

# Does aid save infants lives?

A geospatial impact evaluation of aid effectiveness in Uganda

Synnøve Ravnestad Eikefet



Master thesis

Spring 2019

Department of Comparative Politics  
University of Bergen

## **Abstract**

While there are many studies of how official development aid (ODA) affects economic growth, there are far fewer studies of how aid affects health outcomes. Also, most of the studies of aid effectiveness have been cross-country studies. These studies have been criticized for lacking country specificity and a growing number of influential voices are questioning their usefulness for aid evaluations. There is clearly a lack of systematic studies of aid effectiveness below the country level. In this paper, I aim to fill a gap in the literature by researching how ODA affects infant mortality at the subnational level in Uganda. By matching geocoded data on the placement of aid projects with information on infant mortality from geocoded Demographic Health Surveys, and using a quasi-experimental difference-in-differences strategy, I am able to analyze if geographical proximity to active aid projects reduces infant mortality. The unit of analysis is 124 100 children born by 30 550 mothers. The results show that geographical proximity to active aid projects reduces infant mortality in most of the models. The finding is however surrounded by some uncertainty since the significance disappears in the most conservative test of aid. I also find evidence that projects are placed in areas that on average have lower infant mortality than non-aid locations. This suggests that aid projects do not reach those who need them the most. The various mechanisms studied in this paper all have the direction we would expect from the theory. This indicates that the intermediate factors suggested to be important in explaining infant mortality in the theory section, are in fact important explanatory factors for infant mortality.

## Acknowledgements

Denne masteroppgåva markerer slutten på mine studiar ved Institutt for Samanliknande politikk i Bergen. På slutten av denne reisa er det mange som fortener ein stor takk.

Rettleiaren min Tor Midtbø fortener ein veldig stor takk. Han har tatt seg god tid, stilt kloke spørsmål og gitt kloke svar som har vore uvurderlige for å ende opp med dette resultatet. Takk og til Siri Gloppen for hjelp i startfasen av masteroppgåva, og til forskingsgruppa ”Demokrati og utvikling” for nyttige tilbakemeldingar på prosjektskisse og kapittelutkast.

Takk til Ruben Berge Mathisen for både fagleg støtte og sosial hygge. Det er veldig inspirerende å vere saman med ein som ser så klart kva forskning kan bidra med, og det er generelt givande å omgås ein som stort sett aldri gir livet dårlegare enn terningkast 4.

Ein stor takk til Mammo og Pappen. Takk for at de er dei fine folka de er, og for at de har gitt meg gratis mat, fyr i omnen, varme ord i tyngre tider, og tullete ord i lettare tider. Takk til Eirik for å ha lært meg å stå opp for meg sjølv, ta kampar når det er naudsynt, og samstundes for å ha synt meg at ein kjem langt utan å stresse!

Takk Ane Berland Opheim for gode lunsjar, middagar, latter og alvor, og ikkje minst for å minne meg på at master er ”no problama!”

Takk til mine medstudentar på Sofie Lindstrøm. Samhaldet på kullet har vore fantastisk, og både stafett, festar, fjelltur, lange lunsjar og middagar har vore vitamininnsprøyting i kvardagen.

Takk til CMI for flott leseplass, kulinariske lunsjar og sosialt fellesskap. Det har vore veldig inspirerende å omgås så mange dyktige og hyggelege folk!

Ein stor takk til dei dyktige forskarane Andreas Kotsadam og Ryan Briggs for å ha svart på mine epostar, og hjelpt meg framover. Eg blei fødd på ei gylden grein i universet. Er det noko eg verkeleg kjenner på etter å ha nytta eitt år av livet til å lære om bistand og spedbarnsdødelegheit er det takksemd for at eg har fått dei moglegheitene eg har. Det er ikkje ein sjølvfølgje å i det heile overleve sitt første år, og langt mindre å leve så godt som det eg har gjort.

Takk!

## Table of Contents

1. Introduction .....	1
1.1 Overview and research question.....	1
1.2 Why study infant mortality and aid effectiveness? .....	2
1.3 Contribution.....	4
1.4 Central Findings .....	5
1.5 Structure.....	5
2 Uganda.....	6
2.1. Uganda at a glance.....	6
2.2 Infant mortality globally and in Uganda.....	7
2.2.1 Regional differences in infant mortality within Uganda .....	9
2.2.2 Regional disparities in key maternal and newborn health interventions ....	10
2.3. Aid globally and to Uganda.....	12
2.3.1 Subnational placement of aid projects.....	13
2.4 Why geographical proximity to projects should matter .....	14
3 Theory and literature .....	15
3.1 Defining infant mortality and related concepts .....	15
3.2. Defining foreign aid.....	16
3.3 What causes infant mortality? .....	17
3.4 How can aid reduce infant mortality?.....	18
3.4.1 Theoretical arguments for aid.....	19
3.4.2 A closer look at how aid can affect determinants of infant mortality .....	19
3.4.1 Provide maternal education .....	20
3.4.2 Provide access to health services and vaccinations .....	21
3.4.3 Provide water and sanitation.....	22
3.4.4 Provide nutrition.....	22
3.4.4 Reduce poverty .....	23
3.5 Geographical proximity to projects .....	24
3.6. Theoretical arguments against aid .....	24
3.6.1 Bad allocation of aid.....	26
3.7 Literature Review: Empirical findings on the connection between infant mortality and aid.....	27
3.7.1 Cross-country studies .....	28
3.7.2 Case studies .....	32
3.7.3 Meso-level studies .....	33
4 Data and Measurement .....	35
4.1. Case selection .....	35
4.2 Datasets.....	37
4.2.1 AidData.....	37
4.2.2 Demographic Health Surveys.....	38
4.3 The dependent variable – Infant mortality .....	39
4.3.1 Limitations and strengths to the measure .....	40
4.4 Independent variable – Official development assistance .....	41
4.4.2 Inactive 5/10/15/20 .....	41
4.4.3 Limitations to the measure .....	42
4.5 Control variables.....	42
4.5.1 Multiple births .....	43
4.5.2 Birth order.....	43
4.5.3 Gender .....	44

4.5.4 Birthyear .....	44
4.5.5 Censored .....	44
4.5.6 Suspended .....	44
4.6 Operationalization of variables .....	44
4.7 Mechanisms .....	45
4.8 Missing data .....	47
4.9 Descriptive statistics .....	47
4.9.1 Overview of project types, precision code 1 .....	47
4.9.2 Breakdown of projects and locations by start year, precision code 1 .....	47
4.9.3 Breakdown of projects and locations by end year, precision code 1 .....	48
4.9.4 Project and location breakdown by donor, precision code 1 .....	49
5 Analytical strategy and methods .....	51
5.1 Methodical and theoretical reasons for a subnational study .....	51
5.2 How to evaluate? .....	53
5.2.1 Difference-in-differences .....	53
5.2.2 The benefits and limitations of a Geospatial Impact Evaluation .....	55
5.3 Matching AidData and DHS-data based on geographical proximity .....	55
5.3.1 Choosing the geographical division .....	56
5.3.2 Choosing the size of the buffers .....	57
5.3.3 Creating the buffers .....	58
5.4 Choice of precision level on the data .....	58
5.5 Arguing for a Causal Relationship .....	60
5.6 The case for linear probability model .....	61
5.6.1 Assumptions .....	62
5.7 Model specification .....	63
5.7.1 Robust standard errors .....	64
5.7.2 Mother fixed effects .....	64
6 Results .....	66
6.1 Descriptive statistics .....	66
6.1.1 First difference - Areas with an active project versus areas not receiving aid .....	66
6.1.2 Second difference - Active areas versus inactive areas .....	67
6.1.3 Difference-in-differences .....	67
6.2 Linear probability model .....	68
6.3 Mother fixed effects .....	70
6.4 Robustness checks .....	71
6.4.1 Under-five mortality .....	72
6.4.2 Mother-fixed effects for under-five mortality .....	73
6.4.3 Health aid .....	74
6.4.4 Lower precision-level on the data .....	75
6.4.5 Logistic regression .....	76
6.5 Mechanisms .....	79
6.5.1 Mechanisms at the level of the mother .....	79
7 Discussion and conclusion .....	81
7.1 Discussion .....	81
7.2 Conclusion .....	86
References .....	88
Appendix .....	98

## List of Tables and Figures

Figure 2.1 Infant mortality globally. ....	8
Figure 2.2 Graph over infant mortality trend in Uganda from 1954-2017.....	8
Table 2.1 Infant mortality within the regions of Uganda. ....	9
Figure 2.3 Infant mortality in all DHS-clusters.....	10
Table 2.2 Regional disparities in key maternal and newborn health interventions.....	11
Figure 2.4 Map showing the global reception of aid per capita in 2011.....	12
Figure 2.5 Official development assistance to Uganda 1970-2016.....	12
Figure 2.6 Official development assistance to developing countries 1970-2016.....	12
Figure 2.7 Regional placement of aid projects.....	13
Figure 3.1 A visual representation of the connection between infant mortality and related concepts.....	16
Figure 3.2 Conceptual framework of the hierarchy determining infant mortality.....	19
Figure 3.3 Model showing the various factors that aid can affect.....	20
Table 3.1 Overview of cross-country studies looking at the connection between infant mortality and aid.....	31
Table 4.1 Overview of countries with available data from DHS and AidData.....	36
Table 4.2 Precision level on the AidData.....	38
Figure 4.1 Infant mortality ratio and birth order in the DHS-data used in this study..	43
Table 4.3 Operationalization of the dependent, independent and control variables....	45
Table 4.4 Operationalization of the variables used in the analyses of possible mechanisms.....	46
Table 4.5 Overview of project types, precision code 1.....	47
Table 4.6 Breakdown of projects and locations by start year, precision code 1.....	48
Table 4.7 Breakdown of projects and locations by end year, precision code 1.....	49
Table 4.8 Project and location breakdown by donor, precision code 1.....	50
Figure 5.1 The difference-in-differences like approach applied in this paper.....	54
Figure 5.2 Uncertainty level for aid projects with precision code 2.....	59
Figure 5.3 Uncertainty level for aid projects with precision code 1.....	59
Figure 5.4 Map with buffers of varying sizes around all aid projects with precision code 1 and known start-date.....	63
Figure 6.1 Infant mortality rate in different areas.....	67
Table 6.1 Linear probability models.....	69
Table 6.2 Mother fixed effects.....	70
Table 6.3 Under-five mortality.....	72
Table 6.4 Under-five mortality with mother-fixed effects.....	73
Table 6.5 Health aid.....	74
Table 6.6 Lower precision-level on the data.....	76
Table 6.7 Logistic regression.....	77
Table 6.8 Table comparing findings from the logistic regression with results from the LPM.....	78
Table 6.9 Mechanisms.....	80
Figure 4.1a Visual representation of all aid projects in Nepal.....	98
Table 5.1a VIF-scores for the variables.....	98
Table 6.5a Mechanisms 5 km.....	99
Table 6.6a Mechanisms 15 km.....	99
Table 6.7a Mechanisms 20 km.....	100

## List of Acronyms

CRS	Coordinate Reference System
DAH	Development Assistance for Health
DD	Difference-in-differences
DHS	Demographic and Health Surveys
GIE	Geospatial Impact Evaluation
IM	Infant Mortality
IMR	Infant Mortality Rate
LPM	Linear probability model
NGO	Non Governmental Organization
ODA	Official Development Assistance
OECD	Organization for Economic Cooperation and Development
RCT	Randomized Control Trial
SDG	Sustainable Development Goal
UNICEF	United Nations Children's Fund
WHO	World Health Organization

# 1. Introduction

## 1.1 Overview and research question

Does aid work? 146.6 billion US dollars were given in official development assistance (ODA) by some of the biggest donors in 2017 (Organisation for Economic Co-operation and Development 2018b) under the assumption that the money would lead to economic development and increased welfare in the receiving countries (Organization for Economic Co-operation and Development 2019). However, the effectiveness of foreign aid in reducing poverty, and improving welfare is subject to debate. Most of the studies of aid effectiveness are cross-country studies (Kulipanova 2013, 243-244), and the majority of them focus on the relationship between aid and general development indicators such as economic growth or democracy (Gebhard et al. 2008, 2). A growing number of influential voices have begun to challenge the usefulness of cross-country studies for confirming or challenging the effect of aid (Riddell 2007, 224). Firstly, these studies are criticized for lacking country-specificity (Bourguignon and Leipziger 2006, 4-6). Secondly, they are not good at discovering small and localized effects of aid (Dreher and Lohmann 2015, 421; Kotsadam et al. 2018, 59). Some studies of aid effectiveness are also case studies of single programs or projects. The main problem with studies at the micro-level is that the potential for generalization is limited.

In this paper I aim to help bridge the macro-micro divide, and fill a missing middle in the evaluation literature. Specifically, I will conduct a geospatial impact evaluation of aid effectiveness in Uganda, and look at whether aid reduces infant mortality or not. Infant mortality is a very complex phenomenon that can be attributed to a range of distal, intermediate and proximate determinants (Mosley and Chen 1984, 27; Sartorius and Sartorius 2014, 2; Schell et al. 2007, 290). Important causes of infant mortality include lack of education, poor water quality and sanitation, poor quality health systems, malnourishment and poverty. If aid is effective, it can be expected to influence all of these factors. The benefit of the aid projects will be much higher for the people living closer to them, and will decrease for the people living further away. In order for a hospital or a school to be beneficial for an individual it will have to be within the reach of this individual (Briggs 2017, 189-190). Many development projects are aimed at local development, and not necessarily national development (Findley et al. 2011, 1995). If aid is effective we should thus expect that people



who live closer to aid projects will have lower infant mortality. I will evaluate whether the infant mortality is lower amongst children living close to active aid projects than it is for children who do not have any aid projects in their proximity. This will be done by matching geocoded data on the placement of aid projects with information on infant mortality from geocoded Demographic Health Surveys, and using a quasi-experimental difference-in-differences like strategy. The units of analysis is 124 100 children born by 30 550 mothers in Uganda<sup>1</sup>. The general research question for this paper is “is aid effective in reducing infant mortality?” More specifically I will look at:

*“Does geographic proximity to active aid projects reduce infant mortality?”*

In addition to looking at this, due to the research design I will also be able to say something about the placement of the aid projects. More specifically, I will be able to research whether the aid projects are allocated to the places where the infant mortality is highest.

## **1.2 Why study infant mortality and aid effectiveness?**

There are several good societal and methodological reasons for researching infant mortality. Firstly, access to basic health care is an essential human right, which is fundamental to the development process, and health should be included when considering the accomplishments of aid. Development programs and policies are typically employed to change outcomes. The desired outcome varies from program to program, and can be anything from building a road or vaccinating a population to increase the number of children going to school. Whether or not these changes are actually achieved is a crucial public policy question that one ought to look closer at. At best, aid could save millions of lives (see for instance Levine and What Works Working Group 2007). At worst, it may have no impact, or even worsen conditions (see for instance Moyo 2009; Deaton 2013). Development aid used to be of relative minor concerns for governments before, but has become a central focus of attention for the world leaders today (Riddell 2007, 3). McCoy (2017, 539-540) argues that the global health community should work closer with political science in order to have a more critical approach to what constitutes progress, and be able to put equity at the heart of how progress is measured. Looking closer at if aid is effective in reducing infant mortality, and how the

---

<sup>1</sup> The exact number vary a little from model to model.

<sup>2</sup> Lee et al. (1997, 430) find that each component of the human development index is strongly correlated with infant mortality.

<sup>3</sup> I have not been able to find a list of causes only for infant mortality in Uganda.

<sup>4</sup> Briggs (2017, 190) argue that aid for local public goods can be especially valuable because such public goods may be difficult to create for communities due to collective action problems even though the community is getting richer.

<sup>5</sup> This trend can be seen as unfortunate because it fails to consider the importance of longer-term investments in health infrastructure, capacity building and personnel development (Stierman, Ssenooba, and Bennett 2013, 8-

allocation of aid matches the burden of infant mortality is an important contribution in this sense.

Secondly, Goal 3 of the United Nations Sustainable Development Goals (SDG) is to "Ensure healthy lives and promote wellbeing for all at all ages" (United Nations 2018b, 5). If we are to ensure the attainment of this target it is of paramount importance to get a better understanding of the connection between aid and health. In order to ensure that the commitment to "leave no-one behind" is pursued, it is necessary to find out who is receiving the aid. In addition to Goal 3 that specifically focuses on children's health, there is also a tight link between child health and several of the other SDGs such as zero hunger (goal 2), quality education (goal 4), gender equality (goal 5) and clean water and sanitation (goal 6) (Skolnik 2016, 256). Thirdly, most of the research conducted on aid effectiveness has focused on economic development and aid. By strictly focusing on the effect of aid on growth, one risks overlooking important health benefits from aid. Research has shown that economic growth plays a limited role in explaining changes in health outcomes (Soares 2007, 253). Gomanee et al. (2005, 356) argue that if one only considers the impact of aid on growth, one would underestimate the impact of aid on aggregate welfare, and further states that "even in cases where aid had no significant impact on growth, it could still increase welfare". Kosack and Tobin (2006, 207) show nicely in their article that while the concepts "development" and "growth" are often used interchangeably they are indeed two distinct concepts. Economic growth itself does nothing to guarantee a lower infant mortality, and "a poor country with a growing economy may still develop little if the growth merely enriches a small élite, leaving the majority of the population without additional income" (Kosack and Tobin 2006, 207).

Apart from these societal reasons, there are also several good methodological reasons to use infant mortality as the target when researching the effectiveness of aid. Firstly, since infant mortality is more sensitive than life expectancy to changes in economic conditions and health services, it can be considered to be a flash indicator in conditions of the poor (Boone 1996, 293). Secondly, infant mortality can be seen as a proxy for a broad set of human development outcomes since it depends on a variety of factors such as access to medicines and health facilities, water and sanitation, female literacy and many others<sup>2</sup>. Thirdly, infant mortality and other more complex measures of population health are highly correlated, and infant mortality

---

<sup>2</sup> Lee et al. (1997, 430) find that each component of the human development index is strongly correlated with infant mortality.

might thus be seen as an important indicator of the broader population health, and not just of this small segment of the population (Reidpath and Allotey 2003; Schell et al. 2007, 290). Fourthly, compared to a much studied factor in connection with aid, namely Gross Domestic Product per capita, infant mortality will be less susceptible to the fallacy of average. This stems from the fact that the children of the richest will not be one thousand times as likely to survive as the children of the poorest even if they can be a thousand times richer. It will thus be much more difficult for a wealthy minority to affect a nation's IMR (Nuwaha, Babirye, and Ayiga 2011, 1). Lastly, using infant mortality rather than under-five mortality as the research object allows for significantly larger samples than under-five mortality because an analysis of the latter would need to discard data for the children born five years before the survey date rather than one year as is the case with infant mortality (Ssewanyana and Younger 2008, 50).

### **1.3 Contribution**

This study makes several contributions to the small but rapidly growing research field that focuses on local effects of aid. Firstly, to the best of my knowledge this study is the first systematic study of aid and infant mortality in Uganda. Given that Uganda has been among the world's top aid recipients for several decades (Bergo 2015), and has an infant mortality rate that has been reduced substantially but still is much higher than desirable global health standards (Odokonyero et al. 2015, 6) the country is a good study object for aid effectiveness. There are big subnational variation in the level of mortality and aid within Uganda, and the country is a good case for a subnational study like the one conducted in this paper. This paper is also one of the first in assessing infant mortality systematically at the subnational level irrespective of country. The only systematic study of infant mortality at the subnational level that exists to my knowledge, studied Nigeria (Kotsadam et al. 2018). This lack of studies of aid effectiveness on health indicators below the country level represents a clear gap in the literature (Kotsadam et al. 2018, 59).

Secondly, the analyses in the paper also provide an insight into whether aid projects are placed where the needs are highest, more specifically, the analyses will show us if aid projects are placed where infant mortality is highest. Previous research focusing mainly on poverty suggests that projects are not placed where poverty is at the highest in a number of countries (See for instance Nunnenkamp, Öhler and Sosa Andrés 2017, 126; Nunnenkamp, Sotirova and Thiele 2016, 844; Briggs 2014, 194; Öhler and Nunnenkamp 2014, 422; Briggs 2018b, a). Having a better knowledge of where the projects are placed, is important if we want to

achieve the Sustainable Development Goals, and meet the commitment to “leave no one behind”, and reach those who need it the most.

#### **1.4 Central Findings**

\* I find aid to be effective in reducing infant mortality in most of the models. This finding is however surrounded by some uncertainty since the significance of the findings disappear in the most conservative test of aid.

\* The results indicate that projects are placed in areas that on average have lower infant mortality than non-aid locations. This suggests that the projects do not reach those who are furthest behind, and need them the most.

\* The various mechanisms studied in this paper all have the direction we would expect from theory; in active areas there are more respondents with bednets, the wealth is higher, fewer of the respondents report that distance is a problem hindering them from going to the health center, the literacy level and the educational level is higher. All the findings are also significant. This suggests that the intermediate factors suggested to be important in explaining infant mortality in the theory section, are in fact important explanatory factors for infant mortality.

#### **1.5 Structure**

The thesis is divided into seven chapters. The next chapter serves to give a brief introduction to Uganda with a focus on infant mortality and aid allocation. I contrast Uganda with the rest of the world on these two factors, and look at the subnational differences in infant mortality and aid allocation. The purpose of chapter three is to first define the central concepts applied in this paper, namely infant mortality and foreign aid. Next, I present theories of why we would expect aid to reduce infant mortality, and why we would not expect aid to reduce infant mortality. Lastly, I present a literature review including much of the research conducted on infant mortality and aid, and discuss some of the findings. In chapter four, I present the reasoning behind choosing Uganda as a case. I also present the data I will be using and discuss the operationalization of the various variables. In chapter five, I present arguments for a subnational study, and go through the research design and the specific methods chosen to answer the research question. In chapter six, I present the results from various analyses. In chapter seven, I discuss what the findings from the various analyses mean before I attempt to sum up the whole thesis in a conclusion.

## **2 Uganda**

Before studying if aid is effective in reducing infant mortality, and if aid projects are placed where the infant mortality is at its highest, it is fruitful to have a basic understanding of the trend in infant mortality and aid in Uganda, and how these factors vary at a subnational level. The purpose of this chapter is to provide such an overview. In this chapter, I first provide a very brief introduction to the country of Uganda looking at its placement, the culture, the recent history and the health system. Secondly, I look at the infant mortality globally and in Uganda across time and space. I also look at the regional disparities in key maternal and newborn health interventions. The differences in infant mortality loom large both globally, across time, and at a subnational level across Uganda. The differences in key maternal and newborn health interventions are also big across the country. Thirdly, I look at the aid provided globally and to Uganda, and the subnational placement of projects. Lastly, I present empirical arguments for why we should expect infant mortality to be affected by the geographical proximity to aid projects.

### **2.1. Uganda at a glance**

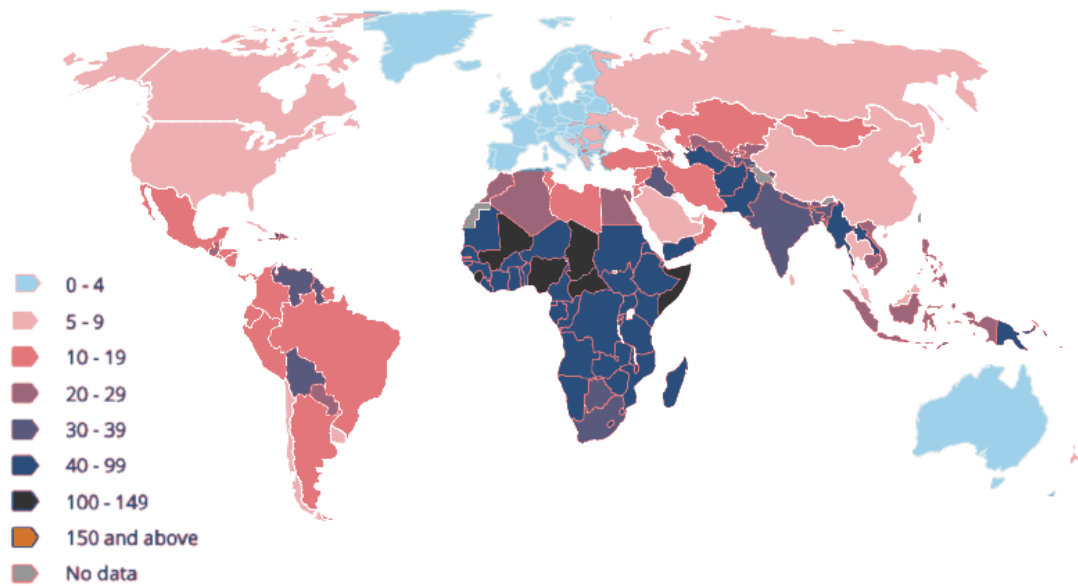
Uganda is a country in East-Central Africa. It is bordered to the west by the Democratic Republic of the Congo, to the north by South Sudan, to the east by Kenya, to the south-west by Rwanda and to the south by Tanzania. It is about the size of the United Kingdom, and covers 241 038km<sup>2</sup> (Central Intelligence Agency 2019). The country has a very young population with as many as 48 percent its 41.48 million inhabitants being under 15 years old in 2016 (World Health Organization 2016). The population consists of dozens of ethnic groups, but a distinction is normally made between the “Nilotic North” and the “Bantu South”. The English language, and Christianity help unite the diverse groups in the country (Ingham et al. 2019). The country is classified as a least developed country (Organisation for Economic Co-operation and Development 2019), and ranked as number 163 on the Human development index in 2014 (World Health Organization 2016). This index is a composite measure of life expectancy at birth, years of schooling and Gross National Income per capita (United Nations Development Programme n.d.). It provides a good alternative to economic growth when measuring the development of a country.

Uganda gained independence from Britain in 1962. After its independence the country has experienced a military coup, followed by a brutal military dictatorship that ended in 1979, and a war lasting from 1980-86. The people in the north of the country were also terrorized for 20 years by a militant group called the Lord's Resistance Army (Ingham et al. 2019). Today, Uganda is the country hosting most refugees on the African continent, and in 2017 Uganda was the country receiving most refugees globally. The country houses more than 1,35 million refugees and asylum seekers (The World Bank 2019b), mainly coming from South-Sudan, the Democratic Republic of Congo, Burundi, Rwanda and Somalia (United Nations Development Programme 2017, 4).

Uganda is reported to have had one of the best health care systems in Africa during the 1960s, but economic declines in the 1970s and 1980s following a civil unrest after a military coup caused a deteriorating health care system (Wilkin 2014, 1423). Wilkin (2014, 1423) argues that there are signs that the access to health care services is improving; she states that most Ugandans now live within five kilometers of a health center, and development programs have caused improved access to HIV/AIDS prevention, outreach, and treatment. There are however big challenges facing the Ugandan health system: The World Health Organization (WHO) reports that the major challenges affecting the Ugandan health system are lack of resources to recruit, deploy, motivate and retain human resources for health; ensuring reliability of health information in terms of completeness of data and timeliness; and ensuring access to essential medicines (World Health Organization 2018b).

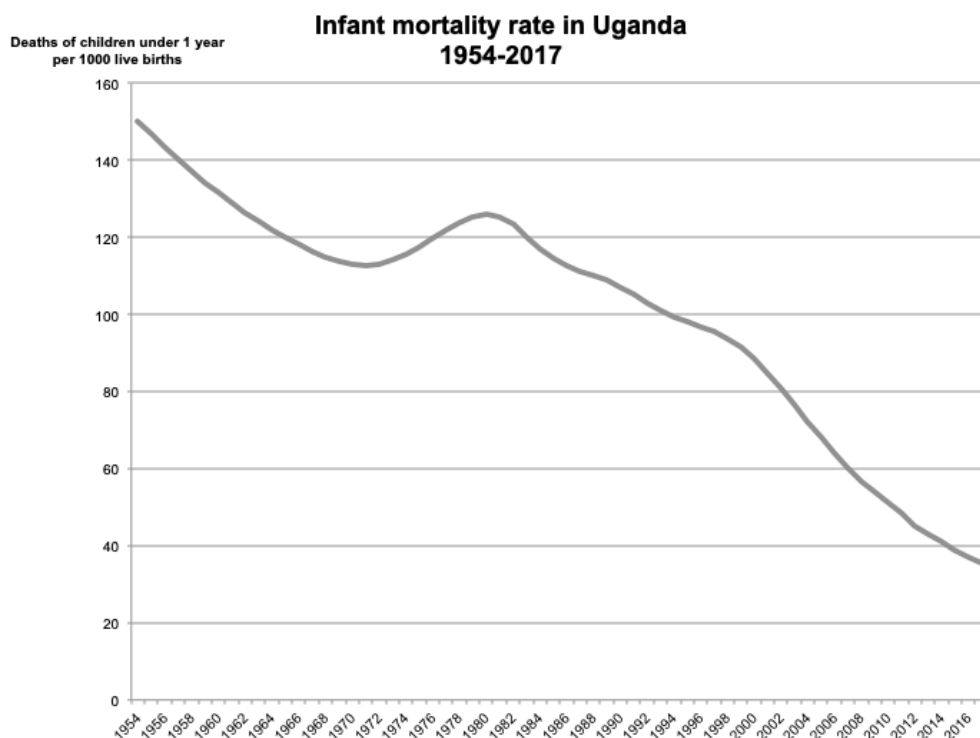
## **2.2 Infant mortality globally and in Uganda**

In 2017 4.1 million children died worldwide before completing their first birthday (United Nations Inter-agency Group for Child Mortality Estimation 2018b, 2). Most of these children die from preventable or easily treatable causes, and almost all reside in poor countries (Barbieri 2015, 21). The Infant Mortality Rate (IMR) of Uganda was 35,4 deaths per 1000 live born in 2017. This implies that almost 1 in 28 babies do not survive to their first birthday. Uganda has the 45<sup>th</sup> highest IMR in the world. It is more than 22 times the number of Iceland which had the lowest IMR with 1,6 deaths per 1000 live born (United Nations Inter-agency Group for Child Mortality Estimation 2018a).



**Figure 2.1 Infant mortality globally.** The map shows the infant mortality rate globally in 2017. Map made by author. Data source: (United Nations Inter-agency Group for Child Mortality Estimation 2018a)

Figure 2.1 shows the infant mortality globally in 2017. As can be seen from the map Africa is clearly the region with the highest infant mortality. Europe is markedly the continent with the lowest infant mortality. It is also clear that there are huge global differences in IMR.



**Figure 2.2 Graph over infant mortality trend in Uganda from 1954-2017.** Data source: (United Nations Inter-agency Group for Child Mortality Estimation 2018a).

Despite a depressing toll of infant mortality in some countries, tremendous progress in reducing it has been achieved both globally and in Uganda. Figure 2.2 shows that there has

been a marked decline in the infant mortality in Uganda from 1954 to 2017. I have not found any explanation as to why we see an increase in the IMR from the mid 1970s to the early 1980s, but the Demographic Health Surveys report that the lack of decline in infant mortality before the mid 1980s probably is caused by the prolonged civil strife in the 1970s and early 1980s which led to a decline in the standard of living and also affected the health infrastructure (Statistics Department/Uganda and Macro International 1996, 99). This might also explain why we see the increase from the mid 1970s to the early 1980s. According to projections the country will reach target 3.2 of the Sustainable Development Goals of reducing under-five mortality to at least as low as 25 per 1000 live births in 2030 if the current annual reduction rate is maintained (Unicef 2018).

### 2.2.1 Regional differences in infant mortality within Uganda

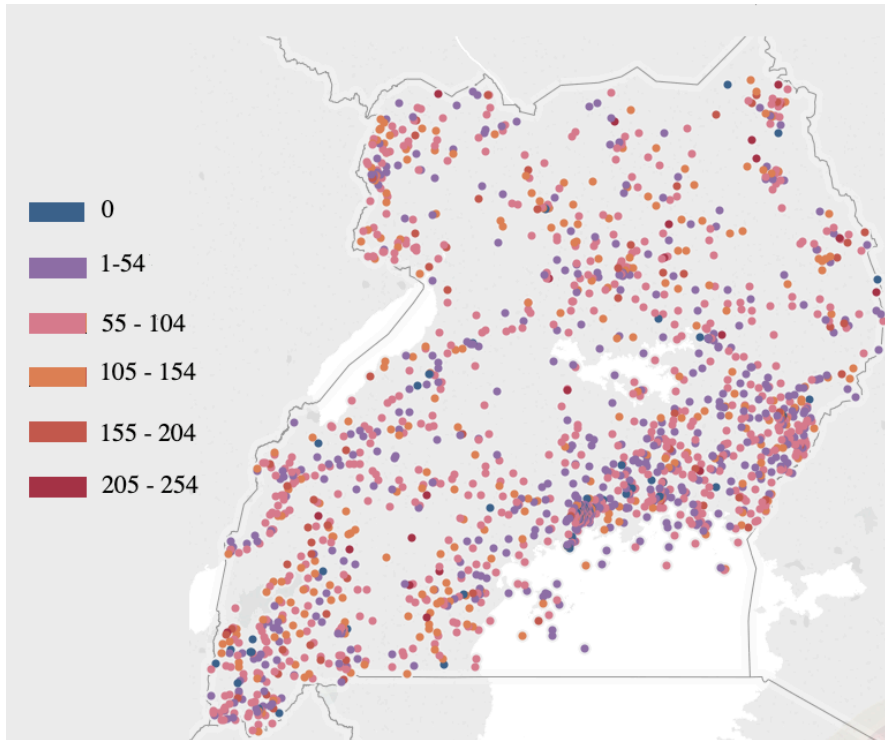
	1991-2000	1997-2006	2002-2011	2007-2016	Average 1991-2016	Reduction from 1991-2016
Northern	105,9	102	80,3	54,5	85,7	20,2
Western	97,8	92,5	72	49,8	78,0	19,8
Central	71,9	74,3	58,6	36,3	60,3	11,6
Eastern	89,3	72	54	43,3	64,7	24,6

**Table 2.1 Infant mortality within the regions of Uganda. Red shading marks the highest IMR, and gray shading marks the lowest IMR. The numbers reported are for the ten years preceding the survey. Data source: (ICF 2000-2016). The regions of Uganda have changed a lot (see chapter 5), but I have used the regions of Uganda have changed a lot (see chapter 5), but I have used the same harmonization between the regions as the DHS-IPUMS used for the Ugandan regions (Boyle, King, and Sobek 2018).**

There are big subnational differences in the level of infant mortality within Uganda. Table 2.1 shows that the northern region has the highest IMR in all years. The central region has the lowest IMR in all the first and the last period surveyed. When looking at the average score for the DHS-surveys from 2000-2016 it is clear that the difference in the IMR between the northern and the central region is 25,4. This implies that 25,4 more infants per 1000 are dying in the northern region, than in the central region. This being said, it is also clear that the northern region is the region that has experienced the second biggest reduction in IMR from 2000 to 2016. Even though there is a general decrease in the country as a whole, it is clear that it varies a lot how much reduction has been achieved within the country. By looking at the country level when conducting an analysis of the effectiveness of aid one misses out on a lot of information. If it is the case that most aid projects are placed in the western region (which seems to be the case, see for instance figure 2.7 in section 2.3.1), and infant mortality



has been reduced the second least there, one might reach a whole different conclusion of aid effectiveness than one would if most of the projects were placed in the east. It is thus important not just to understand the overall level of infant mortality within Uganda, but also to know the subnational levels as well.



**Figure 2.3 Infant mortality in all DHS-clusters. Map showing the infant mortality in all DHS-clusters in the years 2000, 2006, 2011 and 2016. Data source: (ICF 2000-2016). Map made by author with the program Tableau Desktop 2018.3.4.**

Figure 2.3 shows the infant mortality rate in the different DHS-clusters. As can be seen from the map the infant mortality rate varies a lot between different clusters. This is not surprising given that the clusters on average consist of 74,5 individuals. Just a small change in death will thus have big consequences for the calculated IMR. Most clusters, 43 percent, have an IMR of 55-104. Only 4 percent and 1 percent have IMR of respectively 0 and 205-254.

## 2.2.2 Regional disparities in key maternal and newborn health interventions

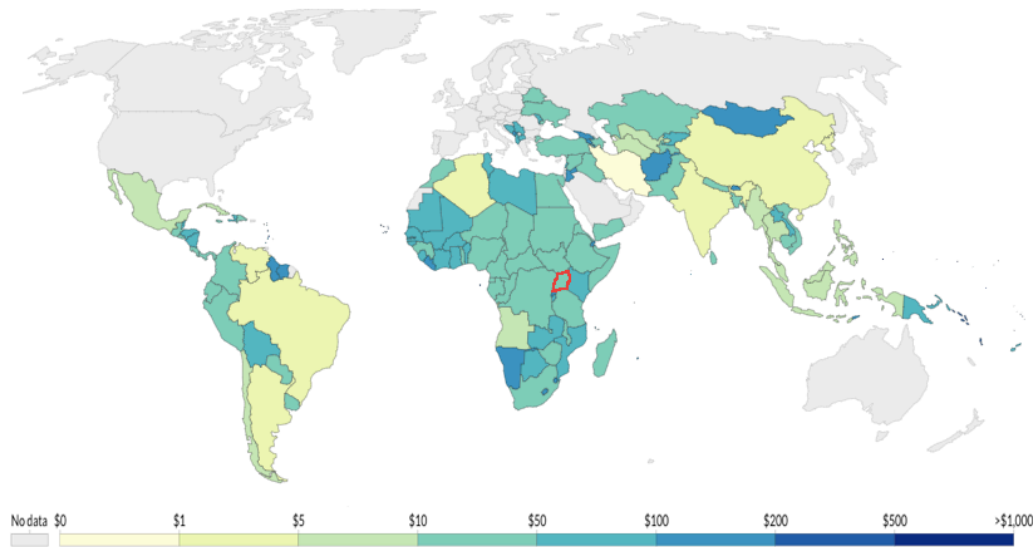
	Demand for family planning satisfied by modern methods (%)	Skilled attendant at birth (%)	Institutional delivery (%)	Postnatal care of mothers within 2 days (%)
Northern	30,5	50,2	48,8	31,7
Western	40,2	49,3	48,8	24,1
Central	50,3	72,2	71,8	44,1
Eastern	36,6	58,1	57,7	31,2
Ratio (highest to lowest)	1,6	1,5	1,5	1,8

**Table 2.2 Regional disparities in key maternal and newborn health interventions. Gray shading marks the lowest coverage, and red shading marks the highest coverage. Data source: Unicef (2016a)**

There are big disparities between different regions in the maternal and newborn health interventions in the country as well. Table 2.2 shows disparities between the regions in key maternal and newborn health interventions in 2011 in Uganda (Unicef 2016a). Table 2.2 shows that the differences loom large within the country. The central region has the highest coverage on all indicators. The western region has the lowest coverage on three out of four indicators, and the northern region has the lowest coverage on one indicator. Although the northern region is the region with the highest infant mortality, the western region is ranging marginally worse than the northern region when it comes to coverage of key maternal and newborn health interventions. This might indicate that it is not only the coverage of health interventions that matters for reducing infant mortality, and that other factors are relevant as well. This argument will be elaborated in the theory chapter.

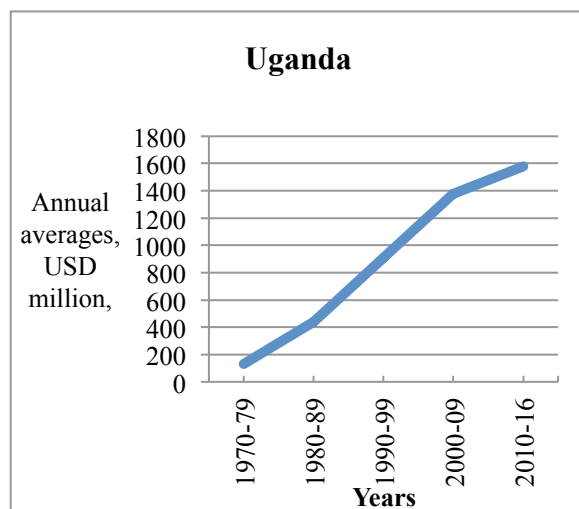
### 2.3. Aid globally and to Uganda

#### Aid received per capita 2011

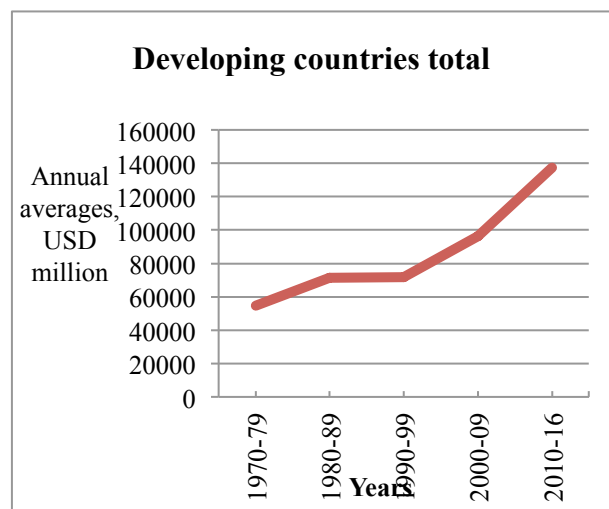


**Figure 2.4 Map showing the global reception of aid per capita in 2011. Uganda has been marked in red by author. Source: Our World in Data (2019).**

Figure 2.4 shows the global reception of aid per capita in 2011. Uganda received 39.71 USD per capita in 2011 (Our World in Data 2019). Like most of the countries in Africa the country received between 10 and 50 USD per capita. From the map it is clear that Africa is the region receiving most of the aid per capita. Uganda has been among the world’s top aid recipients for several decades (Bergo 2015). According to the OECD, the country received 1981 USD million in 2016. The places them as the 19<sup>th</sup> highest receiving country of aid (Organisation for Economic Co-operation and Development 2018a, 13).



**Figure 2.5 Official development assistance to Uganda 1970-2016. Data source: Organisation for Economic Co-operation and Development (2018a, 7)**

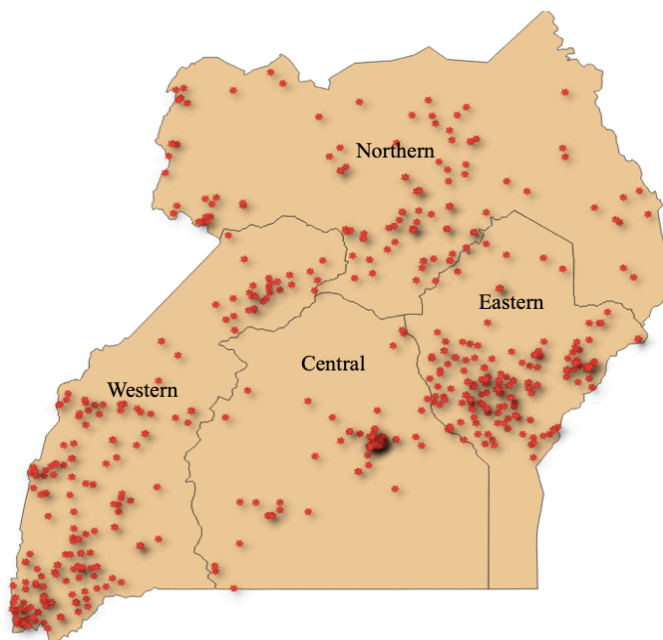


**Figure 2.6 Official development assistance to developing countries 1970-2016. Data source: Organisation for Economic Co-operation and Development (2018a, 7)**

Figure 2.5 and figure 2.6 show the increase in official development assistance, what most people think of as foreign aid (Radelet 2006, 4), in Uganda and the top fifty recipient countries from 1970 to 2016. The increase has been sharp in both Uganda and in the top 50 recipient countries in total, but in Uganda there has been a staggering 1103 percentage increase in the official aid from 1970 to 2016 compared to 152 percentage increase in the top 50 recipient countries (Organisation for Economic Co-operation and Development 2018a, 7). The ratio of aid to Gross National Income peaked at 26 percent in 1992 but has remained at 10 percent or under for the last nine years (The World Bank 2019a). Official development assistance has for years accounted for large parts of the budget, with international donors accounting for as much as 42 percent of the budget in 2006. In later years this number has decreased, and was at 25 percent in 2012-2013, but the government still relies heavily on donations to fund their bills (The New Humanitarian 2012).

### 2.3.1 Subnational placement of aid projects

Figure 2.7 shows the subnational placement of the projects with the most precise geocode (see chapter 4 for more details on the precision of the data) within the different regions. Most of the projects, 34 percent, are placed in the western region. 31 percent of the projects are placed in the eastern region, 21 percent are placed in the northern region, while 14 percent are placed in the central region. The projects placed in the central region seem to be densely placed around the capital of Kampala.



**Figure 2.7 Regional placement of aid projects. Datasource: (AidData 2016)  
Map made by author with the program QGIS 3.4.0 Madeira**

As shown earlier in the chapter, the infant mortality is highest in the northern region, and lowest in the central region. It seems clear that the projects are not located in the region with the highest infant mortality. This may be because infant mortality is reduced in the area where the aid projects are placed, or it may be the case that the projects are not allocated to the areas with the highest infant mortality at the outset. It is the aim of this thesis to answer which of these explanations are most likely.

## **2.4 Why geographical proximity to projects should matter**

The research question in this paper is: “Does geographic proximity to active aid projects reduce infant mortality?” But why would we expect geographical proximity to matter? Looking empirically at Uganda, several reasons allude us to believe that geographical proximity to projects may be an important factor for whether respondents are able to enjoy their services or not. In 2010 only 4 percent of the road network in Uganda consisted of standard paved roads (National Planning Authority 2013, 14). Only 2,55 percent of the households in the four DHS-surveys conducted between 2000 and 2016 report that they have a car, and only 6 percent of the households have a motorcycle or scooter. Only 37 percent of the households owns a bicycle (ICF 2000-2016). This may lead us to think that geographical distance to health centers may pose a challenge for people, and that it matters to have these centers close to be able to use them. In the four Demographic Health Surveys conducted between 2000 and 2016 the respondents have been asked if the distance to the health facility poses a big problem for getting help when they are sick and want medical advice or treatment. 44,2 percent report that distance to the health facility is a big problem for getting help (ICF 2000-2016). This tells us that distance to health facility matters. In 2010 only 15 percent had access to safe piped water (National Planning Authority 2013, 14), and more than half (55%) of rural households spend at least 30 minutes to fetch drinking water (Uganda Bureau of Statistics (UBOS) and ICF 2018, 12). Digging new wells, building new schools and new health centers is important to reduce infant mortality, but in order for a school, a water source, a hospital, or other public goods to be beneficial for an individual, it will have to be within his or her reach (Briggs 2017, 189-190).

### **3 Theory and literature**

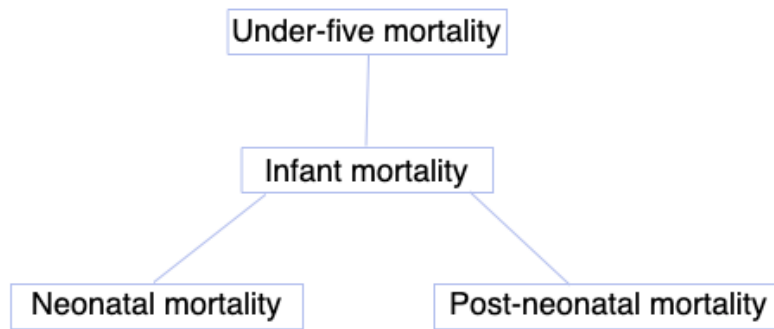
*“International aid is one of the most powerful weapons in the war against poverty.” (United Nations Development Programme 2005, 75)*

*“[...]foreign aid is a process by which poor people in rich countries help rich people in poor countries.”(Bauer 1976, 115)*

Foreign aid is very disputed with both strong supporters, and strong critics. Much of the research conducted on aid effectiveness has focused on aid's macroeconomic impact. Despite massive efforts, the literature has still not provided us with conclusive results as to whether aid has an impact on the macro economy or not. In this chapter I take a different angle at the aid effectiveness debate, and look at how we can expect aid to reduce infant mortality. The chapter is organized as follows: firstly, the definitions of infant mortality, concepts related to infant mortality and aid are discussed. Secondly, I have a closer look at which factors can cause infant mortality. Thirdly, I present arguments at a general level, and a more specific level of how we might expect aid to reduce the mortality. Fourthly, arguments against aid are presented, and I look closer at bad allocation of aid. In the end follows a literature review and presentation of the empirical findings on the connection between infant mortality and aid.

#### **3.1 Defining infant mortality and related concepts**

Infant mortality refers to: “death within the first year of life to persons born alive” (Frisbie 2005, 255). A live birth is defined by WHO as the “complete expulsion or extraction from its mother of a product of conception, irrespective of the duration of pregnancy, which after such separation breathes or shows any other evidence of life” (World Health Organization n.d.-a, Maternal mortality ratio (per 100 000 live births)). Infant mortality rate (IMR) is used in order to be able to compare the infant mortality between different areas, and at different times. This rate is defined as the number of deaths to infants within the first year, expressed per 1,000 live births.



**Figure 3.1 – A visual representation of the connection between infant mortality and related concepts. The figure is made based on the definitions used by the Demographic and Health Surveys (Uganda Bureau of Statistics (UBOS) and ICF 2018, 134)**

Infant mortality is closely related to the concepts under-five mortality, neonatal mortality and postneonatal mortality. Figure 3.1 gives a visual representation of the connection between infant mortality and related concepts. Gerring (2012, 127) argues that specifying how a concept fits within the larger semantic field is central to good conceptualization. Some of the literature presented later in this chapter also deals with the related concepts, and under-five mortality will be used as robustness check when looking at the connection between aid and infant mortality. It is therefore necessary to know the demarcating lines, and not just what is meant by infant mortality.

The various concepts all have death as the defining feature. What separates them is at what age death is occurring. We speak of under-five mortality if the child died between its birth and the fifth birthday. Neonatal and postneonatal mortality combined constitutes infant mortality with neonatal mortality being the probability of dying within the first month. Most of the literature used in the theory-section is specifically written about infant mortality, but some parts are also taken from literature on under-five mortality. Although under-five mortality and infant mortality is not the same, these concepts are very similar with 75 percent of all under-five deaths globally in 2017 happening within the first year (World Health Organization 2018c). The two concepts share many of the same risk factors and causes, and it is not uncommon in the literature to look at both concepts when conducting research on one of them (see for instance Chauvet, Gubert, and Mesplé-Somps 2013; Kotsadam et al. 2018 and Wilson 2011).

### **3.2. Defining foreign aid**

Foreign aid as a concept is not as easily defined as infant mortality. At its broadest, it consists of all resources provided by a donor to a recipient (Riddell 2007, 17). To qualify as aid, the

transfer must be a donation or grant or be on terms more favorable than commercial transactions. The transaction may be direct between individuals, or involve intermediaries such as private charities, foundations, nongovernmental organizations (NGOs), governments or intergovernmental organizations. Private aid is typically voluntary donations from individuals, foundations and corporations to NGOs, religious organizations or charities. In contrast, official aid is government tax revenue used to fund bilateral or multilateral aid programs (Kilby 2011, 358). The resources given can be financial resources or commodities (e.g. food or military equipment) or technical advice and training (Williams 2015). Different motives exist for giving aid; it may be given to address poverty and development needs in the receiving countries, but there might also be strategic or political reasons in the donor country motivating the donation (Riddell 2007, 17-18).

Functionally, aid can be divided into humanitarian relief, development assistance, and military support. Humanitarian relief aims to provide for basic needs in the event of natural or man-made crises. This type of aid does not have development of the country as a long-term goal. Development assistance on the other hand focuses on long-term goals such as reducing the poverty or increasing the welfare of a country (Kilby 2011, 358). Development assistance can support specific projects (project aid), or provide general support to the budget of the receiving country (budget support) (Cordella and Dell' Ariccia 2007, 1260). Budget support gives the recipient governments the greatest control and ownership. Project support on the other hand tends to give greater control to the donor country (Stierman, Ssenooba, and Bennett 2013, 3). The most common type of foreign aid is official development assistance (ODA) (Williams 2015). ODA are flows given to developing countries and multilateral institutions with the main aim of promoting economic development and welfare in the countries. Aid for military or other non-development purposes are thus excluded. The flows are provided as either grants or subsidized loans, and only countries classified as low- or middle-income countries can receive the flows (Organization for Economic Co-operation and Development 2019). Uganda falls into this category, as it is classified as a low-income country (The World Bank 2018).

### **3.3 What causes infant mortality?**

Infant mortality is a complex phenomenon that can be attributed to a range of hierarchical determinants that include distal, intermediate and proximate determinants (Mosley and Chen



1984, 27; Sartorius and Sartorius 2014, 2; Schell et al. 2007, 290). All of these determinants can be looked at as mechanisms causing infant mortality. All distal and intermediate determinants must work through a common set of biological mechanisms, or proximate determinants, to cause infant mortality. There are a number of causes of infant mortality, including poor water quality, poor sanitation, malnourishment of both mother and child, poor quality health systems, lack of education and poverty. Women's status are also reflected in infant mortality rates. In areas where women have few rights, infant mortality rates tend to be high (Treiber 2017).

In the end infant mortality is caused by a biological mechanism. Most deaths globally are due to a small number of diseases and conditions (World Health Organization 2013, 6). Which biological mechanism is the most important varies from country to country, and which age the cohort the child is in. Thirty-five percent of all deaths under-five in Uganda<sup>3</sup> occur among babies aged 0-28 days (neonatal) and are mainly due to preterm birth complications, problems during labor and sepsis. After the first 28 days until the age of five, the majority of deaths are attributable to pneumonia (14%), diarrhea (8%), Malaria (8%) and AIDS (6%) (Countdown to 2030 2018). Both prevention, and treatment will be important to reduce infant mortality.

### **3.4 How can aid reduce infant mortality?**

Aid has a multiple of objectives and ways of working. Once it reaches a country the aim is either to increase economic growth or improve the lives of poor people through the provision of goods or services. Provision of goods can take the form of private goods such as cash transfers, or more typically through public goods such as roads, schools, or health clinics (Briggs 2017, 189-190)<sup>4</sup>.

Before looking more specifically at how aid may affect some of the hierarchical determinants of infant mortality, such as access to water, food, education, health services and reduction of poverty, it is fruitful to look at the theoretical arguments for aid in general. Most of these arguments have originally focused on why aid will create economic growth, but several of the arguments also apply to the debate of aid's effectiveness in reducing infant mortality.

---

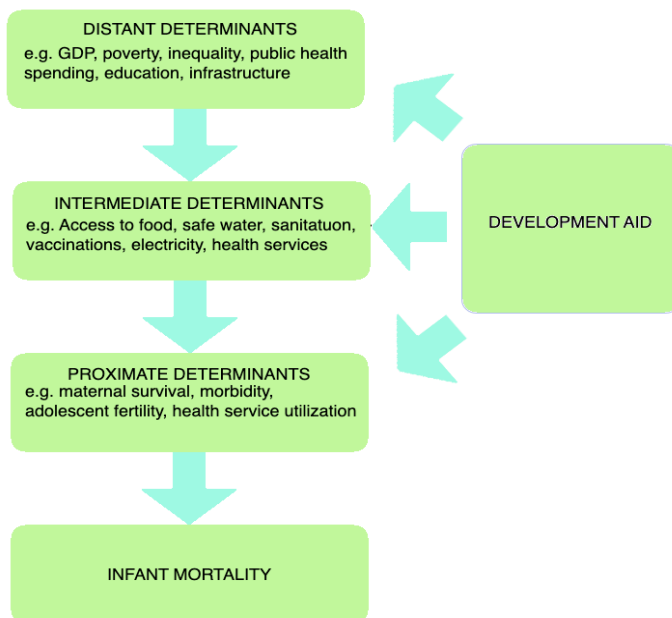
<sup>3</sup> I have not been able to find a list of causes only for infant mortality in Uganda.

<sup>4</sup> Briggs (2017, 190) argue that aid for local public goods can be especially valuable because such public goods may be difficult to create for communities due to collective action problems even though the community is getting richer.

### 3.4.1 Theoretical arguments for aid

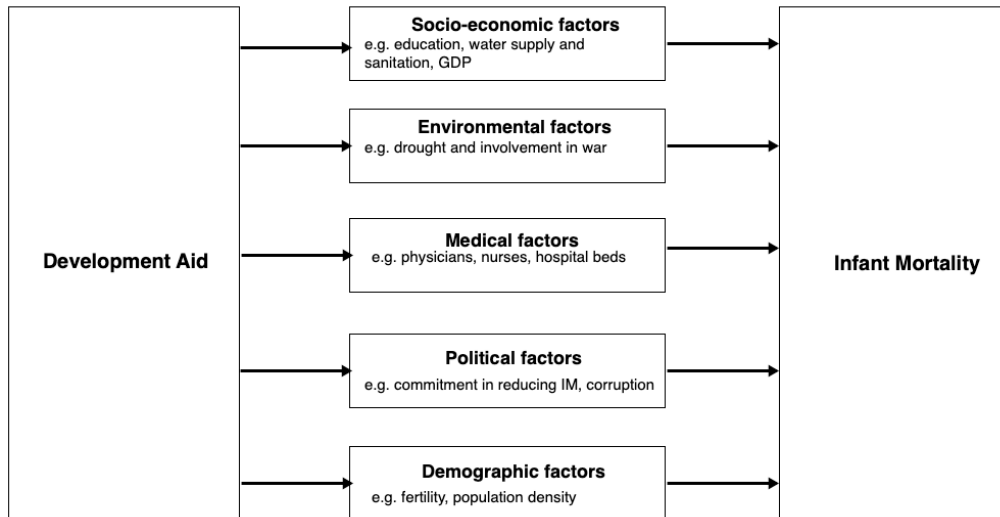
Radelet (2006, 8) identifies three main theoretical arguments used by those who argue that aid might spur growth. Firstly, the classical view is that aid increases savings, which then leads to increased investments. The theoretical underpinnings for this view is the Harrod-Domar growth model (Hansen and Tarp 2000, 377). Secondly, aid may increase the productivity of workers through investments in health or education, which will then lead to increased growth. These two arguments are not just relevant for economic growth, but also for reduction of infant mortality: if government investments, and/or aid are geared towards specific sectors, such as the education sector, the health sector, agriculture, or the water and sanitation sector this may directly reduce infant mortality. Thirdly, aid can spur growth through transferring technology or knowledge from rich countries to poor countries. Such transfer of technology or knowledge may happen in many ways. Charles Kenny (2011) argues in his book “Getting better” that there have been huge gains in health across the world because of the spread of germ theory, hand-washing and antibiotics. Technology and knowledge transfer in other sectors will also have a big potential to reduce infant mortality.

### 3.4.2 A closer look at how aid can affect determinants of infant mortality



**Figure 3.2: Conceptual framework of the hierarchy determining infant mortality. Figure made by author, but based on identical figure in Kotsadam et al. (2018, 62)**

Figure 3.2 posits how aid may affect the various hierarchical determinants of infant mortality. Aid is thought to have an indirect effect on infant mortality by affecting the distal, intermediate and proximate determinants of infant mortality. Far from all factors affecting infant mortality are listed in the figure, but some important factors are given.



**Figure 3.3 Model showing the various factors that aid can affect, which again will be important for infant mortality. The model is made by author, but based on information given in Gbesemete and Jonsson (1993)**

Figure 3.3 shows the same as figure 3.2, but here development aid is shown to affect the different factors, and not the hierarchical levels. Risk factors frequently employed include socioeconomic, demographical, medical, environmental and political (Gbesemete and Jonsson 1993, 155).

Infant mortality is, as can be seen from figure 3.2 and figure 3.3, a very complex process, and aid projects within many different sectors will all undoubtedly have a potential to reduce the mortality if they are effective. The World Health Organization (2013, 9) states that: “To accelerate progress and achieve improved health outcomes for all children, ensuring universal access to high-quality care, safe water and sanitation, safe and nutritious foods and safe housing is crucial, as is access to education, social security and other social services.”

Some of the factors pointed to as important by the WHO are discussed more in detail below.

### **3.4.1 Provide maternal education**

Maternal education has been referred to as a major social determinant of infant mortality both globally (Schell et al. 2007; Sartorius and Sartorius 2014) and in Uganda (Ssewanyana and

Younger 2008). The effect education has on infant mortality is likely a result of longer periods between births, better awareness and utilization of prenatal care and health services, and higher income, which improves infants' health through the ability to purchase goods and services (Sartorius and Sartorius 2014, 11). Schell et al. (2007, 296) state that "Investing in female education might be the most rational intervention that countries can make to prevent avoidable infant deaths.

International aid aimed at providing and improving education in general has been channeled into a variety of interventions such as school feeding programs, teacher education, girls' scholarships, classroom construction, programs to reduce drop-out and curriculum development (Riddell and Niño-Zarazúa 2016, 24). So far there has been a massive focus on increasing the enrolments, attainment and gender parity, and much less focus on the measurement of educational quality, although this has started to change in recent years (Riddell and Niño-Zarazúa 2016, 23-25). To reduce infant mortality it will be important to secure that students graduate from school, and not just that they enroll into the school (Ssewanyana and Younger 2008, 52; Caldwell and McDonald 1982, 264).

### **3.4.2 Provide access to health services and vaccinations**

Given that infant mortality in the end is caused by a biological mechanism, or proximate determinant, it is clear that improving the access to health services and vaccinations will play an important part in reducing the infant mortality. Ssewanyana and Younger (2008, 35) studied Uganda specifically, and unsurprisingly found that improvements in vaccinations for childhood diseases and in general health care services can cause significant reductions in IMR.

To improve child health specifically, the Ministry of Health in Uganda has instituted the nationwide program called Child Health Days Plus. This program aims to improve the health and nutrition status of children by providing them with vitamin A, deworming medication, immunizations and insecticide-treated bednets. These interventions are primarily preventive in nature. Although implemented by the Ministry of Health in Uganda, this program is largely financed by foreign aid (Oliphant et al. 2010). Stierman, Ssengooba, and Bennett (2013) study how donors channel development assistance for health and the extent to which this assistance is aligned with sector priorities in Uganda from 1999-2009. They report that most of the

money are provided as support to short-term projects rather than sector programs planned over the longer term<sup>5</sup>. HIV/AIDS is by far the program area that receives most of the allocated resources (Stierman, Ssenkooba, and Bennett 2013, 5-9).

### **3.4.3 Provide water and sanitation**

Diarrhea is the second leading killer of children under five globally (Liu et al. 2015, 432). In Uganda it is one of three major childhood killers, killing 33 children every day (Unicef 2015). 58 percent of deaths due to diarrhea in lower- and middle income countries are attributable to inadequate access to water, poor hygiene and sanitation (World Health Organization 2014, ix).

23 percent of the population lacked access to “at least basic water”<sup>6</sup> in Uganda in 2015 (World Health Organization and Unicef 2017, 74). Several studies have shown a link between aid to the water and sanitation sector and improvements in aggregate indicators of child health outcomes in a broad sample of countries (Botting et al. 2010, 6; Wayland 2013). International aid to the water sector can help through securing access to safe drinking water, educating people about hygienic behavior, especially the importance of hand washing with soap and the danger of open defecation, and securing access to sanitation facilities (Unicef 2015).

### **3.4.4 Provide nutrition**

Globally, nutrition-related factors contribute to about 45 percent of deaths in children under five years of age (World Health Organization 2018a). Malnutrition is also a sizeable problem in Uganda. Nearly half of all deaths in Ugandan children between 2013 and 2015 were associated with undernutrition (Unicef 2017b). One-third of children under five years old are stunted, which puts Uganda among the 20 countries worldwide with the highest prevalence of undernutrition (The World Bank 2019b). The causes of malnutrition are complex. Kikafunda et al. (1998) studied the dietary and environmental factors influencing stunting in 261 children under 30 months in rural and semi-urban districts in Uganda. They report that low

---

<sup>5</sup> This trend can be seen as unfortunate because it fails to consider the importance of longer-term investments in health infrastructure, capacity building and personnel development (Stierman, Ssenkooba, and Bennett 2013, 8-9).

<sup>6</sup> Basic water is defined as drinking water coming from an improved sourced (a water source free from contamination, that is placed at the premises, and that is available when needed), and provided the collection time is not more than 30 minutes for a round trip (World Health Organization n.d.-b)

economic status and using water from unprotected sources are amongst the social factors that are important in explaining underweight in children (Kikafunda et al. 1998, 7-8). Low breastfeeding rates, poverty, lack of knowledge about nutrition, food insecurity and repeated childhood infections such as diarrhoea, also contribute to undernutrition (Food and Agriculture Organization of the United Nations 2010; Unicef N.D).

Foreign aid may improve the nutritional status in a several ways. Alderman (2007, 1376) states that a common heuristic model of the production of nutrition is based on the role of nutrients, the role of health and sanitation services and the role of child care. Foreign aid may thus help in preventing and treating undernutrition in several ways, either by focusing on the role of food or supplementation, health and sanitation services or child care.

#### **3.4.4 Reduce poverty**

Barbieri (2015, 24) argues that poverty lays at the root of high child mortality in developing countries. At the household level, poverty clearly affects the health of children. Low purchasing power is amongst other things related to poorer nutrition and lack of access to clean drinking water and proper sanitation. At the national level, the relationship between national income and infant mortality is much less systematic. Wealthier countries do clearly have a lower infant mortality rate, but the relationship is not deterministic since countries with the worst health conditions and highest mortality are not always the poorest (Barbieri 2015, 24-25).

An historically important motive for providing aid has been poverty-reduction (Riddell 2007, 91). Both the millennium development goals (MDGs), and the new sustainable development goals (SDGs) have eradication of poverty as a target. Big multinational institutions such as the World Bank and the African Development Bank both have poverty reduction as a central part of their missions (Briggs 2017, 188-189). Aid may reduce poverty either indirectly or directly. Traditionally, aid has been thought to raise average income in the receiving country first, which is then followed by mitigation of poverty. This view is based on the belief that poverty reductions will occur when the incomes rise, an indirect effect of aid so to say. The other manner aid may reduce poverty is directly, through targeting aid to areas where poverty are high, and thus mitigate poverty, instead of expecting aid to raise average incomes in the receiving country (Alvi and Senbeta 2012, 955-956).

### **3.5 Geographical proximity to projects**

In order for a hospital, school, water source or other public goods to be beneficial for an individual it will have to be within the reach of this individual (Briggs 2017, 189-190). Increasing distance to hospital has been shown to be a risk factor for perinatal mortality in Pakistan (Fikree et al. 1997) and under-five mortality in rural areas of Ethiopia (Okwaraji et al. 2012) and Tanzania (Kadobera et al. 2012). Long distance to school is proposed to be one of the explanations of why about three in ten girls and boys age 6-9 have never attended school in Uganda (Uganda Bureau of Statistics and Macro International 2007, 23). The risk of the water becoming contaminated also increases when the water has to be transported longer distances. Collecting water is also often a colossal waste of time for women and girls; time that better could be spent doing something else, like studying or taking care of the family (Unicef 2016b).

The benefit of the aid projects will be much higher for the people living closer to them, and will decrease for the people living further away. Many development projects are aimed at local development, and not necessarily national development (Findley et al. 2011, 1995). If aid is effective we should thus expect that people who live closer to aid projects will have lower infant mortality. This leads me to the first hypothesis:

*“H1: Infant mortality will be lower near active aid projects than in the rest of the country”*

### **3.6. Theoretical arguments against aid**

Those arguing that aid has no effect on growth, and that aid might actually undermine growth also have several theoretical arguments at their hand. Firstly, aid might be wasted, and only benefit an elite (Boone 1996, 322). It may also encourage corruption and undermine local state capacity (Moyo 2009, 49; Deaton 2013, 294-295). If this argument holds true, and the money do not reach those in need, we should not expect neither economic growth nor reduced infant mortality. Muldoon et al. (2011) study health system determinants of infant, child and maternal mortality in UN member countries. Their findings reveal that the more corrupt a government is perceived to be, the stronger the association with increased rates of infant and child mortality. They argue that transparent governance plays an important part to improve population health, and strengthen the health systems (Muldoon et al. 2011, 5). Secondly, aid

may thwart accountability mechanisms and help in keeping a bad government in power, thus postponing reforms that would otherwise have happened. Bauer (1981, 103) argue that aid can encourage dependency and reduce incentives to adopt good policies. If the government does not adopt good policies, this might influence infant mortality just as much as economic growth. This will of course be dependent on which policies that are not adopted. Thirdly, aid will not spur growth because the receiving countries have limited absorptive capacity, which means they will not be able to use aid flows effectively. Such constraints include macroeconomic, institutional, social, cultural, and physical and human resources (Gottret and Schieber 2006, 149). Lack of trained teachers and nurses, bad roads accessibility and weak institutions are all examples of factors that may render aid ineffective for both creating economic growth and reducing infant mortality. Fourthly, aid might crowd out the private sector, and undermine incentives for investment or improvement of productivity from the private sector (Younger 1992, 1587). It can also harm the international competitive position of the recipients because of increased exchange rate or increased domestic money supply (Bauer 1981, 109). Lastly, aid may lead to decreased domestic saving both at a household level and at the level of the government due to its impact on interest rates and government revenue. These three last arguments against aid seem mostly relevant to explain why aid will not create economic growth. That being said, it is important to remember that reduced economic growth might also lead to higher infant mortality, although the relationship is not a very powerful one (Soares 2007, 251).

In addition to those arguing that aid do not have a positive effect on growth, there is also a strand of research that argues that aid has a conditional relationship with growth. These arguments can be placed in three subcategories according to Radelet (2006, 10). One strand argues that the effectiveness of aid is dependent on the characteristics of the recipient country. A second and third strand argues that the practices and procedures of the donors, and the type of activity supported by aid matters. Many of the same conditionalities that are presented for the connection between aid and growth are also found in the empirical studies of the connection between infant mortality and aid. In the literature review I present cross-country studies that find these conditionalities to hold true for aid and infant mortality, and discuss what we would expect to see in Uganda if these arguments are correct.

Problems that are specific for the aid projects may be poorly design, poorly implementation and poorly evaluation (Wilson 2011, 2040). This may be due to wrong decisions as to which



aid ought to be implemented, making over-optimistic assumptions about the capacity of the receiving organizations, and failure to assess the external environment receiving the aid (Riddell 2007, 357). It is also argued that aid is misallocated, and does not reach the people who need it the most. This argument applies both at a country-level, and at a subnational level. If a significant part of aid is allocated for strategic purposes, we should not expect a positive impact in terms of growth or poverty alleviation (Masud and Yontcheva 2005, 4). The data that I possess allow me to look closer at one of the explanations, namely bad allocation of aid.

### **3.6.1 Bad allocation of aid**

From a humanitarian and development perspective aid should be provided to those who need it most. The greater the needs are, the more aid ought to be allocated if the target is to reduce poverty. From the perspective of the donors it may be more reasonable to argue that the taxpayers money should be spent according to its own country's political, commercial and strategic interests. Both arguments are perfectly rational, but they will lead to different allocation of aid, the first being more efficient in reducing poverty and infant mortality.

Much research has been done on the determinants of foreign aid allocation. The majority of work has claimed that donors self-interest plays a large role in determining how much aid a country receives (Hoeffler and Outram 2011, 237). These self-interests may be donors' own commercial interests, donors need for "friendly" voting within the UN, a donors past as a colony power, and political alliances (Hoeffler and Outram 2011; Dollar and Alesina 2000). In a much cited study by Dollar and Alesina (2000) the results show that colonial past and political alliances are major determinants of foreign aid. They find considerable evidence that the pattern of allocation of foreign aid is dictated as much by political and strategic considerations, as by economic needs and policy performance of the recipients. Riddell (2007, 358) argues that there is a major mismatch between aid allocation and humanitarian and development needs. He further states that studies suggests that three times as many people could be lifted out of poverty if ODA was allocated on the basis of need.

The large majority of studies on aid allocation, as is also the case for the studies on aid effectiveness, have mainly been conducted on the cross-country level. Some studies of allocation at the subnational level do however exist. The theoretical argument for targeting aid

to poorer places within countries is essentially the same as the argument for targeting poorer countries. If the goal of aid is to help alleviate poverty<sup>7</sup>, then aid ought to be directed to where the poor people live (Briggs 2018b, 134).

At a subnational level aid has been found to be skewed according to local political incentives (Briggs 2014). Prior research has shown that aggregate foreign aid does not target poverty in India (Nunnenkamp, Öhler, and Sosa Andrés 2017, 126), Malawi (Nunnenkamp, Sotirova, and Thiele 2016, 844), Kenya (Briggs 2014, 194), or across a number of countries in Africa (Öhler and Nunnenkamp 2014, 422; Briggs 2018b, a). Given that previous research finds little aid allocation to the poorer areas, and in some of the studies also to areas with higher infant mortality, I propose the following hypothesis:

*“H2: Aid projects will not be allocated to the areas where the infant mortality is highest”*

### **3.7 Literature Review: Empirical findings on the connection between infant mortality and aid**

Most of the research on the effects of foreign aid has focused on the relationship between aid and general development indicators such as economic growth or democracy (Gebhard et al. 2008, 2). Despite massive efforts, the literature on aid’s macroeconomic impact has still not provided us with conclusive results as to whether aid has an impact on the macro economy or not. Doucouliagos and Paldam (2009) go so far as to entitle their review of the aid effectiveness literature “The Aid Effectiveness Literature: The Sad Results of 40 Years of Research”. Some research has also been conducted on the effect of aid on more specific outcomes such as for instance health outcomes and education outcomes. The results from these studies are not conclusive either when it comes to the question of whether aid actually works or not (Kotsadam et al. 2018, 59). The effectiveness of foreign aid in reducing infant mortality is also subject to debate. Both cross-country studies, case studies and studies at the meso level have been used to study aid effectiveness in reducing infant mortality. The results from cross-country studies are inconclusive, as we have also seen is the case for cross-country studies of aid and economic growth. Case-studies that focus on a specific disease or program exhibit a remarkable degree of consensus, concluding that targeted health aid significantly

---

<sup>7</sup> This is the stated goal of several big multilateral donors (Briggs 2018b, 134).

improves health outcomes in the target area (Pickbourn and Ndikumana 2018, 4). Below follows a review of different cross-country studies and case-studies. Since my study is at the meso-level, there is also a presentation of one study conducted at the meso-level at the end.

### 3.7.1 Cross-country studies

15 cross-country studies that have examined the connection between aid and infant mortality, and two that have studied the connection between under-five mortality and aid are presented in table 3.1. The 16 studies presented in table 3.1 can be separated into three categories based on what the results show when it comes to aids ability to reduce infant mortality: one group find that aid reduces infant mortality, one group find that aid can potentially contribute to reducing infant mortality, but this is conditional on other factors such as policy environment, level of development and so forth, and one group finds that aid is not effective in reducing infant mortality. This is the same pattern that we see for studies of aid and economic growth.

References	Number of countries surveyed and period	Dependent variable(s)	Statistical method	Results	Type of aid
Gomanee et al. (2005)	104 countries from 1980-2000	IM and Human development index	Regressions with unbalanced panels	Aid is associated with lower levels of IM, but only weakly for those countries with higher IM	Overall aid
Gomanee, Girma, and Morrissey (2005)	38 countries from 1980-1998	IM and Human development index	Quantile regressions	Aid is associated with lower IM, and aid has a higher effect in countries with higher IM	Overall aid
Mishra and Newhouse (2009)	118 countries between 1973-2004	IMR	Linear regressions with and without fixed country effects.	Health aid has a beneficial and statistically significant effect on infant mortality	Health aid
Negeri and Halemariam (2016)	43 countries in the period 1990-2010 averaged over 5-years	IMR	Panel data analytical method	Health aid has a statistically significant positive effect on reducing infant mortality	Health aid

AID IS EFFECTIVE	Arndt, Jones, and Tarp (2015)	78 countries in the period 1970-2007	Proximate sources of growth (e.g. physical and human capital), indicators of social welfare (e.g. poverty and IM) and measures of economic transformation (e.g. share of agriculture and industry in value added).	Linear regressions (OLS, LIML, IPWLS)	Overall aid has a significant effect on reducing IM	Overall aid
	Pickbourn and Ndikumana (2018)	47 sub-Saharan African countries between 2000-2013	Number of deaths attributed to diarrhea per 1000 live births in children under five	Linear regression with fixed effects	Increased health aid is associated with lower diarrhea mortality in children under five years	Health aid
AID EFFECTIVENESS IS CONDITIONAL	Burnside and Dollar (1998)	56 developing countries with four year periods between 1970-1993	IM	Linear regressions (OLS, 2SLS)	Aid reduces IM only in a good policy environment	Overall aid
	Gomanee et al. (2003)	38 countries from 1980-1998. Four-year and three-year averages are used	HDI and IM	Regressions with random effects	Higher PPE improves welfare indicators, and aid contributes to welfare only by financing such expenditures. There is an indirect effect of aid, but not a direct effect.	Pro-poor expenditures (PPE), including overall aid
	Navia and Zweifel (2003)	293 observations in the years 1990-1997	Infant mortality rate	Heckman Two-Step Method	Aid makes IM worse in dictatorships. In democracies aid reduces IM	Overall aid
	Masud and Yontcheva (2005)	58 countries between 1990-2001	IM and education	Regressions with unbalanced panel	NGO aid and increased health expenditure per capita reduces IM. No significant impact of total bilateral aid on IM	Overall aid, both bilateral aid and aid by international NGOs.

	Chauvet, Gubert, and Mesplé-Somps (2013)	84 countries from 1992-2004	IM and under-five mortality	Linear regression (OLS, 2SLS)	Aid to the health sector contributes to decreasing child mortality and IM, but the impact is statistically fragile. Overall aid does not reduce child mortality and IM	Health aid and overall aid
	Kizhakethalackal, Mukherjee, and Alvi (2013)	100 developing countries between 1974 to 2005 with eight samples of 4 year averages	Infant mortality rate	Quantile regression	Aid is effective in reducing IM in countries with low IM, but it is not effective in countries with high IM	Health aid
	Mukherjee and Kizhakethalackal (2013)	110 developing countries between 1974-2005 with eight samples of 4 year averages	IMR	Semiparametric nonlinear regression	Health aid does not have any statistically significant impact on IMR, but basic education/consciousness/awareness of people in general can make aid somewhat more effective.	Health aid
	Winkleman and Adams (2017)	183 countries from 2000-2015	Under-five mortality	OLS with country fixed effects	Official development assistance (ODA) seems to be ineffective in low developed countries, but effective in medium developed countries	Overall aid
AID IS NOT EFFECTIVE	Boone (1996)	96 countries with four samples of 5 year averages (1971-75, 76-80, 81-85, 86-90)	IM, primary school ratios and life expectancy	Cross-country panel data analysis	Overall aid has no significant effect on reducing IM	Overall aid
	Williamson (2008)	208 countries with five year intervals between 1973-2004	IM, life expectancy, death rate and immunizations	Fixed effects regression and instrumental variable estimation	Health aid does not have a statistical significant effect on reducing IM	Health aid and overall aid

Wilson (2011)	96 high mortality countries in the period 1975-2005	IM, under-five mortality, life expectancy at birth.	Linear regressions (OLS, DPM, LDV).	Health aid and overall aid has no effect on reducing IM or under-five mortality. Health aid is going to countries where mortality is declining, but it is not causing it.	Health aid and overall aid
---------------	---	---	-------------------------------------	---	----------------------------

**Table 3.1 - Overview of cross-country studies looking at the connection between infant mortality and aid.**

35 percent of the studies in table 3.1 find that aid, either health aid or overall aid, has a significant effect on reducing IM or under-five mortality. 18 percent find that aid has no effect on reducing IM. The remaining studies, 47 percent, find that aid (health aid and overall aid) can have an effect on reducing infant mortality or under-five mortality, but this effect is conditional on factors such as 1) type of aid, 2) policy environment, 3) type of regime, 4) level of infant mortality, 5) indirect effects of aid being taken into account, 6) peoples level of education and 7) a country's level of development. It is hard to see a clear pattern as to why some studies find that aid has an effect, others find no effect, while still others again find an effect conditional on other factors. Health aid and overall aid are both placed in all three categories, the period surveyed and the number of countries varies in all three groups. Two small patterns can be seen: firstly, it seems like the period surveyed in the studies reporting a non-significant effect of aid is longer than in the other two categories, and secondly, it seems like averaging of years is less pronounced in the studies reporting a positive effect of aid than in the other two categories. If these discovered patterns are just random or not, is not clear. It is also clear that many of the conditions put forward such as type of aid, policy environment, type of regime and a country's level of development are also conditionalities that we find in the literature looking at the connection between aid and economic growth.

Five of the studies reporting that aids effectiveness is conditional on other factors point to the fact that aid is effective only in "better working" countries; Burnside and Dollar (1998) find that aid only works in "good policy environments", Navia and Zweifel (2003) report that aid only improves IM in democracies and make it worse in dictatorships, Kizhakethalackal, Mukherjee, and Alvi (2013) find that aid is only effective in reducing IM in countries with low IM. Mukherjee and Kizhakethalackal (2013) find that health aid does not have any statistically significant impact on IMR, but basic education / consciousness / awareness of the people in general can make aid somewhat more effective. Winkleman and Adams (2017) report that official development assistance seems to be effective in medium developed

countries, but not in low developed countries. Several of these arguments speak against there being an effect of aid in Uganda. Firstly, Navia and Zweifel (2003) use data from Alvarez, Cheibub, Limongi and Przeworski 1997, ACLP World Political / Economic Database (Przeworski et al. 2000) to classify countries as either a democracy or a dictatorship, and conclude that aid only works in democracies. According to these data Uganda is classified as a military or civilian dictatorship in the years 1962-2008 except for the period 1980-84 where it is classified as a democracy. One would thereby not expect to find any effect of aid in Uganda if this argument holds. Secondly, Kizhakethalackal, Mukherjee, and Alvi (2013, 1201) state that health aid only help reduce IMR significantly up to the fiftieth quantile. Uganda is placed in a higher quantile than this, and health aid can thus not be expected to be effective. Thirdly, Uganda is classified as a least developed country, and it has been since 1971 (United Nations 2018a). Following Winkleman and Adams (2017) argument that official development assistance is only found to be effective in medium developed countries, but not in low developed countries, one would not expect it to be effective in Uganda. On the other hand, Burnside and Dollar (1998, 14) specifically mention Uganda as a country that has reformed to become a “good policy country” in the 1990s. By a “good policy country” they mean a country with good property rights, low levels of corruption, open trade regimes and macroeconomic stability. If their argument is correct one could thus expect to see an effect of aid in Uganda.

### **3.7.2 Case studies**

Radelet (2006, 9) argues that health is possibly the area where case studies best have been able to document the effect of aid. The book “Case-studies in Global Health – Millions Saved” by Ruth Levine and the What Works Working group (2007) provides examples of twenty different cases where aid has contributed in improving health outcomes. The book stands out because the cases selected have been thoroughly controlled by researchers to ensure the evidence base is of high enough quality. Several of the cases researched in the book shows how aid has been an important factor in reducing infant mortality. Among the selected cases is the success in reducing child mortality in Nepal through the National Vitamin A Program (NVAP). This program was initiated by the government of Nepal with the support of UNICEF, USAID, and local researchers and NGOs, and the program was found to reduce by about half the mortality rate for children under five years of age in Nepal between 1995 and

2000 (Levine and What Works Working Group 2007, 25). Another case highlighted as successful in reducing infant mortality is The National Control of Diarrheal Project of Egypt. This program succeeded in reducing the mortality due to diarrhea among infants by 82 percent in the period 1982-1987. International donors financed 60 percent of the program. Because of the reduction in diarrheal deaths between 1982 and 1989, 300 000 fewer children died (Levine and What Works Working Group 2007, 57). In addition to these two cases several of the other cases discussed in the book have also had consequences in reducing infant mortality, although this has not been the main target of the programs. Preventing HIV/AIDS and sexually transmitted diseases in Thailand, Saving Mothers' Lives in Sri Lanka, Reducing Fertility in Bangladesh and increasing immunization against smallpox, measles and polio have all almost certainly contributed in reducing infant mortality. In addition to case studies looking specifically at the connection between aid and diseases connected to infant mortality there is also a vast body of epidemiological literature showing the effectiveness of various targeted interventions on mortality (Wilson 2011, 2034). These case-studies have given us a huge insight into which interventions can be effective in reducing infant mortality, but the bigger question at hand is if aid is working the way we intend it to. Pickbourn and Ndikumana (2018, 4) argue that studies that focus on the effectiveness of health aid for a specific disease or program exhibit a remarkable degree of consensus, concluding that health aid is efficient in improving health outcomes. Radelet (2006, 9) argues that beyond specific case studies, there is little systematic evidence on the relationship between aid and health. Wilson (2011, 2034) argues that studies that select on the dependent variable to identify successful efforts can contribute little to the larger question at hand.

### **3.7.3 Meso-level studies**

Quantitative research on aid and health outcomes in general at the sub-national level is very scarce, and for the connection between infant mortality and aid at the sub-national level there only exists one previous study to my knowledge. Kotsadam et al. (2018) researches how official development assistance affects infant mortality in Nigeria. Their results indicate clearly that geographical proximity to active aid projects reduces infant mortality. Further, their results indicate that aid projects are established in areas that on average have lower infant mortality than non-aid allocations. This paper is inspired by Kotsadam et al. (2018), but is different in several ways including: the country studied, precision level of the data used, the buffer size and which mechanisms are studied.



It seems apt to agree with De and Becker (2015, 5) who point out that we need a finer lens in order to understand if aid is working or not. The results from cross-country studies seems very fragile to model specifications, and case studies do not provide the level of generalization that may be wanted by taxpayers and politicians when it comes to assessing the effect of aid.

## **4 Data and Measurement**

In this chapter I first present the reasoning behind choosing Uganda as a case. Secondly, I provide a presentation of the datasets I am using for the analyses, and the various limitations and strengths that apply to these. Lastly, the conceptualizations of the dependent, independent and control variables are provided.

### **4.1. Case selection**

There are several good reasons to use Uganda as a case in a study of aids effectiveness in reducing infant mortality. Firstly, as discussed in chapter two, the country has been among the world's top aid recipients for several decades (Bergo 2015). Secondly, the infant mortality is high, but it has also decreased a lot. Thirdly, the fact that there are big subnational differences in both infant mortality and placement of aid projects within the country means there is a good opportunity to use a spatial strategy like the one applied in this study to see if the proximity to aid projects matters. Fourthly, the method applied in this paper is not possible to use if the projects are too densely placed within the country. There needs to be some individuals whom do not have an active or inactive aid project in their proximity, and if the projects are densely placed all over the country one does not get this group. The projects in Uganda are not too densely placed, and the country is thereby an excellent case to study. Given that data on both infant mortality and placement of aid projects are only available for a small amount of countries, it is a lucky circumstance that Uganda offers several good reasons to be studied. Table 4.1 provides a full overview of all countries that have available geocoded data on both infant mortality and placement of aid projects.

Countries with available data on placement of aid projects from AidData	Number of applicable geocoded DHS rounds with information about infant mortality	Number of project-locations	Reason for exclusion
Afghanistan	0	7168	No geocoded DHS-data available
Bangladesh	4	3641	Only data from selected donors
Burundi	2	7562	Only six years between surveys from DHS
Colombia	1	2981	Only one round of DHS-data
Democratic Republic of Congo	2	1750	Only six years between surveys from DHS
Honduras	1	5028	Only one round of DHS-data
Iraq	0	3624	No geocoded DHS-data available
Malawi	3	2523	Only data from selected donors
Nepal	4	20952	Project-locations too densely placed to be used for analysis <sup>8</sup> .
Nigeria	5	1843	Previously studied
Senegal	8	2314	
Sierra Leone	3	2314	Only six years between first and third survey from DHS
Somalia	0	3130	No geocoded DHS-data available
Timor-Leste	2	3506	Only six years between surveys from DHS
Uganda	4	2426	

**Table 4.1 Overview of countries with available data from DHS and AidData**

Compared with the only other eligible case, Senegal, Uganda offers several good reasons to be studied: firstly, more aid commitments are tracked in the dataset covering Uganda. Secondly, the overall infant mortality in Uganda is higher than in Senegal, and it has declined more there than in Senegal. The period covered by AidData is also longer in Uganda than in Senegal if only just so. The period covered by Demographic Health Survey (DHS) on the other hand is longer in Senegal, but when comparing the two countries there are more factors pointing me in the direction to study Uganda than Senegal.

<sup>8</sup> The average number of project-locations for all countries excluding Nepal is 3558. In Nepal the number of project-locations is 20952, and after keeping only projects with precision-code 1 and a known start date there are still 15093 projects left, and these are spread all over the country. This means it is not possible to have three distinct groups with one group not living close to the aid projects. See figure 4.1a in appendix for a visual representation of all aid projects with precision code 1 and a known startdate.

## 4.2 Datasets

To analyze the effects of aid on infant mortality, I geographically matched new spatial data on aid in Uganda over the period 1988-2013 to 133 253 units (children) from four Demographic Health Surveys over the period 2000-2016<sup>9</sup>.

### 4.2.1 AidData

Data on aid come from Uganda AIMS Geocoded Research Release, version 1.4.1 and was published in April 2016 (AidData 2016). The dataset includes all geocoded projects from Uganda’s Aid Management Platform. A total of 565 geocoded projects across 2426 locations between 1988 and 2013 are included in the dataset. The geocoding varies from highly precise GPS points to regional/state and central government levels, and the dataset includes information on the precision of each coding. Table 4.2 shows the precision level of the different categories.

Precision code	Definition
1	“The coordinates correspond to an exact location, such as a populated place or a physical structure such as a school or health center. This code may also used for locations that join other locations to create a line such as a road, power transmission line or railroad”
2	“The location is mentioned in the source as being “near”, in the “area” of, or up to 25 km away from exact location. The coordinates refer to that adjacent location.”
3	“The location is, or is analogous to, a second order administrative division (ADM2), such as a district, municipality or commune.”
4	“The location is, or is analogous to, a first order administrative division (ADM1), such as a province, state or governorate.”
5	The location can only be related to estimated coordinates, such as when a location lies between populated places; along rivers, roads and borders, or more than 25 km away from a specific location. The code is also used when sources refer to parts of a country greater than ADM1 such as a National Park which spans across several provinces.
6	“The location can only be related to an independent political entity, but is expected to be disbursed locally. This includes aid that is intended for country-wide projects as well as larger areas that cannot be geo-referenced at a more precise level.”
7	“The location is unclear. The country coordinates are entered to reflect that sub-country information is unavailable.”
8	“The location can only be related to an independent political entity, but the central government will be the only direct beneficiary (e.g. capacity building, budget support,

<sup>9</sup> The program QGIS version 3.4.0 Madeira, was used to do the matching.

**Table 4.2 Precision level on the AidData. Source: AidData Research and Evaluation Unit (2017, 8)**

In the main analyses I only use the projects with precision code 1 because I want to look at the localized effect of aid. See the methodology chapter for a further discussion of this decision. As a robustness check I also use precision-level 2 and 3, to see if the main findings change.

#### **4.2.2 Demographic Health Surveys**

The demographic data used in the analyses come from Demographic Health Surveys (DHS) conducted over several years in Uganda. These standard DHS surveys are nationally representative household surveys with large sample sizes, usually between 5000 and 30 000 households. The DHS program have wide experience in conducting such surveys, and more than 300 surveys in over 90 countries have been conducted through the program (Croft et al. 2018, 1.2). The surveys are conducted about every 5 years, with the same questions asked in each survey to facilitate comparisons across time and space (The DHS Program n.d.-b). Women of reproductive age (between 15 and 49) are selected to answer questions on various topics including sexual and reproductive behavior, nutrition, HIV and other sexually transmitted infections and background characteristics of the women and their family (The DHS Program n.d.-a). The unit of analysis in the main analyses of this thesis is not the women themselves, but all live births reported by the women. This means that if a mother has given birth to six live children for instance, she gets six entries in the dataset. When studying the mechanisms that theory suggests are important to explain infant mortality I use the 30 550 mothers as the unit of observation.

I use data from the four standard DHS surveys with available geocoded information that have been conducted in Uganda. These surveys were conducted in 2000-2001, 2006, 2011 and 2016. Combining four DHS surveys offers the advantage of a long time series, and a large sample. The sample in this study consists of 133 253 individuals (live births). Having a large sample like this in the study of infant mortality is essential given that infant mortality is a rare event (Mosley and Chen 1984, 29).

The DHS-data are displaced (geomasked) in order to protect the anonymity of the respondents. Respondents in a given area are first gathered in clusters, and then these clusters

are displaced. A cluster can be a city block or apartment building in urban areas, while in rural areas it is typically a village or a group of villages. The population and size of sampled clusters vary between and within countries. The clusters in this study contain 74,5 individuals on average. Urban clusters are displaced a distance up to two kilometers (0-2 km) and rural clusters are displaced a distance up to five kilometers (0-5 km), with a further, randomly-selected 1% (every 100th) of rural clusters displaced a distance up to 10 kilometers (0-10 km). This is done to reduce the risk of disclosure in rural areas (Burgert et al. 2013, vii - 6).

### **4.3 The dependent variable – Infant mortality**

Infant mortality refers to death within the first year of life to persons born alive (Frisbie 2005, 255). A live birth is defined by WHO as the "complete expulsion or extraction from its mother of a product of conception, irrespective of the duration of pregnancy, which after such separation breathes or shows any other evidence of life" (World Health Organization n.d.-a, Maternal mortality ratio (per 100 000 live births)). The variable is a dummy with the value 1 if the child has died in the first eleven months after birth, and 0 if the child has survived.

There are two principal categories of estimation methods for calculating infant and child mortality rates: direct and indirect. Direct calculations use full birth histories containing data on the date of birth of the children, their survival status, and the dates of death or ages at death of deceased children. Indirect methods use information given in censuses or surveys about how many children a woman of reproductive age has ever given birth to and how many are still alive. Different estimation strategies can then be used to obtain a level of infant mortality. The direct method requires data that are usually obtained either through specifically designed surveys, or through vital statistics systems. Unlike the direct method, the indirect methods are very dependent upon several assumptions that may or may not hold true (Croft et al. 2018, 8.2). For many Sub-Saharan countries, the results for indirect estimation are consistently higher than the results of direct estimation (Uganda Bureau of Statistics and Macro International 2007, 111). The indirect methods are especially problematic for countries affected by HIV/AIDS because these countries have a different mortality pattern than what is held by the assumptions of the indirect methods (Croft et al. 2018, 8.2). Uganda is a country highly affected by HIV/AIDS, and Sartorius and Sartorius (2014, 10) report of a potential underestimation with the use of indirect estimation methods of IMR in Uganda. The direct

method of estimation is used by the DHS. Given that well-functioning vital registration systems are not available in Uganda (Unicef 2017a), we need to rely on the mothers providing their full birth histories. In Demographic Health Surveys the mothers are asked to provide information about each child they have given birth to, and the time of death if they died. Among 125 641 children in the dataset, 9792 died before the first birthday. This represents 7,79 percent of the population.

#### **4.3.1 Limitations and strengths to the measure**

An advantage of using infant mortality as a measure is that deaths are definitive events that may be easily measured and aggregated (Mosley and Chen 1984, 29). A retrospective birth history like the one used in this study is susceptible to several data collection errors that are important to be aware of. Firstly, given that this measure is based on mothers telling about all children ever given birth to, and the year of the births, this measure will suffer if the correct information is not given. Kotsadam et al. (2018, 63) report that it is likely that the number of deceased infants is somewhat underreported since it is more probable that mothers will fail to report dead children than living ones. It is believed that such underreporting may increase with the length of time since the child's death. Secondly, only surviving women age 15-49 were interviewed. Data for children of women who died are thus not available. Ssewanyana and Younger (2008, 38) point out that the most important potential bias for calculating infant mortality rates from DHS-data, like is done in this paper, comes from missing women who should have been in the sample, but have died due to AIDS. This will also increase the infant mortality rate given that children born by mothers who have AIDS have a higher risk of dying than children born to mothers without AIDS. The DHS-program, however reports that analyses have shown that this bias is small and has negligible impact on the overall childhood mortality estimates (Uganda Bureau of Statistics and Macro International 2007, 109). Thirdly, misreporting of children's age at death is a potential source of error. Efforts were made to minimize this source of error by reporting the age of death in days if the child died within one month after birth, in months if the child died within the 24 first months, and in years if the child was more than 2 years old (Uganda Bureau of Statistics and Macro International 2007, 110). The preferred source of data is always a vital registration system which records births and deaths on a continuous basis. These systems are however not functioning well in many developing countries (Mikkelsen et al. 2015, 1395). In Uganda it was estimated that only 69 percent of children under five years were registered in 2016 (Unicef 2017a).

#### **4.4 Independent variable – Official development assistance**

Research on aid normally uses the amount of money provided to a project or a country. The approach in this paper is different. Instead of looking at the amount of money disbursed or committed, I look at the geographical proximity of aid projects to respondents. The data used to measure aid in this paper come from Uganda's Aid Management Platform (AMP). AMP does not provide any definition of what is meant by aid, but states that the platform provides information on how "external support is being used to drive social and economic development across the country" (Ministry of Finance n.d.). The Aid Management Platform is incorporated into recipient country government planning processes and allows one to track much of the aid flowing into a country (Briggs 2018a, 905).

The dataset measuring official development assistance includes all geocoded projects from Uganda's Aid Management Platform (AMP). It tracks more than \$12 billion in commitments for 565 geocoded projects across 2426 locations between 1988 and 2013. AMP is the Government's official online database of aid-funded projects and programs in Uganda. It is managed by the Aid Liaison Department in the Ministry of Finance, Planning, and Economic Development. The information in AMP comes from both the Ministry of Finance in Uganda and from development partners. The Ministry of Finance enters key data for all projects where the donor funding is channeled through the Government systems, and development partners can enter data for all projects where the funding is not channeled through the Government systems (Ministry of Finance n.d.). The specific operationalization of the variable is given below.

##### **4.4.1 Active 5/10/15/20/**

The unit is coded as active if there at the time of birth of the child was an ongoing aid project within a given radius of 5 / 10 / 15 / 20 kilometers from the center of the DHS cluster that the unit is part of.

##### **4.4.2 Inactive 5/10/15/20**

The unit is coded as inactive if there was a future project planned within a given radius of 5 / 10 / 15 / 20 kilometers at the time of birth, and no active program was present.



#### **4.4.3 Limitations to the measure<sup>10</sup>**

Several limitations should be taken into considerations. Firstly, Although the data from Uganda's Aid Management Platform represents the best and, to my knowledge, the only available geocoded data of aid projects in Uganda, they do unfortunately provide an underestimate of the total official development aid dollars committed to Uganda. Odokonyero et al. (2018) look specifically at the health aid provided to Uganda, and use data from AidData. They note that the dataset provides an underestimate of the total health aid dollars to Uganda when compared to the Creditor Reporting System of Organization for Economic Cooperation and Development (OECD-CRS), and compared with the Institute for Health Metrics and Evaluation (IHME). AidData indicates that US\$300.6 million was disbursed in health aid in the period 2011-2013, OECD-CRS estimates US\$608.63 million, while IHME reports US\$2344.21 million (Odokonyero et al. 2018, 735). Notwithstanding these limitations the data from AidData represents, to my knowledge, the only source of subnational aid flow data available for Uganda. Secondly, to the extent that mothers have moved since a child's birth, the information of being active or inactive for later children will not be correct. Most immigration is from rural to urban areas (Ssewanyana and Younger 2008, 42). Analyses of the data show that more projects are placed in urban areas. This could mean that some children that are living close to aid projects will be coded as not living close to aid projects. There might thus potentially be a downward bias on the effect of aid.

#### **4.5 Control variables**

In addition to the dependent variables measuring if children lived close to an active or inactive aid project at the time of birth, there is need to control for some other factors that have been shown to affect infant mortality. Choosing which control variables to include is not easy (Seawright 2010, 256). Including too many will lead to an overfitted analysis, that is an analysis that corresponds to closely to a particular set of data and will fail to predict future observations reliably (English Oxford Living Dictionaries n.d.), and including too few will lead to an omitted variable bias which causes the model to be miss-specified (Wooldridge 2016, 78). The variables included here are based on what others have found to be important. I have not included variables at the level of the mother, such as education, living place, or if the

---

<sup>10</sup> AidData have received much criticism for the methodology and quality of the data provided on Chinese involvement in Africa, see for instance (Brautigam 2013). This criticism does not seem to apply to the data I use.

mother breastfed the child or not, as this is controlled for when using mother fixed effects.

#### 4.5.1 Multiple births

Studies show that although twin births constitute a small percentage of total births, they account for a disproportionately large percentage of infant mortality in both developed and less developed countries (Guo and Grummer-Strawn 1993, 495). The DHS-data from 2000-2016 used in this study also show that the chance of dying is much higher when more than one child is born. The infant mortality rate is 247 for multiple births and 71 for single births<sup>11</sup>.

#### 4.5.2 Birth order

The order of birth is relevant to control for when looking at infant mortality. Mishra et al. (2018, 604-605) argue that results from research on birth order and infant mortality often are controversial and mixed, but that one common finding is that first and later-born children are more likely than those in the middle to die young. In the DHS data used in this study, it is also clear that first and later-born children have a higher chance of dying than the ones in the middle. The Infant Mortality Ratio varies between 7,11 percent and 9,53 percent depending on your birth order in the data used.

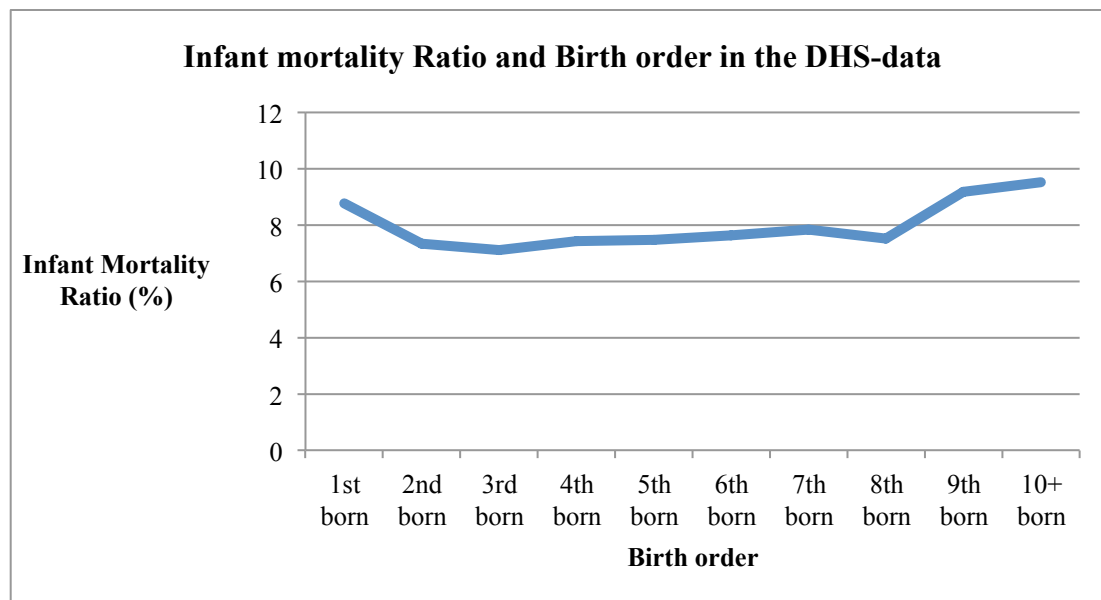


Figure 4.1 Infant mortality ratio and birth order in the DHS-data used in this study.

<sup>11</sup> 1009 out of 4084 multiples died, and 9699 out of 135931 singles died.

### 4.5.3 Gender

Newborn girls are biologically advantaged in surviving to their first birthday. This means that if no social or behavioral factors that reflect deliberate discrimination against either gender are present, boys will tend to have higher infant mortality (Fuse and Crenshaw 2006, 360). The DHS-data show that the chance of boys dying before their first birthday is 8,50 while it is 7,08 for girls. It is thus necessary to control for this.

### 4.5.4 Birthyear

Infant mortality has decreased a lot over time. Many of the active and inactive projects have also been created in the later years. In the models I include a linear variable of the year of birth of the child to control for the general improvement in health over time. The failure to include such time variable could easily overestimate the effect of aid (Kotsadam et al. 2018, 66).

### 4.5.5 Censored

All children who are born within a year after the survey has been conducted are removed from the survey since there is no information about whether they will survive their first year or not.

### 4.5.6 Suspended

All children who are born in an area where there have been active projects before the child is born, but where these programs have been closed down before the child is born are also removed from the survey.

## 4.6 Operationalization of variables

Variable	Original datasource	Coding
Infant mortality	DHS	1 = Infant died within first year (0-11 months) 0 = Infant survived 1 <sup>st</sup> year
Active	DHS + AidData	1 = Child lives close to an ongoing aid project (within 5 / 10 / 15 / 20 km) at the time of birth 0 = Child does not live close to ongoing aid project (within 5 / 10 / 15 / 20 km) at the time of birth
Inactive	DHS + AidData	1 = There is a future project planned within a given radius of 5 / 10 / 15

		/ 20 km of the child at the time of birth, and no active project was present at the time of birth. 0 = There is not a future project planned within 5 / 10 / 15 / 20 km of the child after his/her birth, or the child is already coded as active, and does therefore receive 0 on this variable.
Multiple births	DHS	1 = The child is born in a multiple birth 0 = The child is not born in a multiple birth
Birth order	DHS	A set of dummy variables for the order of birth. For firstborns birth order 1 = 1 for instance.
Gender	DHS	1 = The child is a girl 0 = The child is a boy
Birthyear	DHS	Continuous variable from 1964 to 2016
Censored	AidData + DHS	1 = Child is born within a year after the survey 0 = Child is not born within a year after the survey
Suspended	AidData + DHS	1 = Child is born in an area where there have been active projects before the child is born, but the projects have stopped before the child is born. 0 = Child is not born in an area where there have been active projects before the child is born, but where the projects have stopped before the child is born.

**Table 4.3 Operationalization of the dependent, independent and control variables.**

## 4.7 Mechanisms

In addition to looking at whether infant mortality is lower or not close to active aid projects, I also inspect whether the values on some of the factors suggested to be important to explain infant mortality in the theory-section are different in the active areas and the areas not receiving aid. The analyses of these factors will give us an indication of possible intermediate factors. In these analyses, the 30 550 mothers are the unit of observation. Operationalization of the variables can be seen in table 4.4.

Variable	Original datasource	Operationalization
Active	AidData + DHS	1 = Respondent lives close to an ongoing aid project (within 5, 10, 15, 20 km) at the time of the interview 0 = Respondent does not live close to an ongoing aid project at the time of the interview
Inactive	AidData + DHS	1 = There is a future project planned within a given radius of 5 / 10 / 15 / 20 km of the respondent at the time of the interview, and no active project was present at the time of the interview.

		0 = There is not a future project planned within 5 / 10 / 15 / 20 km of the respondent after the interview, or the respondent is already coded as active, and does therefore receive 0 on this variable.	
Suspended	AidData + DHS	1 = Mother lives in an area where there have been active projects before the interview is conducted, but the projects have stopped before the interview. 0 = Mother does not live in an area where there have been active projects before the interview is conducted, but the projects have stopped before the interview.	
Year of interview	DHS	The year the interview was conducted. Possible values on this variable are 2000, 2001, 2006, 2011 and 2016.	
Variable	Original datasource	Information about the variable	Operationalization
Bednet for sleeping	DHS	Household have bednet for sleeping	1 = Yes 0 = No
Literacy	DHS	Whether a respondent who attended primary schooling can read a whole or part of a sentence showed	0 = Cannot read at all 1 = Can read part of a sentence 2 = Can read a whole sentence
Highest educational level	DHS	Highest education level attended by respondent	0 = No education 1 = Primary 2 = Secondary 3 = Higher
Problem with distance to health facility	DHS	Whether distance to the health facility is a major problem preventing the respondent from getting a medical advice or treatment	0 = No problem 1 = Small problem 2 = Big problem
Wealth index	DHS	This index is a composite measure of a household's cumulative living standard. The index is created by combining data on a household's ownership of selected assets, such as television and bicycles, materials used for housing construction and types of water access and sanitation facilities. The households are then placed into one out of five wealth quintiles ranging from poorest to richest (The DHS Program n.d.-c).	1 = Poorest 2 = Poorer 3 = Middle 4 = Richer 5 = Richest

**Table 4.4 Operationalization of the variables used in the analyses of possible mechanisms.**

## 4.8 Missing data

None of the variables in the main regressions have missing data. There is also very little missing data in the variables that are used to examine the potential mechanisms between infant mortality and aid. The variable with the most missing values is literacy with 2.20 percent missing. The fact that so little data is missing is good for the reliability and validity of the analyses.

## 4.9 Descriptive statistics

### 4.9.1 Overview of project types, precision code 1

Type of project	Number of projects	Number of project locations
Health	24	175
Education	35	104
Government and civil society, general	9	97
Agriculture	7	97
Water supply and sanitation	14	48
Transport and storage	5	15
Energy generation and supply	6	14
Trade policy and regulations	3	6
Other social infrastructure and services	3	4
General budget support	2	2
Conflict prevention and resolution	1	1
<b>Total</b>	<b>109</b>	<b>563</b>

**Table 4.5 Overview of project types, precision code 1.**

Table 4.5 gives an overview of the different project types for all the data with precision code 1. In total there are 109 projects with a total of 563 project locations. Most of the projects are aimed at education, but the health projects are present in more locations. Included in the health category are mainly programs aimed at HIV/AIDS, tuberculosis programs, and programs aimed at strengthening nutrition. In the education-category are mainly projects aimed at post primary education and training, constructing classrooms and improving the school facilities.

### 4.9.2 Breakdown of projects and locations by start year, precision code 1

Start year	Number of projects	Number of project locations
1988	1	4

1991	1	1
1993	1	1
1997	1	1
1999	2	2
2001	3	3
2002	2	7
2003	1	1
2005	1	1
2006	2	38
2007	7	14
2008	9	48
2009	15	114
2010	26	118
2011	13	99
2012	10	90
2013	14	21
<b>Total</b>	<b>109</b>	<b>563</b>

**Table 4.6 Breakdown of projects and locations by start year, precision code 1.**

Table 4.6 shows the breakdown of projects and locations by start year. It is clear that most projects have been started in the later years. 71,5 percent of all projects have been started after 2008. As mentioned earlier in the chapter, it thus becomes important to include a linear variable for the year of birth of the child to control for the general improvement in health over time. By not including such time variable, one could easily overestimate the effect of aid (Kotsadam et al. 2018, 66).

#### **4.9.3 Breakdown of projects and locations by end year, precision code 1**

<b>End year</b>	<b>Number of projects</b>	<b>Number of project locations</b>
1994	1	4
1997	1	1
2000	2	2
2001	2	2
2004	1	1
2005	1	1
2007	2	3
2008	2	2
2009	4	10

2010	14	27
2011	23	62
2012	14	76
2013	22	47
2014	6	89
2015	7	93
2016	2	78
2017	4	57
2018	1	8
<b>Total</b>	<b>109</b>	<b>563</b>

**Table 4.7 Breakdown of projects and locations by end year, precision code 1.**

Table 4.7 shows the breakdown of projects and project locations by end year. It is clear from the table that most projects in the sample have an end date in the later years. 88,9 percent of all projects have the end date after 2008.

#### **4.9.4 Project and location breakdown by donor, precision code 1**

<b>Donors</b>	<b>Number of projects</b>	<b>Number of project locations</b>
United States of America	10	290
Japan	55	94
European Union	5	45
African Development Fund	2	41
International Development Association	5	23
United Nations Development Programme	2	14
China	11	11
Austria	6	9
Ireland	1	8
Organisation of Petroleum Exporting Countries / Kuwait Fund for Development / Arab Bank for Economic Development in Africa / Germany / Belgium / Saudi Fund for Development / South Korea / Islamic Development Bank	1	6
International Development Association / Norway	1	4
Arab Bank for Economic Development in Africa/Organisation of Petroleum Exporting Countries	1	3
Belgium / France	1	3
International Development Association / African Development Fund	1	2
Japan / International Development Association	1	2
Norway	1	2



Spain	1	2
International Bank for Reconstruction and Development	1	1
Netherlands	1	1
Nordic Development Fund / International Development Association	1	1
African Capacity Building Foundation	1	1
<b>Total</b>	<b>109</b>	<b>563</b>

**Table 4.8 Project and location breakdown by donor, precision code 1.**

Table 4.8 shows the number of projects and project locations broken down by the donor. The list includes both multilateral organizations and bilateral donors. Japan is clearly the donor that has most projects. The United States of America on the other hand has far fewer projects, but way more project locations.

## **5 Analytical strategy and methods**

Much research has been conducted on various forms of aid effectiveness, but the results remain inconclusive. In this chapter I first present several methodical and theoretical reasons for conducting a subnational study. Secondly, I go through what is meant by evaluation, and look at how the difference-in-differences strategy can be applied to evaluate. Next, I highlight benefits and limitations of geospatial impact evaluations. Thereafter, I go through the practicalities of matching the data, and the various choices that have to be made when working with geocoded data. This includes choosing the geographical division, choosing the size of the buffers and choosing the precision-level of the data. In order to avoid “cherry-picking” a given size or precision-level of the data, I conduct the analyses in the next chapter with different buffer-sizes and different precision levels. Lastly in this chapter, I argue for a causal relationship before presenting the linear probability model, the assumptions behind it, and the precise model specification.

### **5.1 Methodical and theoretical reasons for a subnational study**

A growing number of influential voices have begun to challenge the usefulness of cross-country studies for confirming or challenging the effect of aid (Riddell 2007, 224). Bourguignon and Leipziger (2006, 4-6) point to several limitations of cross-country analyses, and argue that going forward these analyses need to be supplemented with other approaches that are capable of taking country specificity into account. A geospatial impact evaluation at the subnational level can be such a supplement.

Subnational geospatial analyses provide an intermediate perspective. In studies of aid effectiveness there is a tradeoff between scope and depth. Quantitative studies across several countries give a big scope, and less depth, while quantitative or qualitative studies of concrete projects have a much smaller scope, but a much greater depth. Subnational studies allow for good generalizability, both across time and space. In terms of space it becomes possible to estimate the impact of a multitude of development projects, and in a temporal sense it becomes possible to look at a long time period given that data are available (Isaksson 2017, 14). Such studies allow for better generalizability than studies at the micro-level, whilst at the same time avoiding some of the methodical problems that are inherent in studies at the macro-

level. Subnational studies, such as the one conducted in this paper, can thus help bridge the micro-macro divide, and fill a “missing middle” in aid evaluation and in the academic effectiveness literature (Martorano, Metzger, and Sanfilippo 2018)(Denizer, Kaufmann, and Kray 2013, 288-289; Isaksson 2017, 12; Martorano, Metzger, and Sanfilippo 2018, 3).

The regional allocation of aid is not uniform across regions, and while an overall analysis of the country does not show any effects, the effects of aid might be discernable at a more disaggregated level. A subnational analysis might be better at discovering these small and localized effects compared to a bigger cross-country analysis. If it is the case that the lack of robust results regarding the effect of development aid could be due to the effect of aid being too small and localized to affect aggregate outcomes, as some have suggested, a subnational analysis might be very informative (Dreher and Lohmann 2015, 421; Kotsadam et al. 2018, 59).

Cross-country analyses have amongst other things been criticized for lacking country-specificity (Bourguignon and Leipziger 2006, 4-6). Take Uganda as a case: the country has received a lot of aid, but if the period studied includes civil war years, it might turn out to be a country with high infant mortality as well. If the regression does not control for this, one might then falsely conclude that aid has had no effect on reducing the infant mortality. Focusing on one country allows for a better control over these factors. A great advantage of geospatial impact analyses at the subnational level is that they can control for potential confounding factors at granular geographic levels (Isaksson 2017, 13). One can thus mitigate the omitted variable bias that are inherent in estimating aid impacts with cross-national data (Marty et al. 2017, 2).

Theoretically there is also a good reason to study aid effectiveness at the subnational level. Geocoded data at the country level have only recently become available, and Nunnenkamp, Öhler, and Sosa Andrés (2017, 127) argue that the geography of foreign aid within recipient countries is largely unexplored territory. Dreher and Lohmann (2015, 4) state that the lack of systematic empirical evidence on the effect of aid below the country-level is an important gap in the literature. Newly available subnationally geocoded data open new possibilities for aid evaluation. Combining geocoded aid-data with geocoded data from other sources makes it possible to evaluate the subnational distribution and local effects of aid systematically and on a wide scale (Isaksson 2017, 11).

## **5.2 How to evaluate?**

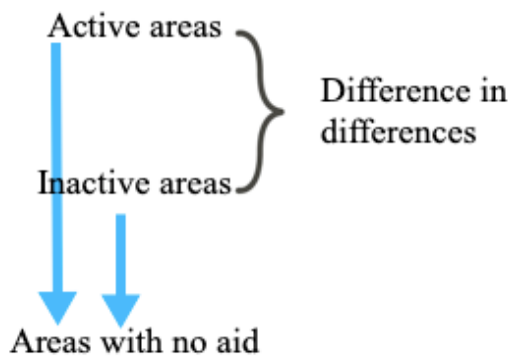
Answering the question “what would have happened with the infant mortality if an aid project had not been created?” is a very demanding task. Yet this is what I aim to do in this paper. When conducting evaluations it is key to hold all factors except the intervention, the aid project in this case, as equal as possible for all the individuals, both treated and untreated. White (2007, 2) argue that what is meant by an impact evaluation is to establish a valid counterfactual. This means trying to answer the question: “what would have happened had the intervention not taken place?” in a reliable way. The idea behind Geospatial Impact Evaluations like the one conducted in this paper is to find “control” cases that are sufficiently similar to the “treated” cases to constitute a viable comparison group (Isaksson 2017, 13). This is done by comparing individuals who live close to the program, but are unlikely to be affected by the aid projects, with others living close to the program who are likely to be affected by the program. It is easier to find sufficiently similar cases for comparison when individuals that are affected, and not affected by an aid project face similar conditions on many other accounts (such as institutional arrangements, culture and so on) (Isaksson 2017, 13-14). There is not one single right way to conduct evaluations that will fit all situations. What constitutes the best way depends on the time, resources and data you have available. One way to conduct an evaluation is with difference-in-differences.

### **5.2.1 Difference-in-differences**

In this study I use a quasi-experimental approach, and a difference-in-differences (DD) like strategy. The difference-in-differences strategy is meant to mimic an experimental research design by studying the differential effect of a treatment (aid) on a treatment group versus a control group (Verbeek 2012, 380-381). DD is a useful technique when it is not possible to randomize the individuals as is the case for this paper (Cook and Wong 2012, 134-156). DD is normally used to estimate the effects of a specific treatment (such as enactment of a law or start of an aid project for instance). Normally one compares the changes in outcome over time between a population that has received a treatment, and a population that has not been treated, and one tries to estimate the effect of the specific intervention (Verbeek 2012, 380-381). A precondition for the difference-in-difference method to hold is the “parallel trend assumption”. This assumption holds that both the treatment group, and the group not receiving treatment would exhibit the same trend in outcome in the absence of treatment. If an

aid project had not been started in an area we should thus expect the trend in infant mortality to be equal in the different areas.

Given that I do not have information for the same clusters over time, the normal DD design is not possible to apply with these data, but a similar approach is possible. I compare three groups: 1) a post-treatment group (those living close to an active aid project at the time of birth), 2) a pre-treatment group (those living close to a project that has not started at the time of birth, but where the project will start after birth), and 3) a control group (those who do not have a current or future aid project in their proximity). By only comparing those living close to an active aid project with the rest of the country I would not take into account that areas receiving aid are not necessarily similar to areas not receiving aid. The strategy is a difference-in-differences like strategy identical to the one used in Kotsadam et al. (2018), and builds on the spatial-temporal strategy presented in Kotsadam and Tolonen (2016) and Knutsen et al. (2017).



**Figure 5.1 The difference-in-differences like approach applied in this paper. Figure made by author.**

Figure 5.1 shows how the difference-in-differences type of estimate is achieved. Specifically I compare the difference in infant mortality in post-treatment individuals (children living in an area with an active project at the time of birth) with control individuals (children living in an area with no active projects or future aid projects), with the difference between pre-treatment individuals (with a future aid project, and no current aid project in their proximity) and control individuals. By including mother-fixed effects I have data on siblings born by the same mother both before and after the start of an active project. I thus get closer to the ideal difference-in-differences strategy by including fixed effects.

### **5.2.2 The benefits and limitations of a Geospatial Impact Evaluation**

BenYishay et al. (2017, 3-4) list several of the advantages of Geospatial Impact Evaluation. Firstly, they are cheaper and faster than other alternatives for evaluations such as Randomized Control Trials. Secondly, it is possible to conduct a GIE in cases where it is not feasible or ethical to determine who should participate in a program through random assignment. Thirdly, GIEs often have stronger external validity and generalizability than RCTs because they often analyze data from an entire country (or even multiple countries). Fourthly, GIE is a very flexible tool that allows the researcher to evaluate either individual projects, or project portfolios.

Newly available geocoded data at the subnational level does provide us with many new and potentially very fruitful opportunities when it comes to conducting aid evaluations. Still, there are some important limitations that one needs to keep in mind when working with these data. Isaksson (2017, 14-16) points to several limitations. Firstly, it is important to keep in mind that the projects being used for the analyses need to be implemented in a well-defined geographic area, such as a town or a district. Projects that are implemented at a higher level, such as at the country-level, cannot be included in the analyses<sup>12</sup>. Secondly, there might be gaps in the data given that many donors and implementing partners do not routinely map their intervention sites. Like mentioned in data chapter, it is the case that AidData does provide an underestimate of the total official development aid dollars committed to Uganda. This makes it difficult to get a full picture of all development projects located in the area. This might lead to both an underestimation and an overestimation of the effect of aid dependent on what is lacking. However, these are the best available data.

### **5.3. Matching AidData and DHS-data based on geographical proximity**

Before one is able to analyze geocoded aid data in a meaningful way it has to be combined with geocoded data from other sources, in this case with data on infant mortality from DHS. By using the latitude and longitude coordinates of the aid projects, and combining these with the latitude and longitude coordinates of survey respondents' location it is possible to identify which respondents live near aid projects. Learning how to match these data is a big challenge when working with geocoded data (Isaksson 2017, 49). Several programs such as ArcGis, QGIS, Stata and RStudio can be used to do the matching. I used the program QGIS, version

---

<sup>12</sup> This includes things such as budget support and debt relief agreements.

3.4.0 Madeira, to combine the datasets, and to create buffers of varying sizes (approximately 5, 10, 15 20 and 25 kilometers) around each respondent. QGIS is a free and open source geographic information system. After matching the data with QGIS I used the program RStudio to systematize the data before conducting the analyses in Stata/IC 15.1<sup>13</sup>. RStudio is a free program for statistical computing and graphics.

### **5.3.1 Choosing the geographical division**

I use buffers as the geographical division in this paper. There are several good reasons for using buffers instead of more traditional divisions such as regions, districts or even grid-cells. Firstly, when using buffers one can actually know that the people live in the proximity of an aid project in a much better manner than if one uses districts or regions. Even though one lives in the same district or region as a project, this does not mean that the project is accessible for the person. If the project is placed far away from the household, but still within the same district, it will probably not be accessible if you don't own a car for instance. As mentioned in chapter two only 2,55 percent of the households in the DHS-surveys conducted between 2000 and 2016 report that they have a car, and only 6 percent of the households have a motorcycle or scooter. Only 37 percent of the households have a bicycle (ICF 2000-2016), and only 4 of the roads were paved in 2010 (National Planning Authority 2013, 14). Secondly, unlike districts or regions, buffers are inherently apolitical entities that are fixed over time. This makes it possible to compare the same buffers over time. Districts and regions on the other hand often change over time. Only two of the four DHS-surveys used in this study divided the respondents into districts, and the number of districts varied from 38 in the survey done in year 2000 to 112 in 2016. Uganda has experienced a near-explosion in the number of districts going from 39 to 80 in less than a decade, and at the beginning of 2019 there were 127 districts in the country<sup>14</sup> (Organisation Internationale de Normalisation 2018). The number of regions that the respondents were divided into has also changed radically in Uganda, from four in the survey done in 2000 to fifteen in the survey done in 2016.<sup>15</sup> It is hypothesized that decentralization and devolving power to local governments would improve health outcomes by improving efficiency and equity, and by bringing the decision makers

---

<sup>13</sup> R-script and Stata do-files are available from author upon request.

<sup>14</sup> (Green 2010, 83) argues that this explosion has functioned as a source of patronage, and that it has helped President Museveni in continuing winning elections.

<sup>15</sup> 2000-survey: Central, Eastern, Northern, Western.

2016-survey: Kampala, Central 1, Central 2, Busoga, Bukedi, Bugishu, Teso, Karamoja, Lango, Acholi, West-Nile, Bunyoro, Tooro, Ankole, Kigezi.

closer to the people (Asfaw et al. 2007, 17). If this hypothesis is correct it will be difficult to study the impact of aid with changing sizes of the districts, since improvements in health outcomes could be due to decentralization, and not aid. Thirdly, unlike grid-cells, buffers can be used even though the data are displaced to protect the anonymity of the respondents. With grid-cells it would be impossible to know for a range of respondents that are placed less than 10 kilometers away from a border which grid they belong in.

### **5.3.2 Choosing the size of the buffers**

The geographical division strategy used in this paper is to create buffers of varying sizes around each DHS-cluster, and thereby inspect if there are aid projects within the buffers or not. We do not know how local the effects of foreign aid are, and it is challenging to decide the size of a buffer. Other researchers have chosen a variety of distances when looking at the local effects of aid. Kotsadam et al. (2018) used buffers of 25 kilometers and 50 kilometers in their analyses of infant mortality in Nigeria. Odokonyero et al. (2015, 8) chose 3, 5 and 7 kilometers in their study of how health aid affects health outcomes in Uganda. In a later revision of their original study, Odokonyero et al. (2018, 735) use buffers with 5- to 50-kilometers radii at 5-kilometer intervals (i.e 5 km, 10 km, 15 km and so on up to 50 km). My approach is to use buffers of varying sizes since it is unclear how localized the effects are. A too small cutoff-distance will quickly decrease the sample of active and inactive individuals, and will increase the probability of defining non-treated individuals as treated and vice versa. A too large cutoff will on the other hand include too many control individuals in the treatment group (Knutsen et al. 2017, 328). All the respondents are displaced to protect their anonymity as seen in chapter four. Urban clusters are displaced a distance up to two kilometers (0-2 km) and rural clusters are displaced a distance up to five kilometers (0-5 km), with a further, randomly-selected 1 percent (every 100<sup>th</sup>) of rural clusters displaced a distance up to 10 kilometers (0-10 km). For this reason I do not chose a buffer smaller than 5 kilometer. Given that there are many aid projects in Uganda, and that they are placed all over the country one will not have any individuals who do not have aid projects in their proximity if the buffers are much bigger than 20 kilometers<sup>16</sup>. Empirically it does also make sense to assume that closeness to aid matter. As seen in chapter 2 only 4 percent of the roads were paved in 2010 (National Planning Authority 2013, 14), only 2,55 percent of the households in the DHS-

---

<sup>16</sup> Odokonyero et al. (2018) use up to 50km in their study of Uganda, but they have much fewer projects included in their study than what I have in this study.



surveys conducted between 2000 and 2016 report that they have a car, and only 6 percent of the households have a motorcycle or scooter, only 37 percent of the households have a bicycle, and 44,2 percent of the respondents report that distance to the health facility is a problem for them to access help (ICF 2000-2016).

### 5.3.3 Creating the buffers

The buffers were created in degrees and not in kilometers. 1 degree of latitude at the equator equals 110,57 kilometers, and given that Uganda is placed on the equator one can use this information to calculate the size of the buffer corresponding to 5, 10, 15 and 20 kilometer<sup>17</sup>. The size of the buffers have a tiny error margin due to the fact that I have used an unprojected coordinate reference system (CRS) in degrees, not meters. The code of the CRS is WG84. It would have been ideal to project the coordinates in a CRS that has meters, and not degrees, as the unit. The consequence of using an unprojected CRS is that the buffers have small margins of error in longitude (not in latitude). The error margin will be zero at the equator, but will be bigger the longer south or north one gets. The biggest error margin will be in the furthest north. However, this error margin only makes the buffer 0,25 percent smaller in longitude than in latitude in the furthest north<sup>18</sup>. It is therefore safe to assume that this will not affect the results.

### 5.4 Choice of precision level

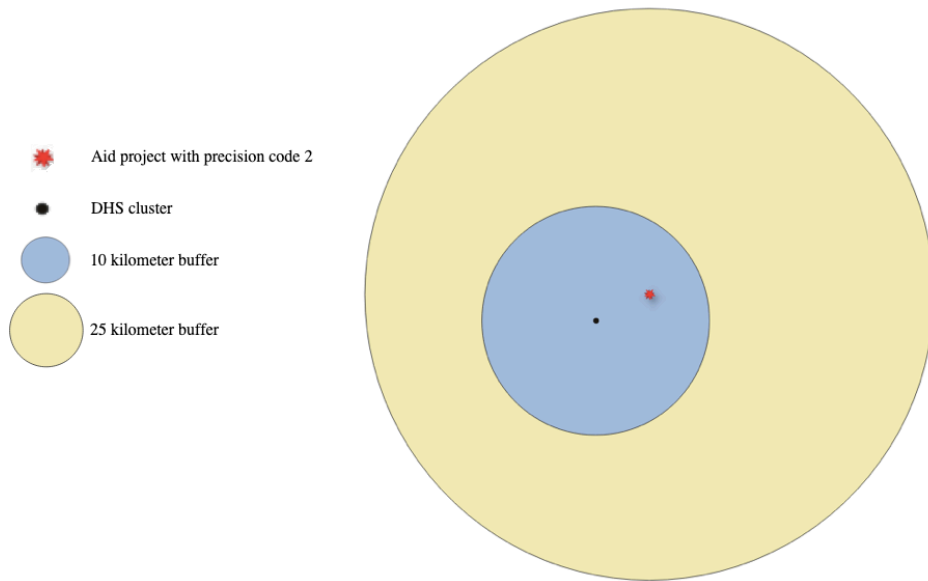
As mentioned in chapter four, the data from AidData have different precision levels, ranging from 1 to 8. When choosing the precision level there is a trade-off between precision and amount of data. Other researchers have chosen different precision levels. Dreher and Lohmann (2015, 424) and Gehring, Kaplan, and Wong (2019, 6) use data that are at the ADM1 and ADM2 level, corresponding to precision level 1-4. Kotsadam et al. (2018, 62) use precision level 1-3. Isaksson and Kotsadam (2018, 148) use precision level 1-2 while Odokonyero et al. (2018, 735) use precision-level 1 like I do in my survey.

---

<sup>17</sup> 110,57 kilometers equals 1 degree of latitude at the equator. The calculation of the 15 kilometer buffer is shown below:

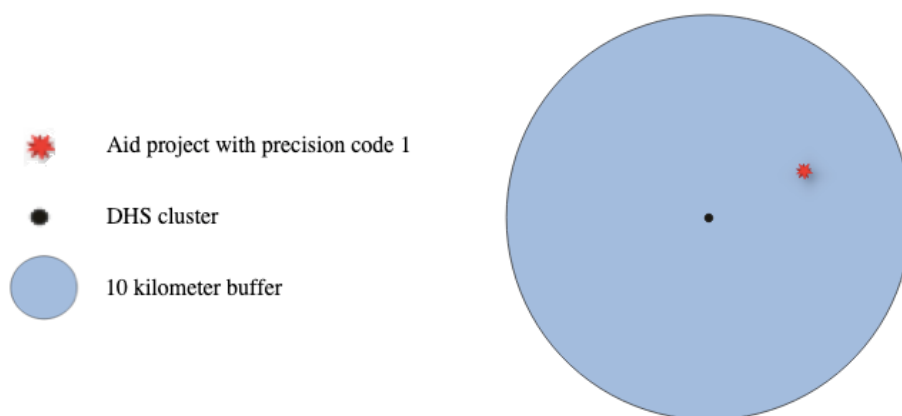
$$\frac{1 \text{ degree}}{110,57 \text{ kilometers}} * 15 \text{ kilometers} = 0,135661 \text{ degrees}$$

<sup>18</sup> The size of the buffer were calculated by this formula:  $\cos(\text{latitude furthest from equator}) * \text{buffersize}$ . For the 15 kilometer buffer this gives:  $\cos(4 \text{ degrees}) * 15 \text{ kilometer} = 14963 \text{ meters}$ . The error margin is then calculated by:  $15000 \text{ meters} - 14963 \text{ meters} = 37 \text{ meters}$



**Figure 5.2 Uncertainty level for aid projects with precision code 2. Figure made by author with QGIS 3.4.0 Madeira and Paint S 5.6.11.**

Figure 5.2 shows graphically the uncertainty level when using data with precision code 2. The blue buffer around the cluster is 10 kilometer, and will always be there given that the DHS displace their clusters by up to 10 kilometers. This means the cluster can be placed anywhere within this buffer. The yellow buffer around the aid project with precision code 2 is 25 kilometers. This means that the aid projects can be placed anywhere within this buffer. By using this precision-level it is not possible to judge if a project is for instance 10 kilometers from a cluster.



**Figure 5.3 Uncertainty level for aid projects with precision code 1. Figure made by author with QGIS 3.4.0 Madeira and Paint S 5.6.11.**

Figure 5.3 shows graphically the uncertainty level when using precision code 1. The blue buffer around the cluster is 10 kilometer, and will always be there given that the DHS

displace their clusters by up to 10 kilometers, but there is no buffer around the aid project, because the destination is known. As a robustness check, and in line with the previous subnational study of infant mortality and aid by Kotsadam et al. (2018) I also conduct an analysis with precision level 1, 2 and 3, and a buffer of 25 kilometer.

## **5.5 Arguing for a Causal Relationship**

Before looking closer at the model specification, and the details of the linear probability model, some general words about causality are in order. There exists three minimum requirements for demonstrating a causal relationship between an explanatory variable X and an outcome Y (Chambliss and Schutt 2010, 132-133). 1) There must be correlation between X and Y, 2) X must come before Y in time – the cause must come before its presumed effect and 3) alternative explanations must be ruled out. The first requirement is easy to fulfill: it only requires that the researcher shows that there is co-variation between X and Y. The second requirement is more tricky to fulfill. Given that I have data over time I am able to see if the aid project was established before or after the birth of the infant, and I exploit this information by creating the variables “active” and “inactive”. The third requirement is usually the hardest to fulfill: except in randomized experiments one cannot be certain that one has controlled for all possible explanations why X and Y correlate.

With the use of the regression analysis I am able to fulfill the first and the second requirement, and partly the third requirement. The regression analysis can establish correlation, and given that I have data over a period of time I can see if the aid project came before or after the death. I try to control for alternative explanations in several ways. The basic regression controls for factors known to potentially affect the results at the level of the child. These variables are the gender of the child, the birthyear, if the child was part of a multiple birth and the order of the birth of the child. In a second model I also apply mother-fixed effects. By doing this I control for all observed and unobserved factors that are shared by siblings. This includes things like the mothers education (Caldwell and McDonald 1982) if she lives in an urban or rural setting (Van de Poel, O'Donnell, and Doorslaer 2009), if she breastfeeds the child (Sankar et al. 2015) and her age at birth (Finlay, Özaltin, and Canning 2011). Given that the data are retrospective, and hence includes children that are born both before and after the start of a project by the same mother, it is possible to compare the death rates of sibling born before and after the start of a project. However, even if I find a

correlation that is unlikely to be spurious between aid and infant mortality, I still do not know if low infant mortality rates in the proximity of aid projects is because the projects were placed in an area with low mortality, or because the projects themselves reduces the infant mortality. Do low infant mortality cause projects to be placed there, or do the projects reduce the mortality in the areas where they are? Luckily I am able to control for this probable selection effect of the aid areas by using a difference-in-differences like strategy, and distinguish between active and inactive areas. In addition to the three minimum requirements for demonstrating a causal relationship, Chambliss and Schutt (2010, 132-134) argue that by identifying the causal mechanisms one can considerably strengthen causal explanations. By conducting an analysis of some mechanisms proposed to be connected to infant mortality I attempt to strengthen the causal explanations.

## **5.6 The case for linear probability model**

I use a linear probability model (LPM) to conduct the analyses. LPM is a multiple linear regression where the dependent variable is zero-one, that is, a dummy variable (Angrist and Pischke 2009, 60-61). It is the same as an ordinary least square (OLS) regression, but where the dependent variable is a dummy-variable. This type of model is often used in economics, but in social sciences and health sciences it is almost always recommended to use a logistic regression when the dependent variable is a dummy variable (Von Hippel 2015). I argue here that there are several good reasons for me to use a linear probability model. Firstly, Deke (2014, 3) conducts Monte Carlo simulations, and argues that the LPM yields estimates of experimental impacts that are just as accurate as those estimated by logistic regression. This also applies to quasi-experimental approaches (Deke 2014, 4). The main reason for this is that the treatment status is a binary variable. Much of the criticism that has been applied to the LPM applies when the independent variable is a continuous variable, but in my case I use a dichotomous independent variable, and in this case the LPM yields estimates of experimental impacts that are just as accurate as those estimated by logistic regression (Deke 2014, 3). Secondly, Mood (2010, 78) argues that if we are only interested in sign and significance of an effect or the average marginal effects, and not in the non-linearity per se, a LPM is reasonable to choose over logistic regression. Thirdly, a big advantage of the LPM over logistic regression is that it is much easier to interpret (Hellevik 2009, 66-67). When the estimates are just as accurate since the independent variables are dummies, it makes sense to choose a model that is easier to interpret, and some recommend to use LPM to help with

interpretability (Columbia University Mailman School of Public Health N.D.). Fourthly, difference in differences are most often calculated from OLS-regressions (Bertrand, Duflo, and Mullainathan 2004, 250).

### **5.6.1 Assumptions**

Even though there are several reasons to choose the linear probability model, there are three main problems with it. Firstly, the classic assumption of the error-term being normally distributed is not fulfilled. The error-term of an LPM has a binominal distribution instead of a normal distribution. This means that the traditional t-tests for individual significance and the F-tests for overall significance are invalid. Secondly, the model may provide nonsensical predictions that are outside the range of 0 to 1 (Pedace n.d.). Thirdly, the standard errors are also heteroskedastic by construction unless the probability does not depend on any of the independent variables (Wooldridge 2016, 227). Although relevant, these issues are not as serious as they may seem. Firstly, when it comes to probability outside the 0-1 interval, this is not necessarily an issue (Hellevik 2009, 61; Mood 2010, 78). Hellevik (2009) shows by way of simulation that the significance probability from linear and logistical analyses are nearly identical. He argues that the “statistical objections to applying linear regression analysis with a dichotomous dependent variable may be put to rest” (Hellevik 2009, 64). Secondly, the issue of heteroskedasticity can be solved by using robust standard errors (Mood 2010, 78), and this is done in this paper.

Given that the LPM has some problems, and that it is more common to use logistic regression when dealing with a dummy-variable as the dependent variable within the social sciences at least, I chose to run additional logit regressions, and calculate the marginal probabilities<sup>19</sup>. The results from these tests (see chapter 5) are similar to the ones from the LPM. This further lends support to using LPM as the estimation strategy. When using logistic regression, there are several assumptions that do not apply compared to when running OLS-regression. The assumption of heteroskedastic and normally distributed residual terms and a linear relationship do not apply (Skog 2004, 360).

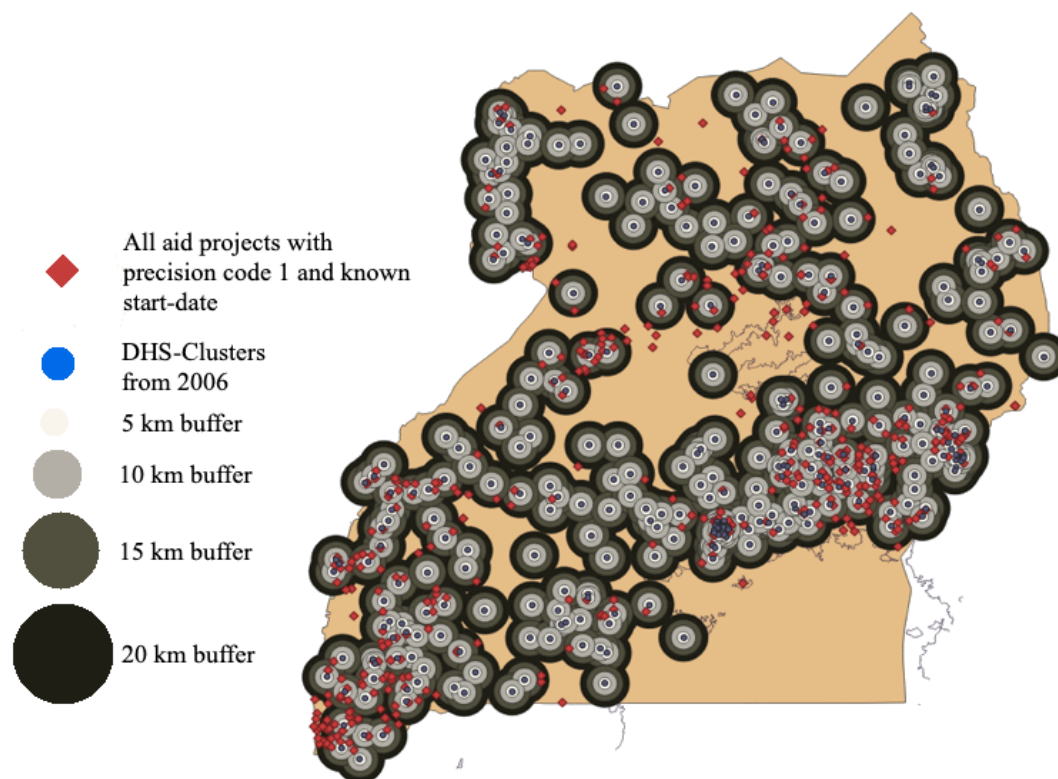
---

<sup>19</sup> Mood (2010, 80) argues that it is advisable to do so given that different estimation strategies fulfill different criterias.

One important issue, that strictly speaking is not an assumption of a regression analysis, but that is still of great concern to investigate is collinearity. Independent variables should not be too strongly correlated with each other, because if they are this will cause problems in estimating the regression coefficients. I can check if there is a problem with multicollinearity in the model by estimating the variance inflation factors (VIF) for the independent variables. VIF values above 10 may merit further investigation (UCLA: Statistical Consulting Group n.d.). I checked the VIF scores for my independent variables, and none of them had an VIF-score above 10. The results from the analyses can be seen in table 5.1a in the appendix<sup>20</sup>.

### 5.7 Model specification

The aid data is linked to repeated cross sectional survey data based on spatial proximity. Specifically, the coordinates of surveyed DHS clusters are used to match individuals to aid project sites for which there are precise point coordinates. The distance from the cluster center points to the aid projects are measured, and clusters are identified as active or inactive depending on whether they are placed within a given cut-off distance or not.



**Figure 5.4 Map with buffers of varying sizes around all aid projects with precision code 1 and known start-date. Map made by author with QGIS 3.4.0 Madeira**

<sup>20</sup> The results presented in the appendix show the VIF-scores of the 5km buffer. I conducted the same analyses for all the other buffersizes as well, and the results came out very similar. None of the variables in any of the models had a VIF-score above 10.

The map in Figure 5.4 shows all 563 project aid locations with precision code 1 and all 336 DHS clusters from 2006. As can be seen there is a good spread of both projects and clusters throughout Uganda.

The baseline regression is given by the equation:

$$Y_{ivt} = \beta_1 \cdot \text{active} + \beta_2 \cdot \text{inactive} + \lambda_t + \theta_{it} + \varepsilon_{ivt}$$

$Y$  is here equal to zero if the child survived its first year, and equal to one if it died within the first year.  $i$  is the child,  $v$  is the cluster and  $t$  is the year of birth.  $\lambda_t$  is the linear trend in the year of birth, and  $\theta_{it}$  symbolizes the control variables included in all the models, namely birth order, gender, and a dummy for being part of a multiple birth (e.g. twins).  $\varepsilon$  is the random error component. Only comparing active individuals to the rest of the country would be equivalent to assuming that the areas receiving aid are equal to the areas not receiving aid. This seems unlikely. By instead looking at the difference between active and inactive children (B1-B2), we get a difference-in-differences type of measure that controls for characteristics that might be specific for areas being selected as project sites.

### 5.7.1 Robust standard errors

The standard errors are a measure of the statistical accuracy of an estimate (Verbeek 2012, 18). To ensure that the standard errors are not underestimated since the coding of individuals as active or inactive is given by their DHS cluster while the infant mortality data are on the individual level the standard errors are clustered at the DHS cluster level. By using robust standard errors I also resolve the issue of heteroskedasticity (Mood 2010, 78).

### 5.7.2 Mother fixed effects

Given that the data are retrospective, and hence include children that are born both before and after the start of a project by the same mothers, it is possible to compare the death rates of siblings born before and after the start of a project. Including mother fixed effects allows me to control for all observed and unobserved factors that may otherwise be spuriously correlated with both infant mortality and aid. This includes things like the mothers education (Caldwell and McDonald 1982) if she lives in an urban or rural setting (Van de Poel, O'Donnell, and Doorslaer 2009), if she breastfeeds the child (Sankar et al. 2015) and her age at birth (Finlay, Özaltin, and Canning 2011). Selection into areas depending on pre-existing level differences

in mortality is completely controlled for as well. In addition it ensures that the estimated effect is not driven by endogenous population changes that may occur as an effect of aid (Kotsadam et al. 2018, 65). Although a very powerful measure of the effectiveness of aid, the model is also very conservative, and two main downsides with the model should be noted. Firstly, it reduces the number of observations drastically. Only mothers that have given birth to a child both before and after a project start are included. This means that the “control group” included in the other model disappears. Secondly, the model only measures the effect of projects that have affected something for the latter birth, but not for the first. All effects of aid that do not change from one sibling to the other will thus not be measured. This means that one risks controlling away the effect of other aid projects. Both of these factors, the reduced number of observations, and only measuring immediate effects of aid, means it will be less likely to have significant findings from this model than from the model not including mother fixed effects. Controlling for mother fixed effects follows the example of the one paper published on the connection between infant mortality and aid at the subnational level (see Kotsadam et al. 2018).



## **6 Results**

In this chapter I present the results from the various analyses conducted. Before I present any analyses I look descriptively at the data and compare the infant mortality in areas with active aid projects, areas that will have an active project in the future, and areas with no current or future active aid projects. After presenting the descriptive statistics I run various analyses in order to control for alternative explanations, and also assess the significance. In the analyses-section, I first present the results from the linear probability model without fixed effects, and the linear probability model including mother-fixed effects. Secondly, I conduct several robustness checks to see if the results change considerably or not. At last, I look closer at some of the mechanisms suggested to be important in explaining infant mortality, and see if these are lower in active aid areas, compared to areas with no aid-projects.

### **6.1 Descriptive statistics**

Before running any regressions it can be fruitful to just look descriptively at the data, and see what the level of infant mortality is for the three groups: the children living close to an active project, the children who do not have an aid project in their proximity, and the children living in areas that will receive a project in the future. In this section I combine the datasets with various buffers into one and look descriptively at the data.

#### **6.1.1 First difference - Areas with an active project versus areas not receiving aid**

I start out by comparing the infant mortality of children born close to an active aid project with the infant mortality of children that live in areas that do not receive aid. The difference is remarkable. 50,63 out of 1000 infants die before turning one year when they have an active aid project in their proximity. In the areas that do not have an aid project in the proximity, there are 82,23 per 1000 infants dying within the first year. This is a difference of 31,6 per 1000 infants, or approximately 38 percent between the different areas. At this point it might be tempting to conclude that aid is effective in reducing infant mortality. Drawing this conclusion already will however be premature. There may be at least two reasons why we see the large difference: firstly, it might be that aid projects are able to reduce the infant mortality of infants living close to them. Secondly, it might also be that the areas receiving aid are different from the areas not receiving aid. It is likely that there is a systematic difference in

various factors between areas receiving aid and areas that do not receive aid. Areas receiving aid may for instance have better infrastructure making it easier to place a project there. Or it may be that projects are placed in areas where the need for a project is higher because the infant mortality is higher (Isaksson 2017, 54 - 65). By only comparing areas with an active project to areas not receiving aid, I will not know which of the explanations hold true. By exploiting the fact that the aid projects have different starting years, and that I have retrospective birth data, I can separate the areas receiving aid into active and inactive and thus come closer to an answer as to which of the explanations seem more reasonable.

### 6.1.2 Second difference - Active areas versus inactive areas

The retrospective nature of the data allows me to take time into consideration. By comparing individuals that live close to an active projects with individuals living close to inactive projects, I am able to control for the potential selection-effect for the aid-areas. When comparing active and inactive areas, we can see a big difference in mortality. 50,63 per 1000 infants are dying before turning one year in the areas that have an active project in the closeness compared to 83,23 per 1000 infants in the areas with inactive projects close. The infant mortality in the areas that do not receive aid is as mentioned 82,23 infants per 1000. There are thus big differences in the infant mortality between the different areas. The difference between active areas and both the inactive areas, and the areas that do not have any aid projects is especially striking.

### 6.1.3 Difference-in-differences

The descriptive results, as presented in figure 6.1, suggest that aid is effective in reducing infant mortality.

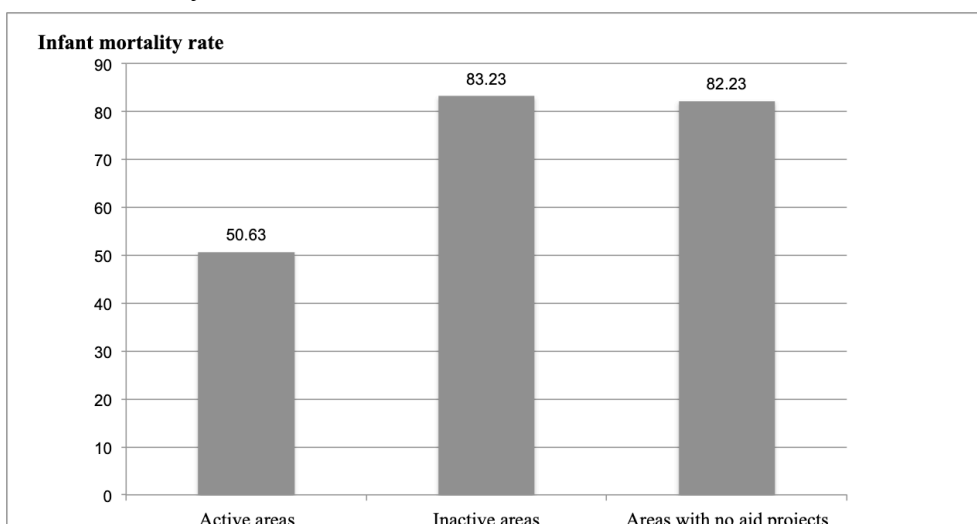


Figure 6.1. Infant mortality rate in different areas

Active areas have a much lower infant mortality rate than both inactive areas and the rest of the country. It also looks like new projects are being placed in areas that have a marginally higher infant mortality than the rest of the country to start with. The results so far thus lend support to “H1: Infant mortality will be lower near active aid projects than in the rest of the country”, but not to “H2: Aid projects will not be allocated to the areas where the infant mortality is highest”.

In order to know if the differences between the different areas are significant, and to be able to control for other explanations we need to run a regression. The regression results will also show us if there are differences between the varying buffersizes, or if the results remain constant.

## 6.2. Linear probability model

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Infant mortality	Infant mortality	Infant mortality	Infant mortality	Infant mortality	Infant mortality	Infant mortality	Infant mortality
Active 5 km	-0.014*** (0.002)	-0.017*** (0.003)						
Inactive 5 km		-0.008*** (0.002)						
Active 10 km			-0.017*** (0.002)	-0.020*** (0.003)				
Inactive 10 km				-0.006** (0.002)				
Active 15 km					-0.016*** (0.002)	-0.017*** (0.003)		
Inactive 15 km						-0.001 (0.003)		
Active 20 km							-0.015*** (0.002)	-0.015*** (0.003)
Inactive 20 km								-0.001 (0.003)
Observatio ns	124 037	124 037	124 297	124 297	124 210	124 210	124 051	124 051

R-squared	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020
Difference in differences		-0.009		-0.014		-0.016		-0.014
F test: active-inactive=0		12.57		29.83		39.58		37.18
P value		>0.000		>0.000		>0.000		>0.000

**Table 6.1 Linear probability models. Robust standard errors clustered at the DHS cluster level in parentheses. All regressions control for a multiple birth dummy, gender, birth order fixed effects, and a linear trend in birth year. \* p<0.1, \*\* p<0.05, \*\*\* p<0.01**

Table 6.1 shows the results from the analyses of four different buffer sizes (5km to 20km). This model will be referred to as the baseline regression in the rest of the paper. All the regressions control for the order of birth of the child, if the child was born as part of a multiple birth, if the child is a girl or a boy and a linear trend in birth year<sup>21</sup>. For “H1: Infant mortality will be lower near active aid projects than in the rest of the country” to be supported, there needs to be a significant difference in differences (DD) between the active areas, and the inactive areas. The coefficients for active areas need to be significantly more negative than the coefficients for inactive areas. If this is the case or not can be tested with a F-test. It is clear from table 6.1 that there is a difference between the active and the inactive areas in all the regressions. What is more, the difference is statistical significant for all the areas as can be seen from the F-test and the p-value. The infant mortality is significantly lower in active areas than in areas with no aid projects. The DD is approximately the same for the 10, 15 and 20 km. It is smallest for the 5 km buffer, which seems contra intuitive given that we ought to expect the biggest difference closer to the people, but it may be that people are more mobile so that the differences do not show. DD is significant for all the regressions, and so far I can conclude that “H1: Infant mortality will be lower near active aid projects than in the rest of the country” is supported. The biggest DD of -0.016 means that there is a reduction of 1.6 percentage points between the active areas and the rest of the country. This means that if the IMR in an area is 82,2, aid will reduce this number to 66,2. There are 16 more infants that will survive per 1000 in active areas compared to areas with no aid projects.

The coefficients of the inactive areas need to be negative, and they need to be significant in order to conclude that aid projects are not allocated to the areas where the infant mortality is

<sup>21</sup> The coefficients are not shown because they are of no substantial interest in this study.

highest. The results in table 6.1 show that all inactive areas have a negative sign, but this effect is only significant for the two smallest buffers. From these results, it thus seems like the infant mortality in inactive areas is significantly lower when one looks close to the children, but not when the buffer sizes increase. The finding that projects are not allocated to the areas where the infant mortality is highest is different from what we saw in the descriptive results, but is due to the regression controlling for other explanations at the level of the child.

There is a slight difference of 260 observations between the model with the most and the fewest individuals. This is because there is a difference in the number of individuals that will be suspended. The percentage of the variance in infant mortality that the independent variables explain collectively can be seen in the R-squared. This number is not very high. This is not surprising given that there are many other important explanations of infant mortality that are not included in the model. The R-squared presented in this model is very similar to what Kotsadam et al. (2018) find in their study of aid in Nigeria.

### 6.3 Mother fixed effects

Variables	(1) Infant mortality	(2) Infant mortality	(3) Infant mortality	(4) Infant mortality
Active 5 km	-0.003 (0.004)			
Active 10 km		-0.004 (0.004)		
Active 15 km			-0.003 (0.004)	
Active 20 km				-0.004 (0.003)
Observations	124 037	124 297	124 210	124 051
R-squared	0.26	0.26	0.26	0.26

**Table 6.2 Mother fixed effects. All regressions control for a multiple birth dummy, gender, birth order fixed effects, and a linear trend in birth year. \* p<0.1, \*\* p<0.05, \*\*\* p<0.01**

The model so far supports “H1: Infant mortality will be lower near active aid projects than in the rest of the country”, and partly “H2: Aid projects will not be allocated to the areas where the infant mortality is highest”. The regressions so far have only controlled for factors affecting the children, but not for factors affecting the mother. Previous research has found many factors at the level of the mother to be important in explaining infant mortality. This

includes things like the mothers education (Caldwell and McDonald 1982) if she lives in an urban or rural setting (Van de Poel, O'Donnell, and Doorslaer 2009), if she breastfeeds the child (Sankar et al. 2015) and her age at birth (Finlay, Özaltin, and Canning 2011). Selection into areas depending on pre-existing level differences in mortality is completely controlled for as well. In addition it ensures that the estimated effect is not driven by endogenous population changes that may occur as an effect of aid (Kotsadam et al. 2018, 65). In table 6.2 I therefore introduce mother fixed effects. When applying mother fixed effects, the model essentially only use variation from mothers that have given birth to children both before and after an aid project has started nearby. This allows us to study the impact of aid once all potential confounding factors connected with the mothers are controlled for. As I now compare the same mother before and after aid I only need to include the active coefficient. Due to the fact that only mothers that have given birth to children both before and after the project are included I loose many observations compared to the baseline regression. The baseline regression includes approximately 124 100 children born by approximately 30 550 mothers, while the model including mother fixed effects includes approximately 42 846 children born by 6727 mothers<sup>22</sup>. The coefficients for the various active variables are much smaller than the coefficients in the baseline regression. They all have a negative sign like the coefficients in the baseline regression, but none of the coefficients are significant. This might be due to there being too few observations available to measure any effect, or it might simply be that there is no effect to measure. I discuss these findings further in the next chapter. As I only include active projects in the model, I am not able to say anything about “H2: Aid projects will not be allocated to the areas where the infant mortality is highest” from this model.

#### **6.4 Robustness checks**

How one specifies the model, which data one uses, and which method is applied will of course determine the findings you get. So far I have used buffers with different sizes to see if the results remain the same. I have also applied mother fixed effects. Both of these things; varying the size of the buffers, and applying fixed effects can be seen as forms of robustness checks. In this section I further wish to carry out other robustness checks. I will look at a different dependent variable, under-five mortality, use data with a lower precision level, look

---

<sup>22</sup> The regression table above shows more individuals. Individuals with no variation over time will not be dropped from the model when running fixed effects, but they will not be used to estimate the coefficients of interest. They are included to help improve efficiency, and improve the estimation of r-squares. It is not recommended to drop these individuals (Kotsadam 2018, 65).

specifically at health aid and conduct a logistic regression to see if the findings are susceptible to change, or if they remain stable. If the results remain stable across different specifications this adds more credibility to the conclusions.

#### 6.4.1 Under-five mortality

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Under-five mortality	Under-five mortality	Under-five mortality	Under-five mortality	Under-five mortality	Under-five mortality	Under-five mortality	Under-five mortality
Active 5 km	-0.026*** (0.004)	-0.035*** (0.005)						
Inactive 5 km		-0.015*** (0.004)						
Active 10 km			-0.035*** (0.004)	-0.042*** (0.005)				
Inactive 10 km				-0.013*** (0.004)				
Active 15 km					-0.029*** (0.004)	-0.035*** (0.005)		
Inactive 15 km						-0.009** (0.004)		
Active 20 km							-0.026*** (0.004)	-0.033*** (0.006)
Inactive 20 km								-0.009* (0.005)
Observations	96 333	96 333	96 361	96 361	96 337	96 337	96 340	96 340
R-squared	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021
Difference in differences		-0.020		-0.029		-0.026		-0.024
F test: active-inactive=0		20.38		45.40		36.07		32.64
P value		> 0.000		> 0.000		> 0.000		> 0.000

**Table 6.3 Under-five mortality. Robust standard errors clustered at the DHS cluster level in parentheses. All regressions control for a multiple birth dummy, gender, birth order fixed effects, and a linear trend in birth year.**

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

The results for under-five mortality are similar to what I find when looking at infant mortality; the coefficients have the same direction for both active and inactive areas as in the baseline regression. “H2: Aid projects will not be allocated to the areas where the infant mortality is highest” is more strongly supported in this model than in the baseline regression studying infant mortality because the findings are significant at least at the 0.1-level for all the buffer sizes. The projects are placed in areas that have lower under-five mortality at the outset, but the projects still seem to reduce the under-five mortality as can be seen from the difference in differences. The difference in differences is bigger for under-five mortality than for infant mortality. It appears that overall aid is more effective in reducing under-five mortality than infant mortality. These results are in line with what Kotsadam et al. (2018) find in their study of Nigeria. All children born within five years of the survey need to be removed from the sample since we do not know whether they will survive the first five years or not. This means that we have a smaller sample size in these regressions than in the baseline regressions researching infant mortality. The sample size is approximately 96 340 children in the under-five mortality regressions, compared to approximately 124 100 children for the infant mortality.

#### 6.4.2 Mother-fixed effects for under-five mortality

	(1)	(2)	(3)	(4)
Variables	Under-five mortality	Under-five mortality	Under-five mortality	Under-five mortality
Active 5 km	-0.010 (0.006)			
Active 10 km		-0.005 (0.008)		
Active 15 km			-0.004 (0.007)	
Active 20 km				-0.007 (0.006)
Observations	96 333	96 361	96 337	96 340
R-squared	0.289	0.288	0.289	0.289

**Table 6.4 Under-five mortality with mother-fixed effects. Robust standard errors clustered at the DHS cluster level in parentheses. All regressions control for a multiple birth dummy, gender, birth order fixed effects, and a linear trend in birth year. \* p<0.1, \*\* p<0.05, \*\*\* p<0.01.**

The results from the model including mother-fixed effects for under-five mortality are similar to the results from the model with mother-fixed effects for infant mortality. All regressions



have a negative coefficient, the coefficient is bigger than for infant mortality thus indicating that aid is more effective in reducing under-five mortality, but the results are not significant. Only 47 401 children born by 8031 mothers are included in this model, compared to 96340 children born by 23364 mothers in the model not including fixed effects. The coefficients go in the same direction as they would if “H1: Infant mortality will be lower near active aid projects than in the rest of the country” was to be supported. However, the coefficients are not statistically significant, therefore providing no conclusive support to H1.

### 6.4.3 Health aid

Variables	(1) Infant mortality	(2) Infant mortality	(3) Infant mortality	(4) Infant mortality	(5) Infant mortality	(6) Infant mortality	(7) Infant mortality	(8) Infant mortality
Active 10 km	-0.013*** (0.004)	- 0.016*** (0.004)						
Inactive 10 km		- 0.013*** (0.002)						
Active 15 km			- 0.009*** (0.003)	- 0.012*** (0.003)				
Inactive 15 km				- 0.010*** (0.002)				
Active 20 km					- 0.009*** (0.003)	- 0.011*** (0.003)		
Inactive 20 km						- 0.007*** (0.002)		
Active 25 km – pc123							-0.012*** (0.002)	- 0.011*** (0.003)
Inactive 25 km – pc123								0.002 (0.003)
Observatio ns	125 090	125 090	124 813	124 813	124 965	124 965	123 682	123 682
R-squared	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020
Difference in differen s		-0.003		-0.002		-0.004		-0.013
F test: active- inactive=0		0.34		0.16		1.28		26.27
P value		0.558		0.688		0.259		> 0.000

**Table 6.5 Health aid. Robust standard errors clustered at the DHS cluster level in parentheses. All regressions control for a multiple birth dummy, gender, birth order fixed effects, and a linear trend in birth year. \* p<0.1, \*\* p<0.05, \*\*\* p<0.01**

When only including health projects, the regressions show that the infant mortality is statistically lower in both active and inactive areas than in areas with no aid projects. This tells us that areas that receive health aid have a lower mortality than areas that do not receive health aid. The difference between the active areas and the inactive areas are however not significant for any of the buffer sizes except the 25 km buffer size that includes data at a lower precision level. We can thus only conclude that health aid areas have a lower mortality than areas without health aid, but we cannot state that this is because health aid has reduced the mortality. This finding might be due to the fact that health aid does not have an effect in reducing infant mortality, or it might be that there are not enough active and inactive projects to measure any effect in the smaller buffers, but that there are enough projects to measure an effect in the bigger buffer that also includes projects at more imprecise levels. The model with the 25km buffer, and projects at the precision level 1, 2 and 3 include 309 project locations, while the other models with projects only at precision level 1 include 175 project locations. “H1: Infant mortality will be lower near active aid projects than in the rest of the country” is not supported in any of the models with data at precision level 1. “H2: Aid projects will not be allocated to the areas where the infant mortality is highest” is supported from the results in all the models with data at precision level 1. A 5 kilometer buffer is not included in the analyses simply because there would be too few active and inactive individuals with so few projects.

#### 6.4.4 Lower precision-level on the data

Variables	(1)	(2)	(3)
	Infant mortality	Infant mortality	Infant mortality
Active 25 km	-0.014*** (0.002)	-0.015*** (0.006)	-0.003 (0.003)
Inactive 25 km		-0.001 (0.006)	
Observations	124 915	124 915	124 915
R-squared	0.020	0.020	0.262
Mother fixed effects	No	No	Yes
Difference in differences		-0.014	
F test: active- inactive=0		33.07	
P value		> 0.000	

**Table 6.6 Lower precision-level on the data. Robust standard errors clustered at the DHS cluster level in parentheses. All regressions control for a multiple birth dummy, gender, birth order fixed effects, and a linear trend in birth year. \* p<0.1, \*\* p<0.05, \*\*\* p<0.01**

In line with the one paper published on the subnational effect of aid on reducing infant mortality I also studied data with a lower precision level. I studied data with precision level 1, 2 and 3, and a buffer size of 25 kilometer. Given the imprecision of the data, 25 km is the smallest buffer size one can apply. Given that Uganda has so many aid-projects, one will not get one group of children that do not have aid projects in the proximity if one applies a buffer size that is much bigger than 25 kilometers. Looking at “H1: Infant mortality will be lower near active aid projects than in the rest of the country”, the results supports this hypothesis. The infant mortality is significantly lower in the active areas than in the inactive areas. The difference between the active and the inactive areas is -0.014. This is about the same difference as what I found for the 10, 15 and 20 kilometer buffer in the baseline regression that only included precision-level 1 data, and it means that per 1000 infants, there are 14 more infants that will survive in active areas compared to in areas with no aid projects if the mortality at the outset was 8,22 percent. From the f-test one can see that the difference between the active and the inactive areas is statistically significant. Looking at “H2: Aid projects will not be allocated to the areas where the infant mortality is highest”, the results do not support this hypothesis. The coefficient for the inactive areas is negative as expected from the hypothesis, but the value is very low, and it is not statistically significant. In the same way as for the other models including mother fixed effects, the coefficient for the active areas implies that the infant mortality is lower there than in the rest of the country when applying mother-fixed effects, but this coefficient is not significant, and is therefore providing no conclusive support to H2.

### 6.4.5 Logistic regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	Infant mortality	Infant mortality	Infant mortality	Infant mortality	Infant mortality	Infant mortality	Infant mortality	Infant mortality
Active	0.755***	0.720***						
5 km	(0.034)	(0.034)						
Inactive		0.906***						
5 km		(0.028)						
Active			0.709***	0.688***				
10 km			(0.033)	(0.035)				
Inactive				0.935**				
10 km				(0.030)				
Active					0.733***	0.727***		
15 km					(0.031)	(0.035)		
Inactive						0.988		
15 km						(0.033)		
Active							0.754***	0.751***
20 km							(0.030)	(0.038)
Inactive								0.994
20 km								(0.039)
N infants	124 037	124 037	124 297	124 297	124 210	124 210	124 051	124 051

**Table 6.7 Logistic regression. Robust standard errors clustered at the DHS cluster level in parentheses. All regressions control for a multiple birth dummy, gender, birth order fixed effects, and a linear trend in birth year. \* p<0.1, \*\* p<0.05, \*\*\* p<0.01**

As presented in the methods chapter, the linear probability model automatically breaches some of the assumptions behind the Ordinary Least Squares regression such as a normally distributed error term, predictions outside of 0 and 1, and homoscedastic error terms. Logistic regression have other weaknesses compared to the linear probability model, such as more difficult interpretation and problems with interaction effect (Mood 2010, 73), but it is more common to use at least in social sciences when the dependent variable is a dummy (Von Hippel 2015). As a robustness check I conducted a logistic regression, and calculated the probabilities to see if the results for the baseline regression remained the same with the logistic regression. The coefficients presented in table 6.7 are odds ratios. An odds ratio is simply the ratio between two odds<sup>23</sup>. Remember that my explanatory variables, active and inactive, are both dummy-variables with 1 being active/inactive, and 0 being not

<sup>23</sup> Odds is here defined as the probability that something will happen divided by the probability that it will not happen. If the probability of infant mortality is 8%, then the odds will be  $0,8/0,92 \approx 0,87$ .

active/inactive. In the table presented above one can see that all the odds ratios are below 1. This means that the chance of death decreases when going from not active to active, and from not inactive to inactive. Another way of looking at this is that being below 1 means lower chance of death, and above 1 means higher chances of death. Being below 1 is equivalent to the negative sign in front of all the coefficients in the baseline linear probability model. Given that odds-ratios can be a bit confusing, and difficult to understand, I also calculated the predicted probabilities of death when the dummy (active and inactive) had the value 1, and when it had the value 0. In table 6.8 I compare the findings from the logistic regression with the results from the LPM.

	Marginal effects (logistic)			Marginal effects (LPM)		
	Active Margins	Inactive Margins	DD (Active-inactive)	Active Margins	Inactive Margins	DD (Active-inactive)
Model 1	1,8			1,4		
Model 2	2,1	0,7	1,4	1,7	0,8	0,9
Model 3	2,1			1,7		
Model 4	2,4	0,5	1,9	2,0	0,6	1,4
Model 5	2,0			1,6		
Model 6	2,0	0,1	1,9	1,7	0,1	1,6
Model 7	1,8			1,5		
Model 8	1,8	0,1	1,7	1,5	0,1	1,4

**Table 6.8 Table comparing findings from the logistic regression with results from the LPM.**

As can be seen from table 6.8 the baseline regression and the logistic regression provide us with similar results. The significance level of the various models are all the same, and the coefficients have the same direction in both the logistic regression and in the linear probability model. The logistic models estimates a bigger DD than does the LPM, but the differences between the models gets smaller as the radius increases. When it comes to “H2: Aid projects will not be allocated to the areas where the infant mortality is highest” the results show the same as the baseline regression. All inactive areas have a log-odds below 1, thereby indicating that the infant mortality is lower in inactive areas than in the rest of the country, but this finding is only significant for the smallest buffer sizes. In the same manner as for the baseline regression it thus seems like the infant mortality is significantly lower when one looks close to the children, but not when the buffer sizes increase.

## 6.5 Mechanisms

The results from the different models presented so far all go in the in the same direction, thus indicating that aid is effective in reducing infant mortality, but whether these results are significant or not varies between the different models. I continue the analysis by looking closer at some of the mechanisms proposed to be connected to infant mortality in the theory-section. The mechanisms I inspect are: if the household have bednets to protect against malaria, the wealth index of the household, if distance to the health center has caused a serious problem to access help, and if the mother is literate and what her highest educational level is. The analyses will give us an indication of possible intermediate factors, as these factors are likely to be important for child survival. The analyses of the mechanisms in this section are a bit different from the other analyses conducted in this paper. The unit of analysis is not the children as in the other analyses, but the mother at the time of the interview. I employ the same difference-in-differences strategy as previously. The mothers are coded as active/inactive/suspended based on the year of the interview, and all regressions include the interview-year as a control variable to control for a linear trend in time. In this section I present the mechanisms studied for the 10 kilometer buffer size. The results for the 5km, 15km and 20km buffer are all presented in 6.1a-6.3a in the appendix. The results are fairly constant across varying buffer sizes.

### 6.5.1 Mechanisms at the level of the mother

<b>Variables</b>	<b>(1)</b>	<b>(2)</b>	<b>(3)</b>	<b>(4)</b>	<b>(5)</b>
	<b>Bednet for sleeping</b>	<b>Wealth index</b>	<b>Problem distance Health Facility</b>	<b>Literacy</b>	<b>Highest educational level</b>
Active	0.148***	1.166***	-0.185***	0.452***	0.423***
10 km	(0.006)	(0.022)	(0.010)	(0.014)	(0.011)
Inactive	-0.037***	0.144***	0.011	-0.023	0.046***
10 km	(0.007)	(0.025)	(0.012)	(0.017)	(0.013)
Observations	25 793	25 793	25 777	25 140	25 792
R-squared	0.310	0.106	0.081	0.042	0.067
Difference in differences	0.185	1.022	-0.196	0.475	0.377
F test: active-inactive=0	498.02	1293.72	223.87	625.98	671.84

P value	>0.000	>0.000	>0.000	>0.000	>0.000
---------	--------	--------	--------	--------	--------

**Table 6.9: Mechanisms. All models include the interview-year as a control variable to control for a linear trend.**

The regressions in table 6.9 show that all the mechanisms tested have the direction we would expect if aid is significant. There are more bednets in active areas than in inactive areas, and the difference in differences is significant. Active areas are also significantly richer than inactive areas. Distance to the health center is less likely to have caused a serious problem to access help in active areas than in inactive areas and in areas with no aid projects. Mothers are more likely to be both literate and higher educated in active areas compared to in inactive areas, and the rest of the country. The results indicate that the intermediate factors suggested to be important in explaining infant mortality in the theory section, are in fact important explanatory factors for infant mortality. R-squared are much higher for the wealth mechanism, and for the bednet for sleeping variable, than what it is for the models researching infant mortality. This suggests that there is a stronger direct relationship between these factors and aid, than what it is for infant mortality and aid.

## 7 Discussion and conclusion

### 7.1 Discussion

Is aid effective in reducing infant mortality? I have used various model specifications, different estimation strategies, different precision-levels on the data, looked at only health aid, and looked at under-five mortality to come closer to an answer to this important question. The results from the various models all indicate that aid is effective in reducing infant mortality. The mechanisms are also pointing in the direction we would expect from theory. This indicates that the intermediate factors suggested to be important in explaining infant mortality in the theory section, are in fact important explanatory factors for infant mortality. The answer to the question posed in the first line seems to be: “yes, aid is effective in reducing infant mortality”. The “yes” is however surrounded by some uncertainty since the findings in the most conservative test of aid, the model including mother fixed effects, are not significant. This model has one big advantage over the baseline regression, and that is that it controls for a variety of variables that may otherwise be spuriously correlated with both infant mortality and aid. If the findings from the model including mother fixed effects were significant we could thus exclude that there was an omitted variable bias causing the results. Although the model including mother fixed effects would allow us to conclude with “yes” in a stronger manner, two main downsides with the model should be noted. Firstly, the model reduces the number of observations drastically. In the model including mother fixed effects, I only include mothers that have given birth to children both before and after an aid project was started in their proximity. This means that the “control group” included in the baseline regression, the children who do not have an aid project in their proximity, disappear from the regression. The resulting model has far fewer observations than the baseline regression. Roughly 6700 mothers are included in the model as they have given birth to roughly 42 850 children both before and after the project. The baseline regression on the other hand included roughly 124 100 children born by roughly 30 550 mothers<sup>24</sup>. The robust standard error has approximately doubled between the two models, indicating that there is a higher uncertainty surrounding the estimate. There are three factors that influence a standard error, namely: the

---

<sup>24</sup> The precise number of mothers and children vary a little in the different models depending on how many are suspended.



variance surrounding the regression line, the variance in  $X$ , and the number of observations (Midtbø 2007, 92-93). As the number of observations decrease one can expect the robust standard error to increase. Secondly, an important difference between the model including mother fixed effects, and the model not including mother fixed effects is that the first model only measures the effect of projects that we can expect to have a fairly immediate effect. Only projects that have affected something for the latter birth, but not the first birth will be measured. If a new education project has started in the proximity of the mother, but the mother has not attended this project between her two children for instance, this kind of effect will not be measured. The effect that will be measured comes from projects that are more immediate and that the mother has access to, such as clean water, a new health clinic in the proximity, better access to nutrition or increased wealth in the household between the two siblings. All effects of aid that do not change from one sibling to the other will thus not be measured. This model is therefore a very conservative test, but also very powerful measure of aid's effect because it controls for a variety of variables that may otherwise be spuriously correlated with both infant mortality and aid. Although, it is not significant it does not lead me to conclude that aid does not work. It just tells me that there is more uncertainty surrounding the conclusion that aid does reduce infant mortality than what it would have been otherwise. The effect of aid is higher in the baseline regression than in the model including mother fixed effects. The results from the baseline regression suggests that 16 more infants will survive per 1000 in active areas compared to areas with no aid projects.

In previous research it has been suggested that aid could increase infant mortality in dictatorships (Navia and Zweifel 2003). The data they base this conclusion on classifies Uganda as a civil or military dictatorship in all except four years in the period 1962-2008. None of the findings in the various analyses in this thesis support their claim. Findings from this paper also go against the findings of Winkleman and Adams (2017), Gomanee et al. (2003), Kizhakethalackal, and Mukherjee and Alvi (2013). Winkleman and Adams (2017) find official development assistance to be effective only in medium developed countries, but not in low developed countries. This speaks against there being an effect of aid in Uganda. Gomanee et al. (2003) reports that there is just an indirect effect of aid through increased pro-poor expenditure, but they find no direct effect of aid. In contrast to this, my findings show that there is a direct effect of aid. Kizhakethalackal, Mukherjee and Alvi (2013) find aid to be effective in reducing infant mortality in countries with low infant mortality, but not in countries with high infant mortality. Uganda falls into the latter category being a country with

a high infant mortality rate. We should thus not expect to see any effect of aid in Uganda from their argument.

Are aid projects placed where the need is higher? The findings from this study shows that the answer to this question is “no, they are not”. A stable finding in all the models with the most precise data is that projects are placed where the infant mortality is lower than in areas that do not have any aid projects. For the baseline regression this finding is only significant for the smaller buffers, while for health aid and under-five mortality the finding is consistent for all the 5-20 km buffers. There does seem to be a Matthew effect at play here where the areas already having a lower infant mortality than areas that do not have aid projects, are also the areas receiving new projects. There may be several good reasons to place the projects where the infant mortality is lower. Firstly, it may be more cost efficient for organizations to allocate additional projects to where they already have a presence and previous experience (Nunnenkamp, Öhler, and Sosa Andrés 2017). Secondly, it is entirely possible that aid can be used more efficiently in places that are relatively more wealthy (Briggs 2018a, 908). It may also be the case that there are better governing systems in place in the relatively wealthier places that makes it more efficient to provide the aid there. However, this allocation pattern also potentially has some unfortunate consequences. Firstly, the lack of infant-mortality targeting means that those who suffer the highest infant mortality are being left behind, and are least likely to have good clinics or schools in their proximity. Secondly, the current aid allocation may increase inequalities in health within Uganda by providing goods and services to those who already have a lower infant mortality. This is not problematic if one takes a global view of inequality, because even places with low infant mortality rates in Uganda have high rates of children dying compared to many other countries. It does however become problematic if the world community wants to put action behind its words and reach the Sustainable Development goals of “leaving no one behind”, and “reach first those who are furthest behind” (United Nations 2015, 3). Thirdly, Sumner (2012, 7) reports that about 75 percent of the world’s absolute poor live in middle-income countries such as China, Brazil and India. In order to reach the poor in the world, it is therefore not possible to just allocate to the poorest countries. It is also necessary to have country-specificity in mind when allocating resources if the goal is to reach those who need it the most. The consequences of not targeting aid to the poorer areas, or to the areas with higher infant mortality, will be more severe in countries where the differences between different areas loom large, as we saw is the case for Uganda in chapter 2.

Chambliss and Schutt (2010, 132-134) argue that by identifying the causal mechanisms one can considerably strengthen causal explanations. The various mechanisms studied in the analyses all have the direction we would expect from the theory; in active areas there are more respondents with bednets, the wealth is higher, fewer of the respondents report that distance is a problem hindering them from going to the health center, the literacy level and the educational level is higher. All the findings are also significant. This suggests that the intermediate factors suggested to be important in explaining infant mortality in the theory section, are in fact explanatory factors for infant mortality. It does seem like aid is impacting on the mechanisms as suggested from theory. In addition to looking at mechanisms at the mother-level as is done in this paper, it would have been very relevant to examine mechanisms at the level of the children as well, such as the level of vaccination or the birth weight in active areas compared to areas with no aid projects. The DHS program does provide data on vaccination, but the data are unfortunately very incomplete with 92 percent of the respondents having missing values on the variable. With so many respondents having missing values it is not possible to use the variable. The problem with using birth weight as an indicator at the level of the child is that aid may affect the probability of being weighted in the first place. Kotsadam et al. (2018, 68) report that they find indications of this being the case in their paper. For this reason I have only been able to look at mechanisms at the level of the mother. With more complete data on the level of the child, it would be very relevant to also examine the mechanisms at that level.

In order to add more credibility to the conclusions, I conducted several robustness checks. Many of them show the same as the baseline regression: the models using data with a lower precision level, the model looking at under-five mortality and the logistic regression all show results similar to the baseline regression. Foreign aid seems to be more effective in reducing under-five mortality than in reducing infant mortality. This is not very surprising given that the diseases killing most children within the first month are more closely tied to specific health care than what it is for under-five mortality. Such problems include preterm birth complications, sepsis and problems during labor (Countdown 2030 2018).

In addition to looking at overall aid, I also studied health aid. There are several reasons to look at overall aid, and not health aid specifically. Infant mortality can, as seen in the theory chapter, be reduced with aid from a variety of sectors, including the education sector, the

water and sanitation sector, the agricultural sector and the health sector among others. This being said, by looking at overall aid impact on infant mortality, one assumes that all aid has a similar impact on infant mortality. Although infant mortality is caused by a variety of factors as shown in the theory, it is likely that for instance health aid is more closely connected to infant mortality. In order to assess if health aid gives a different estimate of aid effectiveness, I chose to test this sector specific aid. The model including only health aid does not show any significant effect of these projects. This might be because there are too few active and inactive individuals included in the models to find any effect, or it might be that there is no effect. Judging from the name of the health projects, it looks like 62 percent (108 out of 175) of the health projects locations are primary dealing with HIV/AIDS. Although it is true that HIV/AIDS is an important factor when it comes to infant mortality, it is not the most important one<sup>25</sup>. According to the World Health Organization there are seven other diseases and conditions that are more prevalent reasons for under-five mortality in Uganda than AIDS. Only 6 percent of all deaths of children under-five are caused by AIDS (Countdown to 2030 2018). The results from the model only including health aid show that health aid projects are not placed where the infant mortality is at the lowest. Given that the majority of the projects are aimed at HIV/AIDS there may be a good reason for this finding.

The findings in this study have external validity for aid projects with a high precision level in Uganda. It may well be that studies of other countries find aid to be working differently there because the conditions are different there. My findings are partially in line with previous research. In line with Kotsadam et al. (2018), I find aid to be significant in reducing infant mortality in the baseline regression, and mostly across various robustness checks. Contrary to what I find, they do however find a significant effect at the 0.1 level also when applying the mother fixed effects with the linear probability model. In their study of Nigeria, they have a sample of 71 537 children born by 14 071 mothers. The number of mothers they study is more than twice the size of my sample. It is impossible to know whether the findings in the study of Uganda would also have been significant with a bigger sample or not. As argued in chapter 5, it might be the case that the effects of aid are too small and localized to affect aggregate outcomes.

---

<sup>25</sup> Stierman, Sengooba, and Bennett (2013) study the longer term trends in development assistance for health (DAH) in Uganda, and find that increasingly DAH is project-based support mostly is provided to HIV/AIDS. This donor spending on HIV/AIDS appears to be in excess of need (Stierman, Sengooba, and Bennett 2013, 9). Stierman, Sengooba, and Bennett (2013, 9) argue that there is a need to seek fundamental reform in how donors plan, budget and finance DAH if reality is to align better with stated preferences.

## 7.2 Conclusion

The findings from this study can be summed up in three points. Firstly, I find aid to be effective in reducing infant mortality in most of the models. “H1: Infant mortality will be lower closer to the active aid projects” is supported from most of the models. It does appear that aid saves infants lives. This finding is however surrounded by some uncertainty since the significance of the findings disappear in the most conservative test of aid. Secondly, the results indicate that the projects are placed in areas where the infant mortality is lower at the outset. “H2: Aid projects will not be allocated to the areas where the infant mortality is highest” is supported. Thirdly, the various mechanisms studied in this analysis all have the direction we would expect from the theory; in active areas there are more respondents with bednets, the wealth is higher, fewer of the respondents report that distance is a problem hindering them from going to the health center, the literacy level and the educational level is higher. All the findings are also significant. This indicates that the intermediate factors suggested to be important in explaining infant mortality in the theory section, are in fact important explanatory factors for infant mortality. The various robustness-checks do for the most part point in the same direction as the results from the main analyses. This gives me greater confidence in the conclusions.

This thesis has served the purpose of researching an important and insufficiently studied topic, namely aid effectiveness below the country level. By using new geocoded data and conduct a subnational study of aid effectiveness in Uganda I have attempted to bridge the macro-micro divide, and fill a missing middle in the evaluation literature. Using a geospatial impact evaluation like the one conducted in this paper have allowed for better generalizability than studies at the micro-level, whilst at the same time avoiding some of the methodical problems that are inherent in studies at the macro-level, such as lack of country-specificity, and not being able to discover localized effects of aid. The research design allows to control for the fact that aid areas are not selected randomly, whilst at the same time allowing me to look at whether future aid projects are placed where the needs are highest. By using buffers as the geographical division in stead of regions, district or grid cells I can be more confident that the aid projects are actually placed in the proximity of the respondents. Uganda serves as a good case to study due to the big amount of aid it has received, its rate and trend in infant mortality, and not least due to the fact that the amount of aid and infant mortality varies greatly at the subnational level.

Very little research has been conducted on health indicators at the subnational level. This study fills a gap in the literature by providing, to the best of my knowledge, the first systematic study of aid allocation and infant mortality in Uganda. In this paper I chose to study the effect aid has on reducing infant mortality. There are several good reasons to study this. That being said, it is also very challenging to research something as complex as infant mortality that is influenced by so many factors. For future research it might also be useful to look at more specific diseases, and the connection with specific types of aid at the subnational level. This will reduce the ambition-level of the question one attempts to answer, but at the same time it could also increase the precision level at which one is able to answer the question. This study only looked at if there was a project close to the respondent or not. Future research might also benefit from looking more specifically at the number of projects, their duration and the amount of resources received. Answering why aid projects are placed in areas where the infant mortality is lower at the outset is also a possible target for future research. Research attempting to answer such a question would have to look at both how donors allocate money, and how Uganda allocates the money received (Briggs 2018b, 140).

## References

- AidData. 2016. UgandaAIMS\_GeocodedResearchRelease\_Level1\_v1.4.1 geocoded dataset. Williamsburg, VA and Washington, DC: AidData.
- AidData Research and Evaluation Unit. 2017. Geocoding Methodology, Version 2.0. Williamsburg, VA: AidData at William & Mary.
- Alderman, Harold. 2007. "Improving Nutrition through Community Growth Promotion: Longitudinal Study of the Nutrition and Early Child Development Program in Uganda." *World Development* 35 (8):1376-1389. doi: 10.1016/j.worlddev.2007.04.003.
- Alvi, Eskander, and Abera Senbeta. 2012. "Does foreign aid reduce poverty?" *Journal of International Development* 24 (8):955-976. doi: 10.1002/jid.1790.
- Angrist, Joshua D., and Jörn-Steffen Pischke. 2009. *Mostly harmless econometrics : an empiricist's companion*. Princeton: Princeton University Press.
- Arndt, Channing, Sam Jones, and Finn Tarp. 2015. "Assessing Foreign Aid's Long-Run Contribution to Growth and Development." *World Development* 69:6-18. doi: 10.1016/j.worlddev.2013.12.016.
- Asfaw, Abay, Klaus Frohberg, K. S. James, and Johannes Jütting. 2007. "Fiscal Decentralization and Infant Mortality: Empirical Evidence from Rural India." *The Journal of Developing Areas* 41 (1):17-35.
- Barbieri, Magali. 2015. Infant and Child Mortality in the Less Developed World. In *International Encyclopedia of the Social & Behavioral Sciences (Second Edition)*, edited by James D. Wright: Elsevier.
- Bauer, Peter Thomas. 1976. *Dissent on Development: Studies and Debates in Development Economics, Revised Edition*. Cambridge, Massachusetts: Harvard University Press.
- Bauer, Peter Thomas. 1981. *Equality, the Third World, and Economic Delusion*. Cambridge, Massachusetts: Harvard University Press.
- BenYishay, Ariel, Daniel Runfola, Rachel Trichler, Carrie Dolan, Seth Godman, Bradley Parks, Jeffery Tanner, Silke Heuser, Geeta Batra, and Anupam Anand. 2017. A primer on Geospatial Impact Evaluation Methods, Tools, and Applications. AidData Working Paper #44. Williamsburg, VA: AidData at William & Mary.
- Bergo, Håvard. 2015. "Has foreign aid led to economic growth in Uganda?", accessed 8. February 2019. <https://globalriskinsights.com/2015/05/has-foreign-aid-led-to-economic-growth-in-uganda/>.
- Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan. 2004. "How Much Should We Trust Differences-In-Differences Estimates?" *Quarterly Journal of Economics*:249-275. doi: 10.1162/003355304772839588.
- Boone, Peter. 1996. "Politics and the effectiveness of foreign aid." *European Economic Review* 40 (2):289-329. doi: 10.1016/0014-2921(95)00127-1.
- Botting, Marianne J., Edoyo O. Porbeni, Michel R. Joffres, Bradley C. Johnston, Robert E. Black, and Edward J. Mills. 2010. "Water and sanitation infrastructure for health: The impact of foreign aid." *Globalization and Health* 6 (1):1-12. doi: 10.1186/1744-8603-6-12.
- Bourguignon, Francois, and Danny Leipziger. 2006. *Aid, Growth, and Poverty Reduction - Toward a New Partnership Model*. Washington DC: The World Bank.
- Boyle, Elizabeth Heger, Miriam King, and Matthew Sobek. 2018. IPUMS Demographic and Health Surveys: Version 6 [dataset]. IPUMS and ICF. <https://doi.org/10.18128/D080.V6>.

- Brautigam, Deborah. 2013. "Rubbery Numbers for Chinese Aid to Africa." John Hopkins School of Advanced International Studies, accessed 20 April 2019. <http://www.chinaafricarealstory.com/2013/04/rubbery-numbers-on-chinese-aid.html>.
- Briggs, Ryan C. 2014. "Aiding and Abetting: Project Aid and Ethnic Politics in Kenya." *World Development* 64:194-205. doi: 10.1016/j.worlddev.2014.05.027.
- Briggs, Ryan C. 2017. "Does Foreign Aid Target the Poorest?" 71 (1):187-206. doi: 10.1017/S0020818316000345.
- Briggs, Ryan C. 2018a. "Leaving No One Behind? A New Test of Subnational Aid Targeting." *Journal of International Development* 30 (5):904-910. doi: 10.1002/jid.3357.
- Briggs, Ryan C. 2018b. "Poor targeting: A gridded spatial analysis of the degree to which aid reaches the poor in Africa." *World Development* 103:133-148. doi: 10.1016/j.worlddev.2017.10.020.
- Burgert, Clara R., Josh Colston, Thea Roy, and Blake Zachary. 2013. Geographic displacement procedure and georeferenced data release policy for the Demographic and Health Surveys. DHS Spatial Analysis Reports No. 7. Calverton, Maryland, USA: ICF International: United States Agency for International Development (USAID).
- Burnside, Craig, and David Dollar. 1998. Aid, the Incentive Regime, and Poverty Reduction. In *World Bank Publications: The World Bank*.
- Caldwell, John, and Peter McDonald. 1982. "Influence of maternal education on infant and child mortality: Levels and causes." *Health Policy and Education* 2 (3):251-267. doi: 10.1016/0165-2281(82)90012-1.
- Central Intelligence Agency. 2019. "The world factbook - Uganda." accessed 18. November 2018. <https://www.cia.gov/library/publications/the-world-factbook/geos/ug.html>.
- Chambliss, Daniel F., and Russell K. Schutt. 2010. *Making sense of the social world: methods of investigation*. 3rd edition. ed. Los Angeles: Pine Forge Press.
- Chauvet, Lisa, Flore Gubert, and Sandrine Mesplé-Soms. 2013. "Aid, Remittances, Medical Brain Drain and Child Mortality: Evidence Using Inter and Intra-Country Data." *The Journal of Development Studies* 49 (6):801-818. doi: 10.1080/00220388.2012.742508.
- Columbia University Mailman School of Public Health. N.D. "Difference-in-Difference Estimation." accessed 28 March 2019. <https://www.mailman.columbia.edu/research/population-health-methods/difference-difference-estimation>.
- Cook, Thomas D., and Vivian C. Wong. 2012. "Better Quasi-Experimental Practice." In *The SAGE Handbook of Social Research Methods*, edited by Alasuutari Pertti, Leonard Bickman and Julia Brannen, 134-165. London: SAGE Publications Ltd.
- Cordella, Tito, and Giovanni Dell' Ariccia. 2007. "Budget Support Versus Project Aid: A Theoretical Appraisal\*." *Economic Journal* 117 (523):1260-1279. doi: 10.1111/j.1468-0297.2007.02082.x.
- Countdown to 2030. 2018. "Uganda." accessed 20. April 2019. <http://countdown2030.org/wp-content/uploads/2018/01/Uganda-CD2030.pdf>.
- Croft, Trevor N, Aileen M. J. Marshall, Courtney K. Allen, and et. al. 2018. Guide to DHS Statistics. Rockville, Maryland, USA: ICF: United States Agency for International Development (USAID) & The DHS Program.
- De, Rajlakshmi, and Charles Becker. 2015. The Foreign Aid Effectiveness Debate: Evidence from Malawi. AidData Working Paper #6. Williamsburg, VA: AidData at William & Mary.
- Deaton, Angus. 2013. *The great escape : health, wealth, and the origins of inequality*. Princeton, New Jersey: Princeton University Press.



- Deke, John. 2014. Using the Linear Probability Model to Estimate Impacts on Binary Outcomes in Randomized Controlled Trials. Washington, DC: U.S. Department of Health and Human Services, Administration on Children, Youth and Families, Office of Adolescent Health.
- Denizer, Cevdet, Daniel Kaufmann, and Aart Kraay. 2013. "Good countries or good projects? Macro and micro correlates of World Bank project performance." *Journal of Development Economics* 105:288-302.
- Dollar, David, and Alberto Alesina. 2000. "Who Gives Foreign Aid to Whom and Why?" *Journal of Economic Growth* 5 (1):33-63. doi: 10.1023/A:1009874203400.
- Doucouliaqos, Hristos, and Martin Paldam. 2009. "The Aid Effectiveness Literature: The Sad Results of 40 Years of Research." *Journal of Economic Surveys* 23 (3):433-461. doi: 10.1111/j.1467-6419.2008.00568.x.
- Dreher, Axel, and Steffen Lohmann. 2015. "Aid and growth at the regional level." *Oxford Review of Economic Policy* 31 (3-4):420-446. doi: 10.1093/oxrep/grv026.
- English Oxford Living Dictionaries. n.d. "Overfitting." accessed 27. February 2019. <https://en.oxforddictionaries.com/definition/overfitting>.
- Fikree, Fariyal F., Farid Midhet, Salim Sadruddin, and Heinz W. Berendes. 1997. "Maternal mortality in different Pakistani sites: ratios, clinical causes and determinants." *Acta Obstetrica et Gynecologica Scandinavica* 76 (7):637-645. doi: 10.3109/00016349709024603.
- Findley, Michael G., Josh Powell, Daniel Strandow, and Jeff Tanner. 2011. "The Localized Geography of Foreign Aid: A New Dataset and Application to Violent Armed Conflict." *World Development* 39 (11):1995-2009. doi: 10.1016/j.worlddev.2011.07.022.
- Finlay, Jocelyn E., Emre Özaltin, and David J. Canning. 2011. "The association of maternal age with infant mortality, child anthropometric failure, diarrhoea and anaemia for first births: Evidence from 55 low- and middle-income countries." *BMJ Open* 1 (2). doi: 10.1136/bmjopen-2011-000226.
- Frisbie, William Parker. 2005. "Infant Mortality." In *Handbook of Population*, edited by Dudley L. Poston and Michael Micklin. Boston, Massachusetts: Springer US.
- Fuse, Kana, and Edward M. Crenshaw. 2006. "Gender imbalance in infant mortality: A cross-national study of social structure and female infanticide." *Social Science & Medicine* 62 (2):360-374. doi: 10.1016/j.socscimed.2005.06.006.
- Gbesemete, Kwame P., and Dick Jonsson. 1993. "A comparison of empirical models on determinants of infant mortality: A cross-national study on Africa." *Health policy* 24 (2):155-174. doi: 10.1016/0168-8510(93)90032-K.
- Gebhard, Nathaniel, Katherine Kitterman, Ashley Anne Mitchell, Daniel Nielson, and Sven Wilson. 2008. "Preliminary Results on Health Aid Effectiveness." annual meeting of the American Political Science Association,, Boston, Massachusetts, 28-31 August 2008.
- Gehring, Kai, Lennart Kaplan, and Melvin H.L Wong. 2019. Aid and Conflict at the Sub-National Level: Evidence from World Bank and Chinese Development Projects in Africa. AidData Working Paper #70. Williamsburg, VA: AidData at William & Mary.
- Gerring, John. 2012. *Social science methodology : a unified framework*. 2nd ed, *Strategies for social inquiry*. Cambridge: Cambridge University Press.
- Gomanee, Karuna, Sourafel Girma, and Oliver Morrissey. 2005. "Aid, public spending and human welfare: evidence from quantile regressions." *Journal of International Development* 17 (3):299-309. doi: 10.1002/jid.1163.

- Gomanee, Karuna, Oliver Morrissey, Paul Mosley, and Arjan Verschoor. 2003. "Aid, Pro-Poor Government Spending and Welfare." *CREDIT Working Paper No. 03/03*. doi: <http://dx.doi.org/10.2139/ssrn.412244>.
- Gomanee, Karuna, Oliver Morrissey, Paul Mosley, and Arjan Verschoor. 2005. "Aid, Government Expenditure, and Aggregate Welfare." *World Development* 33 (3):355-370. doi: 10.1016/j.worlddev.2004.09.005.
- Gottret, Pablo, and George Schieber. 2006. *Health Financing Revisited: A Practitioner's Guide*. Washington D.C: World Bank. <https://openknowledge.worldbank.org/handle/10986/7094>
- Green, Elliott. 2010. "Patronage, District Creation, and Reform in Uganda." *Studies in Comparative International Development* 45 (1):83-103. doi: 10.1007/s12116-009-9058-8.
- Guo, Guang, and Laurence M. Grummer-Strawn. 1993. "Child Mortality Among Twins in Less Developed Countries." *Population Studies* 47 (3):495-510. doi: 10.1080/0032472031000147266.
- Hansen, Henrik, and Finn Tarp. 2000. "Aid effectiveness disputed." *Journal of International Development* 12 (3):375-398. doi: 10.1002/(SICI)1099-1328(200004)12:33.0.CO;2-M.
- Hellevik, Ottar. 2009. "Linear versus logistic regression when the dependent variable is a dichotomy." *Quality and Quantity* 43 (1):59-74. doi: 10.1007/s11135-007-9077-3.
- Hoeffler, Anke, and Verity Outram. 2011. "Need, Merit, or Self-Interest-What Determines the Allocation of Aid?" *Review of Development Economics* 15 (2):237-250. doi: 10.1111/j.1467-9361.2011.00605.x.
- ICF. 2000-2016. Uganda Demographic and Health Survey 2000-2016 (Datasets UGBR41FL.DTA, UGBR52FL.DTA, UGBR60FL.DTA, UGBR7AFL.DTA). Funded by USAID. Rockville, Maryland: ICF (Distributor).
- Ingham, Kenneth, Maryinez Lyons, Omari H Kokole, and M. Semakula M. Kiwanuka. 2019. "Uganda." *Encyclopaedia Britannica*, accessed 14. March 2019. <https://www.britannica.com/place/Uganda>.
- Isaksson, Ann-Sofie. 2017. *Geospatial Analysis of Aid - A New Approach to Aid Evaluation. Rapport till Expertgruppen för biståndsanalys (EBA)*.
- Isaksson, Ann-Sofie, and Andreas Kotsadam. 2018. "Chinese aid and local corruption." *Journal of Public Economics*, 159:146-159. doi: 10.1016/j.jpubeco.2018.01.002.
- Kadobera, Daniel, Benn Sartorius, Honorati Masanja, Alexander Mathew, and Peter Waiswa. 2012. "The effect of distance to formal health facility on childhood mortality in rural Tanzania, 2005–2007." *Global Health Action* 5 (1). doi: 10.3402/gha.v5i0.19099.
- Kenny, Charles. 2011. *Getting Better*. New York: Basic Books.
- Kikafunda, Joyce. K., Ann. F. Walker, David. Collett, and James. K. Tumwine. 1998. "Risk factors for early childhood malnutrition in Uganda." *Pediatrics* 102 (4):1-8. doi: 10.1542/peds.102.4.e45.
- Kilby, Christopher. 2011. Foreign Aid. In *Encyclopedia of Global Justice.*, edited by Chatterjee D.K. Springer, Dordrecht.
- Kizhakethalackal, Elsy Thomas, Debasri Mukherjee, and Eskander Alvi. 2013. "Quantile regression analysis of health-aid and infant mortality: a note." *Applied Economics Letters* 20 (13):1197-1201. doi: 10.1080/13504851.2013.799744.
- Knutsen, Carl Henrik, Andreas Kotsadam, Eivind Hammersmark Olsen, and Tore Wig. 2017. "Mining and Local Corruption in Africa." *American Journal of Political Science* 61 (2):320-334. doi: 10.1111/ajps.12268.

- Kosack, Stephen, and Jennifer Tobin. 2006. "Funding Self-Sustaining Development: The Role of Aid, FDI and Government in Economic Success." *International Organization* 60 (1):205-243. doi: 10.1017/S0020818306060097.
- Kotsadam, Andreas, and Anja Tolonen. 2016. "African Mining, Gender, and Local Employment." *World Development* 83:325-339. doi: 10.1016/j.worlddev.2016.01.007.
- Kotsadam, Andreas, Gudrun Østby, Siri Aas Rustad, Andreas Forø Tollefsen, and Henrik Urdal. 2018. "Development aid and infant mortality. Micro-level evidence from Nigeria." *World Development* 105:59-69.
- Kulipanova, Elena. 2013. "How Effective is Development Aid? On Concepts and Methods of Measuring Aid Effectiveness." In *Studying «Effectiveness» in International Relations - A guide for students and scholars*, edited by Hendrik Hegemann, Regina Heller and Martin Kahl. Toronto: Barbara Budrich Publishers.
- Lee, Kwang-Sun, Sang-Chul Park, Babak Khoshnood, Hal-Lung Hsieh, and Robert Mittendorf. 1997. "Human development index as a predictor of infant and maternal mortality rates." *The Journal of Pediatrics* 131 (3):430-433. doi: 10.1016/S0022-3476(97)80070-4.
- Levine, Ruth, and What Works Working Group. 2007. *Case studies in global health : millions saved*. Edited by Richard Riegelman, *Essential public health*. Sudbury, Massachusetts: Jones and Bartlett Publishers.
- Liu, Li, Shefali Oza, Daniel Hogan, Jamie Perin, Igor Rudan, Joy Lawn, Simon Cousens, Colin Mathers, and Robert Black. 2015. "Global, regional, and national causes of child mortality in 2000-13, with projections to inform post-2015 priorities: an updated systematic analysis." *The Lancet* 385 (9966):430-440. doi: 10.1016/S0140-6736(14)61698-6.
- Martorano, Bruno, Laura Metzger, and Marco Sanfilippo. 2018. Chinese Development Assistance and Household Welfare in Sub-Saharan Africa. AidData Working Paper #50: Williamsburg, VA: AidData at William & Mary.
- Marty, Robert, Carrie B. Dolan, Matthias Leu, and Daniel Runfola. 2017. "Taking the health aid debate to the subnational level: the impact and allocation of foreign health aid in Malawi." *BMJ Global Health* 2 (1). doi: 10.1136/bmjgh-2016-000129.
- Masud, Nadia, and Borianna Yontcheva. 2005. "Does foreign aid reduce poverty? Empirical evidence from nongovernmental and bilateral aid." In. Washington, D.C: International Monetary Fund.
- McCoy, David. 2017. "Critical global health: Responding to poverty, inequality and climate change: comment on "Politics, power, poverty and global health: Systems and frames"." *International Journal of Health Policy and Management* 6 (9):539. doi: 10.15171/ijhpm.2016.157.
- Midtbø, Tor. 2007. *Regresjonsanalyse for samfunnsvitere : med eksempler i SPSS*. Oslo: Universitetsforlaget.
- Mikkelsen, Lene, David E. Phillips, Carla Abouzahr, Philip W. Setel, Don de Savigny, Rafael Lozano, and Alan D. Lopez. 2015. "A global assessment of civil registration and vital statistics systems: monitoring data quality and progress." *The Lancet* 386 (10001):1395-1406. doi: 10.1016/S0140-6736(15)60171-4.
- Ministry of Finance, Planning and Economic Development, Uganda. n.d. "About." accessed 3. January 2019. <http://154.72.196.89/portal/node/11>.
- Mishra, Prachi, and David Newhouse. 2009. "Does health aid matter?" *Journal of Health Economics* 28 (4):855-872. doi: 10.1016/j.jhealeco.2009.05.004.

- Mishra, S. K., Bali Ram, Abhishek Singh, and Awdhesh Yadav. 2018. "Birth order, stage of infancy and infant mortality in India." *Journal of Biosocial Science* 50 (5):604-625. doi: 10.1017/S0021932017000487.
- Mood, Carina. 2010. "Logistic Regression: Why We Cannot Do What We Think We Can Do, and What We Can Do About It." *European Sociological Review* 26 (1):67-82. doi: 10.1093/esr/jcp006.
- Mosley, W. Henry, and Lincoln C. Chen. 1984. "An Analytical Framework for the Study of Child Survival in Developing Countries." *Population and Development Review* 10:25-45. doi: 10.2307/2807954.
- Moyo, Dambisa. 2009. *Dead aid : why aid is not working and how there is another way for Africa*. London: Allen Lane.
- Mukherjee, Debasri, and Elsy Thomas Kizhakethalackal. 2013. "Empirics of health-aid, education and infant mortality: a semiparametric study." *Applied Economics* 45 (22):3137-3150. doi: 10.1080/00036846.2012.699186.
- Muldoon, Katherine A., Lindsay P. Galway, Maya Nakajima, Steve Kanters, Robert S. Hogg, Eran Bendavid, and Edward J. Mills. 2011. "Health system determinants of infant, child and maternal mortality: A cross-sectional study of UN member countries." *Globalization and health* 7 (42):1-10. doi: 10.1186/1744-8603-7-42.
- National Planning Authority. 2013. "Uganda Vision 2040." accessed 16. December 2018. [http://www.greengrowthknowledge.org/sites/default/files/downloads/policy-database/UGANDA%29 Vision 2040.pdf](http://www.greengrowthknowledge.org/sites/default/files/downloads/policy-database/UGANDA%29%20Vision%202040.pdf).
- Navia, Patricio, and Thomas Zweifel. 2003. "Democracy, dictatorship, and infant mortality revisited." *Journal of Democracy* 14 (3):90-103. doi: 10.1353/jod.2003.0059.
- Negeri, Keneni Gutema, and Damen Halemariam. 2016. "Effect of health development assistance on health status in sub-Saharan Africa." *Risk Management and Healthcare Policy* 9:33-42. doi: 10.2147/RMHP.S101343.
- Nunnenkamp, Peter, Albena Sotirova, and Rainer Thiele. 2016. "Do Aid Donors Specialize and Coordinate within Recipient Countries? The case of Malawi." *Development Policy Review* 34 (6):831-849. doi: 10.1111/dpr.12186.
- Nunnenkamp, Peter, Hannes Öhler, and Maximiliano Sosa Andrés. 2017. "Need, Merit and Politics in Multilateral Aid Allocation: A District-level Analysis of World Bank Projects in India." *Review of Development Economics* 21 (1):126-156. doi: 10.1111/rode.12259.
- Nuwaha, Fred, Juliet Babirye, and Natal Ayiga. 2011. "Why the increase in under five mortality in Uganda from 1995 to 2000? A retrospective analysis." *BMC Public Health* 11 (1):725. doi: 10.1186/1471-2458-11-725.
- Odokonyero, Tonny, Alex T. Ijjo, Robert Marty, Tony Muhumuza, and Godfrey Owot Moses. 2015. Sub-national Perspectives on Aid Effectiveness: Impact of Aid on Health Outcomes in Uganda. AidData Working Paper #18. Williamsburg, VA: AidData at William & Mary.
- Odokonyero, Tonny, Robert Marty, Tony Muhumuza, Alex T. Ijjo, and Godfrey Owot Moses. 2018. "The impact of aid on health outcomes in Uganda." *Health Economics* 27 (4):733-745. doi: 10.1002/hec.3632.
- Okwaraji, Yemisrach B., Simon Cousens, Yemane Berhane, Kim Mulholland, and Karen Edmond. 2012. "Effect of Geographical Access to Health Facilities on Child Mortality in Rural Ethiopia: A Community Based Cross Sectional Study " *PLoS ONE* 7 (3):1-8. doi: 10.1371/journal.pone.0033564.
- Oliphant, Nicholas P., John B. Mason, Tanya Doherty, Mickey Chopra, Pamela Mann, Mark Tomlinson, Duduzile Nsiband, and Saba Mebrahtu. 2010. "The Contribution of Child Health Days to Improving Coverage of Periodic Interventions in Six African

- Countries." *Food and Nutrition Bulletin* 31 (3):248-263. doi: 10.1177/15648265100313S304.
- Organisation for Economic Co-operation and Development. 2018a. "Development aid at a glance - statistics by region - developing countries." accessed 24. January 2019. <http://www.oecd.org/dac/financing-sustainable-development/development-finance-data/World-Development-Aid-at-a-Glance-2018.pdf>.
- Organisation for Economic Co-operation and Development. 2018b. "Development aid stable in 2017 with more sent to poorest countries." accessed 19. May 2018. <https://www.oecd.org/development/development-aid-stable-in-2017-with-more-sent-to-poorest-countries.htm>.
- Organisation for Economic Co-operation and Development. 2019. "DAC List of ODA Recipients." accessed 20. April 2019. <http://www.oecd.org/dac/financing-sustainable-development/development-finance-standards/daclist.htm>.
- Organisation Internationale de Normalisation. 2018. "Online Browsing Platform (OBP)." accessed 6. December 2018. <https://www.iso.org/obp/ui/-iso:code:3166:UG>.
- Organization for Economic Co-operation and Development. 2019. "Official development assistance - definition and coverage." accessed 20. February 2019. [http://www.oecd.org/dac/stats/officialdevelopmentassistancedefinitionandcoverage.htm - Notes](http://www.oecd.org/dac/stats/officialdevelopmentassistancedefinitionandcoverage.htm-Notes).
- Our World in Data. 2019. "Aid received per capita 2011." accessed 16 April 2019. <https://ourworldindata.org/grapher/aid-received-per-capita?year=2011&time=2000..2016>.
- Pedace, Roberto. n.d. "3 main linear probability model (LPM) problems." accessed 1. April 2019. <https://www.dummies.com/education/economics/econometrics/3-main-linear-probability-model-lpm-problems/>.
- Pickbourn, Lynda, and Léonce Ndikumana. 2018. "Does Health Aid Reduce Infant and Child Mortality from Diarrhoea in Sub-Saharan Africa?" *The Journal of Development Studies*:1-20. doi: 10.1080/00220388.2018.1536264.
- Przeworski, Adam, Michael Alvarez, José Antonio Cheibub, and Fernando Limongi. 2000. *Democracy and Development: Political Institutions and Well-Being in the World, 1950-1990*. edited by Cambridge University Press. Cambridge.
- Radelet, Steven. 2006. *A Primer on Foreign Aid*. Working Paper Number 92. Center for Global Development.
- Riddell, Abby, and Miguel Niño-Zarazúa. 2016. "The effectiveness of foreign aid to education: What can be learned?" *International Journal of Educational Development* 48:23-36. doi: 10.1016/j.ijedudev.2015.11.013.
- Riddell, Roger C. 2007. *Does foreign aid really work?* Oxford: Oxford University Press.
- Sankar, Mari Jeeva, Bireswar Sinha, Ranadip Chowdhury, Nita Bhandari, Sunita Taneja, Jose Martines, and Rajiv Bahl. 2015. "Optimal breastfeeding practices and infant and child mortality: a systematic review and meta-analysis." *Acta Paediatrica* 104:3-13. doi: 10.1111/apa.13147.
- Sartorius, Benn K. D., and Kurt Sartorius. 2014. "Global infant mortality trends and attributable determinants - an ecological study using data from 192 countries for the period 1990-2011." *Population Health Metrics* 12 (1). doi: 10.1186/s12963-014-0029-6.
- Schell, Carl Otto, Marie Reilly, Hans Rosling, Stefan Peterson, and Anna Mia Ekström. 2007. "Socioeconomic determinants of infant mortality: A worldwide study of 152 low-, middle-, and high-income countries." *Scandinavian Journal of Public Health* 35:288-297. doi: 10.1080/14034940600979171.

- Seawright, Jason. 2010. "Regression-Based Inference: A Case Study in Failed Causal Assessment." In *Rethinking social inquiry diverse tools, shared standards, Second edition.*, edited by Henry. E Brady and David Collier, 247-271. Lanham: Rowman and Littlefield.
- Skog, Ole-Jørgen. 2004. *Å forklare sosiale fenomener: en regresjonsbasert tilnærming*. Oslo: Gyldendal Akademisk.
- Skolnik, Richard. 2016. *Global health 101*. 3rd ed. Burlington, Massachusetts: Jones and Bartlett Learning.
- Soares, Rodrigo R. 2007. "On the Determinants of Mortality Reductions in the Developing World." *Population and Development Review* 33 (2):247-287. doi: 10.1111/j.1728-4457.2007.00169.x.
- Ssewanyana, Sarah, and Stephen D. Younger. 2008. "Infant Mortality in Uganda: Determinants, Trends and the Millennium Development Goals." *Journal of African Economies* 17 (1):34-61. doi: 10.1093/jae/ejm004.
- Statistics Department/Uganda, and Macro International. 1996. Uganda Demographic and Health Survey, 1995. Calverton, Maryland, USA: Statistics Department/Uganda and Macro International.
- Stierman, Elizabeth, Freddie Ssengooba, and Sara Bennett. 2013. "Aid alignment: a longer term lens on trends in development assistance for health in Uganda." *Globalization and Health* 9 (7):1-11. doi: 10.1186/1744-8603-9-7.
- Sumner, Andy. 2012. "Where Do The World's Poor Live? A New Update." *IDS Working Paper* 393.
- The DHS Program. n.d.-a. "DHS Model Questionnaires." accessed 5. December 2018. [https://dhsprogram.com/What-We-Do/Survey-Types/DHS-Questionnaires.cfm - CP\\_JUMP\\_16179](https://dhsprogram.com/What-We-Do/Survey-Types/DHS-Questionnaires.cfm - CP_JUMP_16179).
- The DHS Program. n.d.-b. "DHS Overview." accessed 5. December 2018. <https://dhsprogram.com/What-We-Do/Survey-Types/DHS.cfm>.
- The DHS Program. n.d.-c. "Wealth Index Construction." accessed 2. May 2019. <https://www.dhsprogram.com/topics/wealth-index/Wealth-Index-Construction.cfm>.
- The New Humanitarian. 2012. "Aid cuts threaten vital public services." accessed 5. February 2019. <http://www.thenewhumanitarian.org/report/97059/uganda-aid-cuts-threaten-vital-public-services>.
- The World Bank. 2018. "Classifying countries by income." accessed 17. April 2019. <http://datatopics.worldbank.org/world-development-indicators/stories/the-classification-of-countries-by-income.html>.
- The World Bank. 2019a. "Indicators." accessed 18. March 2019. <https://data.worldbank.org/indicator?tab=all>.
- The World Bank. 2019b. "Uganda." accessed 10. May 2019. <http://www.worldbank.org/en/country/uganda/overview>.
- Treiber, Linda A. 2017. Infant mortality rate. In *Encyclopaedia Britannica*.
- UCLA: Statistical Consulting Group. n.d. "Regression with Stata Chapter 2 - Regression Diagnostics." accessed 14. May 2019. <https://stats.idre.ucla.edu/stata/webbooks/reg/chapter2/stata-webbooksregressionwith-statachapter-2-regression-diagnostics/>.
- Uganda Bureau of Statistics, and Macro International. 2007. Uganda Demographic and Health Survey 2006. Calverton, Maryland, USA: UBOS and Macro International.
- Uganda Bureau of Statistics (UBOS), and ICF. 2018. Uganda Demographic and Health Survey 2016. Kampala, Uganda and Rockville, Maryland, USA: UBOS and ICF.
- Unicef. 2015. "Water, sanitation and hygiene (WASH)." accessed 2. February 2019. <https://www.unicef.org/uganda/what-we-do/wash>.

- Unicef. 2016a. Maternal and newborn health disparities: Uganda.
- Unicef. 2016b. "UNICEF: Collecting water is often a colossal waste of time for women and girls." accessed 29. May 2019. <https://www.unicef.org/press-releases/unicef-collecting-water-often-colossal-waste-time-women-and-girls>.
- Unicef. 2017a. "Birth registration - Every child's first right." accessed 25. April 2019. <https://www.unicef.org/uganda/what-we-do/birth-registration>.
- Unicef. 2017b. "Nutrition - Scaling up high impact nutrition interventions." accessed 3. April 2019. <https://www.unicef.org/uganda/what-we-do/nutrition>.
- Unicef. 2018. "Progress for every child country profiles." accessed 3. March 2019. <https://data.unicef.org/resources/progress-every-child-country-profiles/>.
- United Nations. 2015. Resolution adopted by the General Assembly on 25 September 2015.
- United Nations. 2018a. "Least Developed Country Category: Uganda Profile." accessed 27. February 2019. <https://www.un.org/development/desa/dpad/least-developed-country-category-uganda.html>.
- United Nations. 2018b. The Sustainable Development Goals Report 2018. New York.
- United Nations Development Programme. 2005. Human Development Report 2005 - International cooperation at a crossroads: Aid, trade and security in an unequal world. New York, USA.
- United Nations Development Programme. 2017. Uganda's contribution to refugee protection and management. Kampala, Uganda.
- United Nations Development Programme. n.d. "Human Development Index (HDI)." <http://hdr.undp.org/en/content/human-development-index-hdi>.
- United Nations Inter-agency Group for Child Mortality Estimation. 2018a. "Child Mortality Estimates." accessed 9. March 2019. <https://childmortality.org/>.
- United Nations Inter-agency Group for Child Mortality Estimation. 2018b. Levels & Trends in Child Mortality
- Van de Poel, Ellen, Owen O'Donnell, and Eddy Doorslaer. 2009. "What explains the rural-urban gap in infant mortality: Household or community characteristics?" *Demography* 46 (4):827-850. doi: 10.1353/dem.0.0074.
- Verbeek, Marno. 2012. *A guide to modern econometrics - Fourth edition*. West Sussex: John Wiley and Sons Ltd.
- Von Hippel, Paul. 2015. "Linear vs. Logistic Probability Models: Which is Better, and When?", accessed 3. April 2019. <https://statisticalhorizons.com/linear-vs-logistic>.
- Wayland, Joshua. 2013. "A drop in the bucket? The effectiveness of foreign aid in the water, sanitation, and hygiene (wash) sector." Degree of Master of Arts, Faculty of the School of International Service, American University.
- White, Howard. 2007. *Evaluating Aid Impact*. Brighton, UK: United Nations University - World Institute for Development Economics Research.
- Wilkin, Holley. 2014. Uganda. In *Encyclopedia of Health Communications*, edited by Teresa L. Thompson.
- Williams, Victoria. 2015. Foreign aid. In *Encyclopaedia Britannica*.
- Williamson, Claudia R. 2008. "Foreign Aid and Human Development: The Impact of Foreign Aid to the Health Sector." *Southern Economic Journal* 75 (1):188-207.
- Wilson, Sven E. 2011. "Chasing Success: Health Sector Aid and Mortality." *World Development* 39 (11):2032-2043. doi: 10.1016/j.worlddev.2011.07.021.
- Winkleman, Taylor, and Grace Adams. 2017. "An empirical assessment of the relationship between Official Development Aid and child mortality, 2000–2015." *International Journal of Public Health* 62 (2):231-240. doi: 10.1007/s00038-017-0940-2.
- Wooldridge, Jeffrey M. 2016. *Introductory econometrics : a modern approach*. 6th ed. Australia: Cengage Learning.

- World Health Organization. 2013. Study by the World Health Organization on mortality among children under five years of age as a human rights concern.
- World Health Organization. 2014. Preventing diarrhoea through better water, sanitation and hygiene - Exposures and impacts in low- and middle-income countries.
- World Health Organization. 2016. "Uganda key indicators." accessed 18. March 2019. <http://apps.who.int/gho/data/node.cco.ki-UGA?lang=en>.
- World Health Organization. 2018a. "Children: reducing mortality." accessed 6. January 2019. <https://www.who.int/news-room/fact-sheets/detail/children-reducing-mortality>.
- World Health Organization. 2018b. "Country Cooperation Strategy at a glance - Uganda." accessed 11. September 2018. [https://apps.who.int/iris/bitstream/handle/10665/136975/ccsbrief\\_uga\\_en.pdf;jsessionid=5BA6FC83D7049F5B041595768B4864C7?sequence=1](https://apps.who.int/iris/bitstream/handle/10665/136975/ccsbrief_uga_en.pdf;jsessionid=5BA6FC83D7049F5B041595768B4864C7?sequence=1).
- World Health Organization. 2018c. "Global Health Observatory (GHO) data - Infant mortality - Situation and trends." accessed 02.02.19. [https://www.who.int/gho/child\\_health/mortality/neonatal\\_infant\\_text/en/](https://www.who.int/gho/child_health/mortality/neonatal_infant_text/en/).
- World Health Organization. n.d.-a. "Maternal mortality ratio (per 100 000 live births)." <https://www.who.int/healthinfo/statistics/indmaternalmortality/en/>.
- World Health Organization. n.d.-b. "Water sanitation hygiene." accessed 2. May 2019. [https://www.who.int/water\\_sanitation\\_health/monitoring/coverage/monitoring-dwater/en/](https://www.who.int/water_sanitation_health/monitoring/coverage/monitoring-dwater/en/).
- World Health Organization, and Unicef. 2017. Progress on Drinking Water, Sanitation and Hygiene: 2017 Update and SDG Baselines.
- Younger, Stephen D. 1992. "Aid and the Dutch disease: Macroeconomic management when everybody loves you." *World Development* 20 (11):1587-1597.
- Öhler, Hannes, and Peter Nunnenkamp. 2014. "Needs-Based Targeting or Favoritism? The Regional Allocation of Multilateral Aid within Recipient Countries." *Kyklos* 67 (3):420-446. doi: 10.1111/kykl.12061.



## Appendix

### Chapter 4

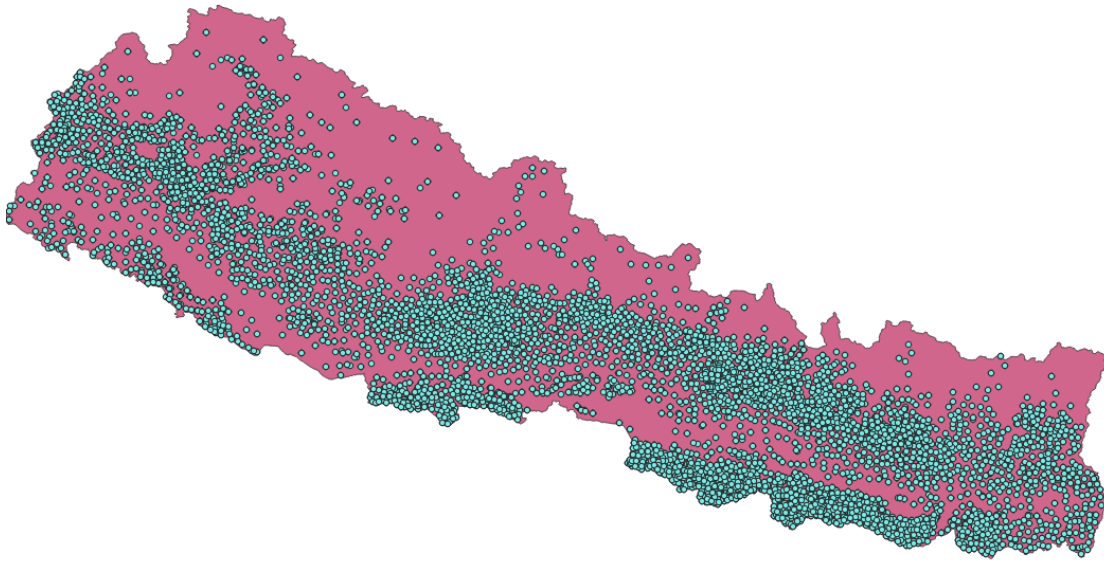


Figure 4.1a Visual representation of all aid projects with precision code 1 and known startdate in Nepal. Total of 15093 projects fall under this category.

### Chapter 5

Variable	VIF	1/VIF
Year	1.30	0.769966
Multiple_birth_dummy	1.01	0.993289
Birth_order_dummy1	9.33	0.107166
Birth_order_dummy2	8.27	0.120979
Birth_order_dummy3	7.16	0.139683
Birth_order_dummy4	6.09	0.164115
Birth_order_dummy5	5.02	0.199034
Birth_order_dummy6	4.09	0.244725
Birth_order_dummy7	3.24	0.308595
Birth_order_dummy8	2.52	0.397541
Birth_order_dummy9	1.94	0.516495
Girl	1.00	0.999855
Active_5km	1.40	0.713902
Inactive_5km	1.14	0.875987
Mean VIF	3.82	

Table 5.1a VIF-scores for the variables

## Chapter 6

### 6.1a Mechanisms at the level of the mother – 5 km

Variables	(1) Bednet for sleeping	(2) Wealth index	(3) Problem distance Health Facility	(4) Literacy	(5) Highest educational level
Active 5 km	0.172*** (0.007)	1.388*** (0.024)	-0.255*** (0.011)	0.536*** (0.016)	0.501*** (0.013)
Inactive 5 km	0.020** (0.008)	0.197*** (0.027)	-0.096*** (0.012)	0.132*** (0.018)	0.168*** (0.014)
Observations	27 442	27 442	27 426	26 780	27 441
R-squared	0.293	0.113	0.088	0.038	0.064
Difference in differences	0.152	1.191	-0.159	0.404	0.333
F test: active- inactive=0	230.45	1265.34	106.29	314.64	374.22
P value	>0.000	>0.000	>0.000	>0.000	>0.000

**Table 6.1a Mechanisms 5 km. All models include the interview-year as a control variable to control for a linear trend.**

### 6.2a Mechanisms at the level of the mother – 15 km

Variables	(1) Bednet for sleeping	(6) Wealth index	(4) Problem distance Health Facility	(2) Literacy	(3) Highest educational level
Active 15 km	0.134*** (0.006)	0.994*** (0.022)	-0.158*** (0.010)	0.414*** (0.014)	0.385*** (0.011)
Inactive 15 km	-0.051*** (0.008)	0.032 (0.027)	0.064*** (0.012)	-0.052*** (0.018)	0.018 (0.014)
Observations	24 935	24 935	24 919	24 292	24 934
R-squared	0.316	0.087	0.081	0.043	0.067
Difference in differences	0.185	0.962	-0.222	0.466	0.368
F test: active- inactive=0	544.71	1207.81	307.52	652.66	677.81
P value	>0.000	>0.000	>0.000	>0.000	>0.000

**Table 6.2a Mechanisms 15 km. All models include the interview-year as a control variable to control for a linear trend.**

### 6.3a Mechanisms at the level of the mother – 20 km

Variables	(1) Bednet for sleeping	(2) Wealth index	(3) Problem distance Health Facility	(4) Literacy	(5) Highest educational level
Active 20 km	0.142*** (0.007)	0.850*** (0.023)	-0.124*** (0.011)	0.358*** (0.015)	0.344*** (0.012)
Inactive 20 km	-0.032*** (0.009)	0.083*** (0.030)	0.085*** (0.014)	-0.074*** (0.019)	0.011 (0.015)
Observations	24 301	24 301	24 285	23 658	24 300
R-squared	0.320	0.064	0.080	0.039	0.062
Difference in differences	0.175	0.766	-0.209	0.432	0.333
F test: active- inactive=0	502.89	774.88	280.84	580.61	568.46
P value	>0.000	>0.000	>0.000	>0.000	>0.000

**Table 6.3a Mechanisms 20 km. All models include the interview-year as a control variable to control for a linear trend.**