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# Essays on Impact Measurements and Sustainable Development Projects: Challenges and Opportunities for the Private Sector

Fatoumata Nankoto Cissé

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**UNIVERSITE PARIS I PANTHÉON SORBONNE**

**Ecole d'Economie de la Sorbonne**

Laboratoire de rattachement : Centre d'Economie de la Sorbonne

*Thèse pour l'obtention du titre de Docteur en Sciences Economiques présentée et soutenue publiquement le 10 mars 2023 par*

Fatoumata Nankoto CISSE

Titre de la thèse

**ESSAYS ON IMPACT MEASUREMENTS AND SUSTAINABLE DEVELOPMENT  
PROJECTS: CHALLENGES AND OPPORTUNITIES FOR THE PRIVATE SECTOR**

**Sous la direction de Mme. Mathilde MAUREL**

Mathilde MAUREL, Directrice de recherche CNRS, Professeur, Université Paris 1 Panthéon-Sorbonne

Jean-Michel SEVERINO, Président du Conseil de surveillance, Investisseurs et Partenaires, France

**Membre du Jury**

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# Résumé

L'utilisation des méthodes d'évaluation d'impact dans le secteur du développement connaît un essor fulgurant depuis une vingtaine d'années. Particulièrement dans l'évaluation des résultats de projets à fort impact local et répondants aux enjeux fixés par les Objectifs du Développement Durable (ODD) des Nations Unies. C'est dans ce contexte que cette thèse, effectuée dans le cadre d'un dispositif CIFRE<sup>1</sup>, s'articule autour de trois travaux empiriques permettant d'identifier des stratégies d'évaluation d'impact adaptées aux exigences des acteurs privés et publics du développement. Ceci, dans le but d'avoir une meilleure connaissance des impacts positifs et négatifs, et directs et indirects des projets financés dans les économies en développement. Le chapitre 1 montre qu'il y a une convergence des méthodes d'évaluation d'impact expérimentale et quasi-expérimentale pour trouver un effet significatif et positif des projets d'électrification décentralisés sur les indicateurs de développement. Par ailleurs, on constate une divergence entre les méthodes expérimentales et quasi-expérimentale quant à la probabilité d'obtenir un résultat négatif des projets déployés en Afrique. Le chapitre 2, co-écrit avec Dr Enoch Owusu-Sekyere et Dr Esther Leah Achandi, analyse l'impact de l'adoption d'une utilité solaire sur les performances socio-économiques des commerçants dans les marchés au Nigéria. S'appuyant sur une enquête terrain originale auprès de 700 commerçants dans 5 marchés au Nigéria ainsi qu'une méthode d'identification permettant de comparer deux groupes de commerçants, cette étude montre que les revenus mensuels moyens des commerçants souscripteurs aux panneaux solaires Rensource ont augmenté de près de 27%. Les souscripteurs connaissent également une baisse des dépenses énergétiques mensuelles moyenne de près de 37%, d'une part. Et d'autre part, une diminution des risques de pollution environnementale et sanitaire. Puis, dans un contexte où les politiques environnementales prennent une place prépondérante dans le financement de projets à impact, les travaux du chapitre 3 reposent une analyse géospatiale innovante qui étudie l'impact d'une politique de biodiversité à travers la création d'espaces protégés sur la consommation de combustibles de cuisson de bois des ménages à Madagascar. Les résultats montrent qu'aux alentours des frontières des aires protégées, la part de bois de cuisson consommée par les groupes de ménages situés à l'intérieur des zones protégées augmente significativement de 0,64 point de pourcentage par rapport à la part consommée des groupes situés en dehors des limites des aires. À l'inverse, la part de charbon de bois consommée par les groupes de ménages situés à l'intérieur des aires protégées a significativement baissé de 0,56 point de pourcentage, par rapport au pourcentage consommé par les groupes résidant à l'extérieur. Ce chapitre met donc en évidence la relation entre les ODD sur la protection environnementale et l'accès à l'énergie durable, dans le but d'appuyer les opérateurs du développement à mieux comprendre et mesurer les effets de leurs politiques.

**Mots-clés :** Evaluation d'impact, Méthode expérimentale, Méthode quasi-expérimentale, Développement Durable, Secteur privé, Energie

**Classification JEL :** C80, C90, O10, Q20, Q40

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<sup>1</sup> Convention Industrielle de Formation par la Recherche

# Abstract

The use of impact evaluation methods in the development sector has grown rapidly over the past twenty years. This is particularly true for the evaluation of the results of projects with a high local impact that meet the challenges set by the United Nations Sustainable Development Goals (SDGs). It is in this context that this thesis, carried out within the framework of a CIFRE<sup>2</sup> program, is structured around three empirical studies that allow the identification of impact evaluation strategies adapted to the requirements of private and public development actors. The aim is to gain a better understanding of the positive and negative, direct and indirect impacts of projects financed in developing economies. Chapter 1 shows that there is a convergence between experimental and quasi-experimental impact assessment methods on the likelihood of project to generate a positive outcome on development indicators. On the other hand, there is a discrepancy between the experimental and quasi-experimental methods to conclude a negative outcome of projects deployed in Africa. Chapter 2, co-authored with Dr. Enoch Owusu-Sekyere and Dr. Esther Leah Achandi, analyzes the impact of solar utility adoption on the socio-economic performances of merchants in Nigeria. Using an original field survey of 700 merchants located in 5 markets, as well as an identification method, this study shows that the average monthly income of merchants subscribing to Rensource solar panels increased by nearly 27%. Subscribers also experienced a decrease in their average monthly energy expenses of nearly 37%, as well as a reduction in environmental and health pollution risks. Then, in a context where environmental policies are taking a prominent place in the financing of impact projects, the work in chapter 3 is based on an innovative geospatial analysis that studies the impact of a biodiversity policy through the creation of protected areas on household consumption of wood cooking fuels in Madagascar. The results show that around the boundaries of protected areas, fuelwood consumption share of household clusters living inside protected areas significantly increases by 0.64 percentage points, compared to the consumption of household clusters located outside the boundaries of the areas. Conversely, charcoal consumption share of households inside protected areas decreases by 0.56 percentage points, compared to the consumption share of those residing outside. This chapter therefore highlights the relationship between the SDGs on environmental protection and access to sustainable energy, with the aim of supporting development practitioners to better understand and measure the effects of their policies.

**Keywords:** Impact evaluation, Experimental method, Quasi-experimental method, Sustainable development, Private sector, Energy

**JEL classification:** C80, C90, O10, Q20, Q40

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<sup>2</sup> Convention Industrielle de Formation par la Recherche

*In memory of my father, Lamine.*

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<sup>3</sup> Fondation pour les Etudes et Recherches sur le Développement International

<sup>4</sup> Convention Industrielle de Formation par la Recherche

<sup>5</sup> Centre d'Economie de la Sorbonne

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<sup>6</sup> Environnement, Social, Gouvernance



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# 1. General Introduction

*“The economic and financial evaluation of investment projects is like Aesop's tongue, because it can be the best or the worst of things: a useful tool for decision-making or a simple cover-up, the simple justification a posteriori of a decision that has already been taken - and like Mr. Jourdain's prose, it is presented today in the guise of a new science, or more modestly, of a set of modern techniques, unknown only a few decades ago” (Bridier and Michailof, 1995).*

## 1.1. Impact evaluations in the development field

In the 1970s, development programs in low-income countries led to the emergence of a need for periodic assessment of their impacts. In order to better guide public and private decision-makers in their development projects, but also to consolidate the information provided by evidence-based impact measures. At the end of the 1970s, entities such as the World Bank (WB) showed a real interest in the analysis of basic needs in several areas: poverty, health, education, infrastructure, nutrition, etc. Impact evaluations can therefore inform development actors about the effectiveness of the activities, which will lead to their continuation, adjustment, or interruption.

As reminded by Pamies-Sumner (2014), impact assessment boomed in the 1990s, a time when donors (public and private) and researchers were questioning the effectiveness of development assistance.

**Tableau 2** Paradigme de l'aide et « gold standards » de l'évaluation

Période	Paradigme dominant de l'aide	Méthode d'évaluation promue	Discipline dominante
Années 1960	Priorité donnée aux infrastructures et à l'agriculture	Analyse coûts-bénéfices ( <i>ex ante</i> )	Finance
Années 1970	Réorientation vers les secteurs sociaux (éducation, santé)	Analyse qualitative	Sciences sociales
Années 1980	Restauration du cadre macroéconomique et ajustement structurel	Modèle macroéconomique	Macroéconomie
Années 1990	« Fatigue de l'aide » : accent mis sur l'efficacité de l'aide et des critères d'allocation fondés sur la bonne gouvernance	Analyse qualitative et régressions économétriques	Macro-économétrie et sciences sociales
Années 2000	Priorité au bas de l'échelle (« <i>bottom of the pyramid</i> »), mais des ambitions contradictoires : une aide modeste (« réduire la pauvreté à petits pas ») ou une aide ambitieuse (OMD) ?	Évaluations d'impact expérimentales/ quasi-expérimentales ; gestion axée sur les résultats	Microéconomie ; statistique
Post 2015 ?	L'aide comme catalyseur /outil de politique publique globale ?	Analyses qualitative et quantitative	Pluridisciplinarité

Source : inspiré de Morra-Imas et Rist (2009).

According to Gertler et al. (2011), prospective impact studies aim to determine whether or not a project has achieved its intended results. Impact measurement is therefore an input to the analysis of the benefits and harms of development projects. Combining the multidisciplinary nature of empirical research tools with the operational realities of project implementation. The authors also emphasize the importance of including all stakeholders during the impact assessment process, starting with the project design. To that extent, impact measurement allows for the identification of changes in people's well-being that can be attributed to a given project. It is therefore essential that the impact evaluation strategy is taken into account from the very beginning of the design of the funded project, with the close collaboration of all stakeholders who have a common vision of the different objectives to be achieved (Duflo, 2005).

There is a real need for public and private development operators to measure their contributions, and to give an accurate picture (positive and negative) of the activities they finance and support. It is therefore necessary to develop and refine tools for measuring direct and indirect impacts, particularly in the area of impact financing. Public and private organizations, most of which carry out social impact activities, have for several years been developing methodological guides for their specific evaluation tools. Capitalizing on their experiences has made it possible to determine and analyze the differences and

similarities between instruments, but also between application processes, in order to define standard impact evaluation mechanisms.

Most of the evaluations published concern agriculture, health, education, or social protection. Whereas, themes such as infrastructure, energy, and the environment, which are attracting increasing amounts of public and private funding, are rarely evaluated. For operators, there is therefore a real challenge to be able to analyze the effects of their activities in Sub-Saharan Africa, through the use of quality evidence-based data. Traditional development organizations (donors, financing institutions) are no longer the only actors to carry out socio-economic and environmental development actions toward the most vulnerable populations. Indeed, a new branch of the private sector, through the impact investment business model which combine financial and extra-financial returns, is becoming more involved in development projects.

The involvement of investors and project promoters must also be based on a proactive and regular approach to data collection and impact studies. However, we have noted throughout this thesis that the time dimension is a key factor in impact analysis. Indeed, some evaluation methods used by development organizations or academic research institutions do not always fit the time and financial constraints of private entities.

Private impact organizations need to make greater use of rigorous evaluation tools to isolate the net impact of their funding, while adapting to their day-to-day operations (flexibility). In particular, by relying on field or remote data collected from companies. In particular, it is possible to rely on field or remote data, through ad hoc surveys (questionnaires, telephone surveys) and national surveys, despite the fragility of public statistical systems in low-income countries (Pamies-Sumner, 2014).

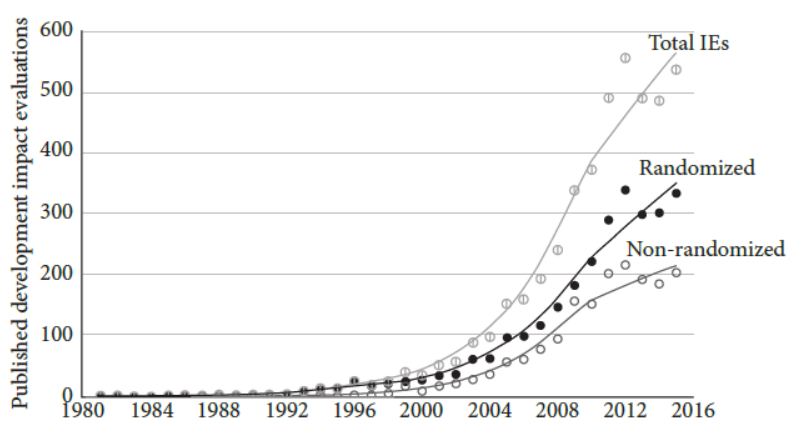
It is also critical to strengthen the independence and objectivity of impact evaluations, which ensure the accountability of public and private decision-makers to the outcomes of their policies and activities (Picciotto, 2020). With the impact investment sector booming, the diversity of rigorous impact measurement tools allows to draw lessons on the impacts generated by investments (Jackson, 2013).

The International Association for Impact Assessment (IAIA) defines impact as the difference between what would happen as a result of a given activity and what would happen if that activity had not taken place (Tol, 2009). According to Severino (2022), the impact ecosystem distinguishes four categories of development project outcomes:

- **Direct impacts** resulting from the project itself.
- **Indirect impacts** mediated by an intermediary and linked to the project environment (vast and difficult to measure).
- The **internality of impacts** produced voluntarily by an organization on a stakeholder as a result of monetary and contractual transactions generated by its activity (access to a good or service, sales, purchases, dividends, etc.).
- The **externality of impacts** produced involuntarily by an organization on a stakeholder, without

monetary counterpart and without compensation unless there is an external intervention or negotiation (pollution, formalization, etc.).

Ravallion (2020) points out that since the 2000s the number of impact assessments published by 3ie has increased thirtyfold, in contrast to the pre-2000 period (Figure 1.1 below). Between 1981 and 2015, 24,501 impact evaluations were counted in the 3ie database. 4,338 evaluations were published between 2000 and 2015, which represents an annual production rate of 271 impact evaluations published since 2000 compared to 9 between 1981 and 1999. The graph below also reveals that the use of randomized control trials (RCTs), which began in the 1980s, has increased significantly over the last 20 years. Since the 2000s, 60% of impact evaluations were RCTs. As of 2015, 333 scientific research papers had used the RCTs method, an annual growth rate of about 20%.



**Figure 1.1 Annual counts of published impact evaluations for developing countries**

*Note:* Fitted lines are nearest neighbor smoothed scatter plots. See footnote 3 in the main text on likely under-counting of non-randomized evaluations in earlier years. Source of primary data: International Initiative for Impact Evaluation.

*Source:* Author, based on 3ie data.

Impact evaluation seeks to determine the extent to which the intervention leads to changes in outcomes (Gertler et al., 2011). Impact evaluation is therefore related to an action by which a given quantity is determined in relation to a benchmark, relying on measurement tools that cover a wide range of technical solutions used (Baudet, 2019). These tools, ranging from indicators (ratios) to methodologies, make it possible to isolate the impact of a project by defining a counterfactual, i.e., by comparing the evolution of a beneficiary population with the situation that would have prevailed if the activity had not been implemented.

## 1.2. Experimental impact evaluation methods

The second half of the twentieth century saw the emergence of a generation of concepts and tools for measuring the impacts of public investment projects, aiming to understand them in a more precise, rigorous and broad manner. Subsequently, these measurement tools were simplified with the appearance of public policy evaluation methods based on the scientific collection of results.

Burtless (1995) points out that the development of randomized evaluations stems from the acknowledgment that there is a limited amount of rigorous empirical evidence on what "works and does not work" in development policies. In the 1960s, randomized impact measurement, inspired by the medical field, was applied to the evaluation of public policies in Northern European countries and in the United States, mainly in the areas of education, taxation, and crime, at a time when the activities of criminal networks in the United States were prolific (Levitt and Dubner, 2005). Thus, many social programs, evaluated by the American organization Manpower Demonstration Research Corporation 1 (MDRC1), had a significant impact on public policy (Burtless, 1995).

However, the real expansion of randomized control trials has taken place in developing countries in the context of the fight against poverty, through an innovative approach to public policy evaluations in the areas of health, education, or microfinance. RCTs also promote strong collaboration between NGOs, governments, and international institutions. This expansion took shape in the 2000s with the creation of the Jameel Lateef Poverty Action Lab (J-PAL) by economists Esther Duflo and Abhijit Banerjee. Their approach is based on the "public" character of impact evaluations, with the aim of legitimizing the scientific rigor of experimental measures derived from evidence-based medicine. This in a context of dwindling financial resources granted to development policies, and a growing demand for accountability of public funds (Bédécarrats et al., 2017). Duflo (2017) points out that public and private donors have been attracted by the technical simplicity and transparency offered by RCTs. Indeed, randomization focuses on key goods and services for local socioeconomic development (Morduch, 2020). In 2018, 65% of impact evaluations conducted by the DIME were randomized controlled trials, compared to 20% for non-experimental methods, which makes the DIME the agency that conducts the most RCTs within the World Bank group (Ravallion, 2020). In 2020, J-PAL reported 1,012 RCTs completed or underway within 83 countries (Ravallion, 2020). According to Labrousse (2020), 952 randomized studies were counted as of June 2019 while the number of RCTs recorded in social sciences was 2,552, a rate of 37.2%. Moreover, the convergence between development economics and behavioral economics is also favorable to the rise of RCTs. This link decision-makers with public and private operational staff in order to better understand the behavior of beneficiaries. Indeed, the purpose of experimental evaluations is to verify that the objectives assigned to a project have been achieved, in order to provide a genuine social and economic added value (Crépon, 2008).

The objective of RCTs is therefore to isolate the impact of an activity between a group of beneficiaries (treated) and a group of non-recipients (control) of a project (Baudet, 2019). The constitution of these

two groups is done randomly, notably through a random draw (lottery, random numbers generated by a computer program, etc.). Duflo (2005) states that impact evaluations determine the causal inference of an activity, empirically demonstrating the extent to which the activity contributed to changing an outcome. Thus, the difference in outcomes between beneficiary and non-beneficiary groups can be measured. The legitimacy of the "gold standard" status of experimental measures has revolutionized the field of impact evaluation, thanks to the validity of the control group (counterfactual). Randomized evaluations are generally considered to be the most rigorous and accurate in producing results. The main purpose of RCT evaluations is therefore to correct for selection bias. Advocates of this measurement tool argue that selection bias is particularly common in studies that use non-experimental methods.

Nevertheless, the "gold standard" status of RCTs is often at the heart of scientific debate. Deaton (2009) points out that while RCTs provide information on the average impact of a policy's effects, they do not identify other components of the distribution such as the median effect of a policy, which could be a modality of interest to public and private operators. Therefore, the average impact of a project obtained through an RCT analysis may be limited for an operator who considers only a specific part of the activity. The application of RCTs is legitimate for specific and precise projects (Bédécarrats et al., 2020). According to Ravallion (2009), RCTs therefore analyze the success and failure factors of an activity, but do not provide any information on the underlying mechanisms (causes and processes). Moreover, randomized studies seem to be a tool limited to small-scale infrastructure projects, as it is more complex to randomize sectoral or macroeconomic reform policies (Ravallion, 2020).

Moreover, Gertler et al. (2011) point out that there are two main limitations to the validity of evaluations. In this case, randomized measurement tools have several empirical limitations that can bias the impacts of a policy:

- **Internal validity:** it is possible, despite randomization, that the comparability of the beneficiary and non-beneficiary groups may be compromised.
  - Indeed, individuals may change their behaviors if they have knowledge of their assignments to the treatment or comparison group (Hawthorne effect).
  - Non-recipients may find a way to access the activity, mainly by making additional efforts (John Henry effect).
- **External validity:** relates to the non-generalizability of the evaluation results in different contexts, as well as to the representativeness of the sample in relation to the target population. The external validity of a project imposes constraints from the design and implementation of the pilot phase (Ravallion, 2020).

From an ethical perspective, RCTs also face many criticisms as the random assignment process can use several perverse effects, such as monetization to benefit a project. Ravallion (2020) reminds that ethically unsound randomized evaluations can be applied in areas where the rights of vulnerable populations are not protected due to insufficient institutional capacity.

Financially, randomized trials are extremely expensive (€500,000 on average), complex to set up and not usable when the sample of beneficiaries is too small (Baudet, 2019). It is therefore complicated to compare the monetary cost of a policy with benefits that are not monetized. Therefore, randomized experiments can only be implemented if there is very strong collaboration between operational staff and evaluators, and this upstream of the project financing process. RCTs therefore represent the bridge between the laboratory and the "natural" analysis of data (List, 2007).

### 1.3. Quasi-experimental impact evaluation methods

On the other hand, Delarue and Cochet (2011) define quasi-experimental methods as an ex-post reconstruction of non-beneficiaries of a project, based on observed and relevant characteristics. Propensity score matching, double-difference estimates, and regression discontinuity are different non-experimental evaluation methods that attempt to address the problem of selectivity bias. This bias arises when beneficiary participation in a project is correlated with project outcomes (Gertler et al., 2011). For example, parameters such as beneficiaries' place of residence can generate a selection bias.

One of the main objectives of impact studies is to reduce this selectivity bias as much as possible by comparing a group of beneficiaries with a group of non-beneficiaries who have exactly the same characteristics, except for the participation in the program. However, some characteristics, specific to each individual, are difficult to observe and measure. To mitigate this bias, Ravallion (2020) suggests to strengthen the quality of the data collected. And according to Delarue and Cochet (2011), the objective of quasi-experimental evaluations is to measure the difference between two situations:

- The one resulting from the implementation of a project.
- The one that would have prevailed if the project had not been implemented (counterfactual).

In other words, the estimation of this counterfactual makes it possible to measure the outcome for beneficiaries if the project had not been implemented. Even though the reconstruction of the "without project" scenario is often based on the subjective choices of the evaluator, its construction makes it possible to avoid making the mistake of attributing to the project the effects that endogenous and exogenous dynamics had on individuals. These dynamics are unobservable factors that could influence the selection of the sample and differentiate beneficiaries from non-beneficiaries. This represents a major methodological challenge, involving multiple conditions detailed below.

Matching methods, which associate beneficiaries and non-beneficiaries on the basis of their common observable characteristics, determine the ex-post counterfactual. It is therefore essential to ensure, at the outset of the evaluation, that the individuals in the two groups have the most similar characteristics possible. Therefore, this impact measurement tool generates an artificial comparison group formed by matched individuals who do not benefit from the project, in order to estimate the counterfactual (Gertler et al., 2011). For example, the Argentinean public employment program *A Trabajar* was evaluated by



Jalan and Ravallion (2003) with participants and non-participants. Using the propensity score, the authors report that the program resulted in an average increase in beneficiaries' earnings equivalent to half the Argentinean gross wage.

While this methodology allows for the correction of selectivity bias, it requires a large sample of data to cover the widest possible range of observable characteristics. It also requires baseline data collected prior to the implementation of the project, in order to control for pre-existing disparities between the two groups. This approach is often restrictive in terms of financial and human resources. Apart from the importance of having a large database, developed prior to the launch of a project, the main limitation of the matching evaluation stems from its strong assumption that it is based solely on the observable characteristics of beneficiaries and non-beneficiaries. However, there are unobservable factors, such as the motivation of individuals, which are in essence omitted and not included in the construction of the matching. In this case, this measurement tool probably mitigates the selectivity bias, but has no impact on the bias induced by these unobservable characteristics. The selectivity bias would therefore remain significant, to that extent the difference between the two groups' average outcomes generated by the unobservables is attributed to the project. Thus, impact evaluation using the matching mechanism is often used as a last resort.

Then, the difference-in-difference (DiD) method estimates the counterfactual by taking into account time-invariant differences between recipients and nonrecipients (Gertler et al., 2011). In other words, it measures the change over time of recipients versus the change of nonrecipients (Le Ster, 2011). While this methodology relies on constraining assumptions by relying on baseline data collected prior to the deployment of a project, it is also a powerful statistical tool. The twofold difference relies mainly in the following steps:

- The first difference is made twice, for the recipient population (before and after the project) and the non-recipient group (before and after the project).
- The second difference is the difference between these first two differences (difference between the recipient group - difference between the non-recipient group).

These two steps correct for the bias associated with the effects of external and time-varying factors on the impact for beneficiaries. Thus, the double difference simultaneously combines two types of comparison between beneficiaries and non-beneficiaries: **before-after** and **with-without**. This measurement tool is one of the least burdensome quasi-experimental strategies. Since it does not require assumptions of assignment or equivalence of characteristics between the two groups. Therefore, Bensch et al. (2013) were able to determine the impact of access to solar electrification among households in Kéné Dougou (Burkina-Faso), through the double difference approach. The authors note that access to solar energy resulted in a 9.1% reduction in home burglaries.

However, the strong assumption of the DiD is that there are equivalent trends between the two groups. This is one of the main limitations of this methodology, since the two groups also have different and unobservable characteristics that may influence the impact of the activity. A test of the validity of equivalent trends can be used to address this issue, by comparing the trends of the two groups before the project is implemented. This requires at least three waves of data for each group: two waves before the project and one ex-post wave. Nevertheless, double-difference impact assessment remains one of the most widely used statistical methods in development economics.

Finally, the regression discontinuity model is an impact evaluation method that is suitable for projects for which an eligibility index is established, as well as a clearly defined threshold to distinguish beneficiaries from non-beneficiaries. These two conditions therefore prevail in the application of this methodology:

- **Eligibility index:** a continuous indicator that classifies the population under study (poverty index, age, etc.).
- **Eligibility threshold:** which determines a level of the index above or below which the population is considered a beneficiary of the project.

Close beneficiaries and non-beneficiaries on either side of the eligibility threshold have similar characteristics. The counterfactual is then estimated by generating a control group composed of non-beneficiaries who are close to the eligibility threshold. The objective is to estimate the impact of a project by focusing only on individuals just below the threshold (non-recipient group) and those just above (recipient group). The model assumes that individuals around the eligibility threshold are very similar, which provides an unbiased estimate of the average local impact around the eligibility threshold. After the project is implemented, this local average difference between the two groups is the impact of the project.

For example, the program to reduce school fees in Colombia (*Gratuidad*) allowed the government to target the beneficiary populations using a poverty index (SISBEN). This index defines two thresholds for eligibility for the program. Within this framework, Urquiola et al. (2013) conducted a RDD analysis, which reveals that the program generated a three-point increase in enrollment for elementary school students in the city of Bogotá. The regression discontinuity approach is therefore often used for the evaluation of social projects, as was the case with the *PROGRESA* program in Mexico, for which Buddelmeyer et Skoufias (2004) found that the results obtained using RDD were similar to those obtained through the experimental evaluation mechanism. The authors also point out that project downsizing or upsizing cannot occur under the use of RDD analysis. Indeed, the RDD method only provides the result of the average local impact which corresponds to the impact around the eligibility threshold, and does not indicate the marginal impact of the project for others who are significantly above or below the threshold and who are not included in the analysis.

This also poses a problem of statistical power, which may be insufficient since the local average impact estimate does not have a large population sample compared to other evaluation methods. Indeed, the wider the eligibility band, the higher the statistical power, since a larger number of observations are taken into account. Finally, it is necessary to take into account the complexity of the relationships between the eligibility threshold and the policy outcome, by applying different functional forms of modeling (linear, quadratic, cubic, etc.).

## 1.4. Motivations

This CIFRE<sup>7</sup> thesis contributes to a better understanding of impact assessment methods for the impact industry, in particular through the interdisciplinary collaboration between academic and operational development actors. The impact investment fund Investisseurs et Partenaires (I&P) provides development outcomes to its investors who support Sub-Saharan African Small and Medium Enterprises (SMEs) and start-ups. This thesis subject supports the methodological work of the operational activities of I&P, through the Impact and ESG<sup>8</sup> matters. The improvement of the impact assessment methodologies is the key to the impact industry, mostly for the development funders. Substantially, these interactions between development actors allow the development of original databases such as the Collaborative Smart Mapping of Mini-grid Actions (CoSMMA) in the first chapter, as well as the access to original field data in the second chapter.

Therefore, the purpose of this thesis is to identify robust impact assessment tools that can be used to measure the direct and indirect effects of small-scale projects funded by development actors. Indeed, development actors are increasingly carrying out sustainable projects with a strong impact on local populations. Thus, it is important to determine the local content of sustainable development activities and to analyze the influence of impact assessment measures on the results of these activities. Therefore, the interest of this thesis is to determine robust and relevant impact assessment tools for impact operators to measure the direct and indirect effects of their investments, according to the perimeter defined by the United Nations Sustainable Development Goals (SDGs). To this end, this work addresses three main issues regarding the role of impact measurement on the direct and indirect results of sustainable development projects. Consequently, these three issues raised in this thesis has direct relevance for private funders such as I&P.

The first chapter provides an understanding of the effects of different impact evaluation methods, through a meta-analysis that compares impact evaluation techniques according to the outcomes of decentralized electrification projects (DEPs). This empirical strategy allows for an analysis of the epistemology of the methodological approaches. The results reveal that there is a convergence of experimental and quasi-

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<sup>7</sup> Industrial Convention for Training through Research

<sup>8</sup> Environment, Social, and Governance

experimental impact evaluation methods to find a significant and positive effect of DEPs on the SDGs' outcomes. In terms of policy decisions, the results of the chapter have major implications for public and private operators in the development field, mainly for the field of small-scale infrastructure projects. Hence, this chapter provides insights on the type of least-cost impact assessments for sustainable development projects.

Then, the second chapter co-authored with Enoch Owusu-Sekyere and Esther Leah Achandi comes at a time when development investors have strong activities in green and decentralized energy in Africa. This study examines the impact of subscribing to Rensource solar energy on Micro, Small & Medium Enterprises (MSMEs) market performance in Lagos, Kano and Ondo states in Nigeria. Our results show that merchants who subscribed to the Rensource solar solution experienced an average increase in revenue of 23-27%, and reduced their average monthly electricity expenses by 36%. With Nigeria being the least reliable in terms of electrification and most populous country in Africa, addressing these issues for this country can highlight the redistributive impacts of small-scale development projects for local communities, on the one hand. On the other hand, help micro, small and medium private energy companies improve their products and customer outreach strategies, which is a key contribution to the relationship between the energy transition and sustainable well-being. Obviously, understanding the impact of the renewable off-grid activity is important in order to make a link between the concessionality of the investment and the outcomes.

Finally, in Madagascar donors are targeting biodiversity programs through the national private sector. These programs support productive activities around protected areas (PAs). Consequently, it is important to know what are the impact of those protected areas in order to create innovate programs which address both environmental and socio-economic targets. Therefore, this third chapter highlights the relationship between biodiversity protection and access to sustainable energy. Indeed, climate change is increasing the environmental regulations implemented by developing countries. From this perspective, this chapter analyzes the impact of protected areas on the consumption share of wood-based cooking fuel of household clusters in Madagascar through an innovative spatial impact assessment based on the use of satellite data, which is an effective tool for measuring environmental externalities. Indeed, in recent years, climate data related to environmental indicators have increased significantly, particularly through NASA<sup>9</sup> data sharing and the creation of free digital platforms such as Digital Earth Africa. In addition, there is increased access to geocoded surveys at the scale of project intervention areas. Thus, geospatial impact evaluation (GIEs) can measure the positive and negative environmental externalities of development projects. The research center (Aiddata) at the College of William and Mary has built a spatial data directory and extraction tool called GeoQuery. BenYishay et al. (2017) point out that the GIEs method is applicable once the geographic coverage relying on GPS and temporal coordinates of an activity's implementation is defined and accurate. The authors also note that geospatial impact assessments have several advantages for project developers and evaluators. GIEs allow for the creation of conditions

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<sup>9</sup> National Aeronautics and Space Administration

similar to RCTs, but without the process of randomly assigning individuals between treatment and control groups (BenYishay et al., 2017). GIEs also rely on quasi-experimental methods of causal inference to measure the impacts of development projects.

The main results suggest that around the boundaries of the protected areas, fuelwood consumption share of treated household clusters significantly increases in 2016 by 0.62 percentage points, compared to the consumption share of the clusters located outside the PAs' boundaries. Conversely, charcoal consumption share of household clusters inside PAs decreases by 0.56 percentage points, compared to the consumption share of those residing outside PAs. These findings emphasize that the effectiveness of environmental must take into account the impacts on local communities. Thus, this study makes a strong contribution to guiding development actors in their policy decisions and investment choices, in order to meet the SDG indicators.

## 2. Introduction générale

*« L'évaluation économique et financière des projets d'investissements est à la fois comme la langue d'Esopé car elle peut être la meilleure ou la pire des choses : un instrument utile pour la décision ou le simple camouflage, la simple justification a posteriori d'une décision déjà prise – et comme la prose de M. Jourdain, elle se présente aujourd'hui sous les traits d'une science nouvelle, ou plus modestement d'un ensemble de techniques modernes, inconnues voilà seulement quelques dizaines d'années » (Bridier and Michailof, 1995).*

### 2.1. Les évaluations d'impact dans le secteur du développement

Dans les années 1970, les programmes de développement dans les pays à bas revenus ont entraîné l'émergence d'un besoin d'appréciation périodique de leurs impacts, afin de mieux orienter les décideurs publics et privés dans leurs projets de développement, mais également de consolider les informations fournies par les mesures d'impacts fondées sur des preuves. A la fin des années 1970, des entités telles que la Banque Mondiale (BM) ont manifesté un réel intérêt pour l'analyse des besoins fondamentaux dans plusieurs domaines : pauvreté, santé, éducation, infrastructures, nutrition, etc. Les évaluations d'impacts permettent donc d'éclairer les acteurs du développement sur l'efficacité ou non des activités menées qui donneront lieu à leur poursuite, à leur ajustement, ou à leur interruption.

Comme le rappelle Pamies-Sumner (2014), l'évaluation d'impact a connu un essor fulgurant dans les années 1990, période à laquelle les bailleurs (publics et privés) et les chercheurs s'interrogeaient sur l'efficacité de l'aide publique au développement.

**Tableau 2** Paradigme de l'aide et « gold standards » de l'évaluation

Période	Paradigme dominant de l'aide	Méthode d'évaluation promue	Discipline dominante
Années 1960	Priorité donnée aux infrastructures et à l'agriculture	Analyse coûts-bénéfices (ex ante)	Finance
Années 1970	Réorientation vers les secteurs sociaux (éducation, santé)	Analyse qualitative	Sciences sociales
Années 1980	Restauration du cadre macroéconomique et ajustement structurel	Modèle macroéconomique	Macroéconomie
Années 1990	« Fatigue de l'aide » : accent mis sur l'efficacité de l'aide et des critères d'allocation fondés sur la bonne gouvernance	Analyse qualitative et régressions économétriques	Macro-économétrie et sciences sociales
Années 2000	Priorité au bas de l'échelle (« <i>bottom of the pyramid</i> »), mais des ambitions contradictoires : une aide modeste (« réduire la pauvreté à petits pas ») ou une aide ambitieuse (OMD) ?	Évaluations d'impact expérimentales/ quasi-expérimentales ; gestion axée sur les résultats	Microéconomie ; statistique
Post 2015 ?	L'aide comme catalyseur /outil de politique publique globale ?	Analyses qualitative et quantitative	Pluridisciplinarité

Source : inspiré de Morra Jimas et Rist (2009).

Selon Gertler et al. (2011) les études d'impact prospectives visent donc à déterminer si un projet a atteint ou non les résultats espérés. La mesure d'impact est par conséquent un apport à l'analyse des bénéfices et des préjudices des projets de développement. Combinant la pluridisciplinarité des outils de recherche empiriques avec les réalités opérationnelles de la mise en œuvre des projets. Les auteurs soulignent également l'importance de l'inclusion de toutes les parties prenantes durant l'évaluation d'impact, et ceux dès la conception du projet. En ce sens, la mesure d'impact permet d'identifier les changements du bien-être des individus qui peuvent être attribués à un projet donné. Il est donc primordial que la stratégie d'évaluation d'impact soit prise en compte dès la conception du projet financé, avec une étroite collaboration de toutes les parties prenantes qui ont une vision commune sur les différents objectifs à atteindre (Duflo, 2005).

Il existe un réel besoin pour les opérateurs publics et privés du développement de mesurer leurs contributions, et de donner une image (positives et négatives) précise des activités qu'elles financent et accompagnent. Il est donc nécessaire de développer et d'affiner des outils de mesure des impacts directs et indirects, notamment dans le domaine de l'investissement à impact. Les organismes publics et privés, ayant pour la plupart des activités à impact social, ont développé depuis plusieurs années des guides méthodologiques d'instruments d'évaluation qui leurs sont spécifiques. La capitalisation de leurs

expériences a permis de déterminer et d'analyser les différences et les similarités entre instruments, mais également entre processus d'application, afin de définir les mécanismes standards d'évaluation d'impact.

Une majorité des évaluations publiées concernent principalement l'agriculture, la santé, l'éducation, ou la protection sociale. Tandis que les thématiques sur l'infrastructure, l'énergie, ou l'environnement, qui drainent des financements publics et privés de plus en plus importants, font peu souvent l'objet d'évaluations. Pour les opérateurs, il existe donc un réel enjeu d'être en mesure d'analyser les effets de leurs activités en Afrique Sub-saharienne, à travers l'utilisation de données probantes et de qualité. Les organismes de développement traditionnels (bailleurs, institutions de financement) ne sont plus les uniques acteurs à mener des actions de développement socio-économiques et environnementaux, auprès des populations les plus vulnérables. En effet, une nouvelle branche du secteur privé, selon le modèle économique de l'investissement à impact et alliant les rendements financiers et extra-financiers, s'implique davantage dans les projets de développement.

L'implication des investisseurs et des promoteurs de projets doit aussi s'opérer sur la stratégie de collecte des données et des études d'impact, en ayant une démarche proactive et régulière. Toutefois, nous avons constaté tout au long de cette thèse que la dimension temporelle est un facteur clé dans l'analyse d'impact. En effet, certaines méthodes d'évaluation utilisées par les organisations de développement ou les institutions de recherche académique ne s'accordent pas toujours aux contraintes temporelles et financières des entités privées.

Les organisations privées à impact doivent recourir davantage à des outils d'évaluation rigoureux pour isoler l'impact net de leurs financements, tout en s'adaptant à leurs activités quotidiennes (flexibilité). Il est notamment possible de s'appuyer sur des données de terrain ou à distance, par le biais d'enquêtes *ad hoc* (questionnaires, sondages par téléphone) et d'enquêtes nationales, malgré la fragilité des systèmes de statistiques publics dans les pays à bas revenus (Pamies-Sumner, 2014).

Il est également primordial de renforcer l'indépendance et l'objectivité des évaluations d'impact qui garantissent les responsabilités des décideurs publics et privés face aux résultats de leurs politiques et activités (Picciotto, 2020). Face à un secteur de l'investissement d'impact en plein essor, la diversité des outils de mesure d'impact rigoureux permet de tirer des enseignements sur les impacts générés par les investissements (Jackson, 2013).

L'association international de l'évaluation d'impact (IAIA<sup>10</sup>) définit un impact comme étant la différence entre ce qu'il adviendrait suite à une activité donnée, et ce qu'il adviendrait si cette activité n'avait pas eu lieu (Tol, 2009). D'après Severino (2022), l'écosystème de l'impact distingue quatre catégories de résultat d'un projet de développement :

- Les **impacts directs** du fait même de la mise en place du projet.

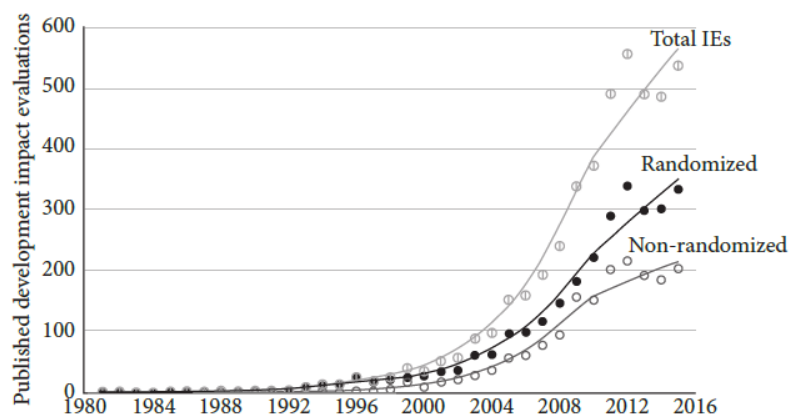
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<sup>10</sup> International Association for Impact Assessment



- Les **impacts indirects** médiatisés par un intermédiaire et liés à l'environnement du projet (vastes et difficiles à mesurer).
- **L'internalité des impacts** qui produit de manière volontaire par une organisation sur une partie prenante du fait de transactions monétaires et contractuelles générées par son activité (accès à un bien ou service, ventes, achats, dividendes, etc.).
- **L'externalité des impacts** produit de manière involontaire par une organisation sur une partie prenante, sans contrepartie monétaire et sans compensation à moins d'une intervention externe ou d'une négociation (pollution, formalisation, etc.).

Ravallion (2020) rappelle que depuis les années 2000 le nombre d'évaluations d'impact publiées par le 3ie a été multiplié par trente, contrairement à la période pré-2000 (Figure 1.1 ci-dessous). Entre 1981 et 2015, 24501 évaluations d'impact ont été comptabilisées dans la base de données 3ie. 4338 évaluations ont été publiées entre 2000 et 2015, soit un taux de production annuel de 271 évaluations d'impact publiées depuis 2000 contre 9 entre 1981 et 1999. Le graphique ci-dessous révèle également que l'usage des RCTs qui a débuté dans les années 1980 a connu un fort accroissement une vingtaine d'années plus tard. Depuis les années 2000, 60% des évaluations d'impact étaient des RCTs. En 2015, 333 papiers de recherche scientifiques avaient utilisé la méthode des essais randomisés, soit un taux de croissance annuel d'environ 20%.



**Figure 1.1 Annual counts of published impact evaluations for developing countries**

*Note:* Fitted lines are nearest neighbor smoothed scatter plots. See footnote 3 in the main text on likely under-counting of non-randomized evaluations in earlier years. Source of primary data: International Initiative for Impact Evaluation.

*Source:* Author, based on 3ie data.

L'évaluation d'impact cherche à déterminer dans quelle mesure l'intervention entraîne des changements des résultats (Gertler et al., 2011). L'évaluation d'impact se rattache donc à une action par laquelle on détermine une grandeur donnée par rapport à un référentiel, en s'appuyant sur des outils de mesure qui recouvrent un large ensemble de solutions techniques utilisées (Baudet, 2019). Ces outils, allant des indicateurs (ratios) aux méthodologies, permettent d'isoler l'impact d'un projet en définissant un

contrefactuel, c'est-à-dire en comparant l'évolution d'une population bénéficiaire par rapport à la situation qui aurait prévalu si l'activité n'avait pas été mise en place.

## 2.2. Les méthodes d'évaluation expérimentales

La seconde moitié du vingtième siècle a vu l'éclosion d'une génération de concepts et d'outils de mesure des impacts des projets d'investissement publics, visant à les appréhender de manière plus précise, rigoureuse et large. Par la suite, ces outils de mesure ont été schématisés avec l'apparition de méthode d'évaluation des politiques publiques, fondées sur une collecte scientifique des résultats.

Burtless (1995) souligne que le développement des évaluations randomisées provient du constat selon lequel il existe un nombre limité de preuves empiriques rigoureuses sur ce qui « marche et ne marche pas » dans les politiques de développement. Dans les années 1960 la mesure d'impact par randomisation, inspirée par le champ médical, fut appliquée pour l'évaluation des politiques publiques dans les pays d'Europe du nord et aux Etats-Unis, principalement pour les secteurs de l'éducation, de la fiscalité, et de la criminalité, à une époque où les activités des réseaux criminels aux Etats-Unis étaient prolifiques (Levitt and Dubner, 2005). Ainsi, de nombreux programmes sociaux, évalués par l'organisation américaine MDRC<sup>1</sup>, ont eu un impact significatif sur les politiques publiques (Burtless, 1995).

Toutefois, la véritable expansion des essais randomisés aléatoires (RCTs<sup>11</sup> en anglais) s'est effectuée au sein des pays en développement dans le cadre de la lutte contre la pauvreté, grâce à une approche innovante des évaluations de politiques publiques dans les domaines de la santé, de l'éducation, ou de la microfinance. Les évaluations RCTs font également la promotion d'une forte collaboration entre les ONG, les gouvernements, et les institutions internationales. Cette expansion s'est concrétisée dans les années 2000, à travers la création du laboratoire Jameel Lateef Poverty Action Lab (J-PAL) par les économistes Esther Duflo et Abhijit Banerjee. Leur approche s'appuie sur le caractère « public » des évaluations d'impact, dans le but de légitimer la rigueur scientifique des mesures expérimentales provenant de *l'evidence-based* en médecine. Duflo (2017) souligne que les bailleurs publics et privés ont été attirés par la simplicité technique et la transparence offertes par les RCTs. En effet, la randomisation met l'accent sur les biens et services clés au développement socio-économique local (Morduch, 2020). En 2018, 65% des évaluations d'impact effectuées par DIME étaient des essais contrôlés randomisés, contre 20% pour les méthodes non-expérimentales, ce qui fait du DIME l'agence qui effectue le plus d'études RCTs au sein du groupe de la Banque Mondiale (Ravallion, 2020). En 2020, le J-PAL faisait état de 1012 RCTs réalisés ou en cours au sein de 83 pays (Ravallion, 2020). D'après Labrousse (2020), 952 études randomisées ont été comptabilisées au mois de juin 2019 tandis que le nombre de RCTs enregistré en sciences sociales était de 2552, soit un taux de 37.2%<sup>12</sup>. De plus, le rapprochement entre l'économie du développement et l'économie comportementale est également favorable à la montée en

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<sup>11</sup> Randomized Controlled Trials

<sup>12</sup> <https://www.socialscienceregistry.org/>

puissance des RCTs, qui opèrent une liaison entre les décideurs et les opérationnels publics et privés, afin de mieux appréhender le comportement des bénéficiaires. En effet, l'objet des évaluations expérimentales consiste à vérifier que les objectifs assignés à un projet ont été atteints, dans le but d'apporter une réelle plus-value sociale et économique (Crépon, 2008).

L'objectif des RCTs est donc d'isoler l'impact d'une activité entre un groupe de bénéficiaires (traité) et un groupe non bénéficiaires (témoin) d'un projet (Baudet, 2019). La constitution de ces deux groupes est réalisée au hasard. La légitimité du statut « d'étalon-or » des mesures expérimentales a révolutionné le domaine de l'évaluation d'impact, grâce à la validité du groupe témoin (contrefactuel). Les évaluations randomisées sont généralement considérées comme les plus rigoureuses et produisant des résultats plus exacts. Les évaluations RCTs ont donc pour principal objectif de corriger le biais lié à la sélection des populations ciblées. Les défenseurs de cet outil de mesure affirment que ce biais est particulièrement fréquent dans les études qui utilisent des méthodes non-expérimentales.

Néanmoins le statut « d'étalon-or » des RCTs est souvent au cœur des débats scientifiques. Deaton (2009) précise que les RCTs fournissent certes des informations sur l'impact moyen des effets d'une politique mais ne permettent pas d'identifier d'autres composantes de la distribution telles que l'effet médian d'une politique, qui pourrait être une modalité d'intérêt pour les opérateurs publics et privés. Par conséquent, l'impact moyen d'un projet obtenu à travers une analyse RCTs peut être limité pour un opérateur qui ne considère qu'une partie spécifique de l'activité. L'application des essais cliniques randomisés est légitime pour des projets spécifiques et précis (Bédécarrats et al., 2020). D'après Ravallion (2009), les RCTs analysent donc les facteurs de succès et d'échec d'une activité, mais ne fournissent aucune information sur les mécanismes sous-jacents (causes et processus). De plus, les études randomisées semblent être un outil limité aux projets d'infrastructures de faibles envergures, dans la mesure où il est plus complexe de randomiser des politiques de réformes sectorielles ou macroéconomiques (Ravallion, 2020).

Par ailleurs, Gertler et al. (2011) rappellent que deux principales limites se posent quant à la validité des évaluations. En l'occurrence, les outils de mesure randomisés comportent plusieurs limites empiriques susceptibles de biaiser les impacts d'une politique :

- La **validité interne** : il est possible, malgré la randomisation, que la comparabilité des groupes bénéficiaires et non bénéficiaires puisse être compromise.
  - En effet, les individus peuvent modifier leurs comportements s'ils ont connaissance de leurs assignations dans le groupe de traitement ou de comparaison (effet Hawthorne).
  - Les individus non bénéficiaires peuvent trouver un moyen d'accéder à l'activité, notamment en faisant des efforts supplémentaires (effet John Henry).
- La **validité externe** : est liée au caractère non généralisable des résultats de l'évaluation dans d'autres contextes, ainsi qu'à la représentativité de l'échantillon par rapport à la population ciblée.

D'un point de vue éthique, les RCTs essuient également de nombreuses critiques étant donné que le processus d'assignation aléatoire peut avoir recours à plusieurs effets pervers, tels que la monétisation pour bénéficier d'un projet. Ravallion (2020) rappelle que des évaluations randomisées non convenables sur le plan éthique peuvent être appliquées dans des zones où les droits des populations vulnérables ne sont pas protégés en raison de capacités institutionnelles insuffisantes.

Sur le plan financier, les essais aléatoires randomisés sont extrêmement coûteux (500 000€ en moyenne) et complexe à mettre en place, et s'avèrent inexploitables lorsque l'échantillon de bénéficiaires est trop restreint (Baudet, 2019). Il est donc compliqué de comparer le coût monétaire d'une politique, avec des bénéfices qui ne sont pas monétisés. Dès lors, les expérimentations aléatoires ne peuvent être mises en œuvre que s'il existe une très forte collaboration entre les opérationnels et les évaluateurs, et ce en amont du processus de financement d'un projet. Les RCTs représenteraient donc le pont entre le laboratoire et l'analyse « naturelle » des données (List, 2007).

### 2.3. Les méthodes d'évaluation quasi-expérimentales

D'autre part, Delarue and Cochet (2011) définissent les méthodes quasi-expérimentales comme étant une reconstitution ex-post de non bénéficiaires d'un projet, sur la base de caractéristiques observées et pertinentes. L'appariement par score de propension, les estimations par doubles différences et la discontinuité des régressions, sont différentes méthodes d'évaluation non-expérimentales qui tentent de résoudre le problème du biais de sélectivité. Ce biais apparaît lorsque la participation des bénéficiaires à un projet est corrélée aux résultats du projet (Gertler et al., 2011). Par exemple, certains paramètres tels que le lieu de résidence des bénéficiaires peuvent générer un biais de sélection.

L'un des principaux objectifs des études d'impact est de réduire au maximum ce biais de sélectivité, en comparant un groupe de bénéficiaires à un groupe de non bénéficiaires qui ont exactement les mêmes caractéristiques, excepté la participation au programme mis en place. Toutefois, certaines caractéristiques, spécifiques à chaque individu, sont difficilement observables et mesurables. Pour atténuer ce biais, Ravallion (2020) suggère de renforcer la qualité des données collectées. Selon Delarue and Cochet (2011), l'objectif des évaluations quasi-expérimentales est de mesurer la différence entre deux situations :

- Celle résultant de la mise en place d'un projet.
- Celle qui aurait prévalu si le projet n'avait pas été mis en œuvre (contrefactuel).

Autrement dit, l'estimation de ce contrefactuel permet de mesurer le résultat pour les bénéficiaires si le projet n'avait pas été mis en œuvre. Quand bien même, la reconstitution du scénario « sans projet » repose souvent sur les choix subjectifs de l'évaluateur, sa construction permet de ne pas faire l'erreur d'attribuer au projet les effets qu'ont eus les dynamiques endogènes et exogènes sur les individus. Ces dynamiques sont des facteurs inobservables qui pourraient influencer la sélection de l'échantillon et différencier les

bénéficiaires des non bénéficiaires. Ceci représente donc un défi méthodologique majeur, impliquant de multiples conditions détaillées ci-dessous.

Les méthodes d'appariements, qui associent bénéficiaires et non bénéficiaires sur la base de leurs caractéristiques observables communes, déterminent le contrefactuel ex-post. Il est donc primordial de s'assurer, dès le début de l'évaluation, que les individus issus des deux groupes possèdent des caractéristiques les plus semblables possibles. Dès lors, cet outil de mesure d'impact génère un groupe témoin artificiel formé par les individus appariés qui ne bénéficient pas du projet, afin d'estimer le contrefactuel (Gertler et al., 2011). Par exemple, le programme d'emploi public argentin *A Trabajar* a été évalué par Jalan and Ravallion (2003) auprès de participants et de non participants. Grâce à l'utilisation du score de propension, les auteurs démontrent que le programme a entraîné une hausse moyenne des revenus des bénéficiaires, équivalente à la moitié du salaire brut argentin.

Cette méthodologie permet certes de corriger le biais de sélectivité, toutefois elle requiert un large échantillon de données afin de couvrir la gamme de caractéristiques observables la plus vaste possible, mais également d'avoir à disposition des données de référence collectées avant la mise en place du projet, afin de contrôler les disparités préexistantes entre les deux groupes. Cette démarche est souvent contraignante sur le plan des ressources financières et humaines. Hormis l'importance de disposer d'une large base de données, développée en amont du lancement d'un projet, la principale limite de l'évaluation par appariement provient de son hypothèse forte reposant uniquement sur les caractéristiques observables des bénéficiaires et non bénéficiaires. Or, il existe des facteurs inobservables, telle que la motivation des individus, qui sont par essence omis et ne sont pas inclus dans la construction de l'appariement. Dans ce cas, cet outil de mesure atténue probablement le biais de sélectivité, mais n'a aucune incidence sur le biais induit par ces caractéristiques inobservables. Le biais de sélectivité resterait donc important, dans la mesure où l'écart entre les résultats moyens des deux groupes générés par les inobservables est attribué au projet. Ainsi, l'évaluation d'impact par le mécanisme d'appariement est souvent utilisée en dernier recours.

Puis, la méthode de la double différence (DD) estime le contrefactuel en prenant en compte les différences invariables dans le temps entre les bénéficiaires et non bénéficiaires (Gertler et al., 2011). Autrement dit, elle mesure le changement au fil du temps des bénéficiaires par rapport au changement des non bénéficiaires (Le Ster, 2011). Cette méthodologie repose certes sur des hypothèses contraignantes en s'appuyant sur des données de référence collectées en amont du déploiement d'un projet, mais constitue également un puissant outil statistique. La double différence repose principalement sur les étapes suivantes :

- La première différence est effectuée deux fois, au niveau de la population bénéficiaire (avant et après le projet) et du groupe des non-bénéficiaires (avant et après).
- La seconde différence qui correspond à la différence entre ces deux premières différences (différence du groupe bénéficiaire – différence du groupe non-bénéficiaire).

Ces deux étapes permettent de corriger le biais lié aux effets des facteurs externes et variables dans le temps, sur l'impact pour les bénéficiaires. Ainsi, la double différence combine simultanément deux types de comparaison entre les bénéficiaires et non bénéficiaires : avant-après et avec-sans. Cet outil de mesure est l'une des stratégies quasi-expérimentales les moins contraignantes. En effet, elle ne requiert pas d'hypothèses d'assignation ou d'équivalence de caractéristiques entre les deux groupes. C'est pourquoi Bensch et al. (2013) ont pu déterminer l'impact de l'accès à l'électrification solaire au sein des ménages de Kéné Dougou (Burkina-Faso), à travers l'approche de la double différence. Les auteurs soulignent que l'accès à l'énergie solaire a permis une réduction des cambriolages à domicile de 9.1%.

Cependant, l'hypothèse forte de la DD repose sur l'existence de tendances équivalentes entre les deux groupes. Cela correspond à l'une des principales limites de cette méthodologie, étant donné que les deux groupes possèdent également des caractéristiques différentes et inobservables qui peuvent influencer sur l'impact de l'activité. Pour pallier à cette limite, il est possible d'effectuer un test en comparant les tendances des deux groupes avant la mise en œuvre du projet. Cela nécessite donc au minimum trois vagues de données pour chaque groupe : deux vagues avant la réalisation du projet et une vague ex-post. Néanmoins, l'évaluation d'impacts par la double différence demeure l'une des méthodes statistiques les plus utilisées dans le domaine de l'économie du développement.

Enfin, le modèle de discontinuité de la régression est une méthode d'évaluation d'impact qui convient aux projets pour lesquels un indice d'éligibilité est établi, ainsi qu'un seuil clairement défini pour distinguer les bénéficiaires des non bénéficiaires. Ces deux conditions prévalent donc à l'application de cette méthodologie :

- Indice d'éligibilité : indicateur continu permettant de classer la population à l'étude (indice de pauvreté, âge, etc.).
- Seuil d'éligibilité : qui détermine un niveau de l'indice au-dessus ou au-dessous duquel la population est considérée comme bénéficiaire du projet.

Les bénéficiaires et non bénéficiaires (proches) se situant de part et d'autre du seuil d'éligibilité ont des caractéristiques similaires. L'estimation du contrefactuel s'effectue alors en produisant un groupe témoin composé des non bénéficiaires qui sont proches du seuil d'éligibilité. L'objectif est d'estimer l'impact d'un projet en se concentrant uniquement sur les individus se situant juste en dessous du seuil (groupe non bénéficiaire) et sur ceux qui se situent juste au-dessus (groupe bénéficiaire). Le modèle fait l'hypothèse que les personnes aux alentours du seuil d'éligibilité sont très similaires, ce qui permet d'obtenir une estimation non biaisée de l'impact moyen local aux alentours de ce seuil d'éligibilité. Après la mise en place du projet, cet écart moyen local entre les deux groupes correspond à l'impact du projet.

A titre d'illustration, le programme de réduction des frais de scolarité en Colombie (*Gratuidad*) a permis au gouvernement de cibler les populations bénéficiaires à l'aide d'un indice de pauvreté (SISBEN). Cet indice définit deux seuils d'éligibilité au programme. Dans ce cadre, Urquiola et al. (2013) ont conduit une analyse RDD, qui révèle que le programme a généré une hausse du taux de scolarisation de trois

points pour les élèves d'écoles primaires dans la ville de Bogota. L'approche par la discontinuité de la régression est donc souvent employée pour l'évaluation de projets sociaux, comme ce fut le cas du programme *PROGRESA* au Mexique, pour lequel Buddelmeyer et Skoufias (2004) ont constaté que les résultats obtenus en utilisant les RDD étaient semblables à ceux obtenus par le mécanisme des évaluations expérimentales. Les auteurs rappellent également que la réduction ou l'extension d'un projet ne peut avoir lieu sous l'utilisation de l'analyse RDD. En effet, la méthode RDD ne fournit que le résultat de l'impact local moyen qui correspond à l'impact autour du seuil d'éligibilité, ce qui n'indique rien de l'impact marginal du projet pour les autres personnes qui sont significativement au-dessus ou en-dessous du seuil et qui ne sont pas dans l'analyse.

Ceci pose également un problème de puissance statistique, qui peut s'avérer insuffisante puisque que l'estimation de l'impact moyen local ne dispose pas d'un échantillon de population important par rapport aux autres méthodes d'évaluation. Ainsi, plus la bande d'éligibilité est large, plus la puissance statistique est élevée étant donné que l'on prend en compte un plus grand nombre d'observations. Enfin, il est nécessaire de tenir compte de la complexité des relations entre le seuil d'éligibilité et le résultat d'une politique, en appliquant différentes formes fonctionnelles de modélisation (linéaire, quadratique, cubique, etc).

## 2.4. Motivations

Cette thèse CIFRE<sup>13</sup> contribue à une meilleure compréhension des méthodes d'évaluation d'impact pour l'industrie de l'impact, notamment à travers la collaboration interdisciplinaire entre les acteurs académiques et opérationnels du développement. Le fonds d'investissement d'impact Investisseurs et Partenaires (I&P) fournit des résultats de développement à ses investisseurs qui soutiennent les petites et moyennes entreprises (PMEs) et les start-ups d'Afrique sub-saharienne. Ce sujet de thèse a des conséquences sur le travail méthodologique des activités opérationnelles d'I&P, principalement à travers les questions de l'impact et de l'ESG<sup>14</sup>. L'amélioration des méthodologies d'évaluation d'impact est essentielle pour l'industrie de l'impact, principalement pour les bailleurs de fonds. De manière substantielle, ces interactions entre les acteurs du développement permettent la création de bases de données originales telles que la Collaborative Smart Mapping of Mini-grid Actions (CoSMMA) dans le premier chapitre, mais également d'avoir accès à des données d'enquête terrain originales dans le second chapitre.

L'objet de cette thèse est donc d'identifier les outils d'évaluation d'impact qui permettent de mesurer les effets directs et indirects des projets de petite échelle financés par les acteurs du développement. En effet, les acteurs publics et privés du développement mènent de plus en plus de projets durables ayant un fort impact sur les populations locales. Ainsi, il est important de déterminer le contenu local des projets en

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<sup>13</sup> Convention Industrielle de Formation par la Recherche

<sup>14</sup> Environnement, Social, et Gouvernance

faveur du développement durable et d'analyser leurs résultats en utilisant différentes mesures d'évaluation d'impact. Par conséquent, l'intérêt de cette thèse est d'identifier des outils d'évaluation d'impact robustes et adaptés aux activités des opérateurs privés du développement, dans le but de mesurer les effets directs et indirects de leurs activités. A cet effet, ce travail répond à trois problématiques principales concernant le rôle des mesures d'impact sur les résultats directs et indirects des projets de développement durable. Par conséquent, ces trois questions soulevées dans cette thèse ont une pertinence directe pour les bailleurs de fonds privés tels que I&P.

Le premier chapitre permet de comprendre les effets des différentes méthodes d'évaluation d'impact, à travers une méta-analyse qui compare les techniques d'évaluation selon les résultats des projets d'électrification décentralisée (DEPs). Cette stratégie empirique permet d'analyser l'épistémologie des approches méthodologiques. Les résultats révèlent qu'il y a une convergence des méthodes d'évaluation d'impact expérimentale et quasi-expérimentale pour trouver un effet significatif et positif des DEPs sur les indicateurs des ODD. En termes de décisions politiques, les résultats du chapitre ont des implications majeures pour les opérateurs publics et privés dans le domaine du développement, principalement pour le domaine des projets d'infrastructure à petite échelle. Ce chapitre a donc une influence sur le type d'évaluations d'impact à moindre coût pour les projets de développement.

Puis, le deuxième chapitre co-écrit avec Enoch Owusu-Sekyere et Esther Leah Achandi intervient à un moment où les investisseurs du développement ont de fortes activités dans le domaine de l'énergie verte et décentralisée en Afrique. Cette étude examine l'impact du système d'énergie solaire Rensource sur les revenus des commerçants dans les marchés du Nigeria. Nous avons mené une enquête de terrain auprès des commerçants des marchés situés dans les États de Lagos, Kano et Ondo. Nos résultats montrent que les commerçants abonnés à la solution solaire Rensource ont vu leurs revenus en moyenne augmenter de 23 à 27%, et ont réduit leurs dépenses mensuelles moyennes en électricité de 36%. Le Nigeria étant le pays le moins fiable en matière d'électrification et le plus peuplé d'Afrique, le fait d'aborder ces questions pour ce pays peut mettre en lumière les impacts redistributifs des projets de développement à petite échelle pour les populations locales, d'une part ; et d'autre part, aider les petites et moyennes entreprises privées du secteur de l'énergie à améliorer leurs produits et leurs stratégies de sensibilisation des clients, ce qui constitue une contribution essentielle à la relation entre la transition énergétique et le bien-être durable. De toute évidence, il est important de comprendre l'impact de l'activité renouvelable hors réseau afin d'établir un lien entre la concessionnalité de l'investissement et les résultats.

Enfin, à Madagascar, les donateurs ciblent des programmes de biodiversité par le biais du secteur privé national. Ces programmes soutiennent les activités productives autour des aires protégées (AP). Par conséquent, il est important de savoir quel est l'impact de ces aires protégées afin de créer des programmes innovants qui répondent à la fois aux objectifs environnementaux et socio-économiques. Le troisième chapitre met donc en évidence la relation entre la protection de la biodiversité et l'accès à l'énergie. En effet, le changement climatique accroît les réglementations environnementales mises en place par les pays en développement. Dans cette optique, ce chapitre analyse l'impact des aires protégées



sur le pourcentage de consommation de combustible de cuisson à base de ligneux des groupes de ménages malgaches, à travers une évaluation d'impact spatial innovante reposant sur l'utilisation de données satellitaires qui sont un instrument de mesure efficace des externalités environnementales. En effet, ces dernières années les données sur les indicateurs environnementaux connaissent un fort accroissement, notamment grâce aux partages de données de la NASA<sup>15</sup> et à la création de plateformes digitales gratuites telles que *Digital Earth Africa*. De plus, il y a un accroissement de l'accès aux enquêtes géocodées à l'échelle des zones d'intervention des projets. Ainsi, l'évaluation d'impacts géospatiale (GIEs<sup>16</sup>) permet de mesurer les externalités environnementales positives et négatives des projets de développement. Le centre de recherche (Aiddata) du Collège de William et Mary a construit un outil de répertoire et d'extraction de données spatiales appelé GeoQuery. BenYishay et al. (2017) soulignent que la méthode des GIEs s'applique dès lors que la couverture géographique s'appuyant sur les coordonnées GPS et temporelle de la mise en place d'une activité est définie et précise. Les auteurs notent également que les évaluations d'impacts géospatiales comportent plusieurs avantages pour les développeurs de projets et les évaluateurs. Les GIEs permettent de créer les conditions similaires aux RCTs, mais sans avoir recours au processus d'assignation aléatoire des individus entre les groupes traités et témoins (BenYishay et al., 2017). Les GIEs reposent également sur des méthodes quasi-expérimentale d'inférence causale pour mesurer les impacts des projets de développement.

Les principaux résultats suggèrent qu'autour des frontières des zones protégées, la part de bois de cuisson consommée des groupes de ménages situés à l'intérieur des zones protégées augmente significativement de 0,62 point de pourcentage, par rapport à la part consommée des groupes situés en dehors des limites des AP. À l'inverse, la part consommée de charbon de bois des groupes de ménages situés à l'intérieur des AP diminue de 0,56 point de pourcentage, par rapport au pourcentage consommé par les groupes résidant à l'extérieur. Ces résultats soulignent que l'efficacité des politiques environnementales doivent prendre en compte les impacts sur les communautés locales. Ainsi, cette étude contribue à l'orientation des acteurs du développement dans leurs décisions politiques et leurs choix d'investissement, afin de répondre aux indicateurs des ODD.

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<sup>15</sup> National Aeronautics and Space Administration

<sup>16</sup> Geospatial Impact Evaluations

# Chapter ONE: Is it possible to evaluate at the lowest cost?

## Evidence from a meta-analysis on decentralized projects

### Abstract

This study compares the estimates of impact evaluation methodologies on the outcomes of decentralized electrification projects (DEPs) in developing countries. The added-value of this meta-analysis concerns the convergence or not of impact evaluation techniques on project outcomes. Therefore, the objective for development actors is to know whether it is possible to evaluate at the lowest cost. Data originate from the Collaborative Smart Mapping of Mini-grid Actions (CoSMMA) developed by the Foundation for Studies and Research on International Development (FERDI). This study is based on a total of 879 measured effects from 22 DEPs evaluated by only 22 studies using experimental and quasi-experimental approaches. Using a multinomial-logit regression, I find that randomized and non-randomized evaluation methods converge on the probability to find positive and negative outcomes of decentralized electricity projects. By estimating a complementary log-log model, projects are most often evaluated as successful when effects on the sustainable development goals (SDGs) 7 (energy basic access) and 9 (information and communication) are tested. Moreover, performing the analysis on a homogeneous sample of DEPs implemented in Africa, I find consistent results with my main estimation. Meaning that the different types of assessment methods converge to conclude a successful outcome of African renewable off-grid projects. Findings from this paper are obviously limited by the small sample of studies included in the meta-analysis, but provide strong evidence for development practitioners in their choices to use the appropriate impact assessment method for small-scale infrastructure projects.

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*The usual disclaimers apply.*

## Introduction

Over the past several decades, debates within the development economics field regarding impact evaluation methodologies have rapidly increased. Impact assessment provides guidance that informs policy-makers and practitioners in their decision-making strategies. Funders and operators increase their investment in impact assessment and strengthen their partnerships with researchers in order to accurately identify the results of their projects and programs. Specifically, the expansion of impact assessment in development economics highlights the lack of knowledge regarding the effects of impact evaluation tools on assessed outcomes.

The need for short and mid-term results increase the demand for diverse, flexible, and rigorous impact measurement tools. To that extent, Africa's Pulse report (2018), published by the World Bank, gathers numerous studies which use several impact assessment techniques. The classic impact methods, performed through quasi-experimental strategies, are based on observational models and standard theories. According to Banerjee (2020), the rise of natural experiments during the last two decades has created new frameworks and theories about poverty and development issues.

This paper contributes to the impact evaluation literature by analyzing whether randomized and non-randomized methods have the same impact or not on the probability of finding success or failure of decentralized electricity projects. Indeed, the assessment of development project outcomes is becoming an increasingly important issue for both academics or public and private operators. Cameron et al. (2016) observe a record of 4,600 published evaluations in June 2018, while only 132 experimental and quasi-experimental evaluations were published prior to 2000. According to development actors, project impact assessments are a key matter in development economics. Different tools and assessment methodologies are used, which mainly rely on experimental and quasi-experimental strategies.

However, the main constraints of impact evaluation arise from statistical and technical characteristics. For instance, there is a mismatch of time frames between academics, investors, and operators in the development field. This is supported by Bédécarrats et al. (2020), who argue that method constraints can force researchers to restrict themselves to short time frames and specific populations or geographic areas, and therefore produce unusable results. On the other hand, the cost of impact evaluation is a major challenge which can constitute on average 10% of the total cost of small-sized projects<sup>17</sup> and can thus influence the choice of methodology employed. For example, the cost of specific methodologies may not be feasible for some private operators and investors for whom short term financial performance and gain are the main decision criteria.

A broad swath of the literature finds evidence of statistical and technical differences among impact evaluation methods (Duflo, 2005), while a minority concludes that, for specific development projects, their outcomes do not really differ according to the methodology that has been used (Rodrik,

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<sup>17</sup> (CLUB-ER et FERDI, 2019)

2008). Currently though, there is limited empirical evidence for measuring the outcomes of development projects through the estimates of different impact assessment methods (Glazerman et al., 2003).

Thus, using an original meta-data set which gathers 151 scientific assessment studies of 483 decentralized electrification projects (DEPs) deployed in 62 developing countries for the period 1981-2019, I contribute to the broader literature of impact assessment by simultaneously comparing the effect of both randomized and non-randomized methodologies on project outcomes. Furthermore, this research highlights the conditions under which there is a discrepancy or convergence of the estimates generated by experimental and quasi-experimental methods. As observed by Camfield and Duvendack (2014), there is a need to conduct meta-analyses, which are still too scarce in development economics.

As meta-analysis is a valuable technical input which allows us to address the matter by comparing the impact of several studies. The interest of the meta-analysis is to provide a consolidated result and to control a certain type of bias from first-hand studies. The main objective of this paper is to identify whether the estimates of impact evaluation methods converge or diverge on the same outcomes of DEPs.

Obviously, the purpose of this paper is not to renew the debate on randomized control trials (RCTs) versus non-RCTs, but to go beyond these discussions by identifying the effects of small-scale infrastructure projects according to the impact assessment methods that has been used. This meta-analysis provides a quantitative literature review that shows that there is no systematic difference between impact assessment methods. However, the conclusions of the meta-analysis highlight economic policy implications which report that the evaluation methods do not have the same cost: randomized control trials and field surveys are very expensive. So, if one can show that there is no difference in the evaluation, that is a key lesson. Consequently, the policy recommendation is to select the least expensive methodology to evaluate electricity access.

Therefore, this study is a plea for economic development actors to adopt an economic perspective rather than a technical one. To shed light on this issue, I use a multinomial logit model to simultaneously analyze the effects of impact evaluation methods on four possible evaluation outcomes based on the characteristics of 22 off-grid systems, which have been evaluated in 22 scientific studies: *proven-favorable*, *proven-unfavorable*, *unproven-favorable*, *unproven-unfavorable*. To the best of my knowledge, there is no other comparative study of impact evaluation techniques applied to small-scale infrastructure projects in developing countries. Indeed, using the results of similar studies to highlight the impact of statistical techniques is challenging. There is only a sole meta-study developed by Berthélemy and Millien (2018) which looks at the impact of DEPs' characteristics on sustainable development.

Empirical findings from my research reveal that there is a convergence between randomized and non-randomized methods on the positive and significant outcome of DEPs. This finding occurs mainly when

the projects have successful impact on energy basic access and information and communication sectors. I also find the same convergence for DEPs which have a negative proven impact on sustainable development effects. These findings are obviously limited by the small sample of papers included in the meta-analysis, but provide strong evidence for development practitioners in their choices to use the appropriate method to assess small-scale infrastructure projects at the lowest cost.

Finally, my robustness tests show that my baseline results hold when I restrict my sample to decentralized projects implemented in Africa. This is a valuable contribution to the discussions concerning the extension and generalization of impact assessment policies, as well as the context settings. This evidence also provides stronger empirical conclusions on the uneven geographical distribution of impact evaluations, which are influenced by the connections between researchers and local entities such as non-governmental organizations (NGOs) (Ravallion, 2020).

This paper presents the related literature and research question in [Section 1](#). In [Section 2](#) the data and the key descriptive statistics are explored. [Section 3](#) sets the methodological strategy. [Section 4](#) presents the main empirical results and [Section 5](#) challenges the robustness of the evidence. Finally, I conclude and discuss the findings in [Section 6](#).

# 1. Related literature and research question

## 1.1. The contribution to the meta-analysis literature in development economics

Stanley and Jarrell (1989, p.161) define meta-analysis as "the regression analysis of regression analyses". Originally developed in medical research, meta-analysis in economics has been used to "calibrate structural models, examine patterns of publication bias, and explain the differences in the results of individuals studies" (Berthélemy and Millien, 2018, p.7). Doucouliagos and Paldam (2007), who perform a quantitative forensic analysis of the aid effectiveness literature.

Meta-studies identify the weakness of primary research and give more precision and representativeness to an estimate of treatment effects (Pang et al., 1999; Simes and Glasziou, 1992; Mugford et al., 1989). The methodology of meta-regressions goes beyond classification studies and qualitative review of structural models and estimates.

In the matter of energy efficiency, Labandeira et al. (2020) conduct a meta-analysis to measure the effects of energy efficiency policies regarding energy demand and the price of associated durable goods. They use 366 research papers on energy efficiency policies, which provide 1,375 estimates of the impact on energy demand and 108 estimates on the price of durable goods that consume energy. They find a significant reduction in energy demand, which is even greater for studies based on experimental designs, mostly because experimental studies are more likely to get published in top ranking journals.

On another issue, Corduneanu-Huci et al. (2021) published a seminal work in the field of political economics by assessing the impact of political environments on public policy design. They argue that RCTs occur mostly in Indian state jurisdictions where political competition is in a paroxysm. The authors identify this relationship through a "supply" (from researchers, institutions, NGOs, and donors) and a "demand" (from governmental decision-makers and channel drivers), which reveals the "political site selection bias" in the RCT field. Their study echoes the debate regarding what impact assessment method selection should be used to evaluate the effects of the Sustainable Development Goals (SDGs). It is shown in [Section 5](#) that this cognitive bias also affects the outcomes generated by off-grid projects.

## 1.2. Why is impact assessment fundamental for development economics?

Pamies-Sumner's study (2014) highlights the wide expansion of impact evaluations of development projects during the 1990s, when funders and researchers in the development field examined the effectiveness of development assistance. According to Gertler et al., (2011), the prospective impact studies aim to measure whether development projects achieved their expected results or not, and thus evaluate several policies to measure these results. Thus, impact measurements allow us to empirically assess the outcomes of projects by ensuring that development actors make the trade-off between the potential benefit and harm of their activities. Empirical investigations allow researchers, donors, policymakers, and operators in development economics to identify what projects work and in which context.

Thanks to the measurement of welfare changes for recipients, impact evaluations are seen today as global public goods, as they reflect reliable toolkits for public and private decision-makers, especially with the fundamental shift in development economics toward the issues of private goods access in rural development, health and educational matters that occurred in the 1970s (Morduch, 2020).

Hence, impact evaluations rely on a wide range of measurement techniques that effectively isolate project impacts (Baudet, 2019). These causal inference methodologies calculate a counterfactual which compares the changes for recipients to the prevailing situation if the project had not been implemented.

However, the greatest challenge of impact assessment is to find out what works and where, under different circumstances (Deaton, 2020). Ravallion (2020) highlights the importance of the choice of impact method according to the identification of the relevant counfounders, the type of project, the budget cost of the evaluation, the sample size covered by a project, and the impact parameters. This allows policymakers and practitioners to acknowledge the benefits and failures of their funded projects. The identification of a project's relevance requires knowledge on structural-econometric methods (Ravallion, 2020). On the other hand, impact evaluations also provide evidence on the efficacy of development projects and can help to improve some aspects of their implementation (Legovini and al., 2015).



### 1.3. Convergence or discrepancy between impact assessment methodologies?

For the past decades, several impact evaluation techniques have been applied in order to analyze the successes and failures of development projects. These methodologies rely mainly on quantitative and scientific parameters, under experimental and quasi-experimental modeling.

Experimental methodologies are mainly based on randomized control trial settings, which isolate the impact of projects by comparing, through a lottery draw, for instance, the behavior of recipients and non-recipients. According to promoters of randomization, such as Esther Duflo (2005) from the J-Pal<sup>18</sup> research laboratory, RCTs enable researchers to measure causal inference and to better correct selection bias, unlike non-randomized techniques. RCTs are considered as the gold standard research design, followed by observational studies (Pang et al., 1999). Therefore, development economists have been widely using RCTs for the past two decades (Deaton, 2020).

However, Rodrik (2008) and Deaton (2009) highlight the lack of statistical power and the operational limits of the randomization approach. Indeed, RCTs encounter the same issues as observational studies of internal validity caused by the circumstances of the project and the behavior of recipients and non-recipients throughout the intervention, as well as by the external validity of the evaluation design, based on the context and the wider application of development projects. These limits raise the question of representativity of the samples compared to the targeted populations. As expressed by McKenzie (2012), this weakens the ability to draw conclusions and would require unrealistic sample sizes. Deaton (2020) adds that RCTs are affected by the same issues of inference and estimation of other methods.

Quasi-experimental methods try to correct these limits and reduce the selection bias by simulating the framework conditions of an experiment with an ex-post design of the counterfactual, such as the matching technique, which identifies and matches recipients to the most equivalent non-recipients based on their observed characteristics. Moreover, the Difference-in-Difference (DiD) approach can estimate the counterfactual for the impact variation of recipients by using the variation of non-recipients. Next, the Regression Discontinuity Design (RDD) measures the local average impact near an index of eligibility, which is a threshold that differentiates beneficiaries and non-beneficiaries. Therefore, the debate regarding the robustness of impact estimates has led to a dichotomy framework between experimental and quasi-experimental methodologies in the sustainable development field (Bédécarrats et al., 2017). To that extent, Lalonde (1986) conducts a replication study of an RCT design of the US Job Training Partnership Act program and finds that several papers show significant disparities between experimental and quasi-experimental methods.

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<sup>18</sup>Abdul Latif Jameel Poverty Action Lab

As one can observe in [Appendix A.1](#), the application gap among impact evaluation methods has increased during the past few decades, mainly with the predominance of RCT studies. The International Initiative for Impact Evaluation (3iE) reveals that more than 300 RCT studies were conducted in 2012 (Review 3ie, 2018). The prevalence of RCTs is also reflective in the decentralized electricity access field, with more than 200 effects measured and recorded in the Collaborative Smart Mapping of Mini-grids Actions (CoSMMA) database developed by the FERDI ([Appendix A.2](#)). This evidence converges with the trend noted by Picciotto (2020), who observes that 62% of impact evaluations included in the 3iE repository used only RCTs, and 5% used a mix of RCTs and quasi-experimental techniques. This finding is supported by Banerjee et al. (2020) who argue that among the development papers published in the top 5-ranked economics journals, the number of RCTs papers went from 0 in 1990 to 10 in 2015. However, the trend presented in [Appendix A.2](#) describes that between 2017 and 2018, the application of quasi-experimental methods was regaining the impact assessment field of decentralized electrification projects.

On the other hand, Heckman et al., (1997) assess that there is a quasi-neutrality of the selection bias when non-experimental techniques are applied. Afterwards, Glazerman et al., (2003) come to a similar finding by synthesizing the design of replication studies which used earnings as an outcome. The authors consider the discrepancy between experimental and non-experimental estimates as the impact bias. They find an alleviation of the bias between experimental and non-experimental estimators, mostly when the matching measure has been applied and the sample is weighted. Vivalt (2020) fails to reject the null hypothesis that effect sizes estimated by RCTs and non-RCTs are the same for a sample of 635 studies in international development. It is worth noting that Buddelmeyer and Skoufias (2004) find an equivalence between the randomized and non-randomized outcomes of Mexico's *PROGRESA* conditional cash transfer program evaluation. Their findings are substantial, given that broader RCT studies have been conducted to assess this same conditional cash transfer program in Mexico (Gertler and Boyce, 2003).

## 1.4. Research question

The aim of this paper is to compare the effects of impact assessment methods on the outcomes of development projects, using data collected in the CoSMMA database and developed by the FERDI (2019). Ravallion (2020) highlights that there is a need for more research on the distribution of estimates from observational studies, and that they should be compared with estimates from RCTs in the same setting. With the introduction of the characteristics and effects of decentralized electrification projects, I address the following research questions: i) Is there a convergence or discrepancy between the impacts of randomized and non-randomized methodologies on the results of decentralized projects? ii) Which evaluation methods are most likely to conclude success or failure of decentralized projects?

Obviously, the RCT versus non-RCT debate is well-known, which is why the additional value of this study is to provide insights and empirical facts to the impact evaluation literature, in line with the meta-analysis conducted by (Berthélemy and Millien, 2018). While most of the studies in the literature perform distinguished analyses of impact methodologies, to my knowledge my empirical study is the first to carry out a simultaneous comparison of impact evaluation techniques for the same setting, which assembles decentralized electricity projects which have been implemented in developing countries.

Furthermore, this research provides evidence that indicates whether experimental and quasi-experimental approaches find divergent or convergent outcomes from decentralized projects. These findings can shed light on best practices that public and private developers can rely on for the impact assessment and monitoring policies of their development projects.

To address the previous questions, this research focuses on small-scale infrastructure projects from the decentralized electrification sector, which enjoys the availability of data and also represents a growing research matter in development economics. As the decentralized electrification sector focuses on the last mile problems context, policymakers and practitioners need to evaluate their investments. In order to test my assumptions, the empirical model analyzes at the baseline data of a homogenous sample of decentralized projects, but one with disparities on governance schemes, geographical locations, and produced effects.

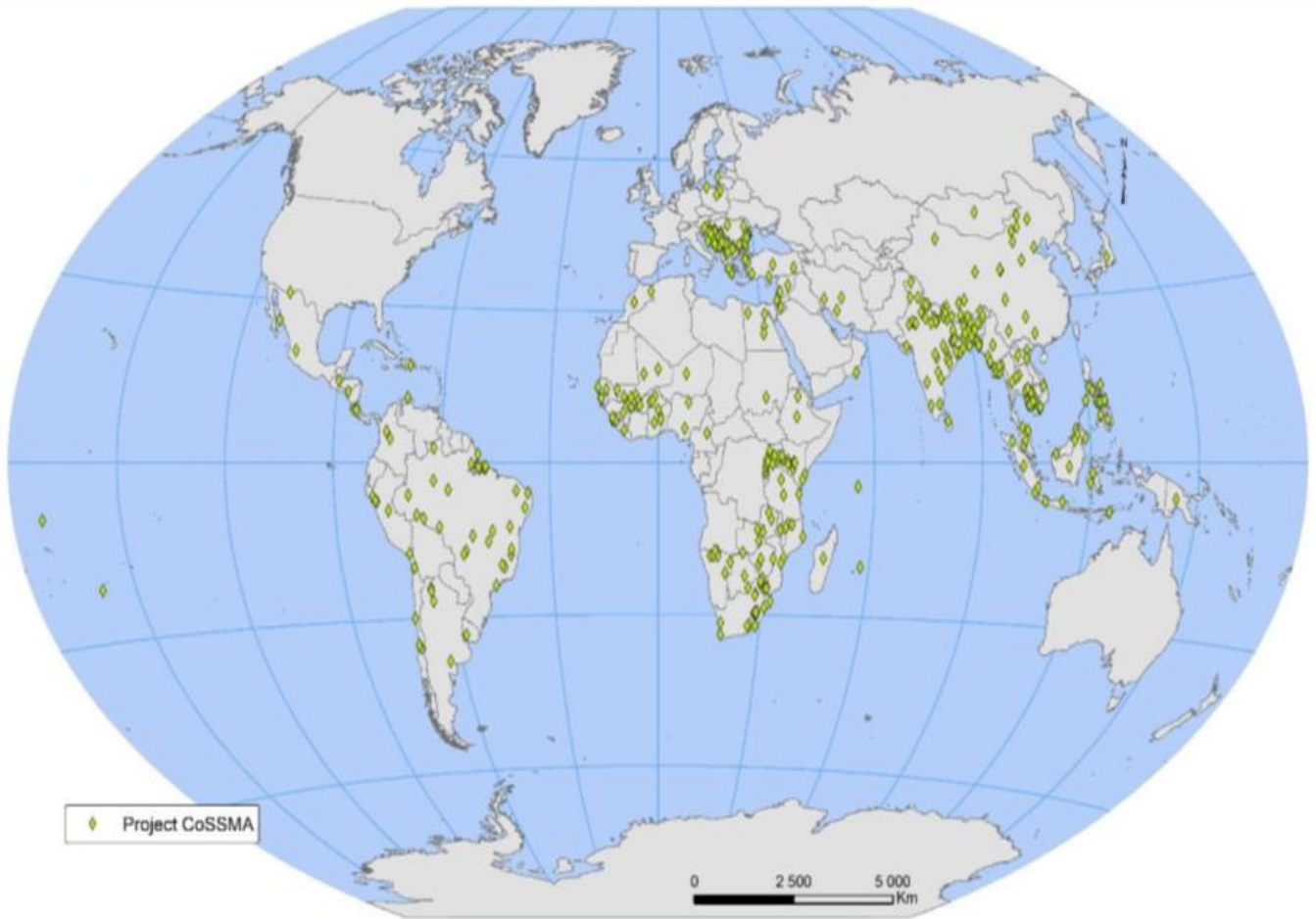
## 2. Data source and stylized facts

### 2.1. The CoSMMA database

Following the methodological steps of Berthélemy and Millien (2018), my study is the first meta-analysis in the development economics literature which attempts to relate impact evaluation techniques with the outcomes generated by off-grid projects. Such an approach is relevant for economists, given that the combination of data from studies using different designs is advantageous to external validity strategies and policy decision-making (Pang et al., 1999).

The CoSMMA database, developed by the FERDI and the University of Paris 1 Panthéon-Sorbonne, is an information instrument for the analysis and comparison of decentralized electrification projects. The CoSMMA illustrates the assessment of socio-economic benefits of decentralized electrification based on the specifications and on the observed, measured, and tested effects of projects, with the aim of highlighting the most efficient projects, namely those which generate the expected socio-economic effects. Therefore, this geographical and technical mapping tool allows the identification of implemented and evaluated projects, as well as for the identification of their impacts on targeted beneficiaries. [Figure 1](#) shows a broad and proper geographical distribution of all the DEPs (all types of technologies) implemented in developing countries and collected by the CoSMMA.

Figure 1: CoSMMA map



Source: CoSMMA, 2018

The source of information of the CoSMMA comes from two large document categories:

- Research papers reviewed by a referee committee and published in a scientific Journal.
- Institutional reports.

In order to display how the CoSMMA was built as well as the selection process of the DEPs, I rely on a Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) scheme in [Figure 2](#). The PRISMA is a diagram which presents “an evidence-based minimum set of items for reporting in systematic reviews and meta-analyses” (Page et al., 2021). [Figure 2](#) demonstrates that the literature of the CoSMMA relies on four scientific and economic database searches gathered by the online *EBSCO* library, through keyword searches which produced six sets of articles called "packs" or "bunches"<sup>19</sup>: *Academic Search Premier*, *Business Source Complete*, *EconLit*, and *GreenFILE*. This sampling by keyword searches gives a random selection of DEP assessment studies. Almost 90% of the evaluation documents are published or working papers from scientific journals, and 10% are from institutional or corporate reports in the energy sector.

As a result of this selection, the CoSMMA has collected the following data:

- **483** decentralized electrification **projects**;
- deployed in **561** **production units**;
- located in **62** **countries**;
- from **151** **scientific assessment documents**;
- that describe **3,162** **observed and tested effects**.

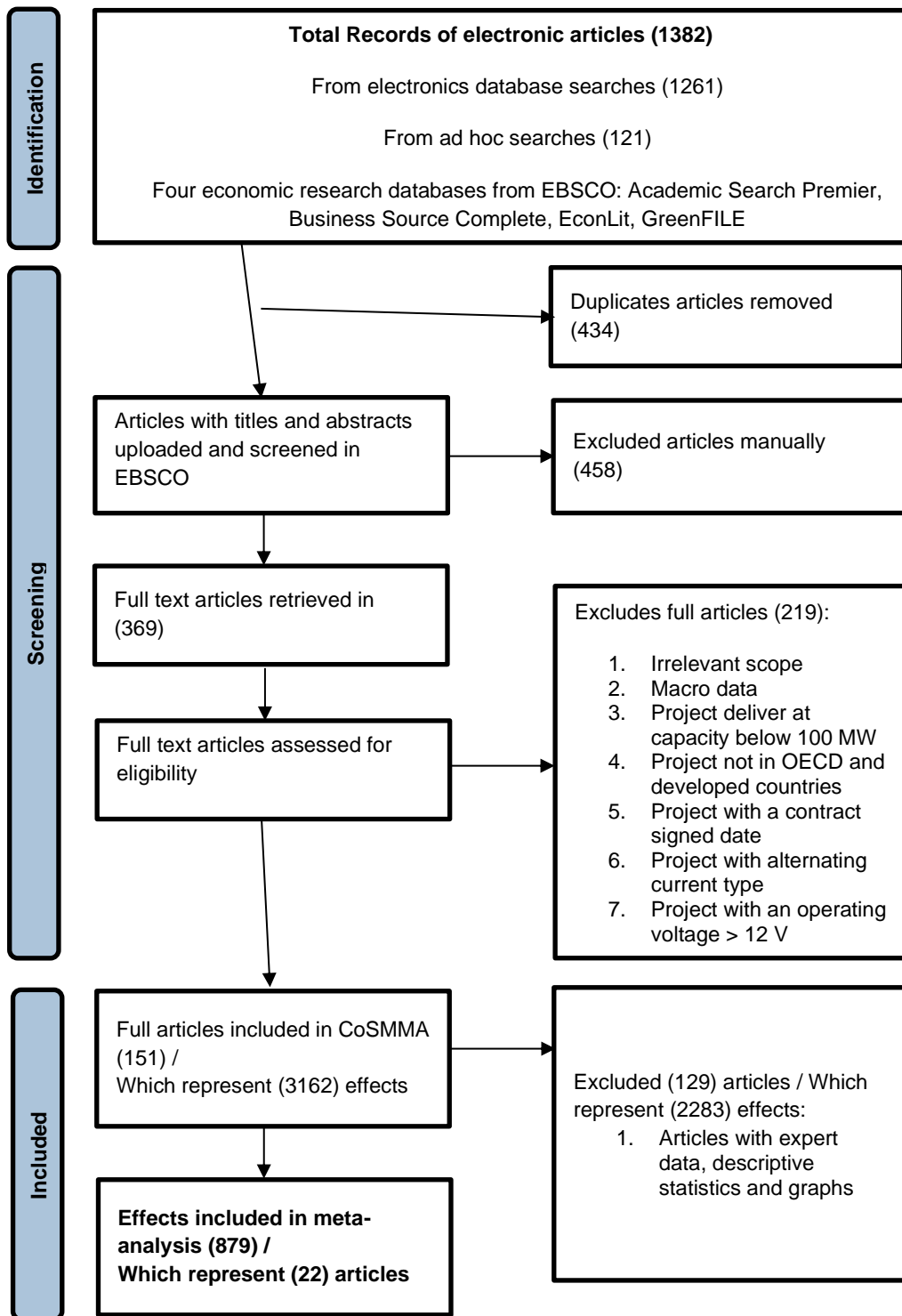
Also, one of the main rules of the CoSMMA data collection is based on the decentralization principle, which relies on the following principles:

- The production, transportation, and distribution of electricity without establishing contracts with the national network.
- The energy generated does not result in a price fixed by a clearing agency.

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<sup>19</sup> See the extraction codes in Millien (2019)

**Figure 2: PRISMA Scheme**



Source: Author

## 2.2. Descriptive statistics

The granularity of the CoSMMA meta-base is at the level of the results generated by the DEPs, not at the scale of the selected studies. The assessment methodologies collected by the CoSMMA are classified as "miscellaneous" (Berthélemy and Millien, 2018), and range from observed effects to measured and tested effects, through descriptive observations. The interest of my paper is that it focuses solely on measured and tested effects in order to analyze the impact of experimental and quasi-experimental approaches on the outcomes of DEPs. This leads to a limitation of the sample of the scientific data presented in [Table 1](#), from 3,162 to 1,775 observations. The subset gathers projects which have been evaluated by econometric measurement tools with standard deviations. Given that, the interest provides to issues in statistical identification is increasing in the economics field (Ravallion, 2020).

**Table 1: Distribution of observed CoSMMA data**

Denomination	Type	Nb of Obs (N)	Distribution
<b>Scientific data</b>	Quantified effect with variance	N>1	1,775
<b>Expert data</b>	Quantified effect without variance	N=1	398
<b>Expert data</b>	Documented effect from research	N=0	868
<b>Expert data</b>	Unmeasured effect	N=0	121
<b>Total</b>			<b>3,162</b>



### 2.2.1. Which evaluation methods are used to assess the impact of decentralized electrification projects?

From the 1,775 scientific data gathered by the CoSMMA, my meta-analysis only focuses on projects that have been evaluated by a variety of econometric identification methods. As a consequence, my meta-study is based on a sample of 879<sup>20</sup> effects which have been assessed by experimental (RCTs), quasi-experimental (DiD and matching), and non-inferable econometrics. Obviously, the granularity of the CoSMMA is at the effect level. However, it is important to highlight that in my analysis, the restriction of the sample to the effect's granularity is based only on the deployment of 22 projects evaluated by 22 studies, as presented in [Appendix A.4](#). Therefore, there is a limit on the variation of projects with respect to evaluation methods used. As displays in [Table 2](#), RCTs were the most used methodology to assess DEPs, followed respectively by matching, DiD, non-inferable econometrics, and Instrumental Variables (IV) methods. Furthermore, it is also key to note that for some projects, two distinct evaluation techniques were used to measure their effects. This echoes the synthetic analysis of the Glazerman et al. (2003) replication studies, where 4 of the 12 studies included in the analysis evaluate the same program. Regarding the CoSMMA meta-base, these are the following projects:

- Lighting Africa Programme conducted by the World Bank Group through the International Finance Corporation (IFC), and implemented in Uganda more specifically in the village of Kyannamukaaka. This program implemented between 2007 and 2011, provided solar lamps to more than 190,000 individuals. To this end, Furukawa's (2012) study evaluates the effects of this program on children's school performance and air quality-related health. On the one hand, the author based his work on a 5-month RCT evaluation of 155 schoolchildren which reveals that the program had moderate effects on improving air quality. On the other hand, the DiD evaluation based on the Uganda National Household Survey 2005/2006 and representing 48,000 households shows a positive impact of the program on improving grades in math and English for more than 600 students.
- The Yeelen Ba's Solar Home Systems (SHS) is a program conducted in Burkina-Faso (Kéné Dougou) in 2009. This large-scale program cost of 5,900,000€, allowed the installation of solar home systems (SHS) with a power of 50W for 318,000 people. It is within this framework that Bensch et al. (2013) evaluated this program through a DiD analysis using a panel data of 58 households, on one hand. And on the other hand, a cross-sectional analysis using the PSM procedure on 270 Yeelen Ba users. The authors stress that the DiD estimator better isolates the socio-economics effects of the program.

Experimental techniques isolate the average impact of a project between random treated and non-treated units, while quasi-experimental methods such as matching, DiD, and IV are observational studies in

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<sup>20</sup> [Appendix A.3](#)

which the assignment is purposive and not random, based on the prior characteristics of the recipient and non-recipient units (Ravallion, 2020).

Units in the treatment and non-treatment groups are designed to ensure that they are similar with respect to the characteristics that may influence the outcome (Picciotto, 2020). Thus, the non-inferable econometrics approach examines the correlation between two variables without rectifying the endogeneity bias problem, hence without a causal inference strategy.

#### 2.2.1.1. Experimental method: Randomized Control Trials

Randomized control trials measure the impact of a project by comparing the mean outcomes for beneficiary units (treated group), those who randomly have access to the project, with other random units who do not benefit (control group) from the project. RCTs are mostly suited to projects with clearly identified beneficiaries and non-beneficiaries in short-time horizon deployments (Ravallion, 2020). RCTs involve experiments in real settings and are more easily suited to private goods than to public goods interventions (Morduch, 2020).

Pritchett (2020) also assesses that, to be successful, RCTs need a clean assignment of units to the treatment and control groups and enough units for adequate statistical power. Hence, the RCT method is better applied to individualized interventions rather than to national development or sector-wide transformations. The analysis of Bédécarrats et al., (2019) provides a descriptive affirmation that less than five percent of RCT impact assessments conducted by the J-PAL have led to scaled-up policy changes.

The interpretation of RCTs requires assumptions and a specific survey, which is characterized by lower sample sizes and higher variances than observational studies for a given budget (Ravallion, 2020). Indeed, the cost of a classic RCTs is rated between \$500,000 and \$1,500,000 (Bédécarrats et al., 2020). The World Bank specifies that RCTs evaluation costs are higher than those of observational studies. The timeframe to implement an experimental approach can range from one year to a decade<sup>21</sup>, considering the time needed to collect baseline data and project effects. RCTs can also require several data collection processes (Gertler et al., 2011).

**Table 2** shows that the RCTs approach has been applied to assess 50% of the effects generated by DEPs. These RCTs evaluations randomly isolated the recipient and non-recipient units of the project's features. Yet RCTs studies have usually faced ethical issues, compared to observational studies (Teele,

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<sup>21</sup> J-Pal website

2014). Moreover, Abramowicz and Szafarz (2020) argue that the principle of equipoise faced in the medical world also exists in the development field, through experimental strategies.

#### 2.2.1.2. Quasi-experimental methods: Matching and Difference-in-Difference

Quasi-experimental studies estimate the causal impact of a project on a targeted population, without random assignment. Assessors use some statistical criteria other than random selection to design the treatment condition of the projects. Non-randomized techniques are particularly used when it is not practical or reasonable to carry out randomization assignments. There are several types of quasi-experimental designs which include matching, double-difference (DiD), and instrumentation (IV) models.

Rosenbaum and Rubin's well-known study (1983) revealed that the predicted values of the propensity score matching model are propensity scores used in selecting observational balanced treatment and comparison groups. The matching approach identifies and matches specific recipients with the most comparable non-recipients, based on their characteristics. This impact evaluation technique has been applied for 28% of the tested effects generated by off-grid projects ([Table 2](#)).

The DiD methodology evaluates the impact of a project by considering the overtime invariant differences between recipients and non-recipients (Le Ster, 2011). Gertler et al. (2011) specify that the DiD estimate compares the average change over time in the treatment group outcome variable with the average change over time in the control group. [Table 2](#) shows that this statistical technique has been used to assess 11% of the effects in my sample.

Then, the IV technique is used in non-experimental evaluations to mitigate the problems of selection bias (Glewwe and Todd, 2022). Selection bias implies that the impact of a project does not come only from the difference in effects between beneficiaries and non-beneficiaries, but instead from other differences between these two groups. In non-experimental assessments it is difficult to find a credible instrument which influence project participation but does not have a direct impact on project's outcomes. That is why the IV method represents less than one percent of the measured effects in my sample ([Table 2](#)).

Unlike randomized experiments, quasi-experimental evaluations are relatively inexpensive. There is no precise estimate of the cost of non-randomized studies, but Gertler et al. (2011) highlight that impact assessment costs do not exceed, on average, 4.5% of the total project cost. Usually, the cost of data collection represents the highest share of the impact assessment cost, an average of 60%. Observational studies can rapidly be conducted (between months and years), as they can rely on existing data from national statistics institutions (Gertler et al., 2011).

**Table 2: Distribution of impact evaluation methods**

<b>Evaluation methods</b>	<b>Effects</b>	<b>Effects (%)</b>	<b>Projects</b>	<b>Projects (%)</b>
<b>Identification - RCT</b>	435	50	7	32
<b>Identification - DiD</b>	98	11	4	18
<b>Identification - Matching</b>	245	28	8	36
<b>Identification - IV</b>	2	0	1	5
<b>Non-Inferable Econometrics</b>	99	11	7	32
<b>Observations</b>	879	100	22	123

### 2.2.2. Impact assessment methods according to the geographic location of decentralized electrification projects

In the context of decentralized projects, [Table 3](#) reveals that RCTs are mainly conducted in the African region with 54% of the measured effects representing 31% of the deployed projects. As well as in Asia with 62% of the effects, represented by 33% of the implemented DEPs. However, most of Asian projects have been evaluated by non-inferable econometrics method (44%), while only 2% of the outcomes generated by the projects in Asia have been estimated using the matching strategy. This descriptive evidence supports the potential *Asian cultural bias* due to the major presence of RCTs advocacy structures in Asian countries, mostly in India, through the implementation of J-Pal experiments. Also, the DiD approach has mostly been used on the African continent, with 19% of the measured effects.

Africa is the continent where most of projects have been deployed, with a total of 59%. Therefore, as a robustness check, I focus my empirical strategy on African off-grid projects. On the other hand, the matching identification mostly took place in Latin America with 77% of the measured effects, as well as for the IV method which has only been used on this continent (2%). Then, non-inferable econometrics strategy was mainly used in Asia (21%). Finally, due to the heterogeneity of evaluation methods across continents, my empirical model is clustered with a bootstrap estimator.

**Table 3: Distribution of impact evaluation methods across locations**

<b>Continents</b>	<b>Effects</b>	<b>Effects (%)</b>	<b>Projects</b>	<b>Projects (%)</b>
<b>Africa</b>				
Identification -RCT	245	54	4	31
Identification -DiD	86	19	3	23
Identification -Matching	100	22	5	38
Identification -IV	0	0	0	0
Non-inferable Econometrics	22	5	1	8
<i>Total</i>	<i>453</i>	<i>51</i>	<i>13</i>	<i>59</i>
<b>Asia</b>				
Identification -RCT	190	62	3	33
Identification -DiD	0	0	0	0
Identification -Matching	52	2	2	22
Identification -IV	0	0	0	0
Non-inferable Econometrics	63	21	4	44
<i>Total</i>	<i>305</i>	<i>35</i>	<i>9</i>	<i>41</i>
<b>Latin America</b>				
Identification -RCT	0	0	0	0
Identification -DiD	12	10	1	20
Identification -Matching	93	77	1	20
Identification -IV	2	2	1	20
Non-inferable Econometrics	14	12	2	40
<i>Total</i>	<i>121</i>	<i>14</i>	<i>5</i>	<i>23</i>
<b>Observations</b>	<b>879</b>	<b>100</b>	<b>22</b>	<b>123</b>

#### 2.2.4. What effects are assessed by the CoSMMA literature?

The CoSMMA has collected a dozen domains of effects, mostly related to the Sustainable Development Goals (SDGs)<sup>22</sup>. In most cases, the measured effects mainly address problems in the educational (24%) and health (20%) sectors, and on energy market access (16%). These effect typologies are related to the basic needs that DEPs address. Consequently, this paper also provides evidence on the impact of evaluation methods on significant positive outcomes on both education and health challenges.

#### 2.2.5. The outcomes of decentralized electrification projects

[Table 4](#) describes the four possible outcomes of tested effects on sustainable development, based on the statistical significance test of their estimates:

- Proven-Favorable
- Proven-Unfavorable
- Unproven-Favorable
- Unproven-Unfavorable

One can note that only 29% of the measured effects have a significant and positive outcome on sustainable development. For instance, these effects are mostly related to: business creation, access to electronic appliances, decrease of respiratory disease prevalence, increase of school attendance. Whereas, 10% of effects lead to a significant project failure, which is caused by an "increase of adoption and maintenance costs" of DEPs, among other factors. Then, [Table 4](#) indicates that most of the tested effects have no significant impact on sustainable development, whether they are favorable (35%) or not (26%).

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<sup>22</sup> [Appendix A.5](#)

**Table 4: Distribution of project outcomes**

<b>Outcomes of effects (4)</b>	Fr	Pct
Proven -Favorable	252	29
Proven -Unfavorable	89	10
Unproven -Favorable	309	35
Unproven -Unfavorable	229	26
<b>Total</b>	879	100

### 3. Specification strategy

#### 3.1. Objective of the comparative analysis

The goal of this paper is to contribute to the methodology debate on the outcomes generated by sustainable projects, through the estimates of experimental and quasi-experimental techniques. This debate has been carried out by development actors under the assumptions driven by the economists of randomized control trials analysis, which rely on the scientific rigor for project assessment and monitoring processes, while observational studies can also alleviate the statistical and operational limits of randomization studies through the design of the control group.

Therefore, the analysis of the convergence and the discrepancy between randomized and non-randomized impact assessment approaches allows the development economics field to develop new practices at both the methodological and operational levels. This is a fundamental contribution to the dynamic development economics sectors, such as decentralized electrification.

### 3.2. Main specification: the role of indicators and controls

This study relies on the direction of tested effects, which are specified by four possible sustainable development outcomes. To that end, a Multinomial Logit (M-Logit) regression is applied to my main specification. This empirical regression allows me to simultaneously analyze the results of each impact evaluation method on each sustainable development outcome. Moreover, according to Berthélemy and Millien (2018), the application of the M-Logit regression is relevant for studies using categorical dependent and explanatory variables. However, one should be aware that the M-logit requires a large size of dataset. As well as, the impossibility to order the effects of the explanatory variables or the disability to detect potential outliers. On the other hand, it is worth mentioning the risk of selection bias of my model, as the projects sampled for this meta-analysis are those that generally have the highest probability of being evaluated by econometric identification methods.

As explained in [Section 2](#), my specification is limited to a scope of effects tested by measurement tools with standard deviations, with the aim of identifying the estimate of each impact assessment method on the probability of evaluating a decentralized project as a success or failure. Therefore, this work mainly focuses on both the significant positive and negative results, even if the global inclusion of outcomes indirectly provides information on factors that can limit the significant results of projects (Berthélemy, 2019). Therefore, the empirical strategy relies on the following equation:

$$P(\text{outcome}_{ip} = k) = \alpha + \beta \cdot \text{Methods}_{ip} + \rho \cdot \text{Effects}_{ip} + \mu \cdot \text{Characteristics}_{ip} + \varepsilon_{ip} \quad (1)$$

Where:

- **Outcome:**  $k$  corresponds to one of the four categorical outcomes of sustainable development projects (proven-favorable, proven-unfavorable, unproven-favorable, unproven-unfavorable);
- **$\alpha$ :** the constant parameter;
- **$\beta, \rho, \mu$ :** parameters to be estimated;
- **Methods:** refers to the impact evaluation methods (RCT, Matching, or DiD);
- **Effects:** nature of measured and tested effects of the projects;
- **Characteristics:** vector of project characteristics based on their technology, geographical location, program cost, and governance;
- **$P$ :** probability of finding one of the four possible outcomes;
- **$p$ :** decentralized project index which varies from 1 to 22;
- **$i$ :** measured and tested effect index which varies from 1 to 879;
- **$\varepsilon$ :** error terms clustered with a bootstrap estimator.



This specification estimates the impact of evaluation strategies on the probability of evaluating significant positive and negative sustainable development project outcomes. The four possible outcomes represent the combination of the direction of the effects (favorable or unfavorable) and their nature (proven or unproven). It is relevant to note that the evaluation methods variable displays in the regression tables compares experimental and merged non-experimental techniques. The empirical regression also takes into account the effects and characteristics of decentralized projects. In addition to that, some projects were evaluated by more than one evaluation method, as specified in [Section 2.2.1](#). Given the small number of projects and studies covered by this meta-analysis, I generate artificial observations by using bootstrap standard-errors. Although it cannot compensate for the insufficient number of 22 projects, this option corrects for sampling bias. The *vce(bootstrap)* option specifies to use the bootstrap for variance-covariance estimation. Moreover, the m-logit model may encounter selection bias problems due to the over-representation of one method compared to others.

To implement the above model, it is necessary to have a range of explanatory variables at the effect level. These key variables are presented in [Appendix A.6](#), which includes control variables based on the project characteristics and effects.

## 4. Empirical results

### 4.1. The impact of evaluation methods on the outcomes of decentralized electrification projects: A Multinomial-logit strategy

This section discusses the effects of impact evaluation estimates on the probability of generating different outcomes, focusing on the four columns of interest presented by [Table 5](#).

#### 4.1.1. The impact of randomized and non-randomized methods

The findings in [Table 5](#) describe the effects of impact methodologies' estimates on the outcomes of DEPs after controlling for their characteristics. The results represent the average marginal effects (AME) of the probability of generating each of four different outcomes. Estimated AME represents the difference between the probability that a given category will generate an outcome and the probability associated with the reference category, denoted as "ref. =" (Millien, 2019, p.101). Columns (1) to (4) show the estimated coefficients for each

outcome on sustainable development. One can observe that the specification finds 252 proven-favorable and 309 unproven-favorable observations, as well as 89 significant and 229 non-significant and negative outcomes.

As shown in column (1), the estimate of the non-RCTs method is not significant (-9.4 pp<sup>23</sup>). Therefore, compared to the experimental method, quasi-experimental methodologies have no significant impact on the probability of finding success outcomes from decentralized projects. The estimate of the non-RCTs techniques converge with the RCTs reference. As a consequence, quasi-experimental methods find equivalent success outcomes on decentralized projects as experimental techniques.

This result goes beyond the findings of Glazerman et al. (2013), who illustrate a decrease in bias between experimental and non-experimental estimators, by synthesizing evaluation studies of labor programs. They consider the discrepancy between experimental and non-experimental estimates through the synthesis of design replication studies. Thus, their work is not based on a meta-analysis as they do not take into account the effect size of interest, such as the impact of a program on a given outcome. While my meta-study provides evidences on the convergence or discrepancy of experimental and quasi-experimental estimates, through the direction of their effects on project outcomes. However, the research of Glazerman et al. (2003) reveals a greater decrease in bias when the sample is weighted and when the matching approach has been applied. This conclusion is therefore consistent with the main finding of my paper.

Consequently, the finding in column (1) point out that quasi-experimental methods provide nearly the same outcome as do experimental approaches. As detailed in [Section 2](#), quasi-experimental methods are less expensive than randomized evaluations but are also considered by a part of the literature as less rigorous than RCTs. In terms of policy decisions, the results in [Table 5](#) have major implications for public and private operators in the development field. As a consequence, the results of this paper find that assessors can rely on both experimental and quasi-experiment methods to measure the impact generated by small-scale infrastructure projects.

One can also observe that the results of the RCTs and non-RCTs evaluation methods converge, regardless of the continent where the projects were deployed. Projects in Asia and Latin America have the same chance of success as DEPs in Africa. Nonetheless, one should be aware of the lack of counterfactual for Latin America, given that [Table 3](#) reminds that no RCTs evaluation have been conducted for Latin American projects.

The convergence of results between randomized and non-randomized evaluations also applies to projects which have effects on basic electricity access (+25 pp). As a matter of fact, effects on

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<sup>23</sup> Percentage points

basic electricity access represent de facto one of the main goals of the decentralized electrification sector. In the same line, DEPs with effects on the access to information and communication have significantly a higher probability of 36 pp to find a positive outcome on sustainable development. There is a strong proximity between the off-grid sector and the telecom sector, especially since the advent of pay-as-you-go (PAYG) payments integrated with solar home system (SHS) panels. The estimates of RCTs and non-RCTs also have a better chance to conclude a success of DEPs when the assessors display an independence note, but the coefficient of this variable is not statistically significant. As displayed in [Appendix A.6](#), the independence note variable is a dummy coded as 1 if assessors write a memo which ensures the independence of the evaluation from the project funder, and 0 otherwise.

Then, some projects gather by the CoSMMA were assessed years after implementation. Therefore, as shown in the [Appendix A.6](#) the delay of evaluation represents the number of years between a project implementation and its impact evaluation. The estimate of delay of evaluation displays in [Table 5](#) is negative (-8.5 pp) and not significant, which means that proven and positive outcomes of DEPs mainly occur in the short term. This finding implies that projects are more likely to generate positive outcomes with scientific evidence when the evaluation occurs shortly after their implementation.

On the other hand, [Table 5](#) also indicates a convergence of results between randomized and non-randomized strategies regarding the failure outcome of decentralized projects, as shown in column (2). Indeed, the estimate of the non-RCTs approaches is not significant (-11 pp) and therefore provides the same probability as RCTs to conclude a proven-negative outcome on sustainable development. Moreover, failed projects are significantly less common in the on outcomes related to gender (-40 pp) and information and communication (-43 pp) matters. These findings echo the study of Cameron et al. (2016) which highlights that RCTs evaluations tend to be concentrated in the education, gender, or health sectors. Unlike quasi-experimental studies which are more common to assess impacts on agriculture, energy, and environment challenges. Thus, there might be a cognitive and academic bias regarding the assessment of the SDG effects, such as for the "political site selection bias" of RCTs identified by Corduneanu-Huci et al. (2021). However, one must take into account the capacity of what can be measured, given that there are many indirect and diffuse effects that are not tangible.

The likelihood of RCTs to conclude a significant negative impact of decentralized projects is not significantly driven by the transparency inclusion of the clear and public role of project stakeholders. As presented in [Appendix A.6](#), this variable takes the value of 1 if access to information on all stakeholders' role in project is publicly available. This covariate is a proxy measurement of the potential asymmetry of information between projects stakeholders and the possible "hidden whale" in project.

The third column in [Table 5](#) also displays the convergence of impact evaluation methodologies on the unproven-positive outcome of DEPs. I find that compared to the RCTs estimate, the non-RCTs one is not significant. Hence, as in column (1), there is no discrepancy between randomized and non-randomized methods on the probability of generating an unproven success of projects. Therefore, randomized and non-randomized methods have the same ability to detect proven and unproven success of projects on sustainable development.

Then, column (4) also supports the convergence between the RCTs and the non-RCTs methods, according to the non-significant estimate of non-RCTs (6.9 pp) techniques. Furthermore, one can also note that publication bias is not an issue in this model given that the estimate for the proxy number of observations is null and not significant for all the four possible outcomes generated. In addition, publication biases depend mainly on the selection of journal editors, who are less likely to publish negative or null results.

Finally, the main findings displayed in [Table 5](#) also hold when the unproven outcomes of DEPs are merged. Indeed, the table presented in [Appendix A.7](#) show that RCTs and non-RCTs methodologies still converge on the probability to conclude a success and a failure of projects. Furthermore, the methods diverge on their likelihood to conclude an unproven impact of projects, with a significant coefficient of 21 pp. Therefore, quasi-experimental approaches have a higher probability to conclude non-significant outcomes of DEPs compared to experimental techniques.

**Table 5: Impact of evaluation methods on the (four) outcomes of decentralized electrification projects - Average Marginal Effect (AME)**

Explanatory variables	(1) Proven-Favorable	(2) Proven-Unfavorable	(3) Unproven-Favorable	(4) Unproven-Unfavorable
<b>Proxy of no. of obs.</b>	-0.000 (0.000113)	0.000 (0.000118)	0.000 (9.69e-05)	0.000 (0.000151)
<b>Delay of evaluation (years)</b>	-0.085 (0.125)	0.038 (0.110)	0.053 (0.237)	-0.007 (0.198)
<b>Eval methods (ref. = RCTs)</b>				
Non-RCTs	-0.094 (0.110)	-0.112 (0.0854)	0.137 (0.156)	0.069 (0.106)
<b>Nature of effects</b>				
Income & living conditions (O1)	0.020 (0.222)	-0.020 (0.165)	0.114 (0.267)	-0.113 (0.275)
Health (O3)	-0.066 (0.0909)	-0.262 (0.272)	0.378*** (0.101)	-0.051 (0.173)
Education (O4)	-0.122 (0.0864)	-0.014 (0.0518)	0.160* (0.0927)	-0.024 (0.0859)
Gender (O5)	0.029 (0.231)	-0.396*** (0.113)	0.140 (0.191)	0.227 (0.157)
Basic access (O7)	0.253*** (0.0700)	-0.073 (0.123)	0.095 (0.0730)	-0.276* (0.165)
Information & communication	0.358** (0.152)	-0.429*** (0.108)	-0.113 (0.312)	0.184 (0.196)
Usable time and leisure	0.065 (0.0976)	-0.055 (0.206)	0.101 (0.104)	-0.111 (0.165)
<b>Technology (ref. = Solar)</b>				
Other	0.582 (0.601)	-0.169 (0.155)	-0.224 (0.642)	-0.188 (0.276)
<b>Location (ref. = Africa)</b>				
Asia	-0.144 (0.231)	0.016 (0.334)	-0.033 (0.588)	0.161 (0.611)
Lat. America	0.271 (0.199)	0.038 (0.172)	-0.269 (0.174)	-0.040 (0.177)
<b>Program cost (ref. = ≤\$100,000)</b>				
>\$100,000	0.082 (0.211)	0.131 (0.423)	-0.117 (0.274)	-0.096 (0.302)
<b>Role of project stakeholders</b>	0.243 (0.392)	-0.082 (0.367)	-0.022 (0.787)	-0.140 (0.734)
<b>Independence note</b>	0.283 (0.394)	-0.348 (0.484)	0.289 (0.821)	-0.223 (0.778)
Observations	542	542	542	542
Obs. nb outcomes	252	89	309	229
Clusters	Yes	Yes	Yes	Yes

Average Marginal Effect of Multinomial Logit regression. LHS: Proven-Favorable, Proven-Unfavorable, Unproven-Favorable, Unproven-Unfavorable. Subset of 879 observations based on DEPs. Ref =: Reference category. Estimates controlled by: Number of observations in evaluation samples (N), Delay of evaluation, Domain of effects, and Project characteristics. Coefficients tell the difference in percentage points from the prediction of referral category. Variance: clustered with bootstrap estimator. The variance-covariance matrix is estimated all at once for all four equations. +p <0.10, \*p <0.05, \*\*p <0.01, \*\*\*p <0.001.

#### 4.1.2. Type II error test of the main results

Given that the estimates of my preferred results are not statistically significant ([Table 5](#)), I conduct a power test. Several error sources can falsely accept the null hypothesis of my model. This null hypothesis determines the convergence between the impacts of RCTs and non-RCTs evaluations on the probability for decentralized projects to generate proven-favorable outcomes. These scientific treatment errors usually come from selection, measurement, and observation biases. Along the same lines, Ravallion (2020) specifies that bias is removed when the treatment status is conditionally exogenous, namely uncorrelated with the error term conditional on the covariates.

As described in [Appendix A.8](#), firstly there is the type I error which occurs when there is a rejection of the null hypothesis when it is true. This error is represented by the significance level of alpha ( $\alpha$ ). On the other hand, the type II error is failing to reject the null hypothesis when it is false. Meta-regressions increase the chances of detect some type II errors in the published papers.

The beta estimate ( $\beta$ ) of the type II error represents the likelihood to attest an impact discrepancy between randomized and non-randomized methods, despite the conclusion that the data failed to confirm this status. The standard threshold set by the literature is beta equals 0.20. Hence, the power of the test can be defined as the probability that one will make the right decision when the null hypothesis is not true, calculated by one minus beta (Daniels and Minot, 2019). According to Pang et al. (1999), the combination of many small studies in a meta-analysis can detect important effects and reduce the possibility of a type II error.

Therefore, I conduct the type II error test for each category of my explanatory variable regarding the four outcomes of [Table 5](#). The test is based on the following power equation using the "power" command in STATA (Weinberg and Abramowitz, 2020):

$$\text{power onemean } H0 \ H1, \alpha (0.05) \ n \ sd \quad (2)$$

Where:

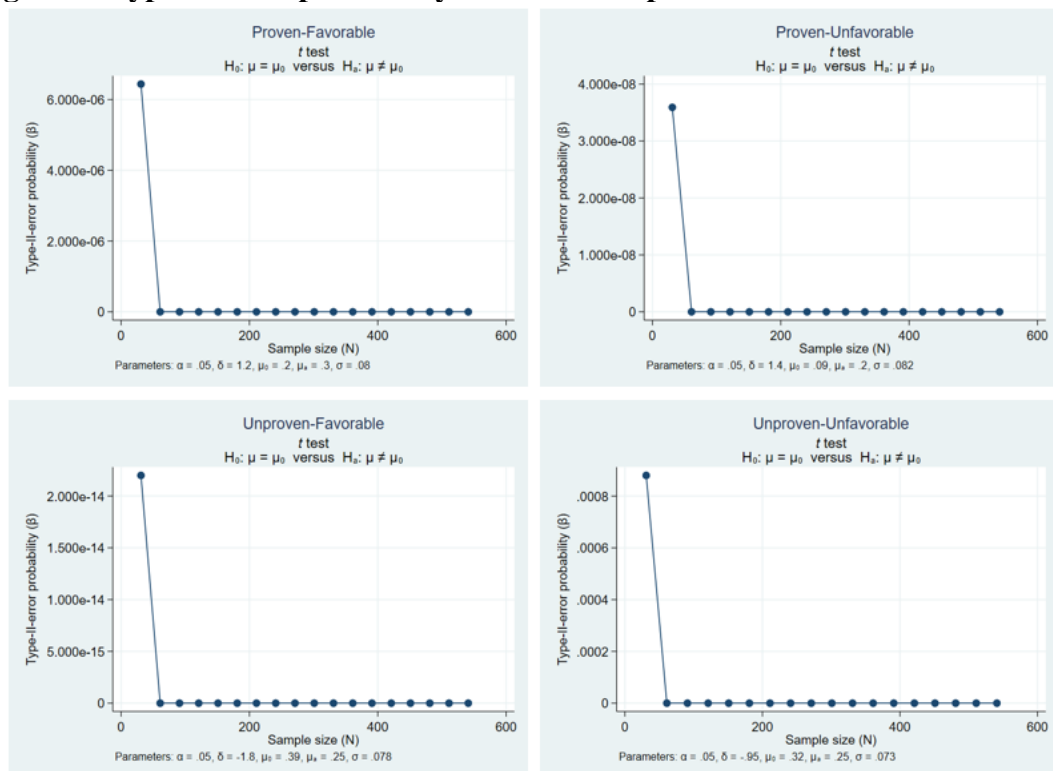
- $H0$  (null hypothesis): convergence of outcomes between RCTs and non-RCTs methods;
- $H1$  (alternative hypothesis): discrepancy of outcomes between RCTs and non-RCTs methods;
- $\alpha$ : alpha corresponds to the significance level at 0.05 by default. It represents the probability that there is a convergence between groups but one concludes that there really is a difference;
- $n$ : sample of the estimation;
- $sd$ : standard deviation.

The beta estimate of the DiD method in [Table 6](#) is equal to 0 for all the four outcomes, which is lower than the threshold fixed at 0.20. Consequently, the decision to accept the null hypothesis is correct. This evidence confirms that there is a convergence of impact between RCTs and non-RCTs methodologies on the likelihood outcomes of decentralized electricity projects. Moreover, the power graph in [Figure 3](#) highlights that the lower the beta estimate, the higher the sample of my empirical model.

**Table 6: Type II error test**

Ho: m = m0 versus Ha: m! = m0									
	alpha	power	beta	N	delta	m0	ma	diff	sd
<b>Proven-Favorable</b>	0.05	1	0	542	0.803	0.205	0.299	0.094	0.117
<b>Proven-Unfavorable</b>	0.05	1	0	542	1.366	0.09	0.202	0.112	0.082
<b>Unproven-Favorable</b>	0.05	1	0	542	-1.769	0.387	0.249	-0.138	0.078
<b>Unproven-Unfavorable</b>	0.05	1	0	542	-0.945	0.319	0.25	-0.069	0.073

**Figure 3: Type II error probability for a one-sample mean test**



## 4.2. The outcomes of DEPs with impact evaluation methods

The distribution of effects in the sample of DEPs is heterogeneous. As presented in [Appendix A.9](#), basic access and information and communication sectors represent 22% of the assessed effects. Indeed, the electrification process is marginally supported by other sustainable development targets (Berthelemy, 2019). The promotion of basic access and information and communication contributes to the United Nations SDG 7 and 9, which are key matters for the well-being of populations in developing countries.

[Table 7](#) describes the impact of evaluation methods on the probability of finding a positive outcome on projects which have positive and significant effects on the basic access and the information and communication sectors. For each type of effect, a Complementary log-log (C log-log) regression is applied to this sub-sample in order to mitigate the limitations due to the low number of observations. The results show that there is no discrepancy between the impacts of experimental and quasi-experimental evaluation approaches on the positive outcomes of decentralized projects in the two identified sectors. The estimates of the non-RCTs methods are not statistically significant for both the basic access and information and communication effects. Consequently, this finding is in line with the results found in [Table 5](#).

The non-experimental evaluation of other off-grid technologies have a significant lower probability to generate a positive outcome on basic access effects (-1.9 pp), compared to projects based on solar technology. However, low cost projects have significantly more chance (+82 pp) to generate a positive impact on energy basic access outcomes. Mainly when the timeframe between a project's commissioning and its evaluation is short (+34 pp). Consequently, assessors should conduct their evaluations over a short-term period in order to find significant positive outcomes on energy basic access, given that the further we go forward in time, the less beneficiaries remember the occurrence of effects from the projects. The literature demonstrates that often RCTs evaluate the short-term impact of causal chains (Bédécarrats et al., 2020). In contrast with the criticism of Ravallion (2009) who notes that there is a "myopia bias" in development applications due to the scarcity of long-term impact evaluations, which allow participants to identify project externalities.



**Table 7: Impact of evaluation methods on findings of proven-favorable effects**

Explanatory variables	(1) Basic Access (O7)	(2) Information & Communication
<b>Proxy of no. of obs</b>	-0.001 (0.000494)	-0.003 (0.00296)
<b>Delay of evaluation (years)</b>	0.341*** (0.0881)	0.352 (2.495)
<b>Eval methods (ref. = RCTs)</b>		
Non-RCTs	-0.044 (0.413)	-0.075 (5.279)
<b>Technology (ref. = Solar)</b>		
Others	-1.946*** (0.716)	-0.664 (3.503)
<b>Program cost (ref. = ≤ \$100,000)</b>		
>\$100,000	0.815** (0.350)	1.971 (11.27)
Constant	-2.082*** (0.367)	-3.528 (16.31)
Observations	193	193
Clusters	Yes	Yes

Notes: Bootstrap standard errors in parentheses. Complementary log-log regression. LHS: basic access (O7), information and communication. Subset of 252 proven-favorable observations. Ref = Reference category. Estimates controlled by: Number of observations in evaluation samples (N), Delay of evaluation, and Projects' characteristics. Coefficients tell the difference in percentage points from the prediction of referral category. Variance: clustered with bootstrap estimator. \* p<0.05, \*\* p<0.01, \*\*\* p<0.001.

## 5. Robustness checks

Given that meta-analyses can present some econometric issues, I have performed a set of robustness tests. As highlighted by Labandeira et al. (2020), meta-studies increase the risk of correlation among the paper-effects, that is mainly due to the use of several studies by the same author or by authors from the same institution. In the electrification off-grid sector, one should be aware that authors may be funded by the same entities and that projects can be implemented by the same operator. As a consequence, I include in this section an additional specification strategy based on a logit estimation technique, as well as the restriction of my sample to DEPs deployed in Africa.

### 5.1. The success and failure of DEPs with impact evaluation methods: Logit strategy

[Table 8](#) describes the findings in [Section 4.1](#) when applying a Logit specification, and removing the nature of effects, the program cost, and the role of stakeholders as control variables. I add information regarding the type of assessor and the presence of a rural electrification agency for each of the decentralized projects. In line with the estimates of my preferred model, the empirical findings reveal that the estimate of the quasi-experimental methods are not statistically significant for both the positive and negative outcomes (columns 1 and 2). The evaluation techniques converge to conclude a success and a failure of DEPs. This evidence is supported by the fact that the type of evaluator has no effect on the chances of finding a proven result. Indeed, development banks and academic entities have the same probability to find a proven outcome of DEPs, compared to public institutions. The findings of the logit model contribute to the better knowledge of project success and failure for academics and development operators.

Moreover, the independence note variable has a positive and significant coefficient (+97 pp) for the proven-favorable outcome of DEPs. Conversely, the coefficient is significantly negative (-1.6 pp) for the proven-favorable outcome of projects. Mostly, funders need to attest *ex-post* the success of the project and they mainly rely on evaluators who are committed to demonstrate positive outcomes. However, the positive sign of the independence note's estimate in column (1) describes that the independence of evaluators from donors' expectations increases the chances of success of DEPs. This finding echoes the work of Berthelemy and Millien (2018) who explain that a large proportion of the papers collected by the CoSMMA report favorable effects without any scientific evidence (unproven). Thus, it appears that my sub-sample of scientific studies was conducted by "genuine assessors". In addition to that, it is more difficult to hide the negative effects of decentralized projects. Indeed, DEPs based on solar or micro-hydropower are mainly designed at a small-scale level and are subject to maintenance issues over time.

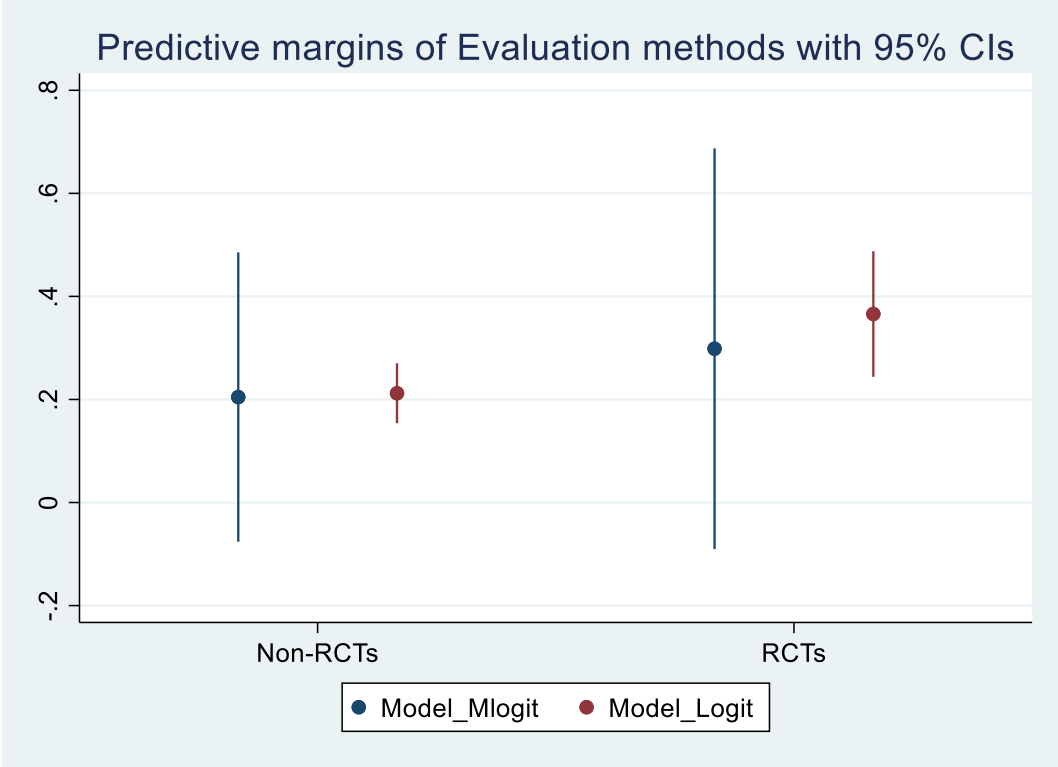
**Table 8: Impact of evaluation methods on the outcomes of decentralized electrification projects - Logit model**

Explanatory variables	(1) Proven-Favorable	(2) Proven-Unfavorable
<b>Proxy of no. of obs</b>	0.000 (0.000333)	-0.000 (0.000327)
<b>Delay of evaluation (years)</b>	0.138 (0.123)	0.0634 (0.149)
<b>Eval methods (ref. = RCTs)</b>		
Non-RCTs	-0.864 (0.576)	-0.008 (0.429)
<b>Technology (ref. = Solar)</b>		
Others	0.389 (1.148)	-1.760 (1.296)
<b>Location (ref. = Africa)</b>		
Asia	-1.109 (0.818)	-0.875 (1.253)
Lat. America	-0.483 (1.065)	1.329 (1.386)
<b>Type of assessors (ref. = minister or pub agency)</b>		
Development bank	-0.458 (1.464)	-0.653 (1.574)
University/School - research lab	-9.58e-05 (1.057)	0.065 (1.633)
<b>Rural electrification agency</b>	-0.606 (0.587)	0.613 (0.868)
<b>Independence note</b>	0.973* (0.584)	-1.595** (0.623)
Constant	-1.067 (1.092)	-1.672 (1.420)
Observations	631	631
Clusters	Yes	Yes

Notes: Bootstrap standard errors in parentheses. Logit regression. LHS: Proven-Favorable & Proven-Unfavorable. Subset of 879 observations based on DEPs. Ref =: Reference category. Estimates controlled by: Number of observations in evaluation samples (N), Delay of evaluation, and Projects' characteristics. Coefficients tell the difference in percentage points from the prediction of referral category. Variance: clustered with bootstrap estimator. \* p<0.05 \*\* p<0.01 \*\*\* p<0.001.

Consequently, the results of the M-Logit and Logit models reach similar conclusions. As illustrated in [Figure 4](#), the predictive margins of evaluation techniques for the proven-favorable outcome shows that evaluation methodologies behave the same way under the M-Logit (ml) and Logit (l) specifications. In addition, one can note that for both models the RCTs techniques seem to be more optimistic by over-estimating the success of DEPs.

**Figure 4: Margin effects of evaluation methods**



## 5.2. The impact of assessment methods on the outcomes of African decentralized electrification projects

To attest the robustness of my main empirical model presented in [Section 4](#), it is interesting to provide findings under different settings. Indeed, policymakers and practitioners want to learn from impact assessment operations and from the performance of measured outcomes in different contexts. Ravallion (2020) argues that one approach to learn from the external validity of projects is to repeat the evaluation in different contexts. Besides, meta-studies facilitate subgroup analysis and can reveal variation of treatment impact across settings (Pang et al., 1999). Therefore, the aim of this section is to analyze if the estimates of experimental and quasi-experimental approaches hold, even in different geographical circumstances.

[Table 3](#) shows that 59% of the DEPs are deployed in the African continent. To that extent, the empirical evidence of this sub-sample analysis is to highlight that my main findings are still robust in a specific geographical context. Mainly if there is an "Asian cultural bias" based on the fact that most of the RCTs evaluations are conducted in Asia, through the notable presence of the J-Pal research laboratory<sup>24</sup>. For instance, it is easier to perform an RCT design in India than in Burkina-Faso, thanks to the access to financial and human resources. India has the largest production of experimental evaluations, mostly due to the presence of local NGOs. Corduneanu-Huci et al. (2021) attest that the location of J-Pal experiments reflects idiosyncratic organizational selection priorities. Moreover, India is the leading host of RCTs experiments in the international development field. Hence, one can expect that my results in [Table 9](#) correct for this "J-Pal effect".

It turns out that the results in column (1) are robust to the African sub-sample. The estimate of non-RCTs techniques is not significant, therefore the convergence of assessment methods on the success of DEPs holds for African projects. This finding is important as it contributes to the debate regarding the limits of RCT studies. Indeed, [Section 2](#) of this paper highlights that one of the major limitations of RCTs evaluations is the external validity of the results. Often, natural experiment evaluation does not generate the same outcomes according to the scale and the location of implemented DEPs. According to Deaton and Cartwright (2018), RCTs remain valid for a specific evaluation of a particular project. Results in [Table 9](#) check the external validity of the different outcomes of decentralized projects gathered in the CoSMMA database. When controlling for the effects, the governance, and the assessment conditions of projects. Thus, this specification is a major contribution to the impact evaluation literature.

However, for the probability to find a proven negative outcome of DEPs, there is a divergence between RCTs and non-RCTs approaches. Column 2 displays that the coefficient of the non-RCTs technique is

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<sup>24</sup> [See references](#)

negative and significant (-30 pp). Therefore, it seems that the quasi-experimental methodologies underestimate the probability of failure of African DEPs, compared to the experimental methods. This finding holds when there is a strong transparency on the role of stakeholders in projects in Africa (+76 pp). This result is quite counter-intuitive given that the inclusion of stakeholders in the governance structure of projects usually contributes to their success and not to their failure.

Furthermore, in contrast with the main Multinomial-logit model, the African sub-sample indicates the presence of publication bias with a small but significant estimate for the negative proven outcome. This may reflect the lack of observations in the African continent compared to the main specification in [Section 4](#)<sup>25</sup>. Indeed, small sample size increases the risk of identifying publication bias (Pang et al., 1999). In addition, Doucouliagos and Paldam (2007) reveal that researchers are influenced by priors<sup>26</sup> and incentives.

On the other hand, the African sub-sample significantly increased the non-RCTs coefficient (+27 pp) regarding the unproven success of projects. Therefore, the evidence supports a divergence of conclusion between experiment and quasi-experimental methods for the not significant success of DEPs.

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<sup>25</sup> [Appendix A.3](#)

<sup>26</sup> The authors list the five most common priors: polishing, ideology, goodness, author history, and institutional interests.

**Table 9: Impact of evaluation methods on the outcomes of African DEPs - AME**

Explanatory variables	(1) (Proven-Favorable)	(2) (Proven-Unfavorable)	(3) (Unproven-Favorable)	(4) (Unproven-Unfavorable)
<b>Proxy of no. of obs.</b>	-0.000 (0.000276)	0.000** (0.000204)	-0.000 (0.000173)	-0.000 (0.000612)
<b>Delay of evaluation (years)</b>	0.0102 (0.128)	0.204 (0.137)	-0.027 (0.220)	-0.187 (0.416)
<b>Eval methods (ref. = RCT)</b>				
Non-RCTs	0.143 (0.262)	-0.300*** (0.0714)	0.265* (0.151)	-0.107 (0.200)
<b>Nature of effects</b>				
Health (O3)	-0.583 (1.157)	-0.259 (0.705)	-0.148 (1.392)	0.990 (1.847)
Education (O4)	-0.916 (1.368)	0.691 (0.632)	-0.552 (1.438)	0.777 (1.591)
Gender (O5)	-0.845 (0.633)	-0.710 (0.719)	-0.214 (1.273)	1.770 (1.677)
Basic access (O7)	-0.702 (0.629)	0.0411 (0.626)	-0.329 (1.273)	0.989 (1.620)
Economic transformation (O8)	-2.126*** (0.745)	-0.795 (0.717)	0.315 (1.461)	2.606* (1.486)
Security (O16)	-0.911 (0.982)	-0.749 (0.776)	-0.211 (1.532)	1.870 (1.465)
Housework	-0.848 (0.939)	-0.690 (0.667)	-0.458 (1.329)	1.996 (1.411)
Information & communication	-0.599 (0.662)	-0.675 (0.665)	-0.507 (1.283)	1.782 (1.408)
Usable time and leisure	-0.419 (0.684)	-0.283 (0.729)	0.161 (1.229)	0.541 (1.518)
<b>Technology (ref. = Solar)</b>				
Others	-0.157 (0.368)	-0.250 (0.165)	-0.032 (0.873)	0.438 (1.043)
<b>Program cost (ref. = ≤ \$100,000)</b>				
>\$100,000	0.144 (0.916)	0.152 (0.247)	-0.070 (0.624)	-0.226 (0.608)
<b>Role of project stakeholders</b>	-0.225 (0.359)	0.762*** (0.116)	-0.420* (0.251)	-0.117 (0.275)
Observations	252	252	252	252
Obs. nb outcomes	108	40	115	101
Clusters	Yes	Yes	Yes	Yes

Notes: Bootstrap standard errors in parentheses. Average Marginal Effect of Multinomial logit regression. LHS: Proven-Favorable, Proven-Unfavorable, Unproven-Favorable, Unproven-Unfavorable. Subset of 252 observations based on African DEPs. Ref =: Reference category. Estimates controlled by: Number of observations in evaluation samples (N), Delay of evaluation, Domain of effects, and Projects' characteristics. Coefficients tell the difference in percentage points from the prediction of referral category. Variance : clustered with bootstrap estimator. +p <0.10, \*p<0.05, \*\* p<0.01, \*\*\* p<0.001.

## 6. Conclusion and discussion

This paper aims to measure the impacts of evaluation methodologies on the outcomes of sustainable development projects. Specifically, the study examines the results of experimental and quasi-experimental methods on the outcomes of decentralized electricity projects. It describes how the estimates of different impact evaluation methods converge or diverge on the outcomes generated by DEPs in developing countries. Following Corduneanu-Huci et al. (2021), this work goes beyond methodological debates and sectoral approaches in the development literature, given that it contributes to gaining insight on impact evaluation policies for sustainable development stakeholders. It is important for the development operators to know whether it is possible to evaluate at the lowest cost. For this purpose, my statistical specification emphasizes whether the randomized and non-randomized methodologies lead to equivalent or different outcomes of DEPs. In order to therefore identifies best practices for public and private development actors.

In the literature, the comparative studies of impact evaluation methods rely mainly on separated comparison models (*between comparison*). For example, Buddelmeyer and Skoufias (2004) find that the RCTs and DiD approaches generate similar outcomes as part of the *PROGRESA* program in Mexico.

Several studies have conducted a comparative analysis of methodologies through a replication of an RCT evaluation by re-estimating the control group with a non-RCT strategy (*within comparison*). This strategy has been used by Glazerman et al. (2003) with the comparison of estimators from RCTs and non-RCTs techniques as part of a welfare program assessment in the United States. My study conducts a simultaneous comparative analysis of the experimental and quasi-experimental methodologies for the evaluation of DEPs by taking into account the project characteristics and their measured effects. In summary, the main findings reveal that RCTs and non-RCTs evaluations generate a similar impact on the probability to conclude a success of decentralized projects. This success mostly concerns the energy basic access and information and communication sectors in developing countries. In addition, experimental and non-experimental methods have the same ability to detect unproven-positive project outcomes. This finding is also consistent to African off-grid projects. The convergence of results between RCTs and non-RCTs methods is also robust for off-grid projects with a proven negative outcome of DEPs.

The evidences provided by my study echoes the conclusion of (Glazerman et al., 2003; LaLonde, 1986), who attest that the bias between experimental and quasi-experimental estimators is limited when the matching technique is applied. The results of this paper highlight that project characteristics and their measured effects are key in determining the convergence of impact evaluation methods on projects' outcomes. The inclusion of characteristics and *ex-ante* priors can provide protection to researchers in cases where they obtain null project results (Vivalt, 2020).



On the other hand, Callon (2006) indicates that the success of some methods relies on the common interests of development field stakeholders. Methodological tools should also be approached on a case-by-case basis, according to the prior knowledge available, the intervention design, and the particularities of the settings in liaison with researchers, field operators, donors, and local beneficiaries (Bédécarrats et al., 2020).

To better choose the appropriate impact evaluation method, it is also important to identify the legal status of the project funders. For instance, RCTs are better suited for private goods such as solar home systems (Hammer, 2017), which are easy to assign across individual households or entities, rather than public goods for which the benefits are shared across many beneficiaries (i.e., off-grid solar systems in a village or a school). Consequently, impact evaluation policies can stimulate development stakeholders to adopt best practices by alternating between experimental and quasi-experimental methods at the lowest cost, based on the project context and characteristics. Ravallion (2020) specifies that methods which yield the most convincing and relevant answers in the context at hand are always the best ones. The planning of a rigorous impact assessment and quality follow-up are also key factors in development project success.

In the years to come, development economics can rely on a range of impact assessment methodologies based on interdisciplinarity and both quantitative and qualitative evidence. As explained by Bédécarrats et al. (2020), the qualitative methods<sup>27</sup> can serve to contextualize project interventions and study the interactions between different entities. Picciotto (2020) adds that qualitative methods are better suited to determine the reasons for success or failure of effects, as they disentangle design issues and implementation problems.

Moreover, these evaluation tools are designed by the questions of interest for stakeholders and by the assumptions of project interventions (Bamberger et al., 2010). There is also an emerging strand of new impact evaluation strategies based on the combination of observational studies and satellite data (CLUB-ER and FERDI, 2019). As a consequence, the development economics field must be strengthened by including more description, more qualitative data, more big data, and more studies (Morduch, 2020). According to Ravallion (2020), the knowledge gains from an evaluation also bring benefits to future projects, which draw on the lessons learned from prior evaluations. Therefore, meta-analyses on the relationship between impact evaluation tools and sustainable development projects should give decision-makers, developers, and academics confidence that they are implementing the best development policy designs.

Finally, the results of this study should be considered with some limitations since the stability of the model is at stake. First, the effects studied in this meta-analysis come only from the evaluation of 22 off-grid projects carried out by 22 scientific works. Thus, it strongly limits the variation of the projects regarding the categories of evaluation methods, even though I used a methodological tool that allows to

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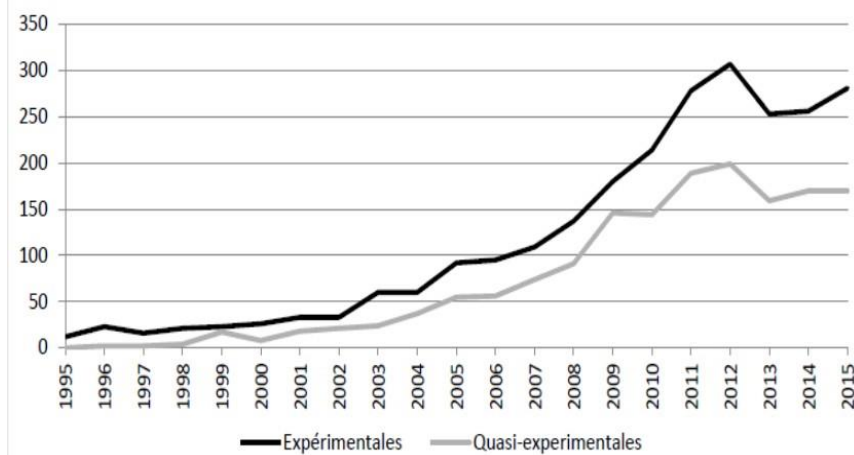
<sup>27</sup> Interviews, focus groups, case studies, beneficiaries' observations, etc.

conduct the meta-analysis on a limited number of papers. Future work on this meta-analysis will need to expand the number of projects collected in the CoSMMA, particularly by incorporating work evaluating more recent off-grid projects. Then, it would be interesting to measure, through a concrete case study, the impact of an evaluation of small-scale electrification projects on sustainable development indicators. In particular, through access to original field surveys. Also, my results are very specific to the energy sector, so their portability might be tricky. Future research should also support the innovative aspect of the CoSMMA strategy by replicating the tool for different sustainable development sectors.

## 7. Appendices

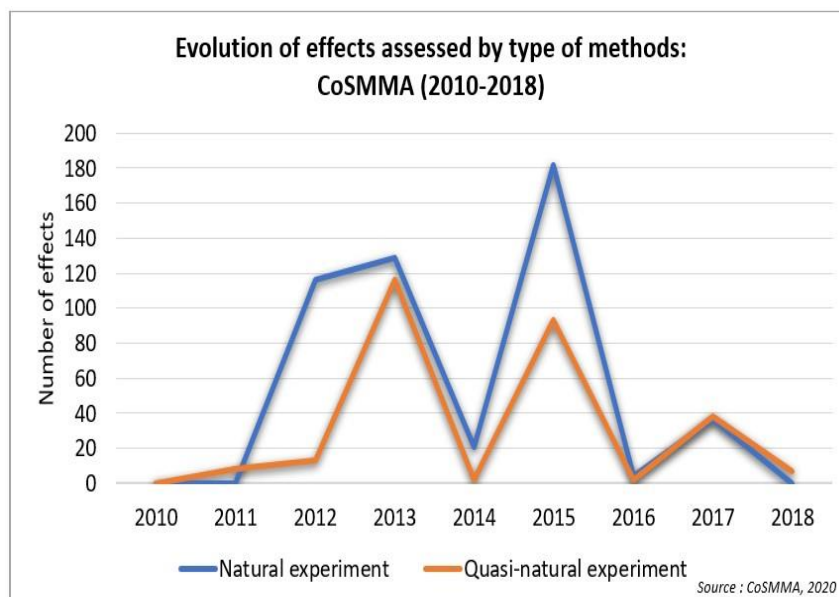
### A.1. The evolution of impact evaluation methods in the development field

Figure 2: Evolution du nombre d'évaluations d'impact dans le champ du développement par type de méthode (1995-2015)



Source : 3ie Impact Evaluation Repository, mis à jour en Août 2016.

### A.2. The evolution of effects assessed by method type: CoSMMA (2011-2018)



Source : CoSMMA, 2020

### A.3. Sample of the studies in the meta-analysis

**Table 13 – Sample size of the main sample and the African sub-sample**

<b>Number of observations in the estimations of the studies</b>			
<b>Subsets</b>	<b>Obs</b>	<b>Mean</b>	<b>Std. Dev.</b>
DEPs subset	879	302	153.0374
African DEPs subset	435	370	123.2001

#### A.4. Projects and studies included in the meta-analysis

<b>Paper</b>	<b>Author</b>	<b>Date</b>	<b>Project</b>	<b>Country</b>	<b>Evaluation Method</b>	<b>Total (effects)</b>	<b>Technology</b>	<b>Size</b>
A First Step up the Energy Ladder? Low Cost Solar Kits and Household's Welfare in Rural Rwanda	Grimm et al.	2017	UN Lighting Africa: Pico-PV kits	Rwanda	RCT	33	Solar	Nano: <1 kW
Do determinants of adopting solar home systems differ between households and micro-enterprises? Evidence from rural Bangladesh	Kurata et al.	2018	SHS adoption by households and micro-enterprises in Bangladesh	Bangladesh	Not inferable econometrics	33	Solar	Nano: <1 kW
From Candles to Light: The Impact of Rural Electrification	Arraiz et Calero	2015	ACCIONA Microenergia Peru (AMP): Luz en Casa	Peru	Matching	93	Solar	Nano: <1 kW
Health and Safety Benefits of Replacing Kerosene Candles by Solar Lamps- Evidence from Uganda	Furukawa	2012	World Bank/International Finance Cooperation: Lighting Africa programme	Uganda	RCT / DiD	116	Solar	Nano: <1 kW
Impacts of Pico-PV Systems Usage using a Randomized Controlled Trial and Qualitative Methods	Grimm et al.	2013	Pico-PV kits in Rwanda	Rwanda	RCT	129	Solar	Nano: <1 kW
Impacts of Solar Lanterns in Geographically Challenged Locations: Experimental Evidence from Bangladesh	Kudo et al.	2015	Rural Electrification in Bangladesh: Solar lanterns	Bangladesh	RCT	182	Solar	Nano: <1 kW
Powering Education	Hassan et Lucchino	2014	Solar lamps distribution in rural Kenya	Kenya	RCT	21	Solar	Nano: <1 kW
The Benefits of Solar Home Systems, An Analysis from Bangladesh	Samad et al.	2013	Government of Bangladesh/World Bank/Infrastructure Development Company Limited (IDCOL): Solar Home System	Bangladesh	Matching	51	Solar	Nano: <1 kW

The provision of solar energy to rural households through a fee-for-service system	Bensch et al.	2013	Yeelen Ba's Solar Home Systems (SHS)	Burkina-Faso	DiD / Matching	65	Solar	Nano: <1 kW
Willingness to Pay for Solar Lanterns: Does the Trial Period Play a Role? Willingness to Pay for Solar Lanterns	Yoon et al.	2016	Solar Lantern distribution	India	RCT	4	Solar	Nano: <1 kW
Does basic energy access generate socioeconomic benefits? A field experiment with off-grid solar benefits power in India	Aklin et al.	2017	Mera Gao Power	India	RCT	4	Solar	Micro: 1 to 100 kW
The geography of energy and education: Leaders, laggards, and lessons for achieving primary and secondary school electrification	Sovacool et Ryan	2016	Sustainable Rural Electrification Project and the Rural Electrification and Network Expansion: School electrification Bhutan	Bhutan	Matching	1	Existing Energy Mix, incl. carbon	Micro: 1 to 100 kW
Satellite Data for the Social Sciences: Measuring Rural Electrification with Nighttime Lights	Dugoua et al.	2018	Electrification and Nighttime luminosity	India	Not inferable econometrics	8	Existing Energy Mix, incl. carbon	Micro: 1 to 100 kW
Rural electrification and energy poverty: Empirical evidences from Brazil	Pereira et al.	2010	Energy sector reforms in Brazil	Brazil	Not inferable econometrics	6	Existing Energy Mix, Renewables Only	Micro: 1 to 100 kW
The local socio-economic impacts of large hydropower plant development in a developing country	de Faria et al.	2017	Hydropower plants in Brazilian counties	Brazil	DiD	12	Hydropower	Mini: 100 kW to 100 MW
Self-Generation and Households' Willingness to Pay for Reliable Electricity Service in Nigeria	Oseni	2017	Self-generation electricity	Nigeria	Matching/ Not inferable econometrics	26	Existing Energy Mix, incl. carbon	Micro: 1 to 100 kW
The economics of sustainable energy for rural development: a study of renewable energy in rural China	Byrne et al.	1998	Chinese Academy of Sciences/Region's New Energy Office/IMAR Planning Commission: renewable energy project in IMAR	China	Not inferable econometrics	22	Fossil Fuels	Nano: <1 kW

The impact of microhydroelectricity on household welfare indicators	Karumba et Muchapondwa	2018	Community -based microhydroelectricity schemes	Kenya	Matching	42	Hydropower	Micro: 1 to 100 kW
Fear of the dark? How access to electric lighting affects security attitudes and nighttime activities in rural Senegal	Bensch et al.	2012	Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ)/Electrification Rurale pour le Sénégal (ERSEN)/ASER	Senegal	Matching	13	Hybrid with Fossil fuel	Nano: <1 kW
Impact of rural electrification on education: a case study from Peru	Aguirre	2014	Law of General Rural Electrification/Directorate General of Rural Electrification: Rural Electrification Programs	Peru	IV	2	Hybrid with Fossil fuel	Mini: 100 kW to 100 MW
Rural electrification in Brazil and implications for schistosomiasis transmission: a preliminary study in a rural community in Minas Gerais State, Brazil	Kloos et al.	2012	Luz para Todos: Infectious disease Schistosoma mansoni	Brazil	Not inferable econometrics	8	Hydropower	Micro: 1 to 100 kW
Impacts of rural electrification in Rwanda	Bensch et al.	2011	Private Sector Participation in Micro-Hydro Power Supply for Rural Development (PSP Hydro)	Rwanda	DiD/Matching	8	Hydropower	Mini: 100 kW to 100 MW
<b>TOTAL</b>	<b>22</b>		<b>22</b>	<b>12</b>		<b>879</b>	<b>6</b>	<b>3</b>
<b>Total RCT (%<sup>28</sup>)</b>					<b>7 (32%)</b>			
<b>Total DiD (%)</b>					<b>4 (18%)</b>			
<b>Total Matching (%)</b>					<b>8 (36%)</b>			
<b>Total Not Inf. Econometrics (%)</b>					<b>6 (27%)</b>			
<b>Total IV (%)</b>					<b>1 (5%)</b>			

<sup>28</sup> Total number of each method / total number of papers (10)

## A.5. Domains of effects

<b>Domains of effects</b>	<b>Freq</b>	<b>Pct</b>
Income & living conditions (O1)	35	4
Health (O3)	174	20
Education (O4)	211	24
Gender (O5)	24	3
Basic Access (O7)	143	16
Economic transformation (O8)	33	4
Community (O11)	1	0
Security (O16)	21	2
Financial transformation	6	0
Housework	40	5
Information & communication	47	5
Usable time & leisure	51	6
Energy (type, costs & faults)	93	11
<b>Total</b>	<b>879</b>	<b>100</b>



## A.6. Descriptive statistics

<b>Variables</b>	<b>Labels</b>	<b>N</b>	<b>Mean</b>	<b>SD</b>	<b>Min</b>	<b>Max</b>
<b>Proxy Nb. Obs.</b>	Number of observations on which the evaluation was conducted	879	5449.51	49042.506	11	516769
<b>Delay of evaluation (years)</b>	Number of years from project implementation to evaluation date	808	3.96	3.719	1	26
<b>Role of project stakeholders</b>	Access to information on all stakeholders' role in project is publicly available	682	0.95	0.227	0	1
<b>Independence note</b>	Independence of assessment	717	0.56	0.496	0	1
<b>Rural Electrification Agency</b>	There is a public electrification agency which promotes decentralized rural electrification	750	0.78	0.412	0	1
<b>Technology</b>	Source of technology					
Solar	Solar energy	879	0.83	0.3744	0	1
Others	Hydropower, Hybrid with Fossil Fuel, Existing Energy Mix, Renewables Only, Existing Energy Mix, incl. Carbon, Fossil Fuels	879	0.17	0.3744	0	1
<b>Program cost</b>	<b>Sum of all investments made in facility materials (Capital Expenses) in year 1</b>					
≥ \$100,000	Program cost is equal or less to \$100,000	704	0.30	0.46	0	1
< \$100,000	Program cost is higher than \$100,000	704	0.70	0.46	0	1
<b>Location</b>	<b>Location of the project</b>					
Africa	Project implemented in Africa	879	0.52	0.5	0	1
Asia	Project implemented in Asia	879	0.35	0.476	0	1

Lat. America	Project implemented in Latin América	879	0.14	0.345	0	1
<b>Type of Assessor</b>	<b>Institution that conducted the project assessment</b>					
Development bank	Assessor is a development bank	736	0.13	0.332	0	1
Minister or public agency	Assessor is a minister or public agency	736	0.42	0.494	0	1
University/School – research lab	Assessor is an academic or scientific institution	736	0.41	0.491	0	1
Other place agency	Assessor is another type of agency	736	0.05	0.21	0	1
<b>Domain of effects</b>	<b>Categories of impacts measured and tested</b>					
Income & living conditions (O1)		879	0.04	0.196	0	1
Health (O3)		879	0.20	0.399	0	1
Education (O4)		879	0.24	0.427	0	1
Gender (O5)		879	0.03	0.163	0	1
Basic Access (O7)		879	0.16	0.369	0	1
Economic transformation (O8)		879	0.04	0.190	0	1
Community (O11)		879	0.00	0.034	0	1
Security (O16)		879	0.02	0.153	0	1
Financial transformation		879	0.01	0.082	0	1
Housework		879	0.05	0.209	0	1
Information & Communication		879	0.05	0.225	0	1
Usable time & Leisure		879	0.06	0.234	0	1
Energy (type, costs & faults)		879	0.11	0.308	0	1

## A.7. Impact of evaluation methods on the (three) outcomes of decentralized electrification projects - Average Marginal Effect (AME)

Explanatory variables	(1) Proven-Favorable	(2) Proven-Unfavorable	(3) Not significant
<b>Proxy of no. of obs.</b>	-0.000 (0.000126)	0.000 (0.000136)	0.000 (0.000133)
<b>Delay of evaluation (years)</b>	-0.084 (0.0766)	0.033 (0.119)	0.050 (0.121)
<b>Eval methods (ref. = RCTs)</b>			
Non-RCTs	-0.105 (0.563)	-0.103 (0.0992)	0.209* (0.115)
<b>Nature of effects</b>			
Income & living conditions (O1)	0.026 (0.137)	-0.027 (0.276)	0.001 (0.277)
Health (O3)	-0.062 (0.0892)	-0.267 (0.326)	0.329 (0.238)
Education (O4)	-0.127 (0.0855)	-0.023 (0.0790)	0.149* (0.0873)
Gender (O5)	0.050 (0.274)	-0.399** (0.161)	0.349*** (0.133)
Basic access (O7)	0.244*** (0.0892)	-0.096 (0.148)	-0.148 (0.106)
Information & communication	0.350** (0.145)	-0.398** (0.172)	0.048 (0.134)
Usable time and leisure	0.067 (0.129)	-0.064 (0.213)	-0.003 (0.157)
<b>Technology (ref. = Solar)</b>			
Other	0.596*** (0.221)	-0.161 (0.217)	-0.435 (0.372)
<b>Location (ref. = Africa)</b>			
Asia	-0.161 (0.340)	0.0193 (0.517)	0.142 (0.403)
Lat. America	0.265 (0.202)	0.050 (0.330)	-0.315* (0.164)
<b>Program cost (ref. = ≤\$100,000)</b>			
>\$100,000	0.072 (0.330)	0.107 (0.581)	-0.179 (0.324)
<b>Role of project stakeholders</b>	0.236 (0.399)	-0.079 (0.696)	-0.157 (0.425)
<b>Independence note</b>	0.309 (0.366)	-0.339 (0.737)	0.030 (0.524)
Observations	542	542	542
Obs. nb outcomes	252	89	538
Clusters	Yes	Yes	Yes

Average Marginal Effect of Multinomial Logit regression. LHS: Proven-Favorable, Proven-Unfavorable, Unproven. Subset of 879 observations based on DEPs. Ref =: Reference category. Estimates controlled by: Number of observations in evaluation samples (N), Delay of evaluation, Domain of effects, and Project characteristics. Coefficients tell the difference in percentage points from the prediction of referral category. Variance: clustered with bootstrap estimator. The variance-covariance matrix is estimated all at once for all four equations. +p <0.10, \*p <0.05, \*\*p <0.01, \*\*\*p <0.001.

## A.8. Type II error test

Decision of the model (sample)		
Reality of the population	Accept H0	Accept H1
H0 is true	Correct decision Probability = $1 - \alpha$ (0.95)	Incorrect decision Probability = $\alpha$ (0.05) <b>Type I error (false positive)</b>
H1 is true	Incorrect decision Probability = $\beta$ (0.2) <b>Type II error (false negative)</b>	Correct decision Probability = $1 - \beta$ (0.8)

## A.9. Distribution of impact evaluation methods across effects

Nature of effects	Freq
<b>Identification – RCTs</b>	
Basic Access (O7)	51
Information & Communication	25
<i>Total</i>	<i>76</i>
<b>Identification – non-RCTs</b>	
Basic Access (O7)	92
Information & Communication	22
<i>Total</i>	<i>114</i>
<b>Total</b>	
Basic Access (O7)	<b>143</b>
Information & Communication	<b>47</b>
<b>N</b>	<b>190</b>

# Chapter TWO: Does subscription to solar energy improve the market performance of Micro, Small & Medium Enterprises? Empirical evidence from selected markets in Nigeria

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## Abstract

This study examines the impact of Rensource solar energy on subscribers in five selected markets in the Nigerian states of Lagos, Kano and Ondo. The study also identifies the drivers of merchants' decisions to subscribe to Rensource solar energy. Data were collected during the months of July and August 2020. A total of 300 subscribers and 400 non-subscribers were sampled. Within each market, non-subscribers were sampled from different sections of the same markets as users. A probit regression model is used to determine what drives merchants to subscribe to Rensource solar energy. We then calculate the average treatment effect (ATE) and average treatment effect on the treated (ATT) using the propensity score matching (PSM) approach to examine the impact of using Rensource solar energy on merchants' performances. The results suggest that subscription to Rensource solar energy has a positive impact on monthly earnings, net income, volumes of sales and the profits of merchants. In addition, by subscribing to Rensource solar energy, merchants using the national grid and standby generators can cut down their average monthly expenditure on electricity by 36.64%. Then, our matching analysis also find a drop in environmental risks and health issues for the subscribers. The decision of a merchant to subscribe to Rensource solar energy hinges on a complex set of factors relating to the merchant's personal, business, and product characteristics as well as the supplier's characteristics and electricity supply. By taking into account the merchant, business and product characteristics identified, the future design of business strategies, models and communications can potentially increase the subscriptions to solar energy by businesses in Medium Small and Micro Entreprises (MSMEs) clusters and individuals substantially. Therefore, this study provides evidence for broader awareness creation based on the benefits of solar energy to the private sector in developing countries.

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<sup>32</sup> Global Development Network

## Introduction

The International Energy Agency (IEA) reports that the current global energy crisis has accentuated the urgency and importance, of developing and promoting reliable, cheaper and cleaner energy systems (International Energy Agency, 2022a). At the moment, 600 million people globally do not have access to electricity and majority of these people are in sub-Saharan Africa (International Energy Agency, 2022a). Thus, Sub-Saharan Africa (SSA) has access low electricity. As at 2020, the World Bank estimated that 48% of SSA's populace have access to electricity (World Bank, 2022). In addition, the demand for electricity in SSA is set to increase rapidly and as such attaining affordable and reliable electricity remains an urgent priority.

Currently, most countries in Africa are faced with growing risks of power rationing and total blackouts. This energy crisis has contributed to increasing food crises and poverty in some countries. The energy crises also have health and environmental problems resulting from the use of generators. For all of these problems, transitioning to clean energy is seen as a promising solution for Africa's energy (Abdul-Salam and Phimister, 2019; International Energy Agency, 2022). Meanwhile, the per capita use of clean energy in Africa is the lowest globally. Although Africa is considered as the home to 60% of global solar energy resources, only 1% of the population have installed solar power system (International Energy Agency, 2022b). Solar power is regarded as the cheapest source of energy in many parts of Africa. Hence, there is a need to investigate factors that influence uptake of solar energy and the impact it has on users. There is little empirical evidence on the drivers of uptake of solar energy in SSA.

Electricity is Nigeria's leading and most used energy source (Oyedepo 2012). The electricity system in Nigeria has for a long time been centered around the Power Holding Company of Nigeria (PHCN) which accounts for about 98% of the total electricity generation. PHCN mainly relies on both hydropower and thermal power stations. Thermal/fossil energy are the main source of electricity, accounting for about 86% of Nigeria's energy, while the remainder is generated from hydropower sources (Sambo et al. 2010, Oyewo et al. 2018). There is, however, power generation by other agencies such as the Nigerian Electricity Supply Company, which relies on thermal power stations for electricity generation.

The centralized power generation has not been able to meet the demand. The country suffers large power deficits and thus frequent power outages due to rationing and higher power costs (Aremu, 2019). Aremu (2019) notes that irregular electricity supply has led to a high production cost, loss of investors in the domestic economy, escalating unemployment as companies exit due to power costs, increasing customer discontentment with employees of the electricity distributor as well as noise and air pollution from generator use. Indeed, Akuru and Okoro (2014) cite an average estimate for a power backup to minimize the expected power outage costs as usually being three times the cost of the publicly supplied electricity. They further add that the persistent power outages coupled with expensive power backups have resulted in some businesses closing in Nigeria. Some users use generators to meet their power needs (Ferrero 2018). However, the use of generators often results in noise pollution in addition to requiring expensive fuel (Akin and Adejumbi 2017).

The solution to the country's power supply problem can be through a mix of energy source alternatives. Afa and Anireh (2013) suggested that in the face of global electricity market trend with a focus on cleaner, more diverse and more sustainable mix of electricity sources, Nigeria has the resources to meet this target.

Solar energy stands out, as Yohanna and Umogbai (2010) observe, since solar photovoltaic (PV) technology supplies electricity without pollution and requires less maintenance since nothing is consumed or worn out during their operation. Additionally, off-grid solutions have emerged as a cheaper alternative for electricity provision in urban, semi-urban and rural areas (Nigeria Electricity Hub 2019). The off-grid solution has created a lucrative opportunity to rapidly increase rural electrification, where about 55% of the population remains without electricity access (Nigeria Electricity Hub 2019). The potential of the off-grid solution is also very clear in urban areas where some households and business still do not have access to reliable electricity.

Currently, the Rural Electrification Agency (REA) and the Nigerian Ministry of Power launched in 2017 the Energizing Economies Initiative (EEI), a Private Public Partnership (PPP) project which aimed at providing clean, reliable and affordable off-grid energy solutions in a decentralized manner to viable economic clusters such as markets. Through this initiative, the Federal Government has adopted solar mini grids as the primary rural electrification resource to provide renewable electricity to underserved and unserved households and businesses (Nigeria Electricity Hub 2019). The REA is partnering with private sector off-grid energy developers to implement electrification projects across Nigeria and one of the private sector off-grid energy developers is Rensource. These alternatives are however not without their own sets of challenges. For example, for solar installations, initial costs are sometimes prohibitively high (Oghogho 2014). Moreover, the energy sector had initially relied on centrally generated electricity, but recent shifts aim for embedded generation. Oladipo et al. (2018) define an embedded generation (EG) as any electric power production technology that is integrated within distribution systems, close to the point of use. They further add that EG reduces the cost of the on-grid electric power supply.

Rensource has a mission of making Nigeria the first country in the world to rely predominantly on distributed renewables-based power generation. Rensource is a start-up energy company that was founded in 2015. It has about 105 employees, 1500 customers and provides power-as-a-service (PaaS) with open-ended payment plans in Nigeria. The company has a subscription-based B2C and B2B solar and battery-based PaaS model using solar-hybrid systems installed at the user's premises but maintained and serviced by the company. Rensource started with a household powering model but has since 2018 moved on to a micro small and medium-sized enterprise (MSME) model where they supply solar energy to markets. Nonetheless, Rensource still provides routine maintenance and services to its existing household clients. Within the current business model of Rensource, the rollout to new markets is prescribed by the REA. These new markets either have no access to electricity or rely on petrol/diesel generators. Rensource imports HS10000 Powerbox from China and provides power to multiple shops depending on energy usage, with a peak power of 10 kW. Every shop is fitted with a power meter which allows Rensource to monitor their usage and remotely control and limit their



access to a quantum of power, Rensource has partnered with Paga Nigeria's leading mobile payment companies (over 12 million customers) to facilitate payments in its PaaS agreement with end users. Alternatively, customers can make payments at the customer service center.

While some merchants adopt solar energy as soon as it is made available, others within the same market take up the service after seeing how it works. There are personal, socio-economic, institutional and product characteristics of merchants that influence their decision to subscribe to solar energy. Rensource seeks to understand what drives merchants to subscribe to their solar power and how they benefit in order to better manage the rollout. In some instances, Rensource extends its services to other parts of same market. However, empirical evidence on what drives the decision of merchants to subscribe and when to subscribe to Rensource's solar energy is limited. With the power provision plan of Rensource, merchants are expected to benefit from reliable and cheaper solar energy in several ways. However, currently there is no documented evidence on how Rensource customers benefit from Rensource's solar energy. Therefore, the following research questions were addressed using a first-time field data on merchants from five markets:

1. What is the profile of Rensource's customer base?
2. What drives merchants to subscribe to Rensource solar energy?
3. How do Rensource customers benefit from the service?
4. What are the environmental and health effects of Rensource users?

Addressing these gaps can shed light on some features of Rensource's customers, which in turn can help the firm improve its products and customer outreach strategies. This research generates evidence on the benefits attained by merchants who have subscribed to Rensource solar energy. Insights from the study can be used to develop messages for consideration by policymakers and practitioners as well as strengthening the productivity of SMEs. Furthermore, it provides insights to Rensource on areas where they can continue improving in order to meet the needs of their subscribers. As well as insights for the achievement of the Sustainable Development Goals (SDGs) 3 and 13. Findings from this research provide stronger evidence for conclusions on better-informed decision making and the sustainability of Rensource solar energy. Finally, this research contributes to the body of scientific evidence on how solar mini grids can affect SME performances, and their environmental and health issues.

This paper presents the related literature in [Section 1](#). The theory of change is presented in [Section 2](#). [Section 3](#) sets the empirical methodology. [Section 4](#) presents the main empirical results and discussion. Finally, we conclude and detail the policy implications of the findings in [Section 5](#).

# 1. Literature review

In this section we review relevant literature on factors that hinder or enhance the usage of solar energy and the impact of solar energy usage on individuals and SMEs.

## 1.1. Factors that influence subscription to solar energy

Some studies have shown that the adoption of solar PV systems relies on several factors such as access to credit and second-hand market (Abdul-Salam and Phimister, 2019), access to public services and facilities (Blimpo et al., 2020), the national political strategy for the domestic energy sector industry (Behuria, 2020), and the income level (Abdul-Salam and Phimister, 2019; Blimpo et al. 2020 ; Sievert and Steinbuks, 2020). Moreover, the reliability of power supplied is also a major vector that promotes the investment for energy access. Indeed, the analysis conducted by Deutschmann et al.(2021) reveals that senegalese households and firms are willing to pay 24-35% more than the current average price for electricity supply without outages. The 2775 households and 1072 firms surveyed, are willing to pay \$0.17 per kWh more than the current tariffs, mainly in a country where households spend 41% of their monthly electricity expenditures on alternative energy sources to the grid. Furthermore, electrification boosts income-generating activities (Blimpo et al. 2020) as well as the access to information and communication technology (ICT), and education activities (Jacobson, 2007). This field study of Jacobson (2007) from 1999 to 2004 highlights the social uses of solar PV of households in Kenya. However, these studies partly analyze both the determinants of solar PV adoption and the financial returns to MSMEs. While these very small-scale enterprises are the backbone of the low- and middle-income economies. For this purpose, our work strengthens the literature by estimating the drivers of Nigerian MSMEs' adoption of solar technology, as well as the effects of this subscription on their monthly income.

The body of literature on the use of solar energy in Africa is dominated by studies on domestic uses although there are a few brief mentions highlighting small-scale commercial uses such as in street lighting and at community centers (Ondraczek, 2013; Karakaya and Sriwannawit, 2015). Karytsas et al. (2019) highlight solar adoption and use for the non-household sector to incorporate areas such as the commercial sector as areas that need further attention. Therefore, the literature we hereby review is mainly focused on the household adoption of solar. Moreover, the domestic uses of solar highlighted, such as lighting and running small appliances (Khandker et al. 2014), are often similar to the uses by SMEs especially in areas where electricity supply by the national grid has not yet been extended.

In exploring the adoption of solar energy, we note that the decision to subscribe to solar energy is a micro-level decision, taken by the SME owners based on several factors. One of these factors is membership in market associations. Grossman (2020) notes that private groups can provide institutions that support contractual trade. Group membership also connects actors to

networks and De Janvry et al. (2017) note that networks transmit information and affect respondents' willingness to pay. Social learning facilitates the spread of information, and the updating of beliefs (Carattini et al. 2018). Reed et al. (2010) define social learning as a change in understanding that goes beyond the individual to become situated within wider social units or communities of practice through social interactions between actors within social networks. Hogset (2005) maintains that social networks may interact with technology adoption decisions through i) a social learning environment, ii) informal finance that may relax the actor's credit or risk tolerance constraints, and iii) facilitation of collective action where the coordination of adoption is needed due to technological externalities. Miguel and Kremer (2003) nonetheless caution that individual adoption behavior may reflect the priorities of the groups.

Gender may also affect adoption of renewable energy and challenges that are more prominent in relation to gender may impede the adoption of solar power. For example, Energia (2011) notes that in off-grid areas, female-headed households are poorer than male-headed households and have less access to electricity. Danielsen (2012) also observes that generally, women face difficulties in benefitting from energy services. For example, they lack income (which is a barrier for investing in technology that improves the productivity of their labor), they lack access to credit (which limits their ability to pay the upfront costs of improved energy technology or connection fees for the electricity grid), and they have limited access to extension services and education. Such limitations would imply a gendered difference in the adoption of solar technologies, even amongst merchants. Despite the limitations women face in adopting solar energy, Devine-Wright and al. (2007) indicate that women are more willing to pay for renewable energy technologies than men. Moreover, Winther et al. (2018) argue that because men tend to own the houses, have a higher income and make major decisions, women have less agency in systems with fixed connections and high subscription fees compared to decentralized systems of supply. Renewable energy technologies such as solar power systems are often decentralized.

Both higher education and level of income have a correlation with the adoption of solar power systems (Barau et al. 2020, Qureshi et al. 2017). Guta (2018) analyzed the factors that drive a household's decision regarding the adoption of solar energy technology in Ethiopia and found that wealthy households are more likely to adopt solar energy technology compared to poorer ones. Khandker et al. (2010) also demonstrate that high-income households tend to use clean, renewable and convenient sources of energy such as solar and electricity. This can be because wealthier households are more likely to cross the cost hurdle on adoption due to the high initial cost of solar power equipment. Indeed, Qureshi et al. (2017) suggest that higher income has a direct relationship with adoption as it may help in overcoming the cost barrier to adoption.

Education is likely to work through the channel of a positive effect on income and hence expenditure in influencing adoption (Lay et al. 2013). This argument is supported by Rahut and al. (2018) who argue that a high level of education is also associated with an increase in the household earning capacity, which leads to the generation of income to invest in solar energy equipment. Additionally, skills and knowledge gained from environmental education would help in changing human behavior towards the environment (Desa et al. 2012) and the skills development particularly support the uptake of innovative technologies. Indeed

Amankwah-Amoah (2015) suggests that there is a need for capacity enhancement through R&D, education and training to develop the skills of local people to support economic growth and foster innovation across the continent.

The availability of solar equipment is also key in determining its adoption, and where it is not readily available adoption is likely to be low. Indeed, in the Nigerian context, Akinboro et al. (2012) note that solar equipment is not manufactured in Nigeria and is therefore imported. Gulaliyev et al. (2020) argue that installing solar power systems in such a context is an expensive task.

The number of nearby installations affects social inclinations to install solar power (Mezic 2018). Bollinger and Gillingham (2012) hold a similar perspective and note that social interaction (peer) effects are a potentially important factor in the diffusion of new products. They note that an additional installation increases the probability of an adoption in the zip code by 0.78 percentage points. Brugger and Henry (2019) explain that peer effects work through a variety of mechanisms, such as the exertion of social influence on nonadopters and the provision of new information about the true costs and benefits of solar through active communication with solar adopters. In the context of electricity outages, reliance on generators and the subsequent occurrence of fire outbreaks in markets (Ogeah and Omofonmwan 2014), adopters are likely to assert some form of influence on nonadopters. Moreover, Ogeah and Omofonmwan (2014) suggest that markets are a source of livelihood to many people. This suggests that there is a need for more sustainable and reliable electricity with less risk of fire outbreaks. In this way the livelihood of people who depends on the market will be protected.

Lack of financial resources for upfront investment in new equipment and its installation can be a major impediment to adoption of solar energy technologies (Karakaya and Sriwannawit 2015). Installation costs can put off entrepreneurs from adopting them. Alrashoud and Tokimatsu (2019) argue that installation costs are the most significant barrier to adopting residential solar power systems. Bradford (2006) in Amankwah-Amoah (2015) suggests that over 90% of the lifetime cost of a solar power system is paid upfront at the time of installation, which is beyond the reach of most people in Africa. Moreover, there may be other initial requirements such as changing existing appliances (Barau et al. 2020). Lee and Callaway (2018) argued that following installation, the reliability and weekly/monthly fees for the installed power system are crucial whether people decide to become users or not. Lee and Callaway (2018) also observed that in both West and East Africa, decentralized solar power systems are competing with grid systems, in terms of both reliability and tariff features. Moreover, Kariuki (2018) adds that the lack of spare parts and adequate skills to repair or service equipment lead to equipment failure which halts the supply of energy and lowers customer confidence in some renewable energy technologies, therefore hindering adoption.

Knowledge and awareness can generally enhance subscription to solar energy; Qureshi et al. (2017) observe that a lack of awareness in developing countries could add to misinformation amongst potential adopters. In spite of its importance, awareness of solar energy as a source of power is still very low in Nigeria. Akinwale et al. (2014) and Akinboro et al. (2012) note that most users hold a perception that solar energy can only power a few watts of lighting.

Moreover, the common perception that solar energy is to be used only temporarily while waiting for grid power, implies temporary adoption (Kumar et al. 2019). Also, with erratic electricity supply, users are likely to perceive solar power systems as a complementary source rather than a substitute for the national grid.

## 1.2. Impact of solar energy on SMEs

The adoption of solar power systems is likely to impact on users, especially those within the SME sector, and one area of impact is likely to be in profitability of businesses. Adewuyi and Emmanuel (2018) observe that business losses due to electricity outages have been significant, and arise especially from either own generation of power or bribing of electricity officials to mitigate such outages. Babajide and Brito (2020) suggest that the adoption of solar power systems opens up possibilities for additional income generation and results in savings on both fuel costs and environmental costs. The adoption of Rensource solar technology can thus improve the profitability of businesses.

Solar power systems can result in business profitability through an increase in the productive working hours of merchants within markets. Furthermore Booth et al. (2018) note that the productive use of renewable micro-grid systems has a positive impact on local economic activity, value addition to products and services, job creation, and enhanced gender equality. Barman et al. (2017) suggest that extra income can be generated from activities like conducting business during the evening or processing agricultural products in the evening due to the availability of better-quality lighting.

The adoption of solar power is also likely to impact on employment; Dinkelman (2011) studied South Africa's post-apartheid rural electrification program and found that it led to a 13.5% increase in female employment, considering that access to electricity enabled new businesses to produce local goods and services that were previously imported at a higher cost. Additionally, Iyke (2015) argues that electricity consumption is a fundamental driver of economic growth in the Nigerian context, and Yadav al. (2019) reveal that the positive experience of users regarding solar power offers opportunities for solar power businesses to address unmet energy demand and further grow the market in rural communities. Further, jobs created by the productive uses of solar energy can have a multiplier effect as workers spend part of their income on the local economy, resulting in positive externalities through the creation of additional jobs (EUEI-PDF and GIZ 2013).

Although there are benefits to the adoption of solar power systems, very little empirical research has been done on the factors that affect their adoption and the impact of their adoption. Therefore, the value-addition of our study on Rensource micro-utilities in Nigerian markets will highlight the factors that affect adoption and the possible impact of solar power adoption in the Nigerian context.

### 1.3. Renewable transition and energy expenditures

There may be other initial requirements such as changing existing appliances (Barau et al. 2020). Lee and Callaway (2018) argued that following installation the reliability and weekly/monthly fees for the installed power system are crucial whether people decide to become users or not. Lee and Callaway (2018) also observed that in both West and East Africa, decentralized solar power systems are competing with grid systems, in terms of both reliability and tariff features. Furthermore, the lack of spare parts and adequate skills to repair or service equipment leads to equipment failure which halts the supply of energy and lowers customer confidence in some renewable energy technologies, therefore hindering adoption Kariuki (2018).

### 1.4. Environment and health impacts of solar energy adoption

Several studies assessed the health benefits of solar systems projects in developing countries. For instance, the descriptive analysis of Azimoh et al. (2017) looks at the impact of PV solar system on the food security of households through the prism of the cold chain. Indeed, the households living in the village of Tsumkwe (Namibia) experienced an improvement in the storage of food products and medical equipments. Through a matching strategy, Samad et al. (2013) find that the access to solar kits, financed by the Government of Bangladesh in partnership with the World Bank and the Infrastructure Development Company Limited (IDCOL), generated a decreasing incidence of gastrointestinal and respiratory diseases of children and adults. These results are consistent with the findings of Grimm et al. (2013), who conducted a randomized experiment on children in Rwanda. As a matter of fact, the randomized experiment technique has been used in the evaluation of large-scale solar projects in Uganda (Furukawa, 2014) and Bangladesh (Kudo et al., 2015), among others.

In terms of environmental dimension, there are some studies that measure the effect of solar panels on the amount of GHG emissions (Babajide and Brito, 2021; Sapkota et al., 2013; Lahimer et al., 2013; Al Irsyad et al., 2019; Ouedraogo et al., 2015; Sovacool, 2018; Mishra and Behera, 2016; Acker and Kammen, 1996; Rafique et al., 2018; Herwig, 1997; Chauhan and Saini, 2015). Furthermore, there is also a growing interest in assessing the avoided GHG emissions as a result of the implementation of solar projects. For instance, the hybrid solar and wind electrification project in Sitakunda (Bangladesh) allows to avoid the emission of 25 tonnes of Carbon Dioxide per year (Nandi and Ghosh, 2009). Bhattacharyya and Palit (2016) reached the same conclusion for the Off-grid Access Systems for South Asia (OASYS) program in India. As well as for the descriptive study of (Chakrabarty and Islam, 2011). However, there is a lack of impact evaluation on the environmental outcomes of small-scale solar projects on MSMEs. While, these private sector actors are the most exposed to the harmful consequences of fossil fuel energies.

## 2. Theory of change

A theory of change explains how activities are understood to produce a series of outcomes that contribute to achieving the final intended impact (Rogers, 2014) and can also help companies improve their strategy, measurements, communication and partnerships (Harries et al. 2014). The impact pathways and beneficiaries are illustrated in Figure 1 showing the intermediate outcomes required for project outputs to bring real benefits (purpose and goals). The primary beneficiaries of Rensource solar technology are SME owners (merchants, shop keepers) who use solar energy in their operations. With reference to the determinants of usage or adoption of Rensource solar-based micro-utilities, the company interfaces with a number of both internal and external enablers in delivering its products and services to users. While the internal enablers exist within the organization or are within its control, the external enablers are often beyond its immediate control (as a result of social, cultural, economic and political factors, laws, regulations, working with other organizations, etc.) (Harries et al. 2014).

The willingness of SMEs to adopt renewable energy can be influenced by other businesses within the area (Adepoju and Akinwale 2019). Indeed, Ugulu (2016 pp. 147) notes that, “Knowledge is a key problem because people do not believe it works. They must see that it works before they will accept the technology. That was why we installed it to convince people that it works. When they see you using it, they realize it is not just that you want to make a sale, but that it actually works.” Additionally, peer influence is important and an actor’s decision to adopt a technology will be affected by others’ decisions, either from information sharing through the process of social learning, or image motivation in which households may receive utility from the conspicuous consumption of an environmentally-friendly good (Bollinger and Gillingham 2012).

Furthermore, institutional factors also influence the adoption of technology, including government policies such as subsidies to conventional power suppliers which make the traditional sources cheaper than solar power sources for consumers, thus creating an unfair competition for solar power exploitation (Ohunakin et al. 2014). At the macro level, factors such as GDP growth, financial development and trade openness have a long-term relationship with renewable energy technology adoption (Saibu and Omoju 2016). Socioeconomic factors also affect the adoption of solar energy by SMEs (Bada 2011). Indeed, characteristics such as age, education status, occupation, and average income are likely to influence the choice of energy used by households (Baiyegunhi and Hassan 2014) and are also likely to feed into SME energy choices.

## 2.1. Output

In terms of output, the provision of reliable electricity (the solar energy system) is the key output from Rensource. This reliable energy results in an improvement in production, reduction in noise and smoke pollution, reduction in fire outbreaks and subsequent loss of property which are often outcomes of the use of petrol/diesel-powered generators as a backup due to constant power outages.

## 2.2. Intermediate impact

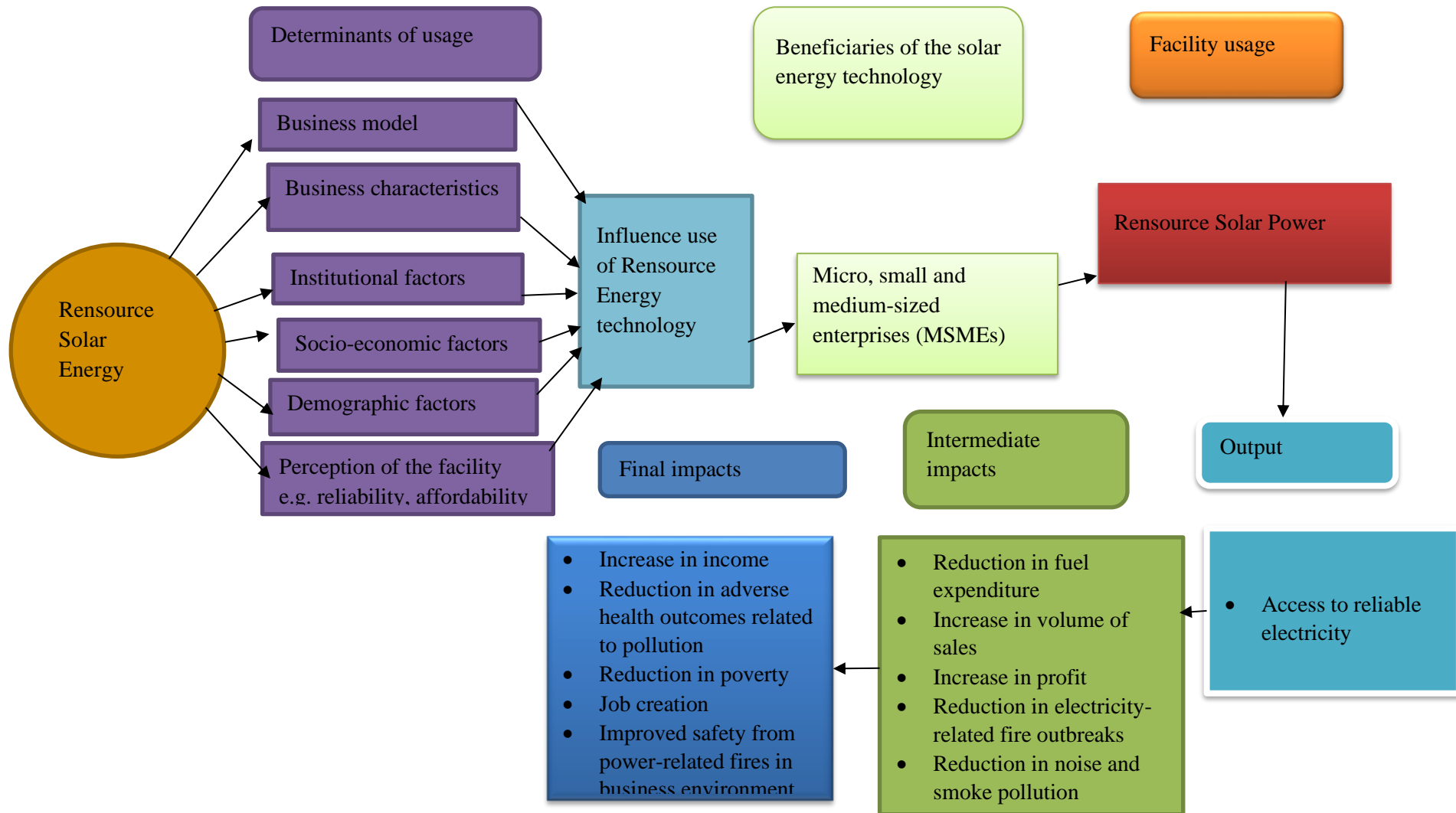
The intermediate impacts are i) reduced risk of fires from generators, ii) increase in volume of sales, leading to increased profit through lighting of shops so that products are more visible and attractive to customer, creation of a more comfortable and friendly environment for customers, testing of electrical appliances to build trust and customer confidence in products, more working hours and days, refrigeration to avoid spoilage and loss of perishable goods, iii) reduction in expenditure on fuel for back-up generators.

## 2.3. Final Impact

In the long term, there can be broader changes in society through the use of the solar-based micro-utility model, leading to an increase in income due to increases in sales and profit as well as expansion of businesses to cover services that require electricity. Business expansion can lead to the employment of more personnel. The use of Rensource solar energy can also reduce exposure to noise and smoke pollution (mainly from standby generators used during power outages from the national grid) thus reducing adverse health outcomes resulting from pollution. Furthermore, the reduction in electricity- or generator-related fires results in improved safety within the physical business environment. These outcomes and intermediate impacts have a direct link to poverty reduction.



**Figure 1: Theory of change**



### 3. Research methodology

#### 3.1. Sampling and data collection

The research is focused on subscription to Rensource solar energy and since the current model of Rensource focuses on markets and not individual households, the focus is on markets as well. Our first-time data includes all merchants in the markets where Rensource operates. The population includes both subscribers to Rensource solar energy and non-subscribers to Rensource in selected markets in the selected states.

The multistage sampling approach was adopted in capturing the targeted population of the study. In the first stage, we purposively selected the states of Lagos, Kano and Ondo because these are areas where Rensource is currently operating. In Kano, Sabon Gari market was selected. Iponri market was selected in Lagos. Isikan, Nepa 1 and Nepa 2 markets were selected in Ondo. A sampling frame of Rensource subscribers in the selected states were provided by Rensource. From these sampling frames, we randomly sampled 180, 75 and 45 subscribers from Sabon Gari, Iponri and Isikan, Nepa 1 and 2, respectively. The different sample sizes were proportional to the total number of subscribers in the various markets. A total of 300 subscribers were selected from a sample frame of 400 merchants (i.e. the treatment group). To gain insights into the causal impact of Rensource solar energy, non-subscribers were also sampled from different sections of the same markets (i.e. the control group). The non-subscribers operating in different sections of the same markets were pointed out by Rensource as potential clients whom they plan to roll out to, in the near future. For instance, in Ondo, after rolling out in Isikan, services were further rolled out in Nepa 1 and Nepa 2. Additionally, Rensource did not have a potential market recommended by the REA at the time of the survey. Sampling frames were prepared for the non-subscribers and from these frameworks 250, 100 and 50 merchants were sampled from Sabon Gari (Kano), Iponri (Lagos) and Isikan, Nepa 1 and 2 (Ondo), respectively. A total of 400 non-subscribers were sampled from a sample frame of 600 merchants. In all, a total of 700 merchants were sampled.

**Table 1: Respondents by state and market**

<b>State</b>	<b>Kano</b>	<b>Lagos</b>	<b>Ondo</b>		<b>Total</b>	
<b>Market</b>	<i>Sabon Gari</i>	<i>Iponri</i>	<i>Isikan</i>	<i>Nepa 1</i>	<i>Nepa 2</i>	
<b>Users</b>	180	75	26	14	5	<b>300</b>
<b>Non-Users</b>	250	100	26	16	8	<b>400</b>
<b>Total</b>	430	175	95	30	13	<b>700</b>

Through a field work, data collection was carried out over the months of July and August 2020. Both qualitative and quantitative data were collected. The combination of both qualitative and quantitative data helps to overcome weaknesses in using only one of the methods and hence, have stronger evidence for a conclusion for better-informed decision making (Creswell and Clark 2007). The original data collected focused on the socioeconomic characteristics of subscribers and non-subscribers in the selected markets. The social, economic, demographic, institutional and technological factors that influence the use of Rensource solar energy were also captured in the customized questionnaire for both users and non-users ([Appendix 12](#)). The structured questionnaire captured information on sales, income and expenditures on diesel, petrol and electricity bills. Lastly, the structured questionnaire solicited information on benefits associated with the use of solar energy.

Due to the COVID-19 pandemic, we contracted a local data collection company (the Development Strategy Centre, Enugu, Nigeria) to collect the data. Face-to-face interviews were conducted. The Development Strategy Centre has research assistants in different states. Three teams were formed to implement the field survey in each of the selected markets. Each team comprised four enumerators who worked under the supervision of one team leader (supervisor). The supervisor monitored the activities of the enumerators carefully to ensure that the data quality was not compromised. Also, at the end of each day of enumeration, the supervisor went through the completed questionnaires to ascertain if there were any data gaps, and these were completed before the team left the market. These were the steps we took as part of our strategy to control data quality during the field survey. Both qualitative and quantitative methods were used to analyze the data collected. The qualitative data were triangulated with the quantitative data to crosscheck the reliability and consistency of the information obtained to ensure a higher accuracy.

### 3.2. Conceptual and empirical framework

Most of the merchants who have subscribed to Rensource solar energy previously had no access to national grid electricity. Only 7% of the subscribers had access to the national grid connection. As a result, the merchants were relying on diesel or petrol for power generation with reports of some fire outbreaks which have resulted in a loss of properties. Some of the markets had access to national electricity, but electricity from the national grid is not reliable. Theoretically, it is assumed that a merchant chooses to subscribe to Rensource solar energy based on the expected benefit, given the available socioeconomic, institutional and technological characteristics. The benefit Rensource seeks to deliver to Nigeria's SMEs including merchants at a profit for itself — is to lower overhead costs through better business practices and free them from the bane of generators. The decision-making process follows three steps:

1. The REA recommends which market to roll out the program.

2. Rensource makes an agreement with the market association of the market chosen by the REA.

3. Individual merchants decide whether to subscribe or not.

Thus, the individual merchants make their decision only at step 3. They are not a randomly selected set of merchants, but have already been subject to both choice processes. Therefore, the study examines the decision of the merchants to subscribe or not. In this study, we determine the impact of subscribing to Rensource solar energy on merchants' income. We denote the benefit of merchant  $i$  conditional on subscribing to Rensource as  $R_S$  and  $R_{NS}$  for non-subscribers. Rationally, the merchant will subscribe to the solar energy if benefits from subscription is higher than non-subscription ( $R_S > R_{NS}$ ). This translates into a binary choice represented as:

$$R_{iS} = Z_i \alpha_S + \varepsilon_{iS} \quad (1)$$

$$R_{iNS} = Z_i \alpha_{NS} + \varepsilon_{iNS} \quad (2)$$

Where  $Z_i$  is a vector of socioeconomic, institutional and technological characteristics and market-level characteristics and location-specific dummies.  $\alpha_S$  and  $\alpha_{NS}$  are parameters to be estimated, and  $\varepsilon_{iS}$  and  $\varepsilon_{iNS}$  are random disturbance terms for subscribers and non-subscribers respectively. The perceived net benefits of subscribing to Rensource solar energy are not known to the researchers. Only the  $Z_i$  vector characteristics are known during the survey. We can represent the net benefit associated with Rensource solar energy subscription by a latent variable  $R_i^*$  ( $R_i^* = R_{iS} - R_{iNS}$ ) and this can be expressed as a function of observable characteristics  $Z_i$  in the form:

$$R_i^* = \alpha Z_i + \mu_i; \quad R_i = 1 [R_i^* > 0] \quad (3)$$

where  $R_i$  is a binary dependent variable that equals 1 for subscribers who subscribed to Rensource solar energy, and 0 otherwise.  $\alpha$  is a vector of parameters to be estimated,  $i$  is the individual merchant indicator, and  $\mu$  is the error term which is generally known as the effect of the unobservables.  $Z$  is a vector of socioeconomic (e.g. age, gender, education, income, employees) institutional (e.g. access to credit, membership of marketing association) and technological characteristics and market-level characteristics (e.g. previous experience with market fire outbreak, type of products) and location-specific dummies.

To determine what drives merchants to subscribe to Rensource solar energy, we used the probit regression model. Given that our data are not based on experimental design, the assignment to treatment is non-random, and thus, merchants that have subscribed to Rensource (i.e. the treatment group) and non-subscribers (control group) may differ not only in their treatment status but also in other characteristics that affect both subscription and the outcome of interest.

To avoid the biases that this may generate, we used matching methods (e.g. nearest neighbor matching (NNM), Kernel-based (KBM) and radius) to find a non-subscribed merchant that is “similar” to a subscribed merchant, allowing us to estimate the impact of subscription as the difference between a subscriber and the matched comparison case. We used the matching estimators to examine the impact of using the Rensource solar energy on shop owners or merchant’s income and fuel expenditure. In this study, matching was done on the kind of product sold by merchants and also on time-invariant characteristics, such as gender and state.

We used the average treatment effect on the treated (ATT) using the propensity score matching (PSM) approach. The PSM was used because it is one of the most important innovations in developing workable matching methods and allows matching problem to be reduced to a single dimension (Heinrich et al. 2010). Some studies have established that PSM eliminates a larger proportion of the systematic differences in characteristics between treated and untreated subjects (Austin 2011; Heckman et al., 1998, Heinrich et al. 2010). The two main advantages of using the PSM are that it is always possible for a binary treatment if sufficient data are available (and so it can be seen as a “method of last resort”) and that it can be done ex-post, including in the absence of baseline data. The drawback is that PSM relies upon matching on observables.

The PSM indicates the pairing of treatment and control units with similar values on the propensity score and possibly other covariates, while removing all the unmatched units (Rubin 2001). Estimating the treatment effects based on the propensity score, requires two assumptions. The first is the conditional-independence assumption (CIA) which requires that the common variables that affect treatment assignment and treatment-specific outcomes be observable. The dependence between treatment assignment and treatment-specific outcomes can be removed by conditioning on the observable variables. The second assumption is that the average treatment effect on the treated ( $ATT_{PSM}$ ) is only defined within the region of common support. This assumption ensures that merchants with the same  $Z$  values have a positive probability of being both subscribers and non-subscribers (Heckman et al., 1998). Once the propensity is computed, the impact of a treatment for an individual merchant  $i$ , noted  $Q_i$ , can be estimated using the Average Treatment Effect on the Treated (ATT) and Average Treatment Effect (ATE).

The ATT is of greater interest in this particular research context than the ATE because it is more realistic to examine the effect of subscription on merchants who have subscribed to use Rensource solar energy. For a Rensource merchant who subscribed with characteristics  $Z_i$ , the expected outcome is stated as:

$$E(Q_{iS} | Z, R = 1) \tag{4}$$

The expected outcome of the same Rensource subscriber had he or she chosen not to subscribed to the solar energy is

$$E(Q_{iNS} | Z, R = 0) \tag{5}$$

The change in outcome (i.e. monthly earnings) due to subscription is the difference between the subscription decision (i.e. equation 4) and non-subscription (i.e. equation 5). This estimate is called the ATT and specified as:

$$ATT_{PSM} = E(Q_{iS} | Z, R = 1) - E(Q_{iNS} | X, R = 1) \quad (6)$$

Thus, the ATT measures the average effect of subscription on merchants that have subscribed to Rensource solar energy. Average Treatment Effect (ATE) on the other hand is defined as the difference between the expected outcome in case of treatment (subscribers) and the expected outcome in absence of treatment (non-subscribers). Generally, the mean impact of subscription is obtained by averaging the impact across all the individuals in the population. This parameter is called the Average Treatment Effect (ATE):

$$ATE = E(Q_{iS} | Z, R = 1) - E(Q_{iNS} | Z, R = 0) \quad (7)$$

$Q_{iS}$  is the monthly earnings of subscribers and  $Q_{iNS}$  is the monthly earnings of non-subscribers. In other words, the ATE is the average impact, at the population level, of moving the non-subscriber population from the untreated group to the treated group (Austin, 2011). Another quantity considered in this study is the Average Treatment Effect on the Treated (ATT). The nearest neighbor matching (NNM), Kernel-based (KBM) and radius approaches are discussed in the next section.

### 3.2.1. Matching steps

The PSM approach should satisfy three main conditions:

- **Conditional independence assumption (CIA)** such as  $([Y(0); Y(1)] \perp T | X)$ , where the potential outcome should be independent from the assignment status (subscription to Rensource or not), conditioned to the set of covariates.
- **Common support assumption** which monitors if the probability between zero and one to get treated or not is the same for each individual, conditioned to the set of observables as defined by  $(0 < P(X) < 1)$ .
- **Balancing assumption** where merchants with the similar score have the same distribution of observables for the treated and the control group, such as  $(T \perp X | b([X]))$ .

The aim of this paper is to estimate the effect of subscription to Rensource on the monthly earnings of merchants, as defined by:

$$Y_i = \alpha + \beta T_i + \delta X_i + \varepsilon_i \quad (8)$$

Where  $Y_i$  is the monthly earnings of the merchants,  $T_i$  represents the treatment to subscribe to Rensource or not,  $X_i$  gather the set of observables for each merchant,  $\beta$  and  $\delta$  are the parameters to be estimated,  $\alpha$  is the constant parameter, and  $\varepsilon_i$  is the unobserved random error. This specification is computed at the individual merchant level ( $i$ ).

Our study respects the first assumption as the wealthiest merchants are not influenced by the subscription to Rensource solar system given that they are mainly connected to their private generator systems (cf: [Table 3](#)). And conversely, the poorest merchants have lower chances to afford the payment for installation of Rensource solar system.

Then, the two other assumptions are presented in [Appendix A.1](#). First, the common support graph shows that after performing the PSM, a large part of our sample is include in the interval [0.3;0.7]. The histogram graphically tests for each stratum of the propensity score. Then, the table which numerically tests for the common support assumption confirms that 695 treated and control merchants are located in the common support interval.

Then, the last step of the PSM process identifies the respect of the balancing assumption. The latter aims to check whether the observable characteristics of the treated and non-treated merchants are still similar after the matching procedure. The Pstest graphs in [Appendix A.1](#) show that the bias between treated and control was greatly reduced after PSM for all merchants' characteristics included in the analysis. For instance, the densities of the age, the income, the education level, and the market location of the users and non-users are closer after matching. Hence, one can conclude that the sample seems sufficiently balanced after the matching process.

### 3.2.2. Nearest neighbor matching

Nearest neighbor matching allowed us to match or pair merchants that have subscribed to Rensource with another 'closest' merchant in the non-subscriber group. Let us assume  $p_i$  and  $p_j$  are propensity scores respectively for merchant  $i$  in the treatment group (Rensource subscribers) and merchant  $j$  in the control group (non-Rensource subscribers), with  $i$  belonging to  $I_1$  (the set of Rensource subscribers) and  $j$  belonging to  $I_0$  (the set of non-Rensource subscribers). We defined a neighborhood  $C(P_i)$  which contained a non-Rensource subscriber  $j$  ( $j \in I_0$ ) as a match for a Rensource subscriber  $i$  ( $i \in I_1$ ) if the absolute difference of propensity scores was the smallest among all possible pairs of propensity scores between  $i$  and  $j$  such as:

$$C(P_i) = \min_j \| p_i - p_j \|, \text{ with } j \in I_0$$

(9)

Once a merchant  $j$  in the non-Rensource subscribers group was found to match a merchant  $i$  in the Rensource subscribers group, that merchant  $j$  was removed from  $I_0$  without replacement. In the event that for each merchant  $i$  in the Rensource subscribers group there was only a single merchant  $j$  from the non-Rensource subscribers group which was found to fall into  $C(P_i)$ , then the nearest neighbor matching would be called a pair, or one-to-one, matching. Otherwise, if for each merchant  $i$  in the Rensource subscribers group, we found  $n$  non-Rensource subscribers falling into  $C(P_i)$  as matches, then the nearest neighbor matching would be said to be a one-to-many matching. In practical terms, using the statistical software STATA, we implemented

the nearest neighbor algorithm of Becker and Ichino (2005). Nearest neighbors are not identified by comparing each Rensource subscriber to every single non-Rensource subscriber, but rather by first sorting all observations (merchants) by the estimated propensity score and then searching forward and backward for the closest non-Rensource subscriber(s) in the control group. If for a merchant  $i$  in the treatment group, the forward and backward matches happened to be equally good, then the algorithm randomly drew either the forward or backward matches.

### 3.2.3. Radius matching

In the previous definition of matching, we did not assign or impose any restrictions on the distance between  $p_i$  and  $p_j$ . This implies that even if  $\|p_i - p_j\|$  was large or, in other words, a non-Rensource subscriber  $j$  was very different on the estimated propensity score to a Rensource subscriber  $i$ , the non-Rensource subscriber  $j$  was still considered a good match to the Rensource subscriber  $i$ . Therefore, to overcome bias that might arise from wrongly identifying the suitable non-Rensource subscriber  $j$  in the control group, we selected the Rensource subscriber  $i$  as a match for the non-Rensource subscriber  $j$  only if the absolute distance of propensity scores between the group of Rensource subscriber and non-Rensource subscriber complied with the following condition:

$$\|p_i - p_j\| < \epsilon \tag{10}$$

Where  $\epsilon$  is a pre-specified tolerance for matching, also known as a caliper.<sup>33</sup> Radius matching is a variant of caliper matching that was developed by Dehejia and Wahba (2002). The rationale behind radius matching is to use not only the nearest neighbor within each tolerance level or caliper, but rather all of the comparison non-Rensource subscriber within the caliper. Radius matching therefore made it possible to use more (or fewer) merchants when good matches were (or were not) available and avoided the risk of bad matches between merchants. We computed the ATT using the algorithm from Becker and Ichino (2005) implemented in STATA. The algorithm allowed us to restrict the analysis to those Rensource subscribers matched to a “control”<sup>34</sup> non-Rensource subscriber that lay within a defined radius.<sup>35</sup>

### 3.2.4. Kernel matching

The kernel matching estimator compares the outcome of each treated Rensource subscriber to a weighted average of the outcomes of all the non-Rensource subscribers, with the highest weight being placed on those with scores closest to the treated merchant. One major advantage of these approaches is the lower variance, which is achieved because more information is used.

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<sup>33</sup> Rosenbaum and Rubin (1985) recommended using 0.25x standard deviation of the estimated propensity score of the analysis sample as the caliper size.

<sup>34</sup> In the event of multiple best controls, the average outcome of those controls was used.

<sup>35</sup> We followed Becker and Ichino (2005) and used 0.1 as a predefined radius.



A drawback of this methods is that some of the observations used may be poor matches. Hence, we imposed the common-support condition in the estimation. We used the kernel function and the bandwidth parameter in the estimation.

## 4. Results and discussion

### 4.1. Descriptive results

#### 4.1.1. Distribution of users and non-users by gender, education, shops status and ownership

[Table 2](#) presents the distribution of gender, education, shops status and structure of business owners. The results show that 64.3% of Rensource users are men and the remaining 35.7% are women. For the non-users, men constitute 66% of the sample and women constitute 34%. The results indicate that female ownership of businesses relative to men is low. Chi-square test results indicate that there is no significant difference in male and female proportions between the users and non-users of Rensource solar energy. Regarding the educational status of merchants, the results show that most of the users and non-users have completed secondary school education. However, the proportion of non-users that have completed secondary school education is significantly higher ( $\chi^2=7.44$ , P-value=0.05) than that of users of Rensource solar energy. In addition, the percentage of Rensource users that have completed tertiary or university education is higher than that of non-users and a Chi-square test indicated that the difference is statistically significant ( $\chi^2=7.90$ , P-value=0.04). This means that Rensource users are more likely to have higher level of education. The percentage of merchants that have attained primary school education does not differ between users and non-users. One can observe that about 82% of both users and non-users of Rensource solar energy are working in rented shops. Family-owned shops (i.e. the shop belongs to the entire family) in both categories of respondents are about 3%, whereas, 16% and 15% of non-users and users respectively, own their shops (i.e. the shop belongs to an individual). The results also show that there are no differences in the ownership status of shops used by users and non-users of Rensource solar energy, as indicated by the insignificant Chi-square estimate.

**Table 2: Distribution of users and non-users (in percent)**

Variable	Users (N=300)	Non-Users (N=400)	Chi-Square
<b>Gender</b>			
Male	64	66	$\chi^2 = 0.21$ , P-value=0.65
Female	36	34	
<b>Education</b>			
Adult education	1	1	$\chi^2 = 5.44$ , P-value=0.25
No formal schooling	9	8	
Primary	20	20	
Secondary <sup>a</sup>	45	52	
Tertiary/University <sup>b</sup>	25	19	
<b>Status of shops</b>			
Rented	82	82	$\chi^2 = 0.14$ , P-value=0.93
Owner	15	16	
Family owned	3	3	
<b>Ownership structure</b>			
Sole proprietorship	95	96	$\chi^2 = 6.89$ , P-value=0.07
Partnership	3	4	
Association	1	-	
Other	0	-	

<sup>a</sup>  $\chi^2 = 7.44$ , P-value=0.05

<sup>b</sup>  $\chi^2 = 7.90$ , P-value=0.04

In terms of ownership structure of businesses, most of the users and non-users of Rensource solar energy are in sole proprietorship. Only 3.3% of users and 4% of non-users are in partnership. To summarize, the results in Table 2 show that Rensource subscribers are mainly men who completed secondary education, and are working in rented shops managed under sole proprietorship.

#### 4.1.2. Descriptive statistics of users and non-users, and enterprise characteristics

[Appendix A.2](#) provides the descriptive statistics on some of the variables in the sample. The average age of business owners using Rensource solar energy is 44 years. The oldest Rensource client is 82 years and the youngest is 17 years old. For the non-Rensource users, the average age of business owners is 42 years with minimum and maximum ages of 18 and 72 years, respectively. The average age of businesses using Rensource solar energy is 13 years and that of businesses that are not using Rensource solar energy is 12 years. The oldest business among the Rensource users is 40 years and amongst non-users is 50 years. The average household sizes of both Rensource users and non-users are 5 and a standard deviation of 3.

The proportion of Rensource users' and non-users' household income from trading ranges from 1% to 100%. However, the average proportion of household income from trading is 2% higher for non-users compared to users of Rensource solar energy. In terms of monthly income earned from trading, [Table 3](#) shows that Rensource users on average earn ₦ 145,926 (\$326) whereas non-users earn ₦ 116,436 (\$260). Notwithstanding the maximum income earned by both groups is ₦ 800,000 (\$1,785). Rensource users on average have two employees in their shops with a maximum of fifteen whereas non-users typically employ three people with a maximum of sixteen. Both Rensource users' and non-users' typically have one branch of their shops.

In [Appendix A.2](#), we present some merchants and enterprise characteristics for users and non-users of Rensource solar energy for different gender groups. The results in [Appendix A.2](#) show that among the users of Rensource solar energy, male business owners are on average three years older than females whereas there was no significant difference in age between males and females in the non-users group as indicated by the T-test results. For both users and non-users of Rensource solar energy, the results indicate that a larger proportion of the household income of male business owners emanates from trading compared with female business owners, as indicated by a significant mean difference of 32%. In terms of monthly income from trading, we found that females earn more income than males. Specifically, females using Rensource solar energy earn ₦ 6,587 (\$15) more than males using the same solar energy from Rensource whereas females in the non-users group earn ₦ 21,530 (\$48) more than males. In terms of number of employees and shop branches, the results indicate that there are no significant differences between males and females in both the users and non-users groups.

### 4.1.3. Energy cost of users and non-users

The results in [Table 3](#) further show that the average business owner is 44 years old while the average age of the businesses for Rensource users is 13 years and for non-Rensource users is 12 years. The monthly electricity bill of Rensource users who had connection to the national grid (only 7%) prior to subscription ranged from ₦ 200 (\$0.45) to ₦ 36,000 (\$80) with an average bill of ₦ 3,152 (\$7), whereas non-users on average paid ₦ 3,139 (\$7) per month for electricity with a minimum of ₦ 300 (\$0.67) and a maximum of ₦ 30,000 (\$67). A t-test for difference in means indicated that there is no significant difference in the mean electricity bill paid by Rensource users and non-users. In terms of fuel cost, the results indicate that Rensource users on average spent ₦ 10,888 (\$24) on fuel for generators per month prior to subscription to Rensource whereas non-users on average spent ₦ 8,022 (\$18) on fuel for generators per month. A significant mean difference of ₦ 2,866 (\$6) was found using the t-test for difference in means between Rensource users and non-users. Notwithstanding this, the maximum cost for users and non-users is about ₦ 80,000 (\$179) and ₦ 100,000 (\$223), respectively. After subscribing to Rensource, the results indicate that the average monthly bill was ₦ 5,144 (\$11) with minimum and maximum bills of ₦ 300 (\$0.67) and ₦ 20,000 (\$45), respectively. *In terms of fuel cost, subscribers of Rensource who were only using generators prior to subscription on average saved ₦ 5,744 (\$13) on fuel cost. Rensource subscribers who were previously relying solely on national grid were, after subscription, paying ₦ 1,992 (\$4) more for reliable solar energy from Rensource.*

Comparing the average cost of fuel per month for non-users to the Rensource average bill per month, we found that the average fuel cost is ₦ 2,878 (\$6) higher than the average cost of Rensource solar energy per month. Nonetheless, the average monthly cost for electricity from the national grid is less than the average cost of Rensource solar energy per month. This is expected because of the frequency of electricity outages that merchants experience. In terms of fuel cost, subscribers to Rensource on average save ₦ 5,744 (\$13). However, it is worth mentioning that due to the unreliability of the national grid electricity, some merchants (25% of subscribers) resorted to using both the national grid and generators. They automatically switched to generators when the national grid went off, *hence incurring costs on both fuel for generators and the national grid. Using a before and after comparison, the results suggest the combined average cost of electricity and fuel for generators per month (i.e. ₦ 14,040 / \$31) is higher than the average bill of ₦ 5,144 (\$11) per month paid for Rensource solar energy. Thus, the subscribers of Rensource on average save about ₦ 8,896 (\$20) per month, and this represents a 36.64% reduction in electricity expenditure.*

The merchant and enterprise characteristics for users and non-users of Rensource solar energy for different states are presented in Appendix [A.3](#) and [A.4](#). In addition, the merchant and enterprise characteristics were computed across different product categories and presented in [Appendix A.5](#).

**Table 3: Merchants and enterprise characteristics for users and non-users of Rensource solar energy**

Variable	Description	Users (N=300)				Non-Users (N=400)			
		Min	Max	Mean	Std. dev	Min	Max	Mean	Std. dev
Age	Age of business owner in years	17	82	44 <sup>a</sup>	11	18	72	42 <sup>a</sup>	11
Household size	Number of people in the household	1	15	5 <sup>b</sup>	3	1	17	5 <sup>b</sup>	3
Household income	Proportion of household income from trading (%)	10	100	77 <sup>a</sup>	28	8	100	79 <sup>a</sup>	27
Monthly income	Average monthly income from trading (₦) <sup>36</sup>	5000	800000	145926 <sup>a</sup>	146018	3000	800000	116436 <sup>a</sup>	113128
Business age	Age of business in years	1	40	13 <sup>b</sup>	9	1	50	12 <sup>b</sup>	8
Employees	Number of employees	1	15	2 <sup>b</sup>	2	1	16	3 <sup>b</sup>	2
Branches	Number of shop branches	1	7	1 <sup>b</sup>	1	1	6	1 <sup>b</sup>	1
Electricity bill <sup>37</sup>	Electricity bill [price per month] (₦) for national grid	200	36000	3152 <sup>b</sup>	3705	300	30000	3139 <sup>b</sup>	2857
Rensource bill	Rensource solar energy bill [price per month] (₦)	300	20000	5144	3780	-	-	-	-
Fuel cost <sup>38</sup>	Amount spent on fuel (petrol/diesel) for generators per month (₦)	490	80000	10888 <sup>a</sup>	8501	500	100000	8022 <sup>a</sup>	8315

Note: **Rensource Users:** generator only users =55 (18%), National grid only users=22 (7%), Both =74 (25%), No electricity (neither generator nor national grid) =149 (50%). **Non-Users:** generator only users =167 (42%), National grid only users=37 (9%), Both =85 (21%), No electricity (neither generator nor national grid) =111 (28%)

<sup>a</sup> Means of variables with “a” indicate that the means are significantly different between users and non-users using t-test for difference in means

<sup>b</sup> Means of variables with “b” indicate that the means are not significantly different between users and non-users using t-test for difference in means

<sup>36</sup> Exchange rate US\$ 1: ₦ 380 (Source: Central Bank of Nigeria)

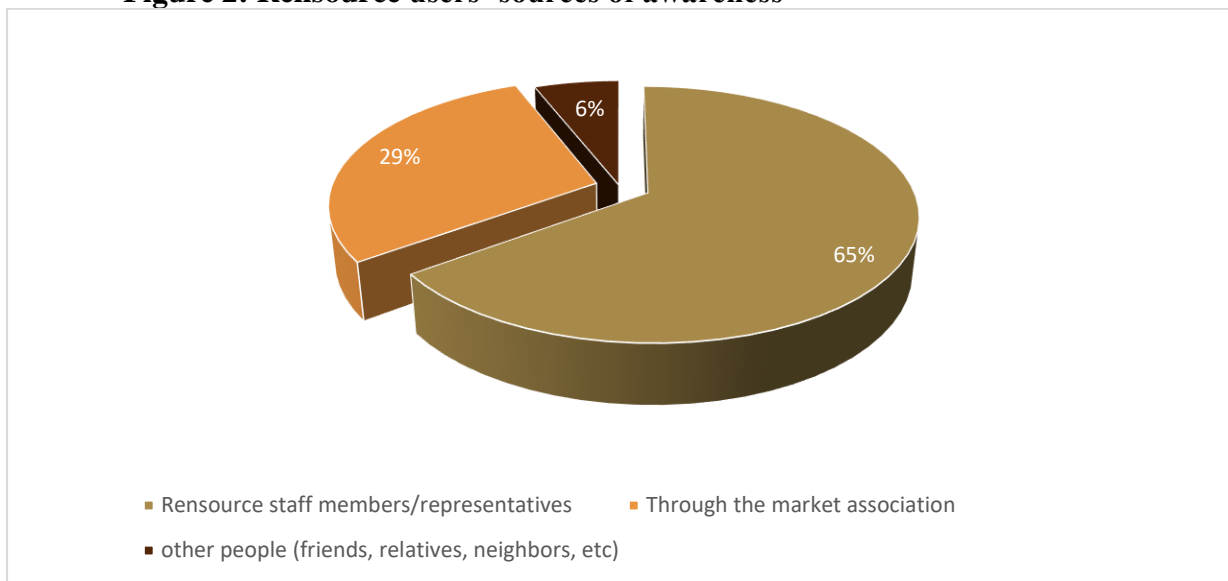
<sup>37</sup> Values for Rensource users are electricity bill in price per month prior to subscription

<sup>38</sup> Values for Rensource users are fuel cost for generators prior to subscription

#### 4.1.4. Sources of awareness

We asked Rensource users about how they had heard of Rensource solar energy prior to subscription, and the results indicate that most of them (65%) had heard about Rensource solar energy through their staff and representatives, as indicated in [Figure 2](#). In addition, 29% of the users had heard about Rensource through the market associations while 6% of them knew about Rensource through other people, including friends, relatives and neighbors. Rensource has representatives and sales agents who collect subscription fees in the various markets. These representatives and sales agents are paid workers and hence this practice contributes to job creation for the sales agents but enhances market awareness about Rensource services.

**Figure 2: Rensource users' sources of awareness**



## 4.2. Determinants of merchants' choice of electricity supplier

### 4.2.1. Drivers of choice of electricity supplier for users and non-users

**Table 4** presents the merchants' ranking of different characteristics of electricity and electricity providers that influence their choice of electricity supplier. It is worth mentioning that the question asked was in relation to electricity suppliers in general and not specifically about Rensource. The results indicated both users and non-users of Rensource rank reliability of electricity supply as the most important characteristic that influences their choice of a given source of electricity. This ranking can be attributed to user fatigue with frequent power outages that has plagued the energy sector. Indeed, frequent outages are the main factors of income loss and economic and social costs in the economic sectors (Carmona and Gómez, 2013; Chakravorty et al., 2014). The second most important attribute is affordability of the electricity as ranked by both categories of merchants. The 3<sup>rd</sup> and 4<sup>th</sup> most important attributes for Rensource users are ease of access and flexibility of use whereas non-users consider flexibility of use and installation cost as the 3<sup>rd</sup> and 4<sup>th</sup> most important attributes that determine their choice of electricity supplier. The 5<sup>th</sup>, 6<sup>th</sup> and 7<sup>th</sup> most important attributes that determine their choice of electricity supplier are risk of fire outbreak, installation cost and frequency of maintenance. In contrast, non-users rank flexible payment plan, risk of fire outbreak and frequency of maintenance as the 5<sup>th</sup>, 6<sup>th</sup> and 7<sup>th</sup> most important attributes that determine their choice of electricity supplier. Both users and non-users rank prone to theft and no alternative source as the least important factors that determine their choice of electricity supplier.

**Table 4: Energy drivers of choice of electricity suppliers**

Characteristics	Users (N=300)		Non-Users (N=400)	
	Mean Rank	Rank	Mean Rank	Rank
Reliability	10.82	1 <sup>st</sup>	8,98	1 <sup>st</sup>
Affordability (user fees)	9.51	2 <sup>nd</sup>	8,61	2 <sup>nd</sup>
Ease of access	9.04	3 <sup>rd</sup>	7,54	8 <sup>th</sup>
Flexibility of use	9.03	4 <sup>th</sup>	8,48	3 <sup>rd</sup>
Risk of fire outbreak	8.83	5 <sup>th</sup>	7,75	6 <sup>th</sup>
Installation cost	8.65	6 <sup>th</sup>	8,14	4 <sup>th</sup>
Frequency of maintenance	8.38	7 <sup>th</sup>	7,58	7 <sup>th</sup>
User-friendliness	7.90	8 <sup>th</sup>	7,30	9 <sup>th</sup>
Noise generation	7.85	9 <sup>th</sup>	6,92	11 <sup>th</sup>
Flexible payment plan	7.81	10 <sup>th</sup>	7,97	5 <sup>th</sup>
Air pollution	7.18	11 <sup>th</sup>	6,90	12 <sup>th</sup>
Health problems	6.88	12 <sup>th</sup>	7,18	10 <sup>th</sup>
Environmental problems	6.61	13 <sup>th</sup>	-	-
Prone to theft	5.87	14 <sup>th</sup>	6,05	13 <sup>th</sup>
No alternative supplier	5.65	15 <sup>th</sup>	5,59	14 <sup>th</sup>
Kendalls W	0.125		0.079	
Chi-Square	523.75***		406,40***	
Degree of freedom	14		13	

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

Kendall's ranking of the attributes was used and the significant chi-square allows us to reject the null hypothesis that there is no agreement among the merchants regarding the ranking of the attributes.



### 4.3. Intermediate impacts

In this section, the merchants were asked to indicate if the electricity they were currently using had affected their volumes of sales and profit. The results are presented in [Table 5](#). The results indicate that about 34% of the users of Rensource solar energy observed changes in volumes of sales. When asked what kind of change was observed, the results indicate that 34% of users observed increases in volumes of sales ranging from 3% to 100% with an average of 39%. In terms of gross profit, 37% of Rensource users indicated that they have observed increases in profit ranging from 3% to 100%, with an average increase of 34%. It is worth mentioning that none of the users of Rensource solar energy observed a decrease in volume of sales and profit. We used qualitative findings to pinpoint uses of the solar energy that increase volumes of sales and profit. The qualitative finding revealed that the uses of the solar energy that increase monthly earnings and profitability include:

- *Lighting of shops for more product visibility and customer attraction. In the merchants' own words: "The light brightens the shop and make the goods more attractive"; "More patronage as a result of constant light. Customers see my goods displayed for sale"; "Attracting more customers through brightening the shop and make goods look attractive"; "My shop has never been in darkness since I joined and customers sees my goods for patronage"; "my shop is now bright, customers can now see my goods clearly"; "The light generated by solar has made my shop brighter and enables my customers to differentiate between colors of cloth and the other, thereby making me to have more customers"; "before Rensource solar, my shop used to be dark as a result customers don't patronize my goods that much but with solar and steady light my shop is bright and customers can see my good very well"; "It plays a major role of showcasing our products and making customers buy them through illumination and beauty enhancement".*
- *Creating more comfortable and friendly environment for customers. In the merchants' own words: "I use it to power the fans which provides comfort for my customers when they come into my shop"; "The fan makes our customers comfortable to carry out business with us"; "comfort of customers in a well-lighted office"; "it has provided comfort and friendly environment to customers and regular accessibility".*
- *Testing electrical appliances to build trust and customer confidence in products. In the merchants' own words: "We use the solar energy for testing any electrical appliances for a customer without having to look for another shop to do same"; "using the solar to recharge and test my goods for my customers"; "to test the electronic stoves before selling to customers and they will tell others to come because they trust me".*
- *More working hours and days. In the merchants' own words: "it has increase the time I spent in my shop"; "I stay longer in the shop than I used to because of Rensource solar energy and it has increased my sales and profitability"; "I now stay longer in the shop unlike before and by staying longer I make more profit"; "Use of solar has helped me utilize the lighting hours"; "it increases the number of days spent in shop". Indeed Matungwa (2014) observes that PV solar has provided merchants with an opportunity to do business even at night because of lighting.*

- *Additional machines to increase productivity. In the merchants' own words: "Additional electric machines and manpower have been added due to Rensource solar energy"; "we can now use electric sewing machines for efficiency".*
- *Refrigeration to avoid spoilage and loss of perishable goods. In the merchants' own words: "use to power the fridges for perishable goods and products"; "the use of fridges has reduced losses due to spoilage and this increases profit".*

For non-users who were mostly using generators, the results indicate that 32% and 38% observed changes in their volumes of sales and profit, respectively. Out of the 32% that observed changes in volumes of sales, 70% observed increases in volumes of sales averaging 54% while 30% observed decreases in volume of sales averaging 23%. In terms of profit, 71% of those who observed changes recorded increases in profit averaging 50%. Notwithstanding, 29% observed decreases in profit ranging from 5% to 100%, with an average of 19%. It is worth mentioning that the sale and profit values discussed are self-reported figures from respondents and may be subject to biases such as incorrect recalls by respondents.

**Table 5: Effects of current electricity source on sales and profit**

Outcome variable	Frequencies	Change type	Proportion of change		
			Mean (%)	Min (%)	Max (%)
<b>Rensource users (N=300)</b>					
Change in volume of sales	Yes (N=101)	Increase (N=101)	39	3	100
		Decrease (N=0)	-	-	-
	No (N=199)				
Change in profits	Yes (N=111)	Increase (N=111)	34	3	100
		Decrease (N=0)	-	-	-
	No (N=189)				
<b>Non-Rensource users (400)</b>					
Change in volume of sales	Yes (N=128)	Increase (N=89)	54	3	100
		Decrease (N=39)	23	5	100
	No (N=272)				
Change in profits	Yes (N=152)	Increase (N=108)	50	3	100
		Decrease (N=44)	19	5	100
	No (N=248)				

[Appendix A.6](#) presents results on electricity-related fire outbreaks and estimated losses. The results show that 29% of the users of Rensource solar energy had experienced electricity-related fire outbreaks prior to subscription. The number of outbreaks before subscribing to Rensource ranges from one to four with an average of one. The average estimated losses from the fire outbreaks are about ₦ 1,886,442 (\$4,210). Notwithstanding this, the maximum estimated loss was ₦ 10,000,000 (\$22,317). All the Rensource users indicated that they had not experienced any fire outbreak following subscription to Rensource, and this means that by avoiding electricity-related fires, Rensource users on average had saved an estimated ₦ 1,886,442 (\$4,210). For the non-users, the results show that 15% of them have experienced

electricity-related fire outbreaks on average about twice and a maximum of four. The average estimated loss was ₦ 1,039,675 (\$2,320) and the maximum estimated loss amounted to ₦ 8,000,000 (\$17,854).

There are no significant differences in number of fire outbreaks. The mean difference between users' and non-users' average estimated losses due to fire outbreaks is ₦ 846,766 (\$1,890). However, it is important to mention that the fire outbreaks reported for Rensource users were recorded prior to subscription. None of the Rensource users reported any fire outbreak after subscription. Hence, comparing the average estimated loss due to fire outbreaks for users prior to subscription to the zero cost due to no fire outbreaks after subscription shows that subscribing to Rensource saves merchants from losing an average of ₦ 1,886,441.56 (\$421,006) to electricity-related fire outbreaks. Fire outbreaks attributed to power outages have been reported and Cobin (2013) notes that the widespread use of personal generators during frequent power outages has been one of the common causes of fire outbreaks.

## 4.4. Empirical Results on incomes

### 4.4.1. Factors influencing merchants' subscription to Rensource solar energy

In [Table 6](#), we present probit estimates of factors influencing subscription to Rensource solar energy. It is worth mentioning that the explanatory variables kept in the probit model are the ones that satisfied the balancing property of the propensity score (Maffioli et al. 2009). We performed t-tests of equality of means before and after the matching to validate if the PSM succeeds in balancing the characteristics between treated and untreated groups. The results from the t-test revealed that after matching (see [Appendix A.7](#)), there were no significant difference in the means of variables kept in the probit model, suggesting that matching helped reduce the bias associated with observable characteristics.

The results in [Table 6](#) show that the proportion of household income from trading has negative and significant influence on subscription to Rensource solar energy. This is probably because the livelihood of those households is highly affected by the state of the business. Mainly as the initial capital cost in solar energy and its batteries is high compare to diesel generators (Babajide and Brito, 2021). Thus, the investment in solar energy constitutes a barrier to solar PV adoption in Nigeria. Indeed, the sampled merchants are mainly micro-SMEs, a category of SMEs in Nigeria that Etuk et al. (2014) describe as those that operate at the subsistence level mainly to provide employment and income to their owners.

Not being a member of a merchant group was found to be negative and significant. This implies that business owners who do not join merchant groups or associations are less likely to subscribe to Rensource solar energy, relative to those who are members of merchant groups or associations. Even if Rensource works with market associations through the REA, about 78%

of our surveyed merchants are not members of market groups. Which makes it more difficult for actors like Rensource to reach merchants not affiliated to a group.

In terms of business characteristics, we found that the number of **shop branches** has a positive and significant influence on subscription to Rensource solar energy at 1%, suggesting that merchants with more branches are more likely to subscribe to Rensource solar energy. This can rise through the channel of income; that those who own more than one shop also have higher incomes and are able to overcome the cost hurdle of solar subscription. Furthermore, it can also be the case that a bigger proportion of their household income comes from the shops and therefore investing in solar is an investment into a venture that directly supports much of their livelihoods, especially in light of constant power outages.

The **fire outbreak** variable is positive and significant at 1% level, suggesting that merchants that have experienced electricity-related fire outbreaks over the past five years are more likely to subscribe to Rensource solar energy, compared with those that have not experienced an electricity-related fire outbreak before. This finding related to fire outbreaks is supported by Ogeah and Omofonmwan (2014) who opined that frequent power outages have led to reliance on generators and the subsequent problem of frequent fire outbreaks poses a challenge to markets and as such, merchants in markets are more likely to adopt a more reliable and safer energy source. Merchants who have **access to credit** for the business are more likely to subscribe to Rensource solar energy, as indicated by the significant and positive coefficient for credit access variable. Credit eases the cost constraint on merchants which Qureshi et al. (2017) note as the most significant barrier in the diffusion of solar PV system.

In terms of the **kind of product traded**, the results indicate that merchants who sell **clothes** (shoes and textiles) products are more likely to subscribe to Rensource solar energy, compared with those selling products in the reference category (i.e. manufacturing, stationery, sewing and agrochemicals). Manufacturing, stationery and sewing often require higher power to operate which may be limiting for users if solar is unable to sufficiently power the machinery they use. This can be more so during periods when the sun's intensity is not as great; knowing that foods products for instance usually require preservation. Hafner et al. (2018) argue that energy is a key input at all stages of the food value chain, cold storage such as provided by ice makers particularly, can allow communities to store fish (food) for longer periods of time Kyriakarakos et al. (2020). Although with a positive and non-significant parameter, merchants operating beauty salons and selling cosmetic products are more likely to subscribe to Rensource solar energy. Indeed, beauty salons need electricity for most of their services. To that extent, Anane (2016) notes that beauty salons are amongst the businesses that heavily depend on electricity in business operations.

Then, we found that the **reliability** of the energy source is highly significant and positive and this implies that merchants who rank the reliability of a given energy supply as a very important driver in their decision to subscribe to Rensource solar energy. This is supported by Eronini (2014) who found that a regular power supply is enough motivation for the adoption of solar energy and is further supported by Lee and Callaway (2018) who propose that decentralized solar power is competing with grid systems in terms of reliability.

Finally, the cost of fuel does not influence the probability to subscribe to Rensource solar energy. Indeed, the low and not significant coefficient of fuel cost confirms the fact that merchants do not rank this factor as one of the main drivers of solar adoption ([Table 4](#))

**Table 6: Probit estimates of factors influencing subscription to Rensource solar energy**

Variables		Coefficient	R. std error	t-value
<b>Merchant characteristics</b>				
Age	Age of business owner in years	0.007	0.005	1.41
Gender	1 if business owner is male, 0 otherwise	0.010	0.150	0.07
Education	Years of formal education	0.004	0.011	0.37
Household size	Number of people in the household	-0.009	0.018	-0.50
Household income	Proportion of household income from trading (%)	-0.005*	0.002	-2.06
Non-Membership	1 if business owner is not member of merchant group, 0 otherwise	-0.356*	0.151	-2.36
Sabon Gari (Kano)	Name of market	-0.062	0.383	-0.16
Iponri (Lagos)	Name of market	0.136	0.384	0.35
Isikan (Ondo)	Name of market	0.159	0.407	0.39
NEPA 1 (Ondo)	Name of market	0.049	0.444	0.11
<b>Business characteristics</b>				
Employees	Number of employees	-0.024	0.030	-0.78
Owned shop	1 if shop is individual or family owned, 0 otherwise	0.211	0.144	1.47
Fire outbreak	1 if fire outbreak occurred in the past five years, 0 otherwise	0.586***	0.130	4.50
Credit access	1 if merchant has access to credit for the business, 0 otherwise	0.326*	0.139	2.34
Branches	Number of shop branches	0.204*	0.099	2.05
<b>Product traded</b>				
Food products	1 if the merchant sells food products, 0 otherwise	-0.247	0.196	-1.26
Clothing, shoes, bags & textiles	1 if the merchant sells clothing, shoes, bags and textiles, 0 otherwise	0.455**	0.138	3.29
Electronics	1 if the merchant sells electronics, 0 otherwise	0.166	0.184	0.91
Cosmetics	1 if the merchant sells cosmetics and operates a beauty salon, 0 otherwise	0.081	0.218	0.37
Homeware & kitchenware	1 if the merchant sells home and kitchen products, 0 otherwise	0.096	0.367	0.26
<b>Energy characteristics</b>				
Reliability	1 if reliability of energy source is ranked as very important, 0 otherwise	1.189***	0.145	8.18
Fuel Cost	Amount spent on fuel (petrol/diesel) for generators per month (₦)	-0.000	0.000	-1.00
Cons				-2.139***
Pseudo R <sup>2</sup>				0.15
Wald chi2(19)				117.71
Number of observations				700

\*, \*\*, \*\*\* denote 10%, 5% and 1% significant levels respectively

#### 4.4.2. Propensity score matching results: Average treatment effect on the treated (ATT) and average treatment effect (ATE) of Rensource subscription on monthly earnings and fuel expenditure of merchants

In [Table 7](#) we present the results of the average treatment effect on the treated (ATT) of Rensource subscription on the monthly earnings of merchants following the PSM approach. The ATT results show the effect of the subscription on those current merchants who have subscribed to use Rensource solar energy. We found from [Table 7](#) below that across all propensity score matching specifications, Rensource subscribers had significantly higher monthly earnings than non-subscribers. Specifically, the effect of subscription on Rensource subscribers is an increase in monthly earnings of 27% (₦ 31,259<sup>39</sup>) from the nearest neighbor matching (NNM). The NNM was based on 300 treated and 400 control merchants using bootstrapping approaches. The region of common support is [0.04; 0.86]. From the radius and kernel matching, the effect of subscription on Rensource subscribers is an increase in monthly earnings of 23% (₦ 27,633<sup>40</sup>) and 24% (₦ 28,265<sup>41</sup>), respectively. These findings are supported by the Babajide and Brito (2020) who observe that the possibilities of additional income generation and saving on fuel cost through the adoption of solar energy was comparable to the reliance on the existing electricity grid in its current state.

Our ATT findings indicate an income growth range of businesses between \$73 and \$82. The magnitude of our outcomes are higher than several results identify by the literature (Sapkota et al. 2013; Chakrabarty and Islam, 2011). For instance, Mollik et al. (2016) find from a documented research an increase of household incomes by \$12 for programs conducted in the Division of Dhaka in Bangladesh. Furthermore, the ratio of change in monthly earnings from 23% to 27% echoes the work of Sánchez et al. (2015) who find that the access to renewable technologies in a Brazilian program increase the revenues of households by 35.6%. Also, the average income of Rensource users and non-users are respectively about \$384 and \$306 (see [Table 3](#)). At the macroeconomic level, the monthly minimum wage in Nigeria is equivalent to \$79 (₦ 30,000<sup>42</sup>), while the monthly living wage has been estimated at \$114 (₦ 43,200<sup>43</sup>). But, the increase of the monthly earnings of merchants who subscribed to Rensource solar facility is still lower compared to the average monthly salary which is about \$1,226 (₦ 465,843<sup>44</sup>) in 2022. In 2017, the median monthly salary was about (₦ 300,000) \$724 (Babajide and Brito, 2021).

In addition, the results of the OLS strategy ([Appendix A.8](#)) confirms that the decision of subscribing increases the monthly earnings by ₦ 28,208 (\$65), even if we do not control for counterfactuals.

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<sup>39</sup> \$70

<sup>40</sup> \$62

<sup>41</sup> \$63

<sup>42</sup> <https://www.statista.com/statistics/1119133/monthly-minimum-wage-in-nigeria/>

<sup>43</sup> <https://tradingeconomics.com/nigeria/living-wage-individual#:~:text=Living%20Wage%20Individual%20in%20Nigeria%20averaged%2042500%20NGN%2FMonth%20from,updated%20on%20March%20of%202022.>

<sup>44</sup> <https://nigerianorator.com/average-salary-in-nigeria/>

**Table 7: Average treatment effect on the treated (ATT) of Rensource subscription on the monthly earnings of merchants**

Outcome variables	Nearest neighbor matching <sup>45</sup>	% change	Kernel matching <sup>46</sup>	% change	Radius matching <sup>47</sup>	% change
<b>Monthly earnings<sup>48</sup></b>	31259** (12525.918)	27%	28265** (11392.192)	24%	27633** (11139.389)	23%

Notes: These results are based on propensity score matching. Standard errors are in parentheses; \*p-value < 0.1, \*\* p-value < 0.05, \*\*\* p-value < 0.001

In addition to the ATT results in [Table 7](#), we included average treatment effect (ATE) results in [Table 8](#). The ATE results show that Rensource subscribers had significantly higher monthly earnings than non-subscribers. Rensource subscribers earn ₦ 40,946 (\$108), which represents a 36% increase in monthly earnings more than non-subscribers of Rensource solar energy using nearest neighbor matching (NNM). Furthermore, Rensource subscribers earn ₦ 29,841 (\$79) which represents a 25% increase in monthly earnings more than non-subscribers of Rensource solar energy using kernel matching. And the radius matching approach also provides positive and significant monthly earnings of ₦ 33,066 (\$76), which is an increase by 28%. The high ATE values compared with the ATT are not surprising given that the two approaches are not drawn from the same population. The ATE takes into account differences between control and treatment group characteristics. The ATE estimates show what non-subscribers of Rensource solar energy would have obtained if they were moved from the untreated group to the treated group at the population level, whereas the ATT, as mentioned earlier, compares what subscribers would have obtained if they decided not to subscribe. The ATT estimates are more relevant in this study than a simple difference between subscribers and non-subscribers as the ATE estimates suggest. In addition, the results show that monthly fuel expenditures have a negative impact on the earnings of subscribers. However, this finding is not significant at any of the conventional statistical levels.

We further matched the monthly earnings on gender, state, product kind, and market location after the ATE estimation using exact match (ematch) (Cattaneo 2010). The exact matching allowed us to restrict matches to only those subjects who are in the same gender, state, product, and market categories. The results for the exact matching on gender reveals that within the same gender category, Rensource subscribers had higher monthly earnings (₦ 30,475<sup>49</sup>) than non-subscribers, with the difference being statistically significant at 5% level.

In terms of state, Rensource subscribers had significantly higher monthly earnings (₦ 31,829<sup>50</sup>) than non-subscribers. In addition, within the same product category, the results show that

<sup>45</sup> Nearest neighbor matching: treated (N=300), control (N=400)

<sup>46</sup> Kernel matching: treated (N=300), control (N=400)

<sup>47</sup> Radius matching: treated (N=300), control (N=400)

<sup>48</sup> Exchange rate 1US\$: 380₦ (Source: Central Bank of Nigeria)

<sup>49</sup> \$68

<sup>50</sup> \$71



Rensource subscribers had higher monthly earnings (₦ 28,961<sup>51</sup>) than non-subscribers, with the difference being statistically significant at 5% level. This is an expected result, and Ritchie and Roser (2019) note that availability (and affordability) of electricity and clean fuels is strongly related to income. Roche and Blanchard (2018) also add that solar energy can be designed for income-generating activities.

On the other hand, a within markets analysis has been applied in order to pinpoint the local effect of subscription to Rensource services. Subscribers had significantly higher monthly earnings than non-subscribers. This difference prevails mainly at the Iponri market in Lagos State with an estimate of ₦ 31,738 (\$73), and followed respectively by markets in Kano and Ondo states. Our outcomes echoes the findings of Kumar (2014) with the analysis of income convergence and electricity consumption in India for the periods 1990-1991 and 2011-2012. The author reveals that (i) the disparities of grid connection among Indian states decreased, and (ii) there is a beta convergence between income and energy consumption among the states. Which means that poorer states quickly caught up their delay of energy network plants. Moreover, amongst the states, Lagos and Kano have the highest average monthly salary<sup>52</sup> at ₦ 524,933 (\$1214) and ₦ 150,000 (\$347) respectively.

**Table 8: Average treatment effect (ATE) of Rensource subscription on the monthly earnings of merchants**

Outcome variables	Nearest neighbor matching <sup>53</sup>	% change	Kernel matching <sup>54</sup>	% change	Radius matching <sup>55</sup>	% change
<b>Monthly earnings</b>	40946 <sup>***</sup> (11194.62)	36%	29841 <sup>**</sup> (9938.507)	25%	42646 <sup>***</sup> (10848.561)	37%
<b>Exact matching on:</b>						
<b>Monthly earnings</b>	Gender				30475 <sup>**</sup> (9927.024)	
	State				31829 <sup>***</sup> (9968.477)	
	Product kind				28961 <sup>**</sup> (9876.024)	
	Sabon Gari market (Kano State)				30690 <sup>**</sup> (9997.266)	
	Iponri market (Lagos State)				31738 <sup>***</sup> (9885.889)	
	Isikan market (Ondo State)				30493 <sup>**</sup> (9961.788)	
	NEPA 1 market (Ondo State)				30077 <sup>**</sup> (9940.798)	
	NEPA 2 market (Ondo State)				28293 <sup>**</sup> (9732.333)	

Notes: These results are based on propensity score matching. Standard errors are in parentheses; \*p-value < 0.1, \*\* p-value < 0.05, \*\*\* p-value < 0.001.

<sup>51</sup> \$64

<sup>52</sup> <https://www.currentschoolnews.com/job/salary-of-workers-in-nigeria/>

<sup>53</sup> Nearest neighbor matching: treated (N=300), control (N=400)

<sup>54</sup> Kernel matching: treated (N=300), control (N=400)

<sup>55</sup> Radius matching: treated (N=300), control (N=400)

#### 4.4.3. Propensity score matching results: Average treatment effect on the treated (ATT) and average treatment effect (ATE) of Rensource subscription on monthly net income of merchants

In order to support the results of Rensource subscription on average income of merchants, we conduct a set of robustness tests. We precisely analyze the impact of subscription on the net income generated by merchant's businesses. It is relevant to take account of the trade-off between the increase of the revenues and the costs of Rensource' services. Therefore, the net income is a proxy which measure the subscription cost<sup>56</sup> and the monthly fees of the PV utilities. We construct the net income index as the difference between (i) the monthly earnings and (ii) the monthly bill after subscription. This relation can be expressed as the following function:

$$NI_i = \beta R_i + \alpha Z_i + \mu_i \quad (10)$$

Where  $NI_i$  is the net income proxy for subscribers and non-subscribers to Rensource solar energy.  $R_i$  is a binary dependent variable that equals 1 for subscribers who subscribed to Rensource solar energy, and 0 otherwise.  $\alpha$  is a vector of parameters to be estimated.  $Z$  is a vector of socioeconomic, institutional, technological, market-level, and location-specific dummies characteristics as defined in Section 5.  $i$  is the individual merchant indicator, and  $\mu$  is the error term which is generally known as the effect of the unobservables.

In [Table 9](#) we present the results of the ATT of Rensource subscription on the monthly net income of merchants who have subscribed. We found that the effect of subscription on Rensource subscribers is an increase in monthly net income of 27% (₹ 26,692) from the nearest neighbor matching. The NNM was based on 300 treated and 400 control merchants using bootstrapping approaches. From the kernel matching, the effect of subscription on Rensource subscribers is a significant increase in monthly net income of and 24% (₹ 22,976). The radius matching indicates similar results as the Kernel framework, with an increase of monthly net income of 23% (₹ 22,323) at 5% level of significance. The increase of net revenues is mainly important for merchants who installed Rensource solar system and paid the subscription fee. On average the installation cost of Rensource solar solution is about ₹ 3,413 (\$9)<sup>57</sup>. Hence, the cost of subscription to Rensource solar energy represent about 11% of the average net income increase of subscribers. Our finding is lower than the study of Kurata et al. (2018) who find that the average cost of SHS adoption for micro-entreprises in Bangladesh is about \$185. However, the installation cost of solar PV usually decrease overtime (Taele et al. 2012).

Furthermore, the ATE results in [Table 9](#) show that Rensource subscribers have higher net income of \$105 (₹ 27,502) than non-subscribers, which represents a 35% increase using the NNM. This difference is statistically significant at 1% level. From the kernel matching, the effect of subscription on Rensource clients generate an increase of the monthly net income of merchants by \$76 (₹ 24,013), which represent a 24% change at 5% level of significance. The

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<sup>57</sup> [Appendix A.9](#)

parameter of the radius matching is also positive and significant, with an increase of net income by around 23%. Overall, our ATE's outcomes converge with the recent results issued by the literature. For instance, the macroeconomic analysis of Ben Jebli et al. (2020) studies the relationship between renewable energy consumption and the value-added generated by industrial and service activities during 1990 and 2015. The authors classified 102 countries by income levels, and find that the use of renewable energies increases the values-added of both industrial and service for the global panel.

The magnitude of our net income outcome is slightly less important than those of the monthly earnings of merchants. Indeed, the latter indicator represents the direct income generated by businesses and do not deduct the monthly energy fees for both users and non-users of Rensource solar panels. Still, our findings are higher than the results of the literature, such as the study of Bernardo and Kilayko (1990) which identifies the positive effect of a farmer program in the Panay Island (Philippines) on the agricultural net income (\$29.15/yield per hectare).

**Table 9: Average treatment effect (ATT) of Rensource subscription on the monthly net income of merchants**

<b>Monthly net income<sup>58</sup></b>	<b>Nearest neighbor matching<sup>59</sup></b>	<b>% change</b>	<b>Kernel matching<sup>60</sup></b>	<b>% change</b>	<b>Radius matching<sup>61</sup></b>	<b>% change</b>
<b>ATT</b>	26692** (11714.876)	23%	22976** (11259.307)	20%	22323** (11093.867)	19%
<b>ATE</b>	27502*** (10149.37)	24%	24013** (9711.639)	20%	26080** (11117.131)	21%

Notes: These results are based on propensity score matching. Standard errors are in parentheses; \*p-value < 0.1, \*\* p-value < 0.05, \*\*\* p-value < 0.001

<sup>58</sup> Exchange rate 1US\$: 380₦ (Source: Central Bank of Nigeria)

<sup>59</sup> Nearest neighbor matching: treated (N=300), control (N=400)

<sup>60</sup> Kernel matching: treated (N=300), control (N=400)

<sup>61</sup> Radius matching: treated (N=300), control (N=400)

## 4.5. Impact on the cost of energy: fuel cost

### 4.5.1. Factors influencing merchants' subscription to Rensource solar energy

[Table 10](#) present the probit estimates of factors influencing subscription to Rensource solar energy. It is worth mentioning that the explanatory variables kept in the probit model are the ones that satisfied the balancing property of the propensity score (Maffioli et al. 2009).

Our probit specification shows that the proportion of **household income from trading** has negative but not significant influence on subscription to Rensource solar energy. This result echoes the fact that several merchants are still connected to the national grid, while paying electricity fees after subscription to Rensource. Indeed, the use of the national grid system as a source of energy is positive and significant at 1% level. The informations provided in [Table 3](#) show that Rensource users suffer from a higher cost of national electricity bill.

Merchants who have **access to credit** for the business are more likely to subscribe to Rensource solar energy, as indicated by the significant and positive coefficient for credit access variable. A more reliable and sustainable energy source increases the opportunities of access to financing (Warnecke and Houndonougbo, 2016).

In terms of the **kind of business traded**, the results indicate that merchants who own either **retail or wholesale businesses, or both** are more likely to subscribe to Rensource solar energy. On the one hand, retail businesses often require a higher power as they cover manufacturing and services stores, specifically with in-person customer businesses. On the other hand, wholesale businesses usually store commodities, such as food products. For which their trading requires constant access to energy, in order to preserve the cold chain and the storage of rapidly perishable foods.

The **reliability** of the energy source is highly significant and positive, at 1% level of confidence. This is mainly due to the strong dependence of merchants on generators backup. Even if they are not the majority, a large part of Rensource users have a backup generator system<sup>62</sup>. Whereas, the access to electricity through the national grid increases the probability of merchant to subscribe to Rensource facility. The energy supplies by the national grid is volatile and unreliable, and the substitution towards solar energy provides a cleaner and a more sustainable electrification strategy (Urmee and Md, 2016).

In terms of **energy characteristics**, we find that user who used to consume a higher amount of electricity (KWh) were more likely to subscribe to Rensource solar system. But this finding is not significant.

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<sup>62</sup> [Appendix A.10](#)

**Table 10: Probit estimates of factors influencing subscription to Rensource solar energy**

Variable		Coefficient	R. std error	t-value
<b>Merchant characteristics</b>				
Gender	Age of business owner in years	-0.00878	.1471741	-0.06
Age	1 if business owner is male, 0 otherwise	0.00334	.0051768	0.64
Education	Years of formal education	0.00416	.0115263	0.36
Household size	Number of people in the household	0.00373	.0184065	0.20
Household income	Proportion of household income from trading (%)	-0.00358	.0021915	-1.63
Non-Membership	1 if business owner is member of merchant group, 0 otherwise	0.240	.1431599	1.68
Market	Market locations	0.00360	.0731989	0.05
<b>Business characteristics</b>				
Employees	Number of employees	0.0110	.0264263	0.41
Credit access	1 if merchant has access to credit for the business, 0 otherwise	0.292*	.1362663	2.15
Owned shop	1 if shop is individual or family owned, 0 otherwise	0.0975	.1381405	0.71
Wholesale	1 if merchant is a wholesale business, 0 otherwise	0.624*	.3098061	2.02
Retail	1 if merchant is a retail business, 0 otherwise	0.595*	.2523979	2.36
Both wholesale & retail	1 if merchant is both wholesale and retail business, 0 otherwise	0.620*	.2556971	2.42
<b>Energy characteristics</b>				
Reliability	1 if reliability of energy source is ranked as very important, 0 otherwise	1.166***	.1450629	8.04
Electricity usage	Electricity (per KWh) usage after subscribing to Rensource solar energy: 1 if usage is higher, 0 if usage is lower or same amount	-0.0846	.1077221	-0.79
Cons		-1.949***		
Pseudo R <sup>2</sup>		0.1		
Wald chi2(19)		93.40		
Number of observations		690		

\*, \*\*, \*\*\* denote 10%, 5% and 1% significant levels respectively

#### 4.5.2. Propensity score matching results

In order to look at the effect of Rensource subscription on the energy costs, we analyze the impact of subscription on the fuel cost of merchants. The adoption of renewable energy solutions has an effect on the fossil expenditures of users. Therefore, it is relevant to analyze the evolution of the fuel cost for Rensource users. This relation can be expressed as the following function:

$$FC_i = \beta R_i + \alpha Z_i + \mu_i \quad (11)$$

Where  $FC_i$  is the fuel the cost for subscribers and non-subscribers to Rensource solar energy.  $R$  is a binary dependent variable that equals 1 for subscribers who subscribed to Rensource solar energy, and 0 otherwise.  $\alpha$  is a vector of parameters to be estimated.  $Z$  is a vector of characteristics as defined in [Table 10](#).  $i$  is the individual merchant indicator, and  $\mu$  is the error term which is generally known as the effect of the unobservables.

The first row of [Table 11](#) presents the results of the matching specification of Rensource subscription on the fuel expenses of subscribers' merchants. We find that for the NNM approach the fuel cost increases by 2%, but this result is not significant. The results in [Table 3](#) show that prior to subscription, the fuel cost was higher for Rensource subscribers (₺ 10,888) compare to non-subscribers (₺ 8,022). Moreover, the fossil fuel expenditure is higher than the Rensource bill, with a difference of ₺ 5,744 (\$15). This finding indicates that Rensource users are no longer using generator, and their switch to solar energy means that they no longer pay for the fuel of the generator. Hence, this result shows that subscribers would have paid ₺ 88 (\$0.20) more if they did not subscribe. On the opposite, the Kernel and Radius matching assess a decline of fuel cost by 11% for Rensource users. But these results are also not significant.

Furthermore, the ATE results in [Table 11](#) also show that there is a not significant increase of fuel cost after subscription to Rensource, for all the NNM and the Radius approaches. While, the coefficient of the Kernel matching is negative and not significant.

**Table 11: The impact of Rensource subscription on the monthly fuel cost of merchants**

Fuel Cost	Nearest neighbor matching <sup>63</sup>	% change	Kernel matching <sup>64</sup>	% change	Radius matching <sup>65</sup>	% change
<b>ATT</b>	88 (729.548829)	2%	-549 (646.543201)	-11%	-593 (641.086094)	-11%
<b>ATE</b>	67 (520.0313)	1%	-216 (590.2125)	-4%	599 (598.872174)	13%

Notes: These results are based on propensity score matching. Standard errors are in parentheses; \*p-value < 0.1, \*\* p-value < 0.05, \*\*\* p-value < 0.001

We also performed t-tests of equality of means before and after the matching to validate if the PSM succeeds in balancing the characteristics between treated and untreated groups. The results from the t-test revealed that after matching<sup>66</sup>, there were no significant difference in the means of variables kept in the probit model, suggesting that matching helped reduce the bias associated with observable characteristics.

## 4.6. Environmental and health effects

### 4.6.1. Environmental and health drivers of choice of electricity suppliers

[Figure 3](#) presents the merchants' ranking of different characteristics of health and environmental factors that influence their choice of electricity supplier. It is worth to recall that the question asked was in relation to electricity suppliers in general and not specifically about Rensource. The results highlighted both users and non-users of Rensource rank noise of electricity supply as the most important characteristic that influences their choice of a given source of electricity. This ranking can be attributed to the fact that users are faced constant noise from operating generators. Indeed, generators cause noise pollution (Babajide and Brito, 2021). The second most important attribute is the air pollution of the energy source. It is followed by the 3<sup>rd</sup> and 4<sup>th</sup> most important attributes, which are health and environmental issues. Generators carry health and environmental risks and given that 12% of Nigerian household have diesel generators, their emissions generate among others 0.16 million tons of Carbon dioxide (CO<sub>2</sub>), 154 tons of Sulfur dioxide (SO<sub>2</sub>), and 4069 tons of Nitric oxides (NOX) which are the main factors to climate change (Babajide and Brito, 2021). Consequently, the access to solar energy source reduces these emissions of GHG<sup>67</sup> (Islam et al., 2018; Lahimer et al., 2013; Sarraf et al., 2013; Bhattacharyya and Palit, 2016; Al Irsyad et al., 2019; HOWARD-GRENVILLE et al., 2014; Williams, 1997; Herwig, 1997).

<sup>63</sup> Nearest neighbor matching: treated (N=300), control (N=400)

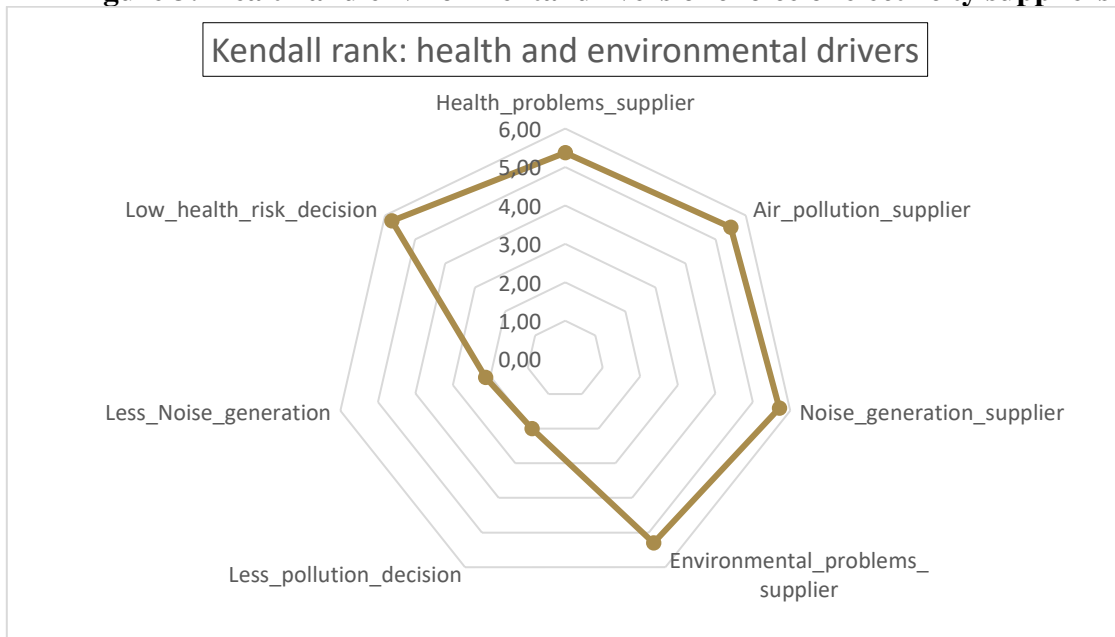
<sup>64</sup> Kernel matching: treated (N=300), control (N=400)

<sup>65</sup> Radius matching: treated (N=300), control (N=400)

<sup>66</sup> [Appendix A.11](#)

<sup>67</sup> Greenhouse gases

**Figure 3: Health and environmental drivers of choice of electricity suppliers**



#### 4.6.2. Propensity score matching results

In the sustainable development field, environmental and health issues are broad subjects addressed by the literature of renewable energy sources. Studies usually find that the adoption of renewable energy systems increases the alleviation of environmental and health effects compared to fossil plants.

In the first instance, adoption of off-grid clean energy decreases the emissions of CO<sub>2</sub> and other GHG (Chakrabarty and Islam, 2011; Ouedraogo et al. 2015; Bhattacharyya and Palit, 2016; Pode et al. 2016). Through a techno-economic analysis, Islam et al. (2018) show that the substitution from diesel generator, kerosene, and grid system to hybrid solar PV and biomass system reduced the emission of CO<sub>2</sub> by 91%, 75%, and 89% respectively. On the other hand, Rafique et al. (2018) specify with a HOMER<sup>68</sup> simulation that the adoption of solar PV lead to a reduction of GHG emissions of 934\$.

On the other hand, renewable power can tackle the health issues generated by traditional energy systems. For instance, access to green energies increases the capacity to store foods, vaccines, and medication products in refrigerator appliances (FAVRETTO et al., 2014; Betzold, 2016). The prominent work of Gonzalez-Eiras and Rossi (2011) shows that the privatization of electricity companies in Argentina during the 1990s allowed the reduction of child mortality, through the improvement of the cold chain system. The evaluation of Sambodhi (2017) in

<sup>68</sup> Hypergeometric Optimization of Motif EnRichment is a suite of tools for Motif Discovery and next-gen sequencing analysis.



Kulabira area in India assess that the rate of vulnerability for women to respiratory ailments with PV electrification compare to kerosene lamps decline by 2 percentage points.

Therefore, we construct two indexes which measure the level of environmental risks and health issues.

- The environmental index is a dummy indicator which takes the value of 1 if merchants faced an increase in pollution, and 0 otherwise. This index is an aggregation of category variables that inform the nature and the direction of change (increase/decrease/no change/don't know) of pollution indicators. Merchants indicate their perceptions of change from before their adoption of PV Rensource, regarding the following indicators: indoor air, noise, dust, smoke, and heat.
- The health index is also a dummy which gathers two categorical health indicators which are health problems and risk of fire outbreaks. The health index was constructed in the same way as the environmental index and takes the value of 1 if the risk increases, and 0 otherwise.

To measure the impact of Rensource subscription on environmental risks and health issues we rely on the following specification:

$$EI_i = \beta R_i + \alpha Z_i + \mu_i \quad (12)$$

$$HI_i = \beta R_i + \alpha Z_i + \mu_i \quad (13)$$

Where  $EI_i$  and  $HI_i$  are respectively the environment and health indexes for subscribers and non-subscribers to Rensource solar energy;  $R_i$  is a binary dependent variable that equals 1 for subscribers who subscribed to Rensource solar energy, and 0 otherwise;  $\alpha$  is a vector of parameters to be estimated;  $Z$  is a vector of characteristics as presented in [Table 10](#);  $i$  is the individual merchant indicator; and  $\mu$  is the error term which is generally known as the effect of the unobservables.

The outcomes in [Table 12](#) show decrease effects of environmental risks for the users of Rensource solar utilities. The coefficients are negative for the three matching approaches, and they are significant for the Kernel and Radius techniques, at 5% and 1% level respectively. Hence, Rensource solar PV adoption decreases the environmental risks of users between -9.9 and -12 points. Our findings are in line with the study of MacCarty and Bryden (2017), who used a Monte-Carlo probabilistic model to assess that the substitution of kerosene source by solar PV decreases the climat impact by 10%. Therefore, one can conclude that the subscription to Rensource solar panels reduces the environmental impact of users' merchants.

Then, the findings in [Table 12](#) show that the probability of Rensource users to face health drops respectively by -10 and -14 points for the NNM and Radius approaches, at 1% level of significance. The magnitude of health issues is also negative and significant at 5% level for the Kernel technique. Our outcomes are consistent with the findings in the literature of renewable decentralized energy systems. Indeed, studies conducted in Namibia and Kenya demonstrate that the adoption of solar PV utilities has a negative impact on the risk and number of fire accidents compare to kerosene power (Acker and Kammen, 1996; Azimoh et al. 2015).

**Table 12: Average treatment effect on the treated (ATT) of Rensource subscription on environmental risks and health issues of merchants**

Outcome variables	Nearest neighbor matching	Kernel matching	Radius matching
<b>Environmental index</b>	-0.057 (0.048)	-0.117** (0.046)	-0.099* (0.054)
<i>N (treated)</i>	300	300	300
<i>N (control)</i>	159	370	370
<b>Health issues</b>	-0.103*** (0.033)	-0.117** (0.049)	-0.139*** (0.023)
<i>N (treated)</i>	300	300	300
<i>N (control)</i>	159	370	370

Notes: These results are based on propensity score matching. Standard errors are in parentheses; \*p-value < 0.1, \*\* p-value < 0.05, \*\*\* p-value < 0.001

## 5. Summary, conclusions and implications of the findings

This research aimed to examine the impact of Rensource solar energy on subscribers in selected markets in the Nigerian states of Lagos, Kano and Ondo. A total of 700 merchants were sampled, consisting of 300 subscribers (i.e. the treatment group) and 400 non-subscribers (i.e. the control group). Specifically, the study characterized the profile of Rensource’s customer base. In addition, we assessed the drivers of merchants’ decisions to subscribe to Rensource solar energy and, finally, we examined how Rensource merchants benefit from the service. We used descriptive statistics to describe the profile of Rensource’s subscribers and non-subscribers. We employed Kendall’s ranking and probit model to examine the drivers of the merchants’ subscription decisions. We used propensity score matching by nearest neighbor, stratification matching, and radius matching to empirically assess the impact of subscribing to Rensource solar energy on the monthly earnings, the fuel expenditure, and the environmental and health risks of merchants.

In summary, the findings show that in terms of the profile of the subscribers and non-subscribers of Rensource solar energy, both merchant groups are micro, small and medium-sized enterprises (MSMEs) with a similar number of employees, business age, number of branches and household sizes. Both subscriber and non-subscriber businesses are in sole proprietorship. The ownership of the business is dominated by males among subscribers and non-subscribers. Most of the shops used by subscribers and non-subscribers are rented. Most of the subscriber and non-subscriber merchants are secondary school leavers. However, tertiary or university leavers are higher in the Rensource subscribers group. Both merchant groups work in clothing, shoes and textiles, electronics (including phones, computers and accessories), food products (including fresh produce and processed foodstuffs), homeware and kitchenware, manufacturing, tailoring, agrochemicals, stationery (including books, gift cards, graphics and

papers), services (including mobile money and credit transfer), and cosmetics and beauty salon businesses.

In terms of drivers of the merchants' decision to subscribe to Rensource solar energy, the study concludes that the most important attributes of Rensource's solar energy that influenced merchants to subscribe includes reliability, affordability (weekly/monthly user fees), flexible payment plan, ease of access, flexibility of use, low risk of fire outbreak and low health risk of the solar energy. Besides these attributes, we conclude that the proportion of household income from trading and membership of a merchant association increases the likelihood of subscription to Rensource solar energy. In addition, we conclude that individual or family-owned businesses with more branches and which have the right to change appliances in their shops are more likely to subscribe to Rensource solar energy. Merchants that have experienced electricity-related fire outbreaks are also more likely to subscribe to Rensource solar energy. Finally, we conclude that merchants selling fresh and processed food products as well as those operating beauty salons and selling cosmetic products are more likely to subscribe to Rensource solar energy.

In terms of impact, we conclude that Rensource has provided reliable solar energy to merchants who were using the national grid and standby generators as well as those that had no access to neither the national grid nor generators. The provision of reliable solar energy has reduced the burden of some merchants who used to pay electricity bills for the national grid and at the same time incurred the cost of fuel for a generator as well as the cost of the generator itself. Thus, subscription to Rensource solar energy reduces expenditure on electricity. Our empirical results (ATT) suggest that the effect of subscription on Rensource subscribers is an increase in monthly earnings of 27%, 24% and 23% using the nearest neighbor (NN), kernel and radius matching, respectively. The average treatment effect (ATE) also confirmed that the causal effect of subscribing to Rensource solar energy is an increase in monthly earnings. We further conclude that within the same gender, state, product categories, and market locations, Rensource subscribers earn more than non-subscribers.

Then, we went a step further to highlight the robustness of our model with the assessment of the net income of merchants. Indeed, Rensource users should pay electricity bills after their subscription. Our results (ATT) are equivalent to the ATT increase in monthly earnings of subscribers. And the average treatment effect (ATE) is even higher between users and non-users, with an increase in net income of 24%, 20% and 21% using the nearest neighbor (NN), kernel and radius matching, respectively.

Finally, Rensource solar facilities also reduce the perception for users to face environmental risks by 12 points, on the one hand. On the other hand, users also report less health issues thanks to their subscription to Rensource energy system. Indeed, merchants are less in contact with the GHG and fine particles generated by fossil systems. Which consequently reduces the risks of having chronic respiratory and pulmonary diseases. Thus, Rensource offers cleaner, more reliable and flexible energy solutions to a category of the population that is one of the most vulnerable to environment and health risks.

In conclusion, this study suggests that subscription to Rensource solar energy has a positive impact on both the financial and extra-financial parameters of merchants. The decision of merchants to subscribe to Rensource solar energy hinges on a complex set of factors relating to the merchant's personal, business, and product characteristics as well as the supplier's characteristics and electricity supply.

The implications of our findings about the drivers of merchants' decisions to subscribe to Rensource solar energy are important from different perspectives. First, our findings indicate that measures to stimulate more subscription to Rensource solar energy can be designed better by using insights on the merchants' ranking of supplier and electricity characteristics that influence their choice of electricity supplier and adopting communication about solar energy, so it alludes to the whole range of the characteristics ranked highly by merchants. In particular, in terms of advertisement and promotion of Rensource solar energy, the reliability of the solar energy and how much merchants can save on fuel costs and electricity bills relative to the monthly user subscription fees are important factors that need to be highlighted. Secondly, the commonly held view that a firm's choice of electricity supplier depends solely to the extent that it is cheaper should be revisited, since we found that reliability is the most important factor across different gender groups and states.

Also, the future design of business strategies, models and communications that seek to enhance merchants' or individuals' subscriptions to Rensource solar energy can potentially take into account the merchant, business and product characteristics identified to substantially affect the subscription. For instance, Rensource can target more clients through the market associations as well as individual or family-owned shops that have the right to change appliances in their shops to install the solar energy. In addition, Rensource should strive to maintain the constant supply of solar energy and minimize the risk of power outages. This can be done by ensuring routine maintenance and improvement in research on the solar panels.

Considering the benefits of subscription to Rensource solar energy, it may be important to raise broader awareness of the benefits of Rensource solar energy in the private sector, particularly in markets and other states where Rensource is not currently operating. Finally, future research should go deeper into the long-term and indirect analysis, in order to have a broader vision and to support the innovative aspect of the Rensource investment.

The findings of this study should be considered with some identification threats since we relied on cross-sectional data for our empirical analysis. Firstly, panel data would have allowed us to measure the impact from the time the merchants subscribed to Rensource solar energy until differences in earnings and income became evident. Secondly, our customized sample does not include a baseline questionnaire which would have allowed us to have broader informations on users before they subscription to Rensource. To that extent, a randomized experiment to determine the impact of subscription to Rensource solar energy on earnings and income would have been a better measure but data on this were not available. Notwithstanding these caveats, we do not anticipate systematic bias in our analysis due to how our control group was selected as well as the use of different matching methods. Then, future researches should provide further analyses on the opportunities delivered by solar energy systems in terms of access to funding,

market share, and innovation in the goods and services offered by subscribers' merchants. Finally, the use of innovative evaluation strategies, particularly through spatial analysis, would better identify the direct and indirect effects of projects with a strong impact on local populations.

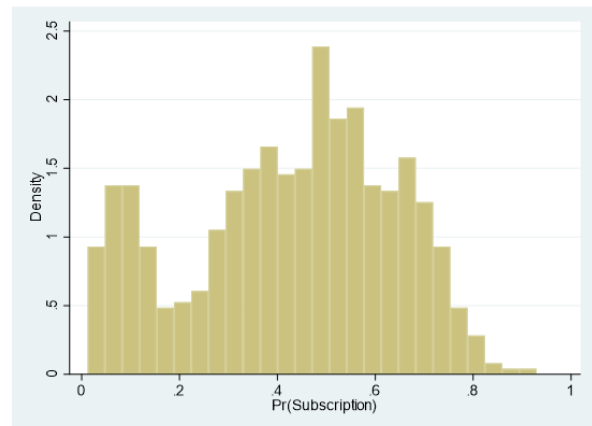
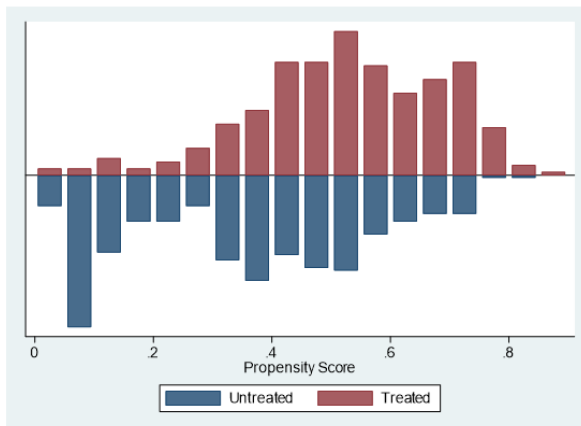
## 6. Appendices

### A.1. PSM sensitivity tests

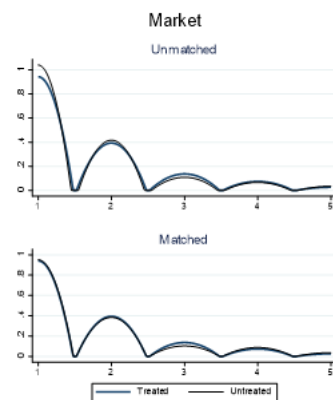
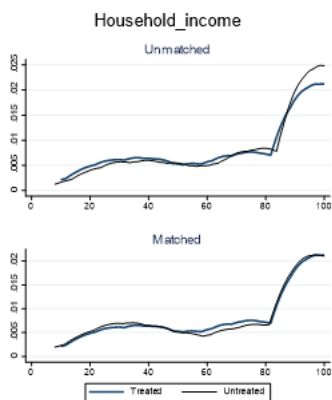
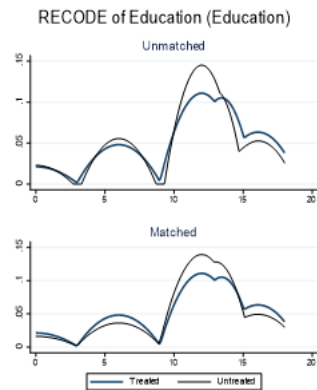
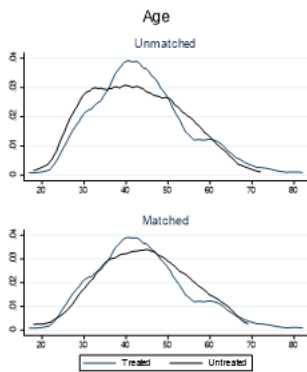
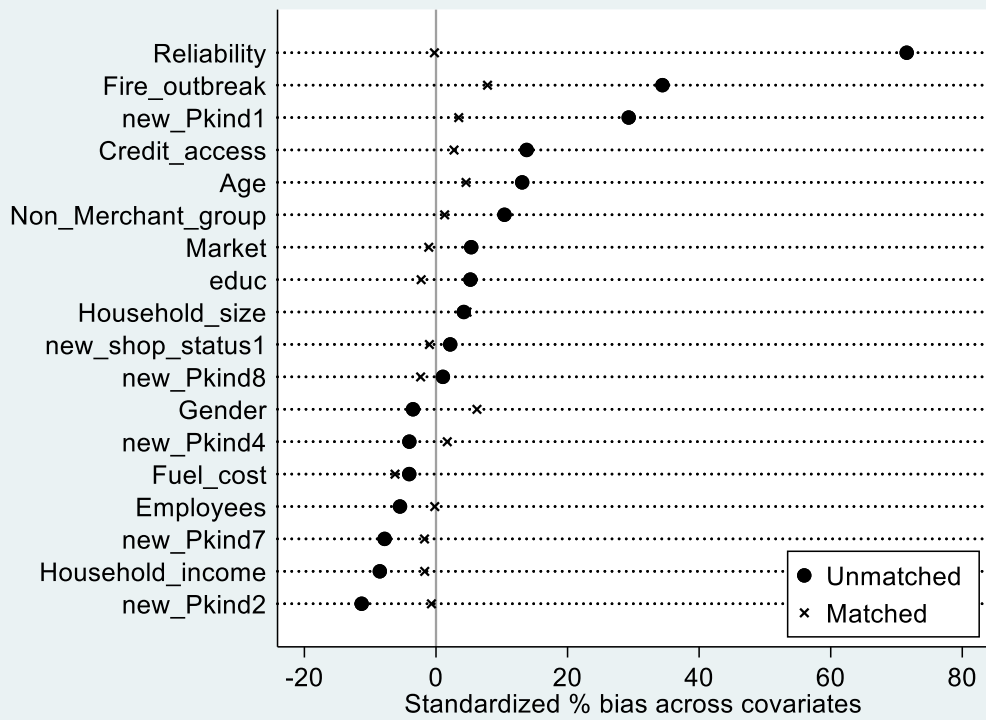
#### Common support table

Treatment Assignment	Common support		Total
	Off support	On support	
Control	0	400	400
Treated	5	295	300
Total	5	695	700

#### Common support graphs



## Pstest graphs



## A.2. Merchants and enterprise characteristics for users and non-users of Rensource solar energy across gender groups

Variable	Users (N=300)				Non-Users (N=400)			
	Gender	Mean	SD	Mean difference (T-test)	Gender	Mean	SD	Mean difference (t-test)
Age	Male (N=193)	45	12	3**	Male (N=264)	42	11	0
	Female (N=107)	42	9		Female (N=136)	42	10	
Household size	Male (N=193)	6	3	1	Male (N=264)	6	4	1
	Female (N=107)	5	2		Female (N=136)	5	3	
Household income (%)	Male (N=193)	88	21	32***	Male (N=264)	87	22	24***
	Female (N=107)	56	28		Female (N=136)	63	28	
Monthly income from trading (₦)	Male (N=193)	143577	151399	-6587	Male (N=264)	109115	106727	-21530*
	Female (N=107)	150164	136366		Female (N=136)	130645	123800	
Business age	Male (N=193)	13	9	2**	Male (N=264)	12	8	1
	Female (N=107)	11	7		Female (N=136)	11	7	
Employees	Male (N=193)	3	2	1	Male (N=264)	3	2	1
	Female (N=107)	2	2		Female (N=136)	2	2	
Branches	Male (N=193)	1	1	0	Male (N=264)	1	1	0
	Female (N=107)	1	1		Female (N=136)	1	1	

\*\*\* p<0.01, \*\* p<0.05, \* p<0



### A.3. Descriptive statistics of Non-Users by State

Variable	Description	Kano (N=250)				Lagos (N=100)				Ondo (N= 50)			
		Min	Max	Mean	Std. dev	Min	Max	Mean	Std. dev	Min	Max	Mean	Std. dev
Age	Age of business owner in years	18	72	43	11	21	63	41	10	22	69	45	11
Household size	Number of people in the household	1	17	6	4	1	16	5	3	1	8	4	2
Household income	Proportion of household income from trading (%)	8	100	88	23	20	100	64	27	15	100	65	26
Monthly income	Average monthly income from trading (₦) <sup>69</sup>	3000	700000	84457	78714	15000	800000	211150	144108	10000	350000	86899	79706
Business age	Age of business	1	40	13	9	1	40	10	6	1	50	11	9
Employees	Number of employees	1	15	2	2	1	16	3	3	1	5	1	1
Branches	Number of shop branches	1	6	1	1	1	4	1	0	1	2	1	0
Electricity bill <sup>70</sup>	Electricity bill [price per month] for national grid (₦)	500	30000	4129	3315	500	70000	2436	1355	300	20000	2063	3697
Fuel cost <sup>71</sup>	Amount spent on fuel (petrol/diesel) for generators per month (₦)	500	50000	6400	6050	2000	100000	11266	10566	1000	15000	3977	3350

<sup>69</sup> Exchange rate US\$ 1: ₦ 380 (Source: Central Bank of Nigeria)

<sup>70</sup> Values for Rensource users are electricity bill in price per month prior to subscription

<sup>71</sup> Values for Rensource users are fuel cost for generators prior to subscription

#### A.4. Descriptive statistics for Users by State

Variable	Description	Kano (N=180)				Lagos (N=75)				Ondo (N=45)			
		Min	Max	Mean	Std. dev	Min	Max	Mean	Std. dev	Min	Max	Mean	Std. dev
Age	Age of business owner in years	17	82	45 <sup>a</sup>	12	26	55	40 <sup>a</sup>	7	27	77	45 <sup>a</sup>	10
Household size	Number of people in the household	1	15	6 <sup>b</sup>	3	1	13	5 <sup>b</sup>	2	1	8	4	1
Household income	Proportion of household income from trading (%)	10	100	89 <sup>a</sup>	21	20	100	57 <sup>a</sup>	28	10	100	60 <sup>a</sup>	31
Monthly income	Average monthly income from trading (₦)	10000	750000	130149 <sup>a</sup>	133191	30000	750000	180667 <sup>a</sup>	136672	5000	800000	151135 <sup>a</sup>	195447
Business age	Age of business	1	40	14 <sup>b</sup>	9	2	22	9 <sup>b</sup>	5	1	37	12 <sup>b</sup>	9
Employees	Number of employees	1	15	3 <sup>b</sup>	2	1	12	3 <sup>b</sup>	2	1	4	2 <sup>b</sup>	1
Branches	Shop branches	1	7	1 <sup>b</sup>	1	1	4	1 <sup>b</sup>	1	1	3	1 <sup>b</sup>	1
Fuel cost	Amount spent on fuel (petrol/diesel) for generators per month (₦)	6000	80000	10547 <sup>a</sup>	12733	490	30000	11870 <sup>a</sup>	4560	6000	6000	6000 <sup>a</sup>	0
Electricity bill	Electricity bill [price per month] for national grid (₦)	500	36000	4017 <sup>b</sup>	3841	500	28000	2247 <sup>b</sup>	3723	200	10000	1619 <sup>b</sup>	1912
Rensource bill	Rensource bill [in price per month] (₦)	1000	12000	5745	2813	1000	20000	5780	5013	300	11200	1948	2273
Increase in sales	Proportion of change of volume of sales	3	100	45	26	5	40	24	9	10	100	33	24
Increase in profit	Proportion of change of electricity bill in profit [in %]	5	100	39	27	5	30	18	7	10	100	28	24
Fire outbreaks	Number of fire outbreaks in the past five years	1	4	1	1	1	3	2	1	-	-	-	-
Cost of fire	Estimated cost of the fire outbreaks to the business (₦)	5000	10000000	2038042	2421539	10000	200000	92500	86357	-	-	-	-

### A.5. Descriptive statistics of users and non-users by product kind

Variable	Description	Clothing, Shoes, Bags & Textiles				Food products [fresh and processed produce]			
		Users (N=148)		Non-users(N=140)		Users (N=27)		Non-users(N=50)	
		Mean	Std. dev	Mean	Std. dev	Mean	Std. dev	Mean	Std. dev
Household income	Proportion of household income from trading (%)	81 <sup>b</sup>	27	82 <sup>b</sup>	26	70 <sup>b</sup>	29	69 <sup>b</sup>	28
Monthly income	Average monthly income from trading (₹)	162011 <sup>a</sup>	154622	119129 <sup>a</sup>	104241	180818 <sup>a</sup>	218555	123355 <sup>a</sup>	109786
Employees	Number of employees	3 <sup>b</sup>	2	2 <sup>b</sup>	2	2 <sup>b</sup>	1	3 <sup>b</sup>	3
Branches	Number of shop branches	1 <sup>b</sup>	1	1 <sup>b</sup>	1	1 <sup>b</sup>	1	1 <sup>b</sup>	1
Electricity bill	Electricity bill [price per month] (₹) for national grid	3742 <sup>b</sup>	4794	3068 <sup>b</sup>	2089	2852 <sup>b</sup>	1589	2717 <sup>b</sup>	1679
Fuel cost	Amount spent on fuel (petrol/diesel) for generators per month (₹)	11473 <sup>a</sup>	10299	8243 <sup>a</sup>	5682	13925 <sup>a</sup>	7488	10164 <sup>a</sup>	9414
Fire outbreaks	Number of fire outbreaks in the past five years	1 <sup>b</sup>	1	2 <sup>b</sup>	1	1 <sup>b</sup>	1	2 <sup>b</sup>	1
Cost of fire outbreak	Estimated cost of the fire outbreaks to the business (₹)	1864408 <sup>a</sup>	222292	808182 <sup>a</sup>	1673051	1643571 <sup>a</sup>	2774192	779333 <sup>a</sup>	1973143
		Electronics [Phones, Computers & Accessories]				Cosmetics & beauty salons			
		Users (N=35)		Non-users (N=52)		Users (N=20)		Non-users (N=44)	
		Mean	Std. dev	Mean	Std. dev	Mean	Std. dev	Mean	Std. dev
Household income	Proportion of household income from trading (%)	70 <sup>a</sup>	30	79 <sup>a</sup>	30	75 <sup>a</sup>	29	83 <sup>a</sup>	23
Monthly income	Average monthly income from trading (₹)	99478 <sup>a</sup>	66671	116403 <sup>a</sup>	97442	86850 <sup>a</sup>	66218	116841 <sup>a</sup>	57988
Employees	Number of employees	2 <sup>b</sup>	1	2 <sup>b</sup>	1	3 <sup>b</sup>	3	4 <sup>b</sup>	3
Branches	Number of shop branches	1 <sup>b</sup>	1	1 <sup>b</sup>	0	1 <sup>b</sup>	0	1 <sup>b</sup>	1
Electricity bill	Electricity bill [in price per month] (₹) for national grid	3164 <sup>a</sup>	1623	4305 <sup>a</sup>	3794	3785 <sup>b</sup>	2039	29223 <sup>b</sup>	6529
Fuel cost	Amount spent on fuel (petrol/diesel) for generators per month (₹)	9625 <sup>a</sup>	3138	6756 <sup>a</sup>	4096	6275 <sup>a</sup>	2038	8125 <sup>a</sup>	6702
Fire outbreaks	Number of fire outbreaks in the past five years	1 <sup>b</sup>	1	1 <sup>b</sup>	1	2 <sup>b</sup>	1	1 <sup>b</sup>	1
Cost of fire outbreak	Estimated cost of the fire outbreaks to the business (₹)	2938333 <sup>a</sup>	3078834	2624111 <sup>a</sup>	3451154	195000 <sup>a</sup>	249015	2020000 <sup>a</sup>	537424

## Appendix A.5: Continued

Variable	Description	Homeware & Kitchenware Users (N=24)		Non-users(N=40)		Manufacturing Users (N=14)		Non-Users(N=21)	
		Mean	Std. dev	Mean	Std. dev	Mean	Std. dev	Mean	Std. dev
Household income	Proportion of household income from trading (%)	66 <sup>a</sup>	30	79 <sup>a</sup>	26	96 <sup>a</sup>	9	91 <sup>a</sup>	23
Monthly income	Average monthly income from trading (₹)	170171 <sup>a</sup>	124555	106393 <sup>a</sup>	70165	200228 <sup>a</sup>	198654	89668 <sup>a</sup>	61364
Employees	Number of employees	2 <sup>b</sup>	2	3	3	3	2	2	1
Branches	Number of shop branches	1 <sup>b</sup>	1	1	0	1	0	1	1
Electricity bill	Electricity bill [price per month] (₹) for national grid	1936 <sup>b</sup>	2073	1967 <sup>b</sup>	1096	3785	2039	5412 <sup>a</sup>	6529
Fuel cost	Amount spent on fuel (petrol/diesel) for generators per month (₹)	10444 <sup>a</sup>	2744	5573 <sup>a</sup>	3076	8000 <sup>a</sup>	0	5533 <sup>a</sup>	2850
Fire outbreaks	Number of fire outbreaks in the past five years	1 <sup>b</sup>	0	1 <sup>b</sup>	0	2 <sup>b</sup>	1	2 <sup>b</sup>	1
Cost of fire outbreaks	Estimated cost of the fire outbreaks to the business (₹)	1100000	1272792	6250000	2500000	268333	249015	453333	537424
<b>Stationery [books, graphics, gift cards]</b>									
		Users (N=18)		Non-Users (N=36)					
		Mean	Std. dev	Mean	Std. dev				
Household income	Proportion of household income from trading (%)	69 <sup>a</sup>	31	69	28				
Monthly income	Average monthly income from trading (₹)	109611 <sup>a</sup>	72048	151825 <sup>a</sup>	171537				
Employees	Number of employees	2 <sup>b</sup>	2	3 <sup>b</sup>	1				
Branches	Number of shop branches	1 <sup>b</sup>	0	1 <sup>b</sup>	1				
Electricity bill	Electricity bill [price per month] (₹) for national grid	3133 <sup>b</sup>	2984	2712 <sup>b</sup>	1695				
Fuel cost	Amount spent on fuel (petrol/diesel) for generators per month (₹)	12031 <sup>a</sup>	11205	9946 <sup>a</sup>	17877				
Fire outbreaks	Number of fire outbreaks in the past five years	2 <sup>b</sup>	1	2 <sup>b</sup>	1				
Cost of fire outbreaks	Estimated cost of the fire outbreaks to the business (₹)	2483333 <sup>a</sup>	3837795	177333 <sup>a</sup>	279788				

<sup>a</sup> Means of variables marked with "a" indicate that the means are significantly different between users and non-users using t-test. <sup>b</sup> Means of variables marked with "b" indicate that the means are not significantly different between users and non-users using t-test.

## A.6. Electricity-related fire outbreaks and estimated losses

Variable	Mean	Min	Max	SD
Rensource users (N=300)				
Number of outbreaks (N=87)	1.37	1	4	0.70
Estimate loss from fire outbreak (₺)	1886441.56	5000	10000000	238264.05
Non-Rensource users (N=400)				
Number of outbreaks (N=61)	1.61	1	4	0.71
Estimate loss from fire outbreak (₺)	1039675,00	1500	8000000	182765.31
	Mean difference (t-test)			
Number of outbreaks	-0.24			
Estimate loss from fire outbreak (₺)	846766.56***			

### A.7. Differences in means after matching (Montly earnings)

Variable	Treated	Control	%bias	t	p>t	V(T)/V(C)
Age	43.967	42.967	9.0	1.12	0.264	1.09
Gender	0.642	0.618	5.1	0.61	0.540	.
Education	10.87	10.995	-2.7	-0.33	0.741	1.13
Household size	5.482	5.159	10.1	1.26	0.209	0.86
Household income	76.587	76.324	1.0	0.11	0.911	0.96
Membership	0.191	0.207	-3.9	-0.49	0.627	.
Market	1.632	1.640	-0.8	-0.10	0.924	0.91
Employees	2.401	2.384	0.9	0.10	0.917	0.80
Owned shop	0.823	0.826	-0.9	-0.11	0.915	-
Fire outbreak	0.301	0.300	0.2	0.02	0.982	-
Credit access	0.261	0.258	0.6	0.07	0.944	-
Food products	0.090	0.084	1.9	0.25	0.800	-
Clothing, Shoes, bags & textiles	0.492	0.482	1.9	0.22	0.822	-
Electronics	0.117	0.125	-2.3	-0.28	0.778	-
Cosmetics	0.080	0.080	0.0	0.00	1.000	-
Homeware & kitchenware	0.027	0.033	-3.7	-0.42	0.674	-
Reliability	0.933	0.936	-0.9	-0.17	0.869	-
Fuel cost	4697.3	4995.3	-3.9	-0.52	0.604	1.57* <sup>72</sup>
Ps-R-square	0.004					
Chi-square	3.10					
p> Chi-square	1.000					
Mean Bias	2.8					
Median Bias	1.9					
B	14.4					
R	.97					
%Var	14					

<sup>72</sup> \*If variance ratio outside [0.80; 1.26]

## A.8. Effect of Rensource subscription on the monthly earnings of merchants (OLS)

	(1) Monthly_earning
Subscription	28208.4** (2.68)
Age	-206.6 (-0.45)
Gender	95.22 (0.01)
Education	1651.6 (1.49)
Household size	2428.9 (1.40)
Household income	422.6* (2.07)
Non-Membership	-27519.8* (-2.03)
Market	29048.0*** (3.94)
Employees	12177.7*** (3.78)
Owned shop	23288.9 (1.83)
Fire outbreak	-4816.0 (-0.39)
Credit access	2679.2 (0.18)
Food products	6331.5 (0.30)
Clothing, shoes, bags & textiles	26231.6* (2.03)
Electronics	4646.3 (0.32)
Cosmetics	7370.2 (0.44)
Homeware & kitchenware	-110981.8*** (-5.69)
Reliability	2483.4 (0.23)
Fuel cost	1.667 (1.79)
_cons	-31472.0 (-0.80)
Pseudo R <sup>2</sup>	14
F	7.09
N	700

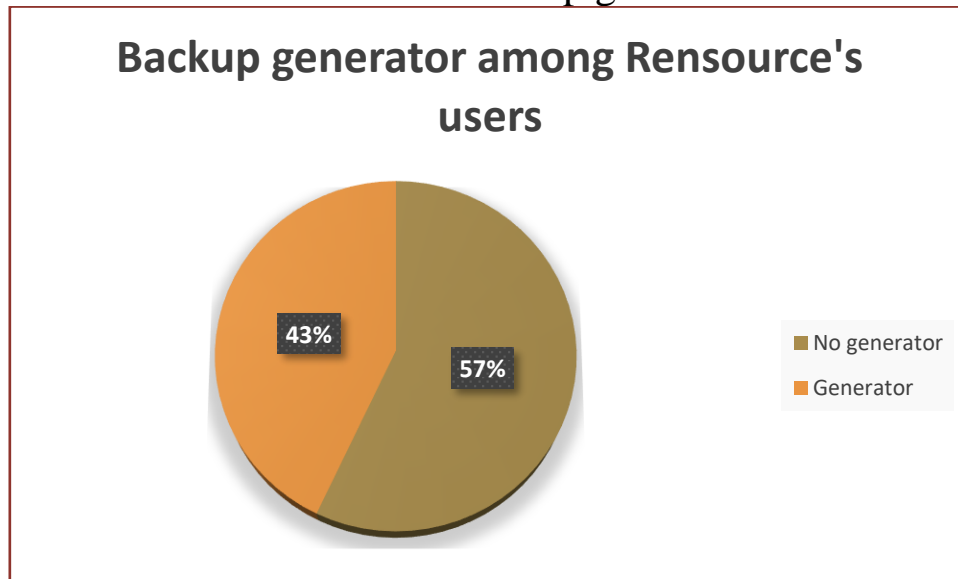
Notes: These results are based on propensity score matching. Standard errors are in parentheses; \*p-value < 0.1,

\*\* p-value < 0.05, \*\*\* p-value < 0.001

### A.9. Summary of subscription cost of Rensource users

Variable	Observation	Mean	Standard deviation	Minimum	Maximum
Subscription cost (₦)	72	3412.5	2236.82	1000	10500

### A.10. Rensource users and backup generators





### A.11. Differences in means after matching (Monthly fuel cost)

Variable	Treated	Control	%bias	t	p>t	V(T)/V(C)
Gender	0.64333	.61417	6.1	0.74	0.461	-
Age	43.937	43.884	0.5	0.06	0.954	0.98
Household size	5.4733	5.4833	-0.3	-0.04	0.969	0.83
Household income	76.565	75.177	5.0	0.59	0.553	0.98
Education	10.853	10.753	2.2	0.26	0.795	1.05
Employees	2.41	2.2867	6.0	0.75	0.454	0.88
Membership	0.19	.17167	4.5	0.58	0.560	-
Credit access	0.26333	.215	11.4	1.39	0.166	-
Reliability	0.93333	.91333	5.3	0.92	0.358	-
Owned shop	0.82333	.84	-4.3	-0.54	0.586	-
Electricity usage	.51667	.52417	-1.5	-0.18	0.854	-
Wholesale	.07667	.07583	0.3	0.04	0.969	-
Retail	.42667	.435	-1.7	-0.21	0.837	-
Both wholesale & retail	.46	.44833	2.3	0.29	0.775	-
National Grid source	.32	.37083	-10.9	-1.31	0.191	-
Ps-R-square				0.008		
Chi-square				6.90		
p> Chi-square				0.975		
Mean Bias				4.4		
Median Bias				4.4		
B				21.5		
R				.78		
% Var				0		

## A.12. Questionnaire of Rensource - Users

### Consent Statement

Sir/Ma,

This interview will take about 15 – 20 minutes to complete. With your permission/consent, I would like to start the interview.

May I now proceed with the interview? (a) Yes [ ] (b) No [ ]

### Survey Quality Control

Questionnaire Serial Number: \_\_\_\_\_ **Rensource** Subscription ID: \_\_\_\_\_

Date of Interview (DD/MM/YYYY): \_\_\_\_\_ Start Time: \_\_\_\_\_ End Time: \_\_\_\_\_

Enumerator's Name: \_\_\_\_\_ Enumerator's ID: \_\_\_\_\_

Town: \_\_\_\_\_ Market: \_\_\_\_\_

### PART A: Respondent's Identification and demographics

- 1) Gender of business owner: (a) Male [ ] (b) Female [ ]
- 2) Age of business owner (in years): \_\_\_\_\_
- 3) Marital status: (a) Single [ ] (b) Married [ ] (c) Divorced [ ]
- (d) Widow/Widower [ ] (e) Others [ ] (Specify) \_\_\_\_\_
- 4) What is the business owner's highest level of education completed?
  - (a) No formal schooling [ ] (b) Primary [ ] (c) Secondary [ ]
  - (d) Tertiary/University [ ] (e) Adult education [ ] (f) Don't know [ ]
- 5) What is your household size (Number of Persons in the household)? \_\_\_\_\_
- 6) What proportion of your household income is from trading? \_\_\_\_\_%
- 7) What is the average monthly earning of your business? ~~N~~ \_\_\_\_\_
- 8) Status of your shop/store: (a) Rented [ ] (b) Owner [ ] (c) Family owned [ ]
- (d) Other [ ]
- 9) Ownership structure of business: (a) Sole Proprietorship [ ] (b) Partnership [ ]
- (c) Association [ ] (d) Other [ ] (Specify) \_\_\_\_\_

### PART B: Business Information

#### i. Business background

- 10) Age of business (in years): \_\_\_\_\_
- 11) Kind of business: (a) Whole sale [ ] (b) Retail [ ] (c) Both wholesale & retail [ ]
- (d) Others [ ] (**Specify**) \_\_\_\_\_
- 12) What kind of products/services you trade in?

- (a) Clothing & textiles [ ] (b) Foods and beverages [ ] (c) Manufacturing [ ]  
 (d) Electronics [ ] (e) Stationery [ ] (f) Other [ ] (*Specify*)

- 13) Number of employees in the business: \_\_\_\_\_  
 14) Does the business owner belong to a merchants group? (a) Yes [ ] (b) No [ ]  
 15) How many branches does the business have? \_\_\_\_\_  
 16) Do you have access to credit for the business? (a) Yes [ ] (b) No [ ]  
 17) Did you apply for credit to install **Rensource** solar energy? (a) Yes [ ] (b) No [ ]

## ii. Electricity Supply to merchants in the market

- 18) What sources of electricity do you have access to in this market? (*Multiple responses allowed*)  
 (a) Generators [ ] (b) National grid [ ] (c) **Rensource** solar energy [ ]  
 (d) Others [ ] (*specify*) \_\_\_\_\_  
 19) Which of the following characteristics of electricity providers determine your choice of supplier? (*Rate the characteristics in order of importance using: 1=very unimportant, 2=unimportant, 3=Neutral, 4=Important, 5=Very important*)  
 (a) Installation cost [ ] (b) Monthly\Weekly user fees [ ] (c) Reliability [ ]  
 (d) Frequency of maintenance [ ] (e) Noise generation [ ] (f) Air pollution [ ]  
 (g) User-friendliness [ ] (h) Risk of fire outbreak [ ] (i) Health problems [ ]  
 (j) Environmental problems [ ] (k) Prone to theft [ ] (l) Others (*list and rate*) \_\_\_\_\_  
 20) When did you Subscribe to **Rensource**? (*month and year*) \_\_\_\_\_  
 21) How did you know about **Rensource** Solar and its benefits?  
 (a) Through the market association [ ] (b) Someone (friends, relative, neighbours, etc) [ ] (c) **Rensource** staff members/ representative [ ] (d) Other [ ] (*Specify*) \_\_\_\_\_  
 22) How important were the following characteristics in your decision to subscribe to **Rensource** solar energy? (*1=very unimportant, 2=unimportant, 3=Neutral, 4=Important, 5=Very important*)  
 (a) Reliability [ ] (b) Affordability [ ] (c) Ease of access [ ]  
 (d) Flexible payment plan [ ] (e) Flexibility of uses [ ] (f) Cleanliness [ ]  
 (g) Less pollution [ ] (h) Low health risk [ ] (i) Low risk of fire outbreak [ ]  
 (j) No alternative source [ ] (k) Other [ ] (*Specify*) \_\_\_\_\_  
 23) Compare to **Rensource** solar energy, how would you rate the following characteristics of the electricity sources you were using before subscribing to **Rensource**? (*1=Low, 2=Medium, 3=High, 4=the same*) [*specify separately for each source*]

S/No	Characteristics	Generator	National Grid	Others (Specify)
A	Installation cost			
B	Monthly\Weekly user fees			
C	Reliability			
D	Frequency of maintenance			
E	Noise generation			
F	Air pollution			
G	User-friendliness			
H	Risk of fire outbreak			
I	Health problems			

J	Environmental problems			
K	Prone to theft			
L	Others ( <i>list and rate</i> )			

24) Are you using more or less electricity [per KWh] after subscribing to **Rensource** solar energy?  
(a) More [ ] (b) Less [ ] (c) Same amount [ ]

25) How much were you paying for electricity [in price per KWh] prior to **Rensource** solar energy and after subscribing to Rensource solar energy?  
(a) **Before:** ₦\_\_\_\_\_ per month: (b) **After:** ₦\_\_\_\_\_ per month

26) i. Did you pay any money at the time of installation of **Rensource** solar system?  
(a) Yes [ ] (b) No [ ]

ii. If YES to 26(i) above, how much did you pay? ₦\_\_\_\_\_

27) Have you changed the kinds of appliances you are using in your shop? (a) Yes [ ] (b) No [ ]

28) If YES in 27 above, explain which appliances were changed and why have you changed them.

Appliance1\_\_\_\_\_Why\_\_\_\_\_

Appliance2\_\_\_\_\_Why\_\_\_\_\_

Appliance3\_\_\_\_\_Why\_\_\_\_\_

Appliance4\_\_\_\_\_Why\_\_\_\_\_

29) i. Has there been a change in the number of days you trade due to **Rensource** solar energy subscription? (a) Yes [ ] (b) No [ ]

ii. If YES to 29(i) above, what kind of change? (a) An Increase [ ] (b) A Decrease [ ]

iii. If YES to 29(i) above, by how many days? \_\_\_\_\_ per month

30) i. Has there been a change in volume of sales due to access to **Rensource** solar energy?

(a) Yes [ ] (b) No [ ]

ii. If YES to 30(i) above, what kind of change? (a) An Increase [ ] (b) A Decrease [ ]

iii. If YES to 30(i) above, what is the proportion of change? \_\_\_\_\_ % (percent)

31) i. Has profitability/productivity changed since subscribing to **Rensource** solar energy?

(a) Yes [ ] (b) No [ ]

ii. If YES to 31(i) above, what kind of change? (a) An Increase [ ] (b) A Decrease [ ]

iii. If YES to 31(i) above, what is the proportion of change in profit? \_\_\_\_\_ %

iv. If YES to 31(i) above, can you pinpoint uses of the solar energy that increase your productivity/profitability? \_\_\_\_\_

\_\_\_\_\_

\_\_\_\_\_

\_\_\_\_\_

32) i. Have you changed your business operations/activities due to access to the **Rensource** solar energy? (a) Yes [ ] (b) No [ ]

ii. If YES to 32(i) above, in which ways have you changed operations? \_\_\_\_\_

\_\_\_\_\_

\_\_\_\_\_

33) i. Were there any fire outbreaks prior to installation of **Rensource** Solar system?

(a) Yes [ ] (b) No [ ]

ii. If YES to 33(i) above, how many fire outbreaks have you recorded in the past five years? \_\_\_\_\_ (Number of cases)

iii. If YES to 33(i), what was the estimated cost of the fire to your business? ₦\_\_\_\_\_

34) i. Has similar fire outbreaks occurred following your installation of **Rensource** Solar?

(a) Yes [ ] (b) No [ ]

ii. If YES to 34(i) above, how often?

- (a) Yes, even more frequently than before [ ] (b) Yes, as frequently as before [ ]  
 (c) Yes, but less frequently than before [ ] (d) No [ ] (e) I don't know [ ]

iii. What has been the main cause(s) of these fires? **List** \_\_\_\_\_

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35) i. Were there any thefts associated to lack of electricity before you installed **Rensource** Solar?

- (a) Yes [ ] (b) No [ ]

ii. If YES to 35(i) above, how many thefts were recorded in the past 12 months? \_\_\_\_\_

iii. If YES to 35(i), what was the estimated loss in the theft to your business? ₦ \_\_\_\_\_

36) Has the installation of **Rensource** solar equipment resulted in any changes in each of these forms of pollution, and what changes have you observed?

Type of Pollution	Has there been a change?		Type of Change			
	Yes	No	Increase	Decrease	No Change	Don't know
Noise						
Dust						
Smoke						
Heat						
Others (Specify)						

37) Have you employed additional workers in your shop due to access to Rensource solar energy?

- (a) Yes [ ] (b) No [ ] If yes, how many people \_\_\_\_\_

38) What are your existing energy (electricity) needs that are not currently being met by **Rensource**?

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39) How should **Rensource** better package its services to meet those needs mentioned above?

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### iii. System Performance

40) i. Is your installed **Rensource** Solar system still functioning well? (a) Yes [ ] (b) No [ ]

ii. If NO to 39(i) above, what kind of problems have you noticed with the system?

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41) i. Have you reported any of these problems to **Rensource** (representatives)?

- (a) Yes [ ] (b) No [ ]

ii. If YES to 40(i) above, have these problems been resolved? (a) Yes [ ] (b) No [ ]

iii. If NO to 40(ii) above, why have these problems not been resolved?

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42) Have you had to replace any parts of the system following initial installations?

- (a) Yes [ ] (b) No [ ]

43) How satisfied were you with the service provided in dealing with problems in service provision?

- (a) Very Dissatisfied [ ] (b) Dissatisfied [ ] (c) Satisfied [ ] (d) Very Satisfied [ ]

## Appendix A.12: Continued (questionnaire of Rensource Non-Users)

### Consent Statement

Sir/Ma,

This interview will take about 15 – 20 minutes to complete. With your permission/consent, I would like to start the interview.

May I now proceed with the interview? (a) Yes [ ] (b) No [ ]

### Survey Quality Control

Questionnaire Serial Number: \_\_\_\_\_ Shop No (Respondent's ID): \_\_\_\_\_

Date of Interview (DD/MM/YYYY): \_\_\_\_\_ Start Time: \_\_\_\_\_ End Time: \_\_\_\_\_

Enumerator's Name: \_\_\_\_\_ Enumerator's ID: \_\_\_\_\_

Town: \_\_\_\_\_ Market: \_\_\_\_\_

### PART A: Respondent's Identification and demographics

- 44) Gender of business owner: (a) Male [ ] (b) Female [ ]
- 45) Age of business owner (in years): \_\_\_\_\_
- 46) Marital status: (a) Single [ ] (b) Married [ ] (c) Divorced [ ]  
(d) Widow/Widower [ ] (e) Others [ ] (Specify) \_\_\_\_\_
- 47) What is the business owner's highest level of education completed?  
(a) No formal schooling [ ] (b) Primary [ ] (c) Secondary [ ]  
(d) Tertiary/University [ ] (e) Adult education [ ] (f) Don't know [ ]
- 48) What is your household size (Number of Persons in the household)? \_\_\_\_\_
- 49) What proportion of your household income is from trading? \_\_\_\_\_%
- 50) What is the average monthly earning of your business? ~~N~~ \_\_\_\_\_
- 51) Status of your shop/store: (a) Rented [ ] (b) Owner [ ] (c) Family owned [ ]  
(d) Other [ ] (*Specify*) \_\_\_\_\_
- 52) Ownership structure of business: (a) Sole Proprietorship [ ] (b) Partnership [ ]  
(c) Association [ ] (d) Other [ ] (*Specify*) \_\_\_\_\_

### PART B: Business Information

#### iv. Business background

- 53) Age of business (in years): \_\_\_\_\_
- 54) Kind of business: (a) Whole sale [ ] (b) Retail [ ] (c) Both wholesale & retail [ ]  
(d) Others [ ] (*Specify*) \_\_\_\_\_
- 55) What kind of products/services you trade in?  
(a) Clothing & textiles [ ] (b) Foods and beverages [ ] (c) Manufacturing [ ]

(d) Electronics [ ]      (e) Stationery [ ]      (f) Other [ ] (*Specify*)

56) Number of employees in the business: \_\_\_\_\_

57) Does the business owner belong to a merchants group?      (a) Yes [ ]      (b) No [ ]

58) How many branches does the business have? \_\_\_\_\_

59) Do you have access to credit for the business?      (a) Yes [ ]      (b) No [ ]

#### v. Access to Electricity Supply in the market

60) What sources of electricity do you have access to in this market? (*Multiple responses allowed*)

(a) Generators [ ]      (b) National grid [ ]      (c) Solar energy [ ]      (d) No electricity [ ]

(e) Others [ ] (*specify*) \_\_\_\_\_

61) Which types of marketing activities do you use each selected sources of electricity identified in 17 above for?

(a) Generators: \_\_\_\_\_

(b) National grid: \_\_\_\_\_

(c) Solar energy: \_\_\_\_\_

(d) Others (*already specified*) \_\_\_\_\_

62) How would you rate the following characteristics of the electricity source you are currently using? (*Rate the characteristics using: 1=Low, 2=Medium, 3=High*)

(a) Installation cost [ ]      (b) Monthly/Weekly user fees [ ]      (c) Reliability [ ]

(d) Frequency of maintenance [ ]      (e) Noise generation [ ]      (f) Air pollution [ ]

(g) User-friendliness [ ]      (h) Risk of fire outbreak [ ]      (i) Health problems [ ]

(j) Environmental problems [ ]      (k) Prone to theft [ ]      (l) Others (*rate and specify*) [ ] \_\_\_\_\_

63) How much are you paying for electricity [in price per KWh] per month? ₦ \_\_\_\_\_

64) How much do you spend on fuel (petrol/diesel) for generators (in case you use a generator) per month? ₦ \_\_\_\_\_

65) i. Have you experienced any fire outbreaks linked to the type of electricity you are currently using?      (a) Yes [ ]      (b) No [ ]

ii. If YES to 22(i) above, how many fire outbreaks have you recorded in the past one year? \_\_\_\_\_ (Number of cases)

iii. If YES to 22(i), what was the estimated loss due to fire outbreak in monetary terms to your business? ₦ \_\_\_\_\_

66) i. Have you recorded any theft cases due unreliable or no electricity in your shop in the past one year?      (a) Yes [ ]      (b) No [ ]

ii. If YES to 23(i) above, how many thefts were recorded in the past 12 months? \_\_\_\_\_

iii. If YES to 23(i), what was the estimated loss in the theft to your business? ₦ \_\_\_\_\_

67) i. Would the number of days you trade change due to a change of your electricity provider? (*This also applies to no electricity*)      (a) Yes [ ]      (b) No [ ]

ii. If YES to 24(i) above, what kind of change?      (a) An Increase [ ]      (b) A Decrease [ ]

iii. If YES to 24(i) above, by how many days? \_\_\_\_\_ per month

68) i. Has your volume of sales been affected by the type of electricity you are using? (*This also applies to no electricity*)      (a) Yes [ ]      (b) No [ ]

ii. If YES to 25(i) above, what kind of change?      (a) An Increase [ ]      (b) A Decrease [ ]

iii. If YES to 25(i) above, what is the proportion of change? \_\_\_\_\_ % (percent)

69) i. Has your profitability/productivity changed due to the type of electricity you are currently using? (a) Yes [ ] (b) No [ ]

ii. If YES to 26(i) above, what kind of change? (a) An Increase [ ] (b) A Decrease [ ]

iii. If YES to 26(i) above, what is the proportion of change in profit? \_\_\_\_\_ %

70) i. Have you changed your business operations/activities due to the type of electricity you are currently using? (a) Yes [ ] (b) No [ ]

ii. If YES to 27(i) above, in which ways have you changed operations? \_\_\_\_\_

\_\_\_\_\_

71) Can you pinpoint uses of your current electricity that increase your productivity/profitability?

\_\_\_\_\_

\_\_\_\_\_

72) Would you subscribe to solar energy if it were made available? (a) Yes [ ] (b) No [ ]

73) If YES to 29 above, how important will the following characteristics influence your decision to subscribe to solar energy? (1=very unimportant, 2=unimportant, 3=Neutral, 4=Important, 5=Very important)

(a) Reliability [ ] (b) Affordability [ ] (c) Ease of access [ ]

(d) Flexible payment plan [ ] (e) Flexibility of uses [ ] (f) Cleanliness [ ]

(g) Less pollution [ ] (h) Low health risk [ ] (i) Low risk of fire outbreak [ ]

(j) No alternative source [ ] (k) Other [ ] (Specify) \_\_\_\_\_

74) If NO to 29 above, what would stop you from subscribing to solar energy? (State all reasons from the most important to least important) \_\_\_\_\_

\_\_\_\_\_

75) Are you aware of any solar energy provider in your market? (a) Yes [ ] (b) No [ ]

76) If YES to 33 above, how did you know/hear about them?

(a) Rural Electrification Agency (REA) [ ] (b) Through the market association [ ]

(c) Someone (friends, relative, neighbours, etc) [ ] (d) Radio [ ] (e) Internet [ ]

(f) Other [ ] (Specify) \_\_\_\_\_

77) Will you be using more or less electricity [per kWh] if you get access to solar energy?

(a) More [ ] (b) Less [ ] (c) Same amount [ ]

78) Would you change the kinds of appliances you are using in your shop if you are to connect to solar powered electricity? (a) Yes [ ] (b) No [ ]

79) If YES to 36 above, explain which appliances need to be changed and why you have to change them.

Appliance1 \_\_\_\_\_ Why \_\_\_\_\_

Appliance2 \_\_\_\_\_ Why \_\_\_\_\_

Appliance3 \_\_\_\_\_ Why \_\_\_\_\_

Appliance4 \_\_\_\_\_ Why \_\_\_\_\_

80) Can you give an estimate of the cost of appliances to be changed due to switching to solar energy? (Cost of the appliances identified in 37 above)

Appliance1 = ~~N~~ \_\_\_\_\_

Appliance2 = ~~N~~ \_\_\_\_\_

Appliance3 = ~~N~~ \_\_\_\_\_

Appliance4 = ~~N~~ \_\_\_\_\_



81) i. Will you change your business operations/activities if you get access to cheap and reliable electricity from solar energy? (a) Yes [ ] (b) No [ ]

ii. If YES to 39(i) above, in which ways will you change your operations? \_\_\_\_\_

\_\_\_\_\_

82) Which types of marketing activities will you use the solar energy for? \_\_\_\_\_

\_\_\_\_\_

83) Will the installation of solar equipment result in any changes in each of these forms of pollution, and what changes have you observed?

Type of Pollution	Will there be a change?		Which type of Change?			
	Yes	No	Increase	Decrease	No Change	Don't know
Noise						
Dust						
Smoke						
Heat						
Others (Specify)						

84) Will you employ more people to work in your shop if you get access to solar energy? (a) Yes [ ] (b) No [ ] If yes, how many people \_\_\_\_\_

85) What are your existing energy (electricity) needs that are not currently being met? \_\_\_\_\_

\_\_\_\_\_

86) How should solar energy providers package their services to meet those needs mentioned above?

\_\_\_\_\_

\_\_\_\_\_

\_\_\_\_\_

# Chapter THREE: Indirect impact of protected areas on wood-based energy cooking consumption of local communities: a geospatial analysis in Madagascar

## Abstract

In low-income countries, most resources such as food, water, and energy fuels are concentrated in forest areas. Some of these areas are classified as protected spaces to preserve threatened ecosystems. However, their classification does not reduce wood collection by people living around the defined boundaries. The example of Madagascar shows that the areas protected for their unique biodiversity are threatened mainly by certain human activities. Indeed, protected areas (PAs) are major sources of energy cooking resources such as fuelwood and charcoal. Therefore, biodiversity conservation may have indirect effects on the choice of cooking energies. To explore how PAs allow the use of fossil energy cooking fuels, I measure the consumption share of fuelwood and charcoal for household clusters located around protected areas' borders in Madagascar. Using the Demographic Household Survey collected in 2011, 2013, and 2016 and the World Data of Protected Area datasets, I provide further information on how biodiversity protection has an indirect impact on wood-based energy cooking consumption. The methodological approach chosen for this study relies on a spatial regression discontinuity design which includes household clusters' characteristics, protected areas' attributes, and topographical parameters. My results suggest that in 2016, around the borders of protected areas the fuelwood consumption share of household clusters located inside the areas increases by 0.61 percentage points, and their consumption share of charcoal drops by 0.56 percentage points. Therefore, the findings of this study are twofold, as it shows that household clusters are constrained to continue cutting wood inside PAs. Indeed, the policy of creating PAs has no effect on the decline of wood collection, on the one hand. On the other hand, household clusters prefer to have less detectable energy inside PAs, while outside they consume more charcoal. This is mainly due to the reform of the Management Code of protected areas in 2015. Finally, my results are consistent to the heterogeneity analyses based on the road and wealth channels.

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*The usual disclaimers apply.*

## Introduction

Madagascar possesses about 12,000 species of plant of which 83% can only be found in the country. Most of these ecosystems are concentrated in the tropical forests (Cooke et al., 2022). The island is world-famous for its unique biodiversity both in term of diversity of plants and animals' species, with about 90% of its fauna and flora being endemic (Hobbs, 2008). However, the Malagasy population is at the stage of extreme poverty, with 81% of the population living with less than \$2.15 per day in 2012 (World Bank, 2023).

According to Blanc-Pamard et al. (2005), the 13 million hectares of forest now cover only about 20% of Madagascar's territory; knowing that every year some 200,000 hectares of forest disappear, mostly in the south and southwest of the island. The authors assessed that deforestation is an irreversible event and results in a massive loss of biodiversity. Indeed, the exploitation of wood contributes to the degradation of the forest ecosystem. The Global Forest Watch (GFW) details that between 2001 and 2019 the island lost 3.89 million hectares of tree cover, which is equivalent to a loss of 23% of its tree cover since 2000<sup>73</sup>. Tree and wood cutting are one of the main causes of severe deforestation.

In Madagascar, the use of woody resource is inevitable due to the lack of reliable alternatives. As a matter of fact, existing energy sources such as gas and electricity are still expensive with low network coverage. In 2020, only 27% of the population had access to electricity (IEA, 2022). Given that the consumption of woody energy-based fuels requires the cutting of forests' trees, it is crucial to engage the conservation of the forest and savannah ecosystems. Consequently, since 1985, 163 protected areas (PAs) have been created in Madagascar. Dudley (2008) described PAs as “geographical spaces, recognized, dedicated and managed, through legal or other effective means, to achieve the long-term conservation of nature with associated ecosystem services and cultural values”. They have a critical role to play in the alleviation of forest and biodiversity loss, and they are major sources of domestic energy for households. PAs are established primarily for biodiversity protection, in order to reduce the level of deforestation and conserve the endangered species.

Hence, in a poor and high demographic pressure country like Madagascar it is essential to assess the indirect socio-economic impacts of PAs on the local communities, through their consumption of fuelwood and charcoal cooking energy, considering that households usually collect the woody themselves and without paying for it. Several studies have attempted to estimate the impact of woody collection on forest cover (Heltberg et al., 2000; Kirubi, 2009; Specht et al., 2015). My analysis goes beyond this matter and measures the effect on wood collection within the PAs, on the one hand. On the other hand, it assesses the effect on the consumption ratio between fuelwood and charcoal.

Environmental decisions in favor to biodiversity protection have a positive and direct impact on forest cover and afforestation. However, there are few studies which analyse the indirect

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<sup>73</sup> [Global Forest Watch, 2022](#)

impact caused by environmental conservation on the cooking energy consumption of extremely poor households, using innovative spatial measurement approaches. Therefore, there is a relationship between environmental protection and access to sustainable energy. Madagascar is an interesting case as it is both a very poor country with only less than 5% of the population who had access to clean energy in 2020<sup>74</sup>, and a biodiversity hotspot. Gardner et al. (2016) note that there is a need for the literature to investigate the socio-economic conditions being experienced by local communities living around PAs, in order to implement the appropriate development policies. Therefore, my study answers to the following research question: what is the impact of PAs on the consumption of wood-based energy cooking of household clusters?

My empirical strategy deviates from existing approaches to better understand the relationship between wood-based energy consumption and protected spaces. I restrict my analysis to terrestrial PAs such as in the meta-analysis of Kandel et al. (2022), which assesses the effect of protected areas on household income. In order to perform a spatial measure of the impact of protected areas on fuelwood and charcoal consumption at the border, I apply a rigorous impact evaluation technique using well-defined counterfactuals.

The findings reveal that fuelwood consumption share of treated household clusters located inside PAs significantly increases in 2016 with a jump of 0.61 percentage points, compared to the fuelwood consumption of the clusters living outside the PAs' boundaries. Conversely, charcoal consumption share of treated household clusters significantly decreases in 2016 by 0.56 percentage points, compared to the consumption share of clusters in the control group. Therefore, one can note that the creation of PAs does not affect the alleviation of wood collection, given that household clusters continue to consume fuelwood because they need energy and they do not have access to efficient and affordable alternatives. But what is changing is the ratio of fuelwood on charcoal consumption at the border. This is related to the tightening of detection policies put in place by the revision of the Code of Management of the protected areas of Madagascar in 2015 (COAP, 2015). This reform provides a better inclusion of socio-economic indicators and activities inside and around PAs, while tightening the use of certain practices such as charcoal production. Then, I also provide evidence that my results remain consistent to the heterogeneity tests based on the road and the wealth channels.

As a consequence, the two objectives of biodiversity protection and energy cooking access are closely related in Madagascar. For this purpose, public and private decision-makers should better understand the impact of environmental policies on local populations.

The remaining of the paper is organized as follows: [section 1](#) details the related literature; [section 2](#) presents the data; [section 3](#) displays the key descriptive statistics; [section 4](#) describes the empirical methodology; [section 5](#) presents the balance tests of the regression discontinuity design; [section 6](#) presents the main results; [section 7](#) challenges the heterogeneity of the evidence; and [section 8](#) includes some key conclusions and recommendations.

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<sup>74</sup> (IEA, 2022)

# 1. Literature review

## 1.1. Protected areas

A few studies have demonstrated the importance of the creation of protected areas in the reduction of deforestation in areas exposed to climatic hazards and biodiversity loss (Andam et al., 2008). To a lesser extent, the effects of public policies in favor of biodiversity preservation on the socio-economic conditions of individuals have also been the subject of more in-depth analyses in recent years. Indeed, Naidoo et al. (2019) observe an increase in household wealth and growth of children living near protected areas with tourism activities in 34 developing countries including Madagascar.

The paper of Baird (2014) also show the usefulness of the Tarangire National Park (Tanzania), through a community-based management and on the education and the access to sanitation for people living in the vicinity of the area. In addition, Andam et al. (2010) reveal that in Costa-Rica and Thailand, communities near protected ecosystems experienced a net decrease in their level of poverty. Ferraro and Hanauer (2014) also arrives at the same conclusions by isolating several determining factors: creation of ecotourism services, public infrastructure (schools, roads, hospitals), and better regulation and management of productive activities on the ecosystem. The meta-analysis of Kandel et al. (2022) on 30 studies provides evidence on the impact of PAs on the welfare of rural households. The results show that studies which analyze PAs located in Africa are less likely to show positive welfare effects than studies from Asia and South America.

In order to collect woody fuels inside protected areas, people must have an authorization from the administrative or the management authorities of the areas which put in place a zoning plan. However, requests for authorization are often not respected and individuals carry out their collection illegally inside the core conservation areas. PAs' managers have a lack of knowledge on how people use natural resources within and around PAs. Especially due to the demographic growth over the last 10 years, migration is a major source of pression on the PAs. Moreover, as the urbanization and the demography increase with a growth rate of 2.6% per year, the consumption of charcoal and fuelwood will continue to increase by 2030. This trend is mostly related to affordability constraints and logistical (road systems) issues regarding clean fuels. With widespread deforestation it gets increasingly difficult to gather wood, and people often have to walk for kilometers to find the wood that meets their cooking needs. As specified by Joshi and Bohara (2017), forest location is an important parameter of Nepalese household's fuel choice decisions. The households closer to the forest have an easy access to the forest resources, and thus more flexibility on their cooking fuels adoption. Then, the Energy Sector Management Assistance Program (ESMAP, 2015) reports gathered several studies that have analyzed the effect of biomass extraction on deforestation, land use, erosion, and desertification. They find that resources used by local communities are threat to the conservation of PAs.

Finally, Jaiswal and Bhattacharya (2013) examine the causes of fuelwood dependence in the PA of Suhelwa Wildlife Sanctuary in India. They apply a field survey of 1,636 households from

55 villages located within 5 kilometers proximity to forest. Using a descriptive method, the results show that fuelwood availability, collection and consumption depend on the family size, distance from forest area, transportation opportunity and economic condition of the household. Indeed, people living around PAs depend on wood-based energy fuels and their collection lead to the degradation of the wildlife and the forest's ecosystem.

## 1.2. The Malagasy context

The United Nations (UN) Sustainable Development Goal (SDG) 7.1.2. promotes the access to “universal clean cooking” (UN, 2022, p. 7). In low-income countries such as Madagascar, households consume mainly primary energy based on woody fuels. According to the Food and Agriculture Organization of the UN (FAO), 50% of global harvested wood is used as fuelwood for cooking, of which 17% is directly converted into charcoal (Charcoal Transparency Initiative, 2022). The rural wood collectors are usually households that are at the Bottom of the Pyramid (BoP) and are marginalized subsistence farmers and pastoralists (Ramana et al., 2014). In 2012, the share of people living below 50% of the median income was about 14% (Humanitarian Data Exchange, 2022). According to the World Bank, Madagascar's gross domestic product (GDP) per capita was about \$515<sup>75</sup> in 2021, which puts the island the tenth lowest in the world<sup>76</sup>.

Two main models have been developed in the energy literature of household fuel transition in low and middle income countries: the energy ladder and the energy stacking models (Joshi and Bohara, 2017). In the energy ladder model, income, fuel prices, and accessibility are the main factors influencing households' fuel choices, while the energy stacking model relies on several socio-economic attributes of the households, such as technical characteristics of fuels and cultural preferences of the society. The stacking model corresponds best to the Malagasy context. Indeed, household's preference for woody energy still increases even though they have access to cleaner and more efficient energy cooking systems. It provides evidence that the consumption of wood-based energy cooking will decrease only when the resources will become scarce. Also, the energy portfolio of households depends on their size, composition, and diversification (World Bank, 2003).

According to some PAs' managers, the socio-economic context of Madagascar shows that access to electricity does not reduce the consumption of woody (Ramamonjy-Ratrimo, 2022). Indeed, the energy needs of households are met by the use of fuelwood and charcoal. This finding is mainly related to sociological habits and preferences (Bacon et al., 2010). In the same sequence, Gerard et al. (2020) study the relationship between households' use of wood and its environmental effects in a peri-urban area of Madagascar. Using both descriptive and inferential statistics from a survey of 1,075 households and fuel retailers in the Municipality of

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<sup>75</sup>[https://data.worldbank.org/indicator/NY.GDP.PCAP.CD?locations=MG&most\\_recent\\_value\\_desc=false](https://data.worldbank.org/indicator/NY.GDP.PCAP.CD?locations=MG&most_recent_value_desc=false)

<sup>76</sup><https://www.visualcapitalist.com/mapped-gdp-per-capita-worldwide/>

Andranonahoatra, they find a significant and positive relationship between socio-cultural and financial parameters and cooking fuel consumption. They estimated that 117 kg/capita of charcoal and 23 kg/capita of fuelwood are consumed each year in the Municipality.

## 2. Data sources

### 2.1. Data

To study the effect of protected areas on woody cooking fuel choices, I use household-level information collected from the Demographic and Health Survey (DHS) in Madagascar under the Malaria Indicator Survey (MIS) collected in 2011, 2013, and 2016. Then, using the Geographic Information System (GIS) software QGIS, I merged the geospatial coordinates of the surveyed households with their closest protected areas displayed by the World Data of Protected Areas (WDPA), as well as with the geographical characteristics of households' locations from the AidData GeoQuery and the Humanitarian Data Exchange (HDX) databases. This combination of databases is performed at the level 3 of the global administrative district division in Madagascar.

#### 2.1.1. Demographic Household Survey

The nationally representative Demographic Household Survey covered all geographical areas of Madagascar, collecting information on a total of 8,066 households in 2011, 7,645 households in 2013, and 11,284 households in 2016 ([Table 1](#)). These surveys provide detailed information on health on various items, as well as different categories of primary cooking fuels. It is also relevant to know that surveyed households are different between each wave.

In the total sample of the three survey waves, the number of households living in rural areas is higher than the number of households in urban areas. Moreover, households are distributed in clusters with a minimum of 25 to 30 households per cluster. Overall, there are 268 clusters in 2011, 284 in 2013, and 375 in 2016. This distribution allows me to perform an analysis based on a pseudo-panel approach, at the cluster level.

The DHS data also includes the Global Positioning System (GPS) of households, which contains informations on the latitude, longitude, and elevation for each surveyed cluster. Their locations are linked to geospatial covariate datasets on environment, health, infrastructure, and population factors (Croft et al., 2018).



**Table 1: Distribution of the Demographic Household Survey**

Survey year	Obs	Clusters <sup>77</sup>	Urban	Rural
2011	8066	268	2069	5997
2013	7645	284	2135	5510
2016	11284	375	1989	9295
<b>Total</b>	<b>26995</b>	<b>667</b>	<b>6193</b>	<b>20802</b>

### 2.1.2. WDPA

The World Database on Protected Areas is a global database developed by the Protected Planet Initiative, which is a joint project of the Conservation of Nature. It is compiled and managed by the UN Environment Programme (UNEP) and the International Union for Conservation of Nature (IUCN). The database gathers spatial and attributes data on marine and terrestrial protected areas located all over the world ([Appendix A.1](#)).

This study only focuses on the polygon data of terrestrial PAs defined by their boundaries. With over eight attributes which describe the characteristics of protected areas, the WDPA provides detailed informations on the identification, the name, the designation type, and the surface of each PA in Madagascar (UNEP-WCMC, 2019). Moreover, data on the IUCN categories, status, and governance type of PAs are also represented.

Indeed, the merged sample shows that 52% of the studied PAs are in the process of being legally and formally designated ([Appendix A.2](#)), while 48% are recognized through legal and formal means. Then, only a few PAs are inscribed under the World Heritage Convention.

When a protected area is created, human activities are restricted according to the IUCN red list classification. This guideline was approved in 1994, following the IUCN General Assembly meeting's conclusions in Buenos Aires. Dudley (2008) detailed that protected areas are classified according to the following system:

- **Category Ia – Strict Reserve Nature:** an area which is protected from all human activities except scientific research and environmental monitoring. The aim is to protect the biodiversity and possibly the geological/geomorphical features of an area.
- **Category Ib – Wilderness Area:** area generally larger and slightly less protected from human visitation than category Ia. Human visitation is limited to a minimum.
- **Category II – National Park:** usually combine ecosystem protection with human visitation and supporting infrastructure. It is subject to educational and recreational tourism which contribute to local economies.
- **Category III – Natural monument:** generally smaller area and centered on a particular natural feature. Hence, the primary focus of management is on maintaining this feature, which generally have a high cultural or spiritual value.

<sup>77</sup> From 25 to 30 households per cluster

- **Category IV – Habitat or species management area:** protect fragments of ecosystems or habitats, which often require continual management intervention to maintain.
- **Category V – Protected landscape or seascape:** land or ocean that have been altered by humans and that rely on continuing intervention to maintain the biodiversity. It is one of the most flexible categories of protected areas, and is able to accommodate contemporary developments (ecotourism, agrobiodiversity, aquatic biodiversity).
- **Category VI – Protected with sustainable use of natural resources:** contain natural areas where biodiversity conservation is linked with sustainable use of natural resources. However, large Category VI protected areas may contain category Ia areas within their boundaries as part of management zoning.

In general, the forestry administration has prohibited the cutting of wood in the forests. But depending on the IUCN classification of the PAs, it may be allowed to collect a certain amount of wood (under supervision). In Madagascar, most of the PAs are classified in categories V (36%) and IV (28%), which allow the implementation of human activities ([Appendix A.3](#)). On the other hand, [Appendix A.3](#) also shows that 28% of PAs rely on a more restricted classification (II) focusing both on the ecosystem protection and monitored tourism, while only 7% of PAs are classified in the strictest category (Ia).

The restriction of access to resources and the practice of human activities linked to the IUCN classification means that when a PA is created, people are compensated in kind (livestock). Therefore, this one-time compensation represents an influx of financial resources. Nevertheless, the individuals living inside or near PAs have a very strong attachment to the property and consider that PA's implementation is an inconvenience which limits their space (Ramamonjy-Ratrimo, 2022).

Then, [Appendix A.4](#) shows that 75% of the sampled PAs are conserved by local communities. These areas are collectively managed by a community of people, through an institutional arrangement. The choice of entrusting governance of PAs to local communities is based primarily on their close relationship with their territories, their capacity to enforce regulations, and their conservation efforts associated with ancestral and cultural values, which earned them the nickname of *fokonolona*. The latter defines the traditional Malagasy term for a domain caretakers as well as the lowest administrative level (Borrini-Feyerabend et al., 2013). Indeed, Gardner et al. (2018) specify that prior to the commitment of the Malagasy government to the “Durban Vision” in 2003, PAs were managed by the State through the Madagascar National Park (MNP) entity which manages a network of 43 PAs (Ramamonjy-Ratrimo, 2022). The local governance delegation was set up a few years later. In this study, 21% of the PAs are managed by government-delegated to Non-Governmental Organizations (NGOs), given that the responsibility is transferred to entities that are not the same public institution. On the other hand, 3% of the PAs rely on the management of not-for-profit organisations such as universities which operate a specific mission and are usually controlled by a board or a regulatory entity. Finally, only 1% of PAs in the sample are managed by a Federal or national ministry, or agency.

### 2.1.3. Geographic data

#### 2.1.3.1. AidData

The AidData platform gathers innovative tools and resources such as GeoQuery. This GIS tool provides a “highly parallelized computational framework to quickly extract massive amounts of spatial information at fully customizable geographic units” with raster layers at a finer resolution (Goodman et al., 2017). In order to perform this analysis, several geospatial data have been used from satellite sensors. Geophysical data from remote imagery such as vegetation cover, elevation, estimated population, precipitations level, and slope are presented in Table 3.

#### 2.1.3.2. Humanitarian Data Exchange

The Humanitarian Data Exchange (HDX) is an open platform for sharing data across crises and organisations<sup>78</sup>. Launched in July 2014, the HDX open source provides geographic data based on the map of Madagascar’s boundaries. The HDX provides information on the Madagascar Road Network as presented on the T-test in Table 3, which is an extraction of roads from Open Street Map. Using QGIS software which allows to analyze spatial relationship between features, I measured the distance (in kilometers) between the DHS household clusters and the nearest road network.

## 2.2. Protected areas and household clusters

The network of 123 marine and terrestrial PAs are presented in [Figure 1a](#). It covers 7,712,364 hectares which represents about 11% of the land and shallow sea surface area. To study the effects of PAs on the share of cooking fuels consumption I focus exclusively on terrestrial PAs, using geospatial information of household clusters in Madagascar. Protected areas information was obtained from the WDPA, and the layers are based on the classification of WGS 1984 data (UNEP-WCMC, 2019). Using the geographic information system QGIS, I measure the distance in kilometers between PAs’ polygons and the DHS household clusters represented by the black spots in [Figure 1b](#).

[Figure 2](#) displays the household clusters dataset around the protected area of Lac Alaotra located in the province of Tamatave (region Alaotra-Mangoro). It is the largest freshwater lake in the country, at an altitude of 750 meters with a total area of 43,000 hectares. The area was designated a Ramsar site on September 9, 2003, and is managed by a federation of village associations. One can note that household clusters inside the PA are represented in yellow spots, while clusters located outside the PA’s boundaries are in black spots. This geospatial

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<sup>78</sup><https://data.humdata.org/dataset/wfp-geonode-madagascar-road-network-main-roads>

distribution allows to use the border of the PA as a treatment which distinguish clustered households located inside to those located outside.

Figure 1: Map of Madagascar showing the networks of protected areas (1a) merged with household clusters (1b)

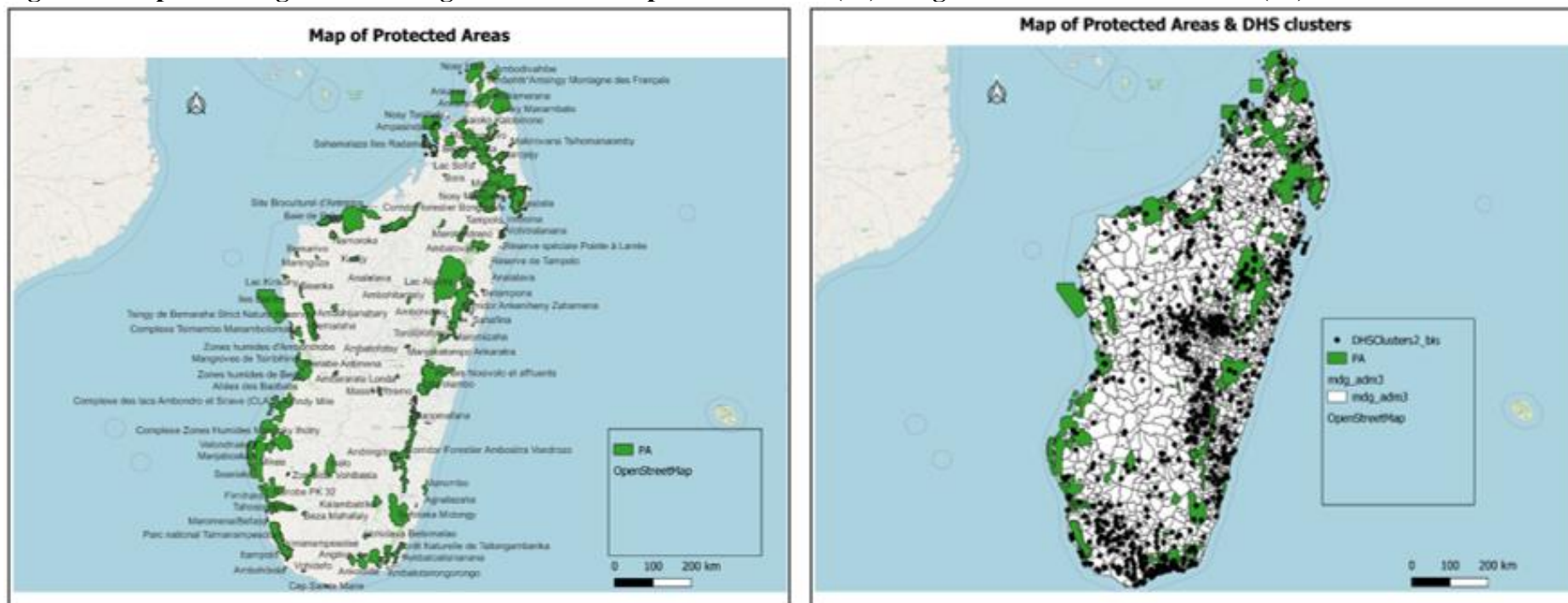
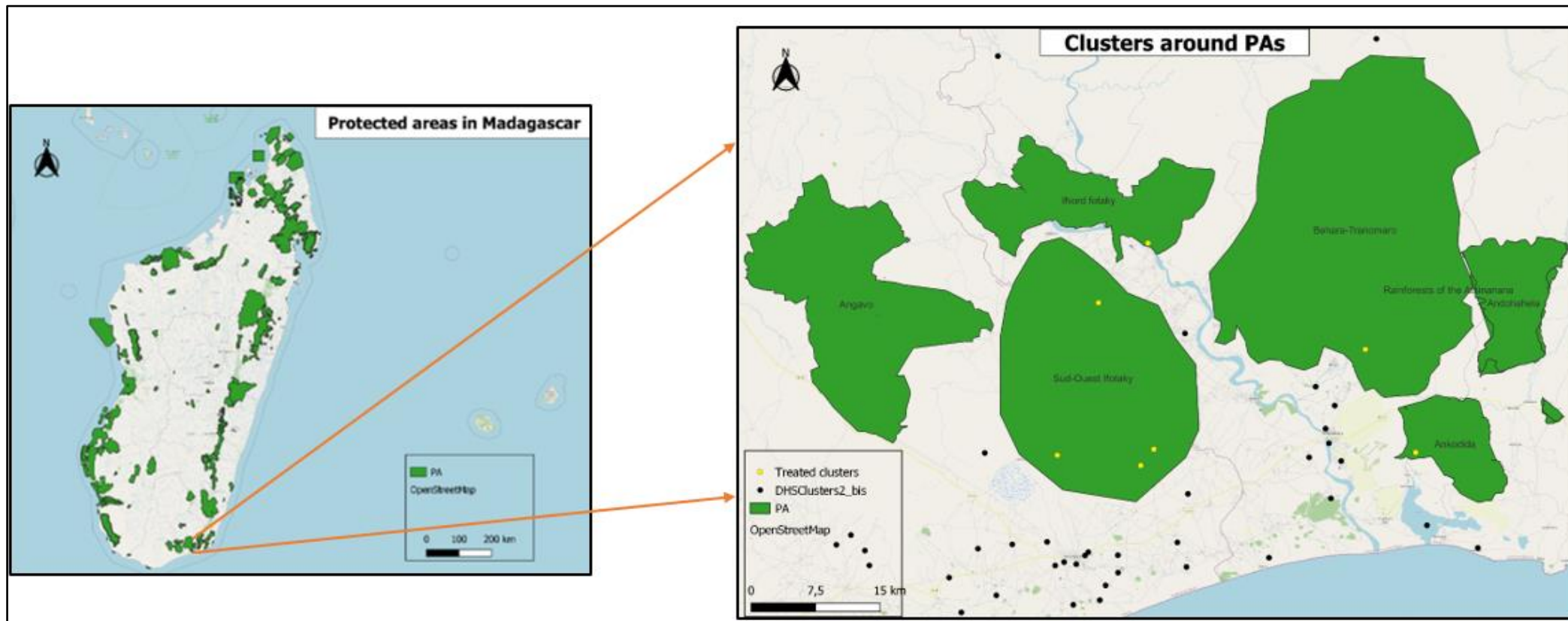


Figure 2: Map showing the household clusters around the protected area of Lac Alaotra



## 3. Descriptive statistics

### 3.1. Cooking fuels

As defined by van Dam (2017), fuelwood is “wood in the rough (from trunks and branches of trees) to be used as fuel for purposes of cooking, heating, and power production”, while “charcoal is known as wood carbonized by partial combustion. To that extent, in this study I refer to woody or wood-based energy as the energy that provides fuelwood and charcoal. In the Malagasy context households do not target PAs according to the quality of the wood or the use to which it will be put, but rather according to the availability of ligneous within these areas. Indeed, Ranaivoson et al. (2017) find that selection of trees for charcoal production is less dependent on quality than on availability of wood. Hence, Malagasy households in the vicinity of PAs collect woody primarily as it is the main available resource in terms of quantity.

[Figure 3](#) describes that the majority of household clusters in the sample (68%) use fuelwood as their primary source of cooking energy. The dependence of Malagasy population to the amenities offered by PAs is extremely high. This is all the truer with the vegetation that makes the wood resource available. Since woody is a resource that is still available despite collection restrictions and constraints legislated for PAs, the consumption of household clusters remains very high.

On the other hand, charcoal is the second main source of cooking fuel with 28% of surveyed household clusters who consumes it. Charcoal is produced through a slow pyrolysis (heating in the absence of oxygen) process of wood and is a favored cooking fuel of urban communities because it has a higher energy density than fuelwood, which reduce the transport cost (Gardner et al., 2016). A household living in the vicinity of a PA consumes on average 5kg of charcoal per week (Ramamonjy-Ratrimo, 2022). In these areas, the consumption and sale of charcoal is not just a pocket of extra income, but mainly a matter of habit and consumption preference.

In Africa, charcoal consumption is increasing with the growth of urban population (Chakravorty et al., 2022). In Madagascar, forests provide charcoal to cities and regions. For example, the regions of Boeny and Atsimo-Andrefana consume charcoal almost exclusively from natural forests (GIZ, 2020). Charcoal is the most used energy source for cooking, due to its affordable price and cleaner burning compared to fuelwood (Bailis et al., 2005; Ellegård, 1996; Girard, 2002; Ezzati and Kammen, 2002). As assessed by van Dam (2017), charcoal is preferred in urban areas because it is easier to carry. Moreover, charcoal includes several advantages compared to fuelwood such as: cleaner and safer, less smoke emission, easier storage, less fire monitoring during cooking, cheaper than modern energy sources (LPG and electricity), more accessible in cities, and sold in retail (Gerard et al., 2020). For instance, in urban areas a gas cylinder is sold for 80,000 Ariary (\$19<sup>79</sup>), while the bag of 50kg of charcoal is sold at only

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<sup>79</sup> Exchange rate US\$ 1: Ar 4214.12 (on August 29<sup>th</sup> 2022)

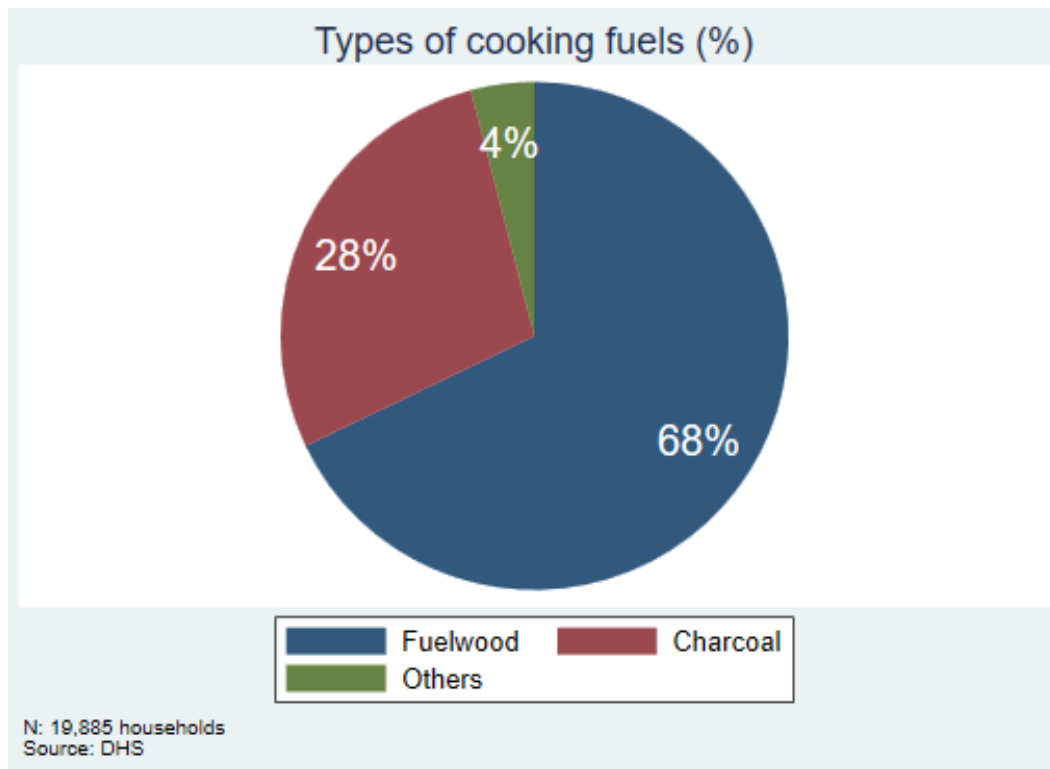
30,000 Ariary (\$7) which represents on average the weekly quantity consumed by an urban household of 4 to 5 people (Ramamonjy-Ratrimo, 2022). Charcoal contains also about 1.8 times more energy per kg than fuelwood, as it is a carbon-rich energy carrier” (van Dam, 2017). According to Charpin et al. (2019), urban households consume an annual average per capita of 104kg of charcoal and 270kg of firewood, whereas rural households consume 513kg of firewood and 91kg of charcoal per person. Before that, Gade and Perkins-Belgram (1986) specified that a daily minimum of 5kg of firewood is needed to cook, which is two or three times higher for large families. Even though gas is more cost-effective and cleaner than charcoal, households have a strong preference for the second fuel cooking energy. This high demand on wood-based energy cooking exacerbates the pressure on the PAs which provide these resources.

Then, at the cluster level only 4% of the surveyed household consume other types of cooking fuels such as biomass (dung, agricultural crop), gas, kerosene, and electricity. To that extent, my analysis focuses exclusively on the two main cooking energy sources, namely fuelwood and charcoal.

Finally, in rural areas 80% of surveyed household clusters consume fuelwood cooking energy against 16% who prefer to use charcoal energy (see [Appendix A.5](#)), whereas in urban districts charcoal is the main consumed cooking energy in front of fuelwood with respectively 69% and 27% of the surveyed clusters. Wealthier household clusters tend to be located in urban areas and use charcoal, while lower-income clusters tend to live in rural areas and mainly consume fuelwood.



**Figure 3: Types of energy cooking fuels**

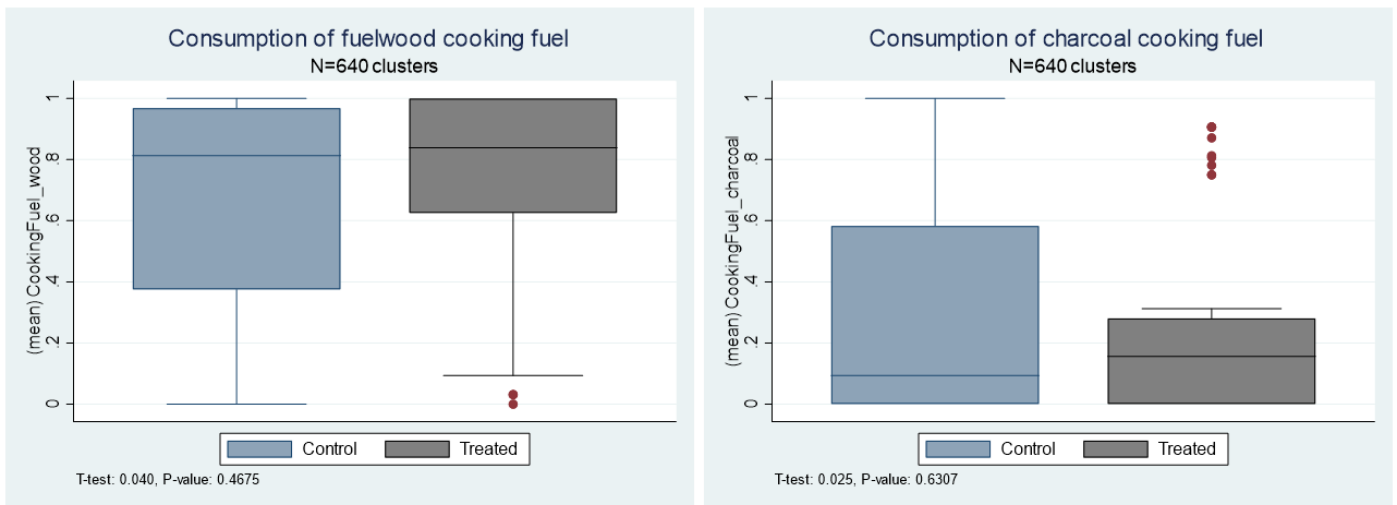


### 3.2. Protected areas and wood-based energy cooking fuels

[Figure 4](#) provides the descriptive statistics on the consumption of woody cooking fuels. The proportion of fuelwood consumption is higher for treated clusters than for those in the control group with average means of 0.715 and 0.675, respectively. On the other hand, charcoal consumption is higher for household clusters located outside PAs than clusters living inside with average means of 0.283 and 0.258, respectively.

Thus, these descriptive results point to more fuelwood and less charcoal use for treated clusters. This may align with the cost of making charcoal in the treated areas, where there is a greater chance of being caught and punished.

**Figure 4: Cooking fuels consumption for treated and control household clusters around PAs**



Furthermore, [Appendix A.6](#) shows that at the PAs' boundaries, fuelwood consumption is higher for treated clusters than for clusters in the control group. This is true up to about 25km near the boundaries of the PAs. Beyond 25km, one can see the fuelwood consumption of household clusters inside the PAs decreases, unlike the consumption of those located outside.

In terms of charcoal consumption, [Appendix A.6](#) displays a high consumption among control household clusters located right at the border, compared to the treated clusters. From 35km onwards the trends are reversed, with a rise in the consumption of charcoal by clusters located in the PAs compared to those outside the PAs.

This mirror effect between cooking fuels and the distance to PAs demonstrates the effects of monitoring strategies against charcoal burning inside PAs. Indeed, deterrence policies near PAs' borders do not encourage people to transform collected woody into charcoal.

### 3.3. Descriptive statistics of the household clusters, protected areas, and geophysical characteristics: among the treated and control groups

[Table 2](#) presents the t-test results of the characteristics of socio-economic status, and protected areas and geographic parameters of treated and control households at the cluster level. The results further show that the average age for the heads of household clusters living inside PAs is 42 years old, while for those living outside PAs is 43 years. The average comparative wealth index (CWI) score of household clusters located in PAs is about -1,737, whereas clusters located outside the PAs have a CWI score of 8,207. The CWI measures the economic status of household clusters based on their asset ownership and housing characteristics, using a principal component analysis (Staveteig and Mallick, 2014). As detailed in the [Section 1](#), clusters located inside PAs are the poorest and are mainly dependent on the resources provided by PAs. Hulme

and Shepherd (2003) assess that poor individuals tend to live in remote rural areas close to forests. Indeed, forests are easy to access and there are not enough dissuasive mechanisms preventing their exploitation (Sunderlin et al., 2005). The t-test result indicates that there is not a significant difference in the mean CWI score between treated and control household clusters. Then, on average treated clusters are mainly located in rural areas (0.159) compared to clusters in the control group (0.228).

In terms of PAs' characteristics, the results indicate that treated clusters on average are located in larger PAs (6 km<sup>2</sup>) managed through a decentralized power to local communities such as NGOs and private structures, and where restrictions are rather moderate (IUCN category V). On another note, control clusters are located near smaller PAs (4 km<sup>2</sup>) which also managed by local communities. Moreover, the average distance in kilometers between clusters and PA's borders is lower for those in the treated group than those in the control group, with a significant difference of 20 km. Since PAs contain the main primary resources, on average household clusters within PAs are closer to water points (34km) than those living outside PAs (58km).

Furthermore, clusters inside PAs are located on land with less rough slopes than those outside PAs with averages of 1.4 and 1.5, respectively. Moreover, the growing season length is higher for treated household clusters than those in the control group, with a significant difference of -1.5. A 12-rank classification for treated clusters shows that they benefited from a growing season between 300 and 329 days, compared to 270-299 days (11 rank) for household clusters in the control group. This result is consistent with the t-test difference in means for the vegetation cover measured by the Normalized Difference Vegetation Index (NDVI). This satellite imagery is a normalized transform of the near-infrared radiation (NIR) for vegetation cover (Didan et al., 2015). On average in 2011, 2013, and 2016, the NDVI of the areas where the treated clusters are located is significantly higher than in the areas where the control clusters reside. However, one can notice that the NDVI level decreases over the years for both treatment groups, but this decline is more pronounced for clusters inside PAs with an average index that drops from 5799 in 2011 to 5563 in 2016. This phenomenon is probably related to the decrease in the overall rainfall level between 2011 and 2016. Also, the demographic pressure around the PAs has been increasing over the same period. This is especially true for the number of individuals who settle just near the PAs, for instance with a significant difference in means between the treated and control group. This is in contrast to the study of Baland et al. (2018) in Nepal, which shows that population growth has reduced fuelwood collection per household by 8%, thanks in part to the availability of alternative energy sources.

Comparing the distance to the nearest road, one can observe that on average both treated and control clusters are located around 3km. In addition to that, a significant mean difference of 280 km from a tourism facility was found between treated and control clusters. Tourism activities and infrastructures are located in areas with a flexible IUCN legislation, such as the PAs classified in category V.

**Table 2: Households, protected areas, and geophysical characteristics for treated and control groups around PAs – at the cluster level**

Variables	Labels	Treated clusters		Control clusters		Difference
		Mean	Sd.	Mean	Sd.	
<b>Household's characteristics</b>						
Household size	Number of household members	4.518	2.17	4.617	2.4	0.11
Head household sex	Head of household gender	1.25	0.433	1.268	.443	0.017
Head household age	Head of household age	42.211	15.589	43.041	15.754	0.901
Head household age <sup>2</sup>	Head of household age squared	2024.563	1503.933	2100.729	1534.683	81.674
Refrigerator	Has refrigerator (Yes = 1; No = 0)	0.026	0.16	0.044	0.206	0.019
CWI	Comparative wealth index	-1736.808	75267.881	8207.045	79861.375	10727.785
Year_wave	Survey years	2013.764	2.139	2013.73	2.102	-0.06
<b>PAs' characteristics</b>						
Ln_REP Area	Surface of protected area (km2) - logarithmic	6.354	2.399	4.302	430.445	-2.052***
IUCN_Ia	Management category Ia of PAs	0	0	0.039	3.002	0.038
IUCN_II	Management category II of PAs	0.112	0.315	0.154	0.194	0.042
IUCN_IV	Management category IV of PAs	0.022	0.147	0.16	0.361	0.138**
IUCN_V	Management category V of PAs	0.334	0.472	0.181	0.367	-0.15**
GOVTYPE_Local	Responsible and accountable entity of PAs: Local communities	0.398	0.49	0.454	0.385	0.056
GOVTYPE_Government	Responsible and accountable entity of PAs: Government-delegated management	0.177	0.382	0.123	0.498	-0.053
<b>Geographic's characteristics</b>						
Urban_Rural	Location (Urban = 1; Rural = 0)	0.159	0.365	0.228	0.419	0.072
LATNUM	Latitude coordinates	-19.274	2.834	-19.612	3.226	-0.32
LONGNUM	Longitude coordinates	47.453	1.419	47.274	1.457	-0.176
Dist_PAs	Neighbor distance (km) to the nearest PA' border	15.377	5.196	35.577	20.901	20.195***

Prox_water	Proximity to water source - km	33.947	30.368	58.248	44.927	24.48***
Cluster altitude	Altitude of clusters locations	587.32	373.476	596.855	547.651	15.875
Slope	Ruggedness of the terrain around a DHS cluster	1.353	1.279	1.514	1.247	0.157
Growing season	Number of days (reported in one of 16 categories) within the period of temperatures above 5°C when moisture conditions are considered adequate for crop growth.	12.405	2.997	10.917	2.752	-1.494***
Irrigation	Area equipped for irrigation	11.95	14.419	4.605	6.567	-7.237***
NDVI 2011	Average Normalized Difference Vegetation Index in 2011	5799.345	1115.855	5161.369	1065.374	-644.677***
NDVI 2013	Average Normalized Difference Vegetation Index in 2013	5767.926	1160.522	5127.305	1095.282	-646.048***
NDVI 2016	Average Normalized Difference Vegetation Index in 2016	5563.182	1045.59	5030.065	1061.55	-537.615***
Mean precip 2011	Yearly average rainfall (mm) in 2011 - UDel	137.034	22.365	133.209	27.968	-3.916
Mean precip 2013	Yearly average rainfall (mm) in 2013 - UDel	129.767	29.089	124.134	34.173	-5.861
Mean precip 2016	Yearly average rainfall (mm) in 2016 - UDel	103.556	23.518	103.218	33.912	-0.338
Landscan global pop_2011	Estimated population count in 2011 (number of people per 1km pixel)	11128.567	7562.851	15032.944	11595.442	3792.258***
Landscan global pop_2013	Estimated population count in 2013 (number of people per 1km pixel)	10952.314	7013.208	15371.109	11879.691	4296.802**
Landscan global pop_2016	Estimated population count in 2016 (number of people per 1km pixel)	11669.053	7416.933	16105.294	12229.93	4308.39**
Dist_roads	Neighbor distance (km) to nearest roads	3.894	4.172	3.084	4.255	-0.84
Dist_tourism	Neighbor distance (km) to the nearest tourism facility	514.413	424.104	801.723	430.445	280.266***

Notes: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. The Two-sample t-test with equal variances indicates that the means are significantly different between treated and control groups.

## 4. Empirical framework

It is difficult to use experimental designs to assess the impact of PAs on cooking fuels consumption of household clusters, as PAs are non-randomly located. Their selections depend on several topographic factors, such as vegetation cover, aridity, rainfall level, biodiversity threat level, etc. Thus, the presence of selection bias requires robust quasi-experimental methodologies which simulates the experimental designs (Kandel et al., 2022). To that extent, this analysis is based on a Regression Discontinuity (RD) model. According to Lee and Lemieux (2010), the RD design was first introduced by Thistlethwaite and Campbell (1960) who present the future academic outcomes of students who have been assigned certificate awards regarding a test score. One of the main advantages of RD design is to provide a “local” randomization around a threshold. Thus, the RDD estimate is an average treatment effects of subjects close to the threshold. The RD technique has been used in several fields of economic studies, such as education (Angrist and Lavy, 1999; Abdulkadiroğlu et al., 2014), health (Card et al., 2008; Almond et al., 2010), information (Anderson and Magruder, 2012), and political economy (Lee et al., 2004). Moreover, the RD design allows to take into account the break induced by the treatment border (cut-point), since it compares means around the cut-point.

In Madagascar, households’ settlements are very close to PA’s borders, where the main resources are concentrated. As a consequence, the use of RDD allows to evaluate the impact for the household clusters close to the borders, which represent the break-even point caused by the treatment (Cunningham, 2021). The RD technique is quasi-similar to randomized experiments in terms of their internal validity. Indeed, the RD estimates are weighted average treatment effects based on the “ex ante probability that the value of an individual’s assignment variable will be in the neighborhood of the threshold” (Lee and Lemieux, 2010). Moreover, the use of satellite information on the location of PAs and clusters provides strong evidence for the development and environmental literature. This echoes the work of Dell (2010) who examines the long term impacts of the mining *mita* on economic development in Peru, using a “multidimensional discontinuity in longitude-latitude space”.

The RD approach requires a continuous running variable *Distance* that assigns household clusters to the treatment, as well as a non-manipulable and arbitrary cut-point denoted *C* which represent the threshold at the border of a PA. In the case of PAs’ impacts on woody cooking energy consumption, household clusters just inside the threshold (PAs’ border) are similar and comparable to those located just outside the threshold, mainly based on their characteristics as displayed in [Table 2](#). This geospatial distribution corresponds to the treatment assignment.

Using a parametric RD model based on the use of every observation in the sample to model the outcome, I am interested in estimating the average treatment effect (Jacob et al., 2012). Let the treatment assignment be denoted by a dummy variable *Inside*  $\in [0; 1]$ , so that we have: *Inside* = 1 if the clusters are located inside a PA ( $Distance \leq C$ ) and *Inside* = 0 if the clusters is located

outside a PA ( $Distance > C$ ). This binary assignment of the observations is known as the sharp design of the discontinuity (Hagemeier et al., 2022).

The RDD only identifies the treatment effect exactly at the border  $C$ . Then, the interaction between the border ( $C$ ) and the treatment ( $Inside$ ) include the difference in slopes on both side of the cut-point. Assuming that there is a linear relationship between  $Distance$  and  $Cooking\ fuels$  which represents the proportion of wood-based energy consumption, the following equation translates the effect of PAs on the consumption of wood-based energy cooking:

$$Share\ of\ households\ at\ the\ cluster\ level\ using\ fuelwood_i = \alpha + \beta_0 Inside_i + \beta_1 Distance_i + \varepsilon_i \quad (1)$$

$$Share\ of\ households\ at\ the\ cluster\ level\ using\ charcoal_i = \alpha + \beta_0 Inside_i + \beta_1 Distance_i + \varepsilon_i \quad (2)$$

Where:

- *Share of households at the cluster level using fuelwood<sub>i</sub>*: proportion of fuelwood energy cooking consumption for households in a cluster  $i$ ;
- *Share of households at the cluster level using charcoal<sub>i</sub>*: proportion of charcoal energy cooking consumption for households in a cluster  $i$ ;
- *Inside*: treatment variable which identifies 1 if the cluster  $i$  is located inside a PA, and 0 otherwise;
- *Distance*: distance in kilometer between a cluster  $i$  and the border of a PA, which is centered at the cutoff  $C$ ;
- $\beta_0$ : coefficient for treatment assignment which represents the marginal impact of PAs at the border;
- $\beta_1$ : estimate for the centered cutoff  $C$  of the *Distance* variable;
- $i$ : cluster index which varies from 1 to 640;
- $\alpha$ : average value of the energy cooking consumption for clusters in the treatment group after controlling the *Distance* variable;
- $\varepsilon$ : random error term which is assumed to be independently and identically distributed.

In RDD, one is only interested in the discontinuity value at the threshold point (Melly and Lalive, 2020). Thus, to minimize bias, the simple local linear estimator is the perfect functional form for the distance variable. Furthermore, to operationalize the local linear estimator I choose a Kernel weighting function that is maximized at the threshold point. Following Cattaneo et al. (2019), I use the triangular Kernel function which optimizes the mean squared error (MSE) in order to obtain an optimal point estimator. In this study, the MSE-optimal bandwidth is assessed by using the robust bias correction strategy. Removing the bias term from the RD point estimator, delivers solid inferences and optimal point estimation (Cattaneo et al., 2019).

Comparing these very similar individuals around the borders, I measure the average causal effect of classified PAs. Based on their socio-economic characteristics presented in [Table 2](#), household clusters just inside the border are very similar to those just outside. The only difference between these groups is the PA's border. Hence, by comparing the mean consumption of fuelwood and charcoal of clusters just inside the PAs to those just outside using the RD approach, I can estimate the local average effect of PAs on fuelwood consumption.

Using STATA statistical software to merge the four data sources, the distribution of the treatment assignment reveals that 7% of the surveyed clusters are located inside PAs, against 93% who live outside PAs ([Table 3](#)).

As explained in [Section 2.1.1](#), I exploit household survey dataset from three waves which allow to perform an analysis based on three regressions. However, the households surveyed are different between each wave. Therefore, I conduct my empirical analysis using a pseudo-panel approach, given that panel data take into account the time invariant factors and control the potential sources of endogeneity while making causal inferences (Wooldridge, 2015). This approach also allows to better capture the complexity of households behaviour under the treatment effects (Hsiao, 2007). Thus, my empirical results rely on the average effect of PAs on the consumption of wood-based energy cooking of both treated and control households at the cluster level ([Table 3](#)).

**Table 3: Summary of the treatment**

<b>Treatment</b>	<b>Freq.</b>	<b>Percent</b>	<b>Cum.</b>
Treated (inside PAs)	1,407	7.08	7.08
<i>Treated clusters</i>	45	7.03	7.03
Control (outside PAs)	18,478	92.92	100.00
<i>Control clusters</i>	595	92.97	100.00
<b>Total</b>	<b>19,885</b>	<b>100.00</b>	
<b><i>Total clusters</i></b>	<b>640</b>	<b>100.00</b>	

## 5. Balance tests

### 5.1. RD Density

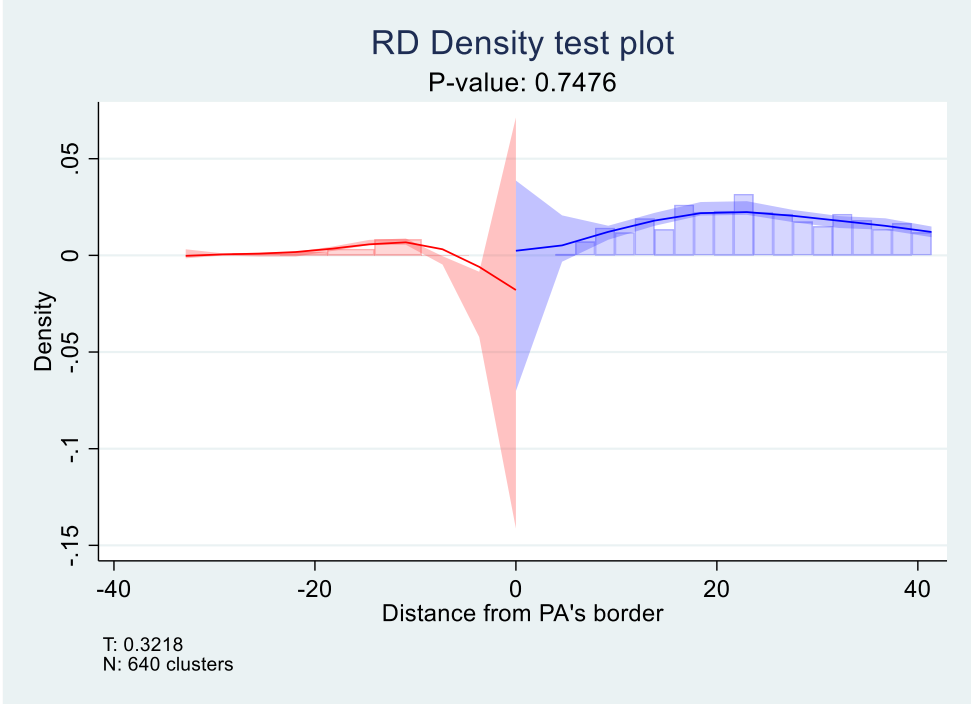
RD design compares the means at the borders from either side, one must be sure that the distribution of the distance variable is smooth across PAs' borders. To that extent, it is relevant to perform a density test to check the bunch of units at the borders (Cunningham, 2021). As highlighted in [Appendix A.7](#), the distribution of the sample is unbalanced at the border. Indeed, the number of observations to the left of the border is much lower from the number of observations to the right. Hence, one can legitimately wonder if households are sorting on the distance variable and close to the border. This manipulation assumes that households are moving just on the other side of the border. Which implies selection bias as their sorting can affects the outcomes variables.

In order to detect this self-selection on the treatment status around the border, I used the package *rddensity* from Cattaneo et al. (2019), “which is based on local polynomial regressions that have less bias in the border regions” (Cunningham, 2021). This approach was originally developed by McCrary (2008), which aims to compare the density of treated and control household clusters near the border.



The null hypothesis associated with the test is that the manipulation of the density at the border is limited. In other words, that there is a continuity of the density functions for treated (red) and control (blue) household clusters at the border. Therefore, the robust value of the RD density statistic is 0.322 and the associated p-value is 0.7476 (Figure 5). Consequently, the test failed to reject the null hypothesis of no difference in the density of treated and control clusters at the border in my RD model. However, this econometric conclusion can be nuanced from an economic point of view, given that households settle mainly in the vicinity of the PAs to access wood resources in particular.

**Figure 5: RD density plot**



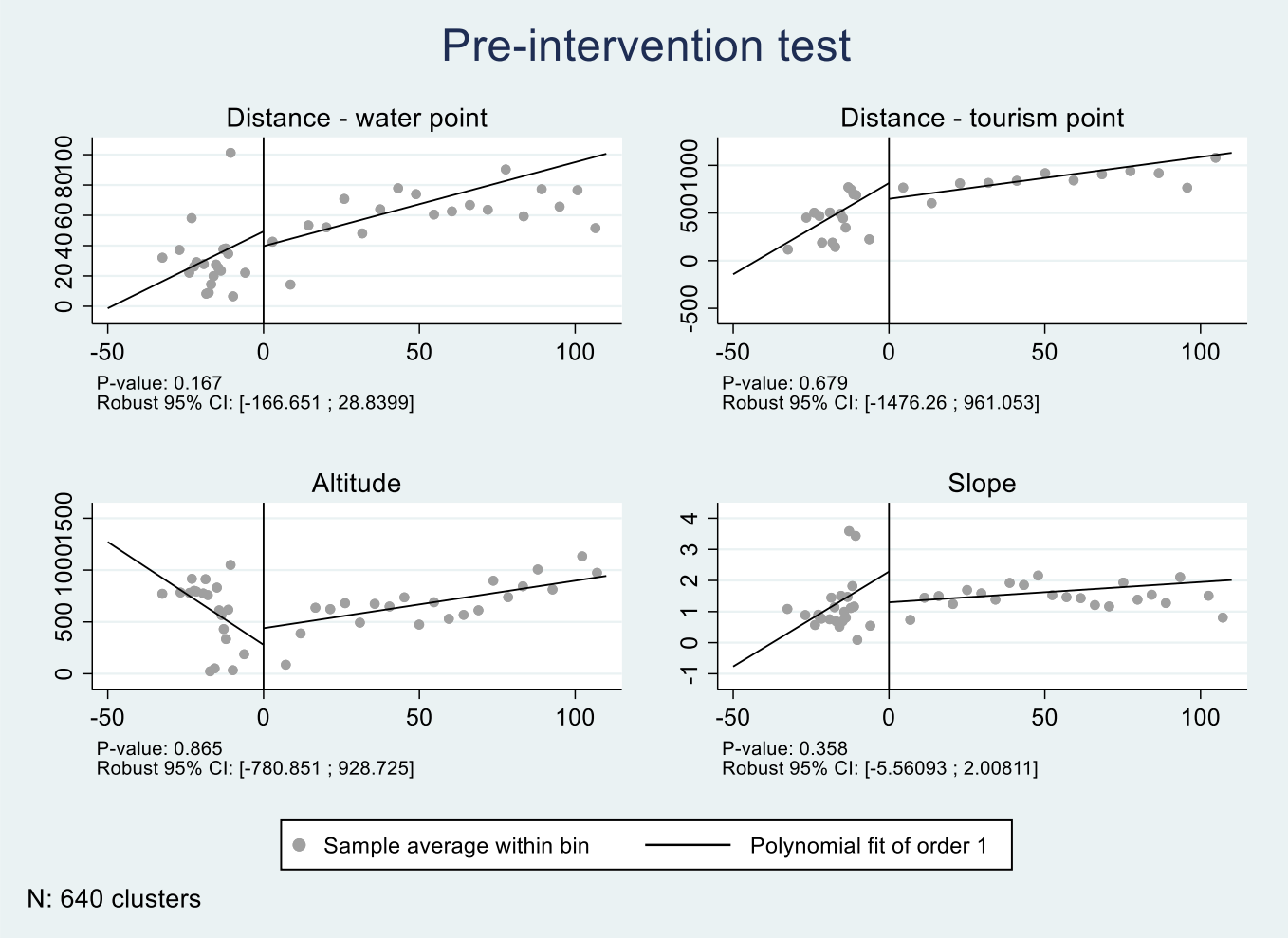
### 5.2. Pre-determined covariates test

A second RD falsification test is the continuity in the distribution of pre-determined covariates at the border. Indeed, if households are not able to control the value of the distance variable around the border, they cannot sort relying on variables that were determined prior the treatment assignment. This hypothesis echoes the baseline characteristics test of the treated and control groups in randomized experiments. This test is implemented by applying the RDD estimator with pre-determined covariates as outcome (Melly and Lalive, 2020). The observed outcome distribution should not be significantly discontinuous at the border. Thus, these pre-determined characteristics should be invariant to change in treatment assignment (Cunningham, 2021). Household clusters just inside the border and those just outside should be similar in covariates that could not have been affected by the treatment choice. Following Lee (2008), I conduct

inference on RD treatment effects using covariates at the true border. If the covariates do not significantly change at the border, the unobservables characteristics do not change either.

The graphical result displays in [Figure 6](#) represents the treated (on the left) and the control (on the right) household clusters at the border for each covariate. The figure does not reveal obvious discontinuities at the border for the distances to water point and tourism facilities, as well as for the altitude and the slope of clusters' locations. Moreover, the statistical analysis reveals that the robust p-values of the pre-intervention covariates are not significant. In other words, there is no empirical evidence that these pre-determined covariates are significantly discontinuous at the cutoff.

**Figure 6: Pre-determined covariates test**



## 6. Empirical results and discussion

### 6.1. Results at the border

In [Figure 7](#), I present the graphical result of the local average treatment effect (LATE) of protected areas on the consumption of woody cooking fuels of household clusters for all year waves, following the RD approach. The LATE equals the “jump” in the graphic at the borders of PAs. Following the strategy of Cattaneo et al. (2017), the data are binned. Which means that different standard deviation is estimated in each bin and the confidence interval based on that standard deviation is centered on the bin mean.

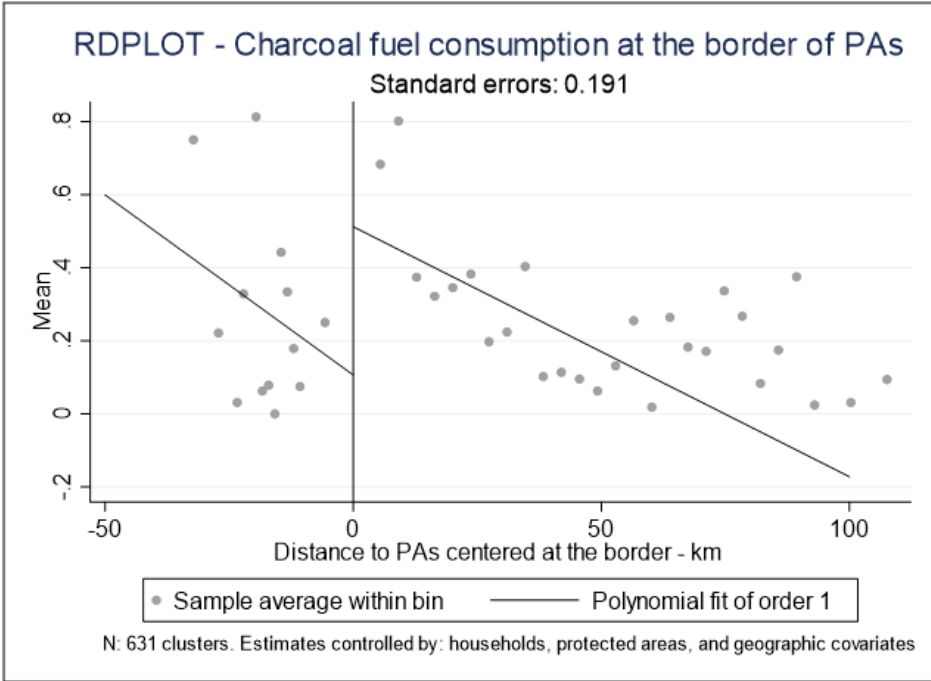
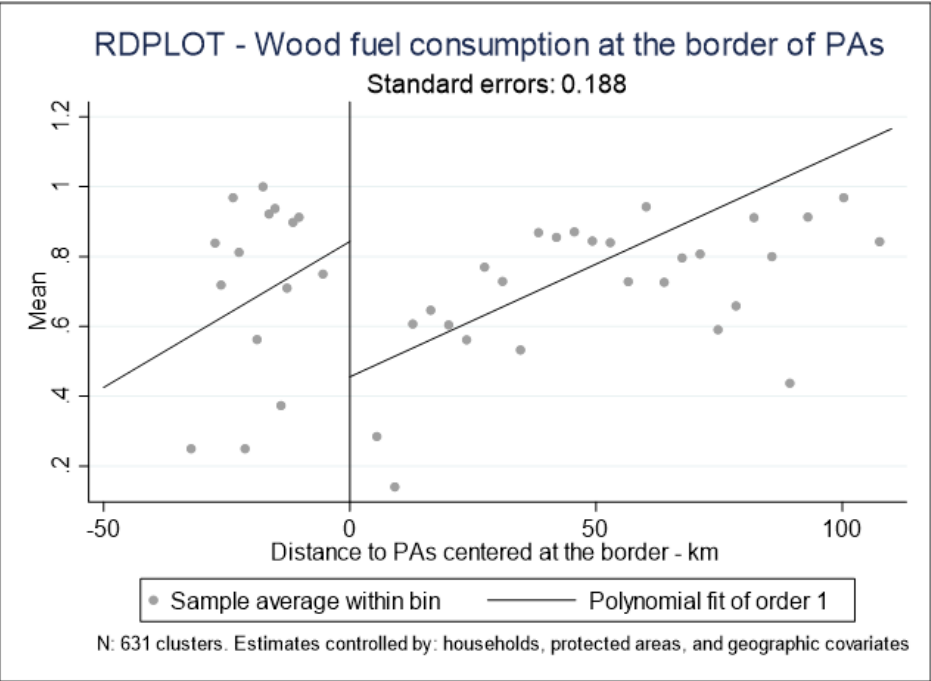
The RD plot reveals that treated clusters just inside PAs’ borders (on the left of the graph) have significantly higher consumption share of fuelwood than the control clusters located just outside the borders (on the right of the graph). Due to the high population density within a 50-kilometer radius around the PAs, the demand for fuelwood to meet household clusters cooking energy needs continues to grow. Conversely, treated clusters at the border of PAs have significantly lower charcoal consumption than clusters living outside. This discontinuity at the border demonstrates that individuals outside may migrate into PAs to collect wood. They collect more wood and transport it out of the PAs so they can produce charcoal. This result echoes the work of Bošković et al. (2023) who demonstrate that in the Indian context, families tend to spend more time getting to the forest and collecting fuelwood. Thus, they collect a larger volume of woody resources. I do not have data on the mobility of household clusters around PAs, but my results are consistent with the findings of the literature.

Moreover, in 2015 the law on the revision of the Code of Management of the protected areas of Madagascar was adopted (COAP, 2015). This law aims to reinforce the commitments made by the Malagasy authorities at the World Parks congress in Sydney in 2014, through the creation of new categories of PAs allowing both biodiversity conservation and sustainable development. The reform also allows the production and/or exploitation in and around PAs. As well as, the decentralization of governance powers to local communities, NGOs, or private sector actors. The 2015 Code revision makes it more difficult for household clusters inside PAs to produce and consume charcoal. This legal constraint does not allow the transformation of the collected woody into charcoal inside PAs. Indeed, charcoal transformation process is highly visible (smoke cloud) and odorous. Control clusters located just outside the border are therefore less likely to be caught and then sanctioned, than those located just inside the border. Moreover, Léa et al. (2013) demonstrate that the prohibition of slash-and-burn cultivation (*hatsake*) based on the classification of a forest as a protected space, means that local populations settled along the borders of PAs produce and consume charcoal out of necessity. This is for example the case in the dense dry forest of Mikea which is managed by the Madagascar National Park (MNP).

Finally, it is important to know that because the RDD estimates locally the average treatment effects around the border, the estimated result does not necessarily apply to the clusters far away from the borders (Hahn et al., 2001). Indeed, the household clusters close to the borders may not be similar to those far from the borders. In any case, the inability of RDD to compute an

average treatment effect for all the clusters in my sample is not a major limitation regarding my question of interest.

**Figure 7: RD plot – Share of fuelwood and charcoal cooking consumption of household clusters at PAs’ borders**



## 6.2. The impact of protected areas on cooking fuels consumption

To go beyond the overall analysis of household clusters cooking fuels consumption, I conduct a sample wave analysis in order to highlight the temporal evolution of their consumption. In [Table 4](#), I present the local average treatment effect at the border of fuelwood and charcoal consumption. One can find that at the border, fuelwood consumption share of household clusters located in the PAs is significantly positive in 2016 (0.62 percentage points). Following Ranaivoson et al. (2017), poverty and the difficulty to access to primary resources means that people settle inside or as close as possible to PAs. As a matter of fact, free access to natural resources is also key element in the increase of fuelwood consumption inside PAs' borders. Indeed, the study of Blanco et al. (2019) reveals that despite the physical burden (splitting and drying), the collection time<sup>80</sup> and travel, the fact that fuelwood is a free and available resource, increases its use. As a consequence, PAs have not effects on the reduction of wood collection, as households continue to consume fuelwood because they do not have access to other efficient and affordable alternatives.

The RD findings also indicate that in 2016 the consumption of charcoal for household clusters located inside PAs and close to the borders significantly decreased by -0.56 percentage points (pp). This result highlights that for those treated clusters, the cost to consume charcoal is higher than for the control group. First of all, the transformation cost from wood to charcoal is mainly related to the carbonization process which requires a significant amount of wood, the use of sand, the availability of a dedicated space, as well as the carbonization time ranging from few hours to several days<sup>81</sup>. Moreover, depending on the technologies used, the species and the humidity of the wood also evolves. During this process the chemical composition of the woody changes due to the high temperatures to produce the charcoal. Thus, to produce 1 ton of charcoal, between 4 and 12 tons of woody are needed<sup>82</sup>. In the literature, Charpin et al. (2019) show that carbonization is always concentrated in the dry season, from August to December, because in rainy days most of the villagers don't go for fuelwood collection.

This finding is consistent with the tightening of the legislation within protected areas in 2015, with the revision of the Code of Management of the protected areas of Madagascar in 2015 (COAP, 2015). The COAP (2015) has reoriented the legislation of the PAs towards new sustainable goals and policies such as: the sustainable use of natural resources, the development of cultural and educational heritage, or the promotion of ecotourism activities. In order to have a better consideration of the socio-economic parameters of the populations living around PAs. Consequently, the risk of detection during the process of transforming woody into charcoal is higher than the simple use of fuelwood. Charcoal production is an ostensible activity with a high probability to get caught and thus risk severe punishments. Moreover, charcoal process takes time, as people burn the woody in a low-oxygen environment inside a kiln to turn it into

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<sup>80</sup> More than 4 hours per week

<sup>81</sup> On average 2 to 3 days

<sup>82</sup> <https://charcoal-transparency.org/page.php?idPage=1>

nearly pure carbon. This process generates hotter burns, less weight and lasts much longer than fuelwood ([Appendix A.8](#)). This risky process can create wildfire, especially in dry areas. And thus, increase the probability to receive a penalty related to forest fires. Charcoal production also leaves debris (small branches) which raises the risk of forest fires and soil erosion. It is within this framework that the reform of the PA Management Code in 2015 clearly stipulates that any fire intentionally lit, provoked, or by communication - any clearing without authorization will be punished by hard labor and a fine ranging from Ar 100,000,000 (\$23,474) to Ar 2,000,000,000 (\$469,484). For a country with a GDP per capita of \$515 in 2021<sup>83</sup>, it is a big risk to produce and consume charcoal inside PAs' boundaries.

Each month, a Malagasy household can use on average one bag of charcoal, costing about 30,000 ariary (\$7). One bag of charcoal provides cooking fuel for a family of five for fifteen days (Zahana, 2022). And preparing the meals based on rice, cassava, or sweet potatoes require water and woody fuels. Hence, even if charcoal fuel brings water to boil in ten minutes, its relative price compared to other woody fuels is higher. That is why poorer households use more fuelwood as it is cheaper than charcoal, with respectively an average cost of 200 Ar/kg (\$0.047) and 632 Ar/kg (\$0.15). This has been theorized by Trefon et al. (2010) as "food offloading", given that fuelwood appears to be a transitional good for low-income households. The latter aspire to access other sources of cooking energy that are much more appropriate, as schematized by the ESMAP (2015) tiers scale.

The work of Gerard et al. (2020) reveal that the stove efficiency of charcoal is higher (23%) than the efficiency of fuelwood (11%), and that in terms of useful energy the latter is more expensive (101 Ar/MJ) than the former (86 Ar/MJ). Which means that one needs more fuelwood to produce the same energy efficiency as using charcoal. Lambe et al. (2015) precise that it takes 6kg of wood per 1kg of charcoal, and the wood-to-charcoal conversion efficiency is around 8% to 20%. In the same order, [Table 4](#) shows a change in the ratio of fuelwood on charcoal consumption at the border which is about 1.1. This ratio is greater than 1, meaning that these two energy commodities are substitutable in the same proportions. But, with a stronger substitution towards fuelwood since the implementation of the COAP (2015) reform, which adds additional disadvantages to charcoal consumption inside PAs. Charcoal is certainly less messy than fuelwood, easier to light and store, gives off more heat, does not require continuous monitoring, and is more affordable than other alternative cooking energy sources (gas, ethanol, oil). Furthermore, law enforcement is a major challenge for PAs mainly with limited resources of surveillance and widely-dispersed patrols. Gardner et al. (2018) precise that in Madagascar neither the MNP nor other PAs' managers have the power to apply the law. The slowness, cost, and lack of human resources during surveillance or arrest procedures make the application of penalties highly inefficient. In parallel, a second legislation named *dina* can be applied by local community promoters. This local and traditional formal legal system relies on the enforcement of laws without resorting to any higher authority, even if it is rare to see members of a community enforcing the law on other members (Gardner et al., 2018). However, household

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<sup>83</sup> <https://data.worldbank.org/country/madagascar>

clusters inside PAs are rational and do not risk detection and legal sanctions. They prefer to increase their fuelwood use and reduce their charcoal consumption.

**Table 4: Fuelwood and charcoal consumption share of household clusters around PAs' borders**

VARIABLES	(1) 2011	(2) 2013	(3) 2016
<b>FUELWOOD</b>	-0.689	-0.249	0.615***
	(0.8639)	(0.2216)	(0.1092)
Robust 95% CI	[-2.382 ; 1.004]	[-0.683 ; 0.185]	[0.401 ; 0.829]
<b>CHARCOAL</b>	0.145	0.260	-0.556***
	(0.4894)	(0.1946)	(0.1100)
Robust 95% CI	[-0.814 ; 1.105]	[-0.122 ; 0.641]	[-0.772 ; -0.341]
N (Households)	5,398	5,747	8,400
N (clusters)	179	184	268
Nb. Treated clusters	13	12	20
Nb. Control clusters	166	172	248
Order Loc. Poly. (p)	1	1	1
Order Bias (q)	2	2	2
BW Loc. Poly. (h)	50	50	50
BW Loc. Poly. (b)	110	110	110
Kernel type	Triangular	Triangular	Triangular

Notes: Robust standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. 2km buffer of the geospatial measures for clusters in urban areas. 5km buffer for geospatial measures for clusters in rural areas. All estimates are computed using a triangular kernel and nearest neighbor heteroskedasticity-robust variance estimators. Bandwidths used (h and b) are data driven MSE-optimal at 50km. Estimates controlled by: households, protected areas, and geographic characteristics. Coefficients tell the difference in percentage points between treated and control groups. Variance: at the cluster level.



### 6.3. The evolution of vegetation cover in protected areas and wood-based energy cooking fuels consumption

The primary objective of the creation of a protected area is to preserve the biodiversity of the ecosystem. However, this ambition attached to the SDG 15<sup>84</sup> can have unintended positive and negative indirect effects on the welfare of local communities. Such as, poverty level (SDG 1), nutrition (SDG 2), access to sustainable and affordable source of energy (SDG 7), and access to a decent source of income (SDG 8).

It is therefore interesting to analyze the evolution of the preservation of the ecosystem on the behavior of household clusters living around PAs. In order to observe whether if there is more or less deforestation if the clusters are inside or outside the protected areas. For this purpose, I look at the evolution of the vegetation cover using the Normalized Difference Vegetation Index (NDVI) observations, derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) imageries in Madagascar. Several studies measured vegetative cover as a function of NDVI, which is also a relevant proxy of deforestation level (Alcántara-Ayala et al., 2006; Lin et al., 2010; Mondini et al., 2011; Pradhan, 2010; Othman et al., 2018). The NDVI is composed of positive values representing the plant biomass. The larger the values, the denser the vegetation. As represented in [Appendix A.9](#), one can see that the vegetation level in the areas where the treated household clusters are located is higher than the vegetation cover in control clusters' areas. Notwithstanding, there is an overall degradation trend of the vegetation index between 2011 and 2016. Only few studies analyzed the impact of forest cover on fuelwood consumption. For instance, Kyaw et al. (2020) assess the impact of forest degradation on the firewood consumption rate in rural area of Myanmar. Their findings indicate that forest degradation negatively affect the consumption rate of firewood. This result is also consistent with the work of Howlader and Ando (2020) who find that new PAs in Nepal reduce the average wood collection by 20-40%. Unlike the studies of (Jagger and Shively, 2014; Jagger and Kittner, 2017) which highlight the importance of distance to forest.

The results presented in [Table 5](#), confirm that the NDVI parameter is decreasing throughout the years, with a greenery index of 2161 in 2011 and 496 in 2013, against 76 in 2016. One can therefore observe the fall of the greenery for the year 2016, which one year after the COAP (2015) reform. This result is in line with the findings in [Table 4](#) given that the consumption share of fuelwood increases for the household clusters living inside the PAs. As a consequence, rise fuelwood consumption is associated with the growth of the deforestation level in PAs. In India, Bošković et al. (2023) find that in regions with lower forest cover associated to a 10% decrease and longer travel times, woody collection increases by 0.52%. Furthermore, the increase in demographic density can also lead to a higher demand for fuelwood collection (Chakravorty et al., 2022).

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<sup>84</sup> Life on land

**Table 5: Share of the vegetation cover index at PAs' borders**

<b>VARIABLES</b>	<b>(1)</b> <b>2011</b>	<b>(2)</b> <b>2013</b>	<b>(3)</b> <b>2016</b>
<b>NDVI</b>	2161 (1739)	496 (708)	76 (244)
Robust 95% CI	[-1247 ; 5568]	[-891 ; 1883]	[-402 ; 554]
N (clusters)	179	184	268
N (Households)	5,398	5,747	8,400
Nb. Treated clusters	13	12	20
Nb. Control clusters	166	172	248
Order Loc. Poly. (p)	1	1	1
Order Bias (q)	2	2	2
BW Loc. Poly. (h)	50	50	50
BW Loc. Poly. (b)	110	110	110
Kernel type	Triangular	Triangular	Triangular

Notes: Robust standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. 2km buffer of the geospatial measures for clusters in urban areas. 5km buffer for geospatial measures for clusters in rural areas. All estimates are computed using a triangular kernel and nearest neighbor heteroskedasticity-robust variance estimators. Bandwidths used (h and b) are data driven MSE-optimal at 50km. Estimates controlled by: households, protected areas, and geographic characteristics. Coefficients tell the greenery unit of NDVI. Variance: at the cluster level.

## 7. Heterogeneity tests: the road and wealth channels

### 7.1. The road channel

In 2021, the population density<sup>85</sup> in Madagascar was about 49 inhabitants/km<sup>2</sup> against 37 inhabitants/km<sup>2</sup> in 2011 (World Bank, 2021a). This demographic rise exacerbates the pressure on the vegetation cover of PAs. Indeed, tree and wood cutting are necessary to meet the energy needs of populations but have an impact on increasing the level of deforestation of protected zones. Chakravorty et al. (2022) precise that “large volumes of fuelwood are transported to nearby urban areas”. For example, most of the firewood used in the capital Antananarivo comes from less than 60km distant forest zone, while the charcoal used in the city mainly comes from 100 km south on the Antananarivo-Antsirabe rail line (Gade and Perkins-Belgram, 1986).

In the southwestern part of the country, charcoal is sold on the side of major roads at about \$1 for a sack the size of a large garbage bag, which is cheap even by Malagasy standards. To transport charcoal to the cities, charcoal bags are settled along the roads<sup>86</sup>. Such as in large villages with the installation of charcoal piles along the *Route Nationale* 9 (Blanc-Pamard et al., 2005). People construct charcoal kilns and then transport the bags to villages and main markets (Ranaivoson et al., 2017).

Consequently, it is relevant to perform a robustness test of my model by analyzing the consumption of woody cooking fuels of treated household clusters according to their proximity to the road. Indeed, the households surveyed in this study live in majority within a radius of 5km of a road axis ([Appendix A.10](#)). To that extent, I first perform my analysis at 1km, 3km, and 5km buffers given that on average, household clusters are located 3.16km from roads. Hence, it is interesting to analyze the consumption of fuelwood and charcoal for clusters very close to roads (1km), those located halfway (3km), and those who are a little further away (5km). Beyond 5km-buffer, there are not enough observations to perform the analysis.

[Table 6](#) presents the results of cooking fuels consumption share of treated household clusters according to their proximity to road axes. First of all, one can observe that fuelwood consumption share of clusters living inside PAs and very close to roads significantly decrease by 1.25 pp. One might stress that the proximity of these clusters to roads give them a better access to charcoal markets. However even if their consumption share of charcoal is positive, the estimate is not statistically significant. The results in [Table 6](#) also show that treated household clusters living at 3 and 5 kilometers from roads have significant higher fuelwood consumption share than control clusters, with respectively an increase of 0.40 pp and 0.68 pp.

On the opposite, the share of charcoal consumption of clusters located inside PAs and further away from the roads (beyond 1, 3, and 5 kilometers) is significantly lower at the border, compared to the consumption of the clusters in the control group. These findings support the

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<sup>85</sup> People per square km of land area

decrease of charcoal consumption share at PAs' borders from my main estimation in [Table 4](#). These results show that household clusters far from road transport infrastructures have less access to the imported charcoal sold in markets. Since I do not have data on charcoal trade, I am not able to control for possible bias of whether household clusters consume imported charcoal in markets or from wood directly cut in the PAs. Nevertheless, the proximity to roads is a suitable proxy that shows that these households consume charcoal from wood cut in the PAs. Then, by being isolated from roads it is still less risky to consume fuelwood than to produce charcoal near PAs' borders. With charcoal production, the cost of being detected is higher for household clusters living inside PAs as the delivery of charcoal to roads rises this probability. On the other hand, the use of a larger sample will allow for in-depth analyses regarding the peripheral areas and highlight the role of the monitoring patrols within the boundaries of PAs.

**Table 6: Fuelwood and charcoal consumption share of household clusters around PAs' borders – according to road distance (km)**

<b>VARIABLES</b>	<b>≤ 1km</b>	<b>&gt; 1km</b>	<b>≤ 3km</b>	<b>&gt; 3km</b>	<b>≤ 5km</b>	<b>&gt; 5km</b>
<b>FUELWOOD</b>	-1.251*	0.502	-0.173	0.405***	-0.027	0.684***
	(0.72501)	(0.18421)	(0.2760)	(0.1062)	(0.2462)	(0.1753)
Robust 95% CI	[-2.672; 0.170]	[0.159 ; 0.881]	[-0.714 ; 0.368]	[0.196 ; 0.613]	[-0.509 ; 0.456]	[0.341 ; 1.027]
<b>CHARCOAL</b>	0.715	-0.574***	0.248	-0.576***	0.089	-0.959***
	(0.91772)	(0.16715)	(0.2290)	(0.0842)	(0.2162)	(0.1493)
Robust 95% CI	[-1.084 ; 2.514]	[-0.902 ; -0.246]	[-0.201 ; 0.697]	[-0.742 ; -0.411]	[-0.335 ; 0.513]	[-1.251 ; -0.666]
N (Clusters)	233	398	443	188	511	120
Treated BW Loc. Poly. (h)	27	33	35	25	35	16
Control BW Loc. Poly. (h)	110	110	110	110	110	110
Nb. Treated clusters	9	36	29	16	34	11
Nb. Control clusters	224	362	253	150	276	105
Kernel type	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular

Notes: Robust standard errors in parentheses. \*\*\* p<0.01 \*\* p<0.05 \* p<0.1. 2km buffer of the geospatial measures for clusters in urban areas. 5km buffer for geospatial measures for clusters in rural areas. All estimates are computed using a triangular kernel and nearest neighbor heteroskedasticity-robust variance estimators. Bandwidths used (h and b are data driven MSE-optimal at 40km for the treated and at 110km for the control. Estimates controlled by: households protected areas and geographic characteristics. Coefficients tell the difference in percentage points between treated and control groups. Variance: cluster at the cluster level.

## 7.2. The wealth channel

In this analysis, one can assume that the wealthiest household clusters are those who consume the most charcoal. Considering that charcoal is a durable commodity, there is a strong possibility that higher income household clusters are potentially using more charcoal, because they can store it. Therefore, it is interesting to perform my analysis according to the economic status of household clusters around PAs' borders.

I measure the share of fuelwood and charcoal consumption for both the richest and the poorest household clusters at the border, by interacting the treatment variable (*Inside*) with the comparative wealth index (*CWI*) variable. [Appendix A.11](#) shows that on average the *CWI* of the sampled clusters is about 7551, with a lowest level at -107761 and a highest level at 2297509. Hence, the sensitivity regarding protected areas must be much greater for the poorer household clusters, which may increase their elasticity. On the other hand, the *CWI* of the wealthiest 25% household clusters is between 53346 and 187717. Unlike the *CWI* of the poorest 25% clusters which is between -67830 and -43791.

The impact of the 25% poorest and the 25% richest clusters located inside PAs on their consumption share of fuelwood and charcoal is presented in the following equations:

$$\text{Fuelwood share}_i = \alpha + \beta_0 \text{Inside} + \beta_1 \text{Inside} * \text{CWI\_Rich}_i + \beta_2 \text{Distance}_i + \varepsilon_i \quad (1)$$

$$\text{Fuelwood share}_i = \alpha + \beta_0 \text{Inside} + \beta_1 \text{Inside} * \text{CWI\_Poor}_i + \beta_2 \text{Distance}_i + \varepsilon_i \quad (2)$$

$$\text{Charcoal share}_i = \alpha + \beta_0 \text{Inside} + \beta_1 \text{Inside} * \text{CWI\_Rich}_i + \beta_2 \text{Distance}_i + \varepsilon_i \quad (3)$$

$$\text{Charcoal share}_i = \alpha + \beta_0 \text{Inside} + \beta_1 \text{Inside} * \text{CWI\_Poor}_i + \beta_2 \text{Distance}_i + \varepsilon_i \quad (4)$$

Where:

- *Fuelwood share*: share of households at the cluster level *i* using fuelwood;
- *Charcoal share*: share of households at the cluster level *i* using charcoal;
- *Inside*: treatment variable which identifies 1 if the cluster *i* is located inside a PA, and 0 otherwise;
- *Inside \* CWI*: interaction term between the treatment and the wealth variables;
- $\beta_1$ : parameter of the interaction variable, to be estimated;
- *Distance*: distance in kilometer between a cluster *i* and the border of a PA, which is centered at the cutoff *C*;
- *i*: cluster index which varies from 1 to 640;
- $\beta_0$ : coefficient for treatment assignment which represents the marginal impact of PAs at the border;
- $\beta_2$ : estimate for the centered cutoff *C* of the *Distance* variable;
- $\alpha$ : average value of the energy cooking consumption for wealthy and poor clusters in the treatment group after controlling the *Distance* variable;
- $\varepsilon$ : random error term which is assumed to be independently and identically distributed.

The results display by [Table 7](#) highlight that the fuelwood share of wealthy household clusters located inside PAs significantly decreases about -0.15 percentage points in 2016 (*Equation 1*).

Conversely, the share of charcoal consumption of these clusters increases significantly by 0.15 percentage points, compared to the consumption of wealthy clusters located outside PAs (*Equation 3*). Then, one can also observe that for the poorer household clusters located inside PAs, their share of fuelwood and charcoal consumption do not significantly change at the border (*Equations 2 and 4*).

According to these findings, wealthy household clusters are the most able to obtain and store charcoal despite legal restrictions. They also have lower financial constraints and may certainly have better access to markets where charcoal is imported and sold.

**Table 7: Fuelwood and charcoal consumption share of wealthy and poor household clusters around PAs' borders**

<b>FUELWOOD</b>	<b>(1)</b>	<b>(2)</b>	<b>(3)</b>
	<b>2011</b>	<b>2013</b>	<b>2016</b>
<b>FUELWOOD</b>			
<i>Equation 1</i>			
Inside*CWI Rich	-0.079 (0.0643)	-0.153 (0.1677)	-0.151* (0.0775)
Inside	-0.141 (0.1600)	0.098 (0.1418)	0.207 (0.1495)
<i>Equation 2</i>			
Inside*CWI Poor	-0.094 (0.1040)	0.246 (0.1499)	0.091 (0.1276)
Inside	-0.066 (0.2246)	-0.362* (0.1894)	0.055 (0.1904)
<b>CHARCOAL</b>			
<i>Equation 3</i>			
Inside*CWI Rich	0.065 (0.0598)	0.025 (0.1108)	0.154** (0.0690)
Inside	-0.057 (0.1364)	-0.010 (0.1034)	-0.254* (0.1495)
<i>Equation 4</i>			
Inside*CWI Poor	-0.007 (0.0696)	-0.188 (0.1201)	-0.061 (0.1192)
Inside	-0.011 (0.2122)	0.361** (0.1497)	-0.116 (0.1836)
Nb. Obs (clusters)	179	184	268
Cluster	Yes	Yes	Yes

Notes: Robust standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. 2km buffer of the geospatial measures for clusters in urban areas. 5km buffer for geospatial measures for clusters in rural areas. Estimates controlled by: households, protected areas, and geographic characteristics. Coefficients tell the difference in percentage points between treated and control groups. Variance: at the cluster level.

## 8. Conclusion and recommendations

This study aimed to analyze the impact of biodiversity conservation policy on the welfare of households in Madagascar. Specifically, the research measured the discontinuity in wood-based cooking fuel energy consumption of households around protected areas' borders for each year wave. Moreover, I examine how the vegetation cover evolves throughout the years. Finally, I assess the driver mechanism between the proximity to roads and the use of woody cooking energies. I use a geospatial regression discontinuity design to empirically evaluate the impact of PAs on the share of fuelwood and charcoal consumption of household clusters located around protected areas' borders. My analysis is based on a three-wave survey of 19,885 households gathered in 640 clusters. The clustering level allows to perform a pseudo-panel analysis with a distribution of 45 household clusters located inside protected areas (i.e. the treatment group) and 595 household clusters located outside protected areas (i.e. the control group).

The findings unveil that at PAs' boundaries the fuelwood consumption share of treated household clusters significantly increases in 2016 with a jump of 0.62 percentage points, while their consumption share of charcoal decreases by 0.56 percentage points. Hence, one can observe that following the reform of the management code of protected areas in 2015 (COAP), household clusters consume more fuelwood on the side of the border that is protected because the probability of being detected and sanctioned is higher for charcoal commodity; even though charcoal has many advantages over fuelwood, in terms of quantity, power, and cleanliness. Indeed, it takes less charcoal than fuelwood to cook the same amount of food (Lambe et al., 2015). In addition, charcoal leaves less debris during cooking than fuelwood. Nevertheless, this substitution from charcoal to fuelwood is due to two factors. Firstly, fuelwood does not need to be transformed. Secondly, after the reform, the probability of detection inside PAs is higher for charcoal. As a consequence, household clusters logically change their consumption share of fuelwood compared to charcoal, as they consume more fuelwood and less charcoal and in the same proportions. Therefore, my analysis shows that there is an effect on the distribution of consumption. The substitution between fuelwood and charcoal is rational for the individuals living around the PAs. Household clusters have a limited number of energy alternatives to choose from, in addition to having a strong budget constraint. Finally, the chapter also details the role of the access to transport infrastructures which is a channel for the transport of charcoal, as well as the wealth channel. On the one hand, treated clusters living far from a road have a significant lower consumption share of charcoal and this result is consistent with my main findings. These clusters are therefore far from the markets where the charcoal is sold, which proves that they consume the charcoal directly processed from wood collected in the PAs. On the other hand, wealthy household clusters at PAs' borders tend to consume more charcoal and less fuelwood given that they may have a better access to market where the charcoal is imported and sold.

The implications of my findings regarding the decision of household clusters living around protected areas to use fuelwood or charcoal as cooking energy are majors. The outcomes indicate that the opportunity costs associated with the cooking fuel types rely on environmental policy reform. Then, as a part of the sustainable development goals (SDGs), this work



highlights the relationship between two targets: environmental protection and access to sustainable energy. Therefore, public decision-makers, investors, and NGOs would benefit from a better understanding of the effects of their policies on the welfare of the beneficiaries. Especially, through the use of innovative, reliable and accessible impact measurement techniques.

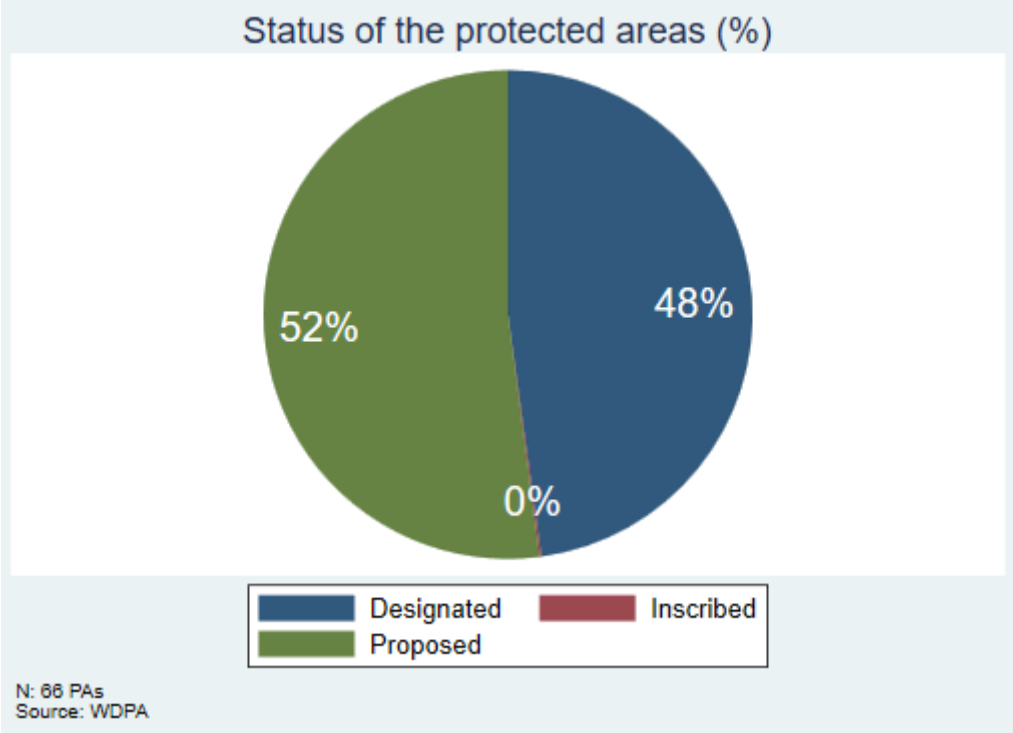
This study should also be considered with some limitations based on the datasets used. Indeed, it would be important to incorporate more details about the mobility of the household around PAs. Individuals collect wood from the PAs and transport it across the borders. Moreover, as shown by the literature, the scarcer the wood resource, the longer they stay to cut the wood (Bošković et al., 2023). Then, it is important to be aware of the endogeneity risk related to the migration flows, as the residential choice might be determined by the proximity to the boundaries of PAs. Besides that, the findings measure the local average treatment effect at the border which leaves no room to assess the potential externalities on the household clusters located far from PAs' borders. Furthermore, the use of the NDVI as a proxy of deforestation can overestimate my results as it takes into account the reflection of greenery emitted from the soil, including agricultural plots. To that extent, the future versions of this work can rely on forest cover data at granular level such as the forestry data of Burgess et al. (2012) and Hansen et al. (2013). Future researches should also strengthen the temporal dimension of the study and provide further empirical analyses on the impact of the new protected areas created in 2015 on households' welfare. In order to ensure this analysis, it would be necessary to have several data sets after the implementation of the COAP (2015) reform. Finally, Geospatial Impact Evaluations (GIEs) methods cannot be applied to all types of projects, especially those dealing with governance issues. It can also be difficult for evaluators to obtain survey data at high spatial resolution. This is especially true given that satellite data evolve over time and can create discontinuities between the pre-implementation period of a project and its completion. Finally, one of the main limitations of GIEs is the spatial and temporal alignment between project data, results, and covariates (survey data). Indeed, some development actors do not map their investments, which consequently limits data access for evaluators (BenYishay et al., 2017). Thus, there is a real need for coordination and information sharing between funders, operators and assessors to have a better knowledge of the impact of their projects.

## 9. Appendices

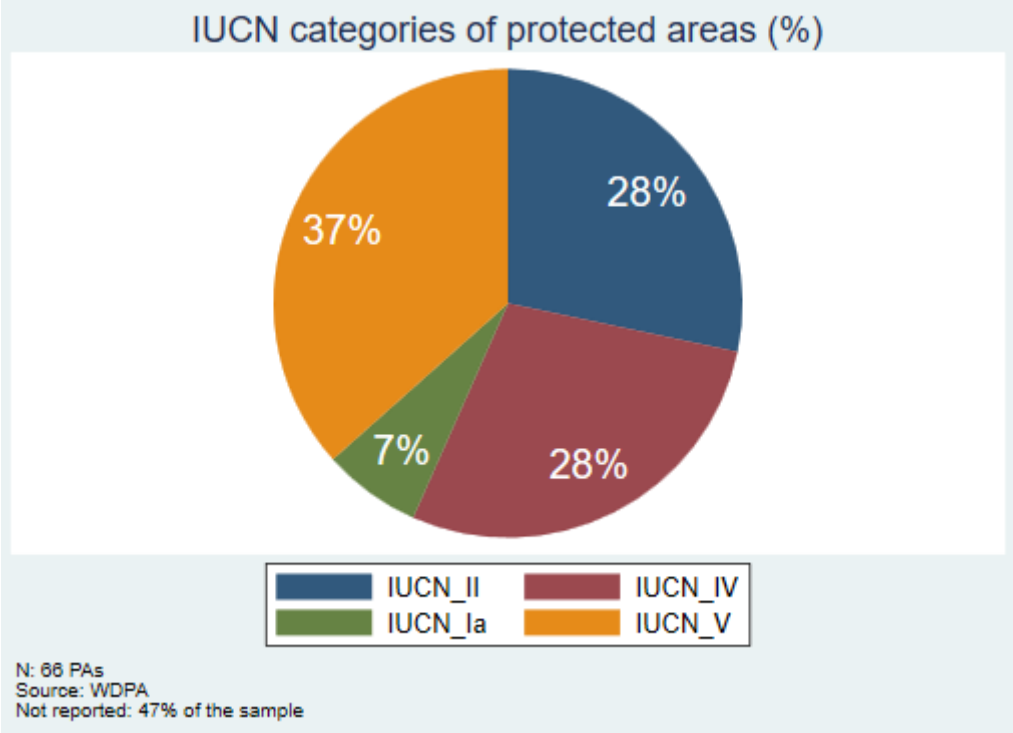
### A.1. WDPA attributes

ATTRIBUTES	DESCRIPTION	OBS.
<b>Number of terrestrial protected areas (PAs)</b>		<b>121</b>
<b>WDPAID</b>	Assigned by UNEP-WCMC. Unique identifier for a protected Area	121
<b>Name</b>	The name assigned to the site in legal texts or by its governance authority	121
<b>Designation Type</b>	<b>The category or type of protected area as legally/officially designated or proposed:</b>	
National	PAs designated or proposed at the national or sub-national level (national parks)	102
International	PAs designated or proposed through international conventions (world heritage sites)	19
<b>International Union for Conservation of Nature (IUCN) categories</b>		
Ia, Ib, II, III, IV, V, VI	Define the restriction of access to resources and the practice of human activities	62
Not Reported	For protected areas where an IUCN management category is unknown and/or the data provider has not provided any related information	55
Not Applicable	Applies only to World Heritage Sites and UNESCO MAB Reserves	4
<b>Status</b>		
Proposed	The PA is in the process of being legally/formally designated. It should be noted that sites may sometimes be functioning as PAs while proposed, as the legal processes of designation may take a long time	60
Designated	The PA is recognized or dedicated through legal/formal means. Implies specific binding commitment to conservation in the long term	59
Inscribed	Only applicable to PAs designated under the World Heritage Convention	2
<b>Governance Type</b>	<b>The governance type describes the entity responsible and accountable for making decisions about how a protected area or OECM is managed</b>	
Collaborative governance	When governance is through various ways in which diverse actors and institutions work together	2
Government-delegated management	Management delegated to another organization (e.g. to a non-governmental organization)	2
Local communities	Under the governance of local communities	43
Non-profit organizations	For example, non-governmental organizations or universities.	1
Not reported	Governance type is not known	73
<b>Surface of PAs</b>	The total PA, in square kilometers	121
<b>Verification</b>		
State verified	The site has been verified by the country or territory's national government	121

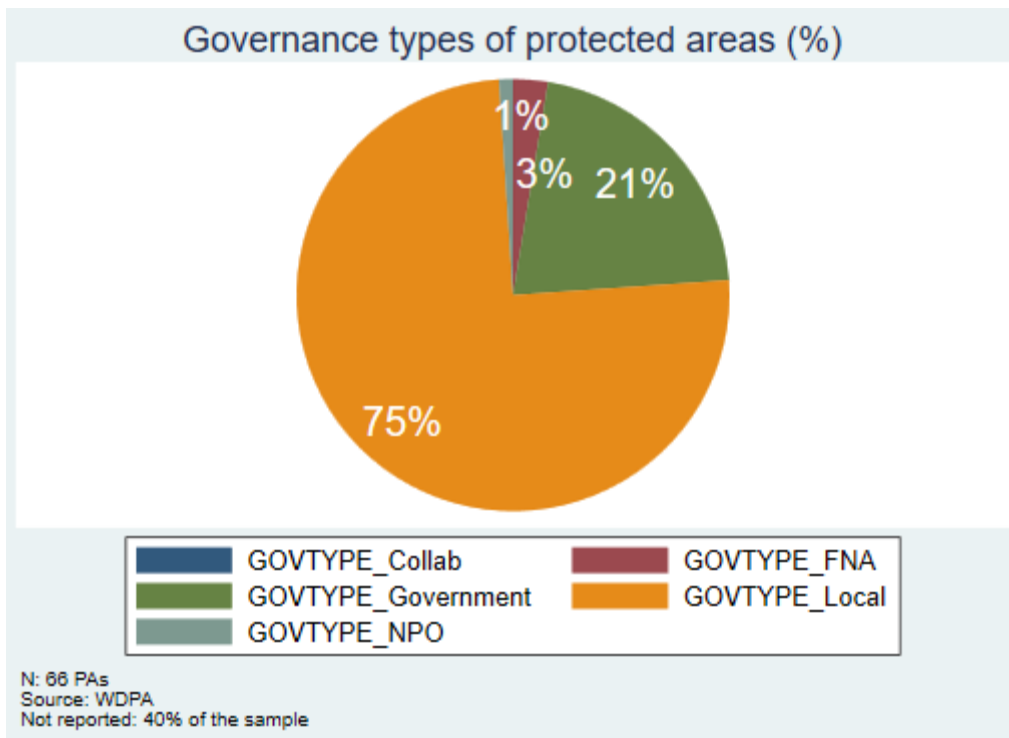
### A.2. Status of protected areas



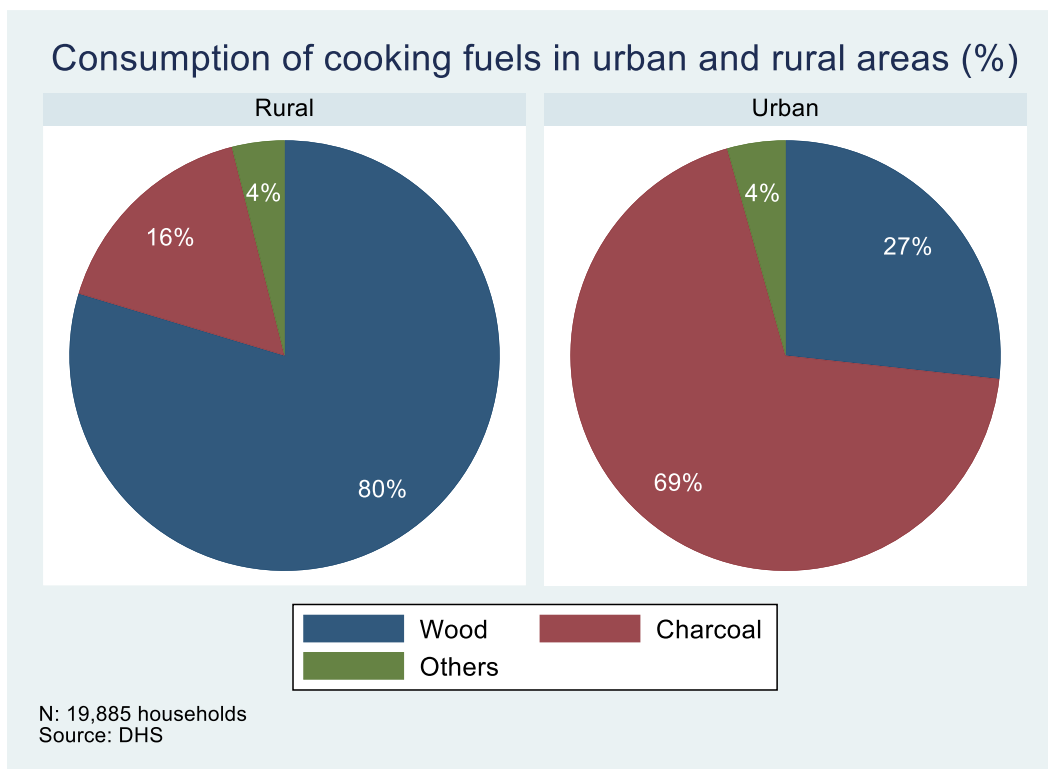
### A.3. IUCN classification of PAs



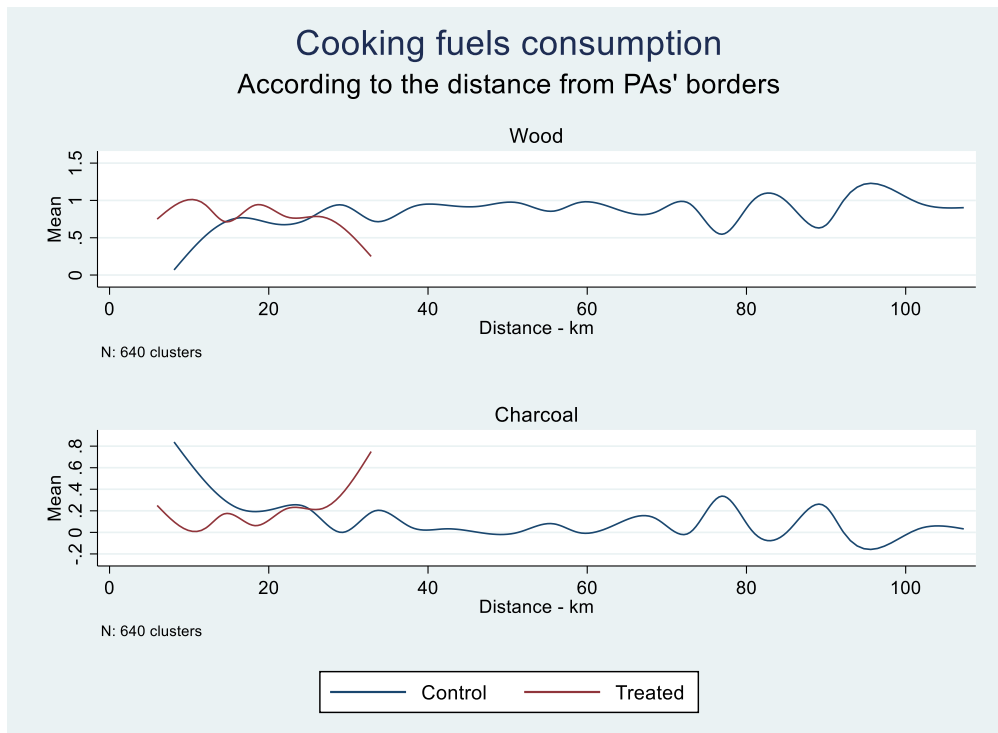
#### A.4. Governance of PAs



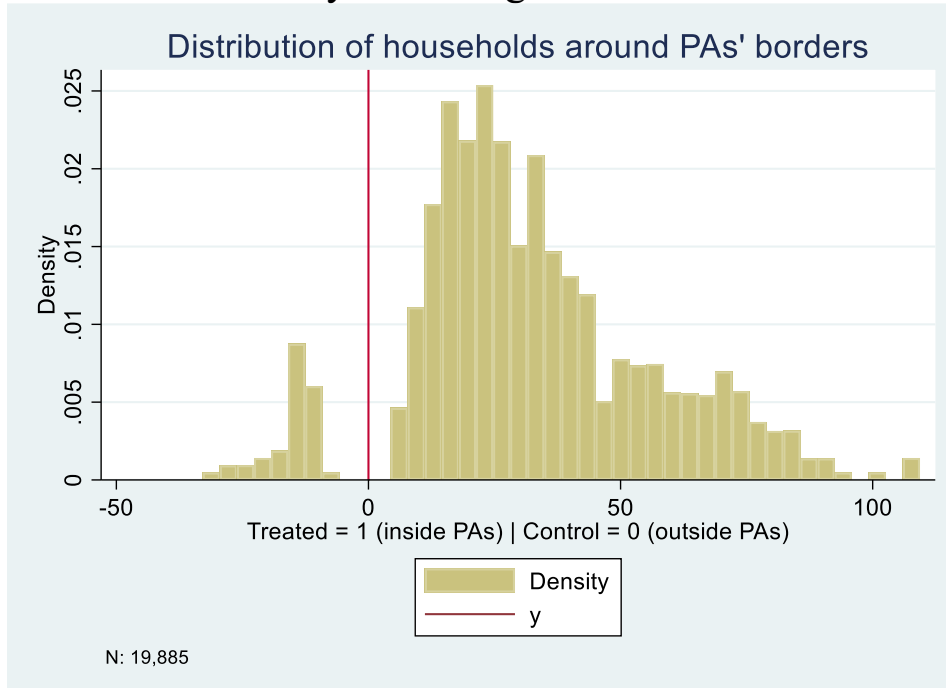
#### A.5. Types of energy cooking fuels in urban and rural areas



## A.6. Cooking fuels consumption for treated and control household clusters around PAs



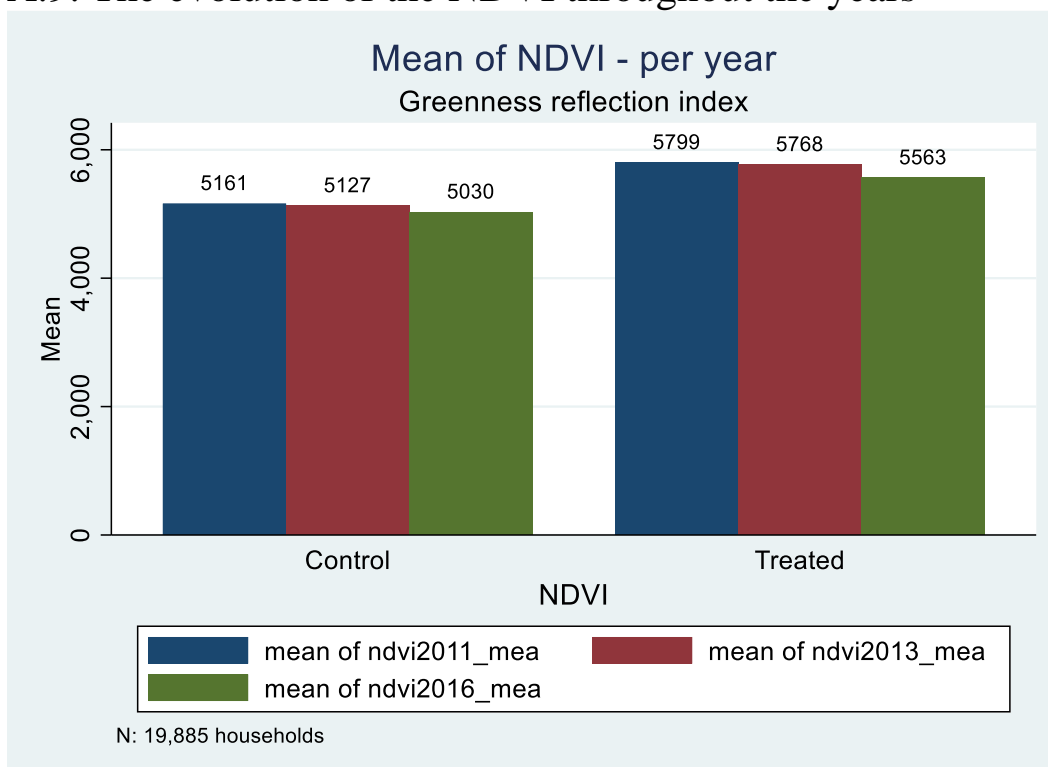
## A.7. Cluster density according to the distance from PAs' borders



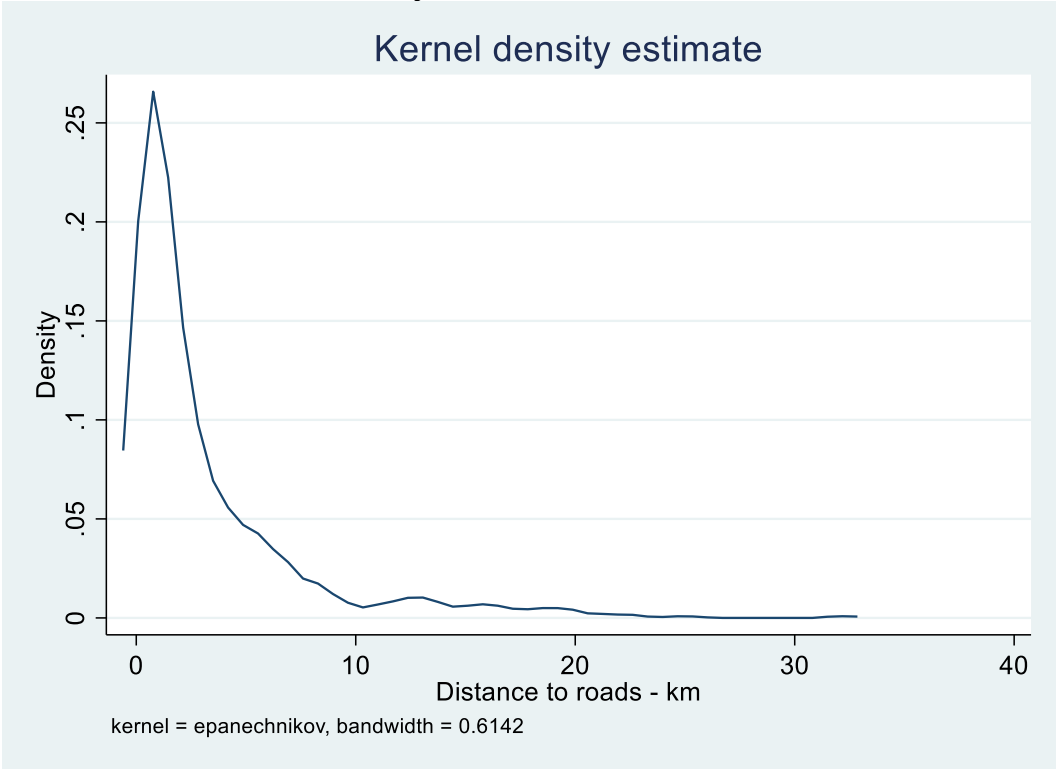
## A.8. Charcoal production and packaging (Filckr)



## A.9. The evolution of the NDVI throughout the years



A.10. The Kernel density of household clusters around roads



A.11. Summary of the comparative wealth index (CWI)

<b>CWI</b>	<b>Obs</b>	<b>Mean</b>	<b>Std. dev.</b>	<b>Min</b>	<b>Max</b>
	640	7551	67312.1	-107761.1	229758.6
Percentiles	<b>1%</b>	<b>25%</b>	<b>50%</b>	<b>75%</b>	<b>99%</b>
	-67830.11	-43791.29	-18438	53345.53	187716.6

## A.12. List of Protected Areas (WDPA)

WDPAID	NAME	DESID_ENG	DATE	DESIG_TYPE
354012	Mikea	National Park	2011	National
303695	Masoala	National Park	1997	National
555549449	Vohidefo	New Protected Area	2015	National
166880	Complexe Tsimembo Manambolomaty	Ramsar Site, Wetland of International Importance	2015	International
555697886	Ampotaka Ankorabe	National Park	2015	National
555697885	Mangabe-Ranomena-Sahasarotra	National Park	2015	National
5026	Manongarivo	Special Reserve	1956	National
555547960	Lac Kinkony	Ramsar Site, Wetland of International Importance	2015	International
555547961	Zone Humide de Mandrozo	Ramsar Site, Wetland of International Importance	2015	International
555626100	Complexe des lacs Ambondro et Sirave (CLAS)	Ramsar Site, Wetland of International Importance	2015	International
20283	Kinkony Lake	Hunting Reserve	2015	National
903062	Rainforests of the Atsinanana	World Heritage Site (natural or mixed)	2007	International
26653	Tsingy de Bemaraha Strict Nature Reserve	World Heritage Site (natural or mixed)	1997	International
901296	Le Lac Alaotra: les zones humides et bassin	Ramsar Site, Wetland of International Importance	2015	International
166881	Parc national Tsimanampesotse	Ramsar Site, Wetland of International Importance	2002	International
903056	Zones humides de Bedo	Ramsar Site, Wetland of International Importance	2007	International
902692	Parc de Tsarasaotra	Ramsar Site, Wetland of International Importance	1980	International
555624671	Zones Humides Ankarafantsika (CLSA)	Ramsar Site, Wetland of International Importance	2002	International
555542728	Rivière Nosivolo et affluents	Ramsar Site, Wetland of International Importance	2015	International
555624680	Complexe des Zones Humides de Bemanevika	Ramsar Site, Wetland of International Importance	2015	International
555624844	Zones humides de l'Onilahy	Ramsar Site, Wetland of International Importance	2015	International
555624845	Zones humides d'Ambondro	Ramsar Site, Wetland of International Importance	2015	International
555624846	Lac Sofia	Ramsar Site, Wetland of International Importance		International
20273	Zombitse Vohibasia	National Park	1997	National
354013	Zahamena	National Park	1997	National
2307	Tsimanampesotse	National Park	2002	National
2306	Tsaratanana	Strict Nature Reserve	1997	National



20287	Ranomafana	National Park	1991	National
10634	Beza Mahafaly	Special Reserve	1986	National
5031	Bemarivo	Special Reserve	1956	National
303702	Bemaraha	National Park	1997	National
2309	Namoroka	National Park	2004	National
2314	Montagne d'Ambre	National Park	1958	National
20272	Befotaka Midongy	National Park	1997	National
5035	Marotandrano	Special Reserve	1956	National
555697884	Ambatofotsy	National Park	2015	National
2305	Marojejy	National Park	1998	National
26070	Mantadia	National Park	2002	National
5041	Cap Sainte Marie	Special Reserve	1962	National
5038	Mangerivola	Special Reserve	1958	National
5027	Kalambatrika	Special Reserve	1959	National
5029	Ivohibe	Special Reserve	1964	National
2312	Isalo	National Park	1962	National
2310	Betampona	Strict Nature Reserve	1997	National
5024	Ankarana	Special Reserve	1956	National
1299	Ankarafantsika	National Park	2002	National
5023	Anjanaharibe_sud	Special Reserve	2015	National
5040	Andranomena	Special Reserve	1958	National
2308	Andringitra	National Park	1998	National
5034	Maningoza	Special Reserve	1956	National
2303	Andohahela	National Park	2007	National
5022	Analamerana	Special Reserve	1956	National
5021	Analamazaotra	National Park	2015	National
5033	Kasijy	Special Reserve	1956	National
5032	Bora	Special Reserve	1956	National
5030	Ambohijanahary	Special Reserve	1958	National
6932	Ambohitantely	Special Reserve	1982	National

5037	Ambatovaky	Special Reserve	1958	National
5036	Tampoketsa Analamaitso	Special Reserve	1958	National
555549450	Angavo	New Protected Area	2015	National
555549451	Behara-Tranomaro	New Protected Area	2015	National
555549452	Sud-Ouest Ifotaky	New Protected Area	2015	National
555549460	Ranobe PK 32	Nouvelle Aire Protégée	2015	National
354011	Réserve de Tampolo	Paysage Harmonieux Protégé	2015	National
352252	Ambohitr'Antsingy Montagne des Français	Paysage Harmonieux Protégé	2015	National
902404	Torotorofotsy	Ramsar Site, Wetland of International Importance	2015	International
352242	Complexe Anjzorobe Angavo	Paysage Harmonieux Protégé	2015	National
352251	Menabe Antimena	Paysage Harmonieux Protégé	2015	National
555697917	Marolambo	National Park	2015	National
352247	INord fotaky	Paysage Harmonieux Protégé	2015	National
352253	Amoron'i Onilahy	Paysage Harmonieux Protégé	2015	National
352243	Ankodida	Paysage Harmonieux Protégé	2015	National
352249	Makira	Natural Park	2012	National
352250	Mandena	Paysage Harmonieux Protégé	2015	National
352255	Ambatoatsinanana	Paysage Harmonieux Protégé	2015	National
352240	Analalava	Special Reserve	2015	National
352256	Corridor Ankeniheny Zahamena	Reserve de ressource naturel	2015	National
352244	Corridor forestier Bongolava	Paysage Harmonieux Protégé	2015	National
352239	Ambatotsirongorongo	Paysage Harmonieux Protégé	2015	National
555697916	Ambararata Londa	National Park	2015	National
555697915	Ambohidray	National Park	2015	National
555697902	Forêt Naturel de Petriky	National Park	2015	National
555697901	Agnakatrika	National Park	2015	National
555697900	Ankarabolava	National Park	2015	National
555697911	Manjakatampo Ankaratra	National Park	2015	National
555697910	Andrafiarena Andavakoera	National Park	2015	National
555697909	Allées des Baobabs	National Park	2015	National

555697898	Réserve spéciale Pointe à Larrée	National Park	2015	National
555697897	Massif d'Ibity	National Park	2015	National
555697896	Oronjia	National Park	2015	National
555697895	Galoko Kalobinono	National Park	2015	National
555697894	Ampasindava	National Park	2015	National
555697893	Makirovana Tsihomanomby	National Park	2015	National
555697908	Loky Manambato	National Park	2015	National
555697907	COMATSA Nord	National Park	2015	National
555697906	Bemanevika	National Park	2015	National
555697905	Mahimborondro	National Park	2015	National
555697904	COMATSA Sud	National Park	2015	National
555697899	Vohidava Betsimalao	National Park	2015	National
555697891	Analavelona	National Park	2015	National
555697890	Analabe-Betanatanana	National Park	2015	National
555697889	Analalava	National Park	2015	National
555697888	Ampanganandehibe-Behasina	National Park	2015	National
555697887	Mahialambo	National Park	2015	National
555697883	Maromizaha	National Park	2015	National
555697882	Massif d'Itremo	National Park	2015	National
555697881	Corridor Forestier Ambositra Vondrozo	National Park	2015	National
555697880	Sahafina	National Park	2015	National
555697879	Beanka	National Park	2015	National
555697878	Forêt Naturelle de Tsitongambarika	National Park	2015	National
555697877	Complexe Zones Humides Mangoky Ihotry	National Park	2015	National
555697875	Complexe Lac Forêt Ambondrobe	National Park	2015	National
555697874	Rivière Nosivolo	National Park	2015	National
555697873	Lac Alaotra	National Park	2015	National
555697871	Complexe des AP Ambohimirahavy Marivorahona	National Park	2015	National
901250	Littoral de Toliara	UNESCO-MAB Biosphere Reserve	2003	International
20017	Mananara Nord	UNESCO-MAB Biosphere Reserve	1989	International

## General conclusion

In this thesis I contribute to a better understanding of impact evaluation methodologies for the impact industry in developing economies: the effects of the different designs of impact measurement on the outcomes of small-scale infrastructure projects; the impact of the renewable off-grid investments on the socio-economic performances of economic clusters; the indirect impact of biodiversity policies on the welfare of local populations.

The first chapter identified the effects of the estimates of impact assessment methods on the outcomes of decentralized electrification projects (DEPs) in developing countries. Applying a meta-analysis design on the innovative CoSMMA<sup>87</sup> database, I showed for each estimate of the RCTs and non-RCTs methodologies their probability of generating positive or negative project outcomes, on the one hand. On the other hand, it allowed to identify to what extent the effects of these methodologies on project outcomes converge or diverge. In the literature, several studies have made comparative syntheses within and between the estimates of the different evaluation methods (Glazerman et al., 2003). Through an identification strategy based on the multinomial logit design, I provided evidences that the estimates of experimental and quasi-experimental impact evaluation techniques converge to the same conclusion on both the proven positive and negative outcomes of DEPs. Mainly for the projects which target the sustainable development goals (SDGs) 7 and 9, dedicated to energy basic access and information and communication. Moreover, performing the analysis on a homogeneous sample of DEPs implemented in Africa, I found consistent results to my main estimation. Meaning that for successful African renewable off-grid projects, the different types of impact methods converge to the proven positive outcome.

Overall, the results of my meta-analysis demonstrate that the estimates of impact assessment methodologies are not neutral in the outcomes generated by small-scale infrastructures projects. This is good news for development actors, who are able to rely on a variety of methods to assess at the lowest cost the impacts of funded projects. This allows funders to have a better knowledge of the impacts generated by their projects, as well as the different impact assessment methods available.

This study opens rich path for future research as scientific knowledge would benefit from capitalizing on the use of tools such as CoSMMA, enriching it with more projects. This would go beyond the decentralized electrification sector, and would help stabilize the identification models used in order to strengthen the contribution of impact evaluation methods in development economics.

The second chapter, co-written with Dr. Enoch Owusu-Sekyere and Dr. Esther Leah Achandi, examines the impact of subscribing to Rensource solar energy on Micro, Small & Medium Enterprises (MSMEs) in economic clusters, such as markets in Nigeria. This case study is based

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<sup>87</sup> Collaborative Smart Mapping of Mini-grid Actions

on primary field data and measures the economic, environmental, and health performances of Rensource's solar panel customers. Investments in the renewable and decentralized energy sector are increasing in the African continent. In particular in Nigeria where the level of electrification remains very low, with about 55% of the population remains without electricity access (Nigeria Electricity Hub 2019). Not to mention the poor reliability of the network with only 14% of respondents to the Afrobarometer survey perform by Hee Eun et al. (2022) stress having electricity that works most/all of the time. The lack of reliable power is a constraint for citizens and businesses, which represent an annual economic loss of \$26 billion, i.e. 2% of the gross domestic product (World Bank, 2021b).

To that extent, we conducted a field data collection between July and August 2020 with 700 merchants in 5 markets where Rensource operates. Our sample is composed of 300 users and 400 non-users of Rensource solar panels. We first identified, through a probit model, the drivers of the merchants' decision to subscribe to Rensource solar energy: reliability, affordability (weekly/monthly user fees), flexible payment plan, ease of access, flexibility of use, low risk of fire outbreak and low health risk of the solar energy. Then, we looked at the profiles of merchants regarding their social characteristics (age, education, household size) and their economic performances (services and products provided, incomes, energy expenditures).

In terms of impact, the propensity score matching design showed that thank to the subscription to Rensource solar energy, subscribers have experienced a growth of their monthly average earnings from trading of about 23% to 27%. As a second result, the net income of the subscribers also increased by 23% (+ \$60) compared to the net income of non-subscribers. Moreover, by subscribing to Rensource solar energy, merchants using the national grid and standby generators can cut down their average monthly expenditure on electricity by 37%. Finally, Rensource solar solution also reduce the perception for users to face environmental risks by 12 points, on the one hand. On the other hand, users also reported less health issues (- 14 points) thanks to their subscription to Rensource energy system.

Our findings highlight that impact evaluations identify the effects of a sector of the future with a strong added value on the economic development, at a local and continental scale. But also, on major global issues such as the environment and health. Future extensions of this research may rely on other evaluation techniques to correct for selection and endogeneity biases, and to reconcile the concessionality of decentralized renewable investments with their impacts.

Finally, the third chapter explored the impacts of a biodiversity program on the welfare of local communities in Madagascar. This program support biodiversity conservation through the creation of protected areas (PAs). Given that in Madagascar, a major part of the population depends on the resources present in these protected areas, it is important to highlight the indirect effects of the program on the use of primary resources of local communities. My analysis focuses on the resource of wood, which is a vital element in the lives of Malagasy households, particularly for its use as cooking fuel. To that extent, I measure the impact of PAs on the share fuelwood and charcoal consumption for the household clusters living inside the PAs. Through an innovative geospatial analysis based on a spatial regression discontinuity design model, I observed the evolution of household clusters consumption around the PAs.

The findings indicated that at PAs' boundaries, the fuelwood consumption share of treated household clusters significantly increases by 0.62 percentage points, compared to the consumption share of clusters living outside the PAs. On the other hand, charcoal consumption share of household clusters inside PAs significantly decreases by 0.56 percentage points, compare to the consumption share of those in the control group. Therefore, these results provide evidence that around the boundaries of the protected areas these two commodities are substitutable. Furthermore, these local average impacts have been accompanied by an increase in the level of deforestation in the areas studied. In fact, the vegetation cover in these areas is constantly decreasing due to high population density around the PAs, which rises the pressure on wood collection. Therefore, the findings emphasize that the creation of protected spaces has no effect on the reduction of wood collection. Then, the COAP (2015) reform of the management code of protected has impacted the household substitution ratio in favor of fuelwood over charcoal. The reform puts forward legislations on biodiversity protection and socio-economic welfare. For instance, charcoal production around the PAs has become much stricter, while the authorization of wood collection (under certain conditions) and the promotion of eco-tourism activities have been taken into account.

The final contribution of this chapter analyzed how the proximity to road for treated household clusters influence their consumption of cooking fuels. I found that treated clusters living far from a road have a higher consumption share of fuelwood and a lower consumption of charcoal, compared to the control household clusters located far from roads. These outcomes are consistent with my main results and highlight that treated clusters consume charcoal from wood cut in the PAs. However, my study is limited by the lack of data on charcoal trade which is a suitable proxy for access to imported charcoal in markets. Then, futures researches much have access to more accurate infrastructure data in order to identify the potential channels through which biodiversity protection programs impact the living conditions of local communities. Finally, I also performed a heterogeneity analysis based on the economic status of the household clusters. The study demonstrated that the 25% wealthiest household clusters located inside PAs have a higher consumption share of charcoal and a lower consumption of fuelwood. Indeed, these household clusters are less financially constrained, and are able to have access to imported charcoal in markets that they can store. Furthermore, the extension of future researches should strenghten the knowledge on the temporal dimension of PAs' creation, in order to measure their effectiveness.

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