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

Jeffrey Pagel *†

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Abstract

Community-driven development (CDD) programs are becoming integral components in the portfolios of international development agencies, but little is known about the environmental effects stemming from such programs. Using satellite-generated forest coverage data, this paper applies a regression discontinuity design (RDD) and a randomized control trial (RCT) to a large-scale CDD program over two different time periods in the Philippines. Eligible municipalities in the RDD period experienced 220 percent more deforestation per year and treated municipalities in the RCT period experienced 126 percent more deforestation per year relative to the control. These results indicate that more focus should be placed on the sustainability of CDD programs.

Keywords: Community-driven Development, Deforestation, Exhaustible Resources and Economic Development, Foreign Aid
JEL: O13, Q32, Q01

*Grantham Research Institute, London School of Economics; Email: j.pagel@lse.ac.uk

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1 Community development and deforestation

The United Nation's declaration of the Millennium Development Goals (MDGs) at the start of the 21st 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 (Stern, 2007; Nabuurs et al., 2007).[1]

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"

[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).

[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).

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 (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 trade-offs 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 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

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

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 a 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 a 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 220 percent more deforestation per year (equivalent to 79 hectares per year) relative to ineligible municipalities. Results from the RCT period indicate that treated municipalities experienced an average of 126 percent more deforestation per year (equivalent to 78 hectares per year) relative to 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 24 percent. Third I investigate sectoral changes, where 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. Fourth, I find evidence that eligible municipalities experienced a corollary increase in migration of 19 percent and limited evidence of reductions in the number of people using wood for cooking fuel. Lastly, I analyze whether the KC program had spillover effects into surrounding municipalities. Within both of the time periods I find that deforestation is expected to increase in surrounding municipalities by 14 to 21 percent with each additional neighbor that is treated by the KC program.

I then explore and provide suggestive evidence on the 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 stems from economic support projects followed by infrastructure projects (including trails, bridges and roads) and education and health facilities. Additionally, similar small-scale subprojects in terms of the subproject construction duration are found to lead to more deforestation, while larger-scale subprojects, in terms of funding, are also found to be correlated with more deforestation.

The results of this study are most closely related to the work by Hess et al. (2021), 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. (2021) 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. (2021). 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. (2021) 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 investments in infrastructure such as trails, bridges and roads, economic support subprojects, education and health facilities, water and electricity subprojects. 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 (Deininger and Minten, 1999; Andersen et al., 2002; 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 (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.

[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 (Miteva et al., 2012; Alix-Garcia and Wolff, 2014). Jayachandran et al. (2017) investigate PES by randomly offering forest-owning 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.

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 2 describes the KC program, how the program was implemented in municipalities and the different types of projects that were undertaken. Section 3 describes the satellite-generated forest cover data and administrative data that are used. Section 4 outlines each of the empirical strategies and models estimated, where a RDD and a RCT exploit the way in which development aid was allocated. Section 5 presents the main results. Section 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, as well as investigates whether there are spillover effects into the surrounding municipalities. Section 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. Section 8 outlines several policy options to potentially mitigate deforestation pressures and then provides concluding remarks.

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 is to empower local communities through increased participation in local governance and implementation and management of poverty reduction projects. Furthermore, the approach seeks to add value to development operations by directly engaging stakeholders in project design and implementation (Labonne and Chase,

2009). The KC program pairs community training with block grants at the village (*barangay*) level that are 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 is assigned to participating municipalities, depending on their size, but the amounts must not be too large or too small for projects and are widely publicized so that stakeholders are 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 is implemented through a five-stage process known as the Community Empowerment Activity Cycle (Beatty et al., 2017) and follows a standard CDD template (Parker, 2005). In general, communities prepare subproject proposals, compete over block grants to finance investments for local public goods, and are 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 conduct a participatory situation analysis, and the results are validated in another assembly where the project preparation team and village representative teams are elected. Village representatives then attend a municipality meeting during which the rules and a subset of subproject ranking criteria are decided upon. Once those criteria are agreed upon, the project preparation teams prepare proposals, which are validated at a village meeting.

Second is the funding phase, when the preparation teams present the proposals and village representatives rank them by deciding the allocation of funds, while accounting for the budget of the municipality's block grant. The selection of subprojects is subject to a competitive process because the allocation of funds does not permit subprojects to be implemented in all villages. Once the inter-*barangay* forum decides which subproject proposals will receive funding, the results are presented in a village assembly.[5] The villages to receive funding then elect the

[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) are equally represented in community proposals. Additionally, Beatty et al.

members of the subproject management committee.

Last is the implementation phase, when subproject proposals are finalized by the committee, validated during a village assembly and then validated by another municipality forum. Even though inter-*barangay* forums are made up of both community representatives and technical advisors, only community representatives can approve a subproject proposal. Once the subproject has been officially approved, village volunteers receive technical assistance to create capacity through training in areas such as project planning, contracting, construction techniques, operations and management, bookkeeping and financial management. Municipalities receive technical assistance with respect to the feasibility of subprojects, project design and budgeting. Technical manuals for small-scale infrastructure are provided to facilitate community involvement in the assessment, delivery and management of such infrastructure. The objectives of these manuals are (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 are 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 A.5 shows the list of implemented subprojects by municipalities.[6]

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

(2017) show that the KC program leads residents to contribute to other civic activities at greater levels, which helps mitigate crowding out concerns.

[6]See Table A.6 in Appendix A.4 for a list of prohibited subprojects.

[7]Implementing guidelines follow the Philippine Environmental Impact Assessment Policy from Department of Environment and Natural Resources Administrative Order (DAO) No. 96-37. The KC program adopts Administrative Order No. 96-37 as a guide for the environmental screening of subprojects. Additionally, the administrative order stipulates that environmentally critical projects (ECPs) and projects within environmentally critical areas (ECAs) require the submission of an environmental impact statement and provides 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*

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 A.3 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 A.4 in the same World Bank report outlines, for each infrastructure activity, the criteria for which an environmental safeguard is 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.

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

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).

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 is 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 is no policy in place regarding enforcement.

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 2019. 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; Hess et al., 2021; Alesina et al., 2019).

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

[9]The GFC defines forest cover as an area in which the biophysical presence of trees or vegetation higher than five meters. A range of canopy densities are estimated for the percent of a pixel that was covered by tree canopy. The main analysis sets the canopy density threshold at 75 percent, but the main results are shown to be robust at 30 percent and 50 percent.

[10]See Appendix A.1 for examples of the pixel level deforestation data included in the GFC database.

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 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 hectares that were deforested. The variable is constructed as a column vector of the number of pixels of forest loss (n), where the ith entry represents the total number of hectares of forest loss in municipality m, for a given year t, or:

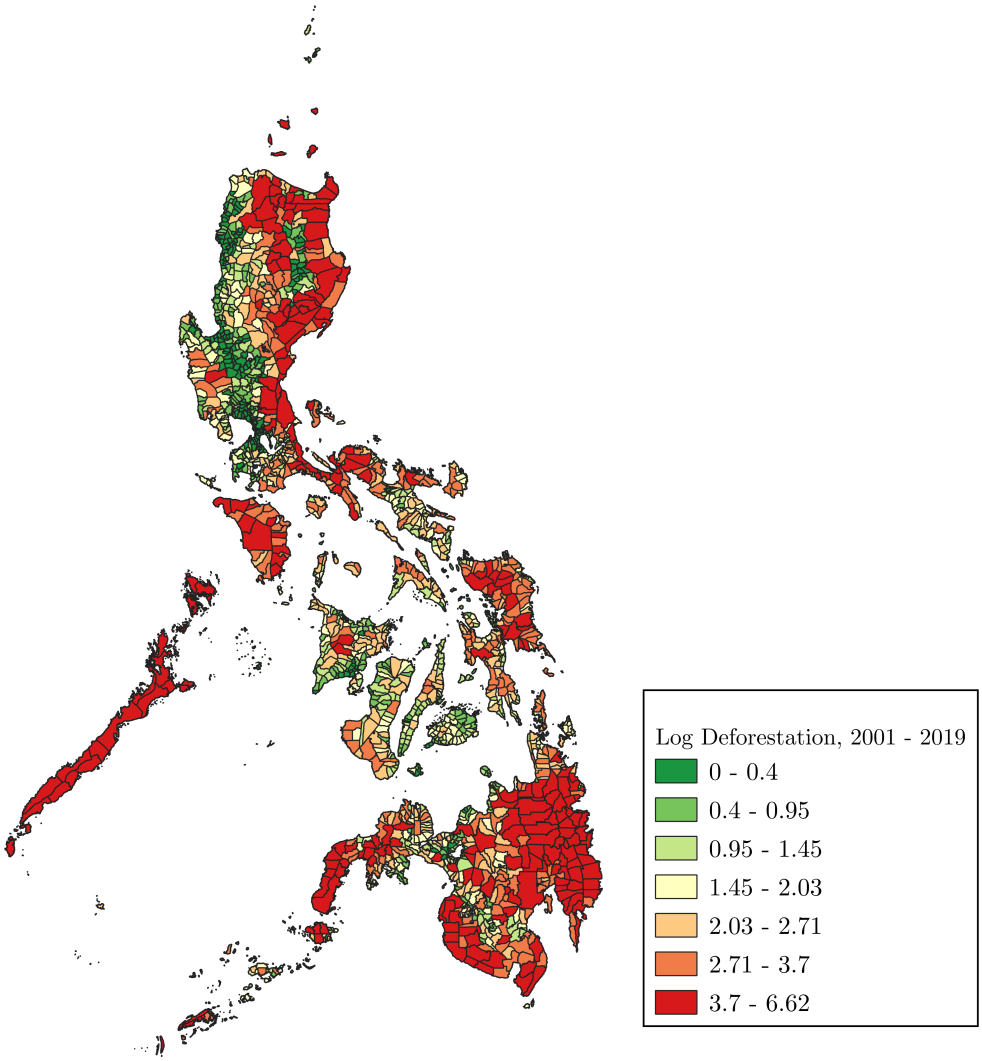
$$Deforestation_{m,t} = \sum_{i=1}^{n} Deforested\ Pixels_{i,m,t} = x_{1,t} + x_{2,t} \ldots + x_{M,t} \tag{1}$$

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 hectare is added. Figure 1 presents a map of average yearly deforestation in log form across Philippine municipalities from 2001 to 2019, while Figure 2 calculates the yearly loss of forest cover in hectares. From 2001 to 2019, the average yearly loss of forest cover across the Philippines was 54,500 hectares and total forest loss was 1,035,501 hectares.

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 subprojects undertaken within communities.

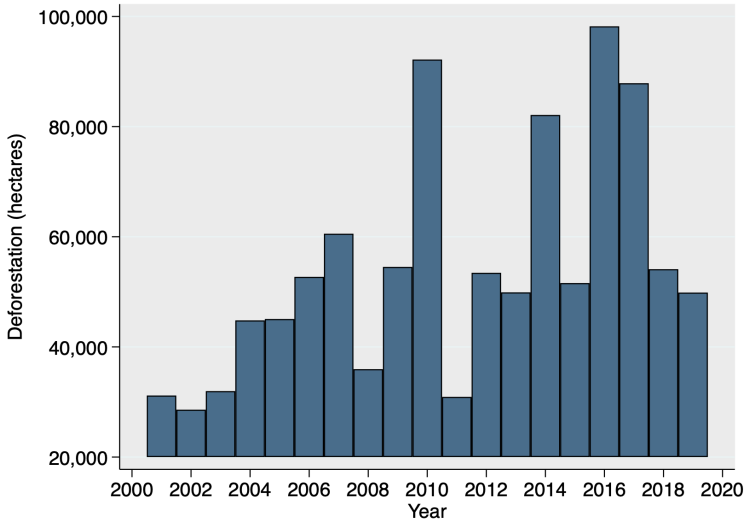
[11] See Figure A.4 and Figure A.5 in Appendix A.2 for the distributions of deforestation in log form for each time period under consideration in this analysis.

Figure 1: Log of deforestation per municipality, 2001 – 2019



Notes: This figure presents a map of deforestation in log form for municipality m from 2001 to 2019. *Source*: Author's own calculations based on the GFC data.

Figure 2: Yearly forest loss



Notes: This graph shows how many hectares were deforested across all Philippine municipalities for a given year t from 2001 to 2019. *Source*: Author's own calculations based on the GFC data.

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 treated municipalities 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.2 provide summary statistics for each of the variables used in the analysis from both time periods.

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 second strategy then analyzes a large-scale RCT of development aid in a later round of the KC program, from 2013 to 2015.

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 CDD 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.[12] Thereafter, a combination of data from the Family Income and Expenditure Survey (FIES) and the 2000 census of the Philippines (Balisacan et al., 2002; Balisacan and Edillon, 2003) was used by the implementers in a poverty mapping methodology to generate poverty levels for each municipality within those 22 eligible provinces.[13] 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

[12] 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 81 provinces.

[13] 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).

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 1 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.8 in Appendix A.6 presents several regressions, in accordance with Imbens and Lemieux (2008) and 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 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.

Next, Figure 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 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.[14] The selection 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

[14]See Appendix A.6, 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 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).

Table 1: Probability of participation in the KALAHI-CIDSS 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

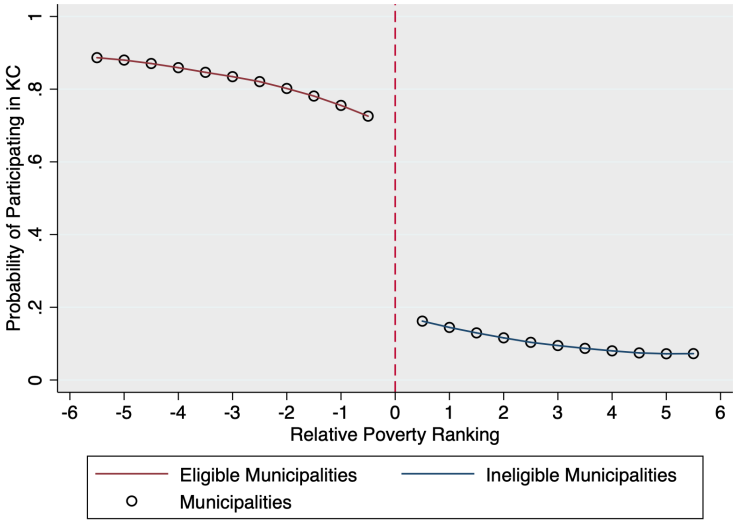
Notes: Columns 1 and 2 report the marginal effects (and standard errors) from a probit regression, while columns 3 and 4 report the estimated coefficients (and standard errors) from an ordinary least squares regression. Robust standard errors are in parentheses. All regressions include municipality fixed 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.

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.

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. In Figure 5, the dataset is broken down by eligible and ineligible municipalities with regard to the average number of hectares 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.

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 a RDD stemming from the assignment of the CDD program. The equation estimated is:

Figure 3: Effect of eligibility on participation in KALAHI-CIDSS



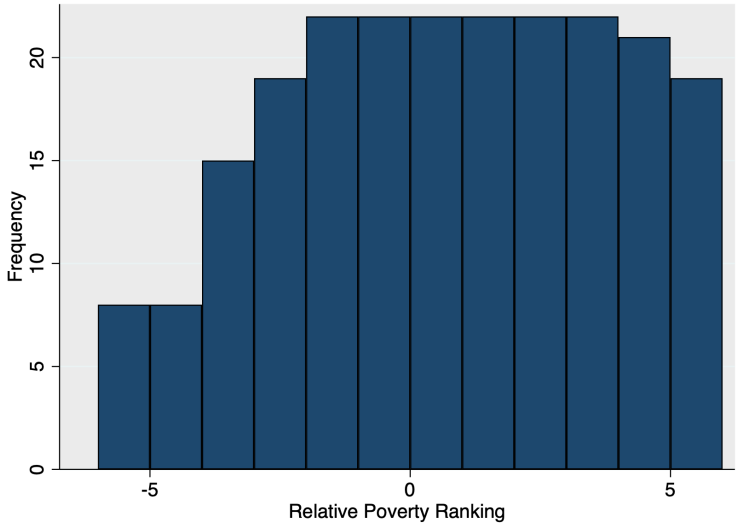
Notes: This figure plots the relationship between the relative poverty ranking and the probability of a municipality's participation in the KC program. Municipalities to the left of 0 are eligible for the KC program, while municipalities to the right of 0 are ineligible. The solid lines represent nonparametric 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.

$$\begin{aligned} Y_{m,t} = \beta_0 + \beta_1 CDD_{m,t} + \beta_2 RPR_m + \beta_3 CDD_{m,t} \cdot RPR_m + X'_m \cdot \delta \\ + \rho_m + \tau_t + \epsilon_{m,t} \end{aligned} \tag{2}$$

where $Y_{m,t}$ is estimated separately for the log of deforestation and an absolute measure of deforestation that accounts for the total hectares 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.[15] Also, the relative poverty

[15]Some eligible municipalities did not participate in the program due to the implementing agency's concerns about violence and safety of their personnel. It could be argued that a fuzzy RDD is preferable to estimate the local average treatment effect, however, following Crost et al. (2014), this study will use a sharp RDD for a couple reasons. First, Crost et al. (2014) show that a large part of the violence occurred during the social preparation stage, which included all eligible municipalities before it was clear who would actually participate

Figure 4: Municipality frequency and relative poverty ranking



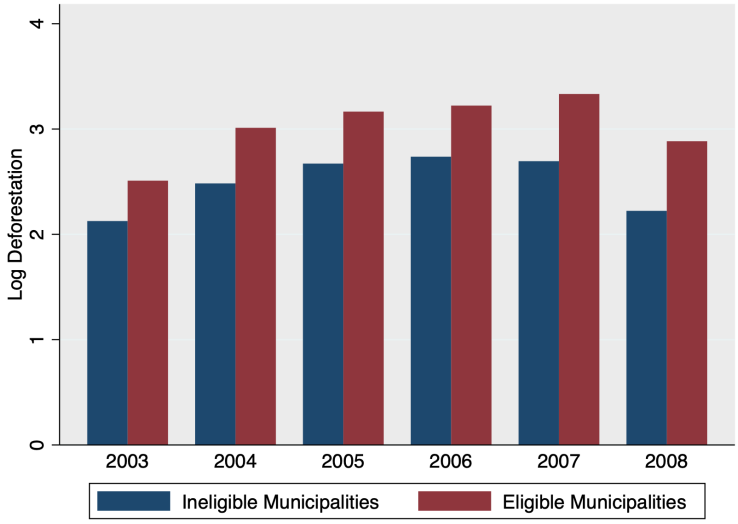
Notes: This figure presents the frequency of municipalities for which a given relative poverty ranking occurs within the bandwidth selection of [-6, 6]. Municipalities to the left of 0 are eligible for the KC program, while municipalities to the right of 0 are ineligible. Furthermore, municipalities 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.

rank of each municipality is introduced as RPR_m. 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.[16] 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

in the program. Once the program's implementation began, no municipalities were dropped. Second, violence within the municipality was not used as an eligibility criterion, and therefore should not have affected the discontinuity. Therefore, the results represent an intention-to-treat (ITT) effect on deforestation stemming from the eligibility status for the KC program. See Table A.7 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.

[16]Religious fractionalization is computed using a standard Herfindahl index. Let municipalities m be $m = 1,\ldots, M$ 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.

Figure 5: Log of deforestation by eligibility status, 2003 – 2008



Notes: This figure graphs the natural log of the number of hectares 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.

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 Lee and Lemieux (2010).

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.[17] The agreement was signed on September 23, 2010 and implementation of the program began on May 25, 2011. Baseline data were

[17]Financing for the second phase 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.

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.[18]

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.[19] 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.[20]

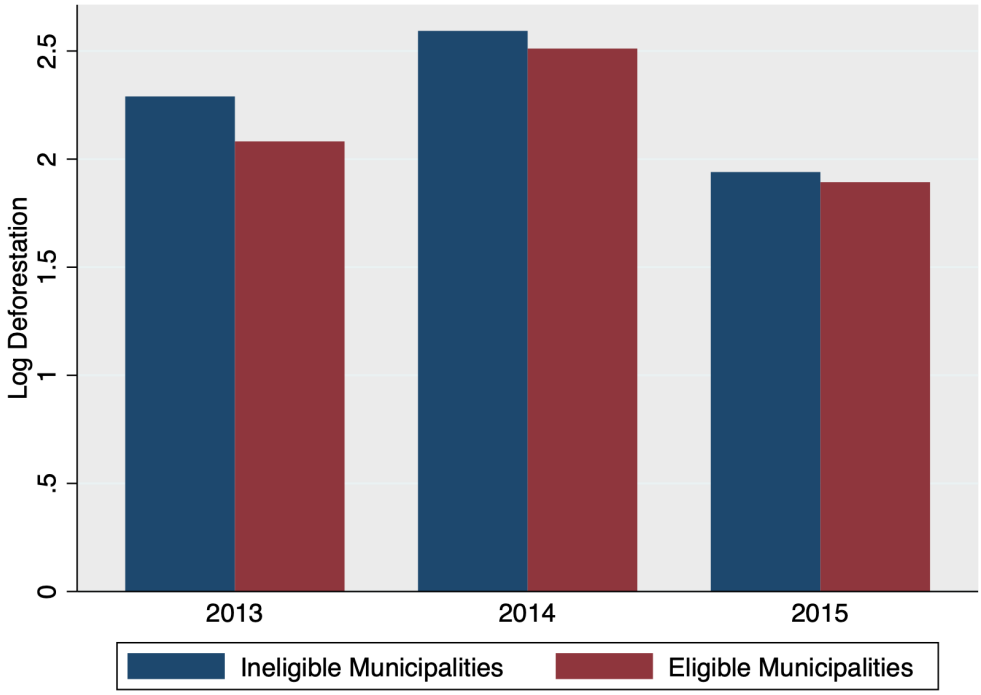
[18]Typhoon Yolanda, one of the strongest storms ever recorded, hit the Philippines on November 7, 2013. Beatty et al. (2017) mitigate concerns about the identification's validity, where they find no statistically significant difference of the impact of typhoon Yolanda between treatment and control municipalities. 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.

[19]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.

[20]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

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 6 shows a breakdown of the data by treatment and control status with regard to the average number of hectares in log form that were deforested from 2013 to 2015. Note that this figure differs from Figure 5, in that control municipalities on average had higher levels of deforestation relative to treatment villages.

Figure 6: Log of deforestation by treatment status, 2013 – 2015



Notes: This figure graphs the natural log of the number of hectares 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 a CDD

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.

program at the municipality level across the Philippines' three main island groups. The equation to be estimated is:

$$Y_{m,t} = \beta_0 + \beta_1 T_{m,t} + X'_m \cdot \delta + \lambda_s + \rho_m + \tau_t + \epsilon_{m,t} \tag{3}$$

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.[21] 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 and an index for religious fractionalization. Last, 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.

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; Jayachandran, 2022). 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

[21] See Appendix A.8, Table A.11, for a balance test between treated and control municipality-level characteristics.

facilities, and water and electricity subprojects. Additionally, the subprojects are small-scale and the construction of such projects does not necessarily require tree felling.

5 Main results

Table 2 presents the results of the RDD analysis, where column 1 shows the results for the log of hectares deforested and column 2 the total number of hectares that were deforested. According to the estimated coefficient, eligible municipalities for the KC program on average deforested 220 percent more per year than ineligible municipalities. In column 2, the estimated coefficient indicates that eligible communities for the KC program on average deforested approximately 79 hectares more per year than ineligible communities. To put this figure into context, the estimated impact represents approximately 209 percent more deforestation in municipalities that received the KC program relative to control municipalities. Additionally, if we scale up the total effect over the treated municipalities and years of the program, the KC program lead to 44,556 hectares of deforestation, about seven-tenths the size of Manila.[22]

Next, Table 3 presents the results of the RCT empirical strategy. Column 1 presents the results for the log of hectares deforested, while column 2 presents the total number of hectares that were deforested. In column 1, treated municipalities experienced on average 126 percent more deforestation per year than control municipalities. In column 2, the estimated coefficient indicates that treated municipalities experienced on average 78 hectares more deforestation per year than control municipalities. The impact represents approximately 117 percent more deforestation in municipalities that received the KC program relative to control municipalities and the scaled effects over the treated municipalities and the years of the program show that the KC program lead to 23,430 hectares of deforestation.[23]

[22] I perform two robustness exercises to reinforce the results found in Table 2. 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.9 presents the estimates from equation 2 using the optimal bandwidth, where the estimates remain similar to Table 2. Second, I test movements along the bandwidth selection by increasing the bandwidth by one from [-6, 6] to [-10, 10]. Table A.10 presents the estimates and the results remain qualitatively similar to Table 2.

[23] I perform two additional robustness exercises to reinforce the results found in Table 2 and Table 3. The first logarithmically transforms the deforestation variable defined in equation 1 to the inverse hyperbolic sine (IHS) of deforestation. 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 deforestation, the IHS function is constructed as: $IHSDeforestation_{m,t} = ln(Deforestation_{m,t} + \sqrt{Deforestation^2_{m,t} + 1})$. The results in Table A.12 remain very

Table 2: Effect of eligibility for KALAHI-CIDSS on deforestation, 2003 – 2008

	(1) Log Deforestation	(2) Deforestation
CDD	2.199***	78.89***
	(0.407)	(21.07)
Observations	1,332	1,332
R-squared	0.883	0.747
Municipalities	222	222
Mean Dep. Var. of Control	2.489	37.759

Notes: This table presents estimates of the effects of eligibility for the KC program on deforestation, identified using a 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.

6 Potential mechanisms and spillovers

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.[24] 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 sub-projects that were implemented, but the hypothesis cannot be tested due to the small sample

similar to the main results in Table 2 and Table 3. The second set of robustness exercises set the canopy density threshold to 30 percent and 50 percent. Table A.13 and Table A.14 present the results, which remain similar to Table 2 and Table 3.

[24] 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.

Table 3: Effect of treatment for KALAHI-CIDSS on deforestation, 2013 – 2015

	(1) Log Deforestation	(2) Deforestation
Treatment	1.262***	78.22**
	(0.326)	(33.04)
Observations	594	594
R-squared	0.885	0.683
Municipalities	198	198
Mean Dep. Var. of Control	2.274	66.411

Notes: This table presents estimates of the effects of eligibility for the KC program on deforestation, identified using a 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 and an index for religious fractionalization. Significant at *p $<$ 0.10, ** p $<$ 0.05, *** p $<$ 0.01.

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.[25] 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 explores 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

[25]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.

fuel as well as whether the KC program had spillover effects into surrounding municipalities.[26]

6.1 Poverty incidence

In Table 4, 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. The following equation will be estimated:

$$\begin{aligned} PovertyIncidence_m = \beta_0 + \beta_1 CDD_{m,t} + \beta_2 RPR_m + \beta_3 CDD_{m,t} \cdot RPR_m \\ + X'_m \cdot \delta + \epsilon_m \end{aligned} \tag{4}$$

where $PovertyIncidence_m$ is the poverty incidence developed by Balisacan et al. (2002) and used as the program's assignment mechanism for a given municipality m. This idea refers to previous work on deforestation and income, to conclude that the effect is unclear (Busch and Ferretti-Gallon, 2017). According to the estimated coefficient in column 1 of Table 4, eligible municipalities in 2009 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 2012, there does not appear to be a statistically significant difference between eligible and ineligible municipalities, but this is expected as the KC program started to be rolled out to ineligible communities after 2009.

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

[26]Post-treatment surveys and data are not available for some of the outcomes to be analyzed, which limits the use of the RCT empirical strategy in this section.

Table 4: Effect of eligibility for KALAHI-CIDSS on poverty incidence

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

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 a 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), 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.

at night, aggregated to an annual frequency with a 1-kilometer resolution.[27] The following equation will be estimated:

$$\begin{aligned} NightLights_{m,t} = \beta_0 + \beta_1 CDD_{m,t} + \beta_2 RPR_m + \beta_3 CDD_{m,t} \cdot RPR_m \\ + X'_m \cdot \delta + \rho_m + \tau_t + \epsilon_{m,t} \end{aligned} \tag{5}$$

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 environ-

[27] In the RDD period, data on nighttime lights come from DMSP-OLS Nighttime Lights Time Series (1992 - 2013) which provides composite aggregates of annual data on lights from cities, towns and other sites with persistent lighting or gas flares, but temporary events such as fires are discarded. In the RCT period, data on nighttime lights come from annual VIIRS Nighttime Lights (2012 - 2020), which provides a new consistently processed time series of annual global nighttime lights from monthly cloud-free average radiance grids.

ment can increase deforestation, such as roads and towns that lower transportation costs to the market (Cropper and Griffiths, 1994; Busch and Ferretti-Gallon, 2017). 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 5, municipalities eligible for the KC program emitted on average 24 percent more nighttime light than ineligible municipalities. Furthermore, the estimated coefficient in column (2) indicates that eligible municipalities emitted 17 percent more nighttime light in the following time period relative to ineligible municipalities. As for the RCT period in column (3) and (4), I find no evidence of changes in nighttime light activity.

Table 5: Effect of eligibility for KALAHI-CIDSS on nighttime light

	(1)	(2)	(3)	(4)
	RDD Period, 2003 - 2008		RCT Period, 2013 - 2015	
	Nighttime Lights	Lag Nighttime Lights	Nighttime Lights	Lag Nighttime Lights
CDD	0.242***	0.169**		
	(0.0725)	(0.0662)		
Treatment			-0.00997	-0.00247
			(0.00618)	(0.00420)
Observations	1,332	1,332	594	594
R-squared	0.921	0.908	0.969	0.987
Municipalities	222	222	198	198
Mean Dep. Var. of Control	0.397	0.358	0.044	0.060

Notes: This table presents estimates of the effects of eligibility for the KC program on nighttime light emitted from the Earth's surface. Columns (1) and (2) are identified using a RDD based on municipalities' relative poverty ranking. Triangular kernel weights are included to give greater weight to observations that are closer to the threshold. The independent variables in columns (1) and (2) include: municipality poverty ranking score, baseline nighttime light, 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. Columns (3) and (4) are identified using a RCT based on whether a municipality was treated by the KC program. The independent variables in columns (3) and (4) include: strata (pair/triplet) dummies, baseline nighttime light, 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 and an index for religious fractionalization. Each regression includes municipality and time fixed effects. Robust standard errors are in parentheses. Significant at *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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:

$$Sector_{i,m} = \beta_0 + \beta_1 CDD_{m,t} + \beta_2 RPR_m + \beta_3 CDD_{m,t} \cdot RPR_m + X'_m \cdot \delta + \epsilon_{i,m} \tag{6}$$

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 6 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.

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:

$$\begin{aligned} OtherChannels_m = \beta_0 + \beta_1 CDD_{m,t} + \beta_2 RPR_m + \beta_3 CDD_{m,t} \cdot RPR_m \\ + X'_m \cdot \delta + \epsilon_m \end{aligned} \tag{7}$$

Table 6: 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	1.186**	-0.220	0.294**	-0.125*
	(0.476)	(0.142)	(0.142)	(0.0714)
Observations	1,332	912	1,332	1,332
R-squared	0.487	0.140	0.174	0.477
Municipalities	222	152	222	222
Mean Dep. Var. of Control	20.267	0.425	1.140	2.178

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 a 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) to (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.

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 (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 7 presents the estimated coefficients. In column (1) I find no evidence of an effect for population, but in column (2) I find corollary 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 19 percent, but the number of people migrating is small relative to the total population. Lastly, in column (3) I find limited evidence of reductions in the number of people using wood for cooking fuel in eligible municipalities.

Table 7: Effect of eligibility for KALAHI-CIDSS on other channels, 2010

	(1) Population	(2) Migration	(3) Wood Cooking Fuel
CDD	-0.0250	0.193***	-0.0975*
	(0.0437)	(0.0686)	(0.0576)
Observations	1,332	1,332	1,332
R-squared	0.311	0.265	0.362
Municipalities	222	222	222
Mean Dep. Var. of Control	8.411	4.385	8.061

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 a 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.

6.5 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 for each of the time periods from 2003 to 2008 and 2013 to 2015, and the drop the treated municipalities. The following equation is estimated:

$$Y_{n,t} = \beta_0 + \beta_1 \, TreatedNeighbors_{n,t} + X'_n \cdot \delta + \tau_t + \epsilon_{n,t} \tag{8}$$

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 8 presents the results of the estimated equation for the RDD and RCT periods. According to the estimated coefficient in column (1), deforestation is expected to have increased in surrounding municipalities by 14 percent with each additional neighbor that was treated by the KC program. As for the RCT period in column (3), I find that for each additional neighbor that is treated by the KC program, deforestation is expected to have increased in surrounding municipalities by 21 percent. In columns (2) and (4) I adjust 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.[28] The results remain very similar to columns (1) and (3). In general 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.

7 Heterogeneous effects

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 and provide suggestive evidence on the heterogeneous effects of subproject characteristics.

[28] For this analysis I follow code provided by Hsiang (2010) to estimate the corrected standard errors.

Table 8: Spillover effects onto neighbors

	(1)	(2)	(3)	(4)
	RDD Results, 2003 - 2008		RCT Results, 2013 - 2015	
	Log Deforestation	Log Deforestation	Log Deforestation	Log Deforestation
Treated Neighbors	0.139**	0.139***	0.211***	0.210**
	(0.0563)	(0.0537)	(0.0708)	(0.0931)
Observations	8,820	8,820	4,389	4,389
R-squared	0.254	0.702	0.253	0.619
Mean Dep. Var.	1.831	1.831	1.872	1.872

Notes: This table presents estimates for the effects of spillovers from treated municipalities of the KC program on deforestation in neighboring municipalities, identified using variation in the RDD and RCT period. In columns (1) and (3) the standard errors are in parentheses and are clustered at the municipality level. 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 50 km. The variable Treated Neighbors is a continuous measure and accounts for the number of neighboring municipalities that were treated by the KC program. Each regression includes time fixed effects. The independent variables include: a dummy for whether the municipality is an island, 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.

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:

$$\begin{aligned} Y_{m,t} = \beta_0 + \beta_1 CDD_{m,t} + \beta_2 Subproject_{i,m,t} + \beta_3 CDD_{m,t} \cdot Subproject_{i,m,t} \\ + \beta_4 RPR_m + \beta_5 CDD_{m,t} \cdot RPR_m + X'_m \cdot \delta + \tau_t + \epsilon_{m,t} \end{aligned} \tag{9}$$

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 A.15 demonstrates how the subprojects are classified by: 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. (2021), 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 A.16 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 9. According to column 1, the subprojects with the greatest impact on deforestation are related to economic support projects followed by infrastructure projects (including trails, bridges and roads) and education and health facilities. Each additional economic support subproject implemented in an eligible municipality, approximately corresponds to an expected increase in deforestation of 116 percent. By contrast, for the absolute level of deforestation in column 2, the ranking of subproject impact changes slightly to economic support, education and health, water and electricity and lastly infrastructure subprojects, which indicates that these results must be taken with some caution.

Table 9: Effect of implemented subprojects on deforestation, 2003 – 2008

	(1) Log Deforestation	(2) Deforestation
CDD x Infrastructure	1.125*	33.56*
	(0.574)	(19.77)
CDD x Education and Health	0.756*	57.36***
	(0.384)	(20.80)
CDD x Water and Electricity	0.480	45.81**
	(0.484)	(21.10)
CDD x Water Protection	-0.482	-16.19
	(0.361)	(20.87)
CDD x Support	1.157**	75.39***
	(0.484)	(24.02)
Observations	3,022	3,022
R-squared	0.323	0.242
Municipalities	222	222
Mean Dep. Var. of Control	2.374	32.018

Notes: This table presents estimates of the effects of implemented subprojects from the KC program for the log of deforestation, identified using a 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.

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:

$$\begin{aligned} Y_{m,t} = \beta_0 + \beta_1 CDD_{m,t} + \beta_2 Scale_{i,m,t} + \beta_3 CDD_{m,t} \cdot Scale_{i,m,t} + \beta_4 RPR_m \\ + \beta_5 CDD_{m,t} \cdot RPR_m + X'_m \cdot \delta + \tau_t + \epsilon_{m,t} \end{aligned} \tag{10}$$

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 $CDD_{m,t} \cdot Scale_{i,m,t}$. The variable $Scale_{i,m,t}$ 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.[29] 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 A.17 breaks down the scale of each subproject at the median into either small (1) or large (2).

Next, Table 10 presents the estimated results with the main focus on the interaction between $CDD_{m,t} \cdot Scale_{i,m,t}$. Through this set of regressions, there appears to be differential effects based on the scale of the subprojects. In column 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 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.

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, a RDD and a RCT are exploited to clearly identify the program's effect on deforestation. Each

[29] 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.

Table 10: 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)	0.894	1.010**	0.429	0.547
	(0.544)	(0.442)	(0.486)	(0.482)
CDD x Scale (2)	0.667	0.354	1.045**	0.957**
	(0.429)	(0.502)	(0.437)	(0.451)
Observations	3,022	3,022	3,022	3,022
R-squared	0.319	0.323	0.322	0.321
Municipalities	222	222	222	222
Mean Dep. Var. of Control	2.374	2.374	2.374	2.374

Notes: This table presents estimates of the effects of subproject scale in the KC program for the log of deforestation, identified using a 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) to (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.

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 220 percent more deforestation per year (equivalent to 79 hectares per year) 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 126 percent more deforestation per year (equivalent to 78 hectares per year) 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 24 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 manufactur-

ing sector, while there is no evidence that changes took place in the mining and extractives industry. Additionally, I find that eligible municipalities experienced a corollary increase in migration of 19 percent, even though the number of people migrating is small relative to the total population. An analysis of spillover effects into surrounding municipalities finds that in both time periods, deforestation is expected to increase in surrounding municipalities by 14 to 21 percent with each additional neighbor that is treated by the KC program. Lastly, I provide suggestive evidence on the heterogeneous effects of different types of subprojects, which indicate that the greatest impact on deforestation stems from economic support projects followed by infrastructure projects (including trails, bridges and roads) and education and health facilities. In addition, similar small-scale subprojects in terms of subproject construction duration are found to be correlated with more deforestation as well as larger-scale subprojects in terms of funding.

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 potentially 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.

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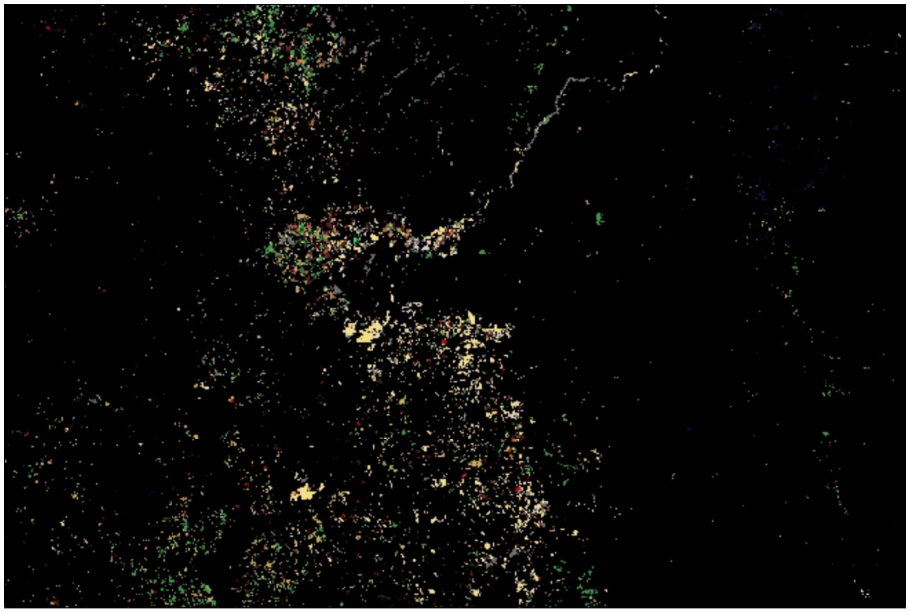
A Appendix

A.1 Examples of pixel-level deforestation data

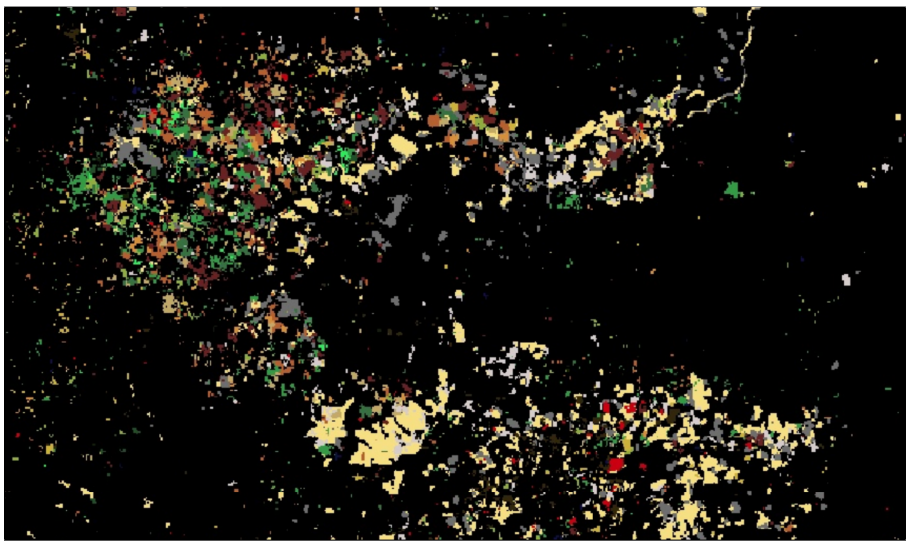
The following figures are intended to illustrate the deforestation data. Figure A.1 provides a high-level satellite view of Philippine deforestation data. In Figure A.2, as the frame zooms in, the spatial distribution of deforestation starts to become clearer, as each color represents a deforested 30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

Figure A.1: High-level view



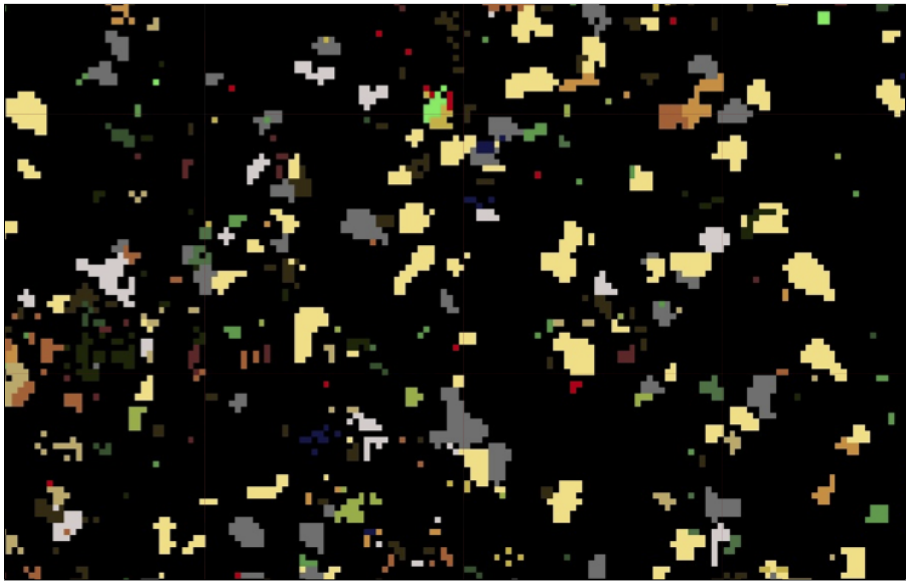
Source: Author's own calculation based on the GFC data using Google Earth Engine.

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.2 Summary statistics

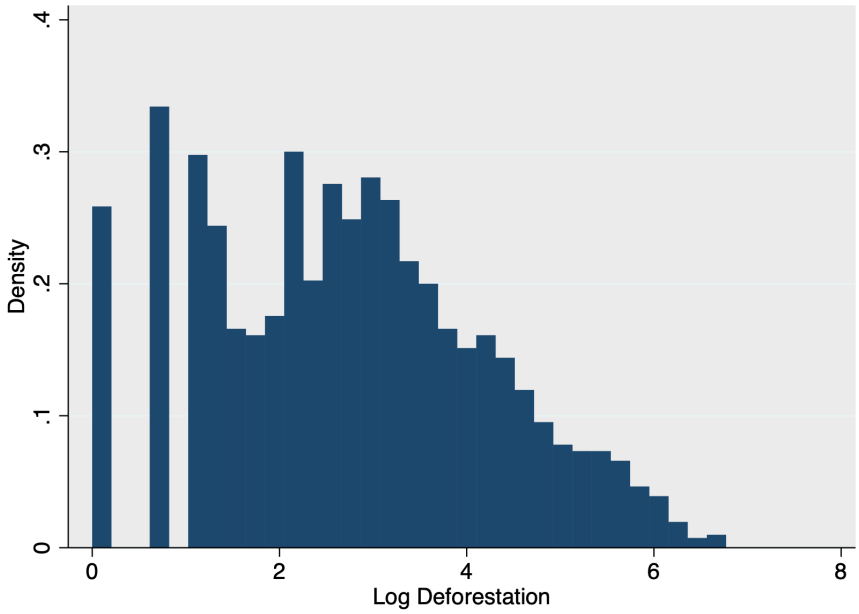
Table A.1: Summary statistics for the RDD period, 2003 – 2008

	Observations	Mean	Std. Dev.	Min	Max
Forests					
Deforestation (ha)	1,332	46.26	91.57	0.00	871.00
Log Deforestation	1,332	2.71	1.53	0.00	6.77
Percent of Surface Area Deforested	1,332	0.00	0.00	0.00	0.05
Baseline Forest Coverage in 2000 (ha)	1,332	13,100.76	18,629.82	126.00	117,501
Municipality Area (ha)	1,332	24,480.66	22,044.37	2,111	129,633
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

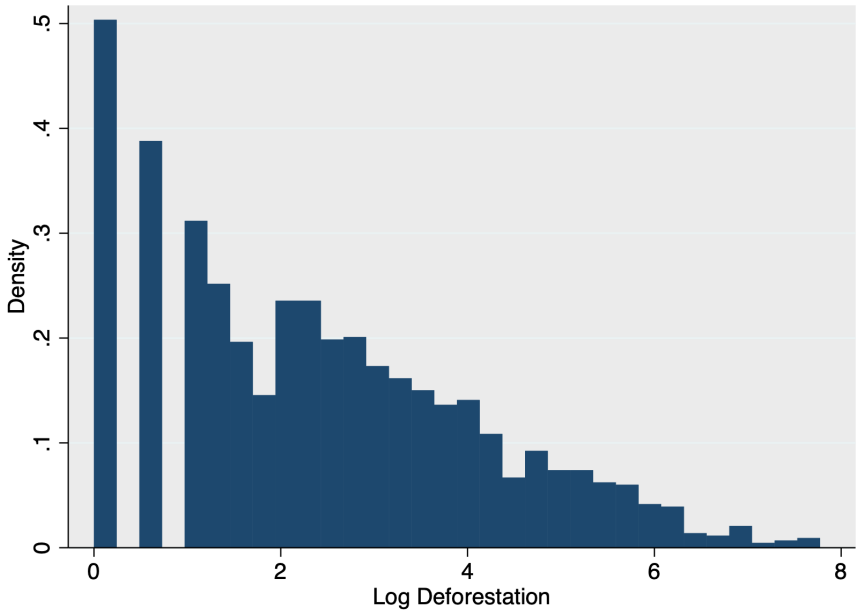
	Observations	Mean	Std. Dev.	Min	Max
Forests					
Deforestation (ha)	594	61.56	188.60	0.00	1,878
Log Deforestation	594	2.22	1.83	0.00	7.54
Percent of Surface Area Deforested	594	0.00	0.01	0.00	0.10
Baseline Forest Coverage in 2010 (ha)	594	11,156.23	16,201.84	5.00	112,516
Municipality Area (ha)	594	19,547.91	22,033.7	896.00	132,120
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
Religious fractionalization index	594	0.28	0.22	0.02	0.81

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.3 KC program specific documents

Table A.3: 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)

Table A.4: 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)

A.4 List of subprojects

Table A.5: 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, miniport / 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.

Table A.6: 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).

A.5 Eligibility for and compliance with the KC program

It should be noted that full compliance with the KC program was not achieved for a number of reasons. 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. Table A.7 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.

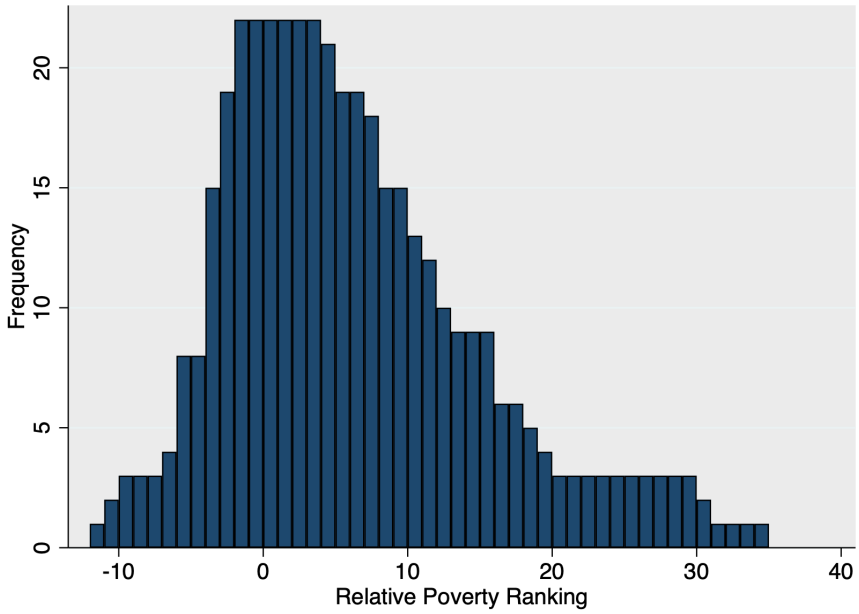
Table A.7: Eligibility and compliance to the KALAHI-CIDSS program

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

A.6 Validity checks of the RDD threshold

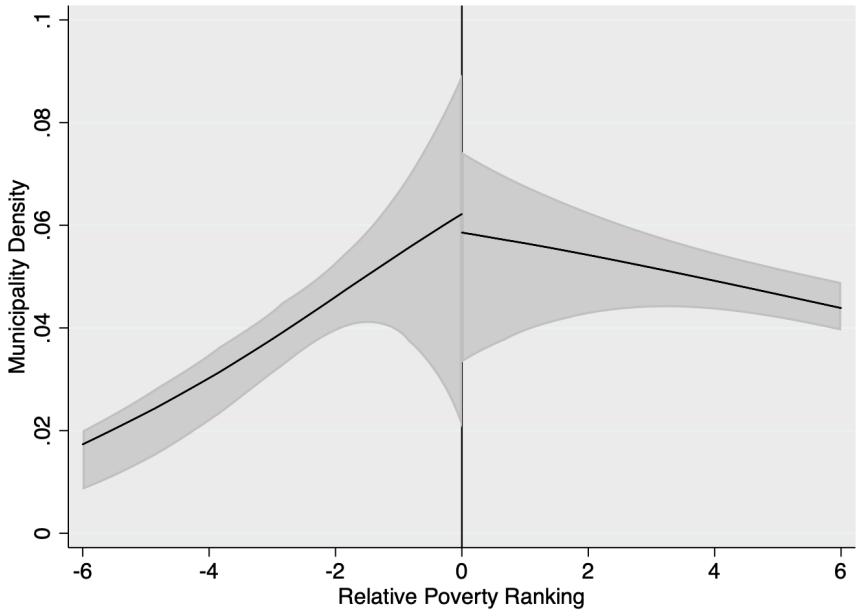
This section details the different tests carried out to check the validity of the RDD empirical strategy.

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.8 to examine whether the baseline covariates observed are "locally" balanced on each side of the threshold. 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.

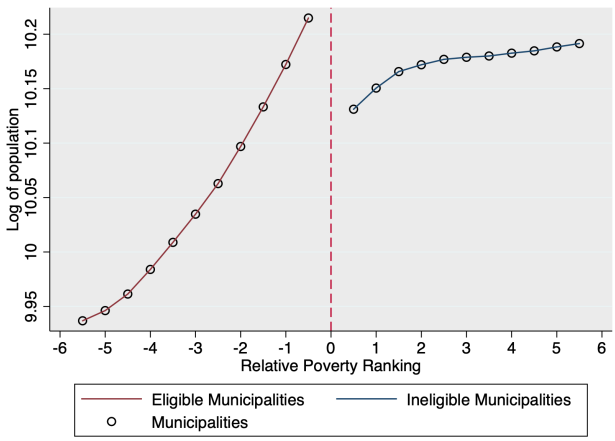
Table A.8: Discontinuous effect on other covariates

	(1) Population	(2) Years of Education for Head of Household	(3) Electricity Access	(4) Percentage with Highway Access	(5) Roofs Made of Strong Materials	(6) Access to Indoor Toilet	(7) Access to Running Water	(8) Religious fractionalization index	(9) Municipality Area (ha)	(10) Baseline Forest Coverage in 2000 (ha)
Eligibility for KC	0.175	-0.170	0.0125	8.905	-0.0198	-0.0270	-0.00988	0.00184	4,303	2,628
	(0.179)	(0.309)	(0.0438)	(8.355)	(0.0596)	(0.0505)	(0.0629)	(0.0673)	(8,623)	(7,890)
Observations	222	222	222	222	222	222	222	222	222	222
R-squared	0.034	0.083	0.138	0.088	0.072	0.113	0.024	0.003	0.050	0.040

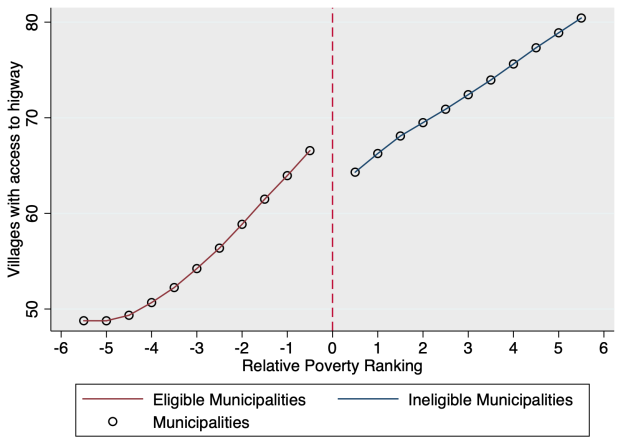
Notes: This table presents a series of regressions to estimate whether the baseline covariates observed are "locally" balanced on each side of the threshold. Robust standard errors are in parentheses. Triangular kernel weights are included to give greater weight to observations that are closer to the 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

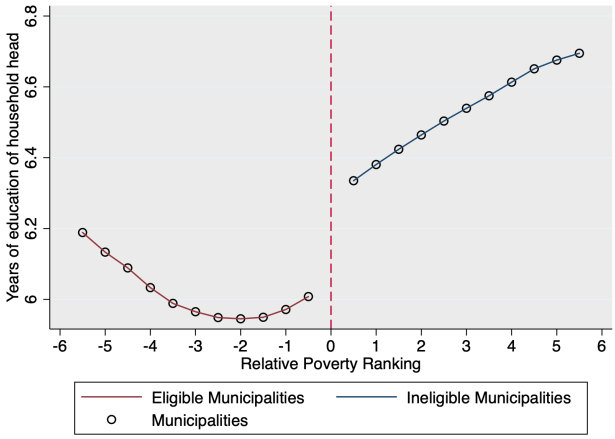
Population



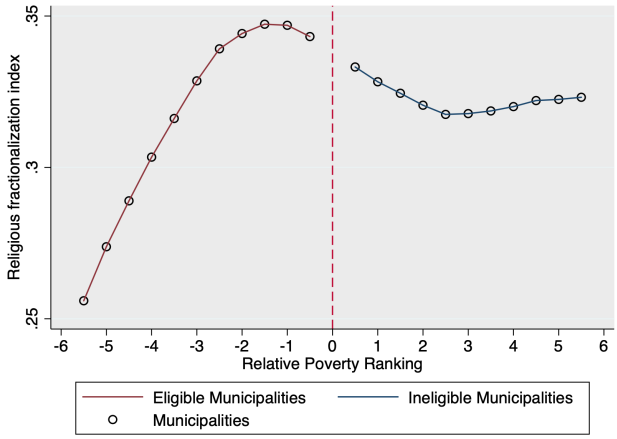
Access to highway



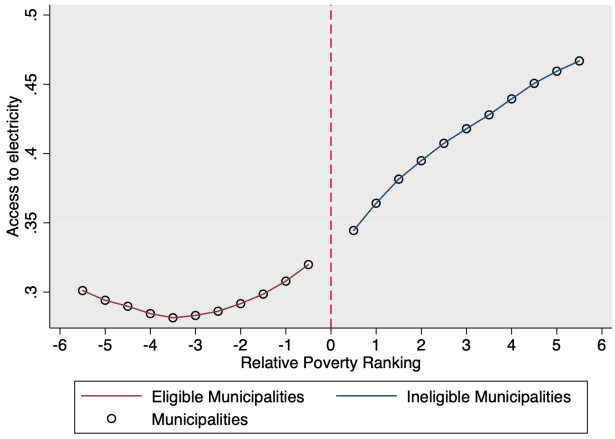
Years of education of household head



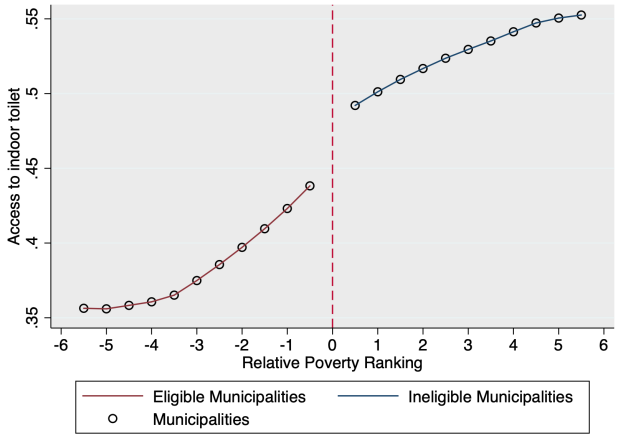
Religious fractionalization



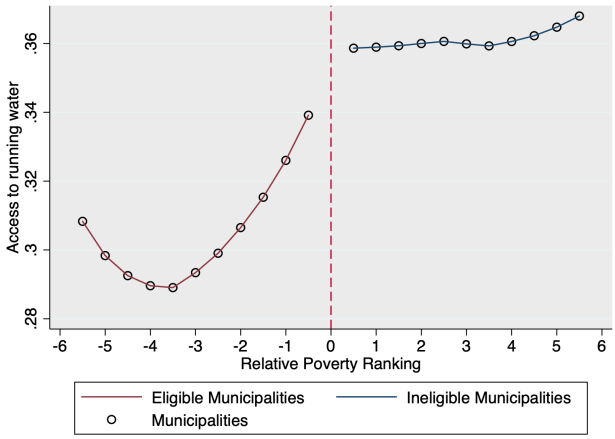
Access to electricity



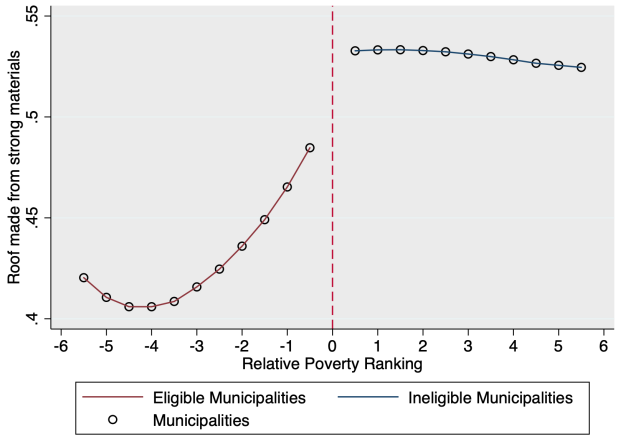
Access to indoor toilet



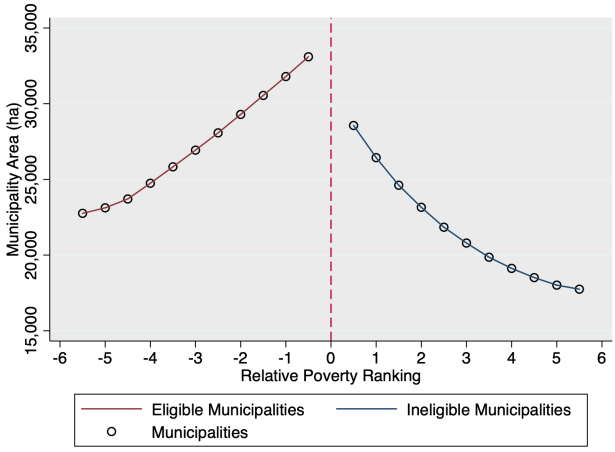
Access to running water



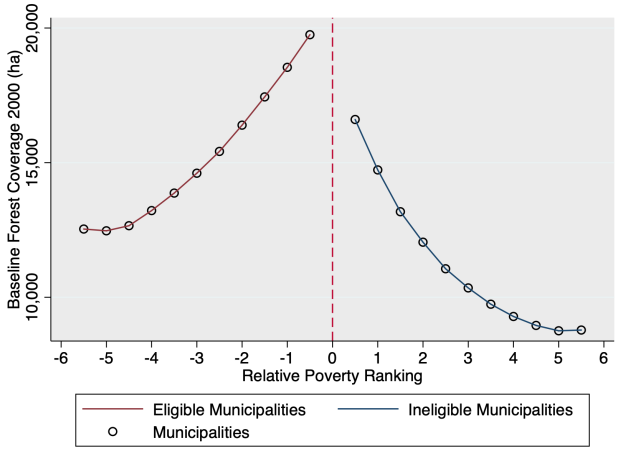
Roof made from strong materials



Municipality Area (ha)



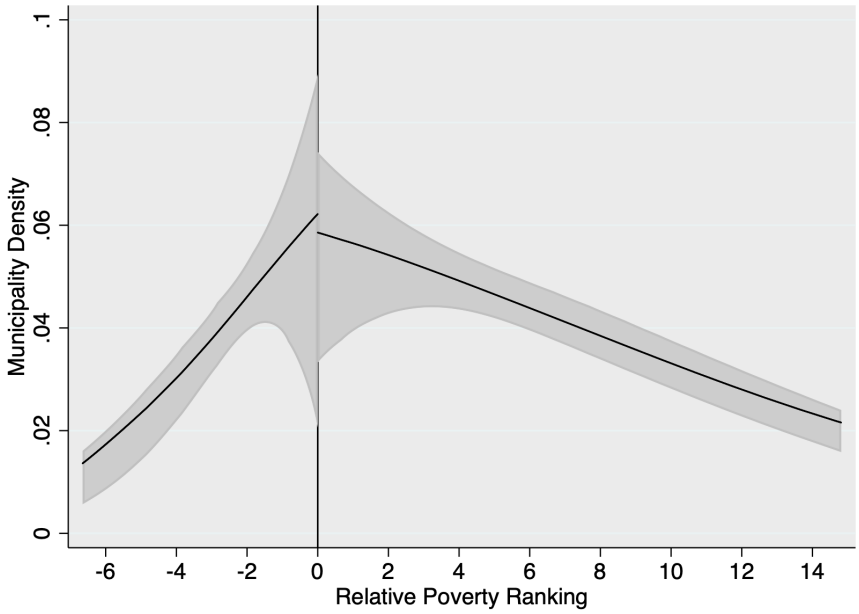
Baseline Forest Coverage in 2000 (ha)



A.7 Robustness checks to bandwidth selection of the main RDD estimation

A.7.1 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.9: Effect of eligibility for KALAHI-CIDSS on deforestation using the optimal bandwidth, 2003 – 2008

	(1) Log Deforestation	(2) Deforestation
CDD	2.192***	108.9***
	(0.447)	(22.56)
Observations	2,076	2,076
R-squared	0.879	0.773
Municipalities	346	346
Mean Dep. Var. of Control	2.390	34.689

Notes: This table presents estimates of the effects of eligibility for the KC program on deforestation, identified using a 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.

A.7.2 Movement along the bandwidth

Table A.10: 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	2.199***	2.168***	0.791**	2.403***	1.638***
	(0.407)	(0.406)	(0.380)	(0.342)	(0.316)
Observations	1,332	1,470	1,596	1,704	1,812
R-squared	0.883	0.883	0.882	0.882	0.881
Municipalities	222	245	266	284	302
Mean Dep. Var. of Control	2.513	2.521	2.551	2.560	2.552
Lower Bound Bandwidth	-6	-7	-8	-9	-10
Upper Bound Bandwidth	6	7	8	9	10

Notes: This table presents estimates of the effects of eligibility for the KC program on deforestation, identified using a 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) to (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.8 Balance test for the RCT

Table A.11: Balance between treated and control municipality-level characteristics

	(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 indoor toilet	0.717	0.711	0.00551
	(0.0143)	(0.0158)	(0.0213)
Fraction of households with access to running water	0.901	0.905	-0.00405
	(0.0101)	(0.0101)	(0.0143)
Religious fractionalization index	0.271	0.282	-0.0109
	(0.0222)	(0.0219)	(0.0312)
Municipality Area (ha)	19,473	19,623	-150.5
	(2,218)	(2,230)	(3,145)
Baseline Forest Coverage in 2010 (ha)	10,823	11,489	-0.112
	(1,551)	(1,715)	(0.203)

A.9 Additional results

A.9.1 Robustness of main results to the inverse hyperbolic sine of deforestation

Table A.12: Effect of eligibility for KALAHI-CIDSS on the IHS of Deforestation

	(1)	(2)
	IHS Deforestation, 2003 - 2008	IHS Deforestation, 2013 - 2015
CDD	2.215***	
	(0.414)	
Treatment		1.287***
		(0.314)
Observations	1,332	594
R-squared	0.883	0.884
Municipalities	222	198
Mean Dep. Var. of Control	3.133	2.915

Notes: This table presents estimates of the effects of eligibility for the KC program on the inverse hyperbolic sine of deforestation. Column (1) is identified using a RDD based on a municipalities' relative poverty ranking. Triangular kernel weights are included to give greater weight to observations that are closer to the threshold. 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) is identified using a RCT based on whether a municipality was treated by the KC program. The independent variables in column (2) include: strata (pair/triplet) dummies, 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 and an index for religious fractionalization. Each regression includes municipality and time fixed effects. Robust standard errors are in parentheses. Significant at *p $<$ 0.10, ** p $<$ 0.05, *** p $<$ 0.01.

A.9.2 Robustness of main results to other thresholds of deforestation

Table A.13: Effect of Eligibility for KALAHI-CIDSS on Deforestation, 2003 – 2008

	(1) Log Deforestation - 30% Threshold	(2) Deforestation - 30% Threshold	(3) Log Deforestation - 50% Threshold	(4) Deforestation - 50% Threshold
CDD	1.993***	79.41***	2.019***	79.85***
	(0.407)	(22.93)	(0.405)	(22.71)
Observations	1,332	1,332	1,332	1,332
R-squared	0.874	0.741	0.876	0.742
Municipalities	222	222	222	222
Mean Dep. Var. of Control	2.63	41.09	2.61	0.67

Notes: This table presents a robustness test for the effects of eligibility for the KC program on deforestation thresholds set at 30 percent and 50 percent, identified using a 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) to (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.

Table A.14: Effect of Treatment for KALAHI-CIDSS on Deforestation, 2013 – 2015

	(1) Log Deforestation - 30% Threshold	(2) Deforestation - 30% Threshold	(3) Log Deforestation - 50% Threshold	(4) Deforestation - 50% Threshold
Treatment	1.141***	86.69**	1.143***	85.11**
	(0.328)	(37.14)	(0.326)	(36.51)
Observations	594	594	594	594
R-squared	0.885	0.695	0.887	0.693
Municipalities	198	198	198	198
Mean Dep. Var. of Control	2.56	83.16	2.52	80.89

Notes: This table presents a robustness test for the effects of eligibility for the KC program on deforestation thresholds set at 30 percent and 50 percent, identified using a 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) to (4) 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 and an index for religious fractionalization. Significant at *p < 0.10, ** p < 0.05, *** p < 0.01.

A.10 Additional tables for section on heterogeneous effects

Table A.15: 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.

Table A.16: 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.

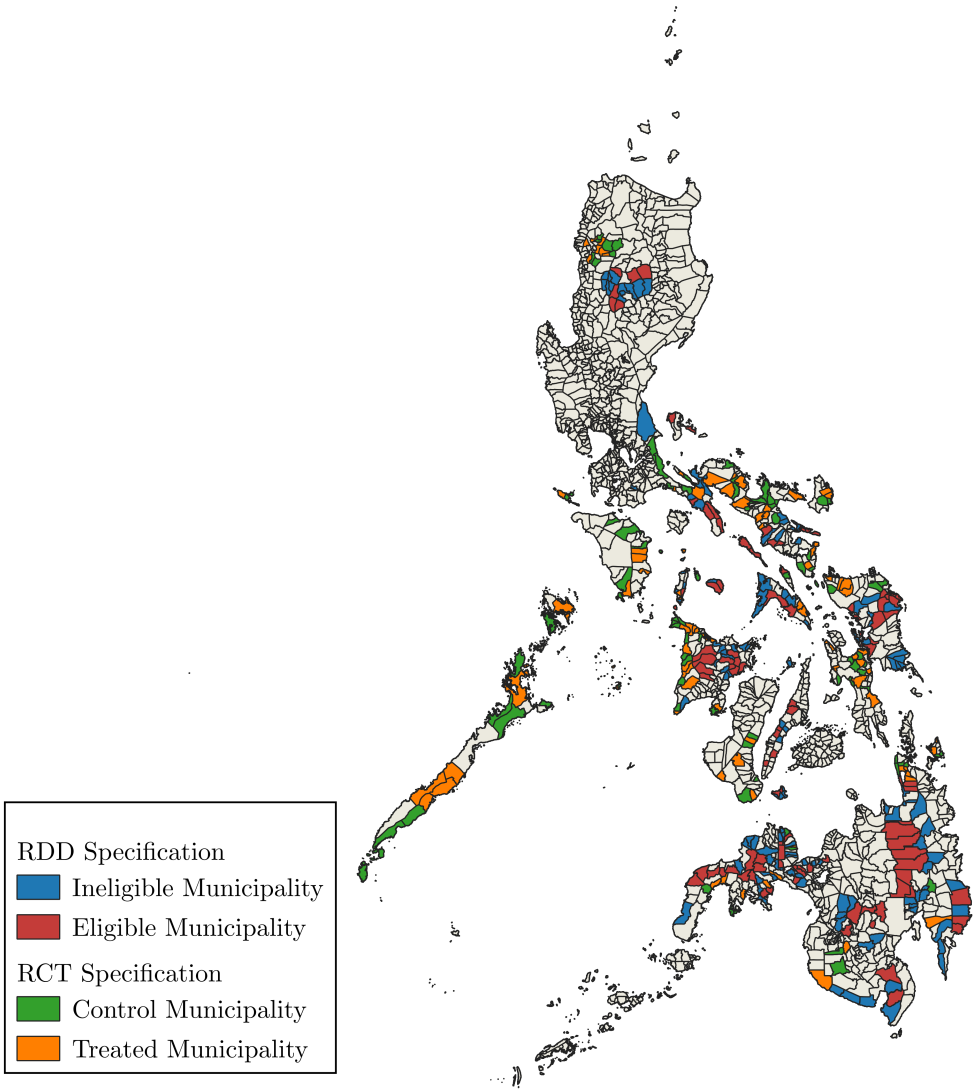
Table A.17: Summary statistics of implemented subprojects, 2003 – 2008

	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).

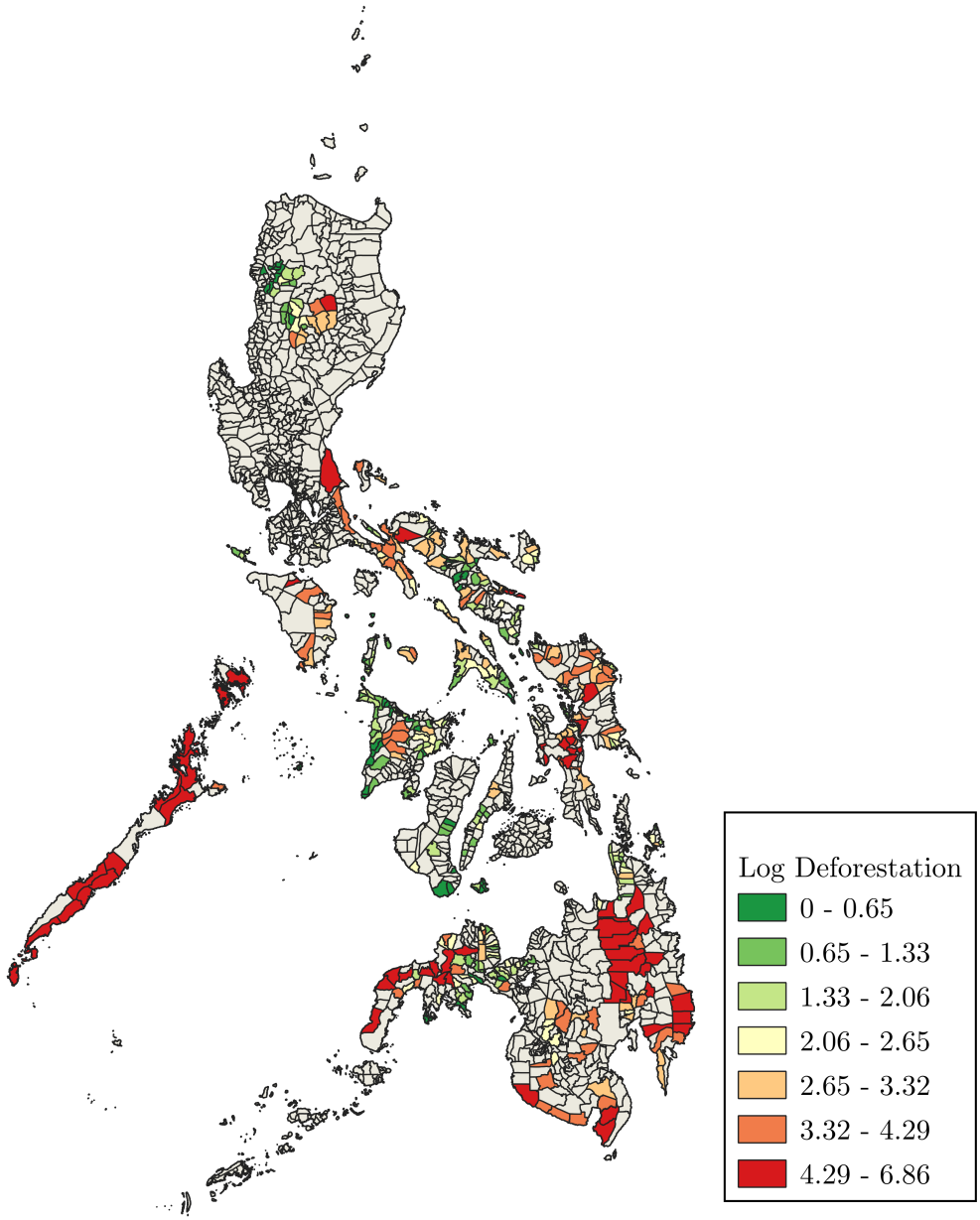
A.11 Mapping data from both time periods

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 empirical strategies. Red and blue shaded municipalities represent eligible and ineligible municipalities within the RDD empirical strategy, respectively. Orange and green shaded municipalities represent treated and control municipalities within the RCT empirical strategy, 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.