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Essays in Development and Environmental Economics

Jeffrey M. Pagel

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PhD candidate:

Jeffrey M. Pagel

Advisors:

Miquel-Àngel Garcia López
Alfonso Herranz Loncán

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Contents

1. Introduction

Fighting poverty and protecting the environment are two of the most urgent challenges facing the international community at the start of the 21^{st} century (United Nations, 2015). One aspect that will be crucial in this challenge is aligning environmental, energy and development policy in order to create a triple dividend between the three policy fields. Additionally, integrating environmental protection policies with poverty reduction strategies is by no means a new concept, but as we continue to think about these challenges, it is important to link environmental and economic components together through a type of development that is economically feasible, socially desirable and environmentally benign.[1] Within each of these challenges lies different possible interventions, but space must be created for public policy to be at the center of these challenges in order to generate the best available evidence and guide our decision making. This dissertation consists of three independent chapters that represent responses to these challenges, and provides empirical evidence that can guide specific policy recommendations in the fields of development economics, and environmental and resource economics.

Universal access to modern energy services is central to the international sustainable development agenda. According to the International Energy Agency (2010, 2017), 1.4 billion people across the world did not have access to electricity, and 2.7 billion people still rely on traditional use of solid biomass. The international development agenda has placed an emphasis on improving access to electricity as well as made large investments in the energy sector throughout developing countries. It is argued that the universalization of access to electric energy in the world is of fundamental importance for the eradication of poverty and the reduction of social inequality (Kaygusuz, 2011). Despite the large investments made in the energy sector to increase rural electrification and the diffusion of modern cooking systems, relatively little is known about the impact such policies have on household well-being (Bonan et al., 2017).

From an individualistic point of view, energy is a material prerequisite to achieving valued capabilities (Nussbaum, 2001). Energy is interconnected with the socio-economic and human development of the individual, and deprivations of energy

[1] Each of these components refer to sustainable development, which can generally be defined as "meeting the needs of the present generation without compromising the needs of future generations."

interact with health and education in different ways to undermine an individual's well-being. In recent years there has been a movement towards multidimensional methodologies built upon the foundations set forth by Alkire and Foster (2007, 2011) and Alkire and Santos (2010) as well as research focused specifically on multidimensional energy poverty (Nussbaumer et al., 2012). Thinking about energy poverty through a multidimensional lens, examines the underlying problems of different types of 'poverties' rather than just poverty, and asks the question of 'poor in what' in addition to 'who is poor'. With the recent movement towards multidimensional analysis, parallel with resources being allocated towards energy programs, understanding how these two areas interact is imperative. Building upon the multidimensional framework set forth by Nussbaumer et al. (2012), the premise of the second chapter of this dissertation is to jointly analyze how multidimensional energy poverty deprivations affect different measures of education in Uganda.

This chapter has three main goals: 1) decompose and quantify the various energy deprivations that individuals suffer from, 2) aggregate the different energy deprivations into an index with contextual weights derived from a Factor Analysis, and 3) use the index to analyze how compounding energy deprivations affect different measures of education and compare the effects of the multidimensional energy poverty index (MEPI) to those of access to electricity.

The first goal builds upon previous work by Nussbaumer et al. (2012) who postulate six energy components: 1) modern cooking fuel, 2) indoor air pollution, 3) access to electricity, 4) household appliance ownership, 5) radio or television, and 6) mobile phone. The sample population is then classified as to whether the respondent has access to electricity or not, and then whether the respondent has achieved other possible energy components within the MEPI. Exploiting the data in this manner demonstrates that access to electricity is unable to capture whether other household energy domains have been achieved.

After motivating the need for the use of a multidimensional framework through descriptive statistics, the study moves to weight each of the energy domains. This is done through a Factor Analysis, which searches for inter-correlations amongst the variables within the index. Using the derived weights, the MEPI is constructed for each individual in the sample.

Last the study applies the MEPI in a regression analysis and compares its effects to that of access to electricity on measures of education. In order to address methodological challenges of attribution, this study draws upon an IV strategy employed by Dinkelman (2011) that uses the land gradient of the community. Where this study differentiates from the previous empirical strategy is it will use the land gradient of rural households. This will be the first time that this IV strategy is employed at the individual/household level.

I find that the MEPI improves upon our understanding as to the effects energy poverty has on measures of education. This is seen in the precision of the estimated coefficients and smaller standard errors as well as the ability of the MEPI to estimate significant results that access to electricity is unable to. The results further demonstrate that there are other important energy mechanisms beyond access to electricity that must be considered within an individual's set of energy capabilities, and this may explain the insignificant or inconsistent findings of previous studies based on simpler indicators (like access to electricity).

Analyzing household energy deprivations from a multidimensional perspective makes several important contributions to the literature on energy poverty. The first is the ability to quantitatively characterize the type of energy poverty an individual suffers from. The methodologies employed in this chapter better illustrate complementary input mechanisms beyond the singular dimension of whether an individual has access to electricity. Furthermore, considering only access to electricity may lead to a misdiagnosis of the true problem, which is that individuals may have access to electricity, but are unable to realize the benefits of the energy through appliances or modern cooking technologies. From a methodological point of view this misdiagnosis may introduce measurement bias into the analysis. The developed MEPI framework attempts to reconcile this problem and expand the literature's ability to measure energy poverty. The second contribution comes from the use of Factor Analysis, which is a model based approach that seeks to reproduce the intercorrelations amongst variables and is focused on explaining the common variance across indicators instead of total variation. This methodology is employed to assign context specific weights to each of the components within the MEPI. This is the first time that energy poverty has been quantitatively characterized in such a manner in order to be used in causal modeling. Additionally, insights gained from the weighting analysis can be used by policy makers to prioritize different energy deprivations. Third a contribution is made through the use of an innovative IV that builds-on the work by Dinkelman (2011), who uses the local land gradient to instrument for access to electricity. This analysis uses the land gradient of the household as an instrument, which provides a more accurate depiction of actual electricity access as the average local land gradient can hide the fact that some households in a community may or may not have electricity.

Chapters 3 and 4 of this dissertation study the interrelated dynamics of development economics, environmental and natural resource economics. In Chapter 3, I focus on how development impacts the environment through the effects that a community-driven development (CDD) program of small-scale infrastructure projects in the Philippines had on forest coverage. In Chapter 4, I analyze the opposite direction by focusing on how a changing environment impacts development.

Specifically, Chapter 4 analyzes the impact of a policy intended to revitalize the mining sector in the Philippines in terms of an unintended increase in malaria cases.

The loss of forest coverage is a global as well as a local and regional environmental concern. Globally deforestation represents around 9 percent of anthropogenic carbon emissions (Le Quéré et al., 2015). Local and regional impacts from deforestation can lead to land degradation such as a reduction in soil fertility, increased runoff into fisheries as well as a loss of biodiversity. Additionally, stemming deforestation in low-income countries is viewed as one of the most cost-effective solutions to reducing global CO_2 emissions (Nabuurs et al., 2007; Stern, 2007).

As developing countries continue to build infrastructure in parallel with their development needs, one challenge to confront is how to meet the development needs in a sustainable manner. One solution could lie in CDD programs, which can best be characterized by the movement of responsibility over resources and planning decisions. This type of program supports a bottom-up approach to development by decentralizing the decision making process to the local level. Where the issue of deforestation and increasing frequency of CDD programs throughout the world come together, is that international donors and multilateral organizations are targeting CDD programs as a strategy for climate change mitigation and adaptation (Arnold et al., 2014).

The objective of Chapter 3 is to examine whether the goals of fighting poverty and protecting the environment are in contradiction by asking whether development aid has unintended environmental effects in regards to deforestation, focusing on a CDD program in the Philippines. This question is derived from several areas. First is in regards to the scarcity of evidence on the environmental impacts of actions designed to reduce poverty, as well as in the opposite direction of the poverty impacts of actions designed to protect the environment (Alpízar and Ferraro, 2020). Second there is surprisingly very little evidence on the impact international aid has on the environment and more specifically forest coverage. Third, even as international donors and multilateral organizations position CDD programs with the parallel strategies of poverty reduction and climate change mitigation and adaptation, little empirical evidence exists on the effects CDD programs have on the environment and forest coverage. This chapter will address each of these areas by providing rigorous empirical evidence of the effects international aid has on deforestation.

In this study, I utilize satellite-generated forest coverage data to analyze the effects development aid has on deforestation through a large-scale CDD program in the Philippines called KALAHI-CIDSS (KC). In order to disentangle this relationship, I exploit the manner in which the CDD program was allocated to municipalities through a regression discontinuity design (RDD) and a randomized control trial (RCT). The former leverages quasi-experimental variation, where the main identifying assumption is that municipalities on either side and close to the eligibility cut-off are systematically similar except that one received the program and the other did not. The later strategy leverages experimental variation between municipalities that were randomly selected via lottery to either be treated by the KC program or remain a part of the control for three years.

I find evidence that indicates the KC program had strong and statistically significant effects on deforestation. Eligible municipalities in the RDD period experienced an average of 236 percent more deforestation and treated municipalities in the RCT period experienced an average of 265 percent more deforestation than the control. In addition, an exploration of underlying mechanisms indicates that the implementation of the KC program led to a stimulation of the economy, which might be the channel through which the program increased deforestation. First I show that the program was successful in one of its stated objectives of poverty reduction, where eligible municipalities at the end of the first wave of the program had a lower level of poverty incidence relative to ineligible municipalities. Second I explore how the program may have affected economic activity by using satellite data of nighttime lights. Eligible municipalities are shown to emit 26 percent more nighttime light relative to ineligible municipalities. Additionally I show that eligible municipalities experienced a corollary increase of inward migration of 22 percent as well as increases in the share of population working in the agriculture, fishing, forestry and manufacturing sectors and a reduction in the transportation, storage and communication sectors.

Then I perform a heterogeneous analysis that investigates specific characteristics of the implemented subprojects. I find that infrastructure projects (including trails, bridges and roads) have the greatest impact on deforestation, followed by those relating to support, education and health facilities. Moreover, an analysis of spillover effects into surrounding municipalities indicates, for each additional neighbor that is treated by the KC program, deforestation increases by approximately 10 percent.

The paper makes several important contributions to the literature and the understanding of the effects development aid has on the environment. First, each of the empirical strategies have the ability to overcome traditional concerns stemming from the non-randomness of aid allocation, in order to uncover a causal estimate of the effects development aid has on deforestation, and more specifically the effect that CDD programs have on deforestation. Second, each of the empirical strategies analyzes the same development program, but from two different time periods in which the Philippines experienced different levels of deforestation. Third is the scale of the program, since this study represents the largest evaluation of the environmental effects that a CDD program has had on deforestation. Additionally the Philippines offers a context that has substantial spatial heterogeneity in terms of economic, social and ecological diversity. Fourth, a rich dataset on subproject characteristics is exploited with information on the type of implemented subproject, the number of household beneficiaries, construction duration and the subproject cost. This information has yet to be exploited for a CDD program and additionally offers a unique dimension to understand how different types of subprojects such as infrastructure, education/health facilities, water/electricity, water protection, and support projects differentially impact the environment. Last, a contribution is made to whether higher levels of poverty lead to more deforestation relative to less poor areas. This refers to the environmental Kuznets curve or the contrasting view of the poverty-environment hypothesis, which remains an open debate in the environmental literature. The latter suggests that as income grows, even at low income levels, the surrounding environmental quality improves, while the former indicates the existence of a non-monotonic relationship where rising living standards first increases pressure on the environment and then later improve them. By exploiting the structure of the RDD, I am able to find limited support for the environmental Kuznets curve.

Chapter 4 focuses on the unintended consequences of changes in development policy. It reverses the previous Chapter's direction of thinking, from how development may impact the environment, to how policy-driven environmental changes may impact development and more specifically health outcomes. In this regard, land transformation and land clearance activities are likely to increase diseases, and roughly one quarter of the global burden of disease can be attributed to environmental changes (Prüss-Üstün et al., 2008).

One disease that is susceptible to such environmental changes is malaria. This is due to the fact that cleared lands are generally more exposed to sunlight and prone to puddle formation with more neutral pH levels that can favor Anopheline larvae development (Patz et al., 2000) as well as a loss of biodiversity can reduce or eliminate species that prey on Anopheline larvae or *Anopheles* mosquitoes (Laporta et al., 2013; Yasuoka and Levins, 2007). Deforestation is one form of land transformation that has been shown to alter the disease ecology of malaria (Berazneva and Byker, 2017; Chakrabarti, 2018; Garg, 2019; Keesing et al., 2010; MacDonald and Mordecai, 2019; Pattanayak and Pfaff, 2009; Tucker et al., 2017). Another form of land transformation that could be potentially linked to the emergence and proliferation of malaria is through mining activities. These have received much less attention in the literature, which has focused on small geographical areas and localized effects of malaria (De Santi et al., 2016; Rozo, 2020; Valle and Lima, 2014) or on a corollary relationship between gold mining and malaria (Barbieri et al., 2005; Caselli and Tesei, 2016; De Santi et al., 2016).

With this in mind, this chapter aims at analyzing whether there is an ecological response from mining activities, by investigating how a change in extractive resource policy in the Philippines led to more cases of malaria. In January 2004, the government of the Philippines launched the Minerals Action Plan (MAP) with the goal of revitalizing the mining sector. As a result, the policy change led to a reduction in the mining permit process between application and the grant of a permit from 3-5 years to 6 months in 2005 (Fong-Sam, 2005).

Using the MAP reform, I exploit two sources of variation in the timing of the MAP reform as well as spatial variation in the distribution of mineral endowments through a difference-in-difference (DID) approach that compares provinces with and without gold deposits before and after the reform. The basic pathway in which gold mining is hypothesized to accelerate the reproductive environment of the *Anopheles* mosquito is through the process of leaving behind slow-moving bodies of water, which happen to be the common location of many gold mines. If the stagnant pools of water are left open, they can provide an ideal breeding site for the *Anopheles* mosquito to reproduce.

I find evidence that is consistent with an ecological response, where the policy change to a more extractive resource position had a statistically significant effect on the incidence of malaria. More specifically, after the MAP reform, provinces with gold deposits had 32 percent more malaria cases relative to provinces without gold deposits. Furthermore, I estimate an event study specification and find that the effects on malaria are persistent 10 years beyond the implementation of the policy. In order to reinforce the empirical strategy, I perform several falsification tests to show that: 1) the effect is specific to the disease ecology of malaria and not related to other diseases, 2) the effect is specific to gold mining and not related to other types of minerals and 3) a permutation inference exercise indicates that the causal effects are not likely to be randomly generated. Last, I investigate other possible mechanisms such as migration or deforestation and find that neither can explain the increase in malaria.

There are three main contributions this chapter intends to make. First, it moves beyond corollary results and provides causal estimates by exploiting the timing of the reform as well as the spatial distribution of geological endowments. Second, it provides the first nation-wide causal estimates of the impact gold mining has on the incidence of malaria. Third, it analyzes a policy that encouraged the expansion of the mining sector. This differentiates from the Rozo (2020) context in Colombia, where the bulk of the argument is placed on the fact that illegal gold miners do not comply with mining regulations and have limited knowledge on measures needed to protect themselves from malaria or safety measures to prevent the reproduction of malaria. Evidence from this chapter indicates that it is not necessarily a legal versus illegal issue, as a legal expansion of the resource extraction sector through the MAP reform also led to an increase in the incidence of malaria.

Finally, Chapter 5 provides concluding remarks. First, it summarizes the main findings from each of the chapters. Then it discusses policy implications that can guide specific policy recommendations in the fields of development and environmental economics.

2. Multidimensional Energy Poverty: A Quasi-experimental Approach Applied to Education

2.1. Multidimensional energy poverty and education

One manifestation of the space created by poverty is the deprivation of energy. From an individualistic point of view, energy is a material prerequisite to achieving valued capabilities (Nussbaum, 2001), and it is argued that the universalization of access to electric energy in the world is of fundamental importance for the eradication of poverty and the reduction of social inequality (Kaygusuz, 2011). From a societal point of view, energy poverty is 'fundamentally a complex problem of distributive injustices' (Walker and Day, 2012, p. 69), and is underpinned by further injustices in recognition and policy making procedures. However, Bonan et al. (2017) state that despite the great effort and investment in the energy sector to increase rural electrification and the diffusion of modern cooking systems, relatively little is known about the impact of such policies on household well-being. Furthermore, the justification of large public programs to improve access to modern energy has often relied on supposed benefits and transformative effects on households' health, education, labor market outcomes and ultimately poverty level, but there is limited evidence to substantiate such impacts, given the methodological challenges of attribution (Bonan et al., 2017). The contradiction between the argument giving fundamental importance to modern energy and the lack of evidence supporting such policies provides the central motivation of the paper.

Universal access to modern energy services is central to the international sustainable development agenda, and strongly cross-cutting with other sustainable development objectives and goals (McCollum et al., 2018). According to the International Energy Agency (2017), 1.4 billion people across the world do not have access to electricity, while 2.7 billion people still rely on the traditional use of solid biomass. If the current trends continue, more people will be without modern energy access in 2030 than today (International Energy Agency, 2010).

Energy is interconnected with the socio-economic and human development of the individual, and the true nature of poverty manifests itself when individuals are deprived on multiple dimensions of human well-being. Measuring the effects of energy on household well-being has been proposed to varying degrees throughout the development literature, but recent empirical studies have provided inconclusive evidence on the impact energy poverty has on well-being and the mechanisms involved. While the evidence of electrification's impact is growing, there is much less work on the mechanisms through which electrification may improve well-being or drive reductions in poverty (K. Lee et al., 2017, 2020).

The reality is that poor households can suffer from energy deprivations beyond access to electricity, and it is important to understand how compounding energy deprivations may affect the well-being of individuals. As an applied example, educational outcomes will be the main focus of this study, as energy is an essential component to the basic needs of everyday life, and is a prerequisite for many educational inputs. Increasing modern energy services can enable inputs needed for education such as providing lighting for studying, narrowing the digital divide through television and information communication technologies, or the utilization of modern appliances in freeing up time from daily drudgeries.

This study mainly contributes to the ongoing debate of rural economics and electrification in low-income regions, and further adds to the human development literature by moving beyond correlations towards causation to better understand the mechanisms of energy. Electricity is an enabling technology, and it is possible that the impacts previous studies ascertain are actually being driven by the availability of unobserved complementary inputs (K. Lee et al., 2017). The main contribution of the paper addresses this point by quantitatively characterizing the type of energy poverty an individual suffers from, to better illustrate the complementary input mechanisms and analyze how compounding energy deprivations affect individual well-being. More specifically, energy poverty scores are generated for each individual to test how multidimensional energy poverty affects different measures of education. A favorable characteristic of the developed framework of multidimensional energy poverty is the ability to account for the intensity and pervasiveness of various energy deprivations. To the best of our knowledge, this is the first empirical evidence through quasi-experimental techniques as to the effects multidimensional energy poverty has on educational outcomes in a developing country. This methodological framework will be tested alongside access to electricity to analyze whether a multidimensional methodology provides a better or complementary measure of estimation for energy poverty. The second contribution this study makes, is by addressing the methodological challenges of attribution. Quasi-experimental techniques in the form of an innovative instrumental variable (IV) strategy is applied to cross-sectional data for rural households in Uganda. Particularly, this study will draw upon an IV strategy employed by Dinkelman (2011) on labor and employment, that uses the average land gradient of the community to measure the effects that access to electricity has on individual well-being. Where this study differentiates from the previous empirical strategy, is it will be the first time that this IV strategy will be employed at the individual/household level.

This study finds that a multidimensional energy poverty measure improves upon our previous understanding as to the effects energy has on measures of education. This is seen in the precision of the estimated coefficients and the smaller standard errors, and the ability of the multidimensional energy poverty index (MEPI) to estimate significant results that access to electricity is unable to. Empirical results indicate that a one standard deviation increase in an individual having access to electricity leads to approximately 2.2 percent of a standard deviation more spending on education, whereas a one standard deviation increase in the MEPI leads to an increase in spending on a child's education by 1.8 percent of a standard deviation. When looking at whether students are ahead/behind in schooling or the number of grades a student attends, the MEPI is able to estimate a statistically significant relationship whereas access to electricity is unable to. The estimated coefficients on the MEPI indicate that less energy poor individuals are ahead in schooling relative to their supposed age per grade. Furthermore, as an individual becomes less multidimensionally energy poor, on average they are likely to go on to attend more grades. Each of these results indicate that there are further gains from energy provisions beyond simply obtaining access to electricity, and may explain the previous literature's inconsistent findings.

The paper is structured as follows. Section 2.2 reviews the literature on the effects different energy deprivations have on measures of education. Then Section 2.3 provides the context of this research through a summary of the geographical characteristics, the energy and education sectors in Uganda, and describes the dataset to be employed in the empirical analysis. Section 2.4 broadly outlines previous measurements of energy poverty, how multidimensional methodologies can improve our understanding of energy poverty and performs a factor analysis (FA) to derive individual specific energy poverty scores. Section 2.5 describes the empirical strategy and postulates the two empirical models to be estimated. Then, Section 2.6 presents the results, Section 2.7 and Section 2.8 provide a discussion and concluding remarks, respectively.

2.2. Literature review

The number of studies attempting to estimate a causal impact of electrification on household well-being has increased in the last decade, but the literature, particularly in Africa, is still fairly limited and not entirely consistent (Bos et al., 2018; Chaplin et al., 2017). Focusing specifically on education, prior research has provided mixed results when attempting to disentangle the mechanisms linking electricity access to different education outcomes. Early studies found access to electricity has a beneficial impact on education (Anderson et al., 1999; Foley, 1992; Wilkins, 2002), but Zomers (1991) presents a series of studies with conflicting results. Recent empirical literature has yet to find consensus on the effects energy has on various measures of education. With regards to the impact on enrollment, M. Barron and Torero (2014) find no effect, and Van de Walle et al. (2015) find a positive effect on enrollment and years of schooling only for girls in India. Other studies confirm such results by Van de Walle et al. (2015), but for both boys and girls (Arraiz and Calero, 2015; Khandker et al., 2012, 2013; Lipscomb et al., 2013). Additionally, Dasso et al. (2015) find access to electricity has no effect on boys' educational outcomes, but increases female school enrollment as well as money spent on girls' education in Peru. In a review of impact evaluation studies, Jimenez (2017, p. 8) generally finds positive effects on enrollment, but states that "the estimates vary widely, and are in many cases nonsignificant or even negative". For other measures of education, Khandker et al. (2009) show in the case of Bangladesh that the duration of school attendance by children is correlated with the duration of access to electricity, and Barnes et al. (2002) indicate that children from homes with access to electricity on average attend school for two years longer than those from homes without access to electricity. However, no effects on enrollment, and negative effects on attendance and school performance are found in other studies on India, Honduras and Uganda, respectively (Burlig and Preonas, 2016; Furukawa, 2014; Squires, 2015).[1] Counterintuitively, Squires (2015) finds in Nicaragua that access to electricity reduces educational attainment. The author provides convincing evidence by matching individual level data with community level electrification dates in order to show that the reduction in education is accompanied by an increase in childhood employment and further demonstrates that improved labor market opportunities due to electricity access led to the increased dropout rates. Other conflicting evidence comes from M. Barron and Torero (2014) and Khandker et al. (2012) who find an increase in hours spent

[1] Furukawa (2014) randomize the treatment of solar lamps to enhance children's learning outcomes for 204 participants in Uganda and find the intervention had negative effects by lowering test scores by 5 points, but increased reported study time by 30 minutes. The data I employ does not include individual test scores, or time spent studying, so a direct comparison of the results is not possible.

studying, while Bensch et al. (2011) find no effect. Chaplin et al. (2017) find connecting to the grid increases the time children spend studying by 12 minutes per day, but also increases TV watching by 73 minutes per day. K. Lee et al. (2020) randomize the expansion of the electric grid with the intervention being a subsidized opportunity to connect to the grid in rural Kenya. Out of the education outcomes, the authors find no meaningful effect on average scores of English and Math tests administered to adolescent children.

All of the previous studies focus solely on access to electricity, which historically has been characterized as a binary variable where a household is either, "on grid" or "off grid", suggesting that they are too far to connect to the national gird (K. Lee et al., 2017). Although this is an important energy component to satisfy for human development, individuals with access to electricity may not be able to take full advantage of it through the use of appliances or may be unable to switch from biomass to modern cooking fuels. In this regard, the development literature has highlighted the importance of other individual components of energy poverty and the limitations or reliance on access to electricity. As Bonan et al. (2017, p. 496) state "from a household perspective, accessible energy does not automatically mean actual access". Later on, descriptive quantitative evidence will be presented that exemplifies this statement, by demonstrating that households who have achieved electricity access still suffer in high proportions from other forms of energy deprivations, such as a reliance on biomass, indoor air pollution, or a lack of household appliance ownership. Thus, relying on a singular dimension such as access to electricity is unable to provide insight as to what energy dimensions the household is poor from and how each dimension contributes to the well-being of the individual. For example, access to electricity is unable to distinguish whether negative well-being outcomes are derived from a household cooking with biomass – which diverts children away from schooling, exposure to hazardous pollutants from indoor air pollution, or the inability to realize the various benefits from refrigeration, entertainment and communication. This limitation reduces the literature's understanding as to the mechanisms electrification may be working through to affect individual well-being.

Research on the mechanisms through which electrification may improve well-being has indicated that other household energy components, such as biomass usage, indoor air pollution, appliance ownership, entertainment and communication may play a more integral part, but empirical evidence is limited. M. Barron and Torero (2017) claim to provide the first empirical evidence that exploits a dataset on minute-by-minute fine particulate matter concentrations to show that household electrification leads to direct and substantial welfare improvements via reductions in indoor air pollution, and justify the finding through the substitution away from bio-fuels towards more traditional sources.[2] This substitution is important not only for health reasons but also because households who rely on traditional fuels can divert children away from school attendance and homework into collecting firewood and other time-consuming manual tasks (Takada and Fracchia, 2007). Furthermore, Gonzalez-Eiras and Rossi (2007) find limited evidence that the introduction of refrigerators on children's health is through better nutrition and less food poisoning.

Other energy components that have received limited attention are the effects from appliances, television/radio and communication technologies. The acquisition of electrical appliances is suggested as one possible mechanism through which electrification may improve well-being (Dinkelman, 2011). The literature also indicates that, after lighting, the first appliance bought by households are television sets (Bernard, 2010). In general, electrified households with access to television/radio and communication may consume more media leading to a greater knowledge of current affairs or changes in social and political ideas. The television has other benefits such as increased awareness about news, politics, birth control and aspirations, and opens the door to increased access to information and political empowerment (M. Barron and Torero, 2014). Daka and Ballet (2011) explain that exposure to radio and television make it easier to understand the languages used in the programs, but on the other side, time spent in front of the television reduces the time spent studying. Nieuwenhout et al. (2000) also found that access to electricity decreased time spent on studies in Tunisia in favor of time spent watching TV. Communication technologies can also have benefits on educational outcomes through the internet. Valer et al. (2014) show that access to electricity improved education outcomes through prolonged hours of school and access to internet. Last, mobile phones allow for greater participation in the market place through mobile banking and money transfers, and permit a greater level of access to information overall (Burrell and Matovu, 2008).

Deprivations of energy may interact with education in different ways to undermine an individual's well-being. Each of the previous mechanisms present a possible channel which can affect the educational outcomes of an individual. The literature indicates that there is a reliance on measuring energy poverty with access to electricity, and very limited research accounting for other energy mechanisms a household may be poor from. In this context, the main objective of this paper is to simultaneously account for various energy mechanisms and understand how overlapping energy deprivations affect measures of education.

[2]Even though the health effects stemming from indoor air pollution have been well documented, several studies show low demand for and usage for nontraditional cookstoves (Hanna et al., 2016; Mobarak et al., 2012).

2.3. Context and data

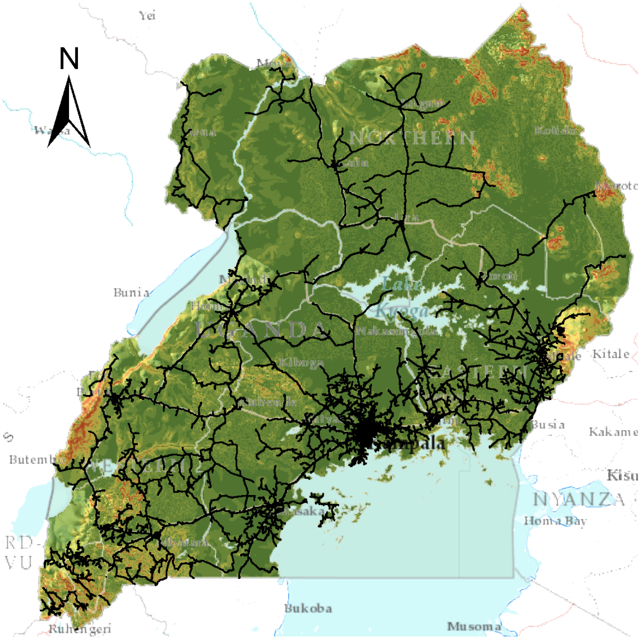
This paper analyzes the effect of multidimensional energy poverty on education in the case of Uganda between 2009 and 2014. The country provides an interesting case study because a high percentage of population still lives in rural areas, where energy deprivation may be more serious. Uganda's demographic density is relatively high compared to other African nations (The World Factbook – Central Intelligence Agency), with much of the population situated in the central and southern parts of the country. The largest cities include Kampala, Jinja, Mbale, Masaka, Entebbe, and Gulu, which all reside in the south except for Gulu. While much of the Ugandan population remains situated in rural areas, about one-sixth of the total population resides in urban areas, and furthermore about one-fourth of the total urban population lives in Kampala. In terms of poverty, Uganda has experienced significant reductions from 56.4 percent in 1992/93 to 19.7 percent in 2012/13 (Ministry of Finance, Planning and Economic Development (MFPED), 2014).

2.3.1. Electricity sector

In Sub-Saharan Africa as a whole, only 38 percent of the population had access to electricity in 2014, a modest increase from 25 percent in 1990 (World Bank, 2016). Within Uganda there have been several reforms aimed at transforming the energy sector since the establishment of the 1999 Electricity Act. In 2002, the Government of Uganda passed a comprehensive policy aimed at meeting the energy needs of Uganda's population for social and economic development in an environmentally sustainable manner (The Republic of Uganda Ministry of Energy and Mineral Development - Rural Electrification Agency, 2012). The Uganda national development plan targets 30 percent grid access by 2020 and 80 percent by 2040, and further increasing generation capacity from 825 MW in 2012 to 2,500 in 2020 and to 41,738 by 2040. In 2013 electricity access in Uganda, defined as access to grid services, was estimated at approximately 15 percent nationally, which translated to 55 percent in urban areas and 7 percent in rural areas (Uganda Bureau of Statistics (UBOS), 2013). Karhammar et al. (2006) estimated that 72 percent of total grid-supplied electricity was consumed by 12 percent of the domestic population concentrated in Kampala metropolitan area and nearby towns of Entebbe and Jinja. The total number of electricity grid customers is growing rapidly at an annual growth rate of 20 percent with an average of 125,000 additional customers per year (Heteu, 2015). Low population densities in the rural areas lead to low access rates due to the high cost of electrification, and even areas where electricity infrastructure is in place suffer from low connection rates, largely because of high connection costs.

Karhammar et al. (2006) estimated the cost of extending electricity lines at $8,000 or more per connection in rural areas of Uganda. Figure 2.1 displays a map of the network of electrical distribution lines as of 2016.

Figure 2.1.: Network of electrical distribution lines



Notes: This figure presents a map of the network of electrical distribution lines as of 2016 throughout Uganda. *Source*: Author's own calculations.

2.3.2. Education sector

As for the educational sector, the system has been in place since the 1960's and has gone through remarkable changes since the Universal Education initiative started in 1997. More schools, institutions, colleges and universities have been established, and the Uganda Investment Authority (2011) claimed that primary school enrollment more than doubled from 3.5 million in 1997 to over 8 million at the end of 2010. The educational system consists of seven years of primary education followed by four years of lower secondary education and two years of upper secondary education. According to the Education Policy and Data Center (2019), the official age of students beginning primary school is 6, and 13 for secondary school, and students can end upper secondary school at the age of 18. However, according to Liang (2002) these official entry ages are "targets", as the de facto starting ages are claimed to be higher. Over the sample period of this study from 2009 – 2014, enrollment in primary education averaged around 8,314,187 students per year, while enrollment in secondary education averaged 1,280,621 students (Uganda Ministry of Education and Sports, 2016). Within primary education over the same period, the percentage of girls to total enrollment averaged around 50 percent, while in secondary education it averaged about 47 percent (Uganda Ministry of Education and Sports, 2016).

2.3.3. Database

The Living Standards Measurement Study dataset to be employed in this study comes from the Uganda Bureau of Statistics (UBOS) – Government of Uganda and was extracted from the World Bank Central Microdata Catalog. Micro-data provide a nationally representative household sample from Uganda, which is intended to track and re-interview 3,123 households through four survey waves 2009/10, 2010/11, 2011/12, and 2013/14, and a control survey performed in 2005/06. The specific objectives of the survey are to provide required information for the monitoring of different development objectives, and provide high quality data on income dynamics and consumption expenditure estimates to monitor poverty. Table A.3 in the Appendix provides the summary statistics for each of the variables used in the analysis. Data is provided on various outcomes of interest that have been used in previous literature on education such as enrollment, the grade or class the respondent is currently attending, schooling years, or amount of money spent on education. The main interest of this empirical study is with the rural areas, which make up over 75 percent of the sample population in each time period.[3] The dataset also provides detailed geo-data for each household and location information at the regional, and district level. Land gradient data, which is the main instrumental variable to be used in the study, comes from the U.S. Geological Survey by Verdin et al. (2007), which provides a global topographical dataset of land gradient that was remotely-sensed as part of the Shuttle Radar Topography Mission (SRTM). The land gradient is represented as a percentage and aggregated at the 1km block level.

2.4. Measurement of energy poverty

This section briefly outlines previous measurements of energy poverty, then builds an argument as to how a multidimensional methodology improves our understanding of energy poverty, and lastly performs a FA to derive energy deprivation coefficients to be used in the empirical analysis. Throughout the past decade, measurements of energy poverty have used the following indicators: electrification rate, ratio

[3] Studying the energy sector in urban areas presents a particular challenge, because theft and illegal use remain a major problem, permitted by insufficient enforcement of rules and regulations (Crousillat et al., 2010).

of energy cost to income, expenditures on energy as a proportion of household expenditures and consumption based measures such as an energy poverty line and average amount of energy being consumed. Electrification rate is a widely used binary outcome of energy poverty, which measures the percentage of households with access to electricity. An issue with this measure is the inability to depict whether the household has the ability to harness the energy and realize the benefits of electricity through appliances. Pagel (2019) presents descriptive quantitative evidence for Latin American households that exploits this issue on the need to categorize energy deprivations based on (1) access/ability, (2) access/no ability, (3) no access/ability, and (4) no access/no ability.[4] The analysis demonstrates that large shares of the sample population reside in the categories of (1), (2) and (4). If access to electricity is employed, the analysis will group categories (1), (2) together, and categories (3), (4) together, leading to a misdiagnosis of the underlying problem. For example, large portions of Haiti's sample population are found to suffer from joint deprivations in access to electricity and the ability to harness it, Nicaragua has large portions of the sample population who have access to electricity, but suffer from an inability to harness it, while Colombia is found to have a large portion of the population with access and ability, roughly a quarter of the sample population with access but no ability, and very few with no access and no ability (Pagel, 2019).

Expenditure measures such as ratio of energy cost to income or expenditures on energy as a proportion of household expenditures may provide an ambiguous representation as to whether a high or low ratio depicts an energy poor household. For example, a high ratio may be the result from a low income level (general poverty) or it may be low due to a household's reliance on bio-fuels, which may not be picked up by monetary measures. Households who rely on bio-fuels for cooking may have a near zero expenditure on energy in real terms, but the real cost is in the time spent collecting the fuels. Fuelwood collection is a time-intensive activity, especially for women and school-aged children, that detracts from more beneficial activities (Barnes, Toman, et al., 2006; Saghir, 2005). Thus, high and low ratios of energy expenditure measures are unable to distinguish energy poor households from non-energy poor ones. Consumption based measures such as an energy poverty line (Barnes et al., 2011; Khandker et al., 2012) or the average amount of energy being consumed by households identified as living below the national general poverty line (V. Foster et al., 2000), suffer from similar issues as previously described. Inherently created by consumption measures, is a binary division between households who can consume energy, relative to households with access to electricity but no ability to harness the energy, combined with households with no access and no ability to

[4] Pagel (2019) defines access to electricity as one if the household has access and zero otherwise, and ability is defined as one if the household has a refrigerator or zero otherwise.

realize energy. Each of these groups suffer from very distinct consumption issues and grouping these categories together can lead to biased results. Consumption based measures are unable to depict the mechanisms driving consumption, and furthermore are unable to distinguish the energy services achieved between households with low, medium and high consumption levels. Finally, a general poverty line as defined by income may further neglect portions of the sample. Barnes et al. (2011) find that the income poor are likely to be energy poor, but not all energy poor are income poor.

2.4.1. Why MEPI?

The previous measures of energy poverty can be considered important components within a household's overall energy needs and can provide critical insight into specific types of energy poverties, but they are unable to account for the various overlapping energy deprivations a household may experience. Within the past few years there has been a movement from the use of single indicators to multidimensional methodologies built upon the foundations set forth by Alkire and Foster (2007, 2011) and Alkire and Santos (2010). Alkire and Santos (2010) developed the Multidimensional Poverty Index (MPI), which measures and captures such multidimensionality by including health (nutrition and child mortality), education (years of schooling and school attendance) and living conditions (cooking fuel, sanitation, water, electricity, floor and assets). Furthermore, the authors find that scrutinizing joint deprivations not only reveals the character of poverty, but also improves the accuracy of the measure, by diminishing its sensitivity to potential inaccuracies in any single indicator. In the case of energy poverty, energy is a necessary input to each of the dimensions in the poverty index and a fundamental component stimulating the capabilities of individuals. In order to capture the different energy deprivations a household may experience, the MEPI as seen in Table 2.1, was developed by Nussbaumer et al. (2012), and provides a framework to understanding multidimensional energy poverty by postulating six energy deprivations within five household energy dimensions.[5] Rethinking energy poverty in a multidimensional approach allows for the inclusion of different possible deprivations individuals may suffer from and enables the ability to understand energy poverty as a whole.

Much of the attention in development policy is focused on expanding access to electricity, but understanding how the various mechanisms within multidimensional energy poverty work is important. Multidimensionality reflects the possible overlapping deprivations households may experience by encompassing multiple essential

[5]The original MEPI includes telephone land lines and mobile phones in the communication dimension. The data to be employed later does not have information on household telephone land lines, and from now on, the communication dimension will only consider mobile phone.

Table 2.1.: Dimensions of energy poverty

1. Modern Cooking Fuel
   - LPG, electricity, kerosene, or solar
2. Indoor Air Pollution
   - Use of biomass fuel (firewood, crop residue, dung or charcoal) and no chimney
3. Access to electricity
4. Household appliance ownership
   - Electric iron, refrigerator, etc.
5. Radio OR television
6. Mobile phone

Notes: This table presents the six different dimensions of energy poverty as defined by Nussbaumer et al. (2012).

energy services needed for household development, from the type of energy being used for cooking to whether the household has the ability to realize energy through appliances, communication, and entertainment.[6] Increasing modern energy services to the poor is essential, and each of these dimensions represent a possible mechanism in which energy deprivations may affect different forms of household well-being. Thinking about energy poverty through a multidimensional lens, examines the underlying problems of different types of 'poverties' rather than just poverty, and asks the question of 'poor in what' in addition to 'who is poor'.

Next, an analysis is performed to provide descriptive quantitative evidence and further motivate the discussion of whether access to electricity provides a complete depiction of energy poverty or not. Table 2.2 first classifies the sample population as to whether the respondent has electricity or not, then as to whether the respondent has 'achieved' other possible energy deprivations within the MEPI. Exploiting the variation of the data in this way improves our understanding of household energy deprivations, by demonstrating that access to electricity is unable to capture specific household energy deprivations. Analyzing the data in this descriptive method

[6]Modern cooking fuel is defined as one if the respondent uses LPG, electricity, kerosene, or solar energy for cooking, and zero if the respondent uses firewood, crop residue, dung or charcoal. Indoor air pollution is defined as one if the household doesn't have a chimney and the fuel the respondent most often uses for cooking is biomass, efficient wood burning, charcoal, other biomass burning, or open fire. Indoor air pollution is coded as zero if there is a chimney present (regardless of the fuel type for cooking), or they use electric, LPG, or kerosene for cooking.

illustrates that 76.9 percent of the sample population who have electricity access, still rely on biomass for cooking. Furthermore, 89.2 percent of the sample with electricity, suffer from indoor air pollution. This echoes evidence by Hanna and Oliva (2015) through a randomized asset transfer program in West Bengal India, that electricity used for lighting increased with a change in economic status, but there was no observable shift toward better stove technologies, e.g. kerosene, electricity, or LPG. Also, the authors find an increase in cow dung as the primary stove fuel, and a corresponding decrease in wood and non-forest timber products. Obtaining electricity is not itself a sufficient condition to relieve individuals from other energy deprivation burdens that may occur in the household. This is illustrated by a large portion of the sample population's inability to harness energy through the use of household appliances, where 50.4 percent of the sample population with electricity do not own a household appliance. Representing the data in this manner further demonstrates that the reliance on the binary measurement of access to electricity disregards other energy facets that are essential to the development of the individual and household.

2.4.2. Factor analysis

Now that the study has descriptively presented the need to account for overlapping energy deprivations, this section will move to operationalize the MEPI in order to empirically test the indicator's ability at estimating the effects of energy poverty. In order to derive context specific deprivation weights for each of the six dimensions, a FA is performed.[7] FA seeks to reproduce the inter-correlations among variables in which the factors represent a common variance of variables, excluding unique variance, and is capable of detecting data structures or causal modeling. This method is preferred for this analysis, as it is model based, and is focused on explaining the common variance across indicators instead of the total variation (Alkire et al., 2015). Scoring coefficients are derived from the FA for each of the parameters in the MEPI, and then normalized so that the MEPI takes on values which sum to one (see Table 2.3).[8] This is done in order to compare the scoring coefficients with the original weights applied to the MEPI by Nussbaumer et al. (2012), as well as to ease the interpretation in the empirical section.

[7]A FA is performed to avoid the general weighting scheme applied by Nussbaumer et al. (2012), who assign relative weights to the various dimensions. The authors recognize the arbitrary nature of the processes and stress the value-laden nature of weighting structures that ought to be adapted to the specificities of the analyses.

[8]The normalized scoring coefficients are computed as: one divided by the sum of the original scoring coefficients (1.24101) derived in the FA, which equals 0.8058. Then, 0.8058 is multiplied by each of the scoring coefficients to derive the new normalized scoring coefficients.

Table 2.2.: Energy deprivations as a percentage of electricity access

Electricity	Energy Deprivation		Sample Size
	Modern Cooking Fuel		
	Yes	No	
No	1.9%	98.1%	41,629
Yes	23.1%	76.9%	1,866
	Indoor Air Pollution		
	Yes	No	
No	95.6%	4.4%	41,881
Yes	89.2%	10.8%	1,891
	Household appliance ownership		
	Yes	No	
No	6.4%	93.6%	42,023
Yes	49.6%	50.4%	1,884
	Radio or television		
	Yes	No	
No	67.1%	32.9%	42,038
Yes	94.4%	5.6%	1,884
	Mobile phone		
	Yes	No	
No	56.3%	43.7%	42,023
Yes	95.8%	4.2%	1,884

Notes: This table presents the different dimensions of energy poverty as a percentage of access to electricity. Access to electricity is first classified as yes/no in the left column. Then the table classifies each of the energy dimensions as yes/no given an individual's response to whether they have access to electricity. *Source*: Author's own calculations.

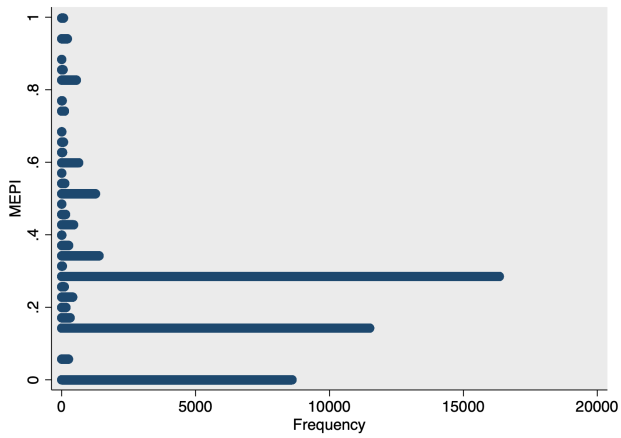
Table 2.3.: Factor analysis scoring coefficients

Variable	Normalized Scoring Coefficient
Modern Cooking Fuel	0.14
No Indoor Air Pollution	0.05
Electricity access	0.31
Household appliance ownership	0.22
Radio or television	0.13
Mobile phone	0.15

Notes: This table presents the scoring coefficients from the factor analysis. Scoring coefficients are first derived for each of the parameters in the MEPI, and then normalized so that the MEPI takes on values which sum to one. *Source*: Author's own calculations.

One of the main assumptions of the FA is that several of the observed indicators depend on the same latent variable structure, and the underlying variable of the MEPI is argued to be electricity. Electricity access is derived to have the highest scoring coefficient confirming the initial expectation of the importance of electricity access in the underlying latent structure of the MEPI. Additionally, the weights derived for this particular dataset in the context of Uganda, differentiate from the arbitrary weighting scheme applied by Nussbaumer et al. (2012). In their work, modern cooking fuel, indoor air pollution, and electricity access are all given a weight of 0.2, while household appliance ownership, radio/television and land line/mobile phone are given a weight of 0.13. Using the FA to derive context specific weights provides a more prescriptive approach to the data, and demonstrates that the general weighting scheme over/under estimates each of the variables.

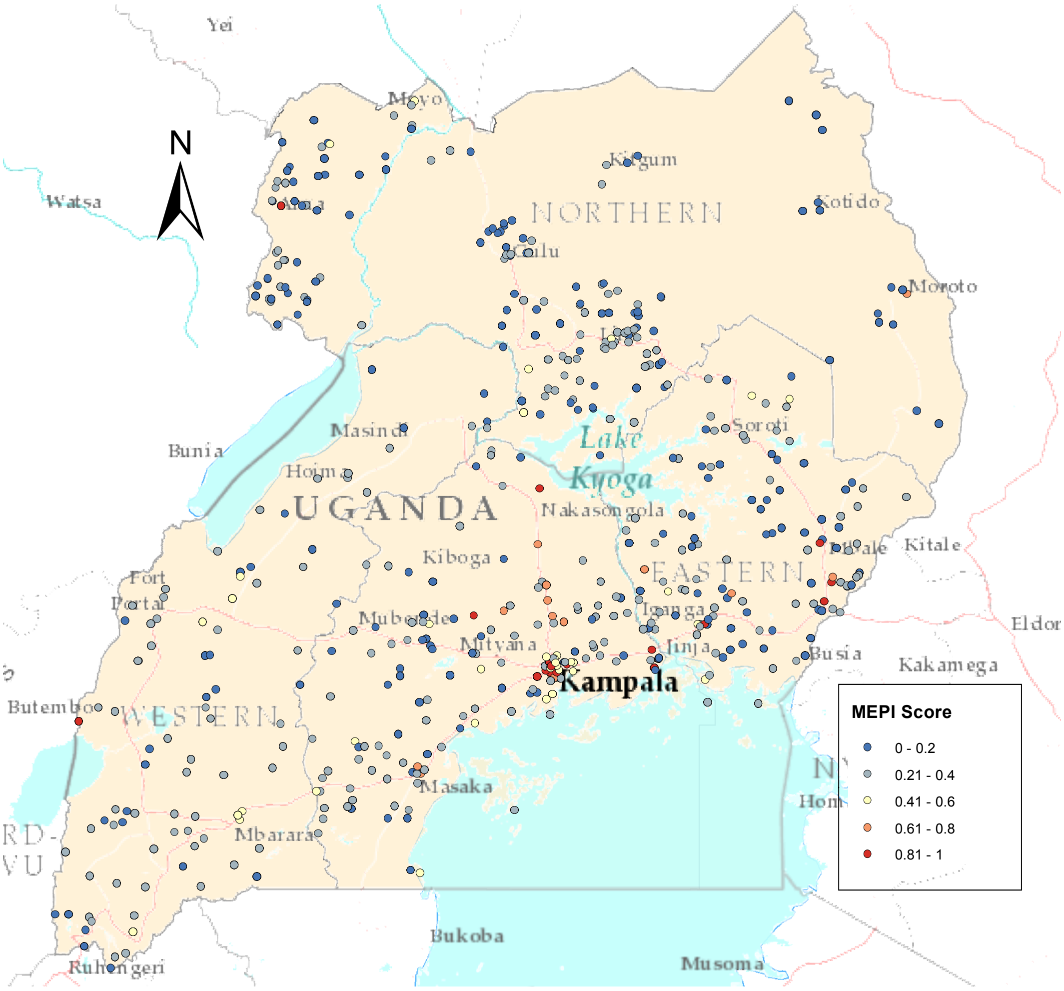
Figure 2.2.: Individual-specific multidimensional energy poverty scores



Notes: This figure presents the distribution of individual-specific MEPI scores. Individuals with energy poverty scores close to zero are considered to be in absolute energy poverty, while individuals close to one represent the non-energy poor. *Source*: Author's own calculations.

Next, the normalized scoring coefficients are multiplied by one if the energy dimension has been achieved, and by zero otherwise, to create a column vector $MEPI_{i,h,t}$. This creates an individual-specific measure of energy deprivation counts, where the i^{th} entry represents a sum of weighted deprivations suffered by individual i, in household h, at time t. Individuals with energy poverty scores closer to zero are considered to be in absolute energy poverty, while individuals close to one represent the non-energy poor. Figure 2.2 shows that much of the sample population resides in the lower ends of the distribution, signifying that Uganda suffers from high levels of multidimensional energy poverty. Furthermore, Figure 2.3 displays rural individuals by quintile MEPI scores across Uganda, and there does not appear to be any sorting or spatial pattern, besides the individuals located around Kampala who appear to be less energy poor.[9] In the next section, two empirical strategies are outlined that will exploit variation from access to electricity and the MEPI in order to estimate an effect on measures of education.

Figure 2.3.: Individual-specific multidimensional energy poverty scores



Notes: This figure presents a map of individual-specific MEPI scores. Individuals with energy poverty scores close to zero are considered to be in absolute energy poverty, while individuals close to one represent the non-energy poor. *Source*: Author's own calculations.

[9]The plotted observations in Figure 2.3 are based on the survey's designation of the household being located in either an urban or rural setting. As for why data points that are designated to be rural appear to be inside Kampala, there are two possible explanations. The geo-locations of households for urban areas are offset by 0 – 2 km, while for rural areas they are offset by 0 – 5 km. An additional 0 – 10 km offset for 1 percent of rural clusters, effectively increases the known range for all rural points to 10 km while introducing only a small amount of noise (Uganda Bureau of Statistics (UBOS), 2010). Last, when zooming in on the map, the data points move further outside the city than can be seen from the entire view of the country map.

2.5. Empirical strategies

Empirical studies in the development literature have provided inconclusive or mixed evidence of electricity's effects on measures of education. Recently, more rigorous evaluation methods have been employed to help mitigate the risks of selection bias through randomized encouragement designs, instrumental variables, and matching techniques. However, the number of studies is still fairly limited (Bos et al., 2018). Previous IVs proposed throughout the literature have often relied on geographic variables, used as a source of exogenous variation to identify household level impacts of electrification. Duflo and Pande (2007) interact the local river gradient with predicted district level dam construction, while Lipscomb et al. (2013) use the time path of estimated electricity network expansion costs. Other proposed IVs include Chakravorty et al. (2014) use of the density of transmission lines in a district, and Van de Walle et al. (2013, 2015) use of straight line distance to nearest power plant, but the problem of endogeneity can be argued to still exist as the placement of transmission lines, and power plant placement are endogenously chosen. Dinkelman (2011) uses local land gradient as an instrument to understand the effects electricity has on employment and labor supply (see also Grogan and Sadanand, 2013).

Energy infrastructure projects are typically large-scale investments and the allocation of funds to regions, groups or people are likely to be correlated with economic outcomes. This complicates the problem of disentangling the impact of electrification on observed and unobserved factors that influence development. Taking inspiration from Dinkelman (2011), a similar IV strategy is proposed here, but using the land gradient at the household level. Dinkelman (2011) uses the average land gradient at the community level, but the micro-data this study is built upon allows for the use of land gradient at the household level, which is a significant improvement. This provides a more accurate depiction of actual electricity access, as the average community land gradient can hide the fact that some households in a community may or may not have electricity.[10] In other words, just because a community has access to electricity, does not guarantee at the household level that there is 'true' access. To the best of our knowledge, this part of the paper will contribute to the literature by being the first to use the land gradient at the household level, which represents a new IV strategy in the development literature to causally attribute the

[10]Uganda has a rapidly expanding solar home system (SHS) market with approximate sales of 10,000 SHSs per year, mainly for residential as well as productive (largely water pumping) and social uses (hospitals and schools) (Heteu, 2015). The number of households in the sample population that have solar panels is approximately 3.3 percent. While representing a minority within the sample population, this study recognizes electricity can be provided by off-grid solutions and would make the derived estimates a lower-bound.

effects electricity has on measures of education.

The empirical strategy first estimates the effect of having access to electricity on measures of education through the IV of land gradient and then estimates a second model of the same specification, but instead substitutes the MEPI in for access to electricity. First, let $Y_{i,h,t}$ represent the outcome of interest (educational outcomes) for individual i, in household h, at time t. In order to address the identification and methodological concerns of attribution, an instrumental variable will be used for household electrification status using the land gradient of the household (Z), while $C_{i,h,t}$ controls for whether an individual has access to electricity by time period t. Last, β_0 represents the intercept term and X' is a vector of control variables for individual i, in household h, at time t. The system of equations to be estimated are:

$$Y_{i,h,t} = \beta_0 + \beta_1 \cdot \widehat{C}_{i,h,t} + X'_{i,h,t} \cdot \delta + \rho_r + \tau_t + (\alpha_i + \varepsilon_{i,h,t}) \tag{2.1}$$

$$C_{i,h,t} = \pi_0 + \pi_1 \cdot Z_h + X'_{i,h,t} \cdot \delta + \rho_r + \tau_t + \gamma_{i,h,t} \tag{2.2}$$

where (α_i + $\varepsilon_{i,h,t}$) and $\gamma_{i,h,t}$ are unobserved, clustered at the individual level to allow for arbitrary dependence between the errors of the individuals and adjust for individual specific correlations. The dependent variables to be tested are represented by $Y_{i,h,t}$, which accounts for how much money has been spent on education in the past year, whether the student is delayed for the age (s)he is supposed to be per grade level, and whether the individual is currently attending a particular grade. The list of controls postulated by X', has been influenced by previous work on the effects electricity has on development outcomes such as Dinkelman (2011), Grogan and Sadanand (2013), Squires (2015), Van de Walle et al. (2013) and Khandker et al. (2012) and includes: natural log of income, age, gender, number of household children broken down into three ranges (under 3, between 3 and 5, and between 6 and 18), and the head of household's marital status, and gender. Furthermore, included in the model are regional and time fixed effects denoted as ρ_r and τ_t, respectively, which control for the unobserved regional-time-invariant effect. This part of the study enables us to establish an initial linkage between electricity and education outcomes.

The idea of the second identification strategy seeks to go beyond the singular dimension of access to electricity and test whether a multidimensional indicator, such as the MEPI, provides a better or complementary measure of estimation. The hypothesis follows that household electrification functions as a precondition to enable the adoption of further technologies. Technologies derived from the provision of electricity therefore increase the household's production function through labor savings, which result in an increased state of welfare. The type of technologies adopted by the household will dictate the magnitude of change within the production function and ultimately the returns to the provision of electricity. The strategy to be employed will be the same as equations (1) and (2) but instead of using electricity access, the MEPI derived through the normalized scoring coefficients from the FA will be used. Once again the land gradient will be used as an IV strategy to instrument for each individual's energy poverty level. Undoubtedly access to electricity is a necessary component to satisfy before addressing a majority of the other energy deprivations a household may experience. This is justified by evidence from the FA indicating that the majority of the scoring coefficient weights are electricity based, enabling a similar identification strategy as equations (1) and (2). For this reason, the following system of equations to be estimated are:

$$Y_{i,h,t} = \beta_0 + \beta_1 \cdot \widehat{MEPI}_{i,h,t} + X'_{i,h,t} \cdot \delta + \rho_r + \tau_t + (\alpha_i + \varepsilon_{i,h,t}) \tag{2.3}$$

$$MEPI_{i,h,t} = \pi_0 + \pi_1 \cdot Z_h + X'_{i,h,t} \cdot \delta + \rho_r + \tau_t + \gamma_{i,h,t} \tag{2.4}$$

where the only change to the system of equations from (1) and (2) is the introduction of the MEPI.

An important aspect of this empirical analysis is to be able to compare the impact of access to electricity with the impact of the MEPI on each measure of education. In order to do this, access to electricity and the MEPI are standardized to have a mean of zero and a standard deviation of one. This enables the MEPI to have an economically meaningful interpretation, but more importantly each of these variables are standardized to the same scale for comparability. After the transformation, access to electricity ranges from [-0.21, 4.69] and the MEPI ranges from [-1.26, 4.64].

As indicated above, several dependent variables will be tested to measure the effects energy poverty has on measures of education and are defined as follows. The first education variable to be tested is named 'Money Spent on Education' and is in log form controlling for the total money spent on a student's education in the past 12 months. A priori the coefficient of this variable is expected to be positive for both electricity and the MEPI, as less energy poverty will likely lead to more money being spent on children's education. The variable named 'Age Difference' attempts to account for whether the student is delayed in school according to the age that (s)he is supposed to be, per respective grade. The variable is constructed by taking the actual age of the student minus the age the student is supposed to be per the grade level (s)he is attending. The sign on the coefficient is expected to be negative as individuals with electricity or lower levels of energy poverty are likely to be ahead in schooling, relative to students without electricity or with higher levels of energy poverty. 'Grade Attending' accounts for the grade that each individual is currently attending and only considers individuals that are currently attending primary and secondary schooling. The intention of this variable is to measure whether individuals with electricity or lower levels of energy poverty go on to attend higher grades.

2.5.1. Threats to validity in the IV strategy

Under each of the IV approaches, the estimates of $\beta_1 \widehat{C}_{i,h,t}$ and $\beta_1 \widehat{MEPI}_{i,h,t}$ are consistent if the following two assumptions are satisfied (conditional upon the controls included in the model):

$$\text{(a) } E(Z_h \ \ \gamma_{iht}) = 0$$

$$\text{(b) } E(Z_h \ \ C_{i,h,t}) \neq 0 \quad \text{or} \quad E(Z_h \ \ MEPI_{i,h,t}) \neq 0$$

where (a) states that the instrument is unrelated to the outcome of interest, except through the probability of access to electricity ($C_{i,h,t}$) or through the inter-correlations amongst the energy poverty variables in the MEPI ($MEPI_{i,h,t}$). Part (b) postulates that the instrument is highly correlated with the probability of access to electricity or the probability of satisfying the set of energy poverty components. Assumption (b) is argued to be satisfied as the two factors that engineers focus on in the location of electrification cables are the geographic factors affecting the generation and transportation of electricity, and load factors related to the demand (Lipscomb et al., 2013). In relation to each of the assumptions, the exclusion restriction is argued to be satisfied as flatter land will make it cheaper to lay distribution cables, but the land gradient is unlikely to directly affect the education outcomes under consideration in this analysis.

One concern with the empirical strategy may contend that individuals non-randomly sort based on the land gradient. There are two complementary responses to this concern. First, the geography of Uganda is advantageous to the empirical strategy, as the country is located on top of a plateau, limited by mountainous regions and valleys (see Figure 2.4). This enables the analysis to observe individuals across different geographical areas of the country on similar land gradients.[11]

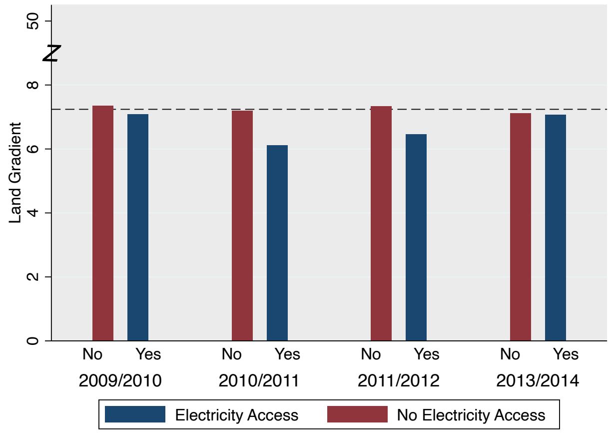
[11] The average land gradient of the sample population is 7.24 percent or 4.14 degrees, while the average land gradient of the communities employed by Dinkelman (2011) is 17.6 percent or 10 degrees.

Figure 2.4.: Terrain of Uganda

Notes: This figure presents a 3D map of the terrain of Uganda. *Source*: Author's own calculations.

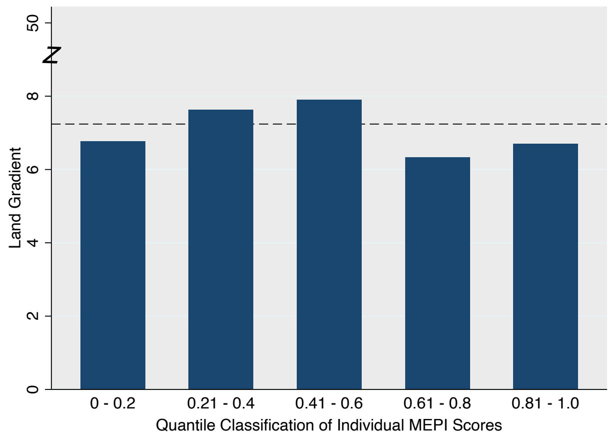
Second, the data can be broken down based on the observable level of energy poverty or access to electricity to further check whether individuals are sorting based on geographical characteristics. Figure 2.5 breaks down the sample population by survey wave and on whether the respondents have access to electricity. Individuals with and without electricity are on similar land gradients within a 2 percentage point band. Furthermore, Figure 2.6 breaks down the MEPI scores into quintiles and plots them against the average land gradient of the sample population. Breaking down the population by quintiles illustrates that each falls within one percentage point on the scale of land gradient. Across the varying levels of multidimensional energy poverty scores, individuals are on very similar land gradients. There does not appear to be evidence that individuals who are less energy poor or lack access to electricity non-randomly sort into less steep areas.

Figure 2.5.: Land gradient and electricity access



Notes: This figure presents the sample population by survey wave for whether the respondent has access to electricity plotted against the average land gradient. The y-axis dotted line represents the average land gradient [7.24 percent] of the sample population. The land gradient of the sample population runs from a minimum of 0 to a maximum of 50 percent. Individuals with or without access to electricity are on very similar land gradients within a 2 percentage point band. *Source*: Author's own calculations.

Figure 2.6.: Land gradient and MEPI score



Notes: This figure presents the sample population broken down by MEPI scores into quantiles and plots them against the average land gradient. The y-axis dotted line represents the average land gradient [7.24 percent] of the sample population. The land gradient of the sample population runs from a minimum of 0 to a maximum of 50 percent. Across the different MEPI quantiles, individuals are on very similar land gradients within a 2 percentage point band and there does not appear to be any evidence that individuals who are less energy poor sort into less steep areas. *Source*: Author's own calculations.

2.6. Results

The coefficients from the two models are presented in three tables. Table 2.4 reports the full sample of rural individuals, Table 2.5 and Table 2.6 perform a heterogeneous analysis by splitting the sample population into primary and secondary education levels, respectively.

In Table 2.4, the sign on the coefficient of land gradient in each of the first stages is negative and follows the a priori sign expectation. Columns one to three indicate that as the land gradient increases, a household is less likely to have access to electricity, while columns four to six indicate that as the land gradient increases, the MEPI score will decrease or a household is more likely to be multidimensionally energy poor. Across all specifications, the magnitude of the estimated coefficients are stable and statistically significant at the one percent level. Additionally, the magnitude of the MEPI in the first stage of columns 4 – 6 is larger relative to the first stage estimates for access to electricity in columns 1-3, indicating the land gradient is picking up other important information beyond electricity access. Furthermore, the F-statistic indicates that the value is over the conventional threshold for determining whether an instrument is sufficiently predictive of the first-stage regression.

Table 2.4.: Effects of energy deprivations on education

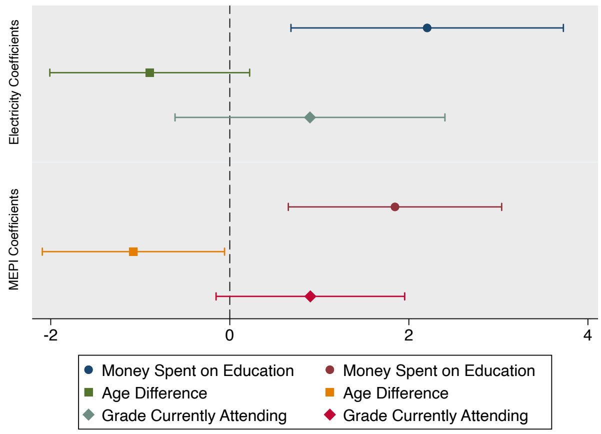
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Money Spent on Education	Age Difference	Grade Currently Attending	Money Spent on Education	Age Difference	Grade Currently Attending
Electricity	2.205***	-0.894	0.896			
	(0.776)	(0.569)	(0.769)			
MEPI				1.845***	-1.076**	0.900*
				(0.608)	(0.519)	(0.537)
First Stage Estimates						
Land Gradient	-0.00514***	-0.00580***	-0.00432***	-0.00663***	-0.00626***	-0.00717***
	(0.00126)	(0.00151)	(0.00114)	(0.00173)	(0.00198)	(0.00170)
Observations	13,524	10,528	14,252	13,271	10,331	13,988
Kleibergen-Paap rk Wald F statistic	16.50	14.77	17.01	14.62	10.02	17.78
AIC	61,365.44	37,091.01	58,451.56	53,759.82	36,233.38	56,082.65
BIC	61,508.17	37,228.98	58,595.29	53,902.19	36,370.99	56,226.02

Notes: This table presents estimates in columns 1-3 for the effects that access to electricity has on different measures of education while columns 4-6 present estimates for the effects that the MEPI has on different measures of education. Standard errors are clustered at the individual level. Each regression includes regional and time fixed-effects. Independent variables include: natural log of income, age, gender, number of household children broken down into three ranges (under 3, between 3 and 5, and between 6 and 18), and the head of household's marital status, and gender. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Focusing on the full sample, the MEPI performs better overall relative to access to electricity in explaining each of the educational outcomes. This is illustrated by the relative test of model quality through the Akaiki information criterion (AIC) and the Bayesian information criterion (BIC). The models employing the MEPI each have AIC and BIC values less than the models employing access to electricity. This provides evidence for a given set of econometric models that only differ in respect to access to electricity and the MEPI, that the preferred models in terms of relative quality are the ones that employ the MEPI.

Next, the estimated coefficients are interpreted. In column 1, the coefficient on electricity is estimated to be positive and statistically significant at the one percent level. A one standard deviation increase in an individual having access to electricity, leads to 2.2 percent of a standard deviation more spending on a child's education, holding all else constant. As for the MEPI coefficient in column 4, a one standard deviation increase in the MEPI leads to an increase of 1.8 percent of a standard deviation more spending on a child's education. In columns 2 and 3, no evidence is found linking access to electricity to the differential between the supposed age and actual age or the grade an individual is currently attending, despite having significant explanatory power from the first stage. On the other hand, according to the estimated coefficient in column 4, as the MEPI increases by one standard deviation, on average an individual is likely to be one year less than the age that they are supposed to be per respective grade. Furthermore, according to the estimated coefficient in column 6, a one standard deviation increase in the MEPI, leads an individual to attend 0.9 grades more. Each of these results indicate the energy provisions that the MEPI accounts for lead to the significant relationship and further provide evidence justifying the need to consider energy provisions beyond access to electricity. Figure 2.7 then plots the estimated coefficients of columns 1 – 6, along with the standard errors, to demonstrate that the MEPI improves the precision of the standard errors around the estimated coefficients. This makes intuitive sense as the MEPI considers factors beyond the binary dimension of access to electricity, by including other technologies that likely effect and improve educational outcomes.

Figure 2.7.: Comparison of estimated coefficients



Notes: This figure presents estimated coefficients (and standard errors) from Table 2.4 for the effects that access to electricity and the MEPI have on different measures of education. Standard errors are clustered at the individual level. Each regression includes regional and time fixed-effects. Independent variables include: natural log of income, age, gender, number of household children broken down into three ranges (under 3, between 3 and 5, and between 6 and 18), and the head of household's marital status, and gender.

Next, the sample is split by primary and secondary education level. One aspect that becomes apparent between the two specifications is that the gains from energy provisions are concentrated in the primary education level. Table 2.5 presents the results of the sample focusing on primary education. Similar to the full sample specification, access to electricity estimates a greater value relative to the MEPI. A one standard deviation increase in an individual having access to electricity, leads to an increase in spending on a child's education by 3.5 percent of a standard deviation holding all else constant. The coefficient on the MEPI is estimated to be 2.9 percent and is significant at the 5 percent level. This result insinuates that as an individual becomes less multidimensionally energy poor, on average they are likely to spend more on education in the past 12 months of the year. The estimates of the MEPI in columns 5 and 6 indicate a significant effect at the 10 percent level and at similar point estimates as the full sample, but these results should be interpreted with caution due to the low F-statistic. Next, the estimated coefficients and standard errors from the specifications are plotted in Figure 2.8. Similar to the full sample, the MEPI improves the precision of the standard errors around the estimated coefficient. Furthermore, the estimated effect of the MEPI is embedded within the range of the access to electricity, as the MEPI methodology is penalizing other energy deprivations beyond the scope of access to electricity. Last, Table 2.6 focuses on students in secondary schooling. Each of the specifications demonstrates that no evidence is found of a statistically significant relationship between either access to electricity or the MEPI and educational outcomes.

Table 2.5.: Effects of energy deprivations on education – primary school sample

VARIABLES	(1) Money Spent on Education	(2) Age Difference	(3) Grade Currently Attending	(4) Money Spent on Education	(5) Age Difference	(6) Grade Currently Attending
Electricity	3.493***	-1.192	1.007			
	(1.338)	(0.727)	(0.731)			
MEPI				2.935**	-1.183*	0.891*
				(1.252)	(0.619)	(0.526)
First Stage Estimates						
Land Gradient	-0.00381***	-0.00443***	-0.00448***	-0.00472**	-0.00513**	-0.00576***
	(0.00128)	(0.00153)	(0.00129)	(0.00189)	(0.00217)	(0.00188)
Observations	10,925	9,079	11,469	10,737	8,924	11,271
Kleibergen-Paap rk Wald F statistic	8.82	8.41	12.03	6.21	5.59	9.42
AIC	55,281.45	31,724.76	40,394.25	50,378.81	29,885.15	37,576.50
BIC	55,420.13	31,859.92	40,533.85	50,517.16	30,019.98	37,715.77

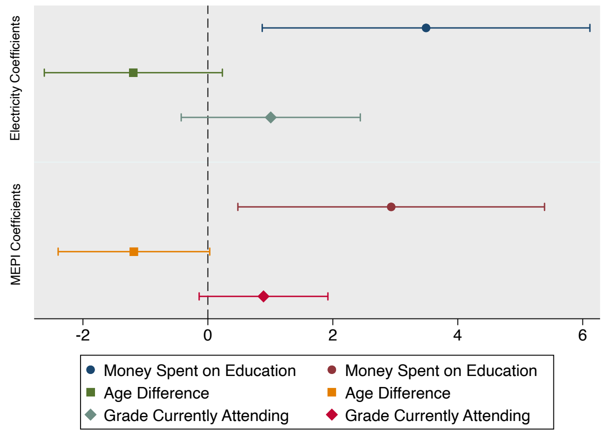
Notes: This table presents estimates for the sample of primary school students where columns 1-3 presents the effects that access to electricity has on different measures of education while columns 4-6 present estimates for the effects that the MEPI has on different measures of education. Standard errors are clustered at the individual level. Each regression includes regional and time fixed-effects. Independent variables include: natural log of income, age, gender, number of household children broken down into three ranges (under 3, between 3 and 5, and between 6 and 18), and the head of household's marital status, and gender. Significant at $^*p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Table 2.6.: Effects of energy deprivations on education – secondary school sample

VARIABLES	(1) Money Spent on Education	(2) Age Difference	(3) Grade Currently Attending	(4) Money Spent on Education	(5) Age Difference	(6) Grade Currently Attending
Electricity	-0.986	0.444	-0.413			
	(1.066)	(0.820)	(0.947)			
MEPI				-0.890	0.291	-0.292
				-1.023	(0.751)	(0.852)
First Stage Estimates						
Land Gradient	-0.00719	-0.00803	-0.00705*	-0.00792*	-0.00922*	-0.00853**
	(0.00440)	(0.00551)	(0.00427)	(0.00436)	(0.00522)	(0.00429)
Observations	1,784	1,449	1,900	1,733	1,407	1,848
Kleibergen-Paap rk Wald F statistic	2.67	2.12	2.73	3.3	3.12	3.95
AIC	7,055.88	4,897.73	6,687.54	6,194.99	4,464.35	6,257.90
BIC	7,160.13	4,998.02	6,792.98	6,298.68	4,564.09	6,362.82

Notes: This table presents estimates for the sample of secondary school students where columns 1-3 presents the effects that access to electricity has on different measures of education while columns 4-6 present estimates for the effects that the MEPI has on different measures of education. Standard errors are clustered at the individual level. Each regression includes regional and time fixed-effects. Independent variables include: natural log of income, age, gender, number of household children broken down into three ranges (under 3, between 3 and 5, and between 6 and 18), and the head of household's marital status, and gender. Significant at $^*p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Figure 2.8.: Comparison of estimated coefficients – primary school sample



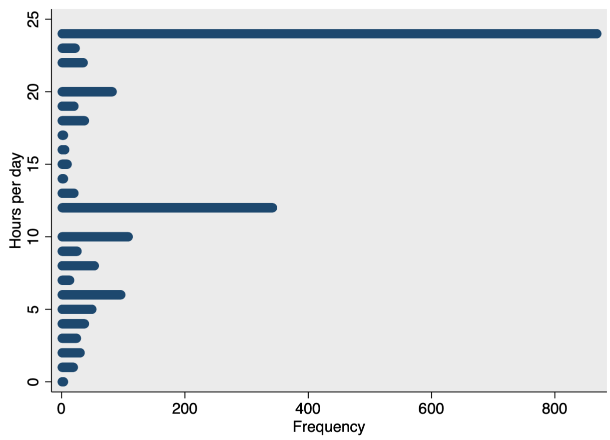
Notes: This figure presents estimated coefficients (and standard errors) from Table 2.5 for the effects that access to electricity and the MEPI have on different measures of education. Standard errors are clustered at the individual level. Each regression includes regional and time fixed-effects. Independent variables include: natural log of income, age, gender, number of household children broken down into three ranges (under 3, between 3 and 5, and between 6 and 18), and the head of household's marital status, and gender.

2.7. Discussion

In order to alleviate poverty, a more comprehensive approach to understanding the importance of household energies is needed, not only in the dimension of access to electricity, but also to guarantee individuals are able to realize affordable, reliable, safe and environmentally benign energy services (Pagel, 2019). The MEPI provides a potential improvement to our understanding of household energy poverties beyond access to electricity by accounting for other energy depravations a household may suffer from. Two descriptive pieces of evidence from the sample population further embody this comprehensive approach and begin to paint a picture of what it means to be energy poor.

The first is the reliability of the electricity provided. Figure 2.9, plots the distribution of population with electricity by the number of hours that their household has electricity service. While 45 percent of the sample population resides in the 24 hour category, there still exists large portions of the sample population that do not receive electricity service for all hours of the day. This is not just specific to rural Uganda, but a problem throughout low-income countries where the electrical grid frequently suffers from blackouts and maintenance problems. In a study of 109 countries using data from two different World Bank-administered surveys on reports from consumers and utilities, Taneja (2017) finds that utilities report just 15 percent of the same outage durations that customers report. This provides an additional layer of complexity, where the demand and supply side offer contrasting realities as to whether electricity is being provided. Blackouts present further challenges as households and small businesses purchase diesel generators for energy compensation. Another aspect of reliability relates to the construction standards. K. Lee et al. (2020) outline issues with the implementation of the study such as sub-standard construction quality, over-billing on transportation, insufficient materials (e.g., poles, cables) or leakages from the sale of construction materials.

Figure 2.9.: Hours per day of power

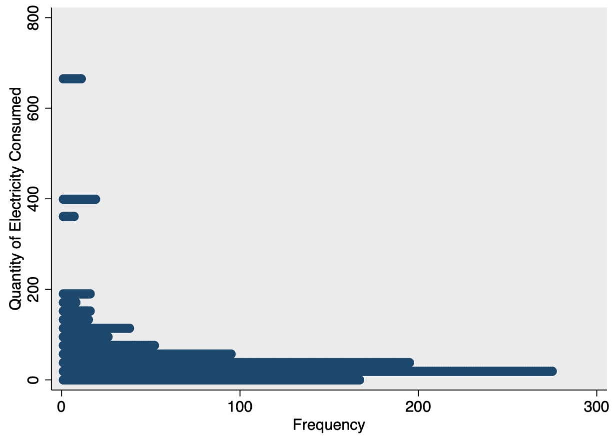


Notes: This figure presents data on the number of hours per day an individual has power. Data in this figure comes from a question asking: How many hours per day do you usually have power, in a season like this? *Source*: Author's own calculations.

Similar to the dimension of energy quality, is the quantity of energy the household is consuming. Figure 2.10 plots the distribution of monthly electricity consumed by households. Households in the sample population consume very low levels of electricity per month, where the average electricity consumption level is 57.9 kWh per month.[12] Even if the grid is reliable, and energy services are provided for 24 hours, households may still be too poor to purchase appliances. K. Lee et al. (2020) find households that were in the treatment arm of rural electrification, acquired few additional appliances and consumed roughly 3 kWh per month. The reliability and continuity of electricity service provisions is a crucial element to consider in order to fully realize the benefits of electricity.

[12]For comparison, the average monthly electricity consumption of a U.S. household utility customer in 2017 was 867 kWh (U.S. Energy Information Administration).

Figure 2.10.: Quantity of electricity consumed



Notes: This figure presents data on household electricity consumption. Data in this figure comes from a question asking: What was the quantity of electricity used? The quantity is kWh for the billing period of the most recent bill, excluding past due charges. *Source*: Author's own calculations.

2.8. Conclusion

Energy is interconnected with the socio-economic and human development of the individual, and the true nature of poverty manifests itself when individuals are deprived on multiple dimensions of human well-being. Throughout the past years, there has been large investments in the energy sector, but recent empirical studies have provided inconclusive evidence on the impact of energy and well-being, both on the effect and the mechanisms. Households can suffer from energy deprivations beyond access to electricity, and it is important to understand how these various energy deprivations may affect the well-being of individuals. By using a multidimensional methodology that is able to account for the intensity and pervasiveness of different energy deprivations, this study presents the first empirical evidence of multidimensional energy poverty's effect on educational outcomes. The results further provide evidence to the ongoing debate of rural economics and electrification in low-income regions and attempts to understand the benefits derived from certain types of energy mechanisms.

Employing a multidimensional energy poverty measure improves upon the previous reliance of access to electricity to understand the effects energy has on measures of education. The results indicate that a one standard deviation increase in an individual having access to electricity leads to approximately 2.2 percent of a standard deviation more spending on education, whereas a one standard deviation increase in the MEPI leads to an increase in spending on a child's education by 1.8 percent of a standard deviation. When focusing on primary education an increase of one standard deviation in an individual having access to electricity, leads to an increase of spending on a child's education by 3.5 percent. Comparing this result to the estimated coefficient on the MEPI, a one standard deviation increase in the MEPI, leads to 2.9 percent of a standard deviation more spending on a child's education. When looking at whether students are ahead/behind in schooling relative to their supposed age per grade, the MEPI finds that less energy poor individuals are ahead. Furthermore, the MEPI finds evidence that individuals with less energy poverty deprivations go on to attend more grades. Each of these results provide evidence that there are further gains to the individual beyond simply obtaining access to electricity. Failure to account for energy deprivations may explain the literature's inconsistent findings linking access to electricity to educational outcomes and the inability to account for different energy mechanisms.

With the large investments being made in the energy sector, based on limited evidence that such policies have positive effects on individual and household well-being, greater research importance needs to be given to different types of energy mechanisms. Much of the international development agenda has placed an emphasis on improving access to electricity, but policies must not stop at simply providing access to electricity. Evidence from this empirical study advance the development literature's understanding of energy poverty and demonstrates there are effects from energy poverties beyond simply having access to electricity. By using a multidimensional methodology, the analysis is able to account for individual specific energy deprivations, and starts to get at different types of energy mechanisms. This study demonstrates that access to electricity provides an initial condition, but this is not a sufficient condition to guarantee individuals will not be deprived on other energy dimensions. The results from this study provide an understanding of the effect from underlying mechanisms within an individual's energy capabilities.

Future research on the effects of energy, need to take into account other forms of deprivations individuals may experience beyond the simple fact of having access to electricity. From a methodological point of view, the developed MEPI framework in this study attempts to expand the literature's ability at measuring energy poverty. A more comprehensive understanding of energy poverty needs to be considered to include other forms of energy deprivations that an individual or household may suffer from. Failure to do so, can introduce measurement biases and provide mixed-evidence on the impact of energy poverty. Furthermore, only considering access to electricity may lead to a misdiagnosis of the true problem, which is, individuals may have access to electricity but are unable to realize the benefits of the energy through appliances or modern cooking technologies.

From a public policy perspective, the developed methodology of the MEPI accounts for different possible household energy poverties and can provide policy practitioners with a more comprehensive picture of energy poverty in order to better address the needs of poor households. The instrument can be deployed to monitor district or regional poverties in order to identify the types of energy poverties that need to be relieved, as well as how resources should be allocated to different areas. In a similar manner, temporal dynamics can be analyzed to see how districts, regions, or the country as a whole is improving in different energy dimensions over time. The instrument can additionally be used at the international scale to track a countries progress relative to countries of a similar development stage. Depending on the energy poverty make-up, the MEPI can provide practitioners with a powerful instrument in order to identify certain poverties, and develop well informed interventions for energy poverty alleviation. The international development goals and energy initiatives have made great advancements in providing electricity access to millions of individuals across the world, but future policies and initiatives should seek to fulfill energy dimensions beyond access to electricity, as these are the dimensions that will bring positive benefits to individual's lives.

A.1. Appendix

A.1.1. Factor analysis

To perform the FA, eigenvalues are first computed for the variables of the MEPI and are set to minimize the necessary number of eigenvalues to retain, while capturing the most interrelated information amongst the energy poverty variables. In order to determine the number of factors to retain, the Kaiser criterion generally states that only eigenvalues over one should be retained. Additionally, a likelihood-ratio test is run and the null hypothesis is rejected that the saturated model fits the covariances well.

Table A.1.: Factor analysis by principal factors methodology

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor 1	1.32	1.01	1.16	1.16
Factor 2	0.31	0.30	0.27	1.44
Factor 3	0.01	0.07	0.01	1.45
Factor 4	-0.06	0.15	-0.05	1.40
Factor 5	-0.21	0.03	-0.19	1.21
Factor 6	-0.24	-	-0.21	1.00
N	54,868			
Retained Factors	1			
Number of Parameters	6			

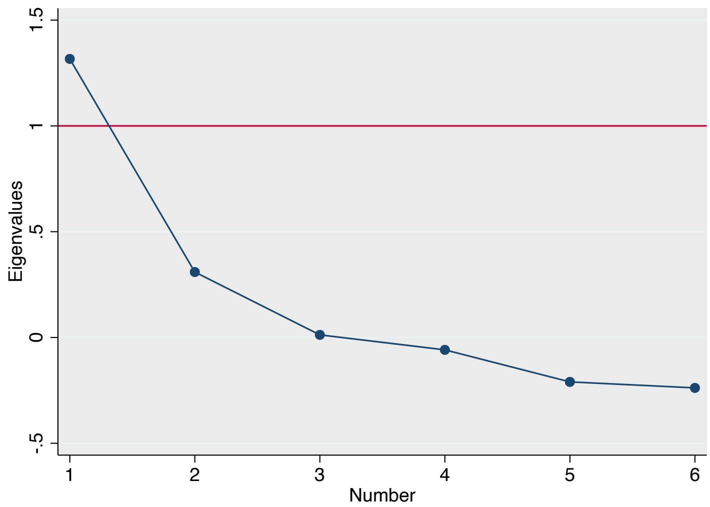
Notes: This table presents the eigenvalues derived from the factor analysis *Source*: Author's own calculations.

Table A.2.: Factor loadings and unique variances

Variable	Factor	Uniqueness
Modern Cooking Fuel	0.4255	0.8189
No Indoor Air Pollution	0.1632	0.9734
Electricity access	0.6793	0.5385
Household appliance ownership	0.5808	0.6627
Radio or television	0.3655	0.8664
Mobile phone	0.4203	0.8233

Notes: This table presents the factor weights derived from the factor analysis for each of the parameters in the MEPI. *Source*: Author's own calculations.

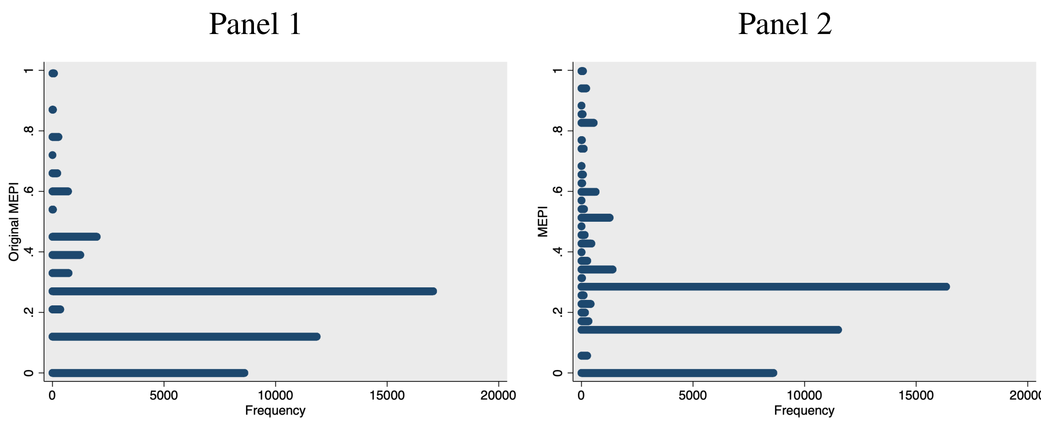
Figure A.1.: Scree plot of eigenvalues after factor analysis



Notes: This figure presents a scree plot for the eigenvalues derived from the factor analysis. The Kaiser criterion generally states that only eigenvalues over one should be retained. *Source*: Author's own calculations.

A.1.2. Comparison of MEPI weighting schemes

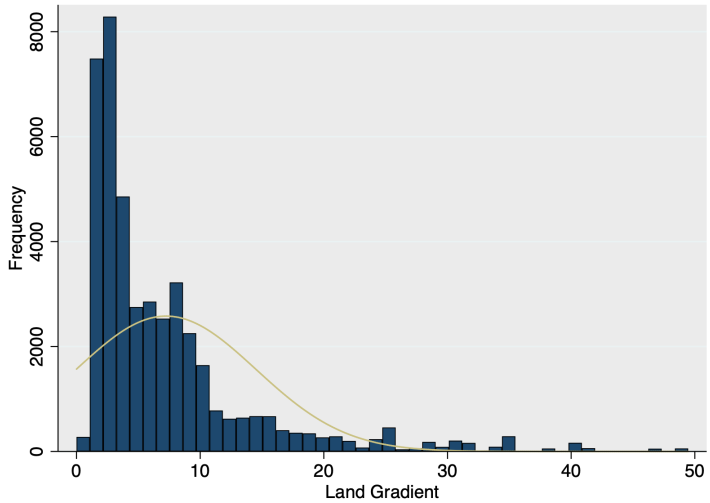
Figure A.2.: Comparison of MEPI weighting schemes



Notes: Panel 1 of Figure A.2 presents the distribution of the MEPI as computed by the original Nussbaumer et al. (2012) weighting scheme and panel 2 presents the MEPI derived through the FA. Each distribution appears to derive similar estimates for individuals who are energy poor, but the distributions differ in the sense of dispersion. In Panel 2 of Figure A.2, the observations are much more dispersed along the distribution relative to panel 1. Using the original weighting scheme penalizes energy deprivations to a greater extent and pushes much of the distribution to the lower bound relative to the weighting scheme applied in this analysis. Mischaracterizing the level of energy poverty amongst individuals could present issues in drawing conclusions as to the severity that energy deprivations can have on outcomes of well-being. For this data sample, panel 2 seems to be able to classify more intricately the level of energy poverty severity better than the original weighting scheme.

A.1.3. Household land gradient

Figure A.3.: Household land gradient



Notes: This figure presents the distribution of land gradient for which individuals in the sample population are observed. *Source*: Author's own calculations.

A.1.4. Summary statistics

Table A.3.: Summary statistics

Variable	Level	Observations	Mean	Standard Deviation
Dependent Variables				
Money spent on education	Individual	16,489	10.83	1.51
Age difference	Individual	12,715	1.95	1.45
Grade attending	Individual	17,313	5.37	3.41
Independent Variables				
Land Gradient	Household	43,716	7.24	7.27
MEPI	Individual	43,097	-8.92E-09	1
Electricity access	Household	44,146	-1.32E-08	1
Log of Total income	Household	37,654	13.61	1.36
Age	Individual	44,230	20.84	18.56
Sex	Individual	44,273	0.49	0.49
Head of household's marital status	Individual	44,128	1.74	1.06
Number of children under three	Household	44,279	0.66	0.76
Number of children between three and five	Household	44,279	0.82	0.8
Number of children between six and eighteen	Household	44,279	3.37	2.13
Head of household's gender	Individual	44,155	0.75	0.43

3. Aid Against Trees? Evidence from a Community-Driven Development Program in the Philippines

3.1. Community development and deforestation

The United Nation's declaration of the Millennium Development Goals (MDGs) at the start of the 21^{st} century declared fighting poverty and protecting the environment as two of the most urgent challenges the international community is faced with. One of the main aspects of environmental protection is the fight against loss of forests, which are a local and global public good. Deforestation not only affects global climate change due to carbon sink losses, but also leads to heavy regional and local externalities such as the removal of watershed protection, reduction in soil fertility, air pollution caused by fires and increased runoff into fisheries; deforestation may even exacerbate droughts, floods and landslides by reducing the land's absorptive capacity (Liscow, 2013). Between 2006 and 2015, land use changes derived mostly from deforestation accounted for nine percent of global anthropogenic carbon emissions, the second largest source of carbon emissions after fossil fuel combustion (Le Quéré et al., 2015). Additionally, curbing deforestation in low-income countries is viewed as the most cost-effective way to reduce global CO_2 emissions (Nabuurs et al., 2007; Stern, 2007).[1]

[1] An increased attention has been given to the depletion of forests, especially due to the recognition of the important role forests play in the global carbon cycle, and the vital buffer they can provide against climate change. Forests provide a host of benefits, from harboring much of the world's biodiversity to reducing atmospheric CO_2. Through photosynthesis, CO_2 and water are pulled from the environment and in return oxygen and glucose are produced. The CO_2 is stored inside the tree by being incorporated into its living tissue as it grows, essentially sequestering it from the atmosphere. They provide a global carbon sink, as they take more carbon out of the air through photosynthesis and wood production than they release through respiration and decay (Pan et al., 2011). Additionally, Griscom et al. (2017) estimate that forests and other ecosystems could provide a third of the total CO_2 reduction required to keep global warming below the 2°C established by the Paris Agreement. However, when a tree dies and decomposes, the accumulated carbon returns to the atmosphere as CO_2. Additionally, trees emit a complex mixture of chemicals, some of which warm the planet (Popkin, 2019).

This paper aims to analyze the extent to which the two goals of fighting poverty and protecting the environment may be at odds with each other, by providing rigorous empirical evidence of the effects of aid on deforestation. More specifically, in this study I analyze the effects of development aid on deforestation through a large-scale community-driven development (CDD) program in the Philippines called KALAHI-CIDSS (KC).[2] In recent years, CDD programs have attracted considerable attention from international aid organizations and national governments as a policy option that seeks to combine poverty reduction strategies with an environmentally sustainable approach. In general, CDD programs support a "bottom-up" approach to development by decentralizing the decision-making process to the local level in order to identify the needs on the ground, and can be characterized by a shift in responsibility for resources and planning decisions.[3] As of June 2019, there were 219 active CDD projects in 79 countries, including 57 countries supported by the International Development Association (IDA), for total lending of $21.6 billion (69 percent of which is IDA) (World Bank, 2020). Additionally, over the past decade the World Bank has spent approximately $50 billion on CDD programs (Mansuri and Rao, 2012), which make up around 10 percent of its lending portfolio (P. Barron, 2011). The World Bank is not alone in this movement, as other large donor agencies have incorporated CDD programs into their lending portfolios, including the Asian Development Bank, the Inter-American Development Bank, USAID, the Japan International Cooperation Agency and the Department for International Development.

Even after decades of debate and analysis and the explosion of randomized anti-poverty interventions, little is known about the environmental impact of actions designed to reduce poverty, or the impact on poverty of actions designed to protect the environment (Alpízar and Ferraro, 2020). Environmental quality is an important component in economic growth, and gaining a better understanding of the magnitudes and mechanisms associated with the tradeoffs between the two has emerged as a key challenge for the developing world (Jack, 2017). In CDD programs, environmental protection can play a role in the participatory process, particularly as donors are targeting CDD strategies for climate change mitigation and adaptation (Arnold et al., 2014). Integrating environmental protection policies with poverty reduction strategies is by no means a new concept, but the positioning of CDDs as a mitigation or adaptation strategy places them in a unique position to link poverty reduction aid to environmental sustainability goals. CDD programs attempt to link environmental and

[2] KALAHI-CIDDS stands for Kapit-bisig Laban sa Kahirapan ("Linking Arms Against Poverty") – Comprehensive and Integrated Delivery of Social Services (KALAHI-CIDSS or KC).

[3] See Casey (2018) for a synthesis of the literature's findings on the effectiveness of CDD programs.

economic components together through a type of development that is economically feasible, socially desirable and environmentally benign. However, even as donors are positioning CDD programs with the parallel strategies of poverty reduction and climate change mitigation and adaptation, little empirical evidence exists on the environmental effects of CDD programs, particularly in terms of deforestation.

With this in mind, this study seeks to improve our understanding of the effects of development aid on the environment by utilizing satellite-generated forest coverage data to measure the impact of CDD programs on deforestation. More specifically, two empirical strategies exploit the manner in which a large-scale CDD program was allocated in the Philippines through a regression discontinuity design (RDD) and a randomized control trial (RCT) to test whether CDD programs have unintended environmental effects with respect to deforestation. The first empirical strategy analyzes a discontinuity in the allocation of the KC program that restricted the eligibility of aid to the poorest 25 percent of municipalities. The discontinuous threshold was arbitrarily created in the assignment of the program, which makes it possible to use an RDD to identify and measure the causal effects of the KC program on deforestation by comparing municipalities just above and below the threshold. The second identification strategy exploits an RCT in which municipalities were randomly assigned to either participate in the KC program or remain part of the control group for three years. Each of the identification strategies makes it possible to overcome traditional concerns stemming from the non-randomness of aid allocation and identify the causal effect of development aid on deforestation. Additionally, each of the empirical strategies will provide evidence from the same CDD program, but from two different time periods during which the Philippines underwent different levels of deforestation, as well as from different municipality locations that were treated.

I find that, in the RDD period, the KC program had a statistically significant effect on deforestation, where eligible municipalities experienced an average of 236 percent more deforestation (equivalent to 957,828 square meters) than ineligible municipalities. Results from the RCT period indicate that treated municipalities experienced an average of 265 percent more deforestation (equivalent to 2,134,685 square meters) than the control as a result of the KC program. Results from of each of the empirical strategies provide robust evidence that the KC program and CDD programs in general have strong and statistically significant effects on deforestation. I then explore several mechanisms that may have been responsible for the increased deforestation. First, I find that eligible municipalities have lower poverty levels by the end of the program. Second, I find economic activity was stimulated as eligible municipalities experienced an increase in nighttime light of 26 percent. In terms of sectoral changes, I find increases in agriculture, fishing, forestry and manufacturing, a reduction in transportation, storage and communication and no evidence of changes in mining and extractives. Also, I find evidence of population changes as eligible municipalities experienced an increase in migration of 22 percent. Lastly, I find no evidence of changes to the number of people using wood for cooking.

I then explore heterogeneous effects of the different types of community-driven projects (called subprojects) based on a unique and detailed dataset of all 5,304 subproject interventions implemented from 2003 to 2008. The dataset includes the type of subproject implemented, completion dates, project costs, the direct number of household beneficiaries and the location of the subprojects. The results indicate that the greatest impact on deforestation stem from infrastructure projects, including trails, bridges and roads, followed by those relating to support, education and health facilities. Additionally, projects with the lowest number of direct beneficiaries, the shortest construction duration and the largest funding are found to cause more deforestation. Another aspect analyzed is whether the subprojects have spillover effects into the surrounding municipalities. I find some evidence of spillover effects at the extensive margin, as deforestation is expected to increase by 10 percent with each additional neighbor that is treated by the KC program, but I find no evidence of an effect at the intensive margin in regards to the number of implemented subprojects by surrounding municipalities. Lastly, this study investigates whether higher levels of poverty lead to more deforestation relative to less poor areas. More formally, this is related to the literature on the environmental Kuznets curve or the contrasting view of the poverty-environment hypothesis (Baland and Platteau, 1996). This remains an open debate in the ecological literature where the latter hypothesis suggests as income grows, even at low income levels, the surrounding environmental quality improves compared to the former hypothesis which suggests that raising living standards first increases pressure on the environment and then later improves them. The evidence provides support to the environmental Kuznets curve.

The results of this study are most closely related to the work by Heß et al. (2020), who analyzed a nationwide CDD program that was randomly assigned at the village level in rural Gambia. The authors showed that the program increased forest loss by around 11 percent, and that the average treatment effect was concentrated in the areas immediately surrounding the villages included in the program. Lastly, no evidence is found to suggest that the increased forest loss in treated villages is due to the participatory approach or the goal of influencing local institutions and decision-making process; rather it is driven by secondary effects relating to either agriculture or non-agriculture projects.

This study differs from Heß et al. (2020) in several important ways. First, the dual empirical strategies provides an unusual ability to study the same national CDD program in two different time periods across different municipalities. The structure of each empirical strategy will be able to provide causal evidence of the average treatment effects of CDD programs on deforestation within each of these time periods. Second, the study is carried out on a much larger scale in terms of the number of implemented subprojects as part of the nationwide Philippines CDD program relative to the Gambian context studied by Heß et al. (2020). Third, the nature of the subprojects and the detailed data analyzed on the subprojects differs. The majority of the projects analyzed by Heß et al. (2020) were related to agriculture, and their study classified the projects using a binary indicator between agriculture and non-agriculture projects. This is in stark contrast to the Philippines CDD program, where the majority of the subprojects are related to investment in infrastructure such as trails, bridges and roads, education and health facilities, water and electricity. The diversity of the implemented subprojects and the richness of the data in terms of project characteristics make it possible to analyze how each of these features may contribute to deforestation. Both of these aspects represent alternative channels through which deforestation may be impacted that have not previously been tested. Lastly, the Philippines offers a large country for analysis that has substantial spatial heterogeneity in terms of economic, social and ecological diversity.

Additionally, the study contributes to the literature on development infrastructure and deforestation. An early study by Pfaff (1999) on Brazil found that increased road density leads to greater deforestation in a county, as well as spillovers into neighboring counties, while government development projects appear to affect clearing, although credit infrastructure does not. Other studies have shown that road infrastructure can actually reduce forest encroachment pressures through an improvement in local development outcomes (Andersen et al., 2002; Deininger and Minten, 1999; Deng et al., 2011). Contrasting evidence can be found in more recent work by Asher et al. (2020), who investigate the construction of new rural roads in over 100,000 Indian villages and the modernization of 10,000 kilometers of national highways, and report that the construction of new rural roads had zero effect on local deforestation, but that the modernization of the national highway caused substantial forest loss. Additionally, BenYishay et al. (2016) investigate the way in which exposure to Chinese development activities affected changes in tree cover in Cambodia and Tanzania and find that these projects slowed forest loss in Cambodia, while faster rates of forest loss occurred in areas near active projects in Tanzania.

Lastly, and more broadly, this work contributes to the literature on increasing economic growth or well-being and changes in forest cover.[4] Busch and Ferretti-Gallon

[4]One policy option that is gaining popularity is payments for ecosystem services (PES), which offers incentives to preserve some type of ecological habitat. Rigorous empirical evidence on the impact of such systems on deforestation is still extremely limited (Alix-Garcia and Wolff, 2014; Miteva et al., 2012). Jayachandran et al. (2017) investigate PES by randomly offering forest-owning

(2017) perform a meta-analysis of more than one hundred spatially explicit studies on the determinants of deforestation and conclude that the effect of changes in rural income is unclear. Furthermore, Zwane (2007) finds that income is positively correlated with land clearing in Peru, while Baland et al. (2010) show that improvements to a household's living standards in Nepal increase the demand for firewood but that the effect is very small. Alix-Garcia et al. (2013) exploit a community-level eligibility discontinuity for a conditional cash transfer program in Mexico to find that an increase in income leads to an increase in demand for resource-intensive goods. Through unconditional livelihood payments to local communities on land outside of the Gola Rainforest National Park bordering Sierra Leone and Liberia, Wilebore et al. (2019) find that the unconditional payments increased land clearance in the short term in a slash-and-burn agriculture system. Opposing evidence is reported by Ferraro and Simorangkir (2020), who investigate an Indonesian national anti-poverty program that transfers cash to poor households and find that the program reduced tree cover loss in villages by 30 percent.

The paper is structured as follows. Section 3.2 describes the KC program, how the program was implemented in municipalities and the different types of projects that were undertaken. Section 3.3 describes the satellite-generated forest cover data and administrative data that are used. Section 3.4 outlines each of the empirical strategies and models estimated, where an RDD and an RCT exploit the way in which development aid was allocated. Section 3.5 presents the main results. Section 3.6 explores potential mechanisms that may impact deforestation such as the incidence of poverty, nighttime light, share of labor by different sectors, population, migration and the use of wood as cooking fuel. Section 3.7 provides a heterogeneous analysis on the implemented subprojects to gain more insight into the first-order effects, such as the type of subproject, the number of direct beneficiaries, duration of construction and funding amount, as well as whether there are spillover effects into the surrounding municipalities. Section 3.8 outlines several policy options to potentially mitigate deforestation pressures, and then provides concluding remarks.

households annual payments of 70,000 Ugandan shillings per hectare to conserve their forest, and found that tree cover declined by 4.2 percent in treated villages relative to 9.1 percent in control villages. Alix-Garcia et al. (2015) evaluate a federal program in Mexico that pays landowners to protect the forest by exploiting panel data and comparing the program's beneficiaries with rejected applicants. The study finds that the program reduced the expected land cover loss by 40-51 percent and generated small but positive poverty alleviation.

3.2. Context of the KALAHI-CIDSS (KC) program

Between 2003 and 2008, the Philippines' Department of Social Welfare and Development (DSWD) began the first round of a nationwide, government-run CDD program called KALAHI-CIDSS (KC), which provided aid through World Bank loans to more than 4,000 villages in 184 municipalities across 42 provinces, thus making it the largest development program in the country during this period. In a later phase, DSWD expanded the same KC program from 2012 to 2015 as a result of an aid agreement between the Government of the Republic of the Philippines and the Millennium Challenge Corporation (MCC).

The main aim of the Philippines' KC program was to empower local communities through increased participation in local governance and implementation and management of poverty reduction projects. Furthermore, the approach sought to add value to development operations by directly engaging stakeholders in project design and implementation (Labonne and Chase, 2009). The KC program paired community training with block grants at the village (*barangay*) level that were designed to enable communities to address self-identified development needs, largely through the financing of public infrastructure or public services called "subprojects" (Beatty et al., 2017). A fixed total amount was assigned to participating municipalities, depending on their size, but the amounts could not be too large or too small for projects and were widely publicized so that stakeholders were aware of the amount of money available. The number of projects and amount of aid disbursed through the first phase of the KC program were substantial. The dataset employed in the analysis contains information on all 5,304 subproject interventions implemented from 2003 to 2008 for a total funding amount of approximately PHP 4,270,000,000 or $86,600,000. Participating municipalities received an average of $448,773 of KC funding, with the average grant at the village level of $16,335.

The KC program was implemented through a five-stage process known as the Community Empowerment Activity Cycle (Beatty et al., 2017) and followed a standard CDD template (A. Parker, 2005). In general, communities prepared subproject proposals, competed over block grants to finance investments for local public goods, and were then responsible for implementing and maintaining those investments (Labonne and Chase, 2009). For simplicity, (Labonne and Chase, 2009) outline the three main phases of participation in the KC program as preparation, funding and implementation.

In the first phase, preparation, volunteers conducted a participatory situation analysis, and the results were validated in another assembly where the project preparation team and village representative teams were elected. Village representatives then attended a municipality meeting during which the rules and a subset of subproject ranking criteria were decided upon. Once those criteria were agreed upon, the project preparation teams prepared proposals, which were validated at a village meeting.

Second was the funding phase, when the preparation teams presented the proposals and village representatives ranked them by deciding the allocation of funds, while accounting for the budget of the municipality's block grant. The selection of subprojects was subject to a competitive process because the allocation of funds did not permit subprojects to be implemented in all villages. Once the inter-*barangay* forum decided which subproject proposals would receive funding, the results were presented in a village assembly.[5] The villages to receive funding then elected the members of the subproject management committee.

Last was the implementation phase, when subproject proposals were finalized by the committee, validated during a village assembly and then validated by another municipality forum. Even though inter-*barangay* forums were made up of both community representatives and technical advisors, only community representatives could approve a subproject proposal. Once the subproject was officially approved, village volunteers received technical assistance to create capacity through training in areas such as project planning, contracting, construction techniques, operations and management, bookkeeping and financial management. Municipalities received technical assistance with respect to the feasibility of subprojects, project design and budgeting. Technical manuals for small-scale infrastructure were provided to facilitate community involvement in the assessment, delivery and management of such infrastructure. The objectives of these manuals were (a) to provide the community with guidelines and tools for reporting, controlling and monitoring ongoing subprojects to ensure quality control and timeliness in implementation; (b) to provide project management with the tools required for technical reviews and quality control; (c) to provide guidelines for operations and maintenance of infrastructure projects; and (d) to provide guidelines on environmental screening (World Bank, 2002, p. 20). Additionally, as part of the project, community facilitators were recruited and trained in each region to undertake information dissemination at the community level, mobilize support and facilitate community involvement in the identification, planning and implementation of subprojects. Table 3.1 shows the list of implemented subprojects by municipalities.[6]

Through a review of internal program documents, some mechanisms were in place

[5]There may be concerns about the possibility of elite capture in which better-connected individuals dominate the subproject selection process and receive a disproportionate share of the benefits. Labonne and Chase (2009) show that the KC subprojects were not subject to elite capture, as the preferences of community and village captains (elected village leaders) were equally represented in community proposals. Additionally, Beatty et al. (2017) show that the KC program led residents to contribute to other civic activities at greater levels, which helps mitigate crowding out concerns.

[6]See Table A.10 in Appendix A.1.9 for a list of prohibited subprojects.

Table 3.1.: List of implemented KC subprojects

1	Road
2	Footbridge / small bridges
3	Access trail / footpath
4	School building
5	Water system
6	Health care center
7	Electrification
8	Day care center
9	Tribal housing / shelter
10	Community transport
11	Economic / livelihood support (training / trading center, market, mini-port / warf)
12	Multi-use building / facility
13	Small scale irrigation
14	Drainage structures (culverts, overflow, spillway)
15	Environmental preservation (artificial coral reef / marine sanctuary)
16	River control / flood control
17	Pre and post-harvest facility
18	Community economic enterprise training, equipment and materials support subprojects
19	Feasibility study
20	Sanitation facilities (toilets, solid waste management system)
21	Sea wall
22	Soil protection (riprap / slope protection / protection railing)
23	Eco-tourism
24	Lighthouse

Notes: This table presents the different types of implemented subprojects by municipalities as part of the KC program.

to mitigate environmental damage stemming from the KC program. The DSWD effectively ensured that the safeguard policies of the World Bank and the government were applied through the use of an Environmental and Social Management Framework and documents related to the Indigenous Peoples Policy Framework and the Land Acquisition, Resettlement and Rehabilitation Framework.[7] Environmental assessments and safeguard policies designed to be triggered were in place, but these were broad in scope. According to an internal project appraisal document by the World Bank (2002, p. 22):

> "Environmental issues arising from the Kalahi-CIDSS Project refer primarily to impacts caused by small-scale infrastructure construction. The environmental impacts caused by such activities are not expected to be significant. The project has designed a negative list of prohibited investments that includes activities with adverse environmental impacts. The project will use an environmental screening procedure that identifies prohibited projects (e.g., community roads into protected areas). Mitigation of negative impacts from sub-projects that are not on the negative list will be addressed through standard operating procedures, which are built into project manuals and training programs." [8]

Additionally, technical reports indicate that environmental assessments were undertaken to varying degrees. Table 3.2 in a report by the World Bank (2002, p. 26) indicates the various safeguard policies that were applied to the KC program. Policies regarding forestry and natural habitats were classified as 'not applicable,' thus revealing the limitations of the program's environmental protection safeguards. Furthermore, safeguard policies were triggered, but only for specific project types with certain characteristics. Table 3.3 in the same World Bank report outlines, for each infrastructure activity, the criteria for which an environmental safeguard is

[7] Implementing guidelines followed the Philippine Environmental Impact Assessment Policy from Department of Environment and Natural Resources Administrative Order (DAO) No. 96-37. The KC program adopted Administrative Order No. 96-37 as a guide for the environmental screening of subprojects. Additionally, the administrative order stipulated that environmentally critical projects (ECPs) and projects within environmentally critical areas (ECAs) required the submission of an environmental impact statement and provided that "no person, partnership or corporation shall undertake or operate any such declared environmentally critical project or area without first securing an Environmental Compliance Certificate (ECC)" (*Environmental and Social Safeguards*, 2002, p. 43).

[8] An additional report claims that "KALAHI-CIDSS infrastructure projects generally are not expected to have adverse environmental effects because of their small scale and location in non-sensitive environmental areas. KALAHI-CIDSS also has a built-in environmental screening mechanism through the negative list. Sub-projects that will involve environmentally harmful technology and practices are at the outset not eligible for funding" (*Environmental and Social Safeguards*, 2002, p. 45).

required. The only activities covered under the KC program are the construction of roads and irrigation systems. With respect to the construction of roads, the policy is triggered for long-road projects (>20 km) or road projects with critical slopes (>50 percent). Depending on the scope of the project, an EIS (Environmental Impact Statement), an IEE (Initial Environmental Examination) or an ECC (Environmental Compliance Certificate) may be required.

Table 3.2.: Safeguard policies

Policy	Applicability
Environmental Assessment (OP 4.01, BP 4.01, GP 4.01)	● Yes ○ No
Natural Habitats (OP 4.04, BP 4.04, GP 4.04)	○ Yes ● No
Forestry (OP 4.36, GP 4.36)	○ Yes ● No
Pest Management (OP 4.09)	○ Yes ● No
Cultural Property (OPN 11.03)	○ Yes ● No
Indigenous Peoples (OD 4.20)	● Yes ○ No
Involuntary Resettlement (OP/BP 4.12)	● Yes ○ No
Safety of Dams (OP 4.37, BP 4.37)	○ Yes ● No
Projects in International Waters (OP 7.50, BP 7.50, GP 7.50)	○ Yes ● No
Projects in Disputed Areas (OP 7.60, BP 7.60, GP 7.60)*	○ Yes ● No

Source: World Bank (2002, p. 26)

Other environmental mitigation efforts were made, including consultation with stakeholders at the environmental screening stage and during drafting of environmental assessment reports. During the project, a total of three consultations were held with the national-level NGO coordination forums of the Caucus of Development NGO Networks and Convergence Coordination. At the meetings, no issues regarding negative environmental impacts caused by the proposed projects were raised, although the consultations were ongoing and intensified during implementation of the projects (World Bank, 2002, p. 22). Lastly, compliance with the safeguard provisions and the list of prohibited investments was ensured through an internal input process, output monitoring and independent external monitoring by consultants, civil society entities and World Bank supervision missions (World Bank, 2002, p. 27). While several reports outline safeguard policies in terms of the entities in charge of monitoring compliance, there was no policy in place regarding enforcement.

Table 3.3.: Environmental safeguard requirements

ACTIVITIES	CRITERIA	REQUIREMENT
Training and institutional assistance	*none*	*Not covered under the Philippine EIS System*
Livelihood Activities (not applicable under KALAHI-CIDSS)	• Backyard animal farms not exceeding 5,000 heads of birds or 2 sows with 20 pigs • Sari-sari (or coop) store • Organic compost/fertilizer production not exceeding 10,000 (50 kg) bags per annum capacity • Cottage industries	- Not covered under the Philippine EIS System - CNC may be issued upon request of proponent
	Livelihood activities with capacities in excess of the threshold	*Submission of duly accomplished IEE Checklist/s as application for ECC*
Rehabilitation of roads & bridges Rehabilitation of irrigation system Rehab of other support systems	with effective expansion of less than 50% service area expansion does not exceed threshold	Not covered under the Philippine EIS System - CNC may be issued upon request of proponent
Construction of roads	Roads with length in excess of 5 km that will traverse an area with critical slope (>50%) Roads with length in excess of 20 km if not traversing an area with critical slope	*Submission of EIS as application for ECC*
	Roads with length in excess of 3 km but less than or equal to 5 km that will traverse an area with critical slope (>50%) Roads with length in excess of 15 km but less than or equal to 20 km if not traversing an area with critical slope	*Submission of IEE as application for ECC*
Construction of roads *(continuation)*	Roads with length less than or equal to 3 km that will traverse an area with critical slope (>50%) Roads with length in excess of 10 km but less than or equal to 15 km if not traversing an area with critical slope	*Submission of duly accomplished IEE Checklist as application for ECC*
	Roads with length less than or equal to 10 km if not traversing an area with critical slope	Not covered under the Philippine EIS System CNC may be issued upon request of proponent
Construction of bridges (Not applicable under KALAHI-CIDSS)	2 lanes with length in excess of 200 meters 2 lanes with more than 10 spans	*Submission of EIS as application for ECC*
	2 lanes with length in excess of 100 meters but less than or equal to 200 meters 2 lanes with more than 6 but less than or equal to 10 spans	*Submission of IEE as application for ECC*
	2 lanes with length in excess of 50 meters but less than or equal to 100 meters 2 lanes with more than 4 but less than or equal to 6 spans	*Submission of duly accomplished IEE Checklist as application for ECC*
	2 lanes with length of less than or equal to 50 meters	Not covered under the Philippine EIS System CNC may be issued upon request of proponent
Construction of Irrigation System	With service area in excess of 1,000 hectares Reservoir storage capacity in excess of 25 million cubic meters Reservoir area (flooded area) in excess of 100 hectares	*Submission of EIS as application for ECC*
	With service area in excess of 700 hectares but less than or equal to 1,000 Reservoir area (flooded area) in excess of 50 hectares but less than or equal to 100 hectares	*Submission of IEE as application for ECC*
	With service area in excess of 350 hectares but less than or equal to 700 Reservoir area (flooded area) in excess of 25 hectares but less than or equal to 50 hectares	*Submission of duly accomplished IEE Checklist as application for ECC*
	With service area of less than or equal to 300	Not covered under the Philippine EIS System CNC may be issued upon request of proponent

These criteria are indicative and will be complemented by an environmental screening procedure, which will take into account investments in water supply, buildings, and other structures not included on this list.

Notes: List of table acronyms: CNC (Certificate of Non-Coverage), ECC (Environmental Compliance Certificate), IEE (Initial Environmental Examination), EIS (Environmental Impact Statement). *Source*: World Bank (2002, p. 72)

3.3. Data

Data on deforestation are derived from a satellite-generated forest cover database called Global Forest Change (GFC), created by Hansen et al. (2013). The database offers global information about forest cover in 2000 and subsequent forest changes between 2001 and 2018. Landsat satellites capture pixel-level images with a 1 arc-second resolution, where GFC classifies forest cover and loss at a spatial resolution of 30 m x 30 m.[9] Baseline data describe forest cover in the year of 2000 by matching spectral signatures reflected off the surface of the Earth to spectral signatures of different land surface types. A binary indicator is then constructed, where each 30 m x 30 m pixel is considered deforested if over 90 percent of the 2000 forest cover or tree canopy has been lost by a given year.[10] The GFC dataset provides data at a superior resolution to alternatives, and its use follows recent empirical work on deforestation (Abman et al., 2020; Alesina et al., 2019; Heß et al., 2020).

Other studies have employed the GFC database but have aggregated the data at a much higher level, thus not fully exploiting the high resolution. BenYishay et al. (2016) aggregated the GFC data to construct an annual outcome measure that captured the cumulative forest loss in 5 km x 5 km cells since 2000. Alternative sources to the GFC provide data at a much lower resolution. These include the FAO dataset described by Keenan et al. (2015) and the MODIS land cover type at a 500 m resolution used by Jagger and Kittner (2017). Vegetation Continuous Fields (VCF) is another database, which produces a continuous, quantitative portrayal of land surface cover at a 250 m pixel resolution, with a sub-pixel depiction of the percentage of cover in reference to the percentage of tree cover, percentage of non-tree cover and percentage of non-vegetated (bare) cover. Asher et al. (2020) justified their use of the VCF over the GFC by claiming that the context of India does not present an increasing deforestation trend and therefore cannot be properly described with binary indicators of deforestation. The VCF database is not employed in this study, as the data are available only from 2000 to 2005. Given that the Philippines presents an increasing deforestation trend, the GFC database is a more appropriate data source.

This study maintains the high spatial resolution of the original GFC database, and the data are constructed as follows. Forest loss is binary in nature, and is defined as a stand-replacement disturbance term or a change from a forest to a non-forest state. The loss of forest cover is only associated with the first year when a significant change in forest cover pixels or the complete removal of tree canopy cover are

[9]The GFC defines forest cover as an area in which the biophysical presence of trees or vegetation higher than five meters accounts for more than 50 percent of the land and may take the form of natural forests or plantations over a range of canopy densities.

[10]See Appendix A.1.1 for examples of the pixel level deforestation data included in the GFC database.

recorded over the year. Two outcome variables are used in the analysis. The first is an absolute measure of deforestation that accounts for the total number of square meters that were deforested. The variable is constructed as a column vector of the number of pixels of forest loss, where the i^{th} entry represents the total number of square meters of forest loss in municipality m, for a given year t, or:

$$Deforestation_{m,t} = \sum_{i=1}^{n} Deforested\ Pixels_{i,m,t} = x_{1,m,t} + x_{2,m,t} \ldots + x_{n,m,t} \tag{3.1}$$

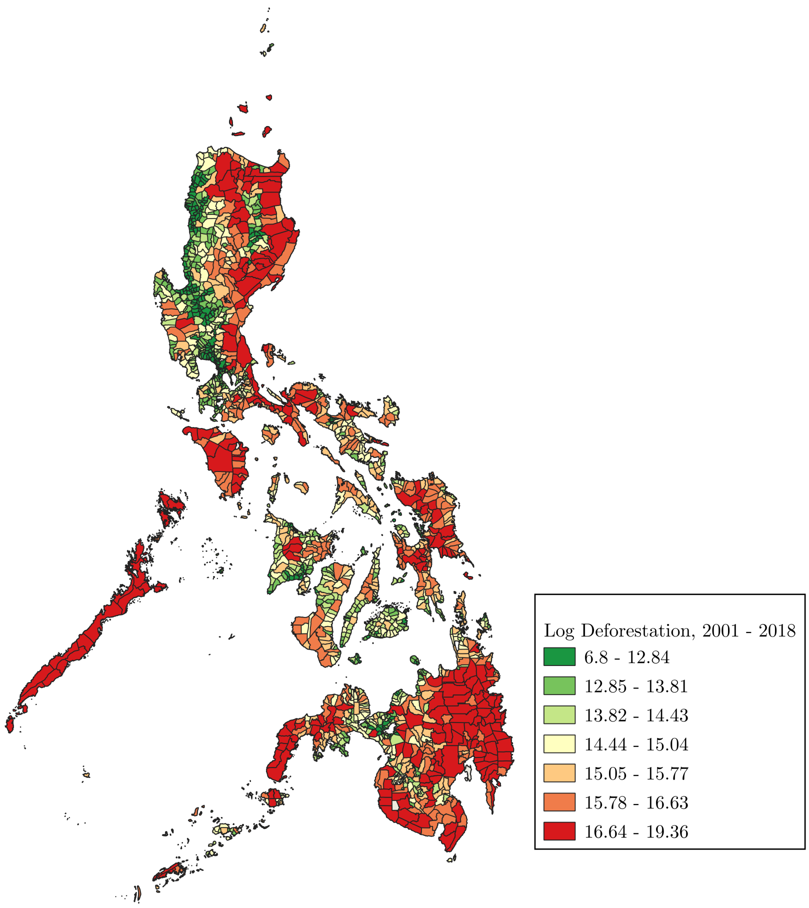
The second outcome variable logarithmically transforms the deforestation variable.[11] Since some municipalities did not experience any deforestation over the sample periods, a small constant of one 30 m x 30 m pixel or 900 square meters is added.[12] Figure 3.1 presents a map of average yearly deforestation in log form across Philippine municipalities from 2001 to 2018, while Figure 3.2 calculates the yearly loss of forest cover in square meters. From 2001 to 2018, the average yearly loss of forest cover across the Philippines was 686,173,391 square meters.

I have obtained data on 5,304 different subprojects that were implemented through the KC program from 2003 to 2008. These data provide information on the types of subprojects completed, project costs, completion dates, direct number of beneficiaries and the location of the project at the village and municipality level. This makes it possible to exploit the heterogenous effects stemming from the different types of infrastructure projects undertaken within communities. Additionally, I have collected data for the RCT portion of the study (2013-2015) from the Millennium Challenge Corporation's (MCC) data repository, which provides data on the municipalities treated in a later phase of the KC program. Other municipality variables used as covariates in the analysis come from the census of the Philippines in 2000 and 2010. Tables A.1 and A.2 in Appendix A.1.2 provide summary statistics for each of the variables used in the analysis from both time periods.

[11] See Figure A.4 and Figure A.5 in Appendix A.1.2 for the distributions of deforestation in log form for each time period under consideration in this analysis.

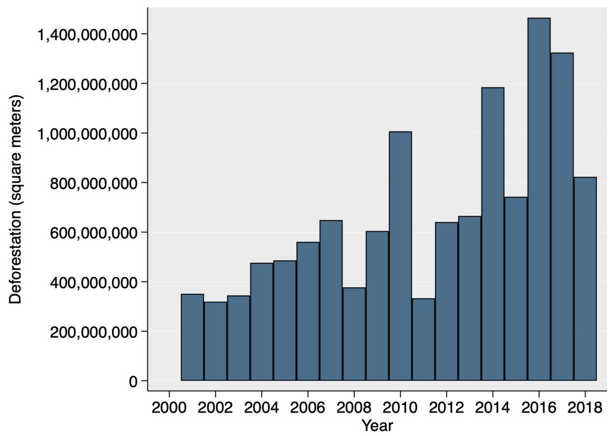
[12] Adding this small constant of one 30 m x 30 m pixel or 900 square meters is the smallest incremental unit measured by the GFC database.

Figure 3.1.: Log of deforestation per municipality, 2001 – 2018



Notes: This figure presents a map of deforestation in log form for municipality m from 2001 to 2018. *Source*: Author's own calculations based on the GFC data.

Figure 3.2.: Yearly forest loss



Notes: This graph shows how many square meters were deforested across all Philippine municipalities for a given year *t* from 2001 to 2018. *Source*: Author's own calculations based on the GFC data.

3.4. Empirical strategies

I implement two empirical strategies to identify the causal effect of CDD programs on deforestation. The first strategy takes advantage of a discontinuity in the allocation of development aid in the first round of the KC program from 2003 to 2008. The study then postulates the second empirical strategy that analyzes a large-scale RCT of development aid in a later round of the KC program, from 2013 to 2015.

3.4.1. Regression discontinuity of the KC program

The first empirical strategy takes advantage of a discontinuous threshold in the first round of the KC program that restricted the eligibility of aid to the poorest 25 percent of municipalities from 2003 to 2008. This is a similar empirical strategy to that employed by Crost et al. (2014) and exploits an arbitrary poverty threshold that the implementing agency used to decide on the eligibility of municipalities to be treated by the program. Exploiting this discontinuous threshold in the assignment of the KC program makes it possible to identify the causal effects that community development programs may have on deforestation by comparing municipalities that are just above and below this threshold.

Forty-two poor provinces were initially identified as eligible for the program, and 22 of these were finally selected for the program's initial phase.[13] Thereafter,

[13]Eligibility for the program was based on the Family Income and Expenditure Survey, in which 40 out of the initial 42 provinces selected were among the country's poorest. Philippines has a total of

a combination of data from the Family Income and Expenditure Survey (FIES) and the 2000 census of the Philippines (Balisacan and Edillon, 2003; Balisacan et al., 2002) was used by the implementers in a poverty mapping methodology to generate poverty levels for each municipality within those 22 eligible provinces.[14] Municipality rankings were based on six indicators (income, food, clothing, shelter, disaster vulnerability and citizen participation) and each indicator was assigned a score on the basis of responses to a number of questions (Balisacan et al., 2002). Municipalities in eligible provinces were then ranked according to their poverty level. Eligibility to participate was restricted exclusively to the poorest quartile of municipalities, and the threshold was therefore calculated as the total number of municipalities within a province divided by four, before being rounded to the nearest integer. The threshold value was then subtracted from the municipalities' actual poverty ranking to obtain the relative poverty ranking. This created the forcing variable or the distance of a municipality's poverty ranking from the provincial eligibility threshold. The richest eligible municipalities had a relative ranking of -0.5 and the poorest ineligible municipalities had a relative ranking of 0.5. Once the eligibility of the municipalities was finalized, facilitators hired by the DSWD engaged with local governments at the village and municipality levels to train community members on how to choose, design and implement subprojects. Since the allocation of the KC program was based exclusively on this poverty ranking and no other criterion, the only variable that should change discontinuously at the threshold is the eligibility of a municipality participating in the program.

Table 3.4 reports the estimated coefficients for the probability of a municipality's participation in the KC program. According to the estimated results of the probit model in column 2, the probability of participation of eligible KC municipalities in the CDD program increases by 52 percentage points across the threshold. A similar point estimate is obtained in the OLS specification in column 4, where the probability of participation increases by 53 percentage points. The targeting procedure based on a municipality's poverty ranking creates a very distinct cut-off for the probability of a municipality's participation in the program. In order to test the plausibility of the identification strategy, Table A.4 in Appendix A.1.4 presents several regressions, in accordance with Imbens and Lemieux (2008) and D. S. Lee and Lemieux (2010), to test the smoothness assumption by regressing other covariates on the discontinuous change of eligibility status for the KC program. Under the

81 provinces.

[14] To ensure that the allocation of the KC program was based on objective criteria, an independent consulting firm was contracted to carry out the estimation. Since this database is no longer available to replicate the poverty scores, this study uses the rankings published by Balisacan et al. (2002) and Balisacan and Edillon (2003) to generate the distance of a municipality's poverty ranking from the provincial eligibility threshold as the forcing variable, similarly to Crost et al. (2014).

identifying assumption of the RDD estimator, assignment to the program close to the threshold is as good as random and, therefore, should not change discontinuously across the threshold. No evidence of a statistically significant relationship is detected in any of the specifications, thus providing further evidence that the threshold value can be interpreted as a causal effect of the treatment stemming from the KC program.

Table 3.4.: Probability of participation in the KC program

	(1) Probit	(2) Probit	(3) OLS	(4) OLS
Eligibility for KC	0.492***	0.519***	0.516***	0.528***
	(0.136)	(0.135)	(0.119)	(0.121)
Observations	222	222	222	222
R-squared			0.463	0.473
Controls	No	Yes	No	Yes

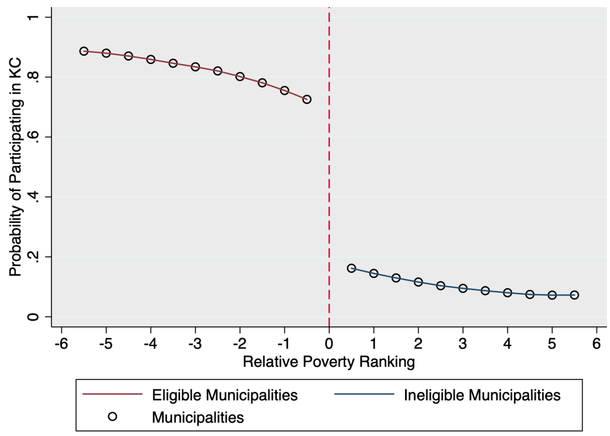
Notes: Columns 1 and 2 report the marginal effects (and standard errors) from a probit regression, while columns 3 and 4 report the estimated coefficients (and standard errors) from an ordinary least squares regression. Robust standard errors are in parentheses. All regressions include municipality fixed effects. Columns 1 and 3 control for the relative poverty ranking score only amongst eligible municipalities, and the full municipality poverty ranking score. Column 2 and 4 control for the relative poverty ranking score only amongst eligible municipalities, the full municipality poverty ranking score, natural log of population, average years of education of the household head, fraction of households with access to electricity, percentage of villages with access to a highway, fraction of houses with roofs made of strong materials, access to an indoor toilet and running water and an index for religious fractionalization. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Next, Figure 3.3 plots the relative poverty ranking against the probability of participation in the KC program to illustrate that the probability of participation decreases sharply across the eligibility threshold. Then, Figure 3.4 plots the relative poverty ranking against the frequency of municipalities that report similar scores. The frequency of poverty rankings decreases with distance from the eligibility threshold, since smaller provinces do not have enough municipalities to fill up those rankings. Plotting the data in this way demonstrates whether there is a discontinuity in the distribution of the forcing variable at the threshold. Looking at either side of the threshold at 0, there appears to be no evidence that the forcing variable has been manipulated by external forces or the implementing agency.[15] The selection

[15] See Appendix A.1.4, Figure A.7, for a sensitivity analysis in accordance with Cattaneo et al. (2018) and Cattaneo et al. (2020) that involves estimation of the discontinuity in the density function

of bandwidths of the relative poverty ranking is set from [-6, 6] and follows a similar bandwidth selection as Crost et al. (2014). Originally, 425 municipalities are included in the dataset, 315 are ineligible and 110 are eligible. After selection of the bandwidths, the yearly sample size is reduced to 222 municipalities, 128 of which are ineligible and 94 are eligible.

Figure 3.3.: Effect of eligibility on participation in KALAHI-CIDSS



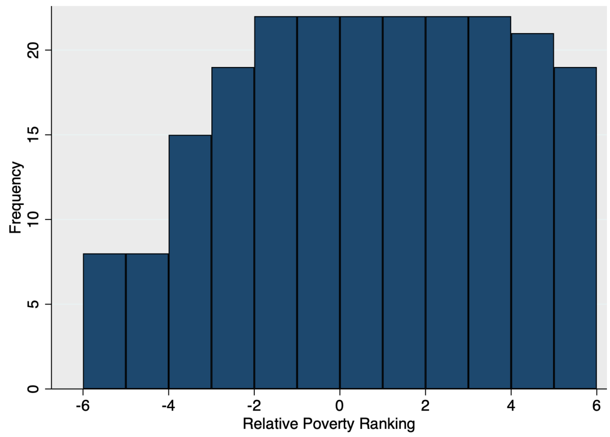
Notes: This figure plots the relationship between the relative poverty ranking and the probability of a municipality's participation in the KC program. Municipalities to the left of 0 are eligible for the KC program, while municipalities to the right of 0 are ineligible. The solid lines represent nonparametric fits from a local linear regression, where each side of the threshold is estimated separately. Triangular kernel weights are included to give greater weight to observations that are closer to the threshold. The figure illustrates that there is a clear jump in the probability of a municipality's participation in the KC program based on the relative poverty ranking. *Source*: Author's own calculations.

Having identified the eligibility threshold and found that there appears to be no evidence that the forcing variable has been manipulated, I move on to presenting descriptive evidence to illustrate the differences between eligible and ineligible municipalities. Figure 3.5 first maps the municipalities by eligibility status to illustrate the spatial distribution of eligible and ineligible municipalities in the Philippines as a part of the KC program. In Figure 3.6, the dataset is broken down by eligible and ineligible municipalities with regard to the average number of square meters in log form that were deforested from 2003 to 2008. In each of the years under consideration, eligible municipalities underwent higher levels of deforestation relative to ineligible municipalities. Next, Figure 3.7 maps the level of deforestation

of the forcing variable at the cutoff to verify that there is no statistical difference in municipality density. I find no evidence to reject the null hypothesis of no difference in municipality density at the threshold (p-value = 0.943).

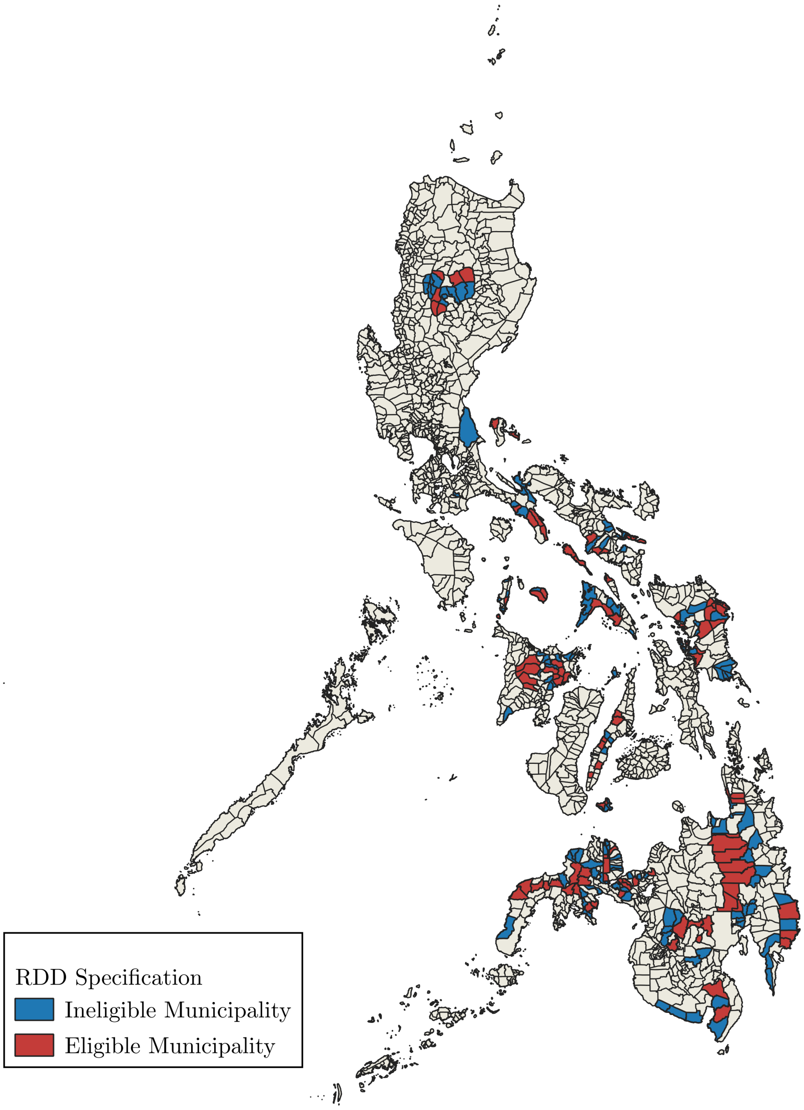
in log form of treated and control municipalities over the sample period. Dark green represents municipalities that had low levels of deforestation and dark red represents municipalities that suffered from high levels of deforestation. Then, Figure 3.8 plots the log of deforestation against the relative poverty ranking to illustrate that, on average, ineligible municipalities suffered less deforestation. While deforestation in eligible municipalities is roughly stable, ineligible municipalities present a decreasing deforestation trend as the poverty level decreases.

Figure 3.4.: Municipality frequency and relative poverty ranking



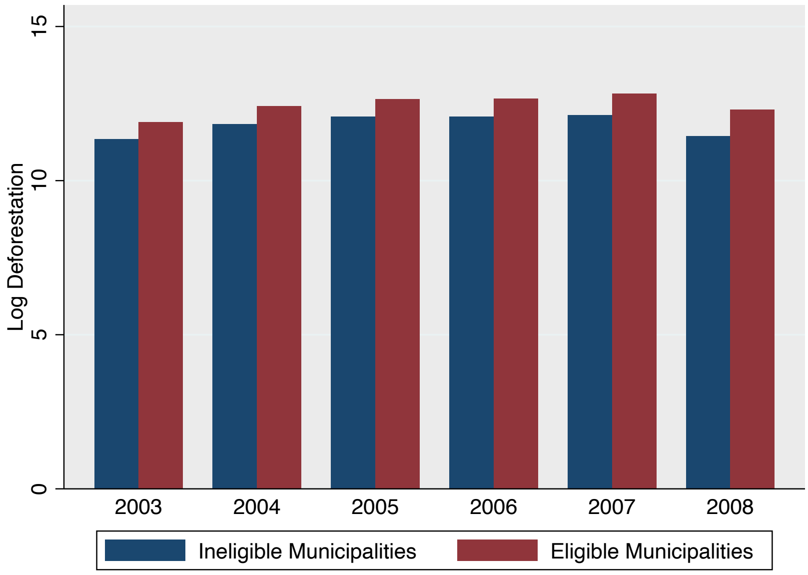
Notes: This figure presents the frequency of municipalities for which a given relative poverty ranking occurs within the bandwidth selection of [-6, 6]. Municipalities to the left of 0 are eligible for the KC program, while municipalities to the right of 0 are ineligible. Furthermore, municipalities just to the left of the threshold of 0 are the richest eligible municipalities within a given province and municipalities just to the right of the threshold are the poorest ineligible municipalities. *Source*: Author's own calculations.

Figure 3.5.: Eligibility status of municipalities for KALAHI-CIDSS, 2003 – 2008



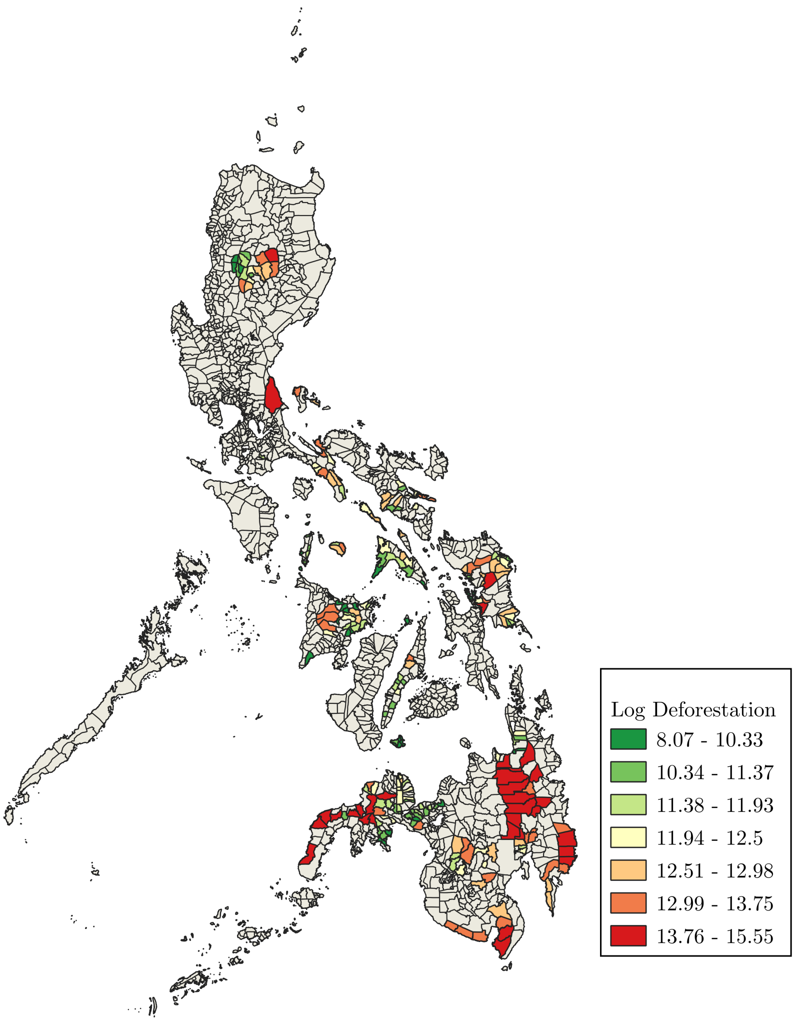
Notes: This figure presents a map of eligible and ineligible municipalities analyzed within the RDD specification. Only municipalities that fall within the [-6, 6] bandwidth were mapped. *Source*: Author's own calculations.

Figure 3.6.: Log of deforestation by eligibility status, 2003 – 2008



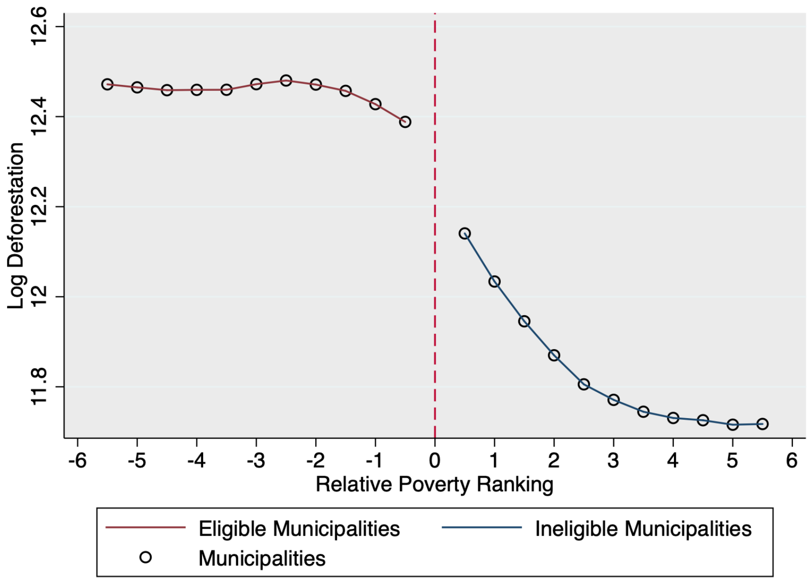
Notes: This figure graphs the natural log of the number of square meters that were deforested in eligible and ineligible municipalities analyzed within the RDD specification for a given year *t* from 2003 to 2008. *Source*: Author's own calculations.

Figure 3.7.: Log of deforestation per municipality, 2003 – 2008



Notes: This figure presents a map of deforestation in log form analyzed within the RDD specification. Only municipalities that fall within the [-6, 6] bandwidth are mapped. *Source*: Author's own calculations.

Figure 3.8.: Log of deforestation and eligibility status



Notes: This figure plots the relationship between the relative poverty ranking and the log of deforestation for eligible and ineligible municipalities. Municipalities to the left of 0 are eligible for the KC program, while municipalities to the right of 0 are ineligible. The solid lines represent nonparametric fits from a local linear regression, where each side of the threshold is estimated separately. Triangular kernel weights are included to give greater weight to observations that are closer to the threshold. *Source*: Author's own calculations.

In order to estimate a causal effect of the KC program on the level of deforestation, I estimate the following equation that takes advantage of an RDD stemming from the assignment of the CDD program. The equation estimated is:

$$\begin{aligned} Y_{m,t} = \beta_0 + \beta_1 CDD_{m,t} + \beta_2 RPR_{m,t} + \beta_3 CDD_{m,t} \cdot RPR_{m,t} + X'_{m,t} \cdot \delta \\ + \rho_m + \tau_t + \varepsilon_{m,t} \end{aligned} \tag{3.2}$$

where $Y_{m,t}$ is estimated separately for the log of deforestation and an absolute measure of deforestation that accounts for the total number of square meters deforested for municipality m, in time t. The main variable of interest is $CDD_{m,t}$, represented as a dummy variable that indicates whether the municipality is eligible to be treated under the CDD program or not.[16] Also, the relative poverty rank of each municipality is

[16]It should be noted that some eligible municipalities did not participate in the program due to the implementing agency's concerns about violence and the safety of their personnel in the selected municipalities. These were therefore replaced by municipalities that came next in the poverty ranking, just above the threshold. Once the program's implementation began, no municipalities were dropped.

introduced as $RPR_{m,t}$. X' is a vector comprising the following controls: the natural log of population, average years of education of the household head, fraction of households with access to electricity, percentage of villages with access to a highway, fraction of households with roofs made of strong materials, access to an indoor toilet and running water and an index for religious fractionalization.[17] The intercept term is represented as β_0, while municipality and time fixed effects are denoted as ρ_m and τ_t, respectively, which control for the unobserved municipality-time-invariant effect. Triangular kernel weights are additionally applied to provide greater weight to municipalities closer to the cutoff and I compute the standard errors as heteroskedasticity-robust standard errors (White, 1980), as recommended by Imbens and Lemieux (2008) and D. S. Lee and Lemieux (2010).

3.4.2. Randomized control trial of the KC program

The second empirical strategy to be tested exploits a large-scale RCT of development aid through the same CDD program and builds upon the earlier phase of the KC program from 2003-2008. Expansion of the CDD program was the result of a five-year pact between the Government of the Republic of the Philippines and the MCC for \$434 million and was implemented by the same Philippine agency, DSWD.[18] The agreement was signed on September 23, 2010 and implementation of the program began on May 25, 2011. Baseline data were collected from April to June of 2012, interim data were collected from February to June 2014 and the final round of data was collected from July to October 2015.[19]

Due to the presence of a small number of municipalities that did not comply with the treatment, it could be argued that a fuzzy discontinuity design may make more sense. However, a sharp discontinuity is argued to be the right option for this analysis, as the majority of non-compliance arises from the implementing agency's fear of violence and for the safety of its workers in some of the initially eligible municipalities. Thus, the majority of non-compliers to the KC program were not endogenously sorting out. Additionally, violence within the municipality was not used as an eligibility criterion, and therefore should not have affected the discontinuity. Therefore, the results represent an average treatment effect on deforestation stemming from the eligibility status for the KC program, regardless of subsequent participation. See Table A.3 in the Appendix for more details on non-compliant municipalities and a breakdown of municipalities by eligibility and whether or not they received treatment under the KC program.

[17] Religious fractionalization is computed using a standard Herfindahl index. Let municipalities m be $m = 1, \dots, M$ and N represent the number of religions. Religious fractionalization (RF) in municipality m is given by: $RF_m = 1 - \sum_{i=1}^{N} s_{m,i}^2$ where $s_{m,i}$ is the share of religion i in municipality m.

[18] Financing for the second phase was derived from a \$59 million World Bank loan and a \$120 million MCC grant. Additional funding came from international funders and local governments (regional, municipality-level and/or village-level), which contributed at least 30 percent of the costs of the KC subprojects implemented in their areas.

[19] Typhoon Yolanda, one of the strongest storms ever recorded, hit the Philippines on November 7, 2013. Beatty et al. (2017) mitigate concerns about the identification's validity, where they find no

The implementing agency DSWD randomly assigned the CDD intervention at the municipality level across the Philippines' three main island groups; 198 municipalities were randomly assigned to participate in the KC program or remain part of the control group for three years. As with the first iteration of the KC program, DSWD targeted the poorest communities across the Philippines from 2011 to 2015. The randomization of the KC program proceeds as follows. Eligibility for participation was based primarily on the poverty level in the municipality and prior experience with KC. Municipalities with prior experience with the KC program in earlier rounds of the program were automatically excluded.[20] Within 48 of the country's poorest provinces targeted by KC, municipalities with a poverty incidence of 70 percent or more automatically participated in the program, while municipalities with a poverty incidence of less than 33 percent were considered ineligible. Poverty levels between 34 and 69 percent were thus eligible to be randomly selected for participation in the KC via lottery. DSWD granted funding to half the municipalities in the province minus one, which means that if there was a high number of municipalities within a province over the 70 percent poverty incidence level, all eligible funding could be taken up by municipalities that were guaranteed participation in the program, thus leaving no funding for municipalities with poverty incidence levels between 34 and 69 percent. Therefore, for a given province, the number of funding slots available to a municipality that entered the random draw was determined by the 50 percent minus one rule, minus the number of municipalities that were automatically eligible for the project. Thus, the probability of participation in the KC program differed by province. To ensure basic comparability between what would ultimately become the treatment and control communities, the Innovations for Poverty Action team matched municipalities within provinces just prior to each lottery based on their poverty incidence, population, land area and the number of villages.[21]

The lottery portion of the CDD intervention encompassed 198 municipalities, where the treatment and control arms of the experiment each consisted of 99 municipalities. Figure 3.9 shows a map of the municipalities by treatment and control status

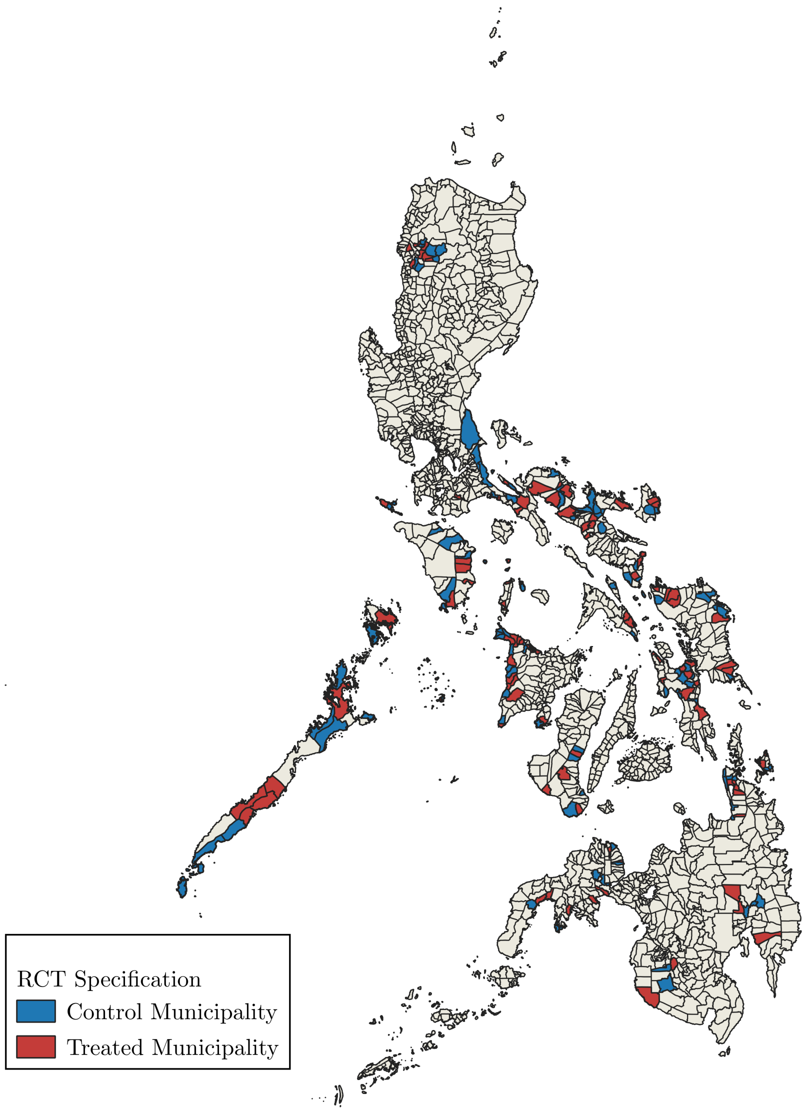
statistically significant difference of the impact of typhoon Yolanda between treatment and control municipalities. In other words, neither the treatment nor the control municipalities were disproportionally affected by the typhoon, and the control can validly serve as a comparable counterfactual.

[20]Twenty duplicate cases are detected in which municipalities were eligible for the KC program in the RDD empirical strategy as well as eligible to be treated by the RCT. According to the eligibility requirements, previous contact with the DSWD should have disqualified the municipality from being treated again. Only two of the 20 duplicate cases are found to be treated in both rounds.

[21]Beatty et al. (2017) justify the four variables used for matching based on the following reasons: poverty incidence is included, since it is the key deterministic variable of treatment status; the number of villages because block grants are provided and subprojects are implemented at the village level; population and land area are included, as these are factors in determining a municipality's Internal Revenue Allotment, which largely determines the financial resources available to the local government and affects counterpart contributions by implementation of the KC in the municipality.

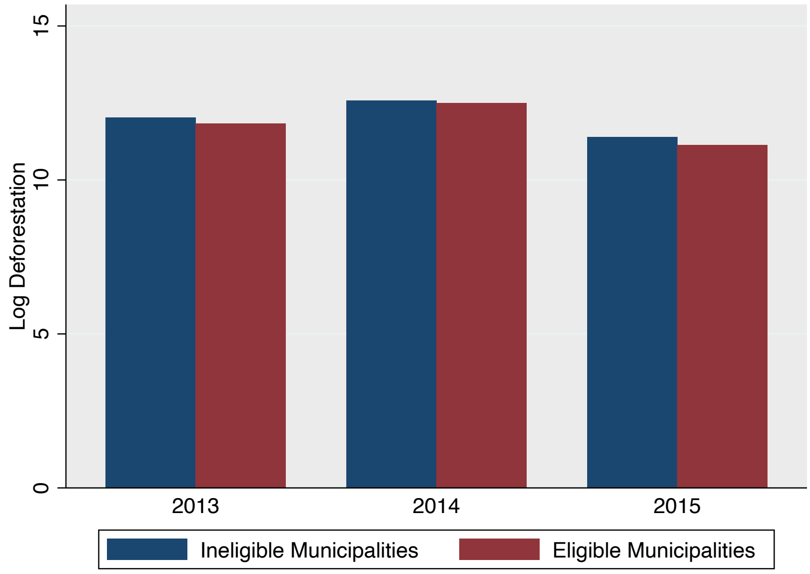
to show the spatial distribution of municipalities included in the RCT intervention. Figure 3.10 then shows a breakdown of the data by treatment and control status with regard to the average number of square meters in log form that were deforested from 2013 to 2015. Note that this figure differs from Figure 3.6, in that control municipalities on average had higher levels of deforestation relative to treatment villages. Lastly, Figure 3.11 shows a map of the deforestation levels of the RCT municipalities over the sample period.

Figure 3.9.: Treatment status of municipalities for KALAHI-CIDDS, 2013 – 2015



Notes: This figure presents a map of the treated and control municipalities analyzed within the RCT specification. *Source*: Author's own calculations.

Figure 3.10.: Log of deforestation by treatment status, 2013 – 2015



Notes: This figure graphs the natural log of the number of square meters deforested for treated and control municipalities analyzed within the RCT specification for a given year t from 2013 to 2015. *Source*: Author's own calculations.

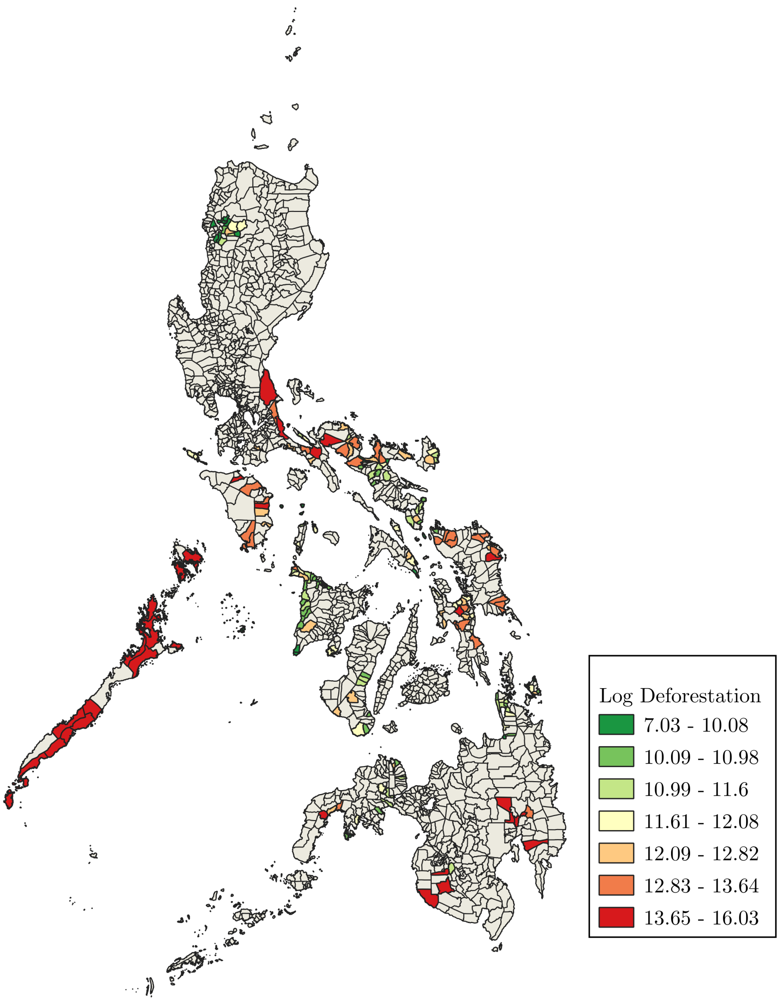
To identify the causal effect of the KC program on the level of deforestation, the second empirical strategy takes advantage of the described large-scale RCT that randomized CDD aid interventions at the municipality level across the Philippines' three main island groups. The equation to be estimated is:

$$Y_{m,t} = \beta_0 + \beta_1 T_{m,t} + X'_{m,t} \cdot \delta + \lambda_s + \rho_m + \tau_t + \varepsilon_{m,t} \tag{3.3}$$

where $Y_{m,t}$ again is estimated separately for the log of deforestation and the absolute level of deforestation for municipality m, in time t. The main variable of interest is $T_{m,t}$, represented as an indicator variable that dictates whether the municipality was in the treatment group of the CDD program at time t. In accordance with Bruhn and McKenzie (2009) and Beatty et al. (2017), strata (pair/triplet) dummies based on the matched pairing completed prior to randomization are included as λ_s, where s indexes strata.[22] Furthermore, X' is a vector of covariates and includes the natural log of population, average years of education of the household head, fraction of households with access to electricity, fraction of households with roofs made of strong materials, access to an indoor toilet and access to running water. Last, the intercept term is

[22]See Appendix A.1.6, Table A.7, for a balance test between treated and control municipality-level characteristics.

Figure 3.11.: Log of deforestation per municipality, 2013 – 2015



Notes: This figure presents a map of deforestation in log form analyzed within the RCT specification. *Source*: Author's own calculations.

represented as β_0, while municipality and time fixed effects are denoted as ρ_m and τ_t, respectively, which control for the unobserved municipality-time-invariant effect.

Both in the cases of the RDD and RCT analyses some ambiguity exists as to the relationship between development aid, changing levels of community well-being and deforestation. Negative effects could be expected, as construction typically involves the conversion of natural habitats, and forests are easy to convert for agriculture and other uses. As the well-being of an area increases, villages may be more likely to expand due to the value of land for settlement and industry, which can result in increased pressure on surrounding forests. Increasing well-being can also raise the demand for resource-intensive goods, which in turn can increase environmental degradation. On the other hand, there could be positive effects due to environmental rules and regulations that may prevent detrimental construction methods. Additionally, an increase in the well-being of an area may increase the demand for environmental amenities (Cropper and Griffiths, 1994). This can raise the demand for environmental resources by either inducing households to invest in those resources or raising the opportunity cost of extractive activities. There is also reason to expect a null effect, as many of the implemented subprojects are physical infrastructure that are likely to be located within village centers such as roads, education and health facilities, and water and electricity subprojects. Additionally, the subprojects are small-scale and the construction of such projects does not necessarily require tree felling.

3.5. Main results

Table 3.5 presents the results of the RDD analysis, where column 1 shows the results for the log of square meters deforested and column 2 the total number of square meters that were deforested. According to the estimated coefficient, eligible municipalities for the KC program on average deforested 236 percent more than ineligible municipalities. In column 2, the estimated coefficient indicates that eligible communities for the KC program on average deforested approximately 957,828 square meters more than ineligible communities. To put this figure into context, the estimated impact represents approximately 194 percent more deforestation in municipalities that received the KC program relative to control municipalities.[23]

[23] I perform two robustness exercises to reinforce the results found in Table 3.5. First I perform an optimal bandwidth selection following Cattaneo et al. (2018) and Cattaneo et al. (2020) which selects the optimal bandwidth range from [-7, 15] as well as tests for statistical differences in the densities around the cutoff (see Figure A.9). Table A.5 presents the estimates from equation 3.2 using the optimal bandwidth, where the estimates remain similar to Table 3.5. Second, I test movements along the bandwidth selection by increasing the bandwidth by one from [-6, 6] to [-10, 10]. Table A.6

Since the allocation of the KC program in the RDD framework was based on a poverty threshold, I investigate whether higher levels of poverty led to more deforestation relative to less poor areas. This is in reference to differing hypotheses such as the poverty-environment hypothesis and the environmental Kuznets curve. The former hypothesis suggests that as income grows, even at low income levels, the surrounding environmental quality improves. Accordingly, stopping environmental degradation first requires the preliminary step of reducing poverty. This relationship is documented by A. D. Foster and Rosenzweig (2003) with respect to forest growth in India, which appears to have been caused by the growth in demand for forest products as a result of income growth, and not by supply-side factors such as land and labor prices in the forestry sector. The latter hypothesis suggests the existence of a non-monotonic relationship, as raising living standards first increases pressure on the environment and later reduces it. To further explore this idea of how poverty interacts with natural resources, an interaction term is introduced between $CDD_{m,t} \cdot RPR_{m,t}$. Eligible municipalities are all similarly poor, as evidenced by the fact that they are eligible for the CDD program, and this interaction can provide evidence regarding the poverty-environment hypothesis and the environmental Kuznets curve. The results in column 2 indicate that richer eligible municipalities underwent more deforestation than poorer eligible municipalities. The positive sign in the interaction term provides evidence in support of the environmental Kuznets curve that predicts that raising living standards first increases pressure on the environment. This result contradicts the idea of the poverty-environment hypothesis that poverty reduction, even at low income levels, leads to an environmental improvement (Baland and Platteau, 1996; A. D. Foster and Rosenzweig, 2003).

Next, Table 3.6 presents the results of the RCT empirical strategy. Column 1 presents the results for the log of square meters deforested, while column 2 presents the total number of square meters that were deforested. According to the estimated coefficient in column 1, treated municipalities experienced on average 265 percent more deforestation than control municipalities. In terms of the aggregate number of square meters that were deforested per year, the RCT empirical strategy estimates a higher point estimate relative to the RDD. According to column 2, treated municipalities experienced on average 2,134,685 square meters more deforestation than control municipalities. Descriptively, this is shown in Figure 3.2, where on average there were higher levels of absolute deforestation throughout the Philippines during the RCT period relative to the RDD period. To put this point estimate into context, the impact represents approximately 185 percent more deforestation in municipalities that received the KC program relative to control municipalities.[24]

presents the estimates and the results remain qualitatively similar to Table 3.5.

[24]In Appendix B.2, an alternative measure of deforestation is analyzed through the percentage

Table 3.5.: Effect of eligibility for KALAHI-CIDSS on deforestation, 2003 – 2008

	(1) Log Deforestation	(2) Deforestation
CDD	2.365***	957,828***
	(0.452)	(281,784)
CDD x RPR	-0.0308	269,137***
	(0.174)	(65,095)
Observations	1,332	1,332
Municipalities	222	222
Mean Dep. Var.	12.090	601,933
Mean Dep. Var. of Control	11.819	493,124
R-squared	0.863	0.738

Notes: This table presents estimates of the effects of eligibility for the KC program on deforestation, identified using an RDD based on municipalities' relative poverty ranking. Robust standard errors are in parentheses. Triangular kernel weights are included to give greater weight to observations that are closer to the threshold. Each regression includes municipality and time fixed effects. The independent variables in columns (1) and (2) include: municipality poverty ranking score, natural log of population, average years of education of the household head, fraction of households with access to electricity, percentage of villages with access to a highway, fraction of houses with roofs made of strong materials, access to an indoor toilet and running water and an index for religious fractionalization. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.6.: Effect of treatment for KALAHI-CIDSS on deforestation, 2013 – 2015

	(1) Log Deforestation	(2) Deforestation
Treatment	2.656***	2,134,685***
	(0.546)	(559,674)
Observations	594	594
Municipalities	198	198
Mean Dep. Var.	11.912	1,069,132
Mean Dep. Var. of Control	11.997	1,148,000
R-squared	0.868	0.707

Notes: This table presents estimates of the effects of eligibility for the KC program on deforestation, identified using an RCT based on whether a municipality was treated by the KC program. Robust standard errors are in parentheses. Each regression includes municipality and time fixed effects, along with strata (pair/triplet) dummies. The independent variables in columns (1) and (2) include: natural log of population, average years of education of the household head, fraction of households with access to electricity, fraction of houses with roofs made of strong materials, access to an indoor toilet and running water. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.6. Mechanisms

There are several mechanisms that may be responsible for the increased deforestation as a result of the KC program. To further explore the potential mechanisms that may impact deforestation, I first review two impact evaluations of the KC program by Labonne (2011) and Beatty et al. (2017), who provide evidence across socioeconomic, institutional and community development domains.[25] I then explore other potential mechanisms. Labonne (2011) finds that the KC program resulted in a six percentage point increase in the proportion of households whose houses were accessible year round, which is thought to be the result of the road subprojects that were implemented, but the hypothesis cannot be tested due to the small sample sizes. Additionally, the program is shown to have a positive impact on household consumption by five percent, a 1.5 percentage point increase in non-food share of consumption, and a four percentage point increase in labor force participation.[26] Beatty et al. (2017) show that the road subprojects led to a reduction in travel time, the costs of obtaining water, the costs of basic services and the costs of transporting agriculture products. No evidence is found that the KC program affected households' overall poverty status, as captured by consumption, assets, housing quality, or households' labor force participation and earnings, although such gains may yet occur beyond the four years during which the project was implemented. Each of these impact evaluations provide evidence as to the potential mechanisms by which deforestation may have been impacted by the KC program. The study now uses post-treatment surveys to explore other possible mechanisms by which the program could have impacted deforestation such as the poverty incidence, nighttime light, share of labor by different sectors, population, migration and the use of wood as a cooking fuel.

of surface area that was deforested. This measure provides a relative measure for the percentage of total surface area that was deforested for a given municipality. The results in Table B.11 indicate that eligible municipalities in the RDD period on average deforested 0.3 percent more surface area and treated municipalities in the RCT period on average deforested 1.0 percent more surface area relative to control municipalities. Such small magnitudes in the percentage of deforested surface area help explain the high marginal effects shown in Tables 3.5 and 3.6, where any small differences between treated and control municipalities in absolute terms translate into high percentage differences.

[25] Labonne (2011) collected data on 2,400 households in 135 villages in 16 municipalities and Beatty et al. (2017) collected data on nearly 6,000 households, village leaders and project staff across 198 municipalities.

[26] Households in treated municipalities are shown to diversify their source of income by working in more than one sector, which may have important long-term implications by mitigating a household's exposure to negative shocks.

3.6.1. Poverty incidence

In Table 3.7, I test whether there is a difference in the poverty incidence by the end of the program, in order to ascertain whether the eligible and ineligible municipalities differ statistically in terms of poverty incidence. This idea refers to previous work on deforestation and income, to conclude that the effect is unclear (Busch and Ferretti-Gallon, 2017). The following equation will be estimated:

$$\begin{aligned} PovertyIncidence_m = {} & \beta_0 + \beta_1 CDD_m + \beta_2 RPR_m + \beta_3 CDD_m \cdot RPR_m \\ & + X_m' \cdot \delta + \varepsilon_m \end{aligned} \tag{3.4}$$

where $PovertyIncidence_m$ is the poverty incidence developed by Balisacan et al. (2002) and was used as the program's assignment mechanism for a given municipality m. According to the estimated coefficient in column 1 of Table 3.7, eligible municipalities in 2003 were likely to have a higher poverty incidence than ineligible municipalities. However, by 2009, eligible municipalities were more likely to have a poverty incidence about 2.4 points lower than ineligible municipalities. This indicates that there was a reduction in the poverty incidence based on a municipality's income, food, clothing, shelter, disaster vulnerability and level of citizen participation. By contrast, as shown in column (3), there does not appear to be a statistically significant difference between eligible and ineligible municipalities by 2012.

Table 3.7.: Effect of eligibility for KALAHI-CIDSS on poverty incidence

	(1) Poverty Incidence - 2003	(2) Poverty Incidence - 2009	(3) Poverty Incidence - 2012
CDD	3.410**	-2.415**	-0.602
	(1.576)	(1.010)	(0.911)
Observations	1,332	1,332	1,332
Municipalities	222	222	222
R-squared	0.438	0.527	0.647

Notes: This table presents estimates of the effects of eligibility for the KC program on differences in the poverty incidence, as developed by Balisacan et al. (2002), identified using an RDD based on the municipalities' relative poverty ranking. Robust standard errors are in parentheses. Triangular kernel weights are included to give greater weight to observations that are closer to the threshold. The independent variables in columns (1), (2) and (3) include: municipality poverty ranking score, natural log of population, average years of education of the household head, fraction of households with access to electricity, percentage of villages with access to a highway, fraction of houses with roofs made of strong materials, access to an indoor toilet and running water and an index for religious fractionalization. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.6.2. Nighttime light

An alternative hypothesis to explore is whether the implementation of subprojects had an effect on economic activity through nighttime light. Nighttime light data can plausibly be used as a proxy for economic activity based on the assumption that lighting is a normal good (Donaldson and Storeygard, 2016) and have previously been used as a proxy for economic activity within fine geographic areas such as subnational administrative units (Hodler and Raschky, 2014). To explore this hypothesis, I use data on the light emitted from the Earth's surface at night, aggregated to an annual frequency with a 1-kilometer resolution.[27] The following equation will be estimated:

$$\begin{aligned} NightLights_{m,t} = \beta_0 + \beta_1 CDD_{m,t} + \beta_2 RPR_{m,t} + \beta_3 CDD_{m,t} \cdot RPR_{m,t} \\ + X'_{m,t} \cdot \delta + \rho_m + \tau_t + \varepsilon_{m,t} \end{aligned} \tag{3.5}$$

where $NightLights_{m,t}$ is estimated separately for (1) the log of nighttime light of a given municipality m in time t and (2) the log of nighttime light of a given municipality m in time $t+1$. The idea of the second dependent variable is to account for the delayed effect that is likely to result from building subprojects in the current period. Different aspects of the built environment can increase deforestation, such as roads and towns that lower transportation costs to the market (Busch and Ferretti-Gallon, 2017; Cropper and Griffiths, 1994). Additionally, built infrastructure can transform remote economies from local subsistence agriculture to market-oriented farming systems (Mertens and Lambin, 2000). According to the estimated coefficient in column (1) of Table 3.8, municipalities eligible for the KC program emitted on average 26 percent more nighttime light than ineligible municipalities. Furthermore, the estimated coefficient in column (2) indicates that eligible municipalities emitted 16 percent more nighttime light in the following time period relative to ineligible municipalities.

[27] The DMSP-OLS Nighttime Lights composite aggregates annual data on lights from cities, towns and other sites with persistent lighting or gas flares, but temporary events such as fires are discarded.

Table 3.8.: Effect of eligibility for KALAHI-CIDSS on nighttime light, 2003 – 2008

	(1) Nighttime Light	(2) Lag Nighttime Light
CDD	0.264***	0.162**
	(0.0824)	(0.0741)
Observations	1,314	1,314
Municipalities	219	219
R-squared	0.920	0.908

Notes: This table presents estimates of the effects of eligibility for the KC program on the log of nighttime light emitted from Earth's surface, identified using an RDD based on the municipalities' relative poverty ranking. Robust standard errors are in parentheses. Triangular kernel weights are included to give greater weight to observations that are closer to the threshold. Each regression includes municipality and time fixed effects. The independent variables in columns (1) and (2) include: municipality poverty ranking score, baseline nighttime light in 2002, natural log of population, average years of education of the household head, fraction of households with access to electricity, percentage of villages with access to a highway, fraction of houses with roofs made of strong materials, access to an indoor toilet and running water and an index for religious fractionalization. Significant at *p < 0.10, ** p < 0.05, *** p < 0.01.

3.6.3. Labor changes by sector

Next, I explore how different sectors may have been impacted by the KC program. The following equation will be estimated:

$$Sector_{i,m} = \beta_0 + \beta_1 CDD_m + \beta_2 RPR_m + \beta_3 CDD_m \cdot RPR_m + X'_m \cdot \delta + \varepsilon_m \qquad (3.6)$$

where $Sector_{i,m}$ is the percentage of people working in a given sector i, for a given municipality m by the year 2010. This series of regressions tests how the composition of various sectors linked to the objectives of the KC program might have changed between treated and control municipalities. The sectors analyzed are (1) agriculture, fishing and forestry, (2) mining and extractives, (3) manufacturing, and (4) transportation, storage and communication. Column 1 of Table 3.9 indicates that there was an increase of 1.2 percent more workers in the agriculture, fishing and forestry sector relative to ineligible municipalities. While this measures the share of the population employed in the agriculture, fishing and forestry sector, the expansion of agricultural land remains one of the main drivers of deforestation (Hosonuma et al., 2012; Kubitza et al., 2018). Additionally, I find that the share of the population employed in the manufacturing sector is higher, and this similarly follows the previous result employing nighttime light or an increase in economic activity or production. Lastly, there appears to have been a small, marginally significant decrease in the share of individuals working in the transportation, storage and communication industry.

Table 3.9.: Effect of eligibility for KALAHI-CIDSS on different sectors, 2010

	(1) Agriculture, Fishing and Forestry	(2) Mining and Extractives	(3) Manufacturing	(4) Transportation, Storage and Communication
CDD	1.153**	-0.226	0.307**	-0.129*
	(0.455)	(0.142)	(0.144)	(0.0711)
Observations	1,332	912	1,332	1,332
Municipalities	222	152	222	222
R-squared	0.515	0.132	0.171	0.489

Notes: This table presents estimates of the effects of eligibility for the KC program on the percentage of people working in different sectors: (1) agriculture, fishing and forestry, (2) mining and extractives, (3) manufacturing, and (4) transportation, storage and communication, identified using an RDD based on the municipalities' relative poverty ranking. Robust standard errors are in parentheses. Triangular kernel weights are included to give greater weight to observations that are closer to the threshold. The independent variables in columns (1)-(4) include: municipality poverty ranking score, natural log of population, average years of education of the household head, fraction of households with access to electricity, percentage of villages with access to a highway, fraction of houses with roofs made of strong materials, access to an indoor toilet and running water and an index for religious fractionalization. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.6.4. Other possible channels: population and resource-intensive consumption

Several other possible channels could be driving the result, such as changes in the municipalities' population and the demand for resource-intensive goods. The following equation will be estimated:

$$\begin{aligned} OtherChannels_m = \beta_0 + \beta_1 CDD_m + \beta_2 RPR_m + \beta_3 CDD_m \cdot RPR_m \\ + X_m' \cdot \delta + \varepsilon_m \end{aligned} \tag{3.7}$$

where $OtherChannels_m$ will be estimated separately for (1) the log of population in 2010, (2) the log of population that migrated in the past 5 years from another municipality or abroad in 2010 and (3) the log of population using wood or other plant fuels as cooking fuel. Population size has been shown to correlate with deforestation, but causality can potentially run in both directions, as deforestation may increase the labor supply and local demand for agricultural products or may increase the population because more cleared land can support more people (Busch and Ferretti-Gallon, 2017). Immigration has also been shown to be a relevant factor behind deforestation in Indonesia (Klasen et al., 2010), but a recent study reports that migration led to greater reforestation in Nepal (Oldekop et al., 2018). In terms of cooking fuel, higher household incomes could either increase or decrease pressure on resource-intensive consumption such as wood used as cooking fuel. Rising incomes may induce demand for land-intensive goods (Alix-Garcia et al., 2013), forest goods (A. D. Foster and Rosenzweig, 2003) or firewood (Baland et al., 2010). Additionally, Bruce et al. (2011) argue that gathering wood for cooking can lead to deforestation. Table 3.10 presents the estimated coefficients. In column (1) I find a marginally insignificant effect for population, but in column (2) I find evidence of a strong and statistically significant effect for migration. According to the estimated coefficient, municipalities' receiving the KC program is correlated with an increase in migration of 22 percent, but the number of people migrating is small relative to the total population. Lastly, in column (3) I find no evidence that eligibility for the KC program resulted in changes to the number of people using wood or other plant based fuels for cooking.

Table 3.10.: Effect of eligibility for KALAHI-CIDSS on other channels, 2010

	(1) Population	(2) Migration	(3) Wood Cooking Fuel
CDD	0.0219	0.224***	-0.0462
	(0.0141)	(0.0615)	(0.0437)
Observations	1,332	1,332	1,332
Municipalities	222	222	222
R-squared	0.945	0.584	0.638

Notes: This table presents estimates of the effects of eligibility for the KC program on different other channels: (1) the log of population in 2010, (2) log of population that migrated in the past 5 years from another municipality or abroad in 2010 and (3) log of population using wood or other plant fuels as cooking fuel, identified using an RDD based on the municipalities relative poverty ranking. Robust standard errors are in parentheses. Triangular kernel weights are included to give greater weight to observations that are closer to the threshold. The independent variables in columns (1), (2) and (3) include: municipality poverty ranking score, natural log of population, average years of education of the household head, fraction of households with access to electricity, percentage of villages with access to a highway, fraction of houses with roofs made of strong materials, access to an indoor toilet and running water and an index for religious fractionalization. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.7. Heterogeneous effects and spillovers

Having established a causal link between the KC program and increased deforestation in treated municipalities, and having highlighted several mechanisms through which deforestation might be affected, I now aim to shed light on the first-order effects of the subprojects on deforestation. The following analysis will exploit the RDD specification stemming from the characteristics of the program's allocation to discern heterogeneous effects and identify possible spatial spillovers into surrounding municipalities.

3.7.1. Effects from specific types of subprojects

A detailed dataset provides information on 5,304 different subprojects but, once the bandwidths of the RDD are applied, the dataset is trimmed down to 1,924 individual subprojects, which becomes the basis for the subsequent analysis. To distinguish whether different subproject types have heterogeneous effects on forest cover, the following equation introduces a classification of individual subprojects implemented by communities. The equation to be estimated is:

$$\begin{aligned} Y_{m,t} = \beta_0 + \beta_1 CDD_{m,t} + \beta_2 Subproject_{i,m,t} + \beta_3 CDD_{m,t} \cdot Subproject_{i,m,t} \\ + \beta_4 RPR_{m,t} + \beta_5 CDD_{m,t} \cdot RPR_{m,t} + X'_{m,t} \cdot \delta + \tau_t + \varepsilon_{m,t} \end{aligned} \tag{3.8}$$

where $Y_{m,t}$ again is estimated separately for the log of deforestation and the absolute level of deforestation for municipality *m*, in time *t*. The main variable of interest in this equation will be the interaction between $CDD_{m,t} \cdot Subproject_{i,m,t}$. The variable $Subproject_{i,m,t}$, is constructed as a column vector for the aggregate number of subprojects *i* implemented in municipality *m*, in time *t*. Since some project types were implemented by only a few municipalities, this study follows the classification used by Beatty et al. (2017) with respect to the same program to perform a heterogeneous analysis on infrastructure projects. Table 3.11 demonstrates how the subprojects are classified by: 1) infrastructure, 2) education and health, 3) water and electricity, 4) water protection, and 5) support.

Table 3.11.: Classification of subprojects

Subproject Classification	Types of Subprojects
Infrastructure	Trail, bridge, and road
Education and Health	Day care, health center, and school
Water and Electricity	Electrification, water system, drainage structure, and irrigation
Water Protection	River project (damn, boulder dike, etc.), sea wall, flood control, soil protection, and environmental protection
Support	Multi-purpose pavement, multi-purpose center / building, community support, sanitation facility, agriculture facility, tribal housing / shelter, community transport, feasibility study, eco-tourism, and lighthouse

Notes: This table presents the different types of implemented subprojects by municipalities following the classification used by Beatty et al. (2017), which are classified as: 1) infrastructure, 2) education and health, 3) water and electricity, 4) water protection, and 5) support.

The estimated coefficients will be able to discern heterogeneous effects deriving from different subproject types in eligible municipalities and whether they have positive or negative effects on forest cover. However, the estimates cannot be causally interpreted, since the subproject types were not randomly assigned, but rather were allocated through a consultation and voting process at the village and municipality level. Thus, this analysis will provide observational evidence of a corollary relationship between different types of subprojects and deforestation. Additionally, this part exploits the substantial heterogeneity in the different types of projects that were implemented. This detailed classification of subprojects improves upon Heß et al. (2020), who create a binary variable of agriculture and non-agricultural subprojects. To account for other potential sources of municipality bias, a list of controls similar to equation (2) is postulated by X', along with time fixed effects denoted as τ_t.

Table 3.12 first presents yearly summary statistics at the municipality level, followed by summary statistics over the course of the sample period at the municipality level. For example, the average municipality implemented 3.7 infrastructure subprojects per year, and about 10.3 infrastructure subprojects between 2003 and 2008.

The results of the estimated equation are presented in Table 3.13. According to column 1, the subprojects with the greatest impact are related to infrastructure, including trails, bridges and roads, followed by support and education and health facilities. Each additional infrastructure subproject implemented in an eligible municipality, approximately corresponds to an expected increase in deforestation of 125 percent. By contrast, for the absolute level of deforestation in column 2, the subprojects with the greatest impact are related to support and infrastructure subprojects are ranked fourth, which indicates that these results must be taken with some caution.

Table 3.12.: Summary statistics of implemented subprojects, 2003 – 2008

		Yearly				2003 - 2008			
	Observations	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Infrastructure	1,924	3.7	3.1	0.0	18.0	10.3	7.3	0.0	31.0
Education and Health	1,924	3.2	3.4	0.0	12.0	8.7	7.1	0.0	24.0
Water and Electricity	1,924	3.6	4.0	0.0	23.0	9.2	6.5	0.0	25.0
Water Protection	1,924	0.3	0.9	0.0	5.0	0.9	1.8	0.0	9.0
Support	1,924	1.3	1.8	0.0	10.0	3.5	3.6	0.0	19.0

Notes: This table first presents yearly summary statistics at the municipality level, and then presents summary statistics over the course of the RDD sample period.

Table 3.13.: Effect of implemented subprojects on deforestation, 2003 – 2008

	(1) Log Deforestation	(2) Deforestation
CDD x Infrastructure	1.257**	426,410*
	(0.608)	(242,353)
CDD x Education and Health	0.800*	726,206***
	(0.418)	(260,883)
CDD x Water and Electricity	0.563	569,565**
	(0.553)	(267,208)
CDD x Water Protection	-0.659*	-204,817
	(0.383)	(260,930)
CDD x Support	1.086**	935,980***
	(0.535)	(307,211)
Observations	3,022	3,022
Municipalities	222	222
Mean Dep. Var.	12.331	681,009
Mean Dep. Var. of Control	11.691	421,273
R-squared	0.330	0.244

Notes: This table presents estimates of the effects of implemented subprojects from the KC program for the log of deforestation, identified using an RDD based on the municipalities' relative poverty ranking. Standard errors are in parentheses and are clustered at the municipality level. Triangular kernel weights are included to give greater weight to observations that are closer to the threshold. Each regression includes time fixed effects. The independent variables in columns (1) and (2) include: municipality relative poverty ranking score, an interaction term between eligibility and the relative poverty ranking score, the natural log of population, average years of education of the household head, fraction of households with access to electricity, fraction of houses with roofs made of strong materials, access to an indoor toilet, access to running water and an index for religious fractionalization. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.7.2. Effect of subproject scale

An alternative hypothesis to explore is whether the scale of the implemented subprojects leads to more or less deforestation. To explore this hypothesis, the following equation is estimated:

$$\begin{aligned} Y_{m,t} = \beta_0 + \beta_1 CDD_{m,t} + \beta_2 Scale_i + \beta_3 CDD_{m,t} \cdot Scale_i + \beta_4 RPR_{m,t} \\ + \beta_5 CDD_{m,t} \cdot RPR_{m,t} + X'_{m,t} \cdot \delta + \tau_t + \varepsilon_{m,t} \end{aligned} \tag{3.9}$$

where $Y_{m,t}$ is again estimated separately for the log of deforestation and the absolute level of deforestation for municipality m, in time t. The main variable of interest is the interaction between $CDD_{m,t} \cdot Scale_i$. The variable $Scale_i$ breaks down the implemented subprojects into two groups (small and large subprojects) and takes the following forms. The first scale variable to be tested is the number of direct household beneficiaries of the subprojects. Next is the subproject duration, expressed as the number of days needed to complete the subproject. Finally, two different cost variables are tested. The first is the size of the block grant provided as part of the KC program, and the second is the total amount of funding used to complete the subproject.[28] Each of these variables is intended to test variation across alternative mechanisms in terms of project scale that may impact deforestation, and to test heterogeneous variation within each type of project scale. Table 3.14 breaks down the scale of each subproject at the median into either small (1) or large (2).

Next, Table 3.15 presents the estimated results with the main focus on the interaction between $CDD_{m,t} \cdot Scale_i$.[29] Through this set of regressions, there appears to be differential effects based on the scale of the subprojects. In columns 1 and 2 the effect appears to be concentrated in the small subset of subprojects, whereas in columns 3 and 4 the effect appears to be concentrated in the larger subset. In other words, the deforestation impact was larger for subprojects that benefited a smaller number of direct beneficiaries, that took less time to complete and that required higher funding. Additionally, the differential between the interacted estimates is much greater for the KC grant amount than the total funds used.

[28] Each of the cost variables are converted from Philippine pesos (PHP) to United States dollars (USD) using historical monthly exchange rates applied to the start date of each subproject implemented.

[29] See Table A.8, for results on the scale of the implemented subprojects and deforestation that employed the absolute level of deforestation.

Table 3.14.: Summary statistics of implemented subprojects, 2003 – 2008

	Observations	Mean	Std. Dev.	Min	Max
Direct HH Beneficiaries (1)	962	95.8	37.3	11	155
Direct HH Beneficiaries (2)	962	318.4	196.9	156	2,011
Subproject Duration (1)	970	119.9	46.0	0	201
Subproject Duration (2)	954	369.2	180.6	202	1,552
KC Grant Amount (1)	962	$7,304	$2,631	$0	$11,634
KC Grant Amount (2)	962	$24,106	$16,147	$11,657	$184,456
Total Funds Utilized (1)	962	$10,690	$3,533	$1,532	$16,727
Total Funds Utilized (2)	962	$33,538	$21,343	$16,743	$210,697

Notes: This table presents summary statistics for various measures of a subproject's scale. The scale of implemented subprojects are broken down into two groups: small (1) and large (2).

Table 3.15.: Effect of subproject scale on deforestation, 2003 – 2008

	(1) Direct HH Beneficiaries	(2) Subproject Duration	(3) KC Grant Amount	(4) Total Funds Utilized
CDD x Scale (1)	1.060*	1.036**	0.419	0.559
	(0.609)	(0.483)	(0.532)	(0.529)
CDD x Scale (2)	0.691	0.545	1.207**	1.106**
	(0.464)	(0.598)	(0.489)	(0.506)
Observations	3,022	3,022	3,022	3,022
Municipalities	222	222	222	222
Mean Dep. Var.	12.331	12.331	12.331	12.331
Mean Dep. Var. of Control	11.691	11.691	11.691	11.691
R-squared	0.328	0.328	0.332	0.329

Notes: This table presents estimates of the effects of subproject scale in the KC program for the log of deforestation, identified using an RDD based on the municipalities' relative poverty ranking. The scale of implemented subprojects are broken down into two groupings at the median: small (1) and large (2). Standard errors are in parentheses and are clustered at the municipality level. Triangular kernel weights are included to give greater weight to observations that are closer to the threshold. Each regression includes time fixed effects. The independent variables in columns (1)-(4) include: municipality relative poverty ranking score, an interaction term between eligibility and the relative poverty ranking score, the natural log of population, average years of education of the household head, fraction of households with access to electricity, fraction of houses with roofs made of strong materials, access to an indoor toilet, access to running water and an index for religious fractionalization. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.7.3. Spillover effects

One aspect that may be a concern is whether development projects have spillover effects into surrounding municipalities. In order to test whether there are spillover effects, I create a dataset of deforestation in all municipalities of the Philippines from 2003 to 2008, excluding the treated municipalities. The following equation is estimated:

$$Y_{n,t} = \beta_0 + \beta_1 TreatedNeighbors_{n,t} + X'_{n,t} \cdot \delta + \tau_t + \varepsilon_{n,t} \tag{3.10}$$

where $Y_{n,t}$ is estimated for the log of deforestation for each municipality n, in time t. The main variable of interest is $TreatedNeighbors_{n,t}$, which is a continuous measure for the number of neighboring municipalities that were treated in time t by the KC program. The intention of this variable is to capture whether there are spillover effects from municipalities that received the KC program into neighboring municipalities. Table 3.16 presents the results of the estimated equation. According to the estimated coefficient in column (1), deforestation is expected to have increased by 10 percent with each additional neighbor that was treated by the KC program. In column (2) I look at the intensive margin, which accounts for the number of subprojects that were implemented by neighbors with the KC program. I find no evidence that the more subprojects implemented by a neighboring municipality with the KC program had an effect on deforestation.[30] The results are consistent with the hypothesis that the implemented subprojects are small-scale and have very direct effects within municipalities, but these effects do not appear to be very strong beyond the municipalities' boundaries. This is in line with a review of CDD programs, where Casey (2018) finds that spillovers are likely to be modest or nonexistent, since villages are likely to fully encapsulate the benefits and costs of subprojects such as a single-site well, a repaired school roof or road projects, which are typically within villages.

[30] See Table A.9 where I perform an additional robustness check by adjusting the standard errors to account for the spatial dependence between municipalities. This is a common solution proposed by Conley (1999) that allows for serial correlation over time as well as spatial correlation among municipalities that fall within a certain distance from each other. Additionally, I follow code provided by Hsiang (2010) to estimate the corrected standard errors. The results remain qualitatively similar to Table 3.16. At the extensive margin, deforestation is expected to increase by 14 percent with each additional neighbor that was treated by the KC program. After adjusting the standard errors, the estimated coefficient is significant at the 5 percent level. At the intensive margin, I again find no evidence that the more subprojects implemented by a neighboring municipality with the KC program has an effect on deforestation.

Table 3.16.: Spillover effects onto neighbors, 2003 – 2008

	(1) Log Deforestation	(2) Log Deforestation
Treated Neighbors	0.106*	
	(0.0630)	
Projects from Treated Neighbors		0.00285
		(0.00733)
Observations	8,820	8,820
Municipalities	1,470	1,470
Mean Dep. Var.	11.085	11.085
R-squared	0.283	0.282

Notes: This table presents estimates of the effects of spillovers from treated municipalities of the KC program on deforestation in neighboring municipalities, identified using an RDD based on the municipalities relative poverty ranking. The variable Treated Neighbors is a continuous measure and accounts for the number of neighboring municipalities that were treated by the KC program. The variable Projects from Treated Neighbors is a continuous measure and accounts for the number of subprojects implemented by neighboring municipalities that were treated by the KC program. Standard errors are in parentheses and are clustered at the municipality level. Each regression includes time fixed effects. The independent variables in columns (1) and (2) include: total number of neighbors, the natural log of population, average years of education of the household head, fraction of households with access to electricity, fraction of houses with roofs made of strong materials, access to an indoor toilet, access to running water and an index for religious fractionalization. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.8. Conclusions

As international development agencies position CDD programs with the parallel strategies of reducing poverty and meeting the sustainable development goals relating to climate change mitigation and adaptation, little empirical research into the environmental impacts of such programs has been carried out. Additionally, very little research into the effects of international aid on deforestation has been undertaken. With these two aspects in mind, the central motivation of this study is to contribute empirical evidence to the ecological and economic literature through the analysis of a large-scale development aid program in the Philippines and its effects on deforestation. To overcome issues related to the non-random allocation of development aid, an RDD and an RCT are exploited to clearly identify the program's effect on deforestation. Each of the empirical strategies provides plausibly exogenous and random variation to estimate the causal impact of CDD programs on deforestation.

I find that in the RDD period, eligible municipalities experienced an average of 236 percent more deforestation (equivalent to 957,828 square meters) than ineligible municipalities as a result of the KC program. Additionally, in the RCT specification, municipalities treated as part of the CDD program experienced an average of 265 percent more deforestation (equivalent to 2,134,685 square meters) than control municipalities. Evidence from each of the empirical specifications provide robust evidence as to the effects of the KC program on deforestation, and more generally the effects of CDD programs on deforestation. An exploration of mechanisms indicate reduced poverty and increased market activities as the main mechanisms driving the impact on deforestation. Eligible municipalities are likely to have lower levels of poverty and a 26 percent increase in nighttime light. The two sectors that appear to have grown as a result of the program are agriculture, fishing and forestry, and the manufacturing sector, while there is no evidence that changes took place in the mining and extractives industry. Additionally, I find that eligible municipalities experienced an increase in migration of 22 percent, even though the number of people migrating is small relative to the total population. Results from the heterogeneous analysis of the implemented subprojects indicate that the largest impacts on deforestation arise from infrastructure subprojects, which include trails, bridges and roads, followed by support, education and health facilities. In addition, subprojects with lower number of household beneficiaries, shorter duration and larger funding, are found to cause more deforestation. Lastly, an analysis of spillover effects into surrounding municipalities, finds deforestation is expected to increase by 10 percent at the extensive margin, but I find no evidence of an effect at the intensive margin in regards to the number of implemented subprojects by surrounding municipalities.

If international organizations want to employ CDD programs as a strategy for climate change mitigation and adaptation, much more attention needs to be paid to the details to address environmental concerns arising from such projects. Through a review of internal documents relating to the KC program, two different policy areas emerge that can be targeted to mitigate deforestation resulting from the CDD program. The first set of policies should target the environmental safeguard policies in place to create a more comprehensive approach and thus mitigate environmental degradation. Development agencies need to incorporate other environmental aspects into their program policies, especially in terms of the safeguard policies regarding forestry and natural habitats that should be included in environmental assessments performed before subprojects are implemented. Additionally, mechanisms that apply to a much broader range of projects should be put in place to monitor and evaluate the impacts of certain subprojects on the environment and to trigger environmental assessments designed to mitigate deforestation and other environmental concerns.

Indicators should be included in the monitoring and evaluation process of CDD programs with a view to mitigating environmental degradation and enforcing the sustainability component CDD programs purport to have. The second area that should be targeted by policies is implementation support provided by programs and additional support in the form of technical assistance at the community level. Each of these support areas could be reformed to include topics related to sustainable development. Technical manuals could include a section on sustainable development and community facilitators could be trained in environmentally sustainable building practices to safeguard against or mitigate environmental degradation.

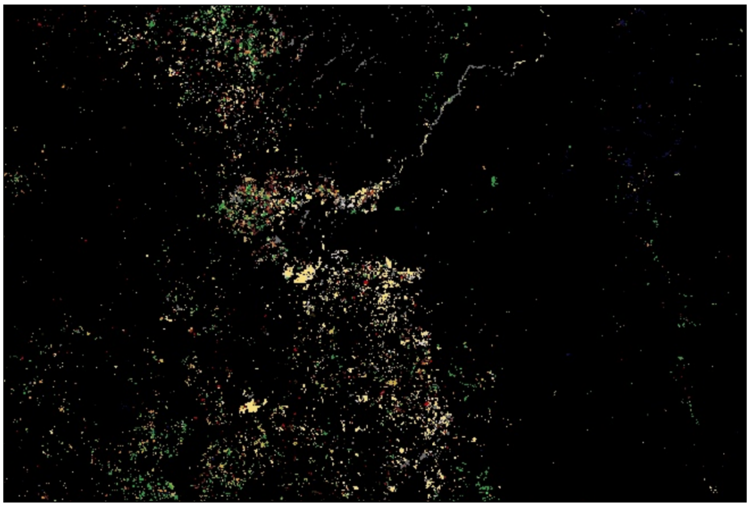
As international development agencies continue to invest heavily in CDD programs, more focus should be placed on the sustainability of such programs and on the way in which CDD programs can be more aligned with forest conservation policies. Poverty alleviation programs should be accompanied by environmental regulations either to correctly price externalities or to establish clear property rights to an environmental good. With this in mind, development agencies need to develop mitigation strategies in order to deter municipalities from deforesting. If international development agencies are able to successfully implement the parallel strategies of CDD programs, i.e., poverty reduction and environmental sustainability, such programs can offer a potentially powerful intervention for development agencies and practitioners.

A.1. Appendix

A.1.1. Examples of pixel-level deforestation data

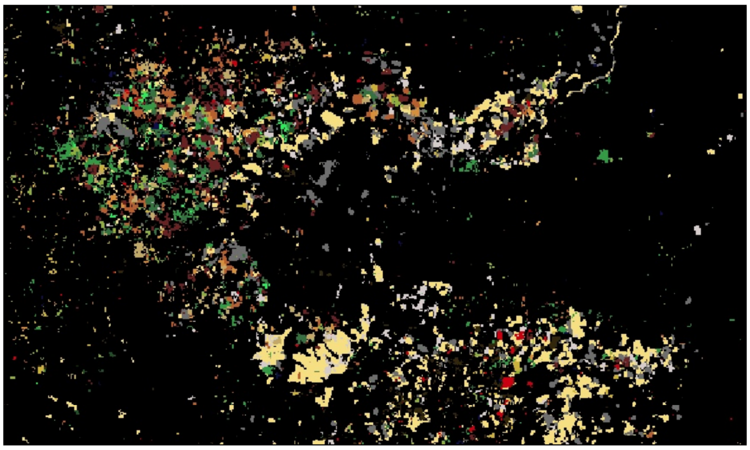
The following figures are intended to illustrate the deforestation data. Figure A.1 provides a high-level satellite view of Philippine deforestation data. In Figure A.2, as the frame zooms in, the spatial distribution of deforestation starts to become clearer, as each color represents a deforested 30 m x 30 m pixel for time *t*. By Figure A.3, individual pixels become much more visible.

Figure A.1.: High-level view



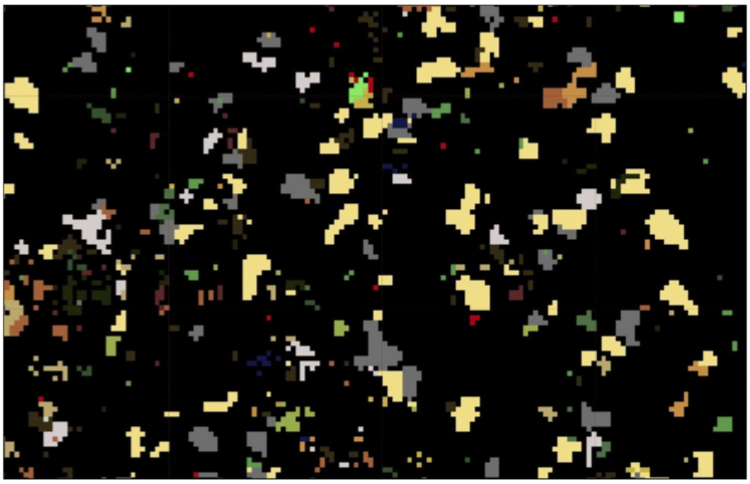
Source: Author's own calculation based on the GFC data using Google Earth Engine.

Figure A.2.: Medium-level view



Source: Author's own calculation based on the GFC data using Google Earth Engine.

Figure A.3.: Close-level view



Source: Author's own calculation based on the GFC data using Google Earth Engine.

A.1.2. Summary statistics

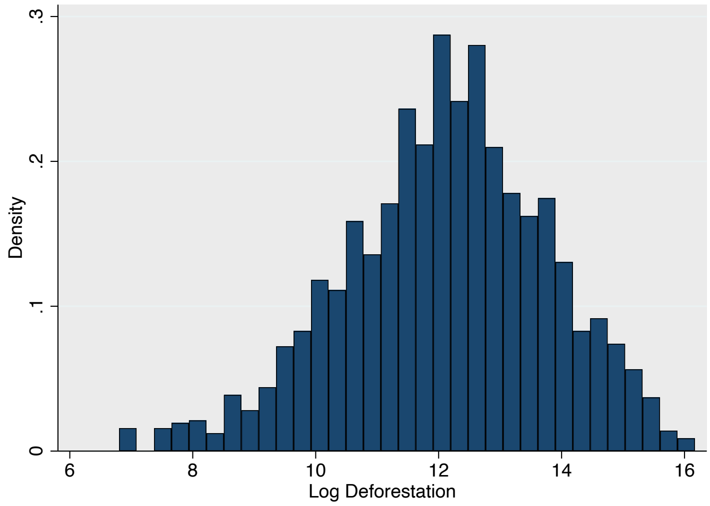
Table A.1.: Summary statistics for the RDD period, 2003 – 2008

Dependent Variables	Observations	Mean	Std. Dev.	Min	Max
Log Deforestation	1,332	12.09	1.72	6.80	16.17
Deforestation (square meters)	1,332	601,933	1,135,372	0.00	10,500,000
Percent of Surface Area Deforested	1,332	0.002	0.003	0.00	0.06
Independent Variables					
Log of population	1,332	10.13	0.65	8.30	11.57
Years of education of household head	1,332	6.30	1.20	2.29	11.96
Fraction of households with access to electricity	1,332	0.36	0.18	0.00	0.93
Percent of villages with access to highway	1,332	66.05	29.77	0.00	100.00
Fraction of households with roofs made from strong materials	1,332	0.49	0.21	0.09	0.94
Fraction of households with access to indoor toilet	1,332	0.47	0.19	0.07	0.91
Fraction of households with access to running water	1,332	0.34	0.23	0.00	0.96
Religious fractionalization index	1,332	0.33	0.24	0.01	0.84

Table A.2.: Summary statistics for the RCT period, 2013 – 2015

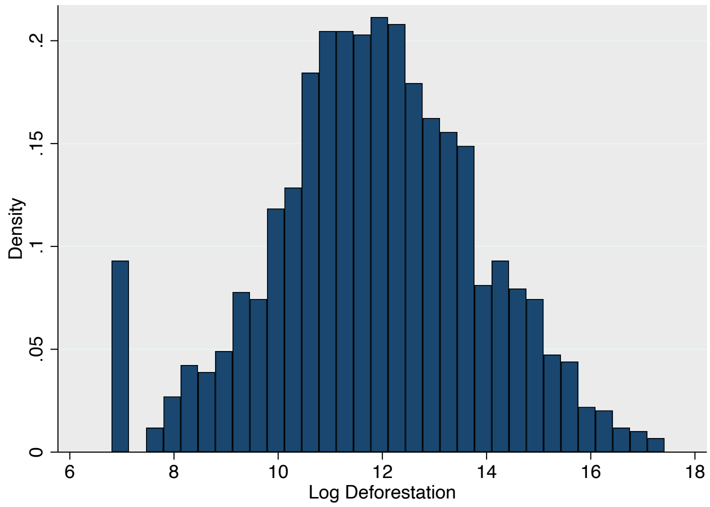
Dependent Variables	Observations	Mean	Std. Dev.	Min	Max
Log Deforestation	594	11.91	2.09	6.80	17.14
Deforestation	594	1,069,132	3,045,221	0	27,800,000
Percent of Surface Area Deforested	594	0.004	0.012	0	0.130
Independent Variables					
Log of population	594	10.15	0.75	7.44	11.78
Years of education of household head	594	8.24	1.01	5.08	10.42
Fraction of households with access to electricity	594	0.71	0.16	0.20	0.98
Fraction of households with roofs made from strong materials	594	0.62	0.17	0.23	0.98
Fraction of households with access to indoor toilet	594	0.71	0.15	0.12	0.97
Fraction of households with access to running water	594	0.90	0.10	0.34	1.00

Figure A.4.: Distribution of deforestation for the RDD period, 2003 – 2008



Notes: This figure plots the density of municipalities for which a given level of deforestation in log form occurs within the bandwidth selection of [-6, 6] in the RDD specification. *Source*: Author's own calculations.

Figure A.5.: Distribution of deforestation for the RCT period, 2013 – 2015



Notes: This figure plots the density of municipalities for which a given level of deforestation in log form occurs in the RCT specification. *Source*: Author's own calculations.

A.1.3. Eligibility for and compliance with the KC program

Table A.3.: Eligibility and compliance to the KC program

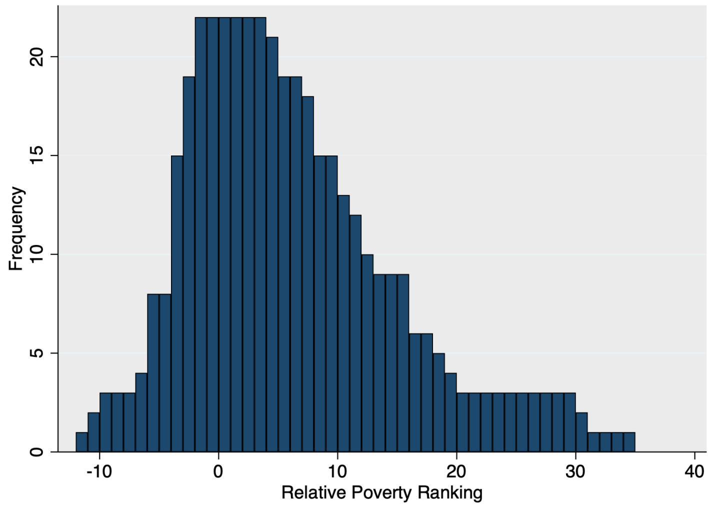
	Received KC subprojects	Did not receive KC subprojects
Eligible	76	18
Not Eligible	13	115

Notes: This table presents a breakdown of municipalities that were either eligible or not eligible for the KC program against municipalities that received KC subprojects or did not receive KC subprojects. Most instances of municipalities that were dropped were intentional decisions by the implementing agency due to concerns about the safety of its personnel, while a couple were dropped from the program due to their failure to comply with the program conditions. Dropped municipalities were thus replaced with municipalities that were next in the poverty ranking and would have been above the threshold. Once the implementation of the program began, no municipalities were dropped.

A.1.4. Validity checks of the RDD threshold

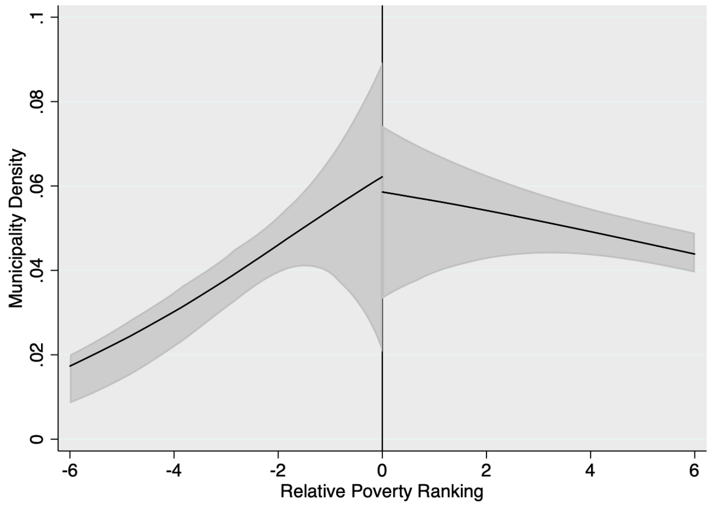
This section details the different tests carried out to check the validity of the RDD empirical strategy.

Figure A.6.: Municipality frequency and relative poverty ranking



Notes: This figure plots all municipalities in the original dataset by the relative poverty ranking against the frequency of binned municipalities that report similar poverty scores. Municipalities to the left of 0 are eligible for the KC program while municipalities to the right of 0 are ineligible. Furthermore, municipalities just to the left of the threshold of 0 are the richest eligible municipalities within a given province and municipalities just to the right of the threshold are the poorest ineligible municipalities. Originally, 425 municipalities are included in the dataset, where 315 are ineligible and 110 are eligible. Around the threshold of 0, there does not appear to be any evidence that the forcing variable has been manipulated.
Source: Author's own calculations.

Figure A.7.: Density smoothness test for relative poverty ranking



Notes: This figure follows Cattaneo et al. (2018) and Cattaneo et al. (2020) and runs a sensitivity analysis that involves estimation of the discontinuity in the density function of the forcing variable at the cutoff to verify that there is no statistical difference in municipality density. The x-axis displays the relative poverty ranking, while the y-axis displays a kernel estimate of the density of municipalities in a given normalized population band. The lines display non-parametric fits to the density function along with 95 percent confidence intervals. I find no evidence to reject the null hypothesis of no difference in municipality density at the threshold (p-value = 0.943). *Source*: Author's own calculations.

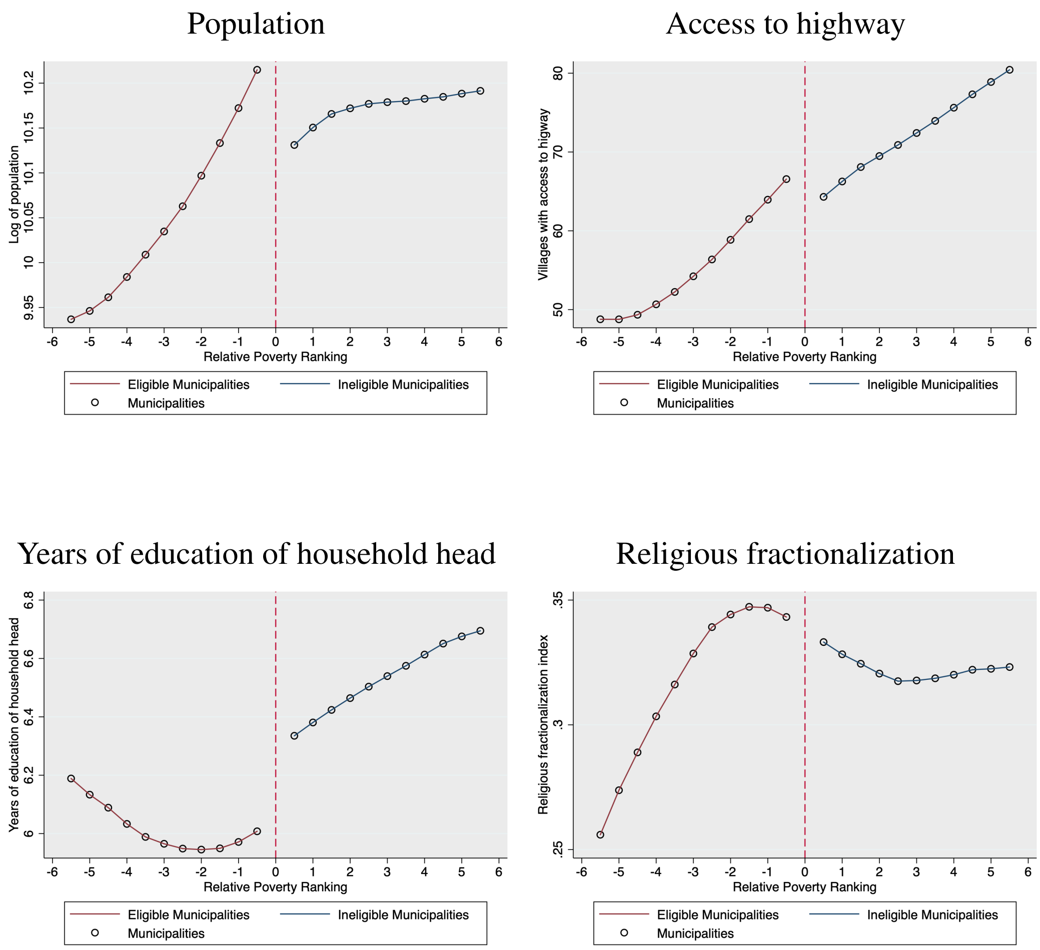
Lastly, a series of regressions are run in Table A.4 to examine whether the baseline covariates observed are "locally" balanced on each side of the threshold. D. S. Lee and Lemieux (2010) suggest performing a formal estimation by replacing the dependent variable with each of the baseline covariates observed. In order for the underlying assumption that predicts local random assignment of the RDD to be valid, a discontinuous change of eligibility status for the KC program should have no significant effect on other covariates. From this set of regressions, there appears to be no evidence that the eligibility status of a municipality had a significant effect on other observable measures. Additionally, figures that show the relationship between the relative poverty ranking and other covariates used in the analysis are included. The solid lines represent nonparametric fits from a local linear regression, where each side of the threshold is estimated separately.

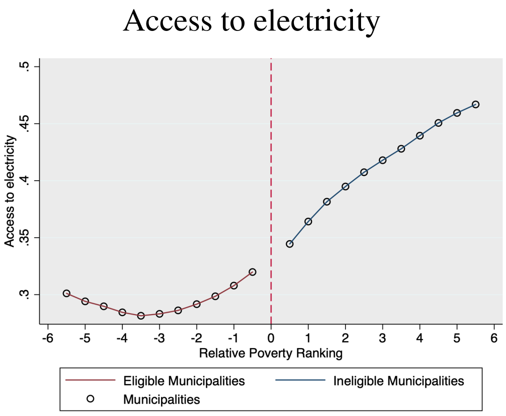
Table A.4.: Discontinuous effect on other covariates

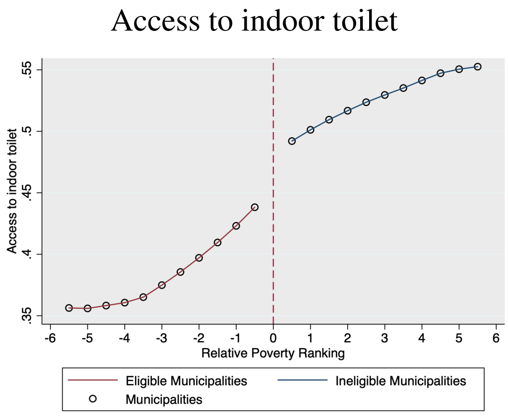
	(1) Population	(2) Percentage with Highway Access	(3) Religious Fractionalization	(4) Electricity Access	(5) Access to Indoor Toilet	(6) Access to Running Water	(7) Roofs Made of Strong Materials	(8) Years of Education for Head of Household
Eligibility for KC	0.175	8.905	0.00184	0.0125	-0.0270	-0.00988	-0.0198	-0.170
	(0.179)	(8.355)	(0.0673)	(0.0438)	(0.0505)	(0.0629)	(0.0596)	(0.309)
Observations	222	222	222	222	222	222	222	222
R-squared	0.034	0.088	0.003	0.138	0.113	0.024	0.072	0.083

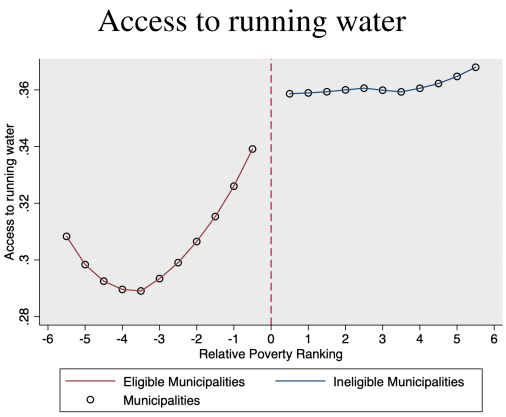
Notes: This table presents a series of regressions to estimate whether the baseline covariates observed are "locally" balanced on each side of the threshold. Robust standard errors are in parentheses. Triangular kernel weights are included to give greater weight to observations that are closer to the threshold. Each regression includes municipality fixed effects. Significant at *p $<$ 0.10, ** p $<$ 0.05, *** p $<$ 0.01.

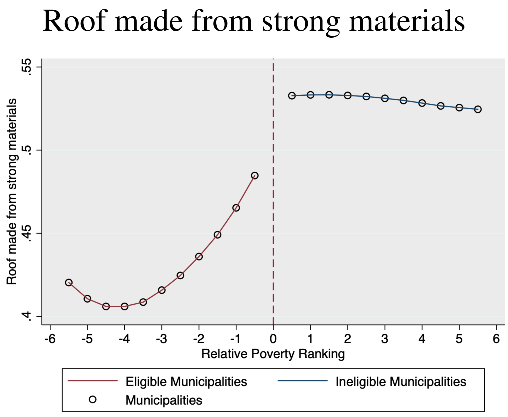
Figure A.8.: Discontinuous effect on other covariates




Access to electricity
Access to electricity
.3 .35 .4 .45 .5
-6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6
Relative Poverty Ranking
Eligible Municipalities
Ineligible Municipalities
Municipalities


Access to indoor toilet
Access to indoor toilet
.35 .4 .45 .5 .55
-6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6
Relative Poverty Ranking
Eligible Municipalities
Ineligible Municipalities
Municipalities

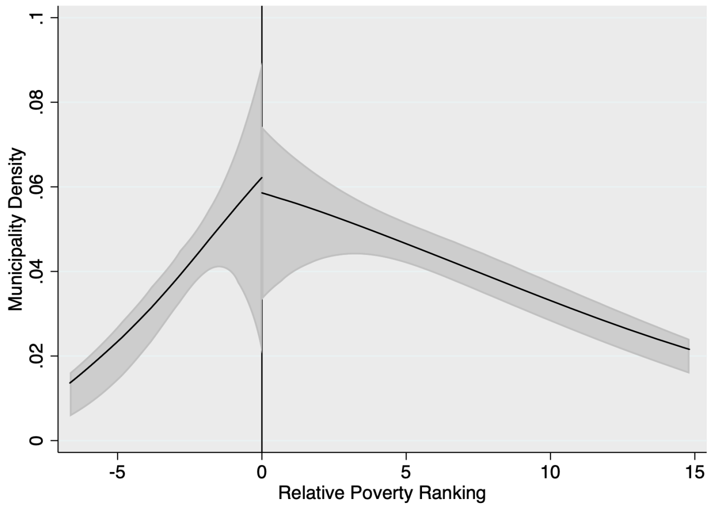

Access to running water
Access to running water
.28 .3 .32 .34 .36
-6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6
Relative Poverty Ranking
Eligible Municipalities
Ineligible Municipalities
Municipalities


Roof made from strong materials
Roof made from strong materials
.4 .45 .5 .55
-6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6
Relative Poverty Ranking
Eligible Municipalities
Ineligible Municipalities
Municipalities

A.1.5. Robustness checks to bandwidth selection of the main RDD estimation

Optimal bandwidth selection

Figure A.9.: Density smoothness test for relative poverty ranking using the optimal bandwidth



Notes: This figure follows Cattaneo et al. (2018) and Cattaneo et al. (2020) that first estimates the optimal bandwidth selection and then runs a sensitivity analysis that involves estimation of the discontinuity in the density function of the forcing variable at the cutoff to verify that there is no statistical difference in municipality density. The x-axis displays the relative poverty ranking, while the y-axis displays a kernel estimate of the density of municipalities in a given normalized population band. The lines display non-parametric fits to the density function along with 95 percent confidence intervals. I find no evidence to reject the null hypothesis of no difference in municipality density at the threshold (p-value = 0.943). The optimal bandwidth selection ranges from [-7, 15]. *Source*: Author's own calculations.

Table A.5.: Effect of eligibility for KALAHI-CIDSS on deforestation using the optimal bandwidth, 2003 – 2008

	(1) Log Deforestation	(2) Deforestation
CDD	2.019***	1,266,033***
	(0.464)	(303,382)
CDD x RPR	0.745***	556,084**
	(0.165)	(243,409)
Observations	2,076	2,076
Municipalities	346	346
Mean Dep. Var.	11.946	515,420
Mean Dep. Var. of Control	11.758	442,413
R-squared	0.856	0.764

Notes: This table presents estimates of the effects of eligibility for the KC program on deforestation, identified using an RDD based on the optimal bandwidth [-7, 15] of municipalities' relative poverty ranking. Robust standard errors are in parentheses. Triangular kernel weights are included to give greater weight to observations that are closer to the threshold. Each regression includes municipality and time fixed effects. The independent variables in columns (1) and (2) include: municipality poverty ranking score, natural log of population, average years of education of the household head, fraction of households with access to electricity, percentage of villages with access to a highway, fraction of houses with roofs made of strong materials, access to an indoor toilet and running water and an index for religious fractionalization. Significant at $^*p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Movement along the bandwidth

Table A.6.: Effect of eligibility for KALAHI-CIDSS on deforestation using movement along the bandwidth, 2003 – 2008

	(1) Log Deforestation	(2) Log Deforestation	(3) Log Deforestation	(4) Log Deforestation	(5) Log Deforestation
CDD	2.365***	2.280***	1.124**	2.863***	1.855***
	(0.452)	(0.481)	(0.465)	(0.439)	(0.394)
CDD x RPR	-0.0308	0.823***	-0.264**	0.570***	0.0561
	(0.174)	(0.132)	(0.131)	(0.0890)	(0.0977)
Observations	1,332	1,470	1,596	1,704	1,812
Municipalities	222	245	266	284	302
Mean Dep. Var.	12.109	12.094	12.102	12.079	12.059
Mean Dep. Var. of Control	11.862	11.875	11.908	11.918	11.912
Lower Bound Bandwidth	-6	-7	-8	-9	-10
Upper Bound Bandwidth	6	7	8	9	10
R-squared	0.863	0.862	0.861	0.861	0.860

Notes: This table presents estimates of the effects of eligibility for the KC program on deforestation, identified using an RDD based on movements along the bandwidth selection by increasing the bandwidth by one from [-6, 6] to [-10, 10] of municipalities' relative poverty ranking. Robust standard errors are in parentheses. Triangular kernel weights are included to give greater weight to observations that are closer to the threshold. Each regression includes municipality and time fixed effects. The independent variables in columns (1)-(5) include: municipality poverty ranking score, natural log of population, average years of education of the household head, fraction of households with access to electricity, percentage of villages with access to a highway, fraction of houses with roofs made of strong materials, access to an indoor toilet and running water and an index for religious fractionalization. Significant at $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

A.1.6. Balance test for the RCT

Table A.7.: Balance between treated and control municipality-level characteristics

Independent Variables	(1) Treatment	(2) Control	(3) Difference
Log of population	10.16	10.14	0.0228
	(0.0760)	(0.0760)	(0.107)
Years of education of household head	8.233	8.249	-0.0155
	(0.100)	(0.103)	(0.144)
Fraction of households with access to electricity	0.715	0.712	0.00305
	(0.0161)	(0.0164)	(0.0230)
Fraction of households with roofs made from strong materials	0.62	0.61	0.0105
	(0.0162)	(0.0175)	(0.0238)
Fraction of households with access to running water	0.901	0.905	-0.00405
	(0.0101)	(0.0101)	(0.0143)
Fraction of households with access to indoor toilet	0.717	0.711	0.00551
	(0.0143)	(0.0158)	(0.0213)

A.1.7. Additional results from the heterogeneity analysis

Table A.8.: Effect of subproject scale on deforestation, 2003 – 2008

	(1) Direct HH Beneficiaries	(2) Subproject Duration	(3) KC Grant Amount	(4) Total Funds Utilized
CDD x Scale (1)	491,601**	689,296***	548,687**	586,352**
	(234,505)	(245,684)	(230,835)	(231,458)
CDD x Scale (2)	574,227**	286,194	536,349**	498,914*
	(260,964)	(240,255)	(259,301)	(261,150)
Observations	3,022	3,022	3,022	3,022
Municipalities	222	222	222	222
Mean Dep. Var.	681009	681009	681009	681009
Mean Dep. Var. of Control	421273	421273	421273	421273
R-squared	0.242	0.244	0.242	0.242

Notes: This table presents estimates of the effects of the scale of KC program subprojects on deforestation, identified using an RDD based on the municipalities' relative poverty ranking. The scale of implemented subprojects is broken down into two groups at the median: small (1) and large (2). Standard errors are in parentheses and are clustered at the municipality level. Triangular kernel weights are included to give greater weight to observations that are closer to the threshold. Each regression includes time fixed effects. The independent variables in columns (1)-(4) include: municipality relative poverty ranking score, an interaction term between eligibility and the relative poverty ranking score, the natural log of population, average years of education of the household head, fraction of households with access to electricity, fraction of houses with roofs made of strong materials, access to an indoor toilet, access to running water and an index for religious fractionalization. Significant at $^*p < 0.10$, $^{**} p < 0.05$, $^{***} p < 0.01$.

Table A.9.: Spillover effects onto neighbors with conley standard errors, 2003 – 2008

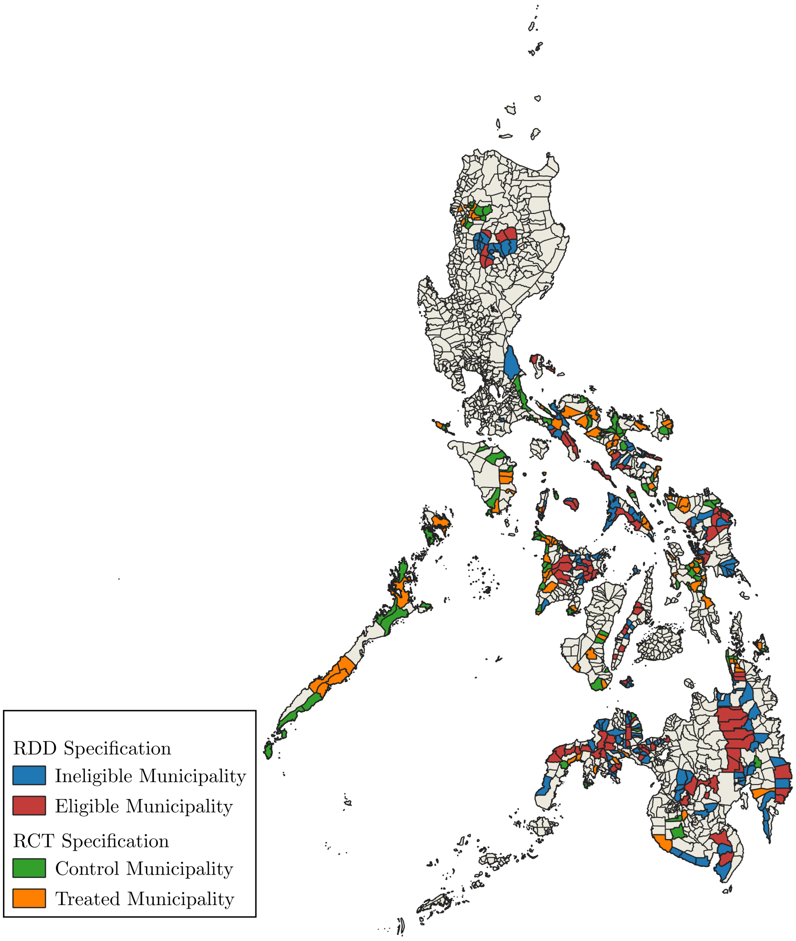
	(1) Log Deforestation	(2) Log Deforestation	(3) Log Deforestation	(4) Log Deforestation
Treated Neighbors	0.107*	0.140**		
	(0.0629)	(0.0624)		
Projects from Treated Neighbors			0.003	0.011
			(0.00732)	(0.00884)
Observations	8,820	8,820	8,820	8,820
Municipalities	1,470	1,470	1,470	1,470
Mean Dep. Var.	11.085	11.085	11.085	11.085
R-squared	0.283	0.974	0.282	0.973

Notes: This table presents estimates of the effects of spillovers from treated municipalities of the KC program on deforestation in neighboring municipalities, identified using an RDD based on the municipalities relative poverty ranking. Columns (2) and (4) adjust the standard errors to reflect the spatial dependency between municipalities as modeled in Conley (1999). Spatial autocorrelation is assumed to linearly decrease in distance up to a cutoff of 500 km. The variable Treated Neighbors is a continuous measure and accounts for the number of neighboring municipalities that were treated by the KC program. The variable Projects from Treated Neighbors is a continuous measure and accounts for the number of subprojects implemented by neighboring municipalities that were treated by the KC program. Standard errors are in parentheses and are clustered at the municipality level. Each regression includes time fixed effects. The independent variables in columns (1)-(4) include: total number of neighbors, the natural log of population, average years of education of the household head, fraction of households with access to electricity, fraction of houses with roofs made of strong materials, access to an indoor toilet, access to running water and an index for religious fractionalization. Significant at $^*p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

A.1.8. Mapping data from both time periods

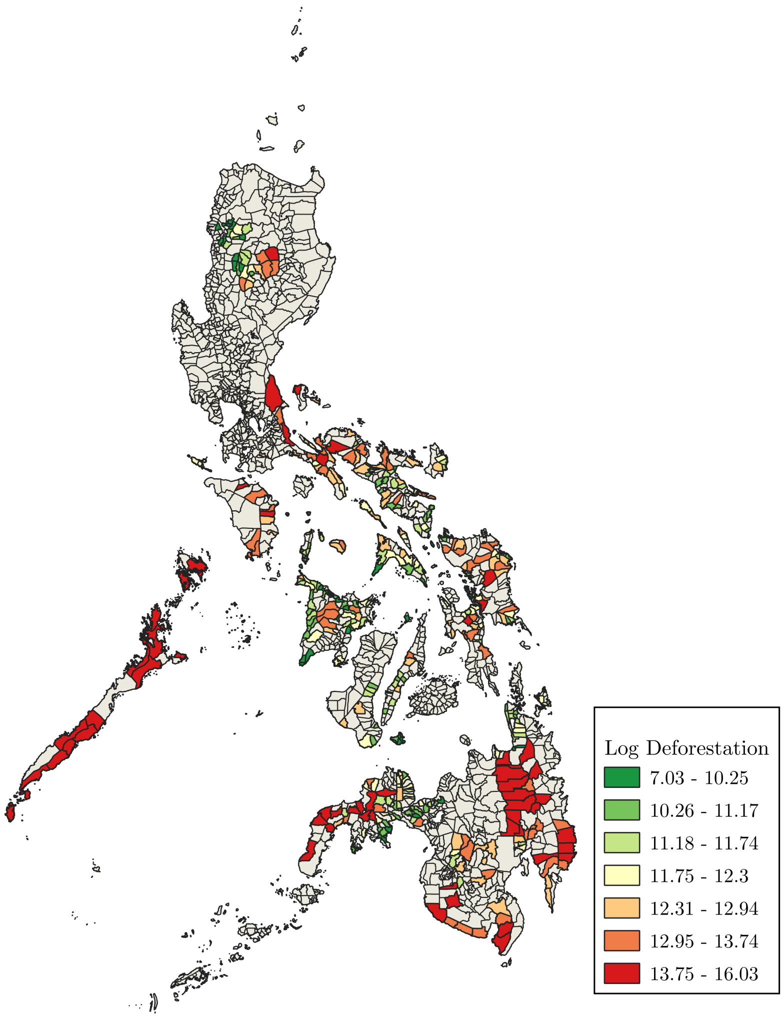
The following two maps illustrate the geographical coverage deriving from the RDD and RCT empirical strategies. The map in Figure A.9 displays municipalities that were either eligible/ineligible to participate in the KC program in round one, as well as treated/control municipalities in the later round of the program. In Figure A.10, the map displays the log of deforestation for all municipalities from both specification periods under consideration in this analysis.

Figure A.10.: Eligibility or treatment status from RDD and RCT specifications



Notes: This figure presents a map of all the municipalities analyzed within the RDD and RCT specifications. Red and blue shaded municipalities represent eligible and ineligible municipalities within the RDD, respectively. Orange and green shaded municipalities represent treated and control municipalities within the RCT, respectively. *Source*: Author's own calculations.

Figure A.11.: Log deforestation from RDD and RCT specifications



Notes: This figure presents a map of deforestation in log form of all municipalities analyzed within the RDD and RCT specifications. *Source*: Author's own calculations.

A.1.9. List of prohibited investments

Table A.10.: List of prohibited subproject investments

1	Weapons, chainsaws, explosives, pesticides, insecticides, herbicides, asbestos, and other potentially dangerous materials and equipment
2	Fishing boats (beyond the weight limit set by the Philippine Bureau of Fisheries and Aquatic Resources) and related equipment
3	Civil works in or that affect protected areas
4	Purchase of or compensation for land
5	Micro-credit and livelihood activities which involve on-lending of project funds
6	Maintenance and operation of facilities that have been the subject of civil works financed by proceeds of the loan
7	Activities that have alternative prior sources of committed funding
8	Recurrent government expenditures, including salaries
9	Civil works for government administration or religious purposes
10	Political and religious activities (including rallies) and facilities and materials related to such activities
11	Activities that employ children below the age of 16 years
12	Activities that exploit an individual or individuals
13	International travel
14	Consumption items

Notes: This table lists certain types of investments with negative environmental or social impacts prohibited as part of the KC program. *Source*: World Bank (2002, p. 26-27).

B.2. Alternative dependent variable

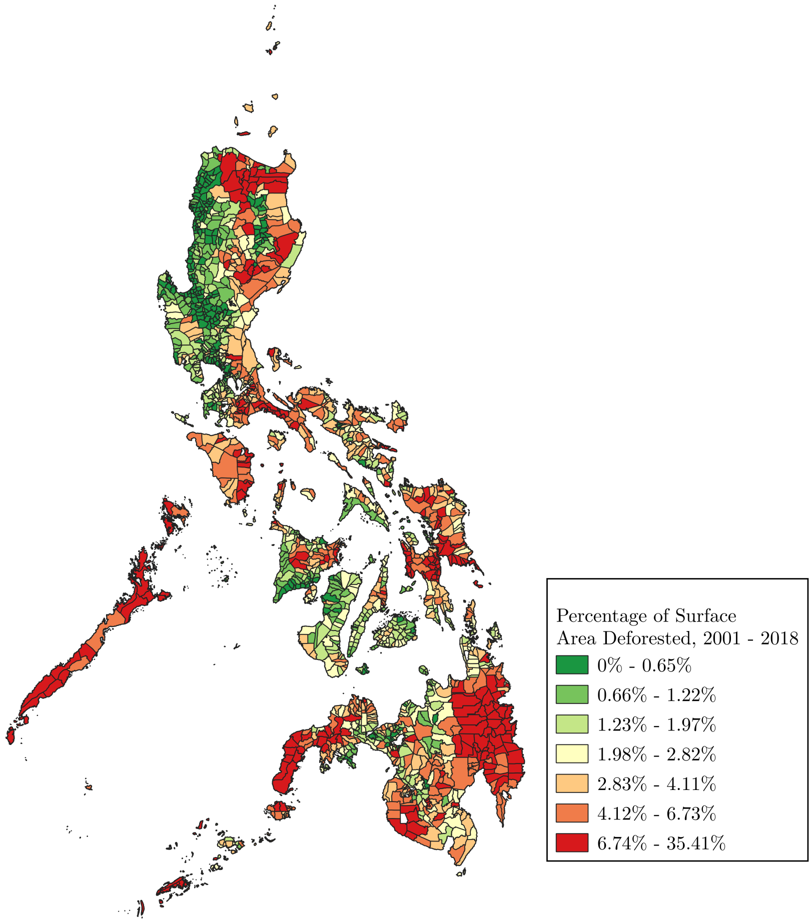
B.2.1. Percentage of surface area deforested

An alternative way to analyze deforestation as a result of the KC program is through the percentage of surface area that was deforested. Using the outcome variable developed in equation (1), deforestation can be transformed into a percentage of the total surface area of municipality m and is constructed as follows:

$$Percent\ Deforested_{m,t} = \frac{Deforestation_{m,t}}{Surface\ Area_m} \tag{.11}$$

$Percent\ Deforested_{m,t}$ provides a relative measure of the percentage of total surface area that was deforested in municipality m in time t. Figure B.12 presents a map of the number of square meters that were deforested as a percentage of the total surface area across Philippine municipalities from 2001 – 2018.

Figure B.12.: Percentage of surface area deforested per municipality, 2001 – 2018



Notes: This figure presents a map of the number of square meters that were deforested as a percentage of the total surface area of municipality m from 2001 to 2018. *Source*: Author's own calculations with the GFC data.

Next, Table B.11 presents the main results, in which column 1 refers to the RDD specification estimated in equation (2) and column 2 refers to the RCT specification estimated in equation (3). In column 1, communities eligible for the KC program deforested on average 0.3 percent more surface area relative to ineligible communities. To put this into context, the average level of deforestation amongst the sample population is 0.2 percent. Similarly to column 2 of Table 3.5, a positive coefficient was found for the interaction term between $CDD_{m,t} \cdot RPR_{m,t}$, which predicts that raising living standards first increases pressure on the environment. In column 2, the estimated coefficient is larger than column 1, where treated municipalities on average deforested 1.0 percent more surface area relative to untreated municipalities. To put this into context, the average level of deforestation in the sample population is 0.4 percent.

Table B.11.: Effect of the KALAHI-CIDDS on percentage of surface area deforested

	(1) Surface Area Deforested 2003 - 2008	(2) Surface Area Deforested 2013 - 2015
CDD	0.00343***	0.0108***
	(0.000876)	(0.00408)
CDD x RPR	0.000865***	
	(0.000196)	
Observations	1,332	594
Municipalities	222	198
Mean Dep. Var.	0.002	0.004
Mean Dep. Var. of Control	0.002	0.005
R-squared	0.456	0.560

Notes: Column (1) presents estimates of the effects of eligibility for the KC program on the percentage of total surface area that was deforested, identified using an RDD based on the municipalities' relative poverty ranking. Robust standard errors are in parentheses. Triangular kernel weights are included to give greater weight to observations that are closer to the threshold. Each regression includes municipality and time fixed effects. The independent variables in column (1) include: municipality poverty ranking score, natural log of population, average years of education of the household head, fraction of households with access to electricity, percentage of villages with access to a highway, fraction of houses with roofs made of strong materials, access to an indoor toilet and running water, and an index for religious fractionalization. Column (2) presents estimates of the effects of eligibility for the KC program on the percentage of total surface area that was deforested, identified using an RCT based on whether a municipality was treated by the KC program. Robust standard errors are in parentheses. Each regression includes municipality and time fixed effects, along with strata (pair/triplet) dummies. The independent variables in column (2) include: natural log of population, average years of education of the household head, fraction of households with access to electricity, fraction of houses with roofs made of strong materials, and access to an indoor toilet and running water. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4. A Natural Resource Curse: The Unintended Effects of Gold Mining on Malaria

4.1. Gold mining and its unintended effects on malaria

In 2018, the World Health Organization (2019) estimated 228 million cases of malaria occurred worldwide, of which approximately 405,000 resulted in death. Despite billions of dollars in investments, approximately one-third of the world (2 billion people) still live in areas infected by malaria, and more people die from it than 40 years ago (Pattanayak and Pfaff, 2009).[1] As the environment continues to be altered, particularly through land transformation and land clearance activities, there are likely to be continued increases in diseases. Roughly one quarter of the global burden of disease can be attributed to environmental changes (Prüss-Üstün et al., 2008).

This paper aims at analyzing whether there is an ecological response from extractive resource activities that exert an influence on the emergence and proliferation of malaria. More specifically, in this study I analyze the effects that gold mining activities have on the incidence of malaria through a nation-wide reform that improved the investment climate in the Philippines' mining sector. The Philippines is the fifth most mineral-rich country in the world for gold, nickel, copper, and chromite. In 2010, the value of its known mineral reserves was estimated at over 1.3 trillion U.S. dollars (Pavlova and Hincks, 2013). The Philippines' largest mineral exports are gold, copper and nickel, which make up over 97 percent of the country's total mineral production. Gold alone accounts for approximately 68 percent of the total value of mineral production in the country.

In January 2004, the government of the Philippines launched the Minerals Action Plan (MAP) with the goal of revitalizing the mining sector through an executive order. The program included over 100 regulatory measures with the main objective

[1] In 2018, governments of malaria endemic countries and international partners invested approximately $2.7 billion in malaria control and elimination efforts (World Health Organization, 2019).

to increase both foreign and domestic investment in the mining sector. Ultimately the mining reform led towards a more extractive resource policy by streamlining the application process for mining permits, increasing the number of issued permits, and made it more difficult to hold up operations through legal challenges. As a result of the reform, the mining permit process reduced the average lag between application and grant of a permit from 3-5 years to 6 months in 2005 (Fong-Sam, 2005). Additionally, the reform is estimated to have generated around $5 billion worth of commitments for new investments by February 2005 (Cruz et al., 2005; Fong-Sam, 2005).

Using the MAP reform, I exploit two sources of variation in the timing of the reform as well as spatial variation in the distribution of mineral endowments through a difference-in-differences (DID) approach that compares provinces with and without gold deposits before and after the reform. This study estimates how a shift in national policy towards a more extractive resource position in the mining sector led to an unintended ecological response regarding an increase in the incidence of malaria. Gold mining sites are typically located within or close to water surfaces, where large pits known as open sky mines are dug and filled with water. If the gold mines are not properly filled back in, slow-moving bodies of stagnant water provide the ideal breeding environment for the *Anopheles* mosquito that carries the malaria disease to propagate and reproduce. I find evidence that is consistent with an ecological response, where the MAP reform had a statistically significant effect on the incidence of malaria. After the MAP reform, provinces with deposits of gold had 32 percent more malaria cases relative to provinces without gold deposits. Additionally, I use an event study approach to shed light on the yearly dynamics of the MAP reform as well as show that the effects on malaria were persistent 10 years beyond the implementation of the policy. In order to reinforce the empirical strategy, I perform several falsification tests. The first test exploits differences in disease ecology to see whether gold mining had an effect on other diseases. In each of these tests, I find no evidence that gold mining after the MAP reform had an effect on dengue, HIV, lower respiratory infections, pneumonia and gastric or duodenal peptic ulcers. Second, I test whether other types of minerals such as copper, nickel, chromium, manganese and iron had an effect on the incidence of malaria, where I find no evidence of an effect. Third, I perform a permutation inference exercise where provinces are randomly selected to be treated by gold deposits to show that the causal impacts are not likely to be randomly generated. Lastly, I examine other possible mechanisms such as migration or deforestation and find that neither can explain the increase in malaria, further suggesting that the causal mechanism is running through gold mining.

This study makes several important contributions to existing work in the literature.

First, it provides the first nation-wide estimates of the impact gold mining has on the incidence of malaria. This substantially differentiates from the previous literature that has been focused on small geographical areas and localized effects of malaria (De Santi et al., 2016; Rozo, 2020; Valle and Lima, 2014) or other health outcomes (von der Goltz and Barnwal, 2019). Additionally, the Philippines context provides a large country to analyze that has substantial spatial heterogeneity in terms of economic, social and ecological diversity. Second, much of the previous literature has focused on a corollary relationship between gold mining and malaria (Barbieri et al., 2005; Castellanos et al., 2016; De Santi et al., 2016). This study moves beyond corollary results to provide causal estimates by exploiting the timing of the reform as well as the spatial distribution of geological endowments. Third, this national policy encouraged the expansion of legal mining operations and made it much easier to obtain mining permits. This differentiates from the context of Rozo (2020) that was focused on illegal gold mining with a bulk of the argument placed on the fact that illegal gold miners do not comply with the rules and have limited knowledge of measures needed to protect themselves against malaria or prevent the reproduction of mosquitoes as the reason for increased incidence of malaria. Evidence from this study indicate that this is not necessarily the case as a legal expansion of the resource extraction sector through the MAP reform led to an increase in the incidence of malaria.

While much of the existing evidence on malaria incidence and gold exploitation has been concentrated on qualitative studies or on documenting correlations, the detection of large-scale effects or causal estimates between the two is rare. In general, an association has been described in the literature between the proximity to gold mining operations and the risk of malaria (Barbieri et al., 2005; Crompton et al., 2002). Barbieri et al. (2005) find an association between malaria prevalence and small-scale gold mining in Northern Mato Grosso of Brazil. In the Brazilian Amazon, Valle and Lima (2014) find that an important predictor of malaria incidence is the proximity to gold mining operations, because high migration rates are often associated with artisanal gold mining. Rozo (2020) investigates the effect of illegal gold mining on malaria incidence in Colombia by exploiting pre-existing geochemical gold anomalies through an instrumental variable approach and shows that there are positive and large effects of illegal gold mining on malaria incidence. Estimates suggest that when areas that contain an illegal gold mine increase by 1 hectare, the annual parasite index for malaria increases by 1.04 cases per 100,000 inhabitants.

Additionally, this study contributes to the literature on the effects mining has on health and well-being, with a particular emphasis on the direct effects. On one side, mining has been shown to have indirect effects on health and well-being. Benshaul-Tolonen (2019) examines the expansion of large-scale gold mining throughout sub-Saharan Africa and finds that local infant mortality rates decrease by more than 50 percent as a result, where the reduction in child mortality is likely due to women's improved access to market opportunities and health care facilities. By assessing the health and wealth impacts of mineral mining from about 800 mines in 44 developing countries, von der Goltz and Barnwal (2019) find that communities exposed to mining enjoy important economic benefits in the medium and long-term, but there are serious health impacts such as an increase in anemia by three to ten percentage points for adult women and an impaired ability to recover hemoglobin levels after blood loss due to pregnancy and delivery. Additionally, D. P. Parker et al. (2016) investigate the effects of the Dodd-Frank Act that discouraged companies from sourcing minerals from the Democratic Republic of Congo. The authors find that the policy increased the probability of infant deaths in villages near the policy-targeted mines by at least 143 percent, and present suggestive evidence that the underlying mechanism is through a reduction in mothers' consumption of infant health care goods and services. On the other side, mining has been shown to have direct effects on health and well-being. High concentrations of particulate matter that are common in close proximity to opencast mines have been shown to increase respiratory disorders (Hedlund et al., 2006; Ross and Murray, 2004).

Last, this study broadly contributes to the strand of literature on negative externalities of mining and extractive resources. Crost and Felter (2020) analyze the MAP to find that the reform led to a large increase in violent conflict, which was most likely due to an increase in competition over control for resource-rich areas. Politically, mining has been shown to increase rent-seeking behavior, conflict and political corruption (Adhvaryu et al., 2020; Berman et al., 2017; Caselli and Michaels, 2013) as well as fuel repressive or destructive activities (Acemoglu and Robinson, 2001; Caselli and Tesei, 2016; Dube and Naidu, 2015; Mitra and Ray, 2014; Nunn and Qian, 2014). Resource booms additionally increase the value of being in power and provide politicians with more resources to exert their influence on the outcome of elections as well as increase resource misallocation to the rest of the economy (Robinson et al., 2006). Large-scale gold mining has been shown to decrease total factor productivity by almost 40 percent in Ghana, with the likely mechanism being the release of environmental pollutants (Aragón and Rud, 2016). In terms of environmental effects, gold mining has been shown to have long-lasting effects which include air, soil and water pollution from arsenic, cyanide and mercury (Eisler, 2004; Veiga et al., 2006). Furthermore, the pollutants released from gold mining activities can travel through rivers and tributaries, which negatively affect the water quality for humans, fish and other wildlife (Uryu et al., 2001). Last, mining has been shown to increase deforestation (Austin et al., 2019; Balietti et al., 2018; Recht et al., 2017).

The paper is structured as follows. Section 4.2 describes what malaria is, the environments in which it persists, and malaria's relationship to mining. Section 4.3 describes the mining and malaria data. Section 4.4 outlines the empirical strategies, identifying assumptions, and the model to be estimated. Section 4.5 presents the main results, performs several robustness tests of the main specification and estimates an event study specification. Section 4.6 performs several falsification tests to reinforce the empirical strategy. Section 4.7 investigates other potential mechanisms through which malaria may be exacerbated such as migration or deforestation. Section 4.8 outlines several policy responses and provides concluding remarks.

4.2. Malaria ecology

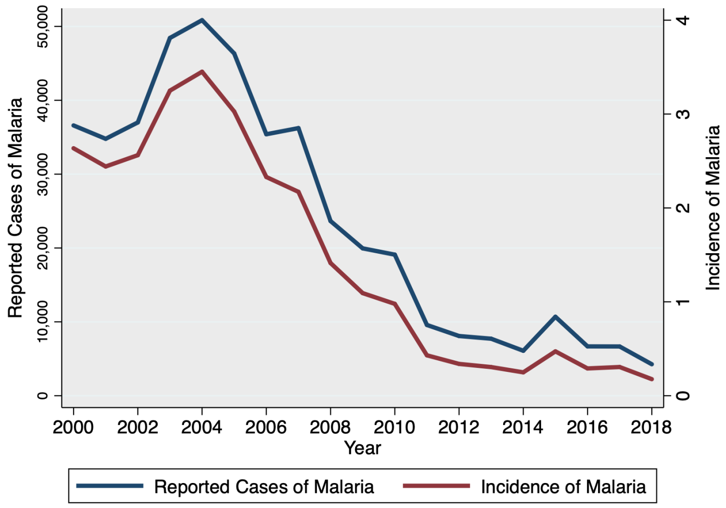
Malaria is an infectious disease that is spread through female *Anopheles* mosquitoes. Transmission occurs after a mosquito becomes infected with malaria by biting an infected person and then the infected mosquito bites a non-infected person.[2] *Anopheles* first take up a sexually differentiated form of the Plasmodium parasite which undergo reproduction in the mosquito, then the resulting sporozoite forms travel to the salivary glands and are injected into a potential host during the mosquitoes next blood meal (Garg, 2019). According to the World Health Organization (2016), malaria is transmitted to humans by five species of parasites that belong to the genus Plasmodium including P. Falciparum, P. Vivax, P. Malariae, P. Ovale, and P. Knowlesi.[3] The first four species of parasite are the most common with an average lifespan of approximately 2 weeks and can travel distances as far as 2km. Figure 4.1 presents data on the number of reported cases and incidence of malaria in the Philippines. Despite a recent decrease, the number of yearly cases is still high. Additionally, the World Health Organization (2019) estimates that the population at risk of malaria in the Philippines has been increasing from 54.4 million in 2010 to 61.9 million in 2018.

Malaria is typically found in tropical and subtropical countries, where higher temperatures allow the *Anopheles* mosquito to thrive. Furthermore, environmental changes either through natural phenomenon or human intervention can alter the

[2]Malaria causes flulike symptoms that may include fever, chills, muscle aches, headache, nausea and in the most severe cases in which the parasite travels to vital organs such as the brain can lead to seizures, coma and in 20-50 percent of cases, death (Gilles, Warrell, et al., 1996). Malaria also causes morbidity through fever, weakness, malnutrition, anemia, spleen diseases, and vulnerability to other diseases (Pattanayak and Pfaff, 2009).

[3]While there is great diversity in the *Anopheles* mosquito species that carry the malaria disease and cases can be classified into each of the five species of parasites, the data to be employed in this analysis only report the general number of malaria cases. However, The Centers for Disease Control and Prevention estimate that 70-80 percent of mosquitoes in the Philippines are P. Falciparum and 20-30 percent are P. Vivax, and P. Knowlesi are rare (Arguin and Tan, 2017).

Figure 4.1.: Reported cases and incidence of malaria in the Philippines, 2000 – 2018



Notes: This figure presents data on the number of reported cases of malaria and the incidence of malaria as the number of new cases of malaria in a year per 1,000 population at risk. *Source*: World Development Indicators.

ecological balance within which vectors and their parasites breed, develop and transmit disease. Ecosystem changes, particularly land transformation, profoundly impact breeding sites, survival probability, density, biting rates, and incubation periods (Pattanayak and Yasuoka, 2008). Additionally, geo-climatic factors such as altitude, climate, temperature and weekly rainfall intensity determine the presence of *Anopheles* breeding sites, vector densities, adult mosquito survival rate, longevity and vector capacity (Imbahale et al., 2011; Texier et al., 2013). Among the various environmental or land-use factors that determine the transmission of malaria, stagnant or slow-moving bodies of water are the most important because they provide the basic requirement for the presence of breeding sites for the occurrence of the *Anopheles* vectors.

The basic pathway in which gold mining can accelerate the reproductive environment of the *Anopheles* mosquito is through the process of leaving behind slow-moving bodies of water, which happen to be the common location of many gold mines. Miners search for alluvial gold deposits, where they dig what are known as open sky mines near rivers and then fill these holes with water. The idea is to separate the heavier gold pieces from the dirt, and when the miners are done they leave pools of water behind. In particular, if these stagnant pools of water are left open, they can provide an ideal breeding site for the *Anopheles* mosquito to reproduce.[4]

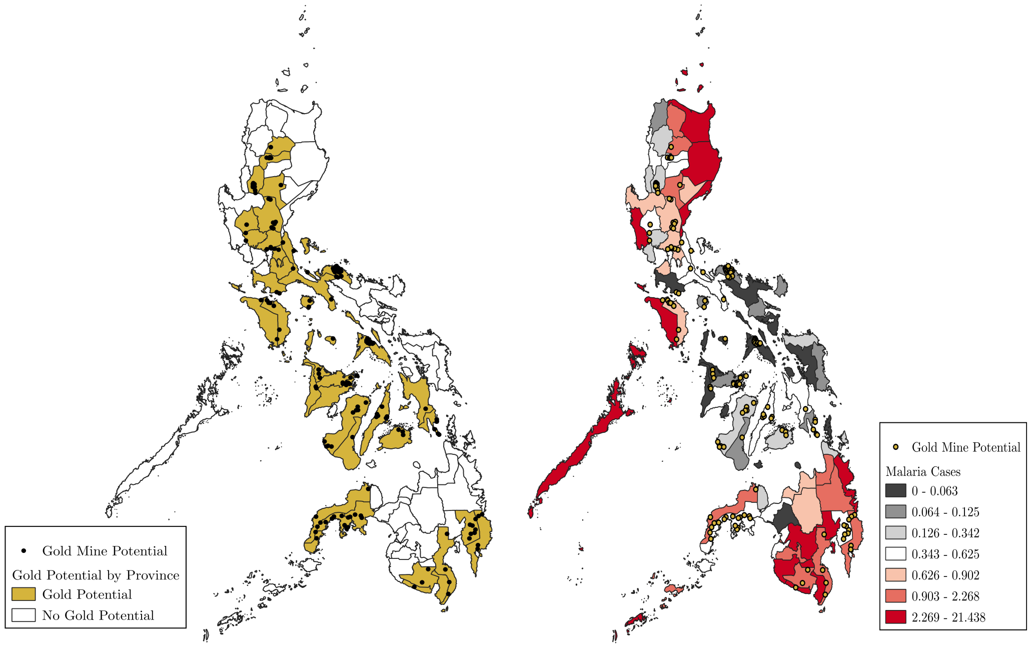
[4] According to the World Health Organization (1982) shaded pools, seepages in forests, footprints, mining pits and irrigation ditches in the open sunlight provide areas for mosquitoes to deposit eggs.

Previous research has only established a corollary relationship between gold mining and malaria. Moreno et al. (2007) find that malaria transmission occurs throughout the year, with the main focus on anthropogenic factors such as gold and gem mining, logging and urbanization.

4.3. Data

This study puts together several sources of administrative data at the provincial level. Data on malaria comes from yearly health reports by the Department of Health and provides the number of malaria cases at the province level. According to Sachs (2003), even deaths due to malaria are often unreported as some deaths may be attributed to other causes and have malaria as a co-factor, but not the principal cause. Digitized geological maps provide data on gold deposits from the Mines of Geosciences Bureau (MGB) which is a part of the Department of Environment and Natural Resources. In Figure 4.2, the left panel presents data on gold deposits throughout the Philippines, showing the spatial variation of provinces with and without gold deposits, while the right panel combines the two main data sources to illustrate the geographic dispersion of mineral deposits along with the incidence of malaria. Socioeconomic variables used as covariates in the analysis come from the census of the Philippines in 2000 and 2010. Geographic variables such as air temperature and precipitation come from Harris et al. (2020) and elevation comes from Jarvis et al. (2008). Table A.1 in Appendix A.1.1 provides summary statistics for each of the variables used in the analysis.

Figure 4.2.: Identifying variation of gold deposits and average yearly number of malaria cases



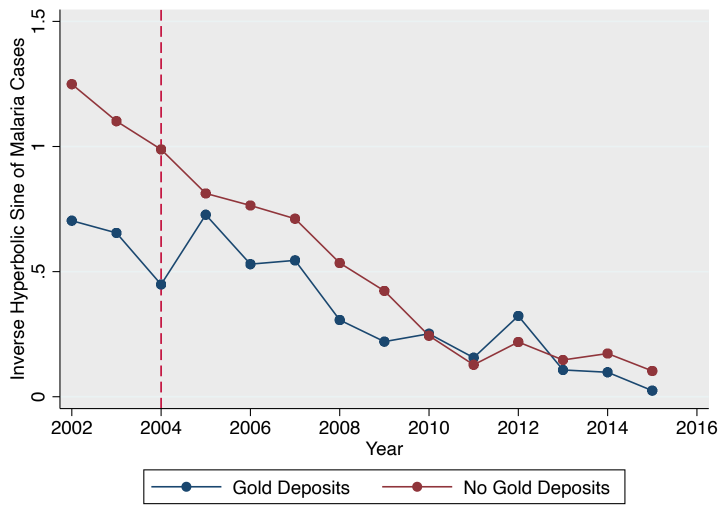
Notes: The left panel presents the identifying variation, where provinces with gold deposits are shaded in yellow, while provinces without gold deposits are white. Each of the dots represent the potential for a gold mine. The right panel combines the two main data sources on malaria incidence and gold mine deposits. The map presents identifying variation, where the shaded provinces represent the average yearly number of malaria cases and the yellow dots represent gold mine potential. *Source*: Author's calculations using digitized mining maps from the Mines of Geosciences Bureau (MGB) and health reports from the Department of Health.

4.4. Identification and empirical strategy

In order to measure how the MAP reform affected the incidence of malaria, a DID empirical strategy is employed that exploits the subsequent reduction in the average lag between application and grant of a mining permit from 3-5 years to 6 months. Using this reform, I exploit the timing as well as the spatial distribution of mineral reserves that compares provinces with and without gold deposits before and after the reform.

There are several key assumptions that must be met in order to check the validity of the DID empirical strategy. The first is the parallel trends assumption, which is intended to show that there are no time-varying differences between the treatment and control areas in the absence of treatment. If the trends of the treatment and control groups moved in tandem before the MAP reform, then they likely would have continued moving in tandem in the absence of the reform. In order to check for parallel trends, at least two serial observations on the treatment and comparison groups are needed before the start of the reform (Gertler et al., 2016). Figure 4.3 shows that before the 2004 MAP reform, the number of malaria cases decreased at a similar rate in both groups but after the reform the number of cases in provinces with gold deposits first increased and then converged with non-gold provinces. Additionally, results from an event study specification (see below, Section 4.5.2) shows that provinces with or without gold deposits prior to the MAP reform were not statistically distinguishable from one another in terms of malaria cases. Provinces with deposits of gold only started experiencing higher levels of malaria and in a timely fashion around the introduction of the MAP reform. Each of these pieces of evidence provide a compelling argument in support of the parallel trends assumption.

Figure 4.3.: Malaria cases by whether provinces have gold deposits



Notes: This figure displays parallel trends of malaria cases between provinces that have gold deposits and provinces that do not have gold deposits. *Source*: Author's own calculations.

The other set of assumptions have to deal with the exogeneity of gold deposits. First is the location of gold deposits. A necessary condition for the presence of a gold mine is a gold deposit, which is a geological anomaly and random (Eggert, 2002). Additionally, Bazillier and Girard (2020) argue that gold deposits are exogenously determined by the geological environment. Second is whether the reform led to the discovery of entirely new deposits in provinces that previously had no known deposits. As Crost and Felter (2020) point out, the approximate location of mineral deposits in the Philippines has been known for decades.

In order to estimate a causal effect of the MAP reform on the incidence of malaria, I estimate the following equation that takes advantage of a DID stemming from the timing of the reform's implementation and the location of gold deposits from 2002 and 2015. The equation to be estimated is:

$$\begin{aligned} Malaria_{p,t} = \beta_0 + \beta_1 MiningReform_t + \beta_2 Gold_p + \beta_3 MiningReform_t \cdot Gold_p \\ + X'_{p,t} \cdot \delta + \rho_p + \tau_t + \varepsilon_{p,t} \end{aligned} \tag{4.1}$$

where $Malaria_{p,t}$ is estimated for the inverse hyperbolic sine of malaria cases for province p, in time t.[5] The main independent variable will be the interaction between $MiningReform_t$, which is a dummy variable indicating before or after the MAP reform in 2004 and the variable $Gold_p$ which is a dummy variable indicating whether the province has gold deposits. Furthermore, X' is a vector of geographical and province level socioeconomic covariates which include: the poverty incidence level, log of population, log of deforestation, elevation, mean air temperature, mean precipitation, ethnic fractionalization, religious fractionalization, average years of education of the household head, fraction of houses with roofs made of strong materials, fraction of houses with walls made of strong materials, fraction of households with access to electricity, access to indoor toilet and running water. The intercept term is represented as β_0, while province and time fixed effects are denoted as ρ_p and τ_t, respectively, which control for the unobserved provincial-time-invariant effect. Throughout the analysis, standard errors are clustered at the province level, to account for the arbitrary correlation within the province in terms of spatial autocorrelation and serial correlation over time.

4.5. Results

Table 4.1 presents the main results. The main finding from the preferred specification in column 4 is that provinces with gold deposits after the MAP reform experience 32 percent more malaria cases relative to provinces without gold deposits. The baseline results in column 1 are robust to the inclusion of geographic controls in

[5] Since some provinces did not experience any cases of malaria, it is more appropriate to use the inverse hyperbolic sine (IHS) transformation of malaria cases in order to accommodate provinces that had zero cases or an undefined log transformation. The IHS transformation approximates the natural logarithm and allows for retaining zero-valued observations (Bellemare and Wichman, 2020) and contrary to the logarithm is well defined around zero (Card and DellaVigna, 2020). The IHS function approximates the log function except for values close to 0, for which it approximates $ln(x) + ln(2)$. Using the absolute measure of malaria cases, the IHS function is constructed as: $IHSMalaria_{p,t} = ln(Malaria_{p,t} + \sqrt{Malaria_{p,t}^2 + 1})$.

column 2, socioeconomic controls in column 3 as well as to the inclusion of both geographic and socioeconomic controls in column 4.[6] The robustness of the results across various specifications, even with the inclusion of socioeconomic controls indicate that the underlying mechanisms is through an ecological response rather than a socioeconomic response. In Table A.2, I look at the intensive margin with the number of gold mine deposits within a province, where the estimated coefficients point in the same direction, but are not statistically significant at conventional thresholds of significance.[7]

Table 4.1.: Gold, MAP and the effect on malaria at the extensive margin, 2002 - 2015

	(1) Malaria Cases (IHS)	(2) Malaria Cases (IHS)	(3) Malaria Cases (IHS)	(4) Malaria Cases (IHS)
Gold	0.0427	-0.957***	0.390	-0.442
	(0.145)	(0.248)	(1.640)	(1.568)
Mining Reform	-1.091***	-1.152***	-2.388***	-2.380***
	(0.162)	(0.163)	(0.503)	(0.501)
Gold x Mining Reform	0.361**	0.358**	0.319**	0.317**
	(0.164)	(0.165)	(0.149)	(0.150)
Observations	1,110	1,110	1,110	1,110
R-squared	0.561	0.562	0.604	0.604
Geographic Controls	No	Yes	No	Yes
Socioeconomic Controls	No	No	Yes	Yes
Mean Incidence	0.459	0.459	0.459	0.459

Notes: This table presents estimates for the effects that gold mining deposits have on the log of malaria cases, identified using a DID based on the timing of the MAP reform as well as the distribution of gold deposits. Standard errors are clustered at the provincial level. Each regression includes province and time fixed effects. Geographic controls include: elevation, mean air temperature, and mean precipitation. Socioeconomic controls include: the poverty incidence level, log of population, log of deforestation, ethnic fractionalization, religious fractionalization, average years of education of the household head, fraction of houses with roofs made of strong materials, fraction of houses with walls made of strong materials, fraction of households with access to electricity, access to indoor toilet and running water. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.5.1. Robustness tests

In order to document the stability of the estimates more generally, I perform several robustness checks of the main estimation. First I re-estimate equation (1) and drop each province in turn. Figure A.1 then plots each of the estimated coefficients

[6] In Table A.3, I estimate equation (1) using an absolute measure of malaria that accounts for the number of cases as the dependent variable, where I find consistent evidence of a significant impact.

[7] In Table A.4, I look at the intensive margin using an absolute measure of malaria cases and find a positive and statistically significant impact.

to illustrate their stability and demonstrate that the standard errors continue to be significant at conventional levels. This exercise additionally indicates that no single province is driving the main results in Table 4.1. Second Bauhoff and Busch (2020) argue that access to local health services affects malaria. In Table A.6 I control for the number of rural health facilities within a province. As expected, health facilities are estimated to have a negative corollary relationship with the number of malaria cases. Regardless of controlling for the number of rural health facilities, the results remain similar to Table 4.1. Third, malaria and gold mines are both located near bodies of water and thus could present a potential threat to the validity of the empirical strategy by introducing spurious correlations to the main estimation. In order to address this possibility, Table A.7 tests the sensitivity of the results to the inclusion of the total surface area of bodies of water within each province and the results remain qualitatively similar. Fourth previous literature argues that malaria risk is highest at intermediate values of temperature and precipitation (Beck-Johnson et al., 2013; Mordecai et al., 2013; Parham and Michael, 2010). Table A.8 tests the sensitivity of the results by additionally controlling for squared terms of temperature and precipitation and the results remain unchanged. Fifth in Table A.9 I test the sensitivity of the results by clustering the standard errors at the regional level and the results still hold. Sixth I additionally control for quadratic time trends in the main specification and the results in Table A.10 remain qualitatively similar. Last, in addition to defining malaria in either the level or IHS transformation, I also test the sensitivity of the main results by defining malaria cases as $log(1 + MalariaCases)$. Thus, in Table A.11 I show that the alternative transformation of the dependent variable does not qualitatively change the results in Table 4.1.

4.5.2. Event study specification

Estimates in Table 4.1 represent a weighted average of the MAP reform and gold deposit effects by year, and thus do not provide information on the magnitude of the effects over time. To further examine and uncover the dynamic effects of the MAP reform and gold deposits, I estimate the following event study specification:

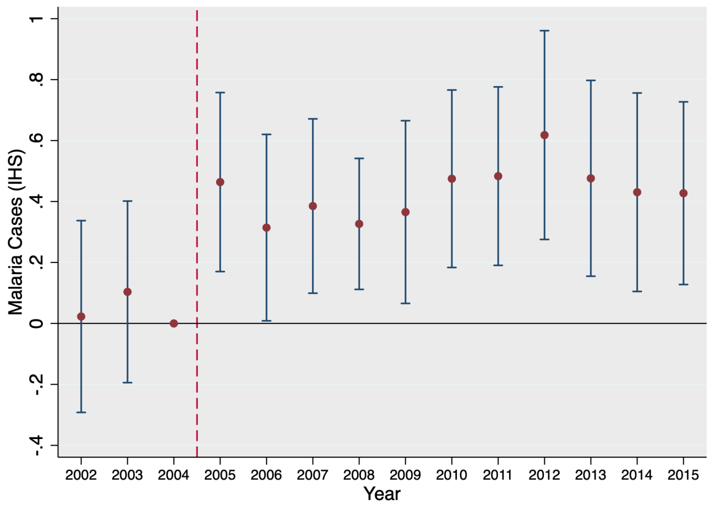
$$Malaria_{p,t} = \rho_p + \tau_t + X'_{p,t} \cdot \delta + \sum_{\phi=-1}^{m} \beta_{-\phi} D_{i,t-\phi} + \sum_{\phi=0}^{q} \beta_{+\phi} D_{i,t+\phi} + \varepsilon_{p,t} \quad (4.2)$$

where $D_{i,t-\phi}$ estimates the leads and $D_{i,t+\phi}$ the lags of the treatment dummy in order to decompose the treatment effect for each year preceding and following the MAP reform. I take the year of the MAP reform as the omitted baseline year of comparison and make all estimates relative to 2004.

This specification is advantageous for two main reasons. The first advantage is to test whether there was any anticipatory behavior prior to the treatment. This is an intuitive way to test for Granger causality (Tewari, 2014) and check whether the pre-policy coefficients are insignificant and display no trend. Instead of controlling for differential pre-MAP trends across provinces, the specification directly tests for the existence of such differentials without imposing a linear structure on the time pattern related to the reform. Insignificant coefficients prior to the reform provide some reassurances to the identifying assumptions of the DID. The second advantage is the ability to trace out the full dynamic trajectory as well as the persistence of the effects.

Results from the estimated equation (2) are plotted in Figure 4.4. First, there does not appear to be any anticipatory effect as the point estimates prior to the reform are insignificant. This result offers evidence that provinces with gold deposits and provinces without gold deposits had similar evolutions in cases of malaria prior to treatment. Second, the effect on malaria is immediately experienced in 2005. Immediately following the MAP reform, provinces with gold deposits experience 46 percent more malaria cases relative to provinces without gold deposits. The estimated yearly effects remain fairly stable between 30 and 60 percent. Last, the figure illustrates how persistent the effects are in that more than 10 years after the reform the effects are still significant.

Figure 4.4.: Gold, MAP and the effect on malaria at the extensive margin, 2002 - 2015



Notes: This figure presents estimates from an event study specification for the effect gold mining deposits have on the log of malaria cases for each year preceding and following the MAP reform. The year immediately preceding the treatment is omitted to make all estimates relative to this year. All treatment estimates are statistically insignificant prior to exposure to the reform. Immediately following the MAP reform, provinces with gold deposits experience 46 percent more malaria cases relative to provinces without gold deposits. Standard errors are clustered at the provincial level. Each regression includes province and time fixed effects. The independent variables include: elevation, mean air temperature, mean precipitation, the poverty incidence level, log of population, log of deforestation, ethnic fractionalization, religious fractionalization, average years of education of the household head, fraction of houses with roofs made of strong materials, fraction of houses with walls made of strong materials, fraction of households with access to electricity, access to indoor toilet and running water.

4.6. Falsification tests

Now that it has been established that provinces with gold deposits after the MAP reform experienced an increase in the number of malaria cases relative to provinces without gold deposits, the study now moves to reinforce the empirical strategy. This section performs several falsification tests by investigating 1) whether gold mining has an effect on other diseases through differences in disease ecology; 2) whether other mineral deposits have an effect on malaria; and 3) a permutation inference exercise where provinces are randomly selected to be treated with gold deposits.

4.6.1. Other diseases

One threat to the validity of the empirical strategy would be if there are unobserved variables that are correlated with both human health outcomes and gold mining deposits that might have an impact on other diseases other than malaria. An important aspect to determine is whether the established relationship between gold mining deposits and the incidence of malaria is specific to the disease ecology of malaria and not generically to other health outcomes. To perform this analysis, this section maintains the same empirical structure as equation (1), but will test the effects of the MAP reform and gold deposits on other diseases such as dengue, HIV, lower respiratory infections, pneumonia and gastric or duodenal peptic ulcers. This follows similar falsification tests performed by Garg (2019) and Rozo (2020) that exploit different epidemiological mechanisms of transmission across diseases. Garg (2019) uses the health measures of measles, diarrhea, respiratory infections and dengue, while Rozo (2020) uses skin rashes, abortion rates, fetal malformation, respiratory, and digestive diseases.[8]

Table 4.2 reports the results of the falsification tests, where I find no evidence of an effect that provinces with gold deposits after the reform had an effect on the number of dengue, HIV, lower respiratory infections, pneumonia or gastric or duodenal peptic ulcer cases. These results indicate that the main channel is through the ecological response of altering the reproductive environment that is specific to malaria.

[8]The disease ecology of malaria differs significantly from dengue even though they are both spread via disease carrying vectors and are predominantly maintained in a human-to-mosquito-to-human cycle. The *Aedes* species (Ae. Aegypti or Ae. Albopictus) which carries dengue have a much shorter flight span compared to the *Anopheles*. Additionally, the *Aedes* species are almost stationary and mostly prevalent in urban areas (Garg, 2019). Since gold mining typically occurs in rural areas, I do not expect there to be a discernible effect between gold mining and dengue.

Table 4.2.: Gold, MAP and the effect on other diseases, 2002 - 2015

	(1) Dengue Cases (IHS)	(2) HIV Cases (IHS)	(3) Lower Respiratory Cases (IHS)	(4) Pneumonia Cases (IHS)	(5) Gastric or Duodenal Peptic Ulcer Cases (IHS)
Gold	3.853***	-1.262	0.714	-0.906	1.441***
	(1.161)	(0.782)	(0.766)	(0.884)	(0.486)
Mining Reform	-1.992***	0.665***	0.669**	0.875***	0.00659
	(0.400)	(0.216)	(0.331)	(0.286)	(0.178)
Gold x Mining Reform	-0.0379	0.0883	0.0189	-0.0253	-0.000250
	(0.159)	(0.0619)	(0.0682)	(0.0582)	(0.0597)
Observations	1,110	1,110	1,104	1,104	1,025
R-squared	0.681	0.472	0.940	0.940	0.926
Geographic Controls	Yes	Yes	Yes	Yes	Yes
Socioeconomic Controls	Yes	Yes	Yes	Yes	Yes
Mean Incidence	1.664	0.192	5.338	5.974	4.309

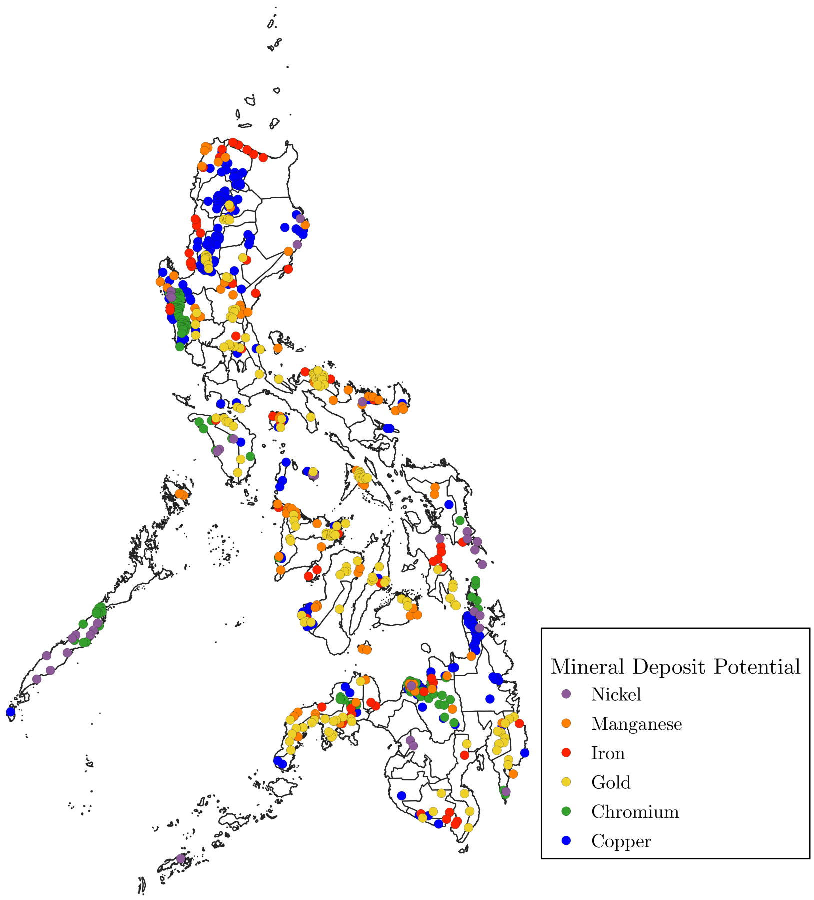
Notes: This table presents estimates for the effects that gold mining has on the inverse hyperbolic sine of Dengue, HIV, Lower Respiratory Infections, Pneumonia and Gastric or Duodenal Peptic Ulcer cases, identified using a DID based on the timing of the MAP reform as well as the distribution of gold deposits. Standard errors are clustered at the provincial level. Each regression includes province and time fixed effects. The independent variables in columns 1-5 include: the poverty incidence level, log of population, log of deforestation, elevation, mean air temperature, mean precipitation, ethnic fractionalization, religious fractionalization, average years of education of the household head, fraction of houses with roofs made of strong materials, fraction of houses with walls made of strong materials, fraction of households with access to electricity, access to indoor toilet and running water. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.6.2. Other minerals

The next falsification test investigates whether the increased incidence of malaria is specific to gold mining, or mining in general. It could be argued that mining in general may have the same negative externalities and that there is nothing particular about gold mining that leads to more cases of malaria. There are several reasons as to why we can expect there to be a link between gold mining and malaria, rather than a link between mining for other minerals and malaria. First, gold mining typically happens near rivers or bodies of water as well as typically demands water in the extraction process. Second, alluvial gold mining areas have more stagnant water surfaces, which provide an ideal breeding site for mosquitoes that transmit malaria. Third, gold mining typically happens on a much smaller scale and is therefore likely to happen near villages. Last, gold mining is likely to be performed in hard to reach places.

To investigate whether there is a link between other mining activities and malaria, this section maintains the same empirical structure as equation (1), but will test the effects of the MAP reform and other mineral activities such as copper, nickel, chromium, manganese and iron on the inverse hyperbolic sine of malaria cases. Figure 4.5 presents data on nickel, manganese, iron, gold, chromium and copper deposits throughout the Philippines, to further illustrate the geographic dispersion of mineral deposits. Table 4.3 then presents the results of the falsification tests, where I find no evidence that the presence of other mineral deposits after the MAP reform had an effect on the number of malaria cases relative to provinces without other mineral deposits.

Figure 4.5.: Mineral deposits in the Philippines



Notes: This figure presents the geographical dispersion of mineral deposits throughout the Philippines, where each of the dots represent the potential for nickel, manganese, iron, gold, chromium, and copper deposits. *Source*: Author's calculations using mining maps from the Mines of Geosciences Bureau (MGB).

Table 4.3.: Other types of minerals, MAP and the effect on malaria, 2002 - 2015

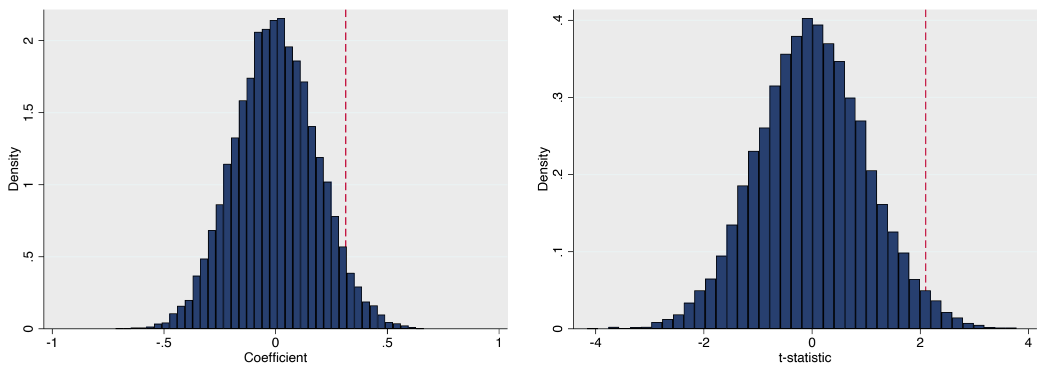
	(1)	(2)	(3)	(4)	(5)
	Malaria Cases (IHS)				
	Copper	Nickel	Chromium	Manganese	Iron
Mineral	-0.109	-0.684	-0.0368	-0.391	-0.0917
	(0.515)	(0.728)	(0.395)	(1.608)	(0.360)
Mining Reform	-2.293***	-2.295***	-2.288***	-2.299***	-2.298***
	(0.515)	(0.505)	(0.505)	(0.508)	(0.499)
Mineral x Mining Reform	-0.00975	-0.0104	-0.0664	0.00381	0.00182
	(0.163)	(0.216)	(0.175)	(0.169)	(0.176)
Observations	1,110	1,110	1,110	1,110	1,110
R-squared	0.599	0.599	0.600	0.599	0.599
Geographic Controls	Yes	Yes	Yes	Yes	Yes
Socioeconomic Controls	Yes	Yes	Yes	Yes	Yes
Mean Incidence	0.459	0.459	0.459	0.459	0.459

Notes: This table presents estimates for the effects other minerals have on the log of malaria cases, identified using a DID based on the timing of the MAP reform as well as the distribution of mineral deposits. Standard errors are clustered at the provincial level. Each regression includes province and time fixed effects. The independent variables in columns 1-5 include: the poverty incidence level, log of population, log of deforestation, elevation, mean air temperature, mean precipitation, ethnic fractionalization, religious fractionalization, average years of education of the household head, fraction of houses with roofs made of strong materials, fraction of houses with walls made of strong materials, fraction of households with access to electricity, access to indoor toilet and running water. Significant at $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

4.6.3. Falsification tests with permutation inference

Last, I run a permutation inference analysis by randomly selecting half of the control provinces to receive the “treatment” of having a gold deposit and see whether the “treatment” has an effect on the incidence of malaria. This analysis is similar to Hoang et al. (2020) and Benshaul-Tolonen (2019) and asks if there is a possibility that the effects shown in the main analysis are simply due to a “lucky draw” that is entirely unrelated to gold deposits. I randomly select half of the control provinces to receive the “treatment” status of having gold deposits, while the other half is assigned to be the “control”. I then replicate the DID regression from equation (1) using the falsified treatment and control groups. The permutation inference test is run through 10,000 iterations and then the distributions of the estimated coefficients and their t-statistics are plotted in Figure 4.6. Each of the distributions exhibit strong normal distributions centered at 0. In each of the panels, the red vertical line indicates the preferred estimation's estimated coefficient and t-statistic obtained from column 4 in Table 4.1, respectively. Both are right-tail outliers and indicate that causal impacts estimated in Table 4.1 are not likely to be randomly generated.

Figure 4.6.: Distributions from permutation inference



Notes: These figures show the distribution of coefficients and t-statistics from a permutation inference where half of the municipalities from the main analysis in the control are randomly selected to either receive the "treatment" of having gold deposits or remain in the "control" of having no gold deposits. The permutation test is run through 10,000 iterations. The red line indicates the estimated coefficient and t-statistic obtained from column 4 of Table 1, respectively. The independent variables include: poverty incidence level, log of population, log of deforestation, elevation, mean air temperature, mean precipitation, ethnic fractionalization, religious fractionalization, average years of education of the household head, fraction of houses with roofs made of strong materials, fraction of houses with walls made of strong materials, fraction of households with access to electricity, access to indoor toilet and running water.

4.7. Other potential mechanisms

The most likely mechanism at play is through the ecological response in which gold mining activities leave behind pools of water that provide the *Anopheles* mosquitoes with an environment to reproduce. This study now investigates whether there are other possible mechanisms though which malaria may be exacerbated such as migration or deforestation.

4.7.1. Migration

Mining is often correlated with migratory behavior either through the labor-intensity that requires migrant labor or through other commercial activities around the mines that attract migrants. Mining activities which often rely on highly mobile populations who migrate, are exposed to mosquito bites due to either long periods of time outdoors or through the living conditions in camps. Additionally, migration of previously unexposed populations to malaria into malaria endemic areas has often led to spikes in malaria cases, as well as returning migrants may introduce malaria parasites to new regions depending on the climate, activities and vector species present (Recht et al., 2017). Migrants can be further exposed to malaria as latent hosts, since they typically have lower incomes and less access to medical facilities (Garg, 2019). Mining operations are typically performed in rural areas and the settlement of these areas can make them more susceptible to outbreaks of malaria due to contact with settlers and vectors, and land clearing activities. Barbieri et al. (2005) show that after the initial stage of settlement, the prevalence of malaria declines for several reasons: 1) less interaction between humans and vectors; 2) the larger extent of cleared land; 3) improvements to housing conditions; 4) better access to health care; 5) greater personal resistance to malaria; and 6) greater knowledge about the disease.

To explore this hypothesis, the following equation is estimated:

$$\begin{aligned} Y_{p,t} = {} & \beta_0 + \beta_1 MiningReform_t + \beta_2 Gold_p + \beta_3 MiningReform_t \cdot Gold_p \\ & + X'_{p,t} \cdot \delta + \rho_p + \tau_t + \varepsilon_{p,t} \end{aligned} \tag{4.3}$$

where $Y_{p,t}$ is estimated separately for 1) the log of population; 2) the log of population that migrated; and 3) the log of younger population who are between the ages of 15 and 49 that migrated to a given province p in time t. The population that migrated is broken-down into two categories as it is likely that the majority of individuals migrating to work in the minerals and extractive sector are of a younger age. Table 4.4 presents the estimated results. In column 1 there is some evidence that after the reform, provinces with gold deposits experienced a corollary increase in population, but in columns 2 and 3, there is no evidence of a change in the population migrating into provinces with gold deposits after the reform.

Table 4.4.: Gold, MAP and the effect on population and migration, 2002 - 2015

	(1) Log Population	(2) Log Migration	(3) Log Younger Migration
Gold	2.123***	2.644*	-7.075
	(0.239)	(1.338)	(4.853)
Mining Reform	0.483***	0.495	0.502
	(0.0694)	(0.547)	(0.473)
Gold x Mining Reform	0.0171*	0.0430	0.0384
	(0.01000)	(0.0483)	(0.0419)
Observations	1,110	1,110	1,110
R-squared	0.997	0.971	0.982
Geographic Controls	Yes	Yes	Yes
Socioeconomic Controls	Yes	Yes	Yes
Dependent Mean	11.253	7.608	6.753

Notes: This table presents estimates for the effects that gold mining deposits have on the log of population, log of population that migrated, and log of younger population that migrated, identified using a DID based on the timing of the MAP reform as well as the distribution of gold deposits. Standard errors are clustered at the provincial level. Each regression includes province and time fixed effects. Geographic controls include: elevation, mean air temperature, and mean precipitation. Socioeconomic controls include: the poverty incidence level, log of population, log of deforestation, ethnic fractionalization, religious fractionalization, average years of education of the household head, fraction of houses with roofs made of strong materials, fraction of houses with walls made of strong materials, fraction of households with access to electricity, access to indoor toilet and running water. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.7.2. Deforestation

Next, I explore a second mechanism that may explain the increase in malaria, which could be related to deforestation. One of the main negative externalities from mining is the loss of forest coverage. Deforestation has been linked to a wide variety of human activities including agriculture development, logging, transmigration programs, road, construction, mining and hydropower (Austin et al., 2019; Patz et al., 2000; Walsh et al., 1993). Gold mining can affect the ecosystem as it starts with vast deforestation (Recht et al., 2017). Additionally, Indian districts with a higher proportion of small mines exhibit significantly greater deforestation per hectare (Balietti et al., 2018), while in the Amazon, mining significantly increased deforestation up to 70 km beyond the mining lease boundaries (Sonter et al., 2017).

Deforestation can alter the disease ecology of malaria in several ways. Cleared lands are generally more exposed to sunlight and prone to puddle formation with more neutral pH levels that can favor *Anopheline* larvae development (Patz et al., 2000). A loss of biodiversity can also affect malaria incidence by reducing or eliminating species that prey on *Anopheline* larvae and *Anopheles* mosquitoes (Laporta et al., 2013; Yasuoka and Levins, 2007). There is a long-standing literature linking deforestation with an alteration of the disease ecology of malaria (Chakrabarti, 2018; Keesing et al., 2010; MacDonald and Mordecai, 2019; Pattanayak and Pfaff, 2009; Tucker et al., 2017). Garg (2019) provides the first causal estimates of the effect that forest loss has on the increased incidence of malaria in Indonesia. Additionally, Berazneva and Byker (2017) find similar evidence that the loss of forest coverage increased malaria incidence around 4.5 percent in children under five in Nigeria.

I investigate the deforestation channel through several exercises. The first estimated equation explores whether the reform had an effect on deforestation:

$$\begin{aligned} Deforestation_{p,t} = {} & \beta_0 + \beta_1 MiningReform_t + \beta_2 Gold_p \\ & + \beta_3 MiningReform_t \cdot Gold_p + X'_{p,t} \cdot \delta + \rho_p + \tau_t + \varepsilon_{p,t} \end{aligned} \tag{4.4}$$

where $Deforestation_{p,t}$ is the log of deforestation for a given province p in time t. Data on deforestation are derived from a satellite-generated forest cover database (Hansen et al., 2013), which provides global information about forest cover in 2000 and subsequent forest changes between 2001 and 2018.[9]

The second exercise explores whether the reform, gold deposits and deforestation had an effect on malaria. The following equation is estimated:

$$\begin{aligned} Malaria_{p,t} = {} & \beta_0 + \beta_1 MiningReform_t + \beta_2 Gold_p + \beta_3 Deforestation_{p,t} \\ & + \beta_4 MiningReform_t \cdot Gold_p \\ & + \beta_5 MiningReform_t \cdot Deforestation_{p,t} \\ & + \beta_6 Gold_p \cdot Deforestation_{p,t} \\ & + \beta_7 MiningReform_t \cdot Gold_p \cdot Deforestation_{p,t} \\ & + X'_{p,t} \cdot \delta + \rho_p + \tau_t + \varepsilon_{p,t} \end{aligned} \tag{4.5}$$

[9] Landsat satellites capture pixel-level images with a 1 arc-second resolution, where GFC classifies forest cover and loss at a spatial resolution of 30 m x 30 m. The GFC defines forest cover as an area in which the biophysical presence of trees or vegetation higher than five meters accounts for more than 50 percent of the land and may take the form of natural forests or plantations over a range of canopy densities.

where $Malaria_{p,t}$ is the inverse hyperbolic sine of malaria cases for province p in time t. The main variable of interest is the triple interaction between the mining reform, gold deposits and deforestation. Since deforestation has been linked as a negative externality to mining, one could expect that these three factors may together explain the increase in malaria.

Table 4.5 presents the results. Columns 1-4 present the results on whether the reform had an effect on deforestation, where I find no evidence that provinces with gold deposits after the reform suffered more deforestation relative to provinces without gold deposits. The results of the triple interaction term in columns 5-8 find no statistical effect that malaria is being effected by deforestation, gold mining and the MAP reform. Additionally, the main results in Table 4.1 control for the level of provincial deforestation. Each of these pieces of evidence suggest that the mechanism through which malaria is increasing is through gold mining, so we can rule out that the effect is running through the deforestation channel.

Table 4.5.: Gold, MAP and deforestation, 2002 - 2015

	(1) Log Deforestation	(2) Log Deforestation	(3) Log Deforestation	(4) Log Deforestation	(5) Malaria Cases (IHS)	(6) Malaria Cases (IHS)	(7) Malaria Cases (IHS)	(8) Malaria Cases (IHS)
Gold	1.195***	1.717***	0.00264	0.00264	3.671*	2.839	3.570	2.777
	(0.153)	(0.225)	(1.133)	(1.133)	(1.905)	(1.995)	(2.319)	(2.369)
Mining Reform	0.0176	-0.0183	-0.00409	-0.00409	4.088***	4.136***	1.984**	2.073**
	(0.203)	(0.197)	(0.247)	(0.247)	(0.762)	(0.789)	(0.924)	(0.932)
Gold x Mining Reform	0.123	0.127	0.127	0.127				
	(0.176)	(0.175)	(0.178)	(0.178)				
Gold x Mining Reform x Deforestation					0.171	0.189	0.149	0.156
					(0.120)	(0.117)	(0.126)	(0.123)
Observations	1,110	1,110	1,110	1,110	1,110	1,110	1,110	1,110
R-squared	0.836	0.836	0.840	0.840	0.592	0.594	0.622	0.622
Geographic Controls	No	Yes	No	Yes	No	Yes	No	Yes
Socioeconomic Controls	No	No	Yes	Yes	No	No	Yes	Yes
Mean Deforestation	15.162	15.162	15.162	15.162				
Mean Incidence					0.459	0.459	0.459	0.459

Notes: Columns 1-4 present estimates for the effects that gold mining deposits have on the log of deforestation, identified using a DID based on the timing of the MAP reform as well as the distribution of gold deposits. Columns 5-8 present estimates for the effects that gold mining, the MAP reform as well as deforestation have on the log of malaria cases, identified using a DID based on the timing of the MAP reform as well as the distribution of gold deposits. Standard errors are clustered at the provincial level. Each regression includes province and time fixed effects. Geographic controls include: elevation, mean air temperature, and mean precipitation. Socioeconomic controls include: the poverty incidence level, log of population, log of deforestation, ethnic fractionalization, religious fractionalization, average years of education of the household head, fraction of houses with roofs made of strong materials, fraction of houses with walls made of strong materials, fraction of households with access to electricity, access to indoor toilet and running water. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.8. Conclusion

As the environment continues to be anthropogenically altered particularly in the form of land transformation and land clearance activities, there is likely to be an increase in the incidence of different diseases. This study improves our understanding of the relationship between natural resource policy and ecology by exploiting how a major shift in the Philippines' extraction policy to reduce the lag in granting mining permits had unintended health effects. More specifically, I provide causal evidence that provinces with gold mining deposits experienced 32 percent more malaria cases relative to provinces without gold deposits after the MAP reform. The main mechanism is argued to be through gold mining's creation of slow-moving bodies of stagnant water, which provide an ideal breeding site for *Anopheles* mosquitoes to propagate and reproduce. Then an event study approach estimates that the MAP reform had persistent effects on malaria 10 years beyond the implementation of the policy. Several falsification tests are performed, which reinforce the empirical strategy and suggest that the effect on malaria is specific to gold mining. An analysis of other possible mechanisms such as migration or deforestation provide no evidence of a statistical relationship, further supporting the ecological mechanism underpinning the relationship between malaria and gold mining.

From a public health policy standpoint, the results indicate that more attention should be given to the challenges ecosystem transformation or degradation poses to the health of individuals. Several different policies can be targeted to mitigate the incidence of malaria resulting from gold mining activities. First, clinics within gold mining communities can provide malaria specific information as to the transmission of malaria and proven anti-malarial interventions. Figure A.2 presents data from the 2003 Demographic and Health Survey for the Philippines that indicates 80 percent of respondents know malaria comes from mosquitoes, while Figure A.3 suggests over 60 percent of respondents believe malaria is spread by mosquitoes. When asked the ways in which malaria can be prevented, the majority of respondents answered eliminate breeding places, followed by mosquito nets, spray house, other and avoid certain foods (Figure A.4). While there is a large portion of the surveyed population who understand where malaria comes from, the share drops substantially when asked about the transmission or methods of malaria prevention. Second, clinics within gold mining regions can provide specialized resources on proven anti-malarial interventions such as insecticide-treated bed nets, indoor residual spraying, or prompt clinical treatment as well as certain environmental management strategies such as drainage or canal linings. The third area for reform is related to mitigation efforts through monitoring and enforcement. This study suggests that the most likely mechanism leading to an increase in malaria is through the stagnant bodies of water that are left behind from gold mining activities. Monitoring compliance with proper mining protocols or rules may limit the stagnant water conditions needed for malaria to propagate and persist.

A.1. Appendix

A.1.1. Summary statistics

Table A.1.: Summary statistics, 2002 - 2015

Dependent Variables	Observations	Mean	Std. Dev.	Min	Max
Malaria Cases	1,110	1.04	3.32	0.00	36.00
Malaria Cases (IHS)	1,110	0.46	0.82	0.00	4.28
Independent Variables					
Gold	1,110	0.45	0.50	0.00	1.00
Gold Deposits	1,110	1.88	3.08	0.00	17.00
Poverty Incidence	1,110	35.44	14.68	4.98	71.31
Log of Population	1,110	11.25	0.84	9.01	12.94
Log of Deforestation	1,110	15.16	1.56	6.80	19.13
Elevation	1,110	319.74	232.58	36.60	1268.83
Mean Air Temperature	1,110	25.97	1.31	21.10	28.00
Mean Precipitation	1,110	220.07	47.38	107.61	398.71
Ethnic Fractionalization	1,110	0.48	0.27	0.02	0.89
Religious Fractionalization	1,110	0.33	0.18	0.03	0.72
Average Years of Education of the Household Head	1,110	7.53	1.03	4.19	10.10
Fraction of Households with Roofs Made of Strong Materials	1,110	0.70	0.19	0.25	0.99
Fraction of Households with Walls Made of Strong Materials	1,110	0.73	0.15	0.25	0.99
Fraction of Households with Access to Electricity	1,110	0.66	0.19	0.16	0.97
Access to Running Water	1,110	0.43	0.17	0.11	0.98
Access to Indoor Toilet	1,110	0.89	0.10	0.53	1.00

A.1.2. Additional results

Table A.2.: Gold, MAP and the effect on malaria at the intensive margin, 2002 - 2015

	(1) Malaria Cases (IHS)	(2) Malaria Cases (IHS)	(3) Malaria Cases (IHS)	(4) Malaria Cases (IHS)
Gold Deposits	0.0170	0.105*	0.0456	0.0512
	(0.0190)	(0.0586)	(0.209)	(0.326)
Mining Reform	-0.986***	-1.046***	-2.336***	-2.307***
	(0.142)	(0.144)	(0.509)	(0.507)
Gold Deposits x Mining Reform	0.0316	0.0310	0.0231	0.0221
	(0.0211)	(0.0217)	(0.0204)	(0.0206)
Observations	1,110	1,110	1,110	1,110
R-squared	0.557	0.558	0.600	0.601
Geographic Controls	No	Yes	No	Yes
Socioeconomic Controls	No	No	Yes	Yes
Mean Incidence	0.459	0.459	0.459	0.459

Notes: This table presents estimates for the effects that the number of gold mining deposits has on the log of malaria cases, identified using a DID based on the timing of the MAP reform as well as the distribution gold deposits. Standard errors are clustered at the provincial level. Each regression includes province and time fixed effects. Geographic controls include: elevation, mean air temperature, and mean precipitation. Socioeconomic controls include: the poverty incidence level, log of population, log of deforestation, ethnic fractionalization, religious fractionalization, average years of education of the household head, fraction of houses with roofs made of strong materials, fraction of houses with walls made of strong materials, fraction of households with access to electricity, access to indoor toilet and running water. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3.: Gold, MAP and the effect on malaria cases at the extensive margin, 2002 - 2015

	(1) Malaria Cases	(2) Malaria Cases	(3) Malaria Cases	(4) Malaria Cases
Gold	-1.483*	-1.973*	0.0773	0.501
	(0.782)	(1.104)	(6.496)	(5.712)
Mining Reform	-3.714***	-3.610***	-6.507***	-6.428***
	(1.062)	(0.933)	(1.814)	(1.784)
Gold x Mining Reform	2.257**	2.265**	2.270**	2.276**
	(0.913)	(0.919)	(0.918)	(0.920)
Observations	1,110	1,110	1,110	1,110
R-squared	0.558	0.558	0.606	0.607
Geographic Controls	No	Yes	No	Yes
Socioeconomic Controls	No	No	Yes	Yes
Mean Incidence	1.038	1.038	1.038	1.038

Notes: This table presents estimates for the effects that gold mining deposits have on the absolute number of malaria cases, identified using a DID based on the timing of the MAP reform as well as the distribution of gold deposits. Standard errors are clustered at the provincial level. Each regression includes province and time fixed effects. Geographic controls include: elevation, mean air temperature, and mean precipitation. Socioeconomic controls include: the poverty incidence level, log of population, log of deforestation, ethnic fractionalization, religious fractionalization, average years of education of the household head, fraction of houses with roofs made of strong materials, fraction of houses with walls made of strong materials, fraction of households with access to electricity, access to indoor toilet and running water. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4.: Gold, MAP and the effect on malaria cases at the intensive margin, 2002 - 2015

	(1) Malaria Cases	(2) Malaria Cases	(3) Malaria Cases	(4) Malaria Cases
Gold Deposits	-0.153	-0.215	-0.0470	-0.506
	(0.0982)	(0.350)	(0.827)	(1.239)
Mining Reform	-3.135***	-3.026***	-6.198***	-6.110***
	(0.854)	(0.737)	(1.795)	(1.770)
Gold Deposits x Mining Reform	0.242**	0.243**	0.215*	0.216**
	(0.112)	(0.112)	(0.108)	(0.108)
Observations	1,110	1,110	1,110	1,110
R-squared	0.550	0.550	0.597	0.598
Geographic Controls	No	Yes	No	Yes
Socioeconomic Controls	No	No	Yes	Yes
Mean Incidence	1.038	1.038	1.038	1.038

Notes: This table presents estimates for the effects that the number of gold mining deposits has on the absolute number of malaria cases, identified using a DID based on the timing of the MAP reform as well as the distribution gold deposits. Standard errors are clustered at the provincial level. Each regression includes province and time fixed effects. Geographic controls include: elevation, mean air temperature, and mean precipitation. Socioeconomic controls include: the poverty incidence level, log of population, log of deforestation, ethnic fractionalization, religious fractionalization, average years of education of the household head, fraction of houses with roofs made of strong materials, fraction of houses with walls made of strong materials, fraction of households with access to electricity, access to indoor toilet and running water. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5.: Gold, MAP and the effect on other diseases, 2002 - 2015

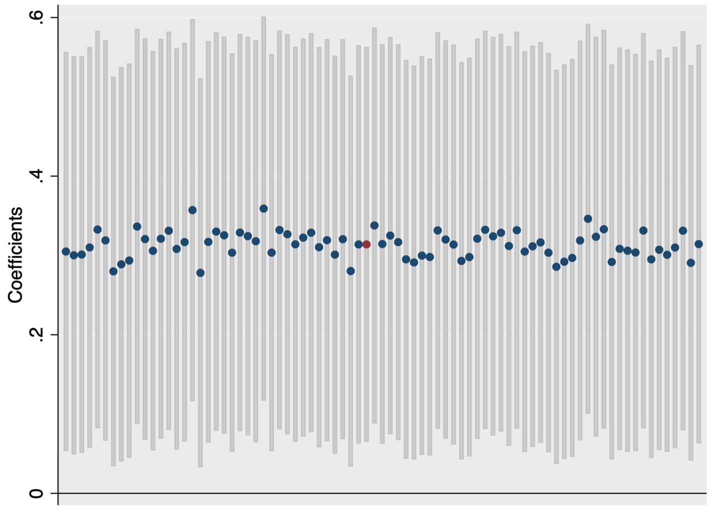
	(1) Dengue Cases	(2) HIV Cases	(3) Lower Respiratory Cases	(4) Pneumonia Cases	(5) Gastric or Duodenal Peptic Ulcer Cases
Gold	3.853***	-1.262	0.714	-0.906	1.441***
	(1.161)	(0.782)	(0.766)	(0.884)	(0.486)
Mining Reform	-1.992***	0.665***	0.669**	0.875***	0.00659
	(0.400)	(0.216)	(0.331)	(0.286)	(0.178)
Gold x Mining Reform	-0.0379	0.0883	0.0189	-0.0253	-0.000250
	(0.159)	(0.0619)	(0.0682)	(0.0582)	(0.0597)
Observations	1,110	1,110	1,104	1,104	1,025
R-squared	0.681	0.472	0.940	0.940	0.926
Geographic Controls	Yes	Yes	Yes	Yes	Yes
Socioeconomic Controls	Yes	Yes	Yes	Yes	Yes
Mean Incidence	5.273	0.293	181.265	347.637	55.304

Notes: This table presents estimates for the effects that gold mining has on the absolute number of Dengue, HIV, Lower Respiratory, Pneumonia and Gastric or Duodenal Peptic Ulcer cases, identified using a DID based on the timing of the MAP reform as well as the distribution of gold deposits. Standard errors are clustered at the provincial level. Each regression includes province and time fixed effects. The independent variables in columns 1-5 include: the poverty incidence level, log of population, log of deforestation, elevation, mean air temperature, mean precipitation, ethnic fractionalization, religious fractionalization, average years of education of the household head, fraction of houses with roofs made of strong materials, fraction of houses with walls made of strong materials, fraction of households with access to electricity, access to indoor toilet and running water. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.1.3. Robustness tests

Change of comparison groups

Figure A.1.: Gold, MAP and the effect on malaria at the extensive margin, 2002 - 2015



Notes: This figure presents a robustness test that estimates the effects that gold mining deposits has on the log of malaria cases by dropping each province one at a time, identified using a DID based on the timing of the MAP reform as well as the distribution of gold deposits. This exercise illustrates the stability of the estimated coefficients and standard errors. The red coefficient is the point estimate obtained in Table 4.1, column 4. Each regression includes province and time fixed effects. Standard errors are clustered at the provincial level. The independent variables include: elevation, mean air temperature, mean precipitation, the poverty incidence level, log of population, log of deforestation, ethnic fractionalization, religious fractionalization, average years of education of the household head, fraction of houses with roofs made of strong materials, fraction of houses with walls made of strong materials, fraction of households with access to electricity, access to indoor toilet and running water.

Controlling for health facilities

Table A.6.: Controlling for health facilities, 2002 - 2015

	(1) Malaria Cases (IHS)	(2) Malaria Cases (IHS)	(3) Malaria Cases (IHS)	(4) Malaria Cases (IHS)
Gold	-0.0135	0.400	0.332	7.023**
	(0.143)	(0.717)	(1.639)	(3.479)
Mining Reform	-1.091***	-1.152***	-2.388***	-2.380***
	(0.162)	(0.163)	(0.503)	(0.501)
Gold x Mining Reform	0.361**	0.358**	0.319**	0.317**
	(0.164)	(0.165)	(0.149)	(0.150)
Health Facilities	-0.00511***	-0.0107***	-0.00528***	-0.0588*
	(0.000242)	(0.00388)	(0.000295)	(0.0313)
Observations	1,110	1,110	1,110	1,110
R-squared	0.561	0.562	0.604	0.604
Geographic Controls	No	Yes	No	Yes
Socioeconomic Controls	No	No	Yes	Yes
Mean Incidence	0.459	0.459	0.459	0.459

Notes: This table presents a robustness test that additionally controls for the number of rural health facilities within each province. Standard errors are clustered at the provincial level. Each regression includes province and time fixed effects. Geographic controls include: elevation, mean air temperature, and mean precipitation. Socioeconomic controls include: the number of health facilities, the poverty incidence level, log of population, log of deforestation, ethnic fractionalization, religious fractionalization, average years of education of the household head, fraction of houses with roofs made of strong materials, fraction of houses with walls made of strong materials, fraction of households with access to electricity, access to indoor toilet and running water. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Controlling for bodies of water

Table A.7.: Controlling for bodies of water, 2002 - 2015

	(1) Malaria Cases (IHS)	(2) Malaria Cases (IHS)	(3) Malaria Cases (IHS)	(4) Malaria Cases (IHS)
Gold	-0.534	-0.620***	0.184	-0.622***
	(1.056)	(0.226)	(1.898)	(0.180)
Mining Reform	-1.059***	-1.102***	-2.377***	-1.103***
	(0.154)	(0.173)	(0.495)	(0.191)
Gold x Mining Reform	0.362**	0.341**	0.319**	0.371**
	(0.165)	(0.167)	(0.149)	(0.165)
Bodies of Water	1.56e-06	2.52e-07	7.16e-07	1.44e-07
	(2.73e-06)	(2.32e-07)	(2.08e-06)	(1.18e-07)
Observations	1,110	1,110	1,110	1,110
R-squared	0.562	0.325	0.604	0.438
Geographic Controls	No	Yes	No	Yes
Socioeconomic Controls	No	No	Yes	Yes
Mean Incidence	0.459	0.459	0.459	0.459

Notes: This table presents a robustness test that additionally controls for the total surface area of bodies of water within each province. Standard errors are clustered at the provincial level. Each regression includes province and time fixed effects. Geographic controls include: total surface area of bodies of water, elevation, mean air temperature, and mean precipitation. Socioeconomic controls include: the poverty incidence level, log of population, log of deforestation, ethnic fractionalization, religious fractionalization, average years of education of the household head, fraction of houses with roofs made of strong materials, fraction of houses with walls made of strong materials, fraction of households with access to electricity, access to indoor toilet and running water. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Sensitivity to squared values of temperature and precipitation

Table A.8.: Sensitivity to squared values of temperature and precipitation, 2002 - 2015

	(1) Malaria Cases (IHS)	(2) Malaria Cases (IHS)
Gold	-0.502*	-0.101
	(0.261)	(1.552)
Mining Reform	-1.165***	-2.384***
	(0.161)	(0.498)
Gold x Mining Reform	0.358**	0.319**
	(0.163)	(0.148)
Observations	1,110	1,110
R-squared	0.565	0.606
Geographic Controls	Yes	Yes
Socioeconomic Controls	No	Yes
Mean Incidence	0.459	0.459

Notes: This table presents a robustness test that additionally controls for the squared terms of temperature and precipitation within each province. Standard errors are clustered at the provincial level. Each regression includes province and time fixed effects. Geographic controls include elevation, mean air temperature, mean air temperature squared, mean precipitation, and mean precipitation squared. Socioeconomic controls include: the poverty incidence level, log of population, log of deforestation, ethnic fractionalization, religious fractionalization, average years of education of the household head, fraction of houses with roofs made of strong materials, fraction of houses with walls made of strong materials, fraction of households with access to electricity, access to indoor toilet and running water. Significant at $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Sensitivity to changes in clustering of standard errors

Table A.9.: Sensitivity to changes in clustering of standard errors, 2002 - 2015

	(1) Malaria Cases (IHS)	(2) Malaria Cases (IHS)	(3) Malaria Cases (IHS)	(4) Malaria Cases (IHS)
Gold	0.0427	-0.957	0.390	-0.442
	(0.188)	(0.632)	(1.650)	(1.668)
Mining Reform	-1.091***	-1.152***	-2.388***	-2.380***
	(0.214)	(0.189)	(0.541)	(0.535)
Gold x Mining Reform	0.361*	0.358*	0.319*	0.317*
	(0.189)	(0.192)	(0.174)	(0.176)
Observations	1,110	1,110	1,110	1,110
R-squared	0.561	0.562	0.604	0.604
Geographic Controls	No	Yes	No	Yes
Socioeconomic Controls	No	No	Yes	Yes
Mean Incidence	0.459	0.459	0.459	0.459

Notes: This table presents a robustness test that changes the clustering of the standard errors to the regional level. Each regression includes province and time fixed effects. Geographic controls include: elevation, mean air temperature, and mean precipitation. Socioeconomic controls include: poverty incidence level, log of population, log of deforestation, ethnic fractionalization, religious fractionalization, average years of education of the household head, fraction of houses with roofs made of strong materials, fraction of houses with walls made of strong materials, fraction of households with access to electricity, access to indoor toilet and running water. Significant at $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Controlling for quadratic time trends

Table A.10.: Controlling for quadratic time trends, 2002 - 2015

	(1) Malaria Cases (IHS)	(2) Malaria Cases (IHS)	(3) Malaria Cases (IHS)	(4) Malaria Cases (IHS)
Gold	0.0436	-0.925***	2.668*	1.619
	(0.144)	(0.150)	(1.582)	(1.542)
Mining Reform	-0.107	-0.128	-0.0827	-0.110
	(0.105)	(0.117)	(0.103)	(0.117)
Gold x Mining Reform	0.361**	0.360**	0.361**	0.361**
	(0.163)	(0.164)	(0.154)	(0.155)
Observations	1,110	1,110	1,110	1,110
R-squared	0.556	0.559	0.583	0.584
Geographic Controls	No	Yes	No	Yes
Socioeconomic Controls	No	No	Yes	Yes
Province-Trends	Quadratic	Quadratic	Quadratic	Quadratic
Mean Incidence	0.459	0.459	0.459	0.459

Notes: This table presents estimates for the effects that gold mining deposits have on the log of malaria cases, identified using a DID based on the timing of the MAP reform as well as the distribution of gold deposits. Standard errors are clustered at the provincial level. Each regression includes province fixed effects and quadratic time trends. Geographic controls include: elevation, mean air temperature, and mean precipitation. Socioeconomic controls include: the poverty incidence level, log of population, log of deforestation, ethnic fractionalization, religious fractionalization, average years of education of the household head, fraction of houses with roofs made of strong materials, fraction of houses with walls made of strong materials, fraction of households with access to electricity, access to indoor toilet and running water. Significant at $*p < 0.10$, $** p < 0.05$, $*** p < 0.01$.

Alternative transformation of the dependent variable

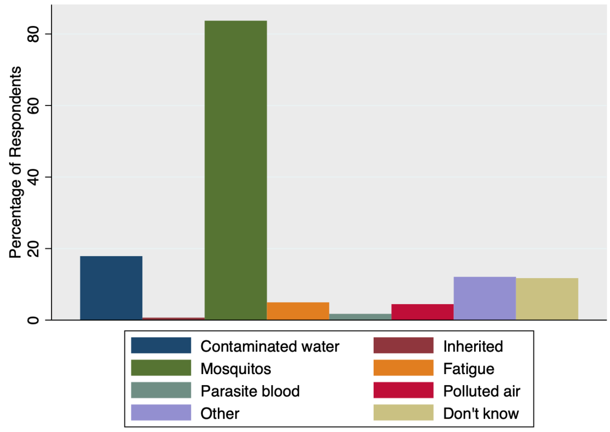
Table A.11.: Alternative transformation of the dependent variable, 2002 - 2015

	(1) Log Malaria Cases	(2) Log Malaria Cases	(3) Log Malaria Cases	(4) Log Malaria Cases
Gold	0.0171	-0.737***	0.274	-0.341
	(0.115)	(0.197)	(1.292)	(1.229)
Mining Reform	-0.865***	-0.909***	-1.876***	-1.868***
	(0.132)	(0.130)	(0.397)	(0.396)
Gold x Mining Reform	0.299**	0.297**	0.268**	0.266**
	(0.130)	(0.131)	(0.118)	(0.119)
Observations	1,110	1,110	1,110	1,110
R-squared	0.567	0.568	0.610	0.610
Geographic Controls	No	Yes	No	Yes
Socioeconomic Controls	No	No	Yes	Yes
Mean Incidence	0.459	0.459	0.459	0.459

Notes: This table presents a robustness test that changes the definition of the dependent variable to $log(1+MalariaCases)$. Each regression includes province and time fixed effects. Geographic controls include: elevation, mean air temperature, and mean precipitation. Socioeconomic controls include: poverty incidence level, log of population, log of deforestation, ethnic fractionalization, religious fractionalization, average years of education of the household head, fraction of houses with roofs made of strong materials, fraction of houses with walls made of strong materials, fraction of households with access to electricity, access to indoor toilet and running water. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

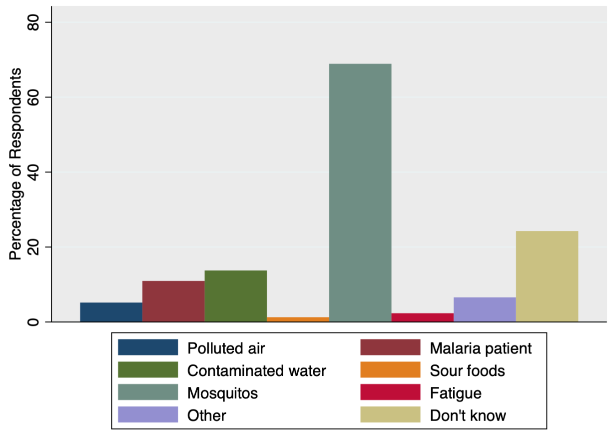
A.1.4. Additional figures using demographic and health survey (DHS) data

Figure A.2.: What causes malaria?



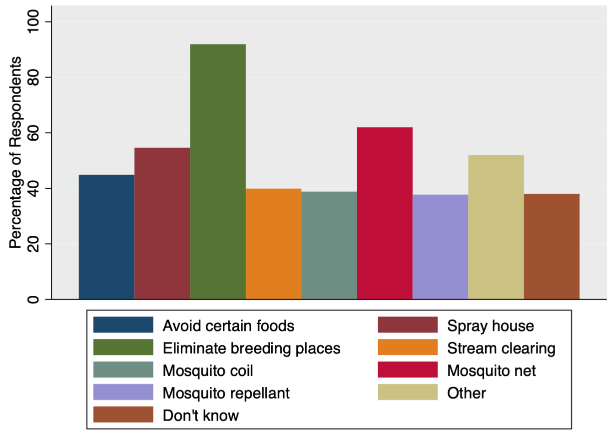
Source: Demographic and Health Survey (DHS) Data (2003)

Figure A.3.: How is malaria spread?



Source: Demographic and Health Survey (DHS) Data (2003)

Figure A.4.: Ways to prevent malaria



Source: Demographic and Health Survey (DHS) Data (2003)

5. Conclusion

Fighting poverty and protecting the environment are two of the most urgent challenges facing the international community today. The three chapters of this dissertation represent specific responses to these challenges, and provide empirical evidence that can guide specific policy recommendations.

Chapter 2 investigates the relationship between energy poverty and educational outcomes. Energy is interconnected with the socio-economic and human development of the individual, and the true nature of poverty manifests itself when individuals are deprived on multiple dimensions of human well-being. In recent years, there has been large investments in the energy sector, but recent empirical studies have provided inconclusive evidence on the impact of energy on wellbeing.

This chapter attempts to build upon the literature in three distinct ways. First, the chapter descriptively decomposes each of the potential household energy deprivations to illustrate that access to electricity is not a sufficient condition to address other components of household energy poverty. Much of the international development agenda has placed an emphasis on improving access to electricity, but this disregards whether individuals actually achieve other household energy components. Exploiting the data in this manner demonstrates that access to electricity is unable to capture whether other household energy domains have been achieved. Second, context specific weights for different energy poverty dimensions are derived through a Factor Analysis in order to construct a multidimensional energy poverty index (MEPI). Third the MEPI is applied in a regression analysis that compares its effects to those of access to electricity on measures of education. Furthermore, an instrumental variable (IV) approach that uses the land gradient of the household is adopted in order to overcome methodological challenges of attribution.

I find that the MEPI improves upon our understanding as to the effects energy poverty has on measures of education. This is shown by comparing the results of the MEPI estimation to that of access to electricity, where the estimated coefficients of the MEPI are more precise in terms of smaller standard errors and the MEPI is able to estimate significant results that access to electricity is unable to. The results suggest that there are further gains to the individual beyond simply obtaining access to electricity and highlight the importance of considering other energy mechanisms within an individual's set of energy capabilities. Failure to account for other possible energy deprivations may also explain the insignificant or inconsistent findings of previous studies based on simpler indicators (like access to electricity).

From a public policy perspective, the developed framework can provide policy practitioners with a more comprehensive picture of energy poverty. The MEPI can be deployed to monitor district or regional poverties in order to identify the types of energy poverties that need to be relieved as well as more efficiently allocate resources to different areas. Additionally, the MEPI can be used to analyze temporal dynamics to see how districts, regions or the country as a whole is improving in different energy dimensions. Last, the developed instrument can be used at the international scale to track a country's progress relative to countries of a similar development stage. Depending on the energy poverty make-up, the MEPI can provide practitioners with a powerful instrument in order to identify certain poverties and develop well informed interventions for energy poverty alleviation.

Next, Chapter 3 investigates the effects that a community-driven development (CDD) program of small-scale infrastructure projects in the Philippines had on forest coverage. The loss of forest coverage is a global environmental concern which represents around 9 percent of anthropogenic carbon emissions as well as a local environmental concern due to reductions in soil fertility, increased runoff into fisheries and a loss of biodiversity. As developing countries build infrastructure projects, one challenge to confront is how to meet their development needs in a sustainable manner. One solution that is gaining popularity amongst international donors and multilateral organizations are CDD programs. This type of program supports a bottom-up approach by localizing the decision making process and can best be characterized by the movement of responsibility over resources and planning decisions. Where these two areas come together is that international donors and multilateral organizations are targeting CDD programs as a strategy for climate change mitigation and adaptation (Arnold et al., 2014).

The overarching objective of this chapter is to examine whether the goals of fighting poverty and protecting the environment are in contradiction by asking whether development aid has unintended environmental effects in regards to deforestation. To answer this question, I utilize satellite-generated forest coverage data to analyze the effects development aid has on deforestation through a large-scale CDD program in the Philippines called KALAHI-CIDSS (KC). More specifically, a regression discontinuity design (RDD) and a randomized control trial (RCT) exploit the manner in which the KC program was allocated in order to test whether CDD programs have unintended environmental effects with respect to deforestation.

I find that the KC program had large and statistically significant effects on forest coverage. Eligible municipalities in the RDD period experienced 236 percent more deforestation (equivalent to 957,828 square meters) than ineligible municipalities, and treated municipalities in the RCT period experienced an average of 265 percent more deforestation (equivalent to 2,134,685 square meters) than the control. Next, I explore several different mechanisms that may be responsible for the increased deforestation, where the evidence indicates that there was increased economic stimulation. First I show that that eligible municipalities have lower poverty levels by the end of the program. Second I find an expansion of economic activity, as eligible municipalities experienced an increase in nighttime light of 26 percent. Third I find that eligible municipalities had an increase in the share of population working in agriculture, fishing, forestry and manufacturing, reductions in transportation, storage and communication and no evidence of changes in mining and extractive activities. Last I find that eligible municipalities experienced a corollary increase in inward migration of 22 percent, and no evidence of changes to the number of people using wood for cooking.

I then explore heterogeneity amongst the implemented subprojects to find two main findings. First I show that infrastructure projects (including trails, bridges and roads) have the greatest impact on deforestation, followed by those relating to support, education and health facilities. Second I explore spillover effects into surrounding municipalities, where I find that for each additional neighbor that is treated by the KC program, deforestation increases by approximately 10 percent.

If international organizations want to employ CDD programs as a strategy for climate change mitigation and adaptation, much more attention needs to be given to the environmental concerns arising from such projects. In order to explore policy recommendations that can be derived from the results of this chapter, I review internal documents relating to the KC program, and two different policy areas emerge that can be targeted to mitigate deforestation. The first area is to create a more comprehensive approach to the environmental safeguard policies. Policies regarding forestry and natural habitats should be included within the environmental assessments. The second is to develop indicators to monitor and evaluate the impacts that certain subprojects have should be put in place as a way to mitigate environmental degradation. Last is to create an enforcement mechanism for entities in charge of monitoring compliance to ensure the projects meet the sustainability component the donors purport them to have. The second area that should be targeted is through the provision of additional implementation support in the form of technical assistance at the community level. This can include information on sustainable development in the technical manuals that are provided to communities as well as training of community facilitators in environmentally sustainable building practices to safeguard against or mitigate environmental degradation.

Last, Chapter 4 focuses on how a changing environment impacts development by analyzing how/to what extent a policy intended to revitalize the mining sector in the

Philippines led to an unintended increase in malaria cases. Roughly a quarter of the global burden of disease can be attributed to environmental changes (Prüss-Üstün et al., 2008). One such disease that is susceptible to environmental changes is malaria, due to the fact that cleared lands are generally more exposed to sunlight and more prone to puddle formation as well as a loss of biodiversity can reduce or eliminate species that prey on Anopheline larvae or *Anopheles* mosquitoes. Deforestation is one form of land transformation that has been shown to alter the disease ecology of malaria (Berazneva and Byker, 2017; Garg, 2019). Mining is another form of land transformation that can theoretically affect the disease ecology of malaria, but has received much less attention in the literature.

This chapter aims to analyze whether there is an ecological response from mining activities, by investigating how a change in extractive resource policy in the Philippines led to more cases of malaria. In January 2004, the government of the Philippines launched the Minerals Action Plan (MAP) with the goal of revitalizing the mining sector. As a result, the policy change led to a reduction in the mining permit process between application and the grant of a permit from 3-5 years to 6 months in 2005 (Fong-Sam, 2005).

To disentangle this relationship, I exploit variation in the timing of the MAP reform as well as spatial variation in the distribution of mineral endowments through a difference-in-difference (DID) approach, which compares provinces with and without gold deposits before and after the reform. The hypothesis follows that gold mining leaves behind slow-moving bodies of water, which provide the perfect reproductive environment for the *Anopheles* mosquitoes.

I find evidence that is consistent with an ecological response, where after the MAP reform, provinces with gold deposits had 32 percent more malaria cases relative to provinces without gold deposits. An event study specification further shows that the effects on malaria are persistent 10 years beyond the implantation of the MAP reform. Then the empirical strategy is reinforced through three falsification tests: 1) the effect is specific to the disease ecology of malaria and not related to other diseases, 2) the effect is specific to gold mining and not related to other types of minerals and 3) a permutation inference exercise indicates that the causal effects are not likely to be randomly generated. Last, I explore other potential mechanisms such as migration or deforestation and find that neither can explain the increase in malaria.

The results indicate that more attention should be given to the effects that ecosystem transformation or degradation pose to the health of individuals. Several different policies can be targeted to mitigate the incidence of malaria resulting from gold mining activities. First, clinics within gold mining communities can provide information on the transmission of malaria and proven anti-malaria interventions. Data from the 2003 Demographic and Health Survey indicate that around 80 percent of the sample population know that mosquitoes cause malaria, but only 60 percent believe malaria is spread by mosquitoes. When asked how malaria can be prevented, respondents are much less certain. A large portion of respondents indicate malaria can be prevented by eliminating breeding places, but are less certain on other methods such as mosquito nets, spray houses, avoidance of certain foods or 'other' methods. Second, clinics within gold mining provinces can provide specialized resources on proven anti-malarial interventions such as insecticide-treated bed nets, indoor residual spraying, or prompt clinical treatment as well as certain environmental management strategies such as drainage or canal linings. Last, more attention should be given to mitigation efforts through monitoring and enforcement. This study suggests that the most likely mechanism leading to an increase in malaria is through the stagnant bodies of water left behind from gold mining activities. Protocols or rules should be put in place to limit the stagnant water left from gold mining that provide the conditions that are needed for malaria to propagate and persist. Additionally, monitoring compliance and oversight of firms or individuals with mining permits may help stem the changes to the ecosystem that are conducive to malaria.

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