.42 |
| Investment | 447 | 466 | 90.37 | 151 | 286 | 49.76 | -180 | 103.17 | 0.08 |
| Total value of drug stock | 634 | 5,820 | 693.00 | 197 | 5,687 | 633.69 | -133 | 939.05 | 0.89 |
| Value of drug purchase | 578 | 1,558 | 243.08 | 188 | 2,008 | 619.92 | 451 | 665.88 | 0.50 |
| **Structural characteristics** | | | | | | | | | |
| No. of days with electricity | 587 | 9 | 0.35 | 149 | 12 | 0.72 | 3 | 0.80 | 0.00 |
| No. Beds | 785 | 52 | 1.66 | 204 | 92 | 5.08 | 40 | 5.35 | 0.00 |
| Birth | 771 | 19 | 0.84 | 191 | 20 | 1.67 | 1 | 1.87 | 0.59 |
| **Staff** | | | | | | | | | |
| Physician | 861 | 5 | 0.51 | 207 | 8 | 1.28 | 3 | 1.38 | 0.02 |
| Nurse | 893 | 16 | 0.84 | 208 | 33 | 4.43 | 17 | 4.51 | 0.00 |
| **Health services** | | | | | | | | | |
| Severe malaria treated | 828 | 41 | 1.78 | 202 | 66 | 3.65 | 25 | 4.06 | 0.00 |
| Inpatients | 786 | 117 | 4.85 | 204 | 192 | 11.96 | 75 | 12.91 | 0.00 |
| No. consultations | 838 | 341 | 19.33 | 202 | 374 | 28.79 | 33 | 34.67 | 0.34 |
| Emergency case | 713 | 49 | 3.78 | 196 | 82 | 8.59 | 33 | 9.39 | 0.00 |
| Length of stay | 726 | 39 | 3.13 | 199 | 38 | 2.30 | -1 | 3.89 | 0.83 |
| Population covered | 190 | 185,141 | 79,665.11 | 104 | 148,563 | 38,452.55 | -36,578 | 88,459.76 | 0.68 |

**Notes:** The unit of observation is health facility and all financial characteristics are expressed in 2018 U.S. Dollars. All indicators correspond to monthly average numbers. The first six columns show the number of observations, sample mean and standard deviation for post-independence and colonial hospitals respectively. The last three columns indicate the difference in means between post-independence and colonial hospitals, the robust standard errors for the difference and the *p*-value of the test of whether the mean coefficients in the two samples are equal.

Table C.2: Colonial investment effect on health facility performance

| | No Control | Access facility | Access facility + Geographic | No Control | Access facility | Access facility + Geographic |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (1) | (2) | (3) |
| *Panel A. Financial characteristics* | **Government Funding** | | | **Investment** | | |
| Colonial settlement | 0.510*** | 0.332** | 0.445*** | 0.481** | 0.307 | 0.306 |
| | (0.166) | (0.160) | (0.168) | (0.214) | (0.240) | (0.250) |
| Medical staff | 1.271*** | 1.047*** | 0.963*** | 0.883*** | 0.849*** | 0.863*** |
| | (0.109) | (0.108) | (0.121) | (0.121) | (0.141) | (0.145) |
| Population served | | | 0.011 | | | 0.066 |
| | | | (0.212) | | | (0.304) |
| Observations | 588 | 441 | 438 | 596 | 423 | 417 |
| R-squared | .338 | .32 | .338 | .303 | .287 | .314 |
| *Panel B. Inputs* | **Beds** | | | **Nurses** | | |
| Colonial settlement | 0.303*** | 0.194*** | 0.125** | 0.203*** | 0.169*** | 0.186*** |
| | (0.052) | (0.054) | (0.051) | (0.055) | (0.056) | (0.056) |
| Medical staff | 0.666*** | 0.591*** | 0.633*** | | | |
| | (0.032) | (0.035) | (0.038) | | | |
| Population served | | | -0.069 | | | 0.165*** |
| | | | (0.051) | | | (0.053) |
| Observations | 976 | 618 | 608 | 976 | 618 | 608 |
| R-squared | .531 | .533 | .565 | .549 | .557 | .619 |
| Provincial FE | Y | Y | Y | Y | Y | Y |

**Notes:** The table presents the OLS estimates of equation 4.4. The dependent variable is indicated as the header over the three rows in each panel. Column (3) controls for both access to facility and the geographic covariates. Robust standard errors clustered by districts (health zones). *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table C.2: Colonial investment effect on health facility performance *(continued)*

| | No Control (1) | Access facility (2) | Access facility + Geographic (3) | No Control (1) | Access facility (2) | Access facility + Geographic (3) |
|---|---|---|---|---|---|---|
| *Panel C. Production function* | **Malaria treated** | | | **Emergency cases** | | |
| Colonial settlement | 0.129 | 0.102 | 0.053 | 0.259** | 0.148 | 0.020 |
| | (0.083) | (0.085) | (0.087) | (0.103) | (0.111) | (0.111) |
| Medical staff | 0.674*** | 0.498*** | 0.509*** | 0.833*** | 0.734*** | 0.742*** |
| | (0.047) | (0.059) | (0.057) | (0.057) | (0.073) | (0.076) |
| Population served | -0.402*** | -0.344*** | -0.276*** | -0.321*** | -0.188* | -0.118 |
| | (0.076) | (0.090) | (0.085) | (0.086) | (0.105) | (0.101) |
| Observations | 1007 | 609 | 607 | 890 | 582 | 580 |
| R-squared | .356 | .315 | .382 | .344 | .312 | .332 |
| *Panel D. Health care demand* | **Outpatient visit** | | | **Deliveries** | | |
| Colonial settlement | 0.039 | 0.064 | 0.021 | 0.112 | 0.138 | 0.204 |
| | (0.063) | (0.064) | (0.068) | (0.115) | (0.121) | (0.132) |
| Physician | 0.542*** | 0.430*** | 0.415*** | | | |
| | (0.034) | (0.043) | (0.051) | | | |
| Midwife | | | | -0.059 | 0.001 | -0.025 |
| | | | | (0.064) | (0.067) | (0.073) |
| Observations | 1012 | 614 | 604 | 701 | 466 | 460 |
| R-squared | .318 | .287 | .309 | .134 | .194 | .207 |
| Provincial FE | Y | Y | Y | Y | Y | Y |

**Notes:** The table presents the OLS estimates of equation 4.4. The dependent variable is indicated as the header over the three rows in each panel. Column (3) controls for both access to facility and the geographic covariates. Robust standard errors clustered by districts. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table C.2: Colonial investment effect on health facility performance *(continued)*

| | No Control (1) | Access facility (2) | Access facility + Geographic (3) | No Control (1) | Access facility (2) | Access facility + Geographic (3) |
|---|---|---|---|---|---|---|
| *Panel E. Structural characteristics* | **Stock-out days** | | | **Days with electricity** | | |
| Colonial settlement | 0.020 | -0.011 | -0.080 | 0.288** | 0.196 | 0.185 |
| | (0.052) | (0.054) | (0.056) | (0.142) | (0.138) | (0.148) |
| Medical staff | 0.068** | 0.036 | 0.090*** | -0.101 | -0.416*** | -0.344*** |
| | (0.027) | (0.029) | (0.030) | (0.074) | (0.098) | (0.094) |
| Population served | | | -0.126** | | | -0.421*** |
| | | | (0.055) | | | (0.147) |
| Observations | 967 | 602 | 593 | 733 | 457 | 453 |
| R-squared | .18 | .216 | .262 | .181 | .177 | .231 |
| Provincial FE | Y | Y | Y | Y | Y | Y |

**Notes:** The table presents the OLS estimates of equation 4.4. The dependent variable is indicated as the header over the three rows in each panel. Column (3) controls for both access to facility and the geographic covariates. Robust standard errors clustered by districts. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table C.3: Colonial investment effect on input utilisation

| | No Control (1) | Access facility (2) | Access facility + Geographic (3) | No Control (1) | Access facility (2) | Access facility + Geographic (3) |
|---|---|---|---|---|---|---|
| | **Bed occupancy** | | | **Length of stay** | | |
| Colonial settlement | -0.068 | -0.067 | -0.081 | 0.329*** | 0.211** | 0.076 |
| | (0.047) | (0.050) | (0.054) | (0.094) | (0.085) | (0.077) |
| Medical staff | 0.109*** | 0.073** | 0.074** | 0.864*** | 0.682*** | 0.752*** |
| | (0.024) | (0.033) | (0.036) | (0.052) | (0.050) | (0.053) |
| Observations | 976 | 618 | 608 | 928 | 600 | 590 |
| R-squared | .14 | .163 | .186 | .435 | .431 | .47 |
| Provincial FE | Y | Y | Y | Y | Y | Y |

**Notes:** The table presents the OLS estimates of equation 4.4. The dependent variable is indicated as the header over the three rows in each panel. Column (3) controls for both access to facility and the geographic covariates. Robust standard errors clustered by districts. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table C.4: Robustness to different cutoff radii for spatial clustering

| Dependent variable | Government funding (1) | Investment (2) | Stock-out days (3) | Days with electricty (4) | Bed capacity (5) | Medical staff (6) |
|---|---|---|---|---|---|---|
| Coefficient | | | | | | |
| Colonial settlement | 0.397** | 0.274 | -0.088 | 0.186 | 0.125*** | 0.186*** |
| Standard errors with following cutoffs | | | | | | |
| 50 km | 0.170** | 0.260 | 0.055 | 0.136 | 0.046*** | 0.054*** |
| 100 km | 0.191** | 0.252 | 0.064 | 0.134 | 0.044*** | 0.056*** |
| 200 km | 0.204* | 0.300 | 0.062 | 0.124 | 0.043*** | 0.054*** |
| 300 km | 0.231* | 0.320 | 0.063 | 0.156 | 0.040*** | 0.049*** |
| *Controls:* | | | | | | |
| Human capital | Y | Y | Y | Y | Y | N |
| Physical capital | Y | Y | Y | Y | N | Y |
| Geographic characteristics | Y | Y | Y | Y | Y | Y |
| Population served | Y | Y | Y | Y | Y | Y |

**Notes:** Variables not shown include provincial fixed effect, log of population served and geographic controls. Following Conley (1999) standard errors are adjusted for spatial dependence by clustering observations within circles of varying distances. The first row reports the coefficient of the colonial settlement from equation 4.4 and the following rows report the standard errors when changing the variance-covariance matrix through a change in the distance cutoff of the spatial clusters. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

TABLE C.5: Decomposition of the colonial investment effect by type and source

| | (1) | (2) | (3) | (1) | (2) | (3) |
|---|---|---|---|---|---|---|
| *Panel A. Financial characteristics* | **Government Funding** | | | **Investment** | | |
| Colonial settlement | 0.405** | 0.880** | 0.688** | 0.231 | -0.154 | 0.034 |
| | (0.168) | (0.347) | (0.318) | (0.254) | (0.471) | (0.411) |
| Hospital type | | | | | | |
| General Referral Hospital | 0.134 | | | 0.552* | | |
| | (0.303) | | | (0.293) | | |
| Private hospital | -1.072*** | | | -0.146 | | |
| | (0.325) | | | (0.377) | | |
| Faith-based hospital | -0.140 | | | 0.238 | | |
| | (0.180) | | | (0.234) | | |
| Colonial type | | | | | | |
| Europeans | | -0.248 | | | -0.476 | |
| | | (0.318) | | | (0.319) | |
| Congolese | | -0.417 | | | 0.745* | |
| | | (0.368) | | | (0.448) | |
| Colonial funding source | | | | | | |
| Colonial government | | | -0.432 | | | 0.454 |
| | | | (0.336) | | | (0.371) |
| Private | | | -0.378 | | | 0.040 |
| | | | (0.451) | | | (0.503) |
| Religious | | | 0.075 | | | 0.195 |
| | | | (0.373) | | | (0.369) |
| Observations | 438 | 438 | 438 | 417 | 417 | 417 |
| R-squared | .373 | .342 | .342 | .324 | .32 | .316 |
| Human and physical capital | Y | Y | Y | Y | Y | Y |
| Geographic characteristics | Y | Y | Y | Y | Y | Y |
| Population served | Y | Y | Y | Y | Y | Y |
| Provincial FE | Y | Y | Y | Y | Y | Y |

**Notes:** The table presents the OLS estimates of equation 4.4 with additional controls for hospital ownership, colonial type and colonial funding source. The dependent variable is indicated as the header over the three rows in each panel. Column (3) controls for both access to facility and the geographic covariates. Robust standard errors clustered by districts. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table C.5: Decomposition of the colonial investment effect by type and source *(continued)*

| | (1) | (2) | (3) | (1) | (2) | (3) |
|---|---|---|---|---|---|---|
| *Panel B. Inputs* | | **Beds** | | | **Nurses** | |
| Colonial settlement | 0.115** | 0.186* | 0.240*** | 0.145*** | 0.133 | 0.038 |
| | (0.050) | (0.097) | (0.089) | (0.054) | (0.111) | (0.098) |
| Hospital type | | | | | | |
| General Referral Hospital | 0.061 | | | 0.194** | | |
| | (0.101) | | | (0.097) | | |
| Private hospital | -0.191* | | | -0.033 | | |
| | (0.109) | | | (0.091) | | |
| Faith-based hospital | 0.224*** | | | -0.251*** | | |
| | (0.047) | | | (0.051) | | |
| Colonial type | | | | | | |
| Europeans | | -0.063 | | | 0.193** | |
| | | (0.067) | | | (0.080) | |
| Congolese | | -0.049 | | | -0.016 | |
| | | (0.097) | | | (0.115) | |
| Colonial funding source | | | | | | |
| Colonial government | | | -0.169** | | | 0.267*** |
| | | | (0.084) | | | (0.098) |
| Private | | | -0.127 | | | 0.145 |
| | | | (0.110) | | | (0.120) |
| Religious | | | -0.050 | | | -0.015 |
| | | | (0.089) | | | (0.098) |
| Observations | 608 | 608 | 608 | 608 | 608 | 608 |
| R-squared | .59 | .566 | .567 | .641 | .622 | .625 |
| Physical capital | N | N | N | Y | Y | Y |
| Human capital | Y | Y | Y | N | N | N |
| Geographic characteristics | Y | Y | Y | Y | Y | Y |
| Population served | Y | Y | Y | Y | Y | Y |
| Provincial FE | Y | Y | Y | Y | Y | Y |

**Notes:** The table presents the OLS estimates of equation 4.4 with additional controls for hospital ownership, colonial type and colonial funding source. The dependent variable is indicated as the header over the three rows in each panel. Column (3) controls for both access to facility and the geographic covariates. Robust standard errors clustered by districts. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

TABLE C.5: Decomposition of the colonial investment effect by type and source *(continued)*

| | (1) | (2) | (3) | (1) | (2) | (3) |
|---|---|---|---|---|---|---|
| *Panel C. Production function* | **Malaria treated** | | | **Emergency cases** | | |
| Colonial settlement | 0.021 | -0.051 | 0.185 | -0.010 | 0.052 | 0.185 |
| | (0.088) | (0.215) | (0.142) | (0.112) | (0.235) | (0.204) |
| Hospital type | | | | | | |
| General Referral Hospital | 0.241 | | | 0.197 | | |
| | (0.154) | | | (0.198) | | |
| Private hospital | -0.217 | | | -0.210 | | |
| | (0.151) | | | (0.215) | | |
| Faith-based hospital | 0.162* | | | 0.021 | | |
| | (0.086) | | | (0.112) | | |
| Colonial type | | | | | | |
| Europeans | | -0.312** | | | -0.384** | |
| | | (0.156) | | | (0.186) | |
| Congolese | | 0.252 | | | 0.117 | |
| | | (0.249) | | | (0.261) | |
| Colonial funding source | | | | | | |
| Colonial government | | | -0.154 | | | -0.165 |
| | | | (0.145) | | | (0.200) |
| Private | | | -0.023 | | | -0.111 |
| | | | (0.208) | | | (0.297) |
| Religious | | | -0.204 | | | -0.245 |
| | | | (0.143) | | | (0.236) |
| Observations | 607 | 607 | 607 | 580 | 580 | 580 |
| R-squared | .403 | .388 | .384 | .341 | .337 | .333 |
| Human and physical capital | Y | Y | Y | Y | Y | Y |
| Geographic characteristics | Y | Y | Y | Y | Y | Y |
| Population served | Y | Y | Y | Y | Y | Y |
| Provincial FE | Y | Y | Y | Y | Y | Y |

**Notes:** The table presents the OLS estimates of equation 4.4 with additional controls for hospital ownership, colonial type and colonial funding source. The dependent variable is indicated as the header over the three rows in each panel. Column (3) controls for both access to facility and the geographic covariates. Robust standard errors clustered by districts. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table C.5: Decomposition of the colonial investment effect by type and source *(continued)*

| | (1) | (2) | (3) | (1) | (2) | (3) |
|---|---|---|---|---|---|---|
| *Panel D. Health care demand* | **Outpatient visit** | | | **Deliveries** | | |
| Colonial settlement | 0.006 | -0.020 | 0.066 | 0.210 | 0.020 | 0.031 |
| | (0.066) | (0.157) | (0.133) | (0.130) | (0.250) | (0.256) |
| Hospital type | | | | | | |
| General Referral Hospital | 0.227* | | | 0.077 | | |
| | (0.127) | | | (0.177) | | |
| Private hospital | 0.185 | | | 0.113 | | |
| | (0.134) | | | (0.191) | | |
| Faith-based hospital | 0.180** | | | -0.094 | | |
| | (0.072) | | | (0.141) | | |
| Colonial type | | | | | | |
| Europeans | | -0.058 | | | -0.008 | |
| | | (0.101) | | | (0.206) | |
| Congolese | | 0.073 | | | 0.246 | |
| | | (0.171) | | | (0.250) | |
| Colonial funding source | | | | | | |
| Colonial government | | | -0.076 | | | 0.220 |
| | | | (0.131) | | | (0.270) |
| Private | | | 0.105 | | | 0.232 |
| | | | (0.158) | | | (0.332) |
| Religious | | | -0.108 | | | 0.158 |
| | | | (0.148) | | | (0.267) |
| Observations | 604 | 604 | 604 | 467 | 467 | 467 |
| R-squared | .321 | .309 | .311 | .186 | .186 | .186 |
| Human and physical capital | Y | Y | Y | Y | Y | Y |
| Geographic characteristics | Y | Y | Y | Y | Y | Y |
| Population served | Y | Y | Y | Y | Y | Y |
| Provincial FE | Y | Y | Y | Y | Y | Y |

**Notes:** The table presents the OLS estimates of equation 4.4 with additional controls for hospital ownership, colonial type and colonial funding source. The dependent variable is indicated as the header over the three rows in each panel. Column (3) controls for both access to facility and the geographic covariates. Robust standard errors clustered by districts. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table C.5: Decomposition of the colonial investment effect by type and source *(continued)*

| | (1) | (2) | (3) | (1) | (2) | (3) |
|---|---|---|---|---|---|---|
| *Panel E. Input efficiency* | **Bed occupancy** | | | **Length of stay** | | |
| Colonial settlement | -0.095* | -0.085 | -0.038 | 0.042 | 0.141 | 0.207 |
| | (0.056) | (0.122) | (0.089) | (0.075) | (0.173) | (0.152) |
| Hospital type | | | | | | |
| General Referral Hospital | 0.163 | | | 0.288** | | |
| | (0.103) | | | (0.112) | | |
| Private hospital | 0.071 | | | -0.174 | | |
| | (0.104) | | | (0.114) | | |
| Faith-based hospital | -0.028 | | | 0.251*** | | |
| | (0.055) | | | (0.074) | | |
| Colonial type | | | | | | |
| Europeans | | -0.244*** | | | -0.323*** | |
| | | (0.085) | | | (0.111) | |
| Congolese | | 0.103 | | | 0.052 | |
| | | (0.139) | | | (0.183) | |
| Colonial funding source | | | | | | |
| Colonial government | | | -0.030 | | | -0.208 |
| | | | (0.088) | | | (0.149) |
| Private | | | -0.090 | | | -0.171 |
| | | | (0.104) | | | (0.179) |
| Religious | | | -0.046 | | | -0.015 |
| | | | (0.090) | | | (0.156) |
| Observations | 608 | 608 | 608 | 590 | 590 | 590 |
| R-squared | .192 | .197 | .186 | .501 | .477 | .473 |
| Human and physical capital | Y | Y | Y | Y | Y | Y |
| Geographic characteristics | Y | Y | Y | Y | Y | Y |
| Population served | Y | Y | Y | Y | Y | Y |
| Provincial FE | Y | Y | Y | Y | Y | Y |

**Notes:** The table presents the OLS estimates of equation 4.4 with additional controls for hospital ownership, colonial type and colonial funding source. The dependent variable is indicated as the header over the three rows in each panel. Column (3) controls for both access to facility and the geographic covariates. Robust standard errors clustered by districts. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table C.6: Colonial investment effect with provincial hospital and ancient colonial settlements

| | HGR only (1) | All hospitals (2) | HGR only (1) | All hospitals (2) |
|---|---|---|---|---|
| *Panel A. Financial characteristics* | **Government Funding** | | **Investment** | |
| Colonial settlement | 0.515*** | | 0.274 | |
| | (0.181) | | (0.282) | |
| Colonial settlement before 1936 | | 0.377** | | 0.134 |
| | | (0.167) | | (0.216) |
| Observations | 349 | 438 | 326 | 417 |
| R-squared | .384 | .335 | .355 | .311 |
| *Panel B. Inputs* | **Beds** | | **Nurses** | |
| Colonial settlement | 0.086 | | 0.150*** | |
| | (0.053) | | (0.056) | |
| Colonial settlement before 1936 | | 0.083* | | 0.187*** |
| | | (0.050) | | (0.057) |
| Observations | 455 | 608 | 455 | 608 |
| R-squared | .566 | .563 | .597 | .619 |
| Human and physical capital | Y | Y | Y | Y |
| Geographic characteristics | Y | Y | Y | Y |
| Population served location | Y | Y | Y | Y |
| Provincial FE | Y | Y | Y | Y |

**Notes:** The table presents the OLS estimates of equation 4.4 with additional controls for hospital ownership and the duration of colonial settlements. For the latter, I construct a dummy equal to one if the medical missions started after 1936. The dependent variable is indicated as the header over the three rows in each panel. Column (1) restrict the data sample to HGR and column reports the estimates with the full data sample of hospitals. Robust standard errors clustered by districts. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table C.7: Matching estimates

| *Panel A. Financial characteristics* | **Government Funding** | | **Investment** | |
|---|---|---|---|---|
| | (1) | (2) | (1) | (2) |
| Colonial settlement | 0.361* | 0.457*** | 0.279 | 0.030 |
| | (0.191) | (0.172) | (0.250) | (0.237) |
| Observations | 439 | 434 | 419 | 412 |
| *Panel B. Inputs* | **Beds** | | **Nurses** | |
| Colonial settlement | 0.211*** | 0.183*** | 0.044 | 0.039 |
| | (0.065) | (0.055) | (0.062) | (0.060) |
| Observations | 618 | 610 | 618 | 610 |
| *Panel C. Outputs* | **Malaria treated** | | **Emergency cases** | |
| Colonial settlement | 0.157* | 0.182* | 0.100 | 0.122 |
| | (0.084) | (0.093) | (0.150) | (0.123) |
| Observations | 617 | 609 | 590 | 582 |
| *Matching covariates* | | | | |
| Human and physical capital | Y | Y | Y | Y |
| Geographic location | Y | Y | Y | Y |
| Population served | N | Y | N | Y |

**Notes:** The table reports the results from a one-to-one nearest neighbour matching procedure with replacement, using the biased-corrected matching estimator proposed by Abadie and Imbens (2011). The matching covariates are the geographic coordinates and population served. Robust Abadie–Imbens standard errors are reported in the parentheses. Government funding is divided by the number of medical staff. Government funding as well as the dependent variables in panel C have also medical staff as a matching covariate. All variables are taken in natural logarithm. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table C.8: Matching estimates by hospital ownership

| Hospital type | Public (1) | Private (2) | Faith-based (3) | HGR (4) | Public (1) | Private (2) | Faith-based (3) | HGR (4) |
|---|---|---|---|---|---|---|---|---|
| *Panel A. Financial characteristics* | **Government Funding** | | | | **Investment** | | | |
| Colonial settlement | 0.470*** | 0.118 | 0.199 | 0.433** | 0.165 | 1.012* | 0.332 | 0.118 |
| | (0.183) | (0.720) | (0.342) | (0.195) | (0.269) | (0.544) | (0.452) | (0.300) |
| Observations | 375 | 74 | 135 | 350 | 349 | 79 | 135 | 328 |
| *Panel B. Inputs* | **Beds** | | | | **Nurse** | | | |
| Colonial settlement | 0.137*** | 0.392** | -0.095 | 0.126** | 0.038 | 0.611*** | 0.338*** | 0.063 |
| | (0.052) | (0.177) | (0.128) | (0.059) | (0.065) | (0.221) | (0.114) | (0.067) |
| Observations | 480 | 134 | 174 | 457 | 480 | 134 | 174 | 457 |
| *Panel C. Outputs* | **Malaria treated** | | | | **Emergency cases** | | | |
| Colonial settlement | 0.132 | 0.488 | 0.092 | 0.174* | -0.024 | -0.127 | -0.097 | 0.099 |
| | (0.087) | (0.656) | (0.135) | (0.103) | (0.120) | (0.352) | (0.265) | (0.128) |
| Observations | 479 | 139 | 174 | 453 | 460 | 125 | 168 | 442 |
| *Matching covariates* | | | | | | | | |
| Human and physical capital | Y | Y | Y | Y | Y | Y | Y | Y |
| Geographic location | Y | Y | Y | Y | Y | Y | Y | Y |
| Population served | Y | Y | Y | Y | Y | Y | Y | Y |

**Notes:** The table reports the results from a one-to-one nearest neighbour matching procedure with replacement, using the biased-corrected matching estimator proposed by Abadie and Imbens (2011). Robust Abadie–Imbens standard errors are reported in the parentheses. Columns (1-4) report respectively the matching estimates for public, private, faith-based and General Referral Hospital (*Hôpital Général de Référence*, HGR). The dependent variable nurse corresponds to the ratio of nurse by the number of beds. Government funding as well as the dependent variables in panel C have also medical staff as a matching covariate. All variables are taken in natural logarithm. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table C.9: First-stage IV estimations

| | Second stage dependent variable: | | | |
|---|---|---|---|---|
| | Government funding (1) | Investment (2) | Bed capacity (3) | Medical staff (4) |
| *Excluded instrument* | | | | |
| Sleeping sickness | 0.502*** | 0.521*** | 0.502*** | 0.498*** |
| | (0.047) | (0.046) | (0.040) | (0.040) |
| Observations | 364 | 338 | 479 | 476 |
| F-statistic | 116.2 | 126.8 | 156.8 | 154.6 |
| Geographic characteristics | Y | Y | Y | Y |
| Population served | Y | Y | Y | Y |

**Notes:** Each column reports the first-stage estimates for the IV regression in table C.10. The dependent variable in the first-stage is the indicator equal to one for the presence of colonial settlement. Variables not shown include log of population served and geographic controls. Following I. Andrews et al. (2019), I use the efficient $F$-statistic for the weak instrument test proposed by Olea and Pflueger (2013) that is robust to heteroscedasticity and clustering (note that in the present case of single endogenous regressor, the $F$-statistic is equivalent to the Kleibergen-Paap statistic). Robust standard errors. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table C.10: IV estimations for public hospitals

| Second stage dependent variable | Government funding | | Investment | | Bed capacity | | Medical staff | |
|---|---|---|---|---|---|---|---|---|
| | OLS | IV | OLS | IV | OLS | IV | OLS | IV |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Colonial settlements | 0.479*** | 0.311 | 0.316 | 0.363 | 0.097* | 0.202** | 0.177*** | 0.110 |
| | (0.175) | (0.334) | (0.265) | (0.433) | (0.051) | (0.094) | (0.058) | (0.111) |
| Population covered | 0.176 | 0.186 | 0.267 | 0.265 | 0.030 | 0.026 | 0.190*** | 0.194*** |
| | (0.225) | (0.212) | (0.238) | (0.230) | (0.066) | (0.063) | (0.061) | (0.059) |
| *Additional controls* | | | | | | | | |
| Medical staff | 0.709*** | 0.733*** | 0.714*** | 0.707*** | 0.553*** | 0.538*** | | |
| | (0.143) | (0.143) | (0.174) | (0.166) | (0.045) | (0.045) | | |
| Beds | | | | | | | 0.683*** | 0.693*** |
| | | | | | | | (0.047) | (0.046) |
| Observations | 364 | 364 | 338 | 338 | 474 | 474 | 474 | 474 |
| R-squared | .385 | .384 | .357 | .357 | .568 | .565 | .613 | .612 |
| 95% AR confidence interval | | [-.411899, .938882] | | [-.482336, 1.11407] | | [-.147482, .316568] | | [ .070989, .431993] |
| *Controls:* | | | | | | | | |
| Human and physical capital | Y | Y | Y | Y | Y | Y | Y | Y |
| Geographic characteristics | Y | Y | Y | Y | Y | Y | Y | Y |
| Population served | Y | Y | Y | Y | Y | Y | Y | Y |

**Notes:** Variables not shown include provincial fixed effect, log of population served and geographic controls. For each dependent variable, the table reports the OLS and IV estimates from the sample of public hospitals. The table also reports the Anderson-Rubin (AR) confidence interval for the Colonial settlements coefficient which formed by inverting the AR test for weak IV. Robust standard errors. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table C.11: IV estimations for General Referral Hospitals

| Second stage dependent variable | Government funding | | Investment | | Bed capacity | | Medical staff | |
|---|---|---|---|---|---|---|---|---|
| | OLS | IV | OLS | IV | OLS | IV | OLS | IV |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Colonial settlements | 0.506*** | 0.421 | 0.249 | 0.446 | 0.083 | 0.212** | 0.154*** | 0.046 |
| | (0.180) | (0.339) | (0.277) | (0.405) | (0.052) | (0.098) | (0.056) | (0.110) |
| Population covered | 0.153 | 0.158 | 0.382* | 0.366 | 0.031 | 0.023 | 0.144** | 0.151** |
| | (0.224) | (0.211) | (0.231) | (0.225) | (0.065) | (0.062) | (0.063) | (0.060) |
| *Additional controls* | | | | | | | | |
| Medical staff | 0.741*** | 0.754*** | 0.587*** | 0.561*** | 0.568*** | 0.551*** | | |
| | (0.148) | (0.149) | (0.173) | (0.161) | (0.043) | (0.042) | | |
| Beds | | | | | | | 0.695*** | 0.709*** |
| | | | | | | | (0.050) | (0.050) |
| Observations | 349 | 349 | 326 | 326 | 455 | 455 | 455 | 455 |
| R-squared | .383 | .383 | .348 | .347 | .565 | .56 | .596 | .593 |
| 95% AR confidence interval | | [-.303646, .987222] | | [-.440855, 1.03785] | | [-.164225, .277551] | | [ .056255, .407909] |
| *Controls:* | | | | | | | | |
| Human and physical capital | Y | Y | Y | Y | Y | Y | Y | Y |
| Geographic characteristics | Y | Y | Y | Y | Y | Y | Y | Y |
| Population served | Y | Y | Y | Y | Y | Y | Y | Y |

**Notes:** Variables not shown include provincial fixed effect, log of population served and geographic controls. For each dependent variable, the table reports the OLS and IV estimates from the sample of HGRs. The table also reports the Anderson-Rubin (AR) confidence interval for the Colonial settlements coefficient which formed by inverting the AR test for weak IV. Robust standard errors. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

TABLE C.12: Aid support to colonial hospitals

| Dependent variable | Aid support | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Colonial settlement | 0.075* | 0.059 | 0.054 | 0.062 |
| | (0.039) | (0.041) | (0.050) | (0.050) |
| Physician | | 0.022 | -0.008 | -0.010 |
| | | (0.018) | (0.025) | (0.025) |
| Population served | | | | -0.047 |
| | | | | (0.036) |
| Observations | 1097 | 1052 | 628 | 620 |
| Provincial FE | Yes | Yes | Yes | Yes |
| Geographic location | No | No | Yes | Yes |
| Population served | No | No | NO | Yes |

**Notes:** The table reports the results from the estimation of equation (4.8) with a linear probability model. Aid support is a binary variable equal to one if the hospital has stock of HIV or tuberculosis related drugs. All variables are taken in logarithm. Robust standard errors are clustered by districts (health zones). *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

## C.1 Data Sources and variables definitions

### C.1.1 DHIS2 data

The following variables are extracted from the DRC DHIS2 (https://snisrdc.com/):

**District population**: Log of population covered by a hospital (approximately equal to district population).

**Government funding**: Funding allocated from the central government to a hospital, usually for covering medical staff salaries. The amount is expressed in 2017 US Dollars, as a monthly average between January 2017 and December 2018.

**Investment**: Log of hospital investment. The amount is expressed in 2017 US Dollars, as a monthly average between January 2017 and December 2018.

**Nurse**: Total number of nurses working in a hospital, including A1, A2 and L2 levels. The amount corresponds to the monthly average between January 2017 and December 2018.

**Beds**: Total number of beds in a hospital as reported in the DHIS2.

**Inpatients**: Monthly average of inpatients between January 2017 and December 2018.

**Outpatient visits**: Monthly average of outpatient visit between January 2017 and December 2018.

**Childbirth**: Monthly average of childbirth between January 2017 and December 2018.

**Malaria treated**: Monthly average of severe malaria cases treated between January 2017 and December 2018. Severe malaria treatment relies on artesunate injection and differs from uncomplicated malaria treatment (artemisinin-based combination therapies).

**Length of stay**: Monthly average number of days that patients stay in hospital between January 2017 and December 2018.

### C.1.2 Historical and modern maps

**Distance to the coast**: The geodesic distance from each hospital to the nearest coastline measured in km. Colonial hospital locations are obtained from multiple maps from colonial archival data between 1929 and 1956. Examples of such maps are presented in figures C.4 and C.5.

**Access**: The geodesic distance from each hospital to the nearest transportation mode, which comprises railways, paved road and main rivers as navigation mode measured in km. The communication channels during the colonial period are obtained from a 1928 map on public services in Belgian Congo from the *Institut Cartographique militaire Service Cartographique du Ministère des Colonies*. Euclidean distances are calculated with ArcGIS.

**Distance to the provincial city**: The geodesic distance from each hospital to the main provincial city during the colonial period measured in km (Leopoldville, Costermansville, Albertville, Elisabethville, Stanleyville).

**Distance to armed conflicts**: The geodesic distance from each hospital to a civilian conflict (defined as political violence and protest). The data is obtained from the Armed Conflict Location and Event Data Project (ACLED) which reports georeferenced information on political violence and protests between January 2017 and December 2018

**Distance to Regional Distribution Centre**: The geodesic distance from each hospital to the nearest Regional Distribution Centre (*Centrale de Distribution Régionale*, CDR). The 19 CDRs across the DRC supply public, private and faith-based health facilities with essential medicines and other pharmaceutical products. The list of CDRs in 2017 was obtained from the Department of Pharmaceuticals and Medicines (*Direction de la Pharmarcie et du Médicament)*, Ministry of Health (`https://http://dpmrdc.org/BASE-DES-DONNEES`).

**Malaria parasite rate**: indicator of the malaria parasite transmission intensity in 2017 obtained from the Malaria Atlas Project to account for the spatial heterogeneity of malaria transmission in the DRC. The *Plasmodium falciparum* parasite rate (PfPR) is an index of malaria transmission intensity which estimates the proportion of children aged 2 to 10 who carries the parasite (Hay and Snow, 2006). Annual median of PfPR in 2017 was obtained at approximately 5 km resolution from the Malaria Atlas Project (https://map.ox.ac.uk).

## C.2 Conceptual framework

The hospital production function is modelled by a Cobb-Douglas function with constant return to scale (CRTS), and the output is given by the following equation

$$y_i = A_i k_i^{\alpha}$$

where $i$ indicates the type of hospital (Colonial $C$, or post-independence $P$) and $k$ refers to the capital to labour ratio $K/L$. The stock of physical capital equals investment

$$K = I$$

Consider the central government's objective which allocates health resources between colonial (with subscript $C$) and post-independence hospitals (subscript $P$) to maximise the overall output production of health services. The government maximisation problem is

$$\underset{k_C,k_P}{Max} A_C k_C^{\alpha} + A_P k_P^{\alpha}$$

subject to the budget constraint

$$\tau(y_C + y_P) \geq k_C + k_P$$

Assume the government health grant is used for investment in physical capital. The government maximisation problem can then be re-written as

$$\underset{k_C}{Max} A_C k_C^{\alpha} + A_P(\tau - k_C)^{\alpha}$$

The First-Order Condition with respect to $k_C$ gives

$$A_C(\frac{1}{k_C})^{1-\alpha} = A_P(\frac{1}{k_P})^{1-\alpha} \tag{C.1}$$