Access to electricity and economic development : determinants of favorable impacts for households

Arnaud Millien

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 17 Septembre 2019 par

Arnaud MILLIEN

ACCESS TO ELECTRICITY AND ECONOMIC DEVELOPMENT: DETERMINANTS OF FAVORABLE IMPACTS FOR HOUSEHOLDS

<u>Sous la direction de M. Jean-Claude Berthélémy,</u>

Professeur Emerite, Université Paris 1 Panthéon Sorbonne, France

<u>Membres du Jury</u>

Mme Mathilde Maurel, Directrice de recherche, CNRS, France

M. Rémi Bazillier, Professeur, Université Paris 1 Panthéon Sorbonne, France

M. Ujjayant Chakravorty, Professeur, Tufts University, USA (Rapporteur)

M. Jörg Peters, Professeur, RWI - Leibniz-Institut für Wirtschaftsforschung, Allemagne (Rapporteur)

M. Patrick Plane, Directeur de recherche, CNRS, France

To those who want more than light

Acknowledgements

I thank Prof. Jean-Claude Berthélémy, who taught me how to build a comprehensive research in development economics, in a spirit of in-depth and relevant problem solving. He gave me a high level of confidence by entrusting me with a senior scientific mission, expecting from a meta-analysis that it consolidates the knowledge of other scientists and can contribute to a credible research agenda around the development goals achieved by electrification projects. Above all, I am thankful for his impressive research supervision, as his visionary insights have always been six months ahead of the research work, and even years for some of the innovations suggested in this area of research.

I thank Prof. Mathilde Maurel, who convinced me to embark on this unique journey. She has always found favorable and benevolent words, whatever the circumstances, supporting this scientific project to its realization, with a brilliant sense of success.

I thank Prof. Jean-Bernard Châtelain, who was my first contact with development economics: 25 years ago, he was the first one who taught me to think "out of the box" by exploring how organized financial markets could help support growth in developing countries. He played a key role in this research by providing concrete advice for conducting a meta-analysis, which for me was a new methodological approach and required a kind of Copernican revolution to understand the change in the objects studied.

This thesis could not have been achieved without the human and financial support of Ferdi. I especially thank Fatou Cissé for her unwavering involvement and support in the construction of CoSMMA. Her passionate desire to learn, her regular and consistent work, her sense of rigor and her memory for the details made the difference when collecting meta-data, which implements a very specific approach to conducting a research survey. I also thank Olivier Santoni and Vincent Nossek for their significant contributions to descriptive statistics. I must finally mention the financial role played by Christophe Angely.

I extend special thanks to the other partners who contributed to the realization of this thesis: Dr. Thomas André for the partnership with Schneider Electric, Carmen Alpin for access to Afrobarometer, Dr. Chris Davis and Dr. Igor Nikolic for access to Enipedia, Seth Goodman for access to AidData, Dr. Paul Stackhouse for permission to use LARC Power Data, the RISE project for access to data on governance, and the French National Research Agency under the ANR-10-LABX-14-01 program for their financial support. I also thank Simon Guédé for his talent in database programming for field surveys.

This thesis could not have been done without the exceptional cultural environment of the University Paris 1 Panthéon Sorbonne for development economics, namely the amazing passion for research and pedagogy of Prof. Josselin Thuilliez, Prof. Rémi Bazillier and Prof. Laetita Duval. I sincerely thank them for their confidence and their sense of teamwork. As part of the Paris Sorbonne Sustainable Development Seminar, I had several opportunities to present my work to other researchers and to receive valuable and advanced comments. Being also involved in the pedagogical team of the development axis, I was able to participate in the teaching of the main econometric methods used in development economics, which was an essential preparation for the construction of the second chapter. I have truly been able to find real professional integration and accelerated synergies, which are key success factors for management.

I also thank Prof. Marie Boltz, Prof. Elisabeth Cudeville and Prof. Laurine Martinoty for their tireless enthusiasm, which makes it possible to be more quickly receptive to their advice. They really helped me learn the professional dimension of research.

As an extension of the cultural dimension, I sincerely wish to thank all the PhD students and doctors who form the daily life of the axis of development economics in Paris I. Dr. Victoire Girard, Dr. Nelly El-Mallakh, Dr. Zaneta Kubik Dr. Stephan Worack, Dr. Rizwan Mushtaq, Dr. Diana Cheung, Etienne Lerossignol, Candice Yandam, Nathalia Cantor-Vargas, Clemence Pougue-Biyong. Through our constantly enriching discussions and cross-cutting expertise, we built together and shared a common vision of development, which is the most valuable intangible asset I have gained from this experience. I must emphasize that I never observed any of these negative behaviors that I have observed under the pressure of a competitive environment in other circumstances or professional places. On the contrary, I met an ever-changing open-minded team, where everyone learns from each other, sharing knowledge, experiences and opinions, with a common sense of problem-solving, and a sense of humility in dealing with the extremely complex and unsolved issues of building sustainable choices for the future. I am convinced that this core of research contribute to forge an international network of expertise and methodology.

I really want to thank all the community of development economists for their openness, which was my highest expectation when I started to follow this PhD track. I found a way to address complex economic questions with a sense of urgency, innovation and common sense.

I would also like to thank the teachers with whom I worked for teaching activities: Prof. Fabrice Rossi, Prof. Fabrice Le Lec and Prof. Catherine Doz. Conducting research teaches how to build knowledge. Teaching brings a renewed experience of what is commonly known and shareable, which helps to draw the line between knowledge and innovation, and is also a solid safeguard in the creative moment of research... I also discovered the scaling up of teaching at a major university. After twenty years of teaching in small master classes, I discovered the implications of going from 30 to almost 800 students. Teaching for all increases the requirement for clarity, for definitions of accepted knowledge and for organization, sometimes almost in a military way. Despite other weaknesses in staff management, the University Paris 1 Pantheon Sorbonne convinced me of the value of producing, stabilizing and disseminating knowledge to a large community of students.

I would now like to thank the large community of students with whom I worked, at Paris 1 Panthéon Sorbonne and previously at Paris Est Créteil University. I cannot name them all, but I hope that everyone can recognize themselves in this thank you. As an energy specialist, the highest capacity I have ever seen comes from human youth. Students have always brought me a constant challenge of improvement, clarity and transmission. Whether by listening attentively, asking questions, annoying their classmates or challenging the teacher, I have never found any trace of malice among young people, but an endless desire to know or obtain more, and my only duty was to let this will support their own path for the future. I do not find the appropriate words to express all the gratitude I feel for what students have brought to my own personal development, and I hope I have also passed on something more than technical elements to the students with whom I am worked.

Finally, I wish to express a personal thank you to my daughter. We went through a very delicate period, which I could neither anticipate nor wish for. At a time when you needed landmarks and certainties, I

engaged in the most uncertain choice of my career. I thought I was engaged in a global transformation and I even thought I could solve some blockages with your mother, which would have brought back the family that you always wanted. It was a mistake, because I did not know how much people can decide never to change, just when I decided to do my best to transform my own way, after going through serious professional difficulties during the financial crisis. I hope that this period of research in development economics, confronted with the unsolved problems of human beings around the world, has brought me a little more humility, even within my own family. Although difficult, I think that this period was beneficial because it taught us that some problems cannot be solved whatever the cost, and that the priorities must sometimes be revised. I learned how brave and patient you are, how hard it is to say things, how long it takes in a human life to learn how to communicate better, how much you can adapt, which is the best proof of your love. I thank you, my daughter, and hope to be able to show you that what seems to be comfortable is only an interaction between luck and personal commitment. But now, as promised, after ten years of post-baccalaureate studies, I'm going back to work … and vacation!

In fact, I leave this laboratory with much less certainty than when I entered. If anything, I gained the conviction that markets cannot all, and that we should not expect everything from markets as magic tools, supporting lazy dogmatic assessments. This work on an important issue for developing countries taught me how important it is to take into account the difference between volatility, which is a measurable and insurable, and uncertainty, which is a permanent and unpredictable threat to success. Sustainability needs thus to be examined more broadly than the price level alone. And because development issues are too complex to be insurable, they require commitment.

The conviction I have gained in this thesis is that we must constantly learn about the development problems of the whole world. In the future, the distinction between "*advanced countries*" and "*developing countries*" will probably be less relevant, as groups of countries will face problems together and will have to come up with solutions that combine different levels of wealth and resources. Otherwise, the "*advanced*" countries will just import the consequences of unforeseen and unresolved events elsewhere in the world. However, I am confident because I know that a network of men and women dedicates time, energy and resources to raise issues that deserve to be addressed for global and local well-being.

Finally, as it is usual to remind, all remaining errors are those of the author.

Contents

List of Figures

List of tables

1. Résumé

Aussi surprenant que cela puisse paraître, l'accès à l'électricité n'a été introduit qu'en 2015 en tant qu'objectif de développement, à l'appui du 7e objectif de développement durable (ODD): «*une énergie abordable et propre*». En 2018, environ un milliard de personnes vivent sans électricité, dont 600 millions en Afrique. La bonne nouvelle est que, pour la première fois, ce nombre a commencé à diminuer, ce qui signifie que le rythme des nouvelles connexions de ménages est désormais plus rapide que la croissance démographique. Les efforts nécessaires sont considérables, mais cette nouvelle tendance montre que tous les acteurs de l'électrification sont sur la voie.

Le 7ème ODD a des implications importantes pour le développement économique, car l'objectif soutient la plupart, sinon tous les autres objectifs de développement durable : la fourniture d'électricité devrait favoriser de nombreuses autres améliorations socio-économiques.

Atteindre l'accès universel avant 2030 nécessitera toutefois 700 milliards de dollars de nouveaux investissements (ESMAP, 2017). Pour éviter tout gaspillage de ressources, des investissements efficaces devront à la fois s'appuyer sur le facteur clef de la demande d'électricité des ménages et trouver les solutions les plus susceptibles de déclencher d'autres objectifs de développement, au-delà de l'accès à l'énergie.

L'objectif étant récent, les recherches économiques sur l'efficacité des projets d'électrification sont en retard: les déterminants de la connexion des ménages et la gamme des bénéfices pour le développement économique restent peu connus. Les recherches antérieures sur l'électrification se sont concentrées sur les modèles de réseaux optimaux, le potentiel théorique et les obstacles au développement de l'électricité. Les avantages de l'électrification pour le développement économique étaient implicitement évidents. Mais les évolutions récentes ont soulevé des questions sur le rapport coût / bénéfice de l'extension du réseau dans une perspective de développement, sur les canaux de la demande d'électricité dans les pays en développement et sur l'efficacité des nouveaux systèmes décentralisés.

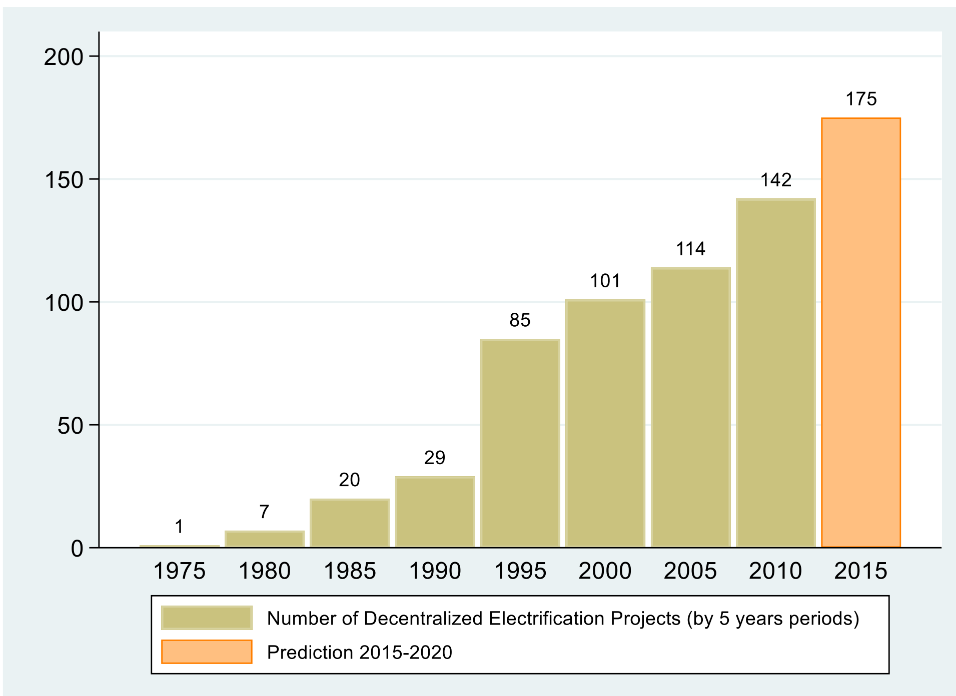
La voie traditionnelle de l'électrification, l'extension du réseau, est confrontée à de nombreux défis: coût marginal d'extension élevé en zone rurale, coûts hyperboliques dans les zones les plus reculées et les plus difficiles (montagnes, îles), accès au financement fragilisé, maintenance et formation insuffisante, pannes et corruption répétées, préférence pour l'exportation de l'électricité produite.

En outre, malgré les efforts considérables déployés pour étendre le réseau dans certains pays (Kenya, Tanzanie), les ménages ne se connectent pas au rythme attendu, largement en deçà du nombre de nouvelles connexions ciblées (Lee et al., 2014), (Chaplin et al., 2017): étendre l'infrastructure de

fourniture d'électricité ne semble donc pas être une condition suffisante pour accroître l'accès à l'énergie moderne.

Dans le même temps, les coûts de production des systèmes décentralisés ont diminué de 60% au cours des cinq dernières années et devraient diminuer au même rythme au cours des cinq prochaines années: la forte diminution des coûts de production place désormais l'électricité solaire au premier rang de la courbe de *merit-order* en 2018.[1] Les nouveaux systèmes décentralisés sont en plein essor (Figure 1) et offrent des solutions réalistes et abordables pour l'accès à l'électricité hors réseau, jusqu'à la plus petite granularité de production avec les Systèmes Solaires Domestiques individuels (SSD).

Figure 1 : Nombre de projets hors réseau recensés dans les pays en développement (échantillon d'étude)



Cependant, la plupart des systèmes hors réseau sont limités en capacité, ne fournissant qu'une puissance limitée aux utilisateurs, ce qui limite la portée des applications possibles et soulève une question légitime quant à leur efficacité pour les autres dimensions du développement économique. En outre, d'autres caractéristiques importantes des Projets d'Electrification Décentralisée (PED) pourraient influer sur leur capacité à avoir des impacts positifs sur le développement, car ces projets sont mis en œuvre par des solutions très hétérogènes, impliquant des choix variés de technologies ou de gouvernance. Par exemple, l'intermittence de l'électricité solaire peut limiter la consommation

[1] La courbe de *merit-order* classe les technologies de production d'électricité en fonction de leur coût marginal de production. C'est la courbe d'offre de l'économie de l'électricité.

d'électricité à des utilisations diurnes, à moins que des batteries ne soient ajoutées aux panneaux photovoltaïques: les impacts du projet sur le développement pourraient donc dépendre de ses choix de conception technologique. La survenance d'impacts positifs pourrait également dépendre des choix de gouvernance. Par exemple, certains accès à l'électricité décentralisée sont vendus par des fournisseurs locaux privés sous forme d'offre groupée, dont le prix peut varier en fonction de l'intensité de la concurrence locale. La variété des choix de gouvernance portant sur le prix, la durée du service ou la sélection des utilisateurs ciblés peut ainsi conduire à de nombreux schémas différents de service d'électricité, ce qui pourrait affecter la probabilité de produire des impacts positifs.

Ainsi, d'une part, le rythme de la demande de connexion au réseau risque d'être beaucoup plus lent que prévu, ce qui menace la soutenabilité économique de l'infrastructure, remettant en question la capacité du modèle d'électrification traditionnel à atteindre des zones non connectées et à apporter un soutien efficace au développement économique. D'autre part, malgré des gains d'opportunité énormes, la contribution des systèmes hors réseau au développement économique reste largement méconnue et son efficacité pourrait être affectée par la diversité de conception des projets.

Cette thèse se propose donc d'explorer quel canal important de la demande d'électricité pourrait influer sur l'extension durable du réseau dans les pays en développement, et quelle est l'efficacité des nouveaux modèles d'approvisionnement par les projets d'électrification décentralisée.

Le premier chapitre teste l'hypothèse selon laquelle la fiabilité du service de l'électricité serait l'élément déterminant de la préférence des ménages pour le raccordement au réseau, constituant alors le principal levier d'une électrification efficace.

La disponibilité permanente diminue l'incertitude quant à l'accès effectif au service d'électricité; à son tour, une incertitude moindre soutient les anticipations de long terme des ménages non connectés sur la disponibilité du courant dans les zones où le réseau est accessible, et donc leur décision de se connecter au réseau national pour une consommation durable d'électricité. Avec des données individuelles sur les ménages kényans, le premier chapitre utilise une méthodologie d'identification robuste pour évaluer la probabilité que les ménages soient connectés au réseau électrique en fonction du niveau de fiabilité du service d'électricité. Il trouve un effet significatif de grande ampleur: une augmentation d'un point de pourcentage de la fiabilité de l'électricité entraîne une augmentation de 0,82 point de pourcentage du nombre de connexions. En fournissant un service d'électricité totalement fiable, les entreprises d'électricité atteindraient leur nombre cible de nouveaux clients 12 mois plus tôt que prévu.

Ce chapitre constate également que les ménages ne sont sensibles qu'à la fiabilité lorsque les coupures sont trop fréquentes, et ce quel que soit leur niveau de richesse ou de pauvreté: ce résultat renforce l'hypothèse de sensibilité à l'incertitude et suggère que la fiabilité pourrait être le facteur de connexion le plus important, avant la richesse des ménages, la distance au réseau et la qualité de construction du bâti.

Comme elle est observable, la fiabilité du service agit sur la confiance des ménages dans la disponibilité à long terme du service électrique. La fiabilité n'est en effet pas le même type de déterminant de la connexion que la richesse, la qualité du bâtiment ou la distance au réseau de distribution: elle ne dit pas seulement quelque chose sur la faisabilité économique ou technique de la connexion, c'est aussi un facteur de contexte qui peut être directement et en permanence observé par tout le monde. Par conséquent, la fiabilité envoie un signal de long terme sur l'engagement de la chaîne d'approvisionnement en électricité à produire, transporter et distribuer de l'énergie sans interruption. Fournir un service d'électricité fiable se révèle ainsi être une condition essentielle pour une électrification durable, parce que la confiance à long terme pour le service peut aider les ménages non connectés à surmonter l'obstacle du coût de connexion, dans la mesure où ils peuvent alors espérer davantage de bénéfices de l'alimentation permanente en électricité que de préjudices liés aux coupures.

Ce chapitre contribue à la littérature existante en révélant la sensibilité des ménages au rapport qualité-prix du service d'électricité, ce qui montre le rôle de la fiabilité dans les préférences des ménages pour la consommation d'électricité. Il s'agit de la première évaluation de la fiabilité du service d'électricité en tant que déterminant important de la décision de connexion des ménages. Elle prolonge les recherches antérieures sur la qualité du service électrique en mettant l'accent sur son rôle pour une électrification efficace. Ce chapitre innove également en introduisant deux instruments innovants et efficaces pour l'identification économétrique: la foudre, mesurée avec des données fines, et la distance jusqu'à la centrale électrique la plus proche, exploitant la contrainte spatiale externe de la dotation aléatoire en ressources d'énergie primaire au Kenya.

Mais la fiabilité n'est pas une condition suffisante. Dans les zones où les coupures sont moins fréquentes, les ménages les plus pauvres sont les moins sensibles à la fiabilité du service d'électricité, qui préoccupe davantage les ménages les plus riches. Ce paradoxe peut s'expliquer par le changement de perception de la nature du service électrique en fonction du niveau de richesse: alors que la demande d'électricité de réseau par les ménages les plus riches est sensible à la fiabilité dans un contexte incertain, l'électricité reste un service de luxe pour les ménages les plus pauvres, donc très sensible au prix et substituable, d'autant plus dans un contexte d'incertitude sur à la livraison du un service. Il reste donc de la place pour des solutions alternatives à l'électrification de réseau, car la fiabilité n'est peut-être pas le levier d'électrification le plus efficace pour les ménages les plus pauvres.

Le deuxième chapitre, co-écrit avec le Professeur Jean-Claude Berthélémy, estime la probabilité que les projets d'électrification décentralisée obtiennent des effets favorables prouvés sur le développement durable (ou «impacts positifs»). Cette évaluation s'appuie sur une méta-analyse de 112 articles revus par des pairs, évaluant des systèmes hors réseau dans des pays en développement. Les effets ont été qualifiés favorables par notre avis d'économistes quant à leur contribution à l'amélioration du bien-être. La méta-base opère une distinction entre les effets estimés par les chercheurs avec des échantillons hétérogènes (données scientifiques) et les effets rapportés avec des statistiques invariantes ou des citations (données expert). Nous appelons «impacts positifs» les effets favorables prouvés avec des données scientifiques et «facteurs clés de succès» les déterminants de ces impacts positifs

Le premier résultat est la rareté des preuves scientifiques des bienfaits de l'électrification décentralisée pour le développement durable. Néanmoins, la rareté des impacts positifs n'a pas empêché de tirer des conclusions sur certains facteurs clés de succès, car les effets indéterminés fournissent de nombreuses observations contrefactuelles, permettant de tirer des conclusions et de consolider les connaissances à partir des résultats scientifiques établis.

Avec des métadonnées limitées, nous avons ainsi pu démontrer le rôle de la capacité, de la technologie et de la gouvernance comme facteurs clés de succès des projets d'électrification décentralisée.

La probabilité d'obtenir des impacts positifs augmente avec la capacité du système, ce qui prouve qu'une capacité limitée peut constituer un obstacle au développement. Ce chapitre souligne également l'apport de la flexibilité et de la disponibilité dans la conception du projet, dans la mesure où les mini-réseaux hybrides ont plus de chances de produire des impacts positifs que les nano-dispositifs solaires. En combinant diverses sources d'énergie primaire, un système hybride évite les coupures de courant dans un environnement aux ressources limitées. Ce deuxième chapitre trouve enfin un effet non linéaire du niveau de décision auquel le projet a été engagé, montrant une courbe en forme de U du rôle de la gouvernance pour l'impact des PED sur l'éducation: les décisions globales et locales sont des facteurs clés de succès, ce qui montre l'avantage de combiner les approches de gouvernance descendantes et ascendantes.

Ce chapitre contribue à la littérature existante en fournissant le premier prototype de métadonnées sur les effets et les caractéristiques des PED, intitulé Collaborative Smart Mapping of Mini-grid Action (CoSMMA). Il s'agit également de la première méta-analyse mesurant la probabilité d'impacts positifs des PED sur le développement durable, consolidant les preuves sur le rôle que jouent une capacité accrue, la flexibilité des systèmes hybrides et les avantages de la combiner les approches de gouvernance descendantes et ascendantes. La méta-base s'appuie également sur une collecte originale de statistiques invariantes et de citations (données expert), élargissant la collecte classique d'effets basés sur des échantillons avec variance (données scientifiques).

Le troisième chapitre classe les meilleures pratiques d'électrification décentralisée, en estimant quels types de projets ont le plus de chance d'atteindre les objectifs de développement durable. Il analyse les déterminants de la probabilité d'impact positif selon les pratiques et indique également quelles natures d'impacts positifs ont été le plus probablement observées par différentes pratiques. Une extension examine les déterminants de la nature des effets favorables observés avec les SSD individuels.

Les projets décentralisés pour les utilisations productives et les services publics, et les micro-réseaux pour l'accès dans les zones reculées sont les pratiques les plus efficaces pour le développement économique. Les SSD individuels et les mini-réseaux privés sont moins efficaces.

La différence d'efficacité entre pratiques provient de différences dans les déterminants de leurs impacts positifs. La probabilité d'impacts positifs augmente avec la capacité des SSD individuels, notamment pour les effets de nature autre que l'énergie et l'accès de base à l'énergie. Cette pratique détermine la relation croissante entre performances et capacité du système, décrite au chapitre 2. Les avantages croissants de la capacité des SHS individuels pourraient trouver leur origine dans des effets favorables sur l'information et la communication. Inversement, les micro-réseaux pour les zones isolées sont plus susceptibles d'avoir des impacts positifs avec une capacité réduite. Les avantages d'installer une capacité réduite pourraient être associés à des effets favorables sur la santé, le temps utilisable et les loisirs.

Ce chapitre constate également que le rôle de la gouvernance des PED en matière d'impact est complexe et dépend de la combinaison des pratiques et de la nature des effets. Pour les SHS individuels, la combinaison des approches ascendantes et descendantes de gouvernance existe principalement pour les impacts sur le 7ème ODD. Pour les micro-réseaux dans les zones isolées, la combinaison des approches locales et globales joue un rôle important pour les effets socio-économiques hors énergie, mais les pays et les provinces ont joué un rôle plus efficace pour l'accès à l'énergie.

Enfin, le troisième chapitre explore la nature des effets en fonction des pratiques, mais touche aux limites de faisabilité de l'analyse empirique en raison du nombre limité de données scientifiques. Les micro-réseaux pour les zones isolées montrent principalement des impacts positifs sur l'information et la communication, et les SHS individuels principalement sur la santé et l'éducation. Les micro-réseaux privés et les projets d'usages productifs et de services publics pourraient favoriser les transformations économiques ou être favorables à l'environnement, mais cette nature d'effets n'a pas encore été prouvée.

Ce chapitre contribue à la connaissance de l'électrification décentralisée avec une typologie empirique des projets hors réseau. Il présente le classement des meilleures pratiques et analyse leurs facteurs clés de succès pour le développement économique. Il fournit également un premier aperçu de la nature des objectifs de développement atteints par les deux pratiques principales de l'électrification décentralisée.

Cette thèse est organisée comme suit. Le premier chapitre évalue la probabilité de connexion des ménages au réseau national au Kenya en fonction de la fiabilité du service électrique. Dans le chapitre deux avec Pr. Jean-Claude Berthélémy, nous estimons la probabilité d'impacts positifs des projets d'électrification décentralisée comme résultant de leur conception initiale. Au chapitre trois, j'évalue les pratiques d'électrification avec une typologie statistique des projets, et j'explore leurs facteurs clés de succès. Je donne une cartographie finale de la nature connue des impacts selon les pratiques d'électrification décentralisée.

2. Introduction

As surprising as it may sound, access to electricity was only introduced in 2015 as a development goal, supporting the 7th Sustainable Development Goal (SDG): "*affordable and clean energy*". In 2018, about one billion people lived without electricity, 600 million of which are living in Africa; the good news is that for the first time, this number started to decrease, which means that access to electricity of households now occur at a faster pace than population growth. The still needed efforts are considerable but the new trend shows that most stakeholders involved in electrification are on the right path.

Reaching the 7th SDG has important implications for economic development, because the objective supports most if not all other SDG. Providing electricity should thus leverage other achievements of economic development.

Reaching universal access before 2030 will require $700 billion new investments (ESMAP, 2017). In order to avoid any waste of resources, efficient investments will need to both identify the key determinant of demand for electricity by households, and find solutions which have the highest chance of achieving other development goals than initial access to energy.

Because the objective has been so recent, economic research turns out to be urgent about evaluating the efficiency of electrification projects: the determinants of connection by households and the range of benefits for economic development remain little known. Past research on electrification focused on optimal grid patterns or theoretical potential and barriers. The benefits of electrification for economic development were implicitly obvious. But recent evolutions raised questions about the cost/benefit ratio of grid extension within a development perspective, the channels of demand for electricity in developing countries, and the effectiveness of new decentralized systems.

The traditional path of electrification, grid extension is facing many challenges: marginal cost of extension in rural area, hyperbolic costs in the most remote and difficult areas (mountains, islands), access to funding, maintenance and training, outages and corruption, preferences for electricity export.

Moreover, despite considerable efforts of grid extension in some countries (Kenya, Tanzania), households do not connect at the expected pace, largely bellow the targeted number of new connections [(Lee et al., 2014), (Chaplin et al., 2017)]: expanding technical features may not be enough to increase access to modern energy.

In the meanwhile, the production costs of decentralized systems decreased by 60% during the last five years and are expected to decrease at the same rate in the next five years: the sharp decrease of production costs actually puts solar electricity at the first place of merit-order curve in 2018 (ESMAP, 2018).[2] New decentralized systems are booming, offering feasible and affordable solutions for off-grid electricity access, down to the smallest granularity of production with individual Solar Home Systems (SHS).

However, most off-grid systems are capacity-constrained, only supplying limited power to users, which restricts the scope of possible appliances and raises legitimate questions about their effectiveness for other dimensions of economic development. In addition, other important features of Decentralized Electrification Projects (DEP) could affect their ability of providing positive impacts for development, because they involve very heterogeneous solutions, implying various choices of technologies or governance. For instance, the intermittency of solar electricity may limit the consumption of electricity to diurnal uses, unless batteries are added to photovoltaic panels: impacts on development could thus depend on the technological design. The occurrence of positive impacts could depend on governance design, too. For instance, some decentralized electricity accesses are sold by private local providers through bundles, the price of which varies according to the local competition intensity. The variety of governance choices regarding price, duration of service, or selection of target users can thus lead to many different electricity service patterns, which in turn could affect the probability of achieving positive impacts.

Hence, on the one hand, the pace of demand for grid connection may be much slower than expected, which in this case threatens the sustainability of infrastructure and questions the ability of traditional electrification model to reach unconnected areas and bring effective support to economic development. On the other hand, despite tremendous opportunity costs, the contribution of off-grids systems to economic development remains largely unknown and their effectiveness could be affected by the variety of projects design.

This thesis wants to explore which important channel of electricity demand may affect sustainable grid extension in developing countries, and which is the effectiveness of new pattern of supply with decentralized electrification projects.

The first chapter tests the hypothesis that the reliability of the electricity service would be the determining factor in households' preference for connection to the grid, thus constituting the main lever of efficient grid extension.

Permanent availability decreases the uncertainty about the effective access to electricity service; in turn, less uncertainty supports the long-term expectations of unconnected households about the availability of electricity in areas where the grid is accessible. Therefore they may confidently decide to

[2] The merit-order curve ranks technologies of electricity production according to their marginal cost. It is the supply curve of electricity economics.

connect to the national grid for a lasting consumption of electricity. With individual data on Kenyan households, the first chapter uses a robust identification methodology to evaluate the probability that households are connected to the electrical grid according to the reliability level of electricity service. It finds a significant effect of large magnitude: a one percentage point increase in electricity reliability yields a 0.82 percentage point increase in connections. Delivering fully reliable electricity service, electricity companies would achieve their targeted number of new customers 12 months earlier than planned.

This chapter also finds that households are sensitive only to reliability where outages are too frequent, regardless of their level of wealth or poverty. This result strengthens the uncertainty assumption and suggests that reliability could be the most import determinant of connection, before households' wealth, distance to the grid and building quality.

This chapter contributes to the existing literature by revealing the sensitivity of households to the price-to-quality ratio of electricity service, which shows the role of reliability in households' preferences for electricity consumption. This is the first assessment of the reliability of the electricity service as an important determinant of the household connection decision. It extends previous research on the quality of electrical service by emphasizing its role for efficient electrification. This chapter also innovates by introducing two innovative efficient instruments for econometric identification: lightning with fine level data, and distance to the closest plant, exploiting the external spatial constraint of random endowment of primary energy source in Kenya.

However, reliability is not a sufficient condition *per se*. In areas where outages are not so frequent, the poorest households are the least sensitive to the reliability of electricity service, which is more a concern for the wealthiest households. This paradox can be explained by the changing nature of electricity service according to the wealth level: while the demand for grid electricity from the richest households is sensitive to reliability in uncertain context, electricity remains a luxury service for the poorest households, therefore very price-sensitive and substitutable, all the more so in a context of uncertainty over the delivery of the service. There is thus still room for alternative solutions to grid electrification, because reliability may not be the most efficient lever for the electrification of the poorest households.

The second chapter, co-written with Pr. Jean-Claude Berthélémy, estimates the probability that Decentralized Electrification Projects achieve proven favorable effects on sustainable development. This evaluation is based on a meta-analysis of 112 peer-reviewed articles evaluating off-grid systems in developing countries. The favorable effects have been qualified by our opinion of economists as to their contribution to improving well-being. The meta-base makes a distinction between effects estimated by researchers with heterogeneous samples (scientific data) and effects reported with invariant statistics or citations (expert data). We call "*positive impacts*" the proven favorable effects with scientific data and "*key factors of success*" the determinants of these positive impacts.

The first result is the scarcity of scientific evidences of decentralized electrification's benefits for sustainable development. Nevertheless, the scarcity of positive impacts has not prevented us from drawing conclusions about some key factors of success, as indeterminate effects provide many counterfactual observations, allowing conclusions to be drawn and knowledge to be consolidated from established scientific results.

With limited metadata, we were able to demonstrate the role of capacity, technology and governance as key factors of success of decentralized electrification projects.

The probability of positive impacts increases with the system capacity, which demonstrates that limited capacity can be a barrier to development. This chapter also highlights the contribution of flexibility and availability in project design, as hybrid mini-grids are more likely to produce positive impacts than Nano-solar devices. By combining various primary energy sources, a hybrid system avoids power outages in an environment with limited resources. This second chapter finally finds a non-linear effect of the decision level at which the project was initiated, showing a U-shaped curve of the role of governance for impact on education: global and local decisions are key success factors, showing the benefit of combining top-down and bottom-up approaches.

This chapter contributes to the existing literature by delivering the first prototype of meta-data on DEP effects and characteristics, which we named Collaborative Smart Mapping of Mini-grid Action (CoSMMA). It is also the first meta-analysis measuring the probability of positive impacts of DEP on sustainable development, consolidating evidence on the role of increased capacity, flexibility of hybrid systems and the benefits of combining top-down and bottom-up approaches of governance. The meta-base also relies on an original collection of invariant statistics and citations (expert data), broadening the classical collection of effects based on samples with variance (scientific data).

The third chapter sorts the best practices of decentralized electrification, estimating which types of projects have the highest chance of achieving development goals. It analyzes the key factors of success of these practices and also indicates which natures of positive impacts were most likely observed by practices. An extension looks at the determinants of the nature of favorable effects observed with Individual SHS.

Decentralized projects for Productive Uses and Utilities, and Micro-grids for access in remote areas have the highest probability of achieving positive impact on economic development. Individual SHS and private mini-grids are less effective.

The difference in effectiveness between practices comes from differences in the determinants of their positive impacts. The probability of positive impacts increases with the capacity of Individual SHS, especially for effects of a nature other than energy and basic access to energy. This practice drives the growing relationship of performance with system capacity found in chapter 2.The growing benefits of Individual SHS capacity could find its origin in favorable effects on Information and communication. Conversely, micro-grids for remote areas are more likely to have positive impacts with reduced capacity. The benefits of installing reduced capacity could be associated with favorable effects on Health, Usable time and leisure.

This chapter also finds that the role of DEP governance for impacts is complex and depends on the combination of practices and natures of effects. For Individual SHS, the combination of bottom-up and top-down approaches mainly exists for impacts on the 7th SDG. For Micro-grids in remote areas the combination of local and global governance plays a significant role for other socio-economic effects, but countries and provinces levels plays a greater significant role for the effectiveness of access to energy.

Finally, the third chapter explores the nature of effects according to practices, but touches on the feasibility limits of the empirical analysis due to the restricted number of scientific data. Micro-grids for remote areas mainly show positive impacts on Information and communication, and Individual SHS mainly on Health and Education. Private Micro-grids and projects for Productive Uses and Utilities could favor Economic transformations or be favorable to Environment, but such natures of effects have not been proven so far.

This chapter contributes to the knowledge of decentralized electrification with an empirical typology of off-grid projects. It presents the ranking of best practices and analyzes their key factors of success for economic development. It also provides a first insight on the natures of development goals achieved by the two main practices of decentralized electrification.

The remainder of this thesis is organized as follows. Chapter one estimates the probability of households' connection to the national grid in Kenya according to the reliability of electricity service. In chapter two with Pr. Jean-Claude Berthélémy, we estimate the probability of positive impacts of decentralized electrification projects as resulting from their initial design. In chapter three, I assess the practices of electrification with a statistical typology of projects, and I explore their key factors of success. Ultimately, I provide a final mapping of known nature of impacts by practices of decentralized electrification.

Chapter ONE : Electricity supply reliability and households decision to connect to the grid

Abstract

This article assesses the implications of grid's reliability for economic development. Achieving the 7th Sustainable Development Goal (SDG) by investing in grid extension is costly and would result in wasting resources, were customers not at the rendezvous by subscribing an electricity contract. So far, empirical research on electrification assumed that any new access to electricity would result in new connections from households without power. This study examines whether uncertainty about outages in under-grid area influences households' decision to connect, despite low reliability of electricity service.

With households' level data from Kenya, this article finds that a one percentage point increase in electricity reliability would yield a 0.82 percentage point increase in connections. Therefore, delivering fully reliable electricity service can help electricity companies to achieve their targeted number of new customers 12 months earlier than planned.

This article also finds that households are sensitive to reliability whatever their wealth or poverty level in areas where outages are too frequent.

These results confirm the uncertainty assumption. Regular and severe outages yield an uninsurable context that changes households expectations about the quality of electricity service, in which households avoid connecting to the grid. Conversely, increasing reliability would attract more customers, sustaining an accelerated pace of effectively connected households.

Keywords: electrification; reliability; outages; Kenya; instrumental variable

JEL: Q4, QO1, O18, O55, C26, C52

Introduction

Achieving the 7th Sustainable Development Goal will be expensive: the cost to increase electricity supply in Africa could amount to $800bn. Moreover, severe and regular shortages might deter households from buying a subscription to the electricity provider, which in turn will increase the marginal cost of grid extension. Consequently, investor risk might increase, which could jeopardize future investment in new infrastructures. The low-quality of electricity service could thus increase the global cost of electrification far higher than the cost of building new plants and lines.

Electricity reliability can impact the sustainability of grid extension in several ways. First, the expected benefits of electrification would vanish if low-quality of electricity service yielded only a small increase in connections. Second, a lack of connections leads to a tenfold increase in the marginal cost of installing new transformers (Lee et al., 2014). Third, regular outages could dramatically reduce investors' expected returns, making them reluctant to fund any new electricity project, whereas sub-Saharan countries' financial resources and access to external funding are scarce. A vicious cycle could thus occur: aging infrastructure increases the frequency of outages, which inhibits subscriptions to the electric service, and thereby reduces the resources available to fund their replacement.

In this context, policy makers and investors cannot focus solely on the expected net present value of projects, which long-run achievement could be affected by a fewer-than-expected number of customers. However, when extending a reliable grid, there is a trade-off between extensive and intensive investments: the first of which fund the building of new generators, transformers and lines, and the second support the construction of new substations, cable capacity and quality, and balancing support ability.

Actually, (Chaplin et al., 2017) have showed that grid extension has only infrastructure effects[3] but does not change agents' behavior. Instead, reliability may change economic behaviors, because regular severe outages create uncertainty, which may change households' consumption or firms' production choices, leading to costly long-run inefficiencies. Conversely, (Chakravorty et al., 2016) proved that the benefits of reliable electrification for economic development could be so high that unit costs of grid extension by households can be covered by welfare gains in a single year.

Costs of connection, distance to transformers, and building quality have been considered as important factors of connection. But empirical works concluded one after the other about their limited impact on the connections' number. (Lee et al., 2014) found that distance to transformer was not significant, and plays only a secondary role once interacted with building quality. (Chaplin et al., 2017) and (Lee et al., forthcoming) brought clear empirical evidences that even strong subsidies have only limited effect on the connections' number, achieving far lower amounts than expected objectives by policymakers.

Reliability of electricity service could thus be an important omitted factor of electricity take-up. Addressing this question is urgent because the economic cost of outages increases exponentially with their duration and uncertainty (Kaseke, 2011).

(Andersen and Dalgaard, 2013) were the first to demonstrate the detrimental impact of electrical outages on growth in sub-Saharan Africa, finding that an increase of 2.3 outages per month reduces

[3] Rising prices of residential lands, rising number of electrified schools or health facilities, higher number of electrified businesses.

annual growth by 1.5 points. Their contribution is all the more important because it relies on lightning as an external instrument (Deaton, 2010) to solve the main identification issue faced by the literature on electrification, namely, the endogenous placement of the grid (Lipscomb et al., 2012), (Van de Walle et al., 2013). Lightning is not only external to grid extension or management but also strongly correlated with outages, although it remains exogenous to the outcome. Hence, lightning captures the causal impact of outages on growth.

With individual data on Kenyan households, this article uses the robust identification methodology of (Andersen and Dalgaard, 2013) to evaluate the impact of reliability on the probability that households are connected to the electrical grid. With lightning as the same strong instrument, the article checks the prediction of the macro-level model with a finer level of observations. Using micro-level data is relevant because (Chakravorty et al., 2014) showed that the impact of electrification can be verified by focusing on the households' revenue with individual data. In addition, the micro-level approach eliminates certain possible confounding factors that must be accounted for at the macro level, such whether the country is resource rich or located on the coast.

As suggested by (Van de Walle et al., 2013), this article also innovates by introducing distance to the closest plant as an instrument for outages, exploiting a peculiarity of energy production in Kenya, which is strongly constrained by the location of primary energy resource, because 75% of the generation capacity is constrained by natural geographical features (i.e., rivers, volcanos and coastal access. This study needs to extend the instrumentation because individual data introduce a finer measurement of variance across sampled units.

Another contribution of this article is that it focuses on one of the channels through which electrical shortages could impact annual growth, i.e., changes in households' behavior due to the uncertainty context. Given that most -if not all- of the literature is based on an underlying assumption of exogenous and homogeneous reliable power supply, disentangling this channel will permit an assessment of whether reliability is a condition for the sustainable development of electricity.

I also extend the referral specification of (Andersen and Dalgaard, 2013) by introducing a poverty index. Actually, (Lee et al., 2014) found that the wealth effect outweighs the impact of distance to transformers, showing that the economic effect is much more important than the technical feasibility. (Chaplin et al., 2017) have also showed a significant relative wealth effect with subsidized fees for connection, and they found a significant distance effect, but in a very short radius (30 m). I thus introduce poverty as the most important control, in order to identify the role of reliability, which I suspect to be an important omitted determinant of connection.

Finally, this article incorporates the notion of “under-grid” households, extending the work of (Lee et al., 2014) at the smallest granularity level : whereas they worked with compound data on households, I exploit the Afrobarometer survey that collects individual information on all household members.

Section I outlines the questions addressed by the literature, and Section II describes the electricity context in Kenya. Section III presents the data, and Section IV explains the identification strategy. Empirical results and robustness checks are provided in sections V and VI. Section VII concludes with a "what-if" scenario.

1. Literature review: known issues and opened questions

1.1. Techno-economic costs of electricity production and reliability

One strand of the literature evaluates the technical-economic costs of electricity production, considering either its output (cost of kWh) or its disruption (cost of outages). The levelized cost of electricity (LCOE) assesses ex ante the economic feasibility of projects, whereas the value of lost load (VoLL) and contingent valuation methods (CVM) evaluate the reliability's benefit, by measuring how much has been or could be lost due to outages.

The LCOE expresses the lifetime unit cost of kWh based on expected investment and future running expenses. Because electricity projects usually require large capital expenses ("capex"), it is crucial for investors to get an *ex-ante* synthetic measurement, in which lower operational expenses ("opex") might ease the recovery delay. This approach involves the producer of electricity in cost structure management before the project is brought to market because, unlike a net present value, the LCOE only takes into account the expected expenses, both upfront and long-term. (Nordman, 2014) uses an LCOE measurement to conduct a cost/benefit analysis of wind power station deployment in the tea sector in Kenya. Comparing distributed generation utilities with grid extension in India, (Harish et al., 2014) couple the LCOE with the loss of consumer surplus and find that the break-even point for an off-grid solution is at least 17 km from the grid, or even 6 km if fuel and oil subsidies in the grid are discounted.

However, the LCOE only provides a techno-economic measurement of the main expected output (i.e., the cost of kWh) based on the project's design and management. In addition, it focuses on internal parameters that are *ex-ante* valuated, and thus does not allow an assessment of the external benefits after the project has been implemented. Notably, the LCOE does not contribute to explain why or how the occurrence of outages could modify firms' or households' economic behavior.

The cost of reliability is defined by the VoLL as the average cost of unsupplied electricity in monetary unit per electricity unit (kWh) (Praktiknjo et al., 2011). Outages are evaluated as the economic loss of surplus that they trigger, not as damages to devices or the production deficit. The VoLL was estimated with Monte Carlo simulations in advanced countries such as Austria (Reichl et al., 2013) ; in German households (Praktiknjo et al., 2011); and after the explosion of a power station in Cyprus (Zachariadis and Poullikkas, 2012).

The VoLL appears to be better suited for advanced countries because its starting point relies on an assumption of full reliability: within a perfect electricity market, the cost of outages is seen as a divergence from the equilibrium. In contrast, in developing countries, the reliability context may be affected by a number of upstream factors, such as a low investment attractiveness ; limited access to funding ; constrained revenues for maintenance and replacement ; poor governance of electricity i.e. insufficient regulation and management of balancing ; inefficiency of transport due to on-line losses (Khandker et al., 2014), (Berthélémy, 2016) ; and the poverty constraint on existing grids, which can trigger theft, pilfering and vandalism of lines or meters (Shah, 2009).

The VoLL also fails to take into account how a context of persistent outages might transform consumers' preferences into constrained choices, because it assumes that the demand for electricity is exogenous and inelastic, whereas context can actually modify per se the demand curve for electricity.

Contingent methods have been used extensively, as noted by (Praktiknjo et al., 2011). Contingent methods rely primarily on the firm's cost management framework, integrating the direct and indirect costs triggered by outages in an attempt to obtain the complete cost of an electricity shortage (Pasha et al., 1989). (Diboma and Tamo Tatietse, 2013) have classified these methods into three segments. The CVM relies on a survey that assesses consumers' willingness-to-pay (WTP) to avoid outages, and their willingness-to-accept (WTA) outages. This method has been used by (Kjolle et al., 2008) to evaluate the cost of outages in Norway. With the contingent ranking method (CRM), consumers are asked to rank outage scenarios. The CRM has been used by (Willis and Garrod, 1997) for a study in the UK. The direct worth (DW) method asks consumers to evaluate their losses given a set of predefined outages scenarios (Küfeoğlu and Lehtonen, 2015). Using this type of survey and invoice data, (Diboma and Tamo Tatietse, 2013) have evaluated the complete cost of power interruptions for firms in Cameroon.

However, the alleged impact relies on households' declarations and thus suffer from two main confounders. First, the survey's participants self-evaluate the cost of outages and could thus yield a Hawthorne effect: they might exaggerate the reported information, as they hope any future quality enhancement of the electricity service resulting from the researcher's interest. In addition, none of those cost studies uses any econometric methodology, and some of them do not even use any observational data. Therefore, they provide no evidence of the causal link between electrical reliability and development.

1.2. How the literature evaluates the impact of outages on firms' investment decision

A second well-developed strand of the literature evaluates the impact of outages on firms behavior, bringing a comprehensive framework of the agents' response to the uncertainty context by self-producing electricity. However, these studies do not explain how a greater reliability could sustain firms production preferences for other goods and services that might support the economic development. Conversely, the level of investment or product variety might be affected by the outages context. In addition, this framework does not apply to households.

Scientific monographs have provided clues about the damaging inefficiencies caused by constrained production choices, whereby persistent outages might ultimately impair the expected benefits of electrification. In Kenya, (Kirubi et al., 2009) observed that handicraft workers constantly switch between manual and electrical tools due to regular outages. In India, (Smith and Urpelainen, 2016) also observed an increase in diesel irrigation pumps after the electrification of villages, despite the fact that those devices are costlier and less efficient than electrical pumps. These short-run constrained choices might lead to long-run inefficiencies; for example, after an eightfold increase in the price of fuel, the poorest farmer in Orissa abandoned high value-added crops for low-return rain-fed farming in open fields (Shah, 2007). Although eastern India is one of the wealthiest areas in the world in terms of groundwater resources, farmers no longer had the means to exploit it, and thus also lost centennial socio-economic know-how.

(Alby et al., 2010) established a theoretical framework that describes the conditions in which a firm would opt to invest in self-generation to cope with the uncertainty context. It relates the probability of acquiring a generator with the number of outages and adjusts the firms' utility for the cost of self-generation.

Recent econometric works have demonstrated the impact of outages on firms decision to self-generate (Allcott et al., 2016), or have considered the combined impact of outages and self-generation on productivity in sub-Saharan Africa (Mensah, 2016). Interestingly, the latter study uses the same instrument as (Allcott et al., 2016) for outages (i.e., the availability of water resources), as well as the parsimonious specification introduced by (Andersen and Dalgaard, 2013). With a difference-in-difference methodology, he finds that investment in self-generation has positive short-run effect on the firm revenue but a negative long-run effect on productivity, due to higher cost of self-produced kWh.

(Oseni and Pollitt, 2015) go further by evaluating the expected benefits of self-insurance in 8 countries in sub-Saharan Africa. Because the economic cost of outages can be enormous[4], this self-insurance is not everywhere affordable. In addition, self-generation does not necessarily reduce the losses caused by electrical shortages because the featured firms might still have large operational vulnerabilities and insufficient means to cope with all other costs stemming from the lack of power. This result is important for it shows that the context of regular outages might cause damages much larger than the capacity to hedge them, which sustains the un-insurable uncertainty rather than the assumption of risk.

Consequently, the frequency of outages does not appear to be the significant determinant for investing in a self-generator; rather, the determining factors are a firm's means or structural constraints, including its size, electrical consumption, trade openness, product variety or the country in which it is located. (Fisher-Vanden et al., 2015) thus advocate the assumption that a firm's expectation of outages -not the actual occurrence of outages- underpins its decision whether to outfit itself with a generator, conditional on its sectoral need and financial means to hedge this risk. Only (Arnold et al., 2006) have attempted to measure the effect of this perception held by firms, using a Probit model in the annex without any instrumentation or controls.

Research on firms yields two important conclusions: first, exploring the impact of outages on agents' behavior is feasible and second, the expectation of regular outages rather than their simple observation might be the true determinant of agents' decision. To the best of my knowledge, this approach has not yet been extended to households. However, the motivation of households to subscribe to electricity might also be rooted in other factors, such as their consumption preferences.

1.3. Evaluating the benefits of electrification or reliability of the electricity service ?

With a much smaller number of works, the last strand of the literature has started to evaluate the benefits of electrification for households, considering its impact on other socio-economic activities, such as the reallocation of time between household members, education, income and health. Certain authors, such as (Andersen and Dalgaard, 2013) and (Chakravorty et al., 2014), started to evaluate the effect of reliability on income at the macro and micro levels, respectively. However none of these studies assesses the potential impact of reliability on households' decision, through favorable conditions of trust that can sustainably change consumption preferences.

[4] In Nigeria, the VoLL of outages is 19 times higher than the price of electricity

1.3.1. Benefits of electrification and strong assumptions of evaluations

A subset of authors has evaluated the impact of electrification from a global perspective. In a seminal work, (Rud, 2012) uses the Green Revolution in India as a natural experiment, employing groundwater availability as an instrument for the share of connected agricultural units. However, the causal impact of industrialization found in that study does not reveal whether firms or households reap greater benefits from electrification. Qualitative studies also relates electrification to socio-economic transformations (Matungwa, 2014) or with electrical appliances (Martins, 2005).

A handful of works have conducted econometric evaluations of the impact of electrification on household outcomes. A referral work, (Dinkelman, 2011) finds a positive impact of electrification on women's employment in South Africa, using the land gradient as an instrument. The electrification program yielded a significant 9% higher level of women's employment in communities that had benefited from it, possibly because increased freedom from home production was converted into greater involvement in micro enterprises.

In Argentina, (Gonzalez-Eiras and Rossi, 2007) tried to assess the impact of electrification on household health based on the use of refrigerators. However, the identification framework did not permit any conclusion regarding heath benefits generated by greater access to refrigeration, thus leaving this important question unanswered.[5]

Other works have produced controversial results regarding women's increased free time and children's education. From 1992 to 2005 in Honduras, (Squires, 2015) found a significant negative impact on school attendance associated with a significant increase of the same magnitude in children's employment. Conversely, (Arráiz and Calero, 2015a) found a positive effect of solar home system installation on education : children spent significantly more time on homework and achieved more years of schooling in the treated group, possibly due to a favorable impact on time reallocation between adult men and women, with the latter group spending more time per day taking care of children. Using the distance to the distribution grid[6] as an instrument, (Aguirre, 2014) also claims a positive impact on education in Peru.

Regarding the instruments used in these studies, although they are exogenous to the outcomes, they do not appear to be fully external to the grid's geographical extension. For instance, although groundwater availability for agricultural units met the exclusion restriction for industrialization in (Rud, 2012), it might nonetheless be a policy driver for building new electrical lines in an area settled by existing agricultural units. Furthermore, as stated by (Dinkelman, 2011), utilization of the land gradient relies on prioritization of the grid's extension as a cost function of the altitude. Finally, distance to the distribution grid, which was used by (Squires, 2015) and (Aguirre, 2014), is exogenous to children's education but is not external to grid extension policy, which might be prioritized based on population density.

As clarified by (Squires, 2015), using the distance to the grid as an instrument relies on strong assumptions. The first assumption is that the grid is always extending and never shrinking; meaning that

[5] Their study establishes a causal relationship between the privatization of energy companies and access to electricity, and an association between privatization and refrigeration but reveals no significant link between privatization and malnutrition or food poisoning

[6] Medium voltage lines

distance to the grid should be a decreasing function of time. The second assumption is that the connection schedule is fully ordered in space, that is, sites are connected in order of their distance to the grid. Finally, it has been shown by (Lee et al., 2014) that distance to transformers have only a small impact on households' decision whether to connect to the grid.

In addition, all of the above mentioned studies rely on the implicit assumption of a fully-reliable extended grid. But the extension itself could be at the origin of more outages, which then reduces the attractiveness of the service : for instance, due to an accelerated grid extension, India suffers from the world's highest level of on-line losses (Khandker et al., 2014), which increases the risk of a tension's fall, and therefore the probability of outages.

In fact, (Aklin et al., 2016) showed that providing an available power has almost the same impact on households satisfaction than electrifying unconnected households. As explicitly clarified by (Lee et al., forthcoming), evaluations should separate clearly two components of electricity distribution : *First, there is an access component, which consists of physically extending and connecting households to the grid […]. Second, there is a service component, which consists of the ongoing provision of electricity.* Extending grids without available power could just result in a stagnating effective share of electrified population, missing the expected target of delivering Sustainable Energy for ALL (SE4ALL).

1.3.2. Evaluating the causal impact of reliability on households behavior

None of the above mentioned studies investigates how reliability might support the socio-economic transformations expected from electrification by modifying firms' or households' economic behaviors. Only few empirical works account for the specific benefit of reliability for economic development.

(Andersen and Dalgaard, 2013) have found that outages have a significant impact on countries' revenue. In 39 countries in sub-Saharan Africa, an increase in outages by one standard deviation reduces growth by almost one standard deviation, providing evidence that electrical reliability has large potential to increase the revenue of developing countries.

(Khandker et al., 2014) address the reliability issue, but only as a complimentary topic to electrification and they do not design a specific identification framework. Nonetheless, they provide the first clues regarding the important impact of reliability on households decision whether to connect, and on their subsequent behavior as electricity consumers. Notably, their results suggest that an improvement of service availability can increase the rate of adoption, and show that access to electricity reduces domestic kerosene consumption; reliability may thus transform constrained choices into preferences, with fewer resources dedicated to kerosene lamps.

But then, a large increase in electricity consumption by connected households has only a small marginal effect on their kerosene-purchasing habits. The observational data shows that under-grid households continue to purchase and consume more biomass for cooking than unconnected households, and this result has also been observed by (Arráiz and Calero, 2015b).

This surprising result suggests that an unobservable parameter could be at work: regular and serious electrical shortages might lead connected households to continue purchasing alternate fuel for lighting.

Only (Chakravorty et al., 2014) have started to evaluate the causal impact of the quality of electricity service on households income, defining quality by the daily availability of electricity. They show that the quality of electricity service strongly increases the income of non-agricultural household income. The marginal impact of reliability appears to be 62% higher than the mere access to the grid.

(Chakravorty et al., 2014) uses the variation of transmission lines density as an instrument for electrification or power quality: higher density of lines is correlated with higher probability to be connected or to receive better quality of power supply. This instrument provides an interesting measurement of the role of grid quality on outages' occurrence.

However, they assess both roles of connection and quality in parallel, but do not investigate whether quality might have itself an effect on the grid's connection.

As noticed by (Van de Walle et al., 2013), "e*fforts to address the identification problem using single cross-sectional surveys are plagued by concerns about the endogenous placement of electricity*". Interestingly, they argue that using the distance to the primary power source would be less of a concern, because the location of primary energy spots is more likely to be independent to the location of households.

(Andersen and Dalgaard, 2013) were the first to assess the causal impact of reliability with an innovative efficient instrument for outages. Actually, lightning meets all three required properties for a valid instrumentation: it is purely random, strongly correlated with the occurrence of outages, and obviously not a direct factor in countries' revenue variations.

1.4. The existing frameworks do not address the uncertainty context of repeated outages

None of the above-discussed studies considers the long-run uncertainty context. However, repeated outages might alter household and firm preferences, turning the latter into constrained choices.

The existing framework in electricity economics provides only an incomplete analysis of the costs of uncertainty. LCOE and VoLL remain limited to endogenous measurable parameters ; they do not assess any external risk factors that might impact the cost of kWh on a broader basis, such as pilfering (Berthélémy, 2016). The latter remain un-priced negative externality: rental behavior around electricity distribution may divert a portion of the common good but also exacerbates the risk of outages in particular locations, thereby worsening the impact of uncertainty as an unaccounted negative externality.

The existing framework also does not explain why reliability might generate lasting changes in households' way of life. Because it is not insurable, uncertainty might change the agents' long-run decisions, such as the equipment rate of electrical devices in households, or the product mix of firms. The question of how reliability might produce long-term reallocation of the agents' preferences, by smoothing their cost function and enabling them to enter into a broader scope of more complex economic applications, remains unanswered.

Furthermore, no work has evaluated the economic impact of outages on agents' behavior while facing uncertainty. Because the VoLL relies on the consumer and producer surplus theory, it is suitable for evaluating a divergence from an initial stable equilibrium, assuming that the cost of any breach in reliability might only equal the distance from this equilibrium.

But the frequency and length of outages might sustain agents' expectations of a persistent low reliability, because from the agents' perspective, shortages are external events. In turn, agents might avoid the service despite their need for it. Those changed expectations could durably alter the ability of the electricity market to achieve a dynamic equilibrium, because underestimated latent demand might lead to an underestimation of the peak load and capacity sizing; consequently, any enhancement in reliability might trigger a larger-than-expected increase of demand, while supply has been kept constrained, triggering worse and lasting outages.

The literature addressing the issue of self-generation opens a door on the behavioral impact of outages. As rational agents observe a context of persistent uncertainty, they expect that the best predictor of tomorrow's reliability is the level of reliability observed in the past. Because uncertainty is not measurable through any law of probability, hedging its expected costs requires continual means to address the occurrence of shortages and hence a persistent counter-solution, such as self-generation. However, the literature has revealed that this strategy is somehow inefficient, most likely because firms might have to pay triple the permanent fixed cost for electricity consumption: once for the fee to connect to the grid, second for the CAPEX for its own generator and third for the OPEX to self-produce. But in parallel, electricity input would be charged only once as a constant fee in the industrial product sold to the final consumer.

A persistent distance from equilibrium could thus change the agent's expectations and hence the economic decision whether to connect and use electricity through a marketable contract; underestimating latent demand could make the disequilibrium even worse for any supply enhancement. To the best of my knowledge, the electricity economics literature lacks a comprehensive framework for the sustainable reliability benefit that the VoLL or electrification evaluation can hardly address.

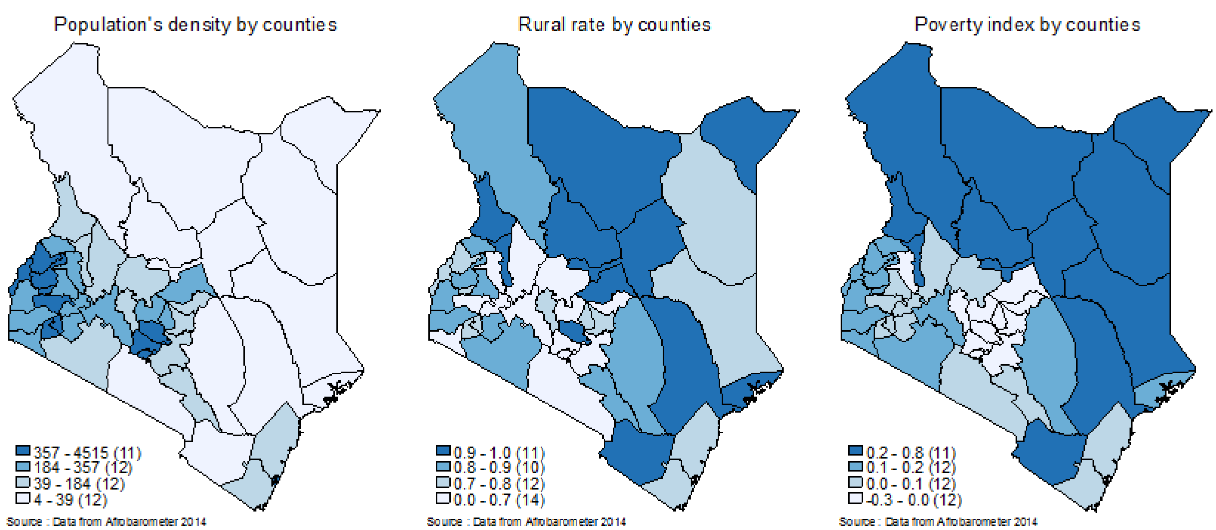
2. Population, Electricity infrastructure and lightning in Kenya

Population doubled in Kenya between 1990 (23.4 million people) and 2014 (46 million people)[7], while the transmission network was still made of 66 kV and 132 kV lines built before independence in 1963 (maps A.10). And between 2009 and 2014, the number of electricity customers (2.766 million, +218%) grew 5 times quicker than installed capacity (1,885 MW, +40%).

However, the peak-load only grew by +41 % (1,468 MW)[8], meaning that new connected households do not consume a high amount of power, which was later empirically proven by (Lee et al., forthcoming) : experimental data shown that those new customers only consumed 2 to 7 kWh per month. Apparently, the pace of new installed capacity did thus sufficiently covered the rhythm of growing peak-load, meaning that reliability issues of electricity service most likely did not arise from a lack of capacity.

The largest city are Nairobi (6.5 million with metro area) in the center-south, Mombassa (1.2 million) on the eastern coast and Kisumu (0.5 million) close to Lake Victoria. Most of the population is in fact distributed in rural area (center map in Figure 2) : the average urban rate was 25.4% in 2015[9], and over 47 counties, only five are more than 50% rural (CRA, 2011). The average population density is 92 per km², which hides large heterogeneity (left map in Figure 2): western area concentrate a numerous rural population (> 300 per km²), while northern and eastern counties are almost empty (<17 per km² in Marsabit, Isiolo, Tana River, Samburu, Wajir, Turkana, Garissa, Lamu and Taita Taveta).

Figure 2: Population, rural rate and poverty by counties in Kenya



For the sake of further instrumentation, it's important to stress that 56% of the electricity produced by Kenya in 2014 originated from natural primary sources (Figure 3, left). A large share came from geothermal origins (19.1%), which continued to grow in 2015 (26.6%). Notably, Kenya owns the largest

---

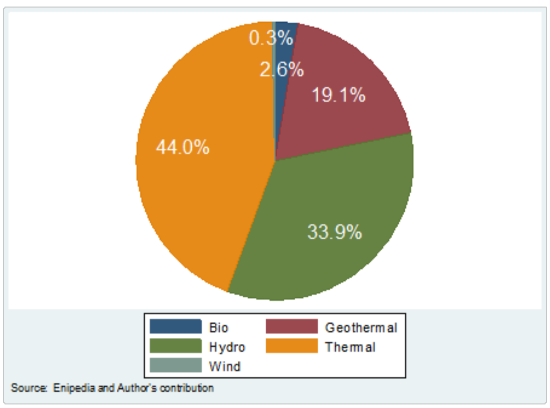
[7] Source : *World Bank*
[8] Source : (KPLC, 2009), (KPLC, 2014)
[9] https://www.worldometers.info/world-population/kenya-population/

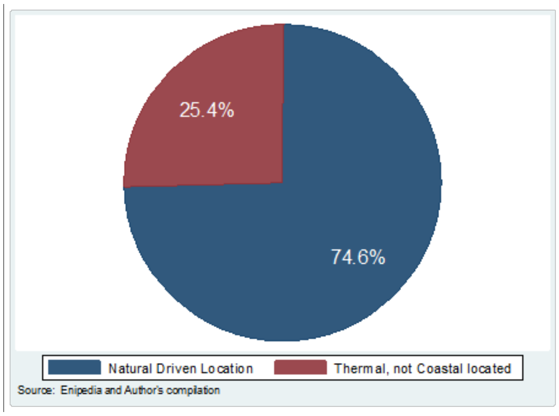
single geothermal plant in the world in Olkaria IV (140 MW), and the geothermal industry produces the cheapest electricity in the country.

In addition, 18.6% of thermal production is located alongside the eastern low-populated coast (Figure 3 : left minus right) and notably is concentrated around Mombassa in order to avoid the transportation cost of fuel: before 2014, a significant share of electricity production must be transported through the old 132 kV-transmission line (see map A.12) from Mombassa to Nairobi (700 km), or farer toward Eldoret (> 1000 km).[10]

Taking into account those coastal thermal plants, almost 75% of produced electricity in Kenya originates from a place that is strongly constrained by the location of the primary source of energy (Figure 3, right).

Figure 3: Energy mix of electricity production in Kenya





The electrical sector in Kenya was reformed in the 1990s (Eberhard and Gratwick, 2005), following the separation scheme between Production (P), Transmission (T) and Distribution (D) (Figure A.1). Production is made by a historical producer (KENGEN), a majority government-owned company that produces over 85% of the country's capacity, and independent power producers (IPP). Under supervision of Electricity Regulatory Commission (ERC), producers contract Purchase Power Agreements (PPA) with the Distribution System Operator (DSO) (KPLC), which is majority government-owned and operates under a Private-Public Partnership (PPP) mandate with ERC. The Transmission System Operator (TSO) is 100% government-owned (KETRACO). The Geothermal Development Company (GDC) is a state-owned Special Purpose Vehicle (SPV) dedicated to the development of geothermal production. The Rural Electrification Authority (REA) is the state agency addressing the issue of unconnected under-grid households in rural areas.[11]

In Kenya vision 2030, building new capacity, extending new transmission lines (above 132 kV) and new distribution lines (below 66 kV) are defined as the two main priorities, leading to two strategic projects:

- a quantified roadmap for building new capacity (5000+ MW in 2016), for which KPLC is responsible,

[10] As shown by comparing maps A.11 and A.12, the 400 kV transmission line between Mombassa and Nairobi only opened after 2014.
[11] REA was changed to Rural Electrification and Renewable Energy Corporation (REREC) in 2019, stressing the high share of renewable resource in the energy mix of Kenya.

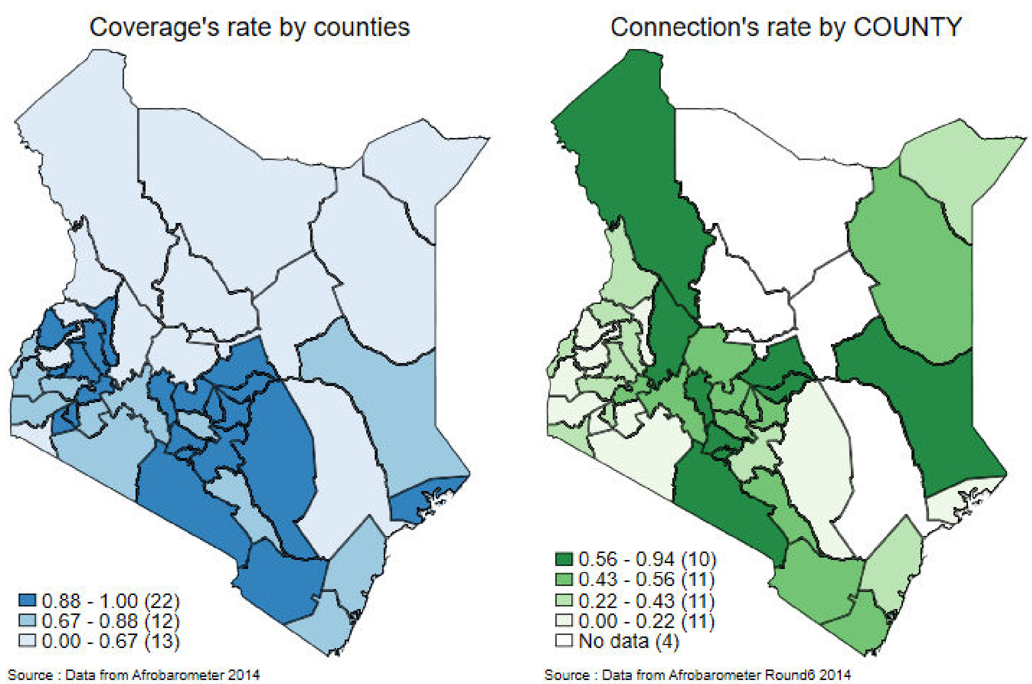
- and the *Last Mile Connectivity* project, which was launched by the REA in September 2015.

As shown by (Figure 4), the connection rate remains below 50% in one-half of Kenya's counties. The *Last Mile Connectivity* project aims at connecting 70% of households by 2017, by extending the grid of distribution lines and transformers. As shown by (Lee et al., 2014), the lack of connections multiplies the marginal cost of grid extension by ten. Therefore, the project includes a special effort for the poorest households, reducing the connection fee from KSh34,000 to KSh15,000[12], which are respectively USD421 and USD186.[13] This program targets 314,000 households around 5,320 selected transformers in first phase.

The average revenue per capita in constant 2010 US$ grew by 17%, from USD 917 in 2009 (one year before the new constitution) up to USD 1076 in 2014.[14]

Therefore, the connection cost for the poor in 2014 was equivalent to 17% of annual revenue in 2010 US$, which is 2 months of income. However, poor people do not earn an average revenue: 43% of households earned less than Ksh10,000 in 2016, and 70% less than Ksh25,000. Were they eligible to the *Last Miles Connectivity* project, the connection cost would actually be equivalent to 7.2 months of income for 70% of people, and more than 1.5 year of income for 43% of them. Even with a subsidy, financing works in order to connect a dwelling to the national grid is a consequential budget for most of the households in Kenya.

Figure 4: Coverage's rate and connection's rate by counties in Kenya



[12] https://www.kplc.co.ke/content/item/1694/last-mile-connectivity-program-q---a
[13] With exchange rate at 0.01240 on November 30th 2010. I use year 2010 as monetary reference year in order to compare with direct reading of some World Bank indicators.
[14] https://data.worldbank.org/indicator/NY.GDP.PCAP.KD?locations=KE

KPLC is rationing supply with planned outages to avoid national blackout, which has generated tensions between firms and households so far. The historical choice has been to prioritize reliability for firms in order to avoid deterring foreign investors from operating in Kenya. As a result, frequent outages could have caused reluctance among households to subscribe because they might consider the cost of service too high given its erratic availability. And thus, a higher number of connections on a limited grid could trigger lower reliability which in turn could be a barrier to further extension.

65% of KPLC's customers are charged by a pre-paid tariff for consumption: this large share of customers seeing a pre-payment on their electricity bill might significantly increase the sensitivity of unconnected households to the quality of electricity service, through reputational knowledge about the price-to-quality ratio of electricity service.

It's also important to mention that the fixed charge on electricity bill due to KLPC only covers the installation, maintenance and customer service by the DSO: the bill does not include any fixed cost for the operation or renewal of the transmission network. In November 2014, 64.5% of the cost of kWh for a typical bill was due for consumption[15], 16.3% for production and 13.3% for VAT. Other costs included: variable adjustment for inflation and foreign exchange rate fluctuation (2.25%), levies for the management of water resource and rural electrification (3.4%), and a tiny fixed levy for the regulatory commission (0.1%). Comparing with the tariff structure in advanced countries, the electricity bill in France for instance covers around 1/3 for production, 1/3 for taxes, and 1/3 for grid's investments in maintenance and renewal of utilities, with a specific fixed cost (TURPE[16]) charged on customers' bill.

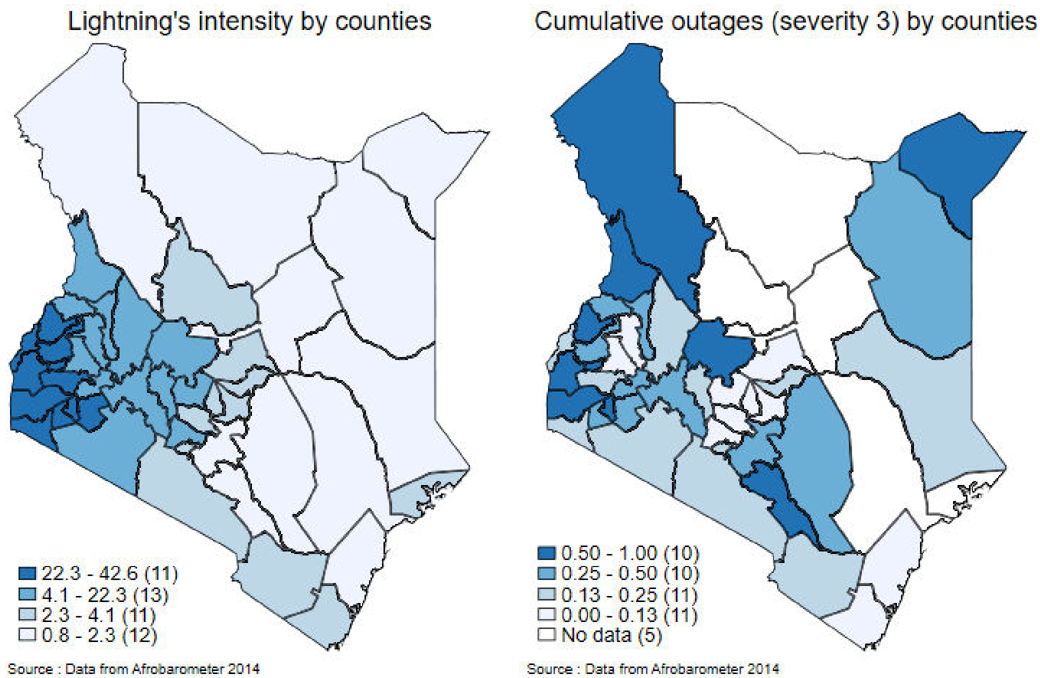
The lack of a specific layer for transmission cost in tariff structure might explain the strong discrepancy between the state of the transmission grid inherited from the independence time in 1963, and the real need for the population in 2014.

Under equatorial latitude, Kenya is also among the countries with the greatest exposure to lightning storms in the world, with a keraunic number that is 9 times higher than that of France. Compared to other sub-Saharan countries, Kenya exhibits a strong heterogeneity in lightning levels, being among the highest in the world in the western mountainous provinces, but comparable to Europe in the eastern regions (Figure 5, left). Randomness, intensity and heterogeneity makes this variable a good candidate to be an instrument for outages.

[15] https://stima.regulusweb.com/

[16] Tarif d'Utilisation des Réseaux Publics d'Electricité

Figure 5: Electrical outages and lightning by counties in Kenya



3. Data, indicators and descriptive statistics

3.1. Data

The data on electrical coverage, connections and outages are obtained from the Afrobarometer survey on Kenya. Afrobarometer is a survey on households covering 36 countries in Africa. It uses a proportional sampling probability that ensures representativeness of surveyed units in each country, according to the size of population in units. The survey is stratified and populated through a random draw at five degrees.

I use round 6 on Kenya (Afrobarometer, 2014), which was released in 2016 with interviews made in 2014. Because the previous interviews from round 5 in Kenya were conducted in 2010, the survey provides observations on a 4-year interval, providing a cross-sectional dataset for the study.

The dataset contains 2,397 observations at the household level, that are segmented by 47 counties and 139 districts, of which 120 districts have access to the grid.

1,989 respondent households live in sampling units with access to electricity. Access to electricity is known thanks to the descriptive part of the questionnaire, which is completed by interviewers who check the presence of grid access in sampled units (Table A.3).

The individual connection is known by individual interviews (Table A.4). In the same question, the interviewer also asks to the household how frequently it observed power availability over the last four years, using a qualitative assessment based on five possible levels (Table A.4) : 1 : never, 2 : occasionally, 3 : half the time, 4 : most of the time, and 5 : all the time. Those categories nurtured the computation of an outages' uncertainty index, about electricity availability.

The Afrobarometer survey also provides descriptive information about the portable assets owned by each household (e.g., radio, television, mobile phone, motor vehicle), the type of water and sanitation to which it has access, the type of shelter in which it lives in and the type of roof on this shelter. Those variables nurtured the computation of a poverty index.

Data on lightning are flash/km²/year. They're sourced from the *LIS/OTD 0.5 Degree High Resolution Full Climatology* (HRFC) dataset, with a 0.5° resolution. These numbers have been averaged for the period 1995-2013, providing a long-term average of lightning intensity, before the observation of households' connection (in 2014). At the districts level, the pixels' resolution was set at 1km, then the average of pixels data was computed within each district, which limits the risk of overlapping.

Climate controls (altitude, temperature and precipitation) are provided by the geographical database of the FERDI, as well as the distance to Mombasa, which is weighted by road quality.

Locations of utilities are provided by Delft University from its Enipedia collaborative database (Davis et al., 2015), whereas the capacity data are supplemented by the author's research, based on cross-checked media investigations, as of 2014.

3.2. Definitions of variables

3.2.1. Under-Grid households and connection status

Relying on *under-grid households*, as in (Lee et al., 2014), this study is performed on households in districts with access to electricity. Nonetheless, because Afrobarometer lacks data on transformers' location, this article defines an *under-grid* household as one living in a district where at least two households from the survey are connected to the grid.

The connection status (*Connection*) is a dummy variable that is equal to 1 for a connected household. The empirical strategy exploits the geographical heterogeneity of the connection rate, which ranges from 94% in Nairobi to 4% in Homa Bay (see Figure 4, right).

3.2.2. Index of uncertainty about the availability of electricity service

Observing outages from households' point of view provides a long term proxy of the uncertain context, in which households must decide for the long term use of electricity supplied by national grid.

I use the observed availability by households in order to compute cumulative functions of outages, as proxies of the uncertain context about the reliability of electricity service. I build a range of uncertainty indexes, following the methodology of severity indexes of drought by (Palmer, 1965).

I use the categories of electricity availability in a reverse order (see table A.5), which provides a scale for the reliability of the electricity service: a low level of availability corresponds to a high intensity of outages. Because the data cover a 4-year interval, availability in this survey cannot be understood as part of the service design, like for instance in (ESMAP, 2015). In the latter, availability refers to the daily duration of electricity access, and it is pre-defined as part of the electricity contract.

Observing a lack of availability over four years rather provides a measurement of outages' intensity, with electrical shortages that can last several days. For instance, a household answering "half the time" gives a proxy about an average outages' intensity around 50%, over a time span of 4 years. In this context, the lack of electricity is comparable to a lasting drought, causing serious impediments to sustainable development. Important decisions of consumption, production, or living conditions are interrupted or changed due to the lack of power, and the uncertainty aversion for such interruptions might deter households that observe repeated lasting outages from connecting to the grid. Therefore, repeated lacks of this important resource over long time periods actually causes an uncertainty context that may change households' expectations for the future, and thus may prevent from observing sustainable favorable socio-economic effects.

3.2.2.1. Intensity of outages by districts, from reported availability by households

First, I compute the rate of outages at the districts' level (ro_d) as the proportion of connected households observing the level of availability *j* in district *d*. For various values of *j*, the outages' intensity is qualified as follows: 1: *total*, 2: *serious*, 3: *partial*, 4: *occasional* (see table A.5).

$$ro_d(j) = \frac{1}{n_d}\sum_{i=1}^{n_d} \mathbb{1}(availability = j), n_d = \text{number of households in the district}$$

For instance, 8.3% of connected households in Baringo Central observe that electrical power is only occasionally available (table A.5), which I use as a measure of *serious* outages' intensity in Baringo Central. In the same vein, 4.8% of households in Igembe report a *total* outages' intensity, 9.5% a *serious* outages' intensity, 47.6% say that outages are only *occasional*, and 38.1% do not observe any outages.

The rate of outages is computed with those households that can observe the availability of electricity service, thus households that are connected to the grid. Among 2397 households in sample, 1017 have a connection (table A.4). However, crossing both questions shown in table A.5, it could be the case that some households answered something about the availability of electricity service, although they live in an area that does not have any access to the electrical grid (table A.3): 46 of such inconsistent observations were filtered from the computation of outages rates. At the end, 971 observations were used for the estimation of outages' rates.

Due to the limited number of observations in sample, 13 districts reported only one connected household. In such cases, the reported outages' intensity would be 100% for the level indicated by this household and 0% for any other level. Outages' rates were estimated only with districts counting at least two connected households.

3.2.2.2. Index of Outages' uncertainty

Second, the *Index of Outages' Uncertainty* $CO_d(q)$ is defined as the cumulative rate of outages in district *d* until level *q*. For any district *d*, $CO_d(5) = 1$

$$CO_d(q) = \sum_{j=1}^{q} ro_d(j)$$

I associate now an arbitrary frequency α with each level *q* in table A.5, using the central denomination ("half the time") as the central quantification ($\alpha = 50\%$). Therefore, the index $CO_d(q)$ provides an empirical proxy of the cumulative probability of outages: P(availability $\leq\alpha$) = P(outages >1- α). However, intermediate values of threshold α remain unknown.

For the sake of illustration, I allocate an heuristic 25% variation for each level below the 5th, using the first level as starting point (P(availability = 0%) =α).[17] For instance in Igembe (table A.5), P(availability ≤ 50%) = 4.8 + 9.5 +0 = 14.3%. In other words, the probability to observe outages more than half of the time in Igembe equals 14.3%. In Westlands, P(availability = 0%) = 4.2%, ie. P(outages = 100%) = 4.2%. Then P(outages > 75%) = 4.2 + 12.5 = 16.7%, and adding further 8.3%, there is a 25% probability to observe outages more than half of the time. What will enter into the regression is the cumulative probability (14.3%, or 16.7%) of outages, but the real frequency α remains unobservable.

3.2.2.3. Why an uncertainty index?

The question on availability in Afrobarometer does not measure directly a probability of outage (Annex A.4). Therefore, I cannot measure the risk of outages by a probability law estimated from a random distribution: for this, I would rather need data on technical failures of the national grid in Kenya, which are hardly accessible and might be affected by a strong disclosure bias, hence a strong measurement error.

However, using households' answers provides several outages' intensities in the same district, which can come either from various subjective perceptions across households, or from outages occurring in smaller area than districts. I assume that the smallest geographic units where outages can occur are districts: therefore, differences between outages' intensities are only due to subjective differences between households of the same district.

I can thus use households' perception in order to proxy the uncertainty of electricity service with external economic agents which are directly affected by supply disruption. The cumulative function of reported outages provides a quantitative proxy capturing uncertainty because it allows ordering households' preferences in the same district, according to subjective probabilities of the event.

In uncertain context, electricity is a substitutable good, as shown by (Kirubi et al., 2009) or (Khandker et al., 2014). There might thus be a hidden acceptance threshold, above which households show tolerance to the outages' context; whereas below this threshold, any new outage will conversely delay the adoption of the service. Because this threshold cannot be observed, the cumulative indicator approximates it with gradual definitions of uncertainty indexes (see Table 1).

[17] The event "availability = never" exists and is thus measurable. To the opposite defining P(availability ≤ 0%) would be a nonsense.

Table 1: Indexes of outages' uncertainty

Level (q)	*Outages' intensities included*	*Qualification*	*Cumulative probability of outages*
1	Total	Restricted Uncertainty index	P(outages= 100%)
2	Total + serious	Serious Uncertainty index	P(outages>75%)
3	Total + serious + partial	Large Uncertainty index	P(outages>50%)
4	Total + serious + partial + occasional	Extended Uncertainty index	P(outages>25%)

Each level q corresponds to a categorical level of availability, as observed by household. With a reversed-scale, answers are transformed into 4 uncertainty indexes. With heuristic assumption about quantification, last column shows the hypothetical cumulative function associated with each level of uncertainty.

The Large Uncertainty index was retained as the most relevant level of reliability measurement. First, this choice was driven by statistical criteria, with respect to significance and robustness of the instrumentation, following a backward-decision chain of 9 statistical tests (Annex A.9). Second, by using the Large index, I can capture a wide range of situations, whereas the Heavy and Serious index would only capture uncertainty in districts that are the most exposed to low reliability; and the Global index would be too large and could not be discriminatory enough.

3.2.3. Poverty index (control)

Following the work of (Booysen et al., 2008), a composite poverty index (*poverty*) is derived from a multi-component analysis (MCA) of the unconnected assets owned by a household (Table 2), using data on water and sanitation facilities, shelter type and roof type. This synthetic index or poverty enriches the work of (Lee et al., 2014) who utilized only wall quality, and it also exploits the richness of the Afrobarometer data.

This index is the linear combination of standardized coordinates of the categories on first axis, weighted by their contribution. It achieves a non-dimensional index between -1 and 1, which is computed for each household, with positive values for the poorest ones; the wealthiest households report thus a negative index.

Table 2: Active variables in the MCA

Q91a	Own radio radio
Q91c	Own motor vehicle, car or motorcycle motor
Q91d	Own mobile phone
Q92a	How often use a mobile phone
Q93a	Source of water for household
Q93b	Location of toilet or latrine sanitation
Q104	Type of shelter of respondent shelter
Q105	Roof of respondent's home roof

Variables on households' assets originate from Afrobarometer 2014 survey. Only non-electrical assets enter into the MCA

The first axis of the MCA concentrates 54% of the inertia, whereas the second (21%) and third axes (3.3%) are largely built from the missing values of certain peculiar categories. Hence, the first axis concentrates a high level of inertia, capturing all meaningful dimensions of wealth. It is thus used as the synthetic composite index, with positive sign for poverty (Table A.7).

Using a synthetic index of poverty, all un-connected assets are taken into account, while avoiding a too high collinearity that would result from introducing all assets simultaneously. And because the index results from an MCA, only the most important partial correlations are kept into the first axis.

3.2.4. Long-term average of lightning (instrument)

I'm computing a long term average of lightning between 1995 and 2013, as a measurement of the weather context in which the Kenyan grid must operate. Lightning can affect the reliability of electricity service because it can be at the origin of a surge, which causes an automatic interruption of power transmission or distribution by circuit-breakers (see table A.6).

I'm thus using lightning as an instrument of outages, but I don't need that lightning explain all variance of outages. In fact, some outages may be due to management choices or other external causes (weather, animal, vehicles) affecting grid management (KPLC, 2016). I'm not looking for an instrument whose variance would explain 100% of the variance of outages' uncertainty, but that is enough correlated with this indicator.

Although the connection is observed at time of interview (November 2014), the decision to connect may result from a long time decision-process. Connecting to the grid is a structuring decision on several dimensions: it may impact the household's budget constraint, change some living conditions or its daily organization. The connection can hardly be considered as an impulsive purchase, but to the opposite, I assume that this decision is strongly affected by a long term context, which shapes long term expectations.

It is thus preferable to use the long term trend of lightning before the decision to connect, instead of a short term measurement over one year at time of the survey. Indeed, this trend provides a measurement of the usual context of lightning that lastingly affects the observations of outages, the latter being at the origin of the household's decision.

3.2.5. Distance to the closest utility (instrument)

The electricity production in Kenya is strongly constrained by the location of primary energy sources, and those natural endowments are largely external to the distribution of population across districts. The old under-sized transmission lines hardly suffice to establish an efficient junction between production's and consumption's locations, which makes the map of utilities orthogonal to the locations where electricity is consumed.

Yet bottlenecks in the grid arise from those discrepancies between the locations of primary energy sources; the old under-sized network of transportation (see maps A.10); and the spatial distribution of population in rural areas (see left map in Figure 2). Bottlenecks in an electrical grid might be at the origin of outages, because voltage's shortfall might rapidly turn into a complete shortage of power.

The distance to the closest plant provides a proxy of bottlenecks' probability, because the distance that electricity can travel without any voltage's step-up mainly depends on the initial potential energy (voltage) at starting point. In addition, on-line losses are twice higher in Sub-Saharan Africa than in advanced countries (Berthélémy, 2016), and they do exacerbate the occurrence of bottlenecks along the lines by shortening the distance that power can reach.

I compute the Weighted distance to the Closest Plant (WCP) as the smallest Euclidian distance between the utility's coordinates and the district's centroid, weighted by the capacity of utility with respect to the total capacity of all utilities in Kenya.[18] Due to the relatively short extend of Kenya, computing a quadratic distance is an acceptable proxy of the ellipsoidal distance on Earth.

3.3. Descriptive statistics on estimation sample

As shown in Table 3, connection status and outages' index were not observable for all households. 1669 households report non-missing values for both dimensions.

Table 3 : Observable Connection Status and Outages

	Connection Status		
Index of Outages' uncertainty	unknown	observed	Total
	No.	No.	No.
unknown	248	320	568
observed	160	1669	1829
Total	408	1989	2397

In each wave of Afrobarometer survey, 2400 households are interviewed. 3 observations were missing in the 2014 survey. Connection status is missing for 320 under-grid households and 568 under-grid households did not answered about electricity availability in their district. Both variables are observables on 1669 households

Because no other variables but connection status and outages had missing values, the estimation sample is delimited by the number of non-missing observations (1669) of connection and outages. This estimation sample covers 90 districts.

As shown in Table 4, 57.4% of households in estimation sample had a connection to the national grid. The electrification rate in-sample (57.4%) is higher than the global electrification rate in Kenya in 2014 (36%)[19] because the estimation sample covers only under-grid households observing reliability: un-connected people might be prone to not answer to the question about power availability in their district.

[18] Distance is divided by the ratio: capacity of the plant / total capacity. A plant is closer if geographic distance is shorter or capacity is higher.

[19] Historical electrification rate in Kenya, source ESMAP.

Table 4: Descriptive statistics for in-sample variables (IVPROBIT)

	count	mean	sd	min	max
Connection	1669	0.574	0.495	0.0	1.0
Large Outages' Uncertainty	1669	0.271	0.280	0.0	1.0
Poverty	1669	-0.037	0.319	-0.9	1.0
Lightning intensity	1669	9.661	10.765	0.6	43.3
Weighted distance to Closest Plant	1669	9.168	7.885	0.3	47.6
Observations	1669				

Estimation sample contains 1669 non-missing observations for outages' uncertainty and connection. Other variables do not show any missing observations. 57.4% of households have a connection. 27.1% observe an outages' uncertainty associated with a probability of outages strictly higher than 50%

The average poverty index is equal to -0.037, spreading between -0.9 and 1.

On average, 27.1% of households across under-grid districts claim about a Large Outages' Uncertainty: the probability that electricity is unavailable at least half of the time equals 27.1% (see section 3.2).[20] This probability can be compared with the referral measurement of reliability, as published by KPLC.[21] The System Average Interruption Frequency Index (SAIFI) is defined as the ratio of total number of customer interruptions / total number of customers served. It's also part of two World Bank's scores in Doing Business and Rise. SAIFI in Nairobi equals 12.0 as of December 2018, which provides a minor in the best place at the best time.[22] This comparison shows that households' observations provide a unique way to achieve a broader transparent estimate of the reliability of electricity service across all under-grid districts in Kenya.

4. Identification strategy

In this study, I test the assumption that uncertainty about the observed reliability of electricity service by households has a significant impact on their decision whether to connect to the grid. Because electricity travels at the speed of light, any outage demonstrates an instant breach of the service supply, and repeated long interruptions of service might deter un-connected under-gird households from paying for a missing supply.

Actually, lasting outages demonstrate a serious market disruption which breaks the contract enforcement, and indeed alters the content of the economic supply: receiving electricity half of the time while regular payments of the bill remain due, may significantly increase the real unit cost of consumed kWh by the household, and causes a hyperbolic uncertainty about the possibility to effectively use electrical appliances. Measuring the sensitivity of households to the quality of electricity service is the logical counterpart of the usual Willingness-To-Pay indicator.

The number of connections is also a key variable for sustainable grid extension, because it has a significant and substantial impact on the marginal cost of grid's extension (Lee et al., 2014): it is thus worthwhile to diagnose to which extent the uncertainty context could act as a barrier to electrification.

[20] P(outages > 50%) = 27.1%
[21] https://www.kplc.co.ke/content/item/795/system-average-interruption-frequency-index-saifi
[22] There was a significant increase of reliability after 2014 (source : Doing Business)

The estimation strategy aims at measuring the causal impact of uncertain reliability on households' connection. To this end, identification is achieved by controlling by the level of households' poverty and by using relevant instruments, in order to neutralize the reverse causality between the number of connected households and the occurrence of an excess peak load that could be at origin of outages. ,

Two first instruments, lightning and lightning in neighbor districts are used as external factors which are significantly correlated with the occurrence of electrical outages.

Distance to the closest power plant is used as a third instrument, in order to capture that part of correlated outages with low technical quality of the electrical network.

4.1. Main specification: roles of indicator, control and instruments

Equation 1 formalizes the effect of outages' uncertainty on the households' decision to connect to the electrical grid. It relies on the parsimonious specification by (Andersen and Dalgaard, 2013), which was also used by (Mensah, 2016).

Equation 1 : Probability of connection as a function of outages' uncertainty

$$Connection_i = a_0 + \mathrm{a}_1 . CO_d(q) + \mathrm{a}_2 . poverty_i + \mathrm{a}_3 . CO_d(q) x\ poverty_i + \mathrm{u_i}$$

where *i* is the household, *d* is the district, and *q* is the level of uncertainty. All estimations are clustered at the district level (*d*).

In this equation, the cumulative rate of outages provides a measurement of the treatment intensity, which is instrumented in a 2SLS estimation. The equation aims thus at estimating the local average treatment effet (LATE) of outages' uncertainty ($CO_d(q)$) on connection (*Connection*), controlling by the household's wealth with poverty index (*poverty*), and using lightning (*lightning*) and Weighted distance to the Closest Plant (*WCP*) as instruments for outages' uncertainty.

The potential cross-effect between uncertainty and individual wealth is captured by introducing an interaction term. For instance, the richest farmers might be only slightly sensitive to the outages context because they may already possess their own generator as self-insurance against shortages. Conversely, in an area that benefits from regular power, households might adopt the electricity contract based only on their financial means.

However, only outages are instrumented. The poverty index is here as an important control that ensures reducing the bias that could arises from omitting this important factor of the decision's connection, as shown by (Lee et al., 2014). Comparing the impact of reliability with the magnitude of the wealth effect will thus be done only for informational purposes.

4.1.1. Cumulative function of Uncertainty

Because in the same district several households may report several levels of outages' intensity, using directly the levels of outages' intensity ($ro_d(j)$) in the model would be hardly feasible for the following reasons :

- choosing any specific level *j* of outages' intensity would make lose all collected information from other households, that claim to observe another level of availability *j'* in the same district ;

- including a range of separated levels in the regression would introduce an obvious collinearity between all levels of reliability, and strongly increase the risk of unstable estimates.

Computing instead a cumulative function aggregates all information in a single index, as a proxy of the uncertainty affecting households. This index canbe used in a regression, without losing any information from choosing a specific level of outages' intensity, neither increasing the risk of unstable estimates from introducing all levels of outages' intensity.

Using a cumulative function brings a better choice than a simple position statistic (average, median) because it introduces some non-linear curvature of the outages' phenomenon into the regression. Marginal effects that will be shown afterward are the derivative of this cumulative function, which means that the estimated sensitivity of the model takes into account the reaction of households up to the least serious outage.

The model captures then a saturation effect up to the smallest incident. This approach is important in a governance perspective: in another context than Kenya, it's fairly admitted that President Wade in Senegal lost his mandate in 2012 after two years of repeated outages, although Senegal was progressively solving the situation.

4.1.2. Main possible sources of endogeneity

The identification strategy must address three risks of endogeneity. First, a major determinant of the number of connections might have been omitted. Second, there is a risk of reverse causality because the high number of connected households in 2014 could cause an excess peak load with respect to installed capacity in Kenya, and thus cause frequent outages. Third, the data are sourced from a survey questionnaire and might be distorted by a measurement error.

By definition, using instrumental variables solves all three risks at once. Lightning and bottlenecks are not related with the global amount of power supply in Kenya, and thus are external causes of outages' occurrence (Deaton, 2010).

Following sub-sections discuss how the choice of control and the relevance of instruments contribute to neutralize the endogeneity of outages in Equation 1.

4.1.3. Potential omitted variables: cost of connection, building quality and distance to transformers.

The literature suggest two important obstacles to grid connection (Lee et al., 2014), (Khandker et al., 2014) : high cost of connection and poor building quality. In fact, the poverty index captures both factors together.

Recent rigorous evaluations based on randomized controlled trials proved with experimental setting that the price effect of connection does exist, but its magnitude is not that important. (Chaplin et al., 2017) found a significant elasticity by -0.1625: a decrease of connection fee by over 80% achieved only +13 percentage points new connected households. (Lee et al., forthcoming) found similar impressive results, and moreover, they measured a decreasing elasticity's magnitude with lower subvention's rate: a 100% subsidy increases grid-electricity adoption by 95 percentage points (-0.95), a 57% subsidy by 23 percentage points (-0.4035), and a 29% subsidy only by 6 percentage points (-0.2069). The smoothing price effect raises a duty to explore reliability as another important factor of connection; however this price effect is significant. Descriptive data also show that the cost of connection weighs more than one year of income for poor households in Kenya. It is thus indispensable to control the identification by the price effect.

Because connection cost is a matter of relative wealth, the poverty index provides a suitable proxy capturing the price effect of connection. In this paper, I do not have individual data on the price of connection (installation cost of the meter and subscription fees to the grid). However, the price might be a strong determinant factor of the connection's decision with respect to the revenue of households. Although I cannot measure the households' budget constraint with flow data (revenue), I built a stock proxy with the poverty index (assets). A sufficient correlation can be reasonably assumed between the wealth of households and their revenue, which means that households can be ranked in the same order according to their wealth or to their income. Therefore, with just an opposite sign, the poverty index provides a measurement of the relative wealth effect with respect to the connection cost.

It can be argued that poverty is "endogenous" to the connection's decision, and this point must be carefully addressed. Endogeneity is a matter of three issues: omitted variables, measurement error, and reverse causality. Other variables that could have been be omitted with respect to the relationship between poverty and connection are: the unreliability of electricity service, which is precisely the main factor of equation 1 ; the distance to the lines which has been shown to be insignificant (Lee et al., 2014); or other factors, which are tested in the robustness section (Table 9) and do not change the sign of estimates for both indexes. As for measurement error, I assume that households tend to underestimate their wealth in many declarative surveys, which means that the poverty index could be overestimated; therefore, the negative coefficient of poverty index could be upward biased toward zero, ie. an attenuation bias.[23]

Connection to electricity can increase households' wealth by increasing their income (Chakravorty et al., 2014), which is a case of reverse causality with poverty. However, I'm focusing on identifying the causality of outages' uncertainty on connection's level, which is the reason why outages' uncertainty is instrumented. Therefore, I just need poverty to avoid missing an important control for outages' uncertainty, whichever can be the direction of its correlation with connection.

Because the *Last Miles Connectivity* may subsidize the cost of connection, some households may in fact achieve a lower relative poverty than observed in Afrobarometer. The poverty index computed with Afrobarometer data may thus be again overestimated, because this subsidy is not taken into account.[24] This subvention might thus upward bias the negative coefficient of outages' uncertainty toward zero (ie. an attenuation bias). This program covers at most 814,200 households[25], which represents 9.3% of the total number of households in Kenya, a proportion that can be considered as the maximal possible bias in my study. Because the subvention is granted to the poor with the same application rules across the country[26], this omitted variable will also not alter the structure of results, and the bias across districts will

[23] I assume that the measurement error does not depend on the value of wealth (Classical Errors-in-Variables assumption).
[24] I can hardly assume that Afrobarometer is correctly representative of this specific subsidy.
[25] https://www.kplc.co.ke/content/item/1120/last-mile-connectivity
[26] Households must live in a radius less than 600m from a selected transformer. 5,320 transformers across all 47 counties were selected.

eventually be the same. In addition, this subsidy started only in 2015[27], after the publication of (Lee et al., 2014) study, and after the 2014 wave of Afrobarometer used in my study. Therefore, I expect this potential bias to not occur in the estimation.

Because the poverty index includes the type of shelter, it also captures building quality, which is thus not omitted from the explanatory factors. However, because the index was built from an MCA, a robustness check should test for any residual correlation of shelter type with the error term.

(Lee et al., 2014) shown that the distance to transformers can play a role through an interaction between distance and building quality (although distance has no direct significant impact on electrification). Were there any residual correlation between connection and distance to transformers in this study, it would be captured by clustering under-grid households in the same district, making the implicit assumption of a distance to a notional centroid transformer.

However, there still might be forgotten or unknown omitted variables, even minor ones: the remaining endogeneity that they could generate would be solved by using instrumental variables.

4.1.4. Efficiency of lightning as an instrument

Lightning is an external random phenomenon that can cause a variety of direct damages to the grid through thermic, mechanical or electrical shocks. When a local strike hits a grid device, it has a strong leverage effect, triggering outages in large areas due to the propagation of excess voltage along the lines, and an overload counter-wave effect caused by the automatic triggering of circuit breakers. These mechanisms make lightning's correlation with outages much higher than the possibility of direct damages to individual connections. The identification exploits then the strong heterogeneity of lightning in Kenya (see Figure 5).

A potential reverse-tide effect might also occur, that is, a power shortage can cause a sudden overload along the electrical wires that in turn could trigger new outages in the neighboring districts (Table A.6). The lightning intensity in surrounding districts is thus also introduced as an instrument.

Other major causes of outages (KPLC, 2016) do not meet the requirements to be used as instruments: wind, rain and floods do not meet the exclusion restriction due to their strong zone effect. Animal contact, tree growth or falling and vehicular collisions easily meet the exclusion restriction but would provide only weak instruments. Vandalism is obviously endogenous to poverty, and the age of installations is not a random factor.

Finally, only lightning meets the three required properties for an instrument: it is purely random, strongly correlated with the occurrence of outages and acceptably not a direct cause of a lower number of individual connections (Table A.6).

Lightning affects the observed number of connections only because it contributes to increase the number of outages, and it has quasi-null probability to strike individual connections, up to the point that it would have direct effect on the number of observed connections (see table A.6). Also important for the exclusion restriction assumption, lightning is not correlated with poverty: crossing left map of Figure 5 and right map of Figure 2 shows that they do not overlap. The correlation is only 12.3% and a further

[27] https://www.afdb.org/fr/projects-and-operations/project-portfolio/p-ke-fa0-010/

collinearity diagnostic shows a VIF equal to 1.02 far below the usual threshold (10), and a condition number equal to 1.21, far below the threshold (30) suggested by (Belsley, 2004).

4.1.5. A heterogeneous grid let electricity production be external to the population location

The energy mix in Kenya depends mostly on primary resources that are geographically constrained and thus strongly determine the deployment of utilities. Overall, 75% of installed capacity is directly related to the country's natural endowments: volcanos, rivers, lakes, wind, and Mombasa harbor on the coast (Figure 3, right).

The distance to the closest generator meets thus the instrumentation requirements because:

- the location of primary energy source is random, and it's external to the places where people live;
- the proximity to a plant cannot be a direct determinant of connection, due to the discrepancy of voltage's norm between transportation and final distribution.

Whether households that are located closer to a utility are more likely to subscribe because they expect fewer outages, it is exactly what the instrument intends to capture.

Because short-run demand for electricity is inelastic, the total power capacity feeding the grid plays a key role in outages' occurrence: having reserve capacity is thus a condition for the supply to meet the peak-load. However, it's not the only condition to avoid outages. As soon as there are some bottlenecks within the network, i.e., insufficient transmission lines capacity, on line losses, lack of substations or balancing features, primary generators will not be able to saturate all parts of the grid with generated electricity. In addition, electricity demand in developing countries is substitutable, which weakens the argument that outages might only be due to a lack of reserve (some agents may give up using electricity, at least for a while, but outages do still occur). The structural quality of the grid must thus be taken into account as a key component of the ability to deliver the service.

In Kenya, there is a strong discrepancy between the location of utilities and the population density in western districts (e.g., 1045 inhabitants/km² in Vihiga: see left map in Figure 2). Utilities are close to energy sources: volcano in the North of Nairobi (Olkaria) or Nakuru (Menengai) for geothermal production; mountains in south-west or in south of Mount Kenya for hydro turbines; the Rift Valley for the large wind project in Turkana. Even the case of power plants around Mombassa can be seen as mainly external to Kenya's development: most of thermal plants are located around Mombassa because it's the only harbor on the eastern coast, used to import oil. They provide much higher power supply than the city's needs, and this electricity is transported with a 700 km line toward Nairobi, through a low-populated bushland area, crossing the national parks of Tsavo and Chyulu (map A.10a). The same line extends then toward Eldoret and Kisumu. In the same vein, the large wind project in Lake Turkana, located far in the North, will need a specific 400kV long transmission line through the desert Rift Valley, toward Eldoret and Nakuru.[28]

Plants' locations were thus mainly not chosen according to the place where people live, and the most powerful ones (like all 365 MW Olkaria units) are not in towns for instance. People also did not choose where they live according to the location of electricity utility; inhabitants of Nairobi and Nakuru could benefit from the proximity of volcanos, but the main rural population of Kenya developed in the western

[28] In 2014, this line was not built yet.

rural area of Lake Victoria, driven by other factors (water, fishery, and pastoralism). As a result, the map of electricity production remains largely external to the map of population.

As shown by map A.10a, all transmission lines in Kenya before 2014 were built before independence (1963) at 66 kV or 132 kV standard, while population grew from 8,105 million in 1960 to 44,83 million in 2013[29], mainly in rural area with lasting low electrification rate.

Due to physical laws, transporting electricity on far distance is mainly a question of difference in potential energy between starting point and destination: the higher the voltage at production place, the farer the point that can be reached.

Substations were built in Kenya, in order to enhance voltage along transportation lines. But they were mostly distributed along the line between Mombassa and Nairobi. The enhancement capacity is clearly not enough to address the risk of bottlenecks, due to long distances between the production centers, and destinations were population is concentrated. The master plan in 2013 expected an ambitious investment of 300 new substations for completion in 2017 (Parsons Brinckerhoff, 2013), which is after this study's date.

In these conditions, a dwelling located closer to a production center (or an enhanced transmission line) might clearly be more likely to receive uninterrupted power than a building far from a primary generator.

In fact, bottlenecks in the transmission network prevent the grid from playing its expected role, which is to transform the random map of energy sources into an even allocation of power, fitting with the place where people live. The poor technical quality of the transmission network, which in a way remains in a comparable state than 70 years before, can instantly transform the power of installed capacity (whatever the amount of supply) into a poor electricity service. The map of plants provides thus an instrumental variable that is like fixed in past time, long before the surveyed period, because the population developed independently of the electricity transmission network.

The distance to the closest plant is thus used as a proxy of the probability of bottlenecks in the transmission network, providing an indicator of grid quality. Under a given state of the transmission network, physical laws of energy ensure that the probability to receive the generated electricity decreases with distance: the distance to closest plant might thus be highly correlated with outages observed by households.

With a similar approach in India, (Chakravorty et al., 2014) used the density of transmission lines as an instrument. However, Kenya is much smaller, has much less transmission lines, and I don't have those data by districts. In fact, taking into account the micro-structure of the grid would also require data on the substations' locations. Nevertheless, I can build a proxy of the grid micro-structure by using the distance between destination district of power and the closest primary generator.

Under the assumption of such a heterogeneous grid, the distance to the closest geographically-constrained utility supports both conditions for instrumentation. The proximity to a power plant may actually be correlated with fewer outages, because the voltage at destination point will be higher if distance is shorter. This distance is also independent from individual connections, and thus meets the

[29] https://data.worldbank.org/country/kenya

exclusion restriction, because the gap between voltage's standards makes it impossible to connect an individual node to a transmission line.

When discussing about "distance to the grid", it is also important to clarify the distinction between the distance to transformers through local distribution lines, and the distance to generators through transmission lines. The first is a proxy for access to distribution, while the latter is a proxy for grid's quality.

As shown by (Lee et al., 2014), the distance to transformers does not play any direct significant role for electrification. The distance plays a role only when a variable related with household's environment (building quality) enters into the energy travel dimension. At least, this empirical evidence strengthens the assumption that grid components belongs to some external dimension with respect to households' decision.

Finally, the two distances play two distinct roles: the first matters for electrification when interacted with building quality, whereas the second is an instrument of reliability. Because transformers feed the last mile of distribution, they are close to the end of the grid and are themselves fed by the transmission lines network; thus, transformers might also suffer the consequence of an upstream tension fall that can turn into a shortage of power. The distance to transformers is thus only an indirect factor of electrification, but not an external cause of outages like the distance to the closest plant through transmission lines.

The transmission network is a technical vector of the quality of electricity service received by households: what matters is not the distance to the distribution network, but the distance that power must travel along transportation lines, from the generator up to its final destination.

It could be argued that the map of transmission lines could be correlated with households' poverty; hence the exclusion restriction of distance to the closest plant would be violated. However, my instrument is not the transmission network density (as in Chakravorty et al., 2014), but the distance between district centroid and the closest generator. In addition, I'm studying under-grid households: in a given electrified district, the distance to the closest generator is the same for rich or poor people, because it depends only on the equipment of the district.

4.1.5.1. A broader discussion on the exogenous electricity infrastructure

Since (Lipscomb et al., 2012), endogeneity of placement of the electricity infrastructure was not often discussed. It's important to address this point when coming to the reliability of electricity supply, because the grid's micro-structure is a key determinant of the ability to deliver power.

As noticed by (Van de Walle et al., 2013), generator settlement is much more constrained by the location of or access to primary energy than by consumption needs. I also consider an exogenous electrical grid, with respect to economic development, for the following reasons.

First, it is important to stress the difference between two models. (Lipscomb et al., 2012) study a macro model on Brazil, relating electricity provision with two development outcomes[30], and assuming a

[30] building values and Human Development Index

homogenous grid. I am studying a question which is one notch ahead, exploring the impact of reliability on effective electrification (connection's decision in under-grid area). Therefore, since I am questioning the quality of electricity service, I must leave the assumption of a homogenous infrastructure that conveys the service, because it is not realistic.

Second, bottlenecks are largely due to the distance from electricity generation. Bottlenecks are structural limitations resulting from production and transmission sizing and organization. They can turn local spiked demand into shortage, because only limited flows of power can reach destination after a long transit. The micro-structure of the grid was not taken into account by (Lipscomb et al., 2012), which assume a homogenous proportion of grid points (electrified connection nodes), all over Brazil. However, traveling at speed light is not a sufficient condition ensuring that all produced electrons will reach their destination. Bottlenecks arise not only from missing reserve, but from the combination of technical features of the grid: initial voltage at production points, distance of transmission, cable capacity, online losses, balancing support ability and density of substations.[31]

Bottlenecks in Kenya result from a past design of the grid that did not evolve (or only few). Using the past state of a variable before treatment is a classical way to set an instrument. In Kenya, the electricity infrastructure is so old, that it can be considered as exogenous to the grid design that would be optimal for the consumption in 2014 : (Lipscomb et al., 2012) also do a similar exercise, comparing the state of the grid now with a simulated grid in past. And (Chakravorty et al., 2016) use a projection of simulated grid in future as an instrument for actual electrification. In Kenya, transmission lines can be considered as a direct observation of the past grid, which cannot properly transform the random distribution of natural endowment and production locations, into an endogenous allocation of energy for the present population across all districts. As a result, the old grid design keeps primary energy endowment external to population distribution.

Third, technical parameters of electricity generation according to local resources largely drive the choice of utilities' placement, running against the assumption of endogeneity of placement with economic development. There are many examples across all technologies, all over the world: nuclear plants need large water flows and are mostly settled along large rivers, lakes or seas. The placement of hydraulic dams is fully determined by large water flows, reserves capacity or steep slopes. Geothermal production is mostly concentrated around natural volcanic activity. Biomass production is strongly constrained by the transportation cost of residues, meaning that projects are mostly developed close to the fields producing crop's residuals (e.g., bagasse). Solar panels are preferably installed according to latitude and radiation of the location. Even fuel plants may be preferably installed close to harbors or refineries, in order to avoid the huge transport costs of the primary resource.

Most of local production parameters support the assumption that electricity infrastructure can remain exogenous to economic development: production is mostly exogenous, and distribution becomes endogenous only if transmission allows a quality mapping of energy with population spatial distribution. The assumption of the grid's placement endogeneity relies instead on the assumption of a homogenous electrical grid, which let the randomness of energy source locations totally disappear. This assumption is

[31] Heterogenous interconnection and lack of coordination in cross-boarder balancing can also alter the grid quality. However, taking into account flows from or toward abroad would make the point of heterogeneous grid too complex.

hard to verify in developing countries, notably in Kenya. The electrical grid in Kenya is so old and far away from an optimal allocation today, that it can be seen as exogenous to the path of economic development.

4.2. Clusters for neighboring effect, and no fixed effects

As noticed by (Khandker et al., 2014), the decision to subscribe to a connection might be partially influenced by peer pressure. Subscribing to electricity may actually result from a positive externality of social network : because electricity is perceived as a luxury good, the leadership of early adopters (Rogers, 2003) might influence households' decision to subscribe. (Bernard and Torero, 2015) brought empirical evidence of such social interactions. Neighbor example may thus affect the dependent variable, which must be taken into account in the identification strategy.

However, with respect to reliability, leaders may also send an opposite signal which contributes to the spill-over of uncertainty aversion by unconnected households. Running in opposite direction, both social motivations could cancel each another, and actually, (Lee et al., forthcoming) did not find any significant effect of the proximity to connected neighbors.

The neighbor example may in fact sustain a more or less sticky diffusion or barrier process: the adoption of electricity might have been much higher in one district than in another because households in the first district have been encouraging each other to subscribe (diffusion) whereas the collective memory of persistent low reliability might have led to a mutual confirmation bias not to subscribe in the second district (barrier). However, cross-sectional data do not allow the observation or estimation of any serial correlation that supports such a process.

I formulate the assumption that the current dispersion of connections across districts as observed in 2014 partially results from such a past diffusion process among the households within each district. Nevertheless, I do not assume the variance in space to be the full result of past variance in time and thus do not make the strong assumption that a cross-sectional regression could be equivalent to a within regression and would explain the dependent variable in the same way. Contrarily, I assume an unobservable past-time variation, while also assuming that its resultant might be observed as a footprint on the present geographical data.

Therefore, the assumption of independent and identically distributed observations in the geographical dimension cannot be hold, leading rather to assume heteroscedasticity among districts.

The neighbor effect is thus captured by clustering all estimations by districts, like (Chakravorty et al., 2014) and (Khandker et al., 2014). Because the model combines an individual-level variable (the poverty index) and an aggregated variable (the Uncertainty index), using clusters also solves the Moulton bias (Moulton, 1990). Specifically, computing the variance-covariance matrix by cluster corrects the under-estimation of standard error that would otherwise results from the use of an aggregated variable. The significance of the coefficients can then be properly diagnosed, avoiding any spurious regression.

I do not use fixed-effects at district level, because the rules of connection are set at national level: tariffs and subsidies are the same across all districts, which are not authorized to change the government policy. The balancing support by KETRACO also occurs at national level. I cannot think about any other peculiarity at districts' level that would alter the household's behavior, with respect to the connection's decision.

4.3. Empirical approach of identification

First OLS estimation checks for any baseline effect and seeks for the relevant level of uncertainty index. Then, a 2SLS estimation identifies the causal impact with all three instruments together.

4.3.1. Uncertainty Index selection

Selection criteria are based on backward-reading of statistical tests (Annex A.9) : the test corresponding to the main statistical objective is verified first, then one checks whether the previous test was already passed successfully, the ante-penultimate test also, and so on, such that all tests composing the decision chain are satisfied. If a test is failed after the first steps were met, one switches to the closest model meeting the same initial set of tests in the decision chain. The selection process was applied independently for OLS and 2SLS estimations.

With this selection process, the Large Uncertainty Index was finally retained for each estimation framework.

4.3.2. Entry models: OLS at district level

Yielding the lowest AIC (1947) and a p-value equal to 0.000, the Large Uncertainty Index was also the best statistical indicator of reliability (*table not shown*), corresponding to Equation 2.

Equation 2 : Probability of connection as a function of Large Uncertainty Index

$$Connection_i = a_0 + \mathrm{a}_1.CO_d(3) + \mathrm{a}_2.poverty_i + \mathrm{a}_3.CO_d(3)x\ poverty_i + \mathrm{u_i}\ (eq.2)$$

Table 5 shows that both indexes (uncertainty and poverty) are significant at the 0.1% level. Their interaction is also significant, at the 1% level. The number of clusters (90) ensures that the standard error is converging to its true value, leading to a proper assessment of the estimates' significance (Annex A.8).

Table 5: Probability of connection (LPM)

	Base b/beta/se	Control b/beta/se	Interaction b/beta/se
Large Outages' Uncertainty	-0.515***	-0.313***	-0.362***
			-0.205
	(0.068)	(0.069)	(0.070)
Poverty		-0.616***	-0.735***
			-0.473
		(0.045)	(0.070)
Large Outages' Uncertainty x Poverty			0.512**
			(0.184)
Constant	0.713***	0.636***	0.637***
	(0.043)	(0.036)	(0.036)
Observations	1669	1669	1669
Clusters	90	90	90
AIC	2242.3	1957.5	1947.4
Adjusted R2			0.23

LPM model (Linear regression), LHS : connection.
Standardized coefficients(beta) are shown only for equations with interaction
SE in parentheses. Variance : Robust cluster by DISTRICT.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The LPM model highlights the negative effect of outages' uncertainty at households level, enlightening a possible channel of the result found by (Andersen and Dalgaard, 2013) at country level: the impact of outages on growth might be rooted in the households' aversion for uncertain reliability.

The poverty index appears to be an important control variable; indeed, the magnitude of outages would have been strongly downward biased (-0.515 instead of -0.313) if poverty had been omitted.

4.3.3. Instrumentation in a linear setting

Because it successfully passed all tests for instrumentation, the Large Uncertainty Index yields a robust model (Table 12 in Annex A.9, equation iSev3iv). The three instruments are strong enough (Stock-Yogo < 30 and first-stage F = 6.7[32]) and would still yield consistent estimates even if they were weak (Anderson-Rubin test : p = 0.000). The model is adequately identified on outages (under-identification test : p = 0.004) which are confirmed to be endogenous (endogenous test : p = 0.016). Finally, the instrumentation yields more consistent estimates than the OLS does (Hausman test : p = 0.02).

Using three instruments, the model is possibly over-identified once the interaction between uncertainty and poverty is introduced (Hansen test : p = 0.092) ; however, over-identification does not make a risk of

[32] As explained in annex A.9, a careful reading of (Staiger and Stock, 1997) allows a finer threshold for first-stage F that can be relaxed to 6 with 3 instruments, keeping the objective of a p-value below 1%, instead of the inaccurate use of a rule-of-thumb.

biasness and estimates will remain robust. Equation 2 with 3 instruments is thus kept as preferred specification.

Table 6 shows more detailed insights on first-stage equations for baseline and preferred specifications. Distance to the closest plant is significantly correlated with outages. In the first-stage of baseline equation, lightning is significant only at 12% level of Student test, which remains an acceptable risk for an ancillary regression. Actually, a simple independence test of pairwise correlations (40%) rejects the null hypothesis of independence. Independence is also rejected between lightning in neighbor districts and outages (39%). Finally, using only lightning and WCP did not provide a satisfactory instrumentation, as F felt bellow 6, Stock-Yogo test could not reject the null hypothesis of weak instruments, and Hansen's p-value felt at 3% (*tables not shown*). This means that propagation effect of lightning must be taken into consideration in a set of three instruments.

In fact, instruments must be considered for their whole correlation with endogenous factor, like a global set of variables ("hyperplan"). With that in mind, Stock-Yogo test shows that the set of three chosen external factors has less than 10% risk to provide weak instrumentation in the baseline specification, which also shows a significant F with comfortable magnitude (14.73). Introducing poverty as control needs then to interact the poverty index with instruments, which "consumes" a part of instrumentation power, because those instruments are not designed for poverty, and although low (24%), some correlation exists between poverty and lightning. However, the F statics remain significant with magnitude above 6, a threshold in accordance with the number of instruments (Staiger and Stock, 1997), and the risk of weak instrumentation remains below 30%. The set of instrumental variables appears thus to be the best solution, according to the objective it is assigned to.

Table 6 : Connection's likelihood (2SLS, 3 instruments) : first-stage equation of CO3

	Baseline (bSev3iv) Coefficients	p-value	Preferred (iSev3iv) Coefficients	p-value
Lightning intensity	0.019	0.111	0.019	0.101
	(0.012)		(0.011)	
Lightning in neighbor	-0.014	0.315	-0.014	0.299
	(0.014)		(0.013)	
Weighted distance to Closest Plant	0.014	0.000	0.013	0.000
	(0.003)		(0.003)	
Lightning intensity x Poverty			0.002	0.912
			(0.022)	
Lightning in neighbor x Poverty			0.002	0.931
			(0.025)	
Weighted distance to Closest Plant x Poverty			0.005	0.218
			(0.004)	
Poverty			0.031	0.610
			(0.062)	
Constant	0.085	0.018	0.100	0.007
	(0.036)		(0.037)	
Observations	1669		1669	
Clusters	90		90	
F test of excluded instruments	14.73		6.71	
p-value	0.0000			

First-stage equation of endogenous CO3 in IV (2SLS) estimation of connection.
Variance : robust cluster by DISTRICT. SE in parentheses.
Excluded Instruments : Lightning, Lightning by neighbors, WCP.
bSev3iv : baseline equation (no poverty, no interaction).
iSev3iv : with poverty and interaction. Instruments are also interacted with poverty index.
First-stage equation must be diagnosed with complete test against weak instruments.
With clustered estimation, KP statistic must be compared to Stock:Yogo thresholds for weak instruments test (null hypothesis : instruments are weak). Stock-Yogo relative bias thresholds for 2 endogenous and 6 exogenous : 15.72 (5%), 9.48 (10%), 6.08 (20%), 4.78 (30%).
Introducing uncertainty alone, there is only 10% probability that instruments were weak. Interacting with poverty weakens the instrumentation because those instruments are not designed for poverty. However, the probability that instruments remain insufficiently correlated with uncertainty (even after interaction) remains below 30%

5. Empirical results

5.1. Impact of Large outages' Uncertainty on the connection decision in a poverty context

Table 7 (col 2) exhibits accurate estimates at the 0.1% level for both main indexes in reduced form.

Table 7: Connection's likelihood (2SLS, 3 instruments)

	Baseline (bSev3iv) Coefficients	Preferred (iSev3iv) Coefficients	Standardized coef.
Large Outages' Uncertainty	-1.082***	-0.806***	-0.456
	(0.203)	(0.167)	
Large Outages' Uncertainty x Poverty		0.479	
		(0.330)	
Poverty		-0.615***	-0.396
		(0.103)	
Constant	0.867***	0.762***	
	(0.072)	(0.061)	
Observations	1669	1669	
Clusters	90	90	
Kleibergen-Paap Wald rank F	14.73	5.97	
Anderson-Rubin	64.1	59.9	
p-value for Anderson-Rubin	0.000	0.000	

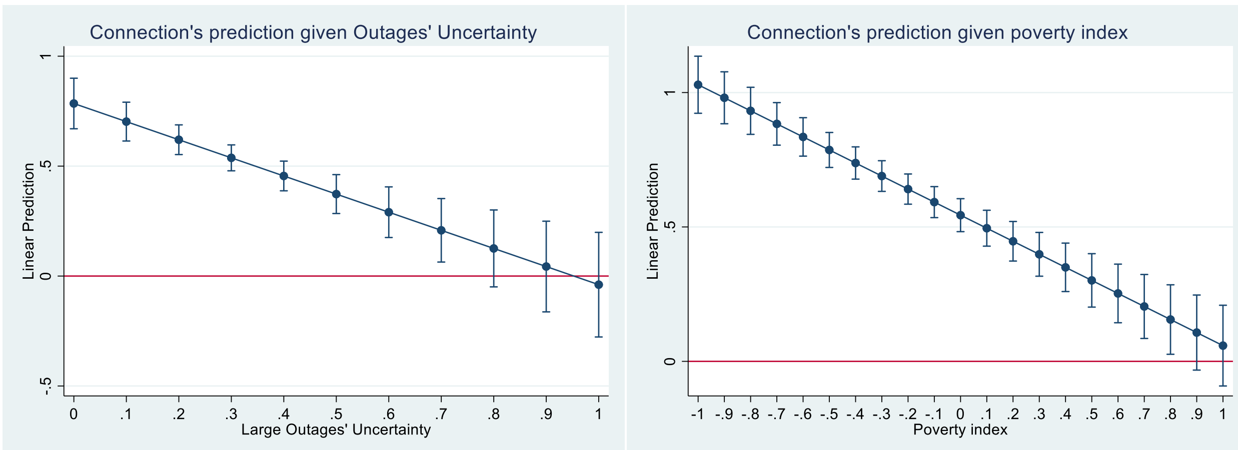
IV (2SLS) estimation. LHS : connection. Variance : robust cluster by DISTRICT. SE in parentheses.
*p<0.05, ** p<0.01, *** p<0.001.*
Instrumented variables : Large Uncertainty Index, Large Uncertainty Index # Poverty index.
Excluded Instruments : Lightning, Lightning by neighbors, WCP, instruments interacted with poverty index.
First-stage equation must be diagnosed with complete test against weak instruments.
With clustered estimation, KP statistic must be compared to Stock:Yogo thresholds for weak instruments test (null hypothesis : instruments are weak). Stock-Yogo relative bias thresholds for 2 endogenous and 6 exogenous : 15.72 (5%), 9.48 (10%), 6.08 (20%), 4.78 (30%).
Introducing uncertainty alone, there is only 10% probability that instruments were weak. Interacting with poverty weakens the instrumentation because those instruments are not designed for poverty. However, the probability that instruments remain insufficiently correlated with uncertainty (even after interaction) remains below 30%

Because the model consistently neutralizes the risks of endogeneity, it can now be confidently used to explore the impact of reliability and to compare this impact with the effect of poverty. Relying on (Williams, 2012) Table A.13 checks the initial conditions of this evaluation.

5.1.1. Predicted likelihood of connection

As shown by Figure 6, the predicted probability of connection decreases with higher unreliability or poverty level. Interestingly, it is also incomplete given outages frequency: the probability of finding connected households reaches only 78% where Large Uncertainty Index equals 0. There might be additional occasional outages that could possibly have a residual effect, deterring households from subscribing to an electricity contract. This point will be further addressed by extending the model to the next uncertainty level (section 7).

Figure 6: Connection's probability given the level of reliability



5.1.2. Marginal effects

How does the prediction of connection change when reliability deviates from its mean or from any other referral values in the sample? Answering this question entails an examination of the slope of the predicted probability of connection given outages frequency (Figure 6, left), with the poverty index fixed at a given level (mean or median).

With the observed values in sample, a 1 percentage point higher frequency of Large Uncertainty outages causes a 0.824 percentage point fewer connected households (Table 8). Comparing the standardized estimates, the average marginal effect (AME) of unreliability (-0.231) is 43% larger than the effect of poverty (-0.161).

This result provides evidence that an unreliable electrical service acts as a serious obstacle to subscriptions and that the impact of low reliability could be greater than that of household poverty.

It is also meaningful to assess the marginal effect of outages at several referral values of outages and poverty.

Table 8: Marginal effects of third uncertainty's outages and poverty

	Average Marginal Effect	Average Marginal Effect (std)	Marginal Effect at Median	Marginal Effect at 1st decile	Marginal Effect at last decile
Large Outages' Uncertainty	-0.824***		-0.817***	-1.088***	-0.642**
	(0.168)		(0.168)	(0.259)	(0.200)
Poverty	-0.485***		-0.528***	-0.615***	-0.280
	(0.059)		(0.064)	(0.103)	(0.157)
Standardized Large Uncertainty		-0.231***			
		(0.050)			
Standardized Poverty		-0.161***			
		(0.020)			
Observations	1669	1669	1669	1669	1669

Conditional marginal effects : margins of connection. SE in parentheses.
Instrumented variables : Large Uncertainty Index, Large Uncertainty Index # Poverty index.
Excluded Instruments : Lightning, Lightning by neighbors, WCP, instruments interacted with poverty index.
Marginal Effects are shown for several reference levels of explanatories : mean, median, deciles.
Effects of poverty are shown only to check significance. Only magnitudes of standardized effects can be compared, knowing that only Outages' Uncertainty is instrumented.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

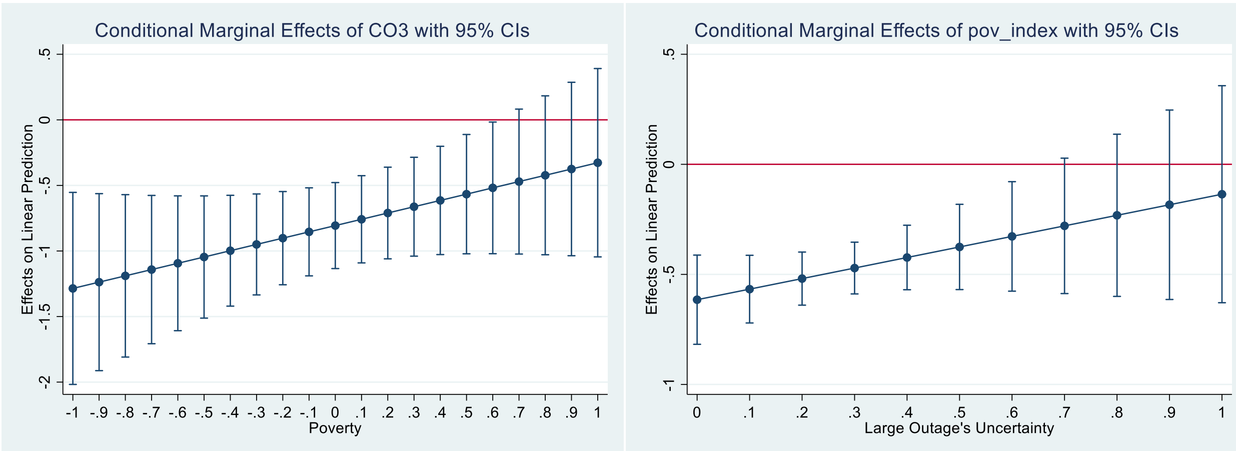
At the median of both explanatory variables (Table 8, column 2), a 1 percentage point higher frequency of Large Uncertainty outages causes a 0.817 percentage point fewer connected households, which is comparable to the average marginal effect (AME).

Furthermore, column 4 (1st decile) and column 5 (last decile) of Table 8 compare districts with the highest and the lowest endowments. Districts in the first decile profit from the highest reliability and concentrate the highest wealth (ie. the lowest poverty). Districts in the last decile are exposed to the highest uncertainty of outages and show the highest share of poor households.

For districts with the lowest endowments, the effect of poverty is not significant: in those districts, households are only sensitive to the outages context (-0.642). Where outages are too high, households are not myopic to the extreme low reliability of electricity service, whichever their wealth level: they value quality for itself.

In the richest districts, households are highly sensitive to electricity reliability (-1.088), even after controlling by the wealth level. In richest districts, households are 69% more sensitive to electricity reliability than in poorest districts.

Figure 7: Marginal effects at means of interacted reliability and poverty



5.1.3. Conditional Marginal effects

The impact of reliability is not the same and is not the same way significant given households' wealth Figure 7, left). For a poverty index above 0.7, outages uncertainty has no significant impact on the connection decision. The poorest households are not sensitive to the uncertainty context caused by repeated severe shortages: extreme poverty cancels the sensitivity to electricity reliability when deciding whether to adopt or not electricity.

In contrast, Large Uncertainty outages have a significant impact on households with a poverty index below 0.7, and the magnitude of the impact is larger for the wealthiest households: households' sensitivity to reliability is growing with their wealth. A possible channel could be the lower reversibility of adoption according to higher wealth : with higher wealth comes a way of life with more electrical uses, which let electricity demand be less substitutable and households be more sensitive to the quality of electricity service.

In a dual approach (Figure 7, right), in districts where Large Uncertainty outages are too frequent (above 70%), the poverty index is not significant. As shown before, an extremely low reliability cancels the wealth effect: in districts overexposed to severe outages, only the lack of reliability matters, whichever the wealth or poverty level of households. This result is important because it confirms the uncertainty assumption: where outages are too frequent, households' budget constraint vanishes, and only the perception of uncertainty about electricity availability leads to the decision to not buy the service. Households are not myopic to the context that acts as the strongest obstacle to subscription, possibly overriding their budget constraint.

On the opposite, in districts that enjoy higher reliability (a Large Uncertainty Index below 70%), the wealth level contributes significantly to households connection: there is a tolerance threshold (outages frequency < 70%) below which the wealth effect plays a significant role in the adoption decision, but above which only the uncertainty context explains the refusal to subscribe.

To summarize, the poorest households are not sensitive to power reliability. Conversely, the wealthiest households are the most sensitive to electricity reliability at adoption time. However, this positive wealth effect occurs only where reliability is greater than 30%; in this case, the wealth effect is significantly positively correlated with reliability. But as soon as reliability falls below 30%, the wealth effect vanishes.

Low reliability has the greatest deterrence effect on unconnected rich households; conversely, if power were more reliable, these households would be the most likely to connect, provided that they live in a district where outages are not too frequent among their neighbors. In the poorest districts, households are not sensitive to the quality of electricity service and this result could come from particularly fragile regions (see section VI).

The policy maker could opt to take action only in districts where reliability is not already too low. However, even in districts in the worst situations (i.e., with the lowest reliability and highest poverty) the policy maker should still prioritize the enhancement of reliability, because under-grid households' decision to subscribe is only sensitive to service uncertainty: in districts where electrical service might have been overly neglected, only the reliability effect dominates. Bringing an unavailable service to market let non-myopic households to recognize its low value, regardless of their wealth.

6. Robustness checks

Table 9 controls for the stability of the Large Uncertainty Index estimate in the preferred specification (column 1), with respect to potential omitted variables (columns 2 – 10).

Table 9: Connection's likelihood (IVREG) - Robustness to additional controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Large Uncertainty	-0.82***	-0.82***	-0.46***	-0.83***	-0.76***	-0.43**	-0.62**	-0.69**	-0.70***	-0.32**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Poverty index	-0.49***	-0.49***	-0.56***	-0.49***	-0.49***	-0.48***	-0.51***	-0.51***	-0.49***	-0.51***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Altitude		-0.00								
		(0.70)								
Precipitation			-0.00***							-0.00***
			(0.00)							(0.00)
Temperature				0.00						
				(0.67)						
Latitude					-0.01					
					(0.44)					
Rural rate						-0.29***				-0.25***
						(0.00)				(0.00)
Wghtd dist. Mombasa							-0.00			
							(0.23)			
Distance to Mombasa								-0.01		
								(0.48)		
Distance to Nairobi									-0.03	
									(0.24)	
Observations	1669	1669	1669	1669	1669	1669	1669	1669	1669	1669

Average marginal effects : margins of connection. SE in parentheses.
Instrumented variables : Large Uncertainty Index, Large Uncertainty Index # Poverty index.
Excluded Instruments : Lightning, Lightning by neighbors, WCP, instruments interacted with poverty index.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Columns 2 to 5 follow (Andersen and Dalgaard, 2013) with altitude replacing the coastal dummy. The impact of outages uncertainty is robust to the inclusion of Altitude (column 2), Temperature (column 4) and Latitude (column 5): introduced one at a time, these variables are not significant and modify the marginal effect of outages uncertainty only slightly.

(Andersen and Dalgaard, 2013) introduced Altitude at macro level, as a proxy for the grid's extension cost across various countries. This control is not significant at individual level, because the connection's fee is fixed and the same for all households across Kenya : as explained in section 2, the KPLC's bill includes a "fixed charge" that covers only the distribution costs. The funding of transmission's network in Kenya remains a channel of investigation[33]. Whatsoever, any variation of the cost of transportation due to difficult terrain is in fact not passed through the fixed tariff to be paid by households. In addition, the household's decision is a matter of relative wealth; therefore, only the comparison of the connection's fee with the household's relative wealth matters, and it's captured by the poverty index.

Precipitation (column 3) seems to be significantly correlated with a lower level of connections in Kenya. This omitted variable does not change the direction of the impact of outages uncertainty, but substantially reduces its magnitude (-0.46); in contrast (Andersen and Dalgaard, 2013) found precipitation to be insignificant. Most likely, rainfall is partially correlated with storms, and thus captures a partial effect of lightning, hence also of outages. As evidenced by the VIF in the 2SLS setting (1.01, not shown), precipitation is fully orthogonal to the hyperplan of the other variables. Therefore, precipitation should have been used as a supplementary instrument to lightning, although satisfaction of the exclusion restriction would have been weaker due to area effect and the model is already adequately identified (see section 4).

Rural location (column 6) is also correlated with a lower level of connections (-0.29), yielding a lower but still negative estimate for the outages uncertainty index (-0.43). In 2014, connections to the electrical grid were less likely to be observed in rural districts of Kenya, but rural location does not change the sign of the evaluated impact.

Taking both variables into account (column 10) reduces the marginal effect of outages uncertainty (-0.32) while maintaining its negative sign.

The results of (Khandker et al., 2014) also suggest a possible arbitrage between electrical connection and the price of kerosene. The latter is approximated by the distance to Mombasa weighted by the condition of the road (column 7), but has no significant impact on the adoption of electricity. In gross value, distance to the main activity centers in Mombasa and Nairobi (columns 8 and 9) is neither significant.

As seen in section 4 and also suggested by the results of (Lee et al., 2014), it is necessary to check for any residual correlation between shelter type and the error term (

Table 10). The referral category is defined by non-traditional formal houses, which account for 73% of the estimation sample. Certain types of shelters have significant residual effect: traditional huts (11% of the estimation sample) are less connected, whereas single rooms (12% of the sample) are significantly more (0.145). However, all shelter types have only a slight impact on the estimated marginal effect of outages (-0.792).

[33] A Security Support Facility was introduced in 2018 tariff's structure, as a payment due to Lake Turkana Wind Power ltd, for the voltage support to the national grid. This payment is passed through customers and adjusted downward for on-line losses.

Table 10: Connection's likelihood (IVREG) - Control by shelter type

	Marginal effect Preferred	Extended
Large Outages' Uncertainty	-0.824^{***}	-0.792^{***}
	(0.168)	(0.155)
Poverty index	-0.485^{***}	-0.405^{***}
	(0.059)	(0.058)
Traditional house / hut		-0.137^{*}
		(0.056)
Temporary structure / shack		-0.063
		(0.092)
Flat in a block of flats		0.074
		(0.048)
Single room in a larger dwelling structure or backyard		0.145^{*}
		(0.059)
Observations	1669	1668

Average marginal effects : margins of connection. SE in parentheses.
Instrumented variables : Large Uncertainty Index, Large Uncertainty Index # Poverty index.
Excluded Instruments : Lightning, Lightning by neighbors, WCP, instruments interacted with poverty index.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A closer examination of the map of the electrical grid in Figure 0 suggests a South-east to North-west development axis that might have left the arid and sparsely populated North-eastern regions at a lower stage. Although the estimation has been clustered by districts, it is worthwhile to check model performance in different macro-areas.

Filtering the North-eastern region (Table 11, column 2) does not substantially change the evaluation. On the opposite, the reliability effect disappears in specific western regions (Rift Valley, Nyanza, and Western) due to the high level of poverty (see right map of Figure 2). As shown by the margin analysis (see section V), outages uncertainty has no effect where poverty level is too high: the disappearance of this effect comes from certain western parts of the country. Along Lake Victoria and Uganda, only poverty deters households from subscribing. The REA should be advised to prioritize the reduction of connection cost in those western regions.

Table 11: Connection's likelihood (IVREG) - Robustness to areas

	(1) Preferred	(2) Without North	(3) Rift Valley	(4) Nyanza	(5) Western
Large Outages' Uncertainty	-0.82***	-0.85***	0.12	-0.27	0.05
	(0.17)	(0.19)	(0.23)	(0.19)	(0.17)
Poverty	-0.49***	-0.51***	-0.68***	-0.61***	-0.48**
	(0.06)	(0.07)	(0.09)	(0.13)	(0.17)
Observations	1669	1629	344	192	104

Average marginal effects : margins of connection. SE in parentheses.
Instrumented variables : Large Uncertainty Index, Large Uncertainty Index # Poverty index.
Excluded Instruments : Lightning, Lightning by neighbors, WCP, instruments interacted with poverty index.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Additional checks have been performed using the -ivvif- procedure incorporated by Roodman in Stata, and a Dfbeta with the OLS specification. The first approach checks the variance inflation factor in the 2SLS framework, and the second aims at identifying the leverage effect of any peculiar individuals in the data. The maximum VIF value (6.93) shows a reasonably low risk of near-collinearity between the dependent variables. Regarding the second check, 39 households report a Dfbeta with respect to outages over 4.8%, which is the relevant threshold for 1,669 observations. Their maximum influence is +13.3% and they are mainly from western counties. Given the negative sign of the outages' coefficient, excluding these households from the sample would make the estimate an even lower negative. Therefore, the evaluated magnitude is conservative. Regarding the poverty index, none of the in-sample households exceeds the threshold.

7. Extended simulation, policy implications and concluding remarks

7.1. Extended simulation: taking into account the least frequent outages

Adding occasional outages to the preferred specification, an extended model (A.14) provides a proxy for the Extended Uncertainty index (Table 1) and suggests that the total effect of reliability may actually be larger than the effect of Large Uncertainty index' identified in section 5.

This extension suggests that the magnitude of the Large Uncertainty index could be even larger than the identified impact (i.e., -1.289 instead of -0.824): the preferred specification thus appears to yield a conservative estimate, while remaining the best identified one. Interestingly, occasional outages have a direct significant negative effect on the probability of connection (-0.835) that comes in addition to the impact of total, serious and partial outages (-1.289). This result suggests a priority to resolve outages at their heaviest uncertainty, starting with the least severe ones.

The marginal effect of the poverty index also increases (-0.465) compared to the preferred specification (-0.615), meaning that occasional outages were an omitted variable with respect to poverty. Taking into account all outages intensities, the sole impact of Large outages' Uncertainty (-1.289) may affect households' connection almost three time more than poverty constraint does (-0.465).

7.2. Concluding remark and recommendations

Outages have *per se* a negative impact on subscription behavior. Supplying more reliable power is thus a prerequisite for gaining new customers, because too frequent outages observed by unconnected households alter their decision whether to buy the service. The expected benefit of acting on the supply side could actually be much greater than merely relaxing the budget constraint of the demand side.

If KPLC were to distribute more reliable power, the quality effect would per se increase the subscription rate, helping the company to significantly grow its customer base. According to the sample observations, 57% of under-grid households were connected in 2014 (see Table 4). Had the electricity company eliminated outages from total to partial intensity, it would have gained a 21-percentage-point higher connection rate (the probability of connection would have been 78%). Based on KPLC's 2014 customer number (2.7 million), the electricity distributor could have gained 567 000 new connections. If it had also been able to resolve all outages, the connection rate would have reached as high as 92%, meaning that KPLC could have gained up to 945 000 new customers. In those conditions, its customer base would have reached 3.645 million as early as 2014, which is almost 33 000 more customers than observed in 2015. With a fully-reliable service, the Kenyan electrical company would have gained more than 12 growth months: full reliability could allow the company to obtain more than one year of additional growth.

Increasing supply may not be enough to solve the reliability challenge because specific bottlenecks do exist within the grid, adding structural risks of outages to customer growth. However, most of projects intending to extend, enhance or build new lines or step-up stations are facing a lack of funding (Zhou and Hankins, 2015) due to their cost, while strategic priority has been put on extending capacity.

Alternatively, the cost of the under-utilized Kenyan grid could be addressed by increasing the reliability of electricity service. The Kenyan government may reach more rapidly the 7th Sustainable Development Goal by increasing the reliability though the building of step-up substations and upgrading transmission lines voltage. Innovative tariff should also be designed such as they would let poor households be more sensitive to reliable service and become more demanding for permanently available power.

7.3. Paths for further research

Important changes occurred after 2014 in Kenya. KPLC started to publish its SAIFI in 2014 in *Doing Business*, which impressively felt from 52.5 in 2014 down to 13.3 in 2019[34], while the real GDP per capita in constant 2010 US$ grew only from USD1,076 in 2014 up to USD1,169 in 2017 (+10.8%). In the meanwhile, the whome electrification rate impressively grew from 36% in 2014 up to 56% in 2016.[35]

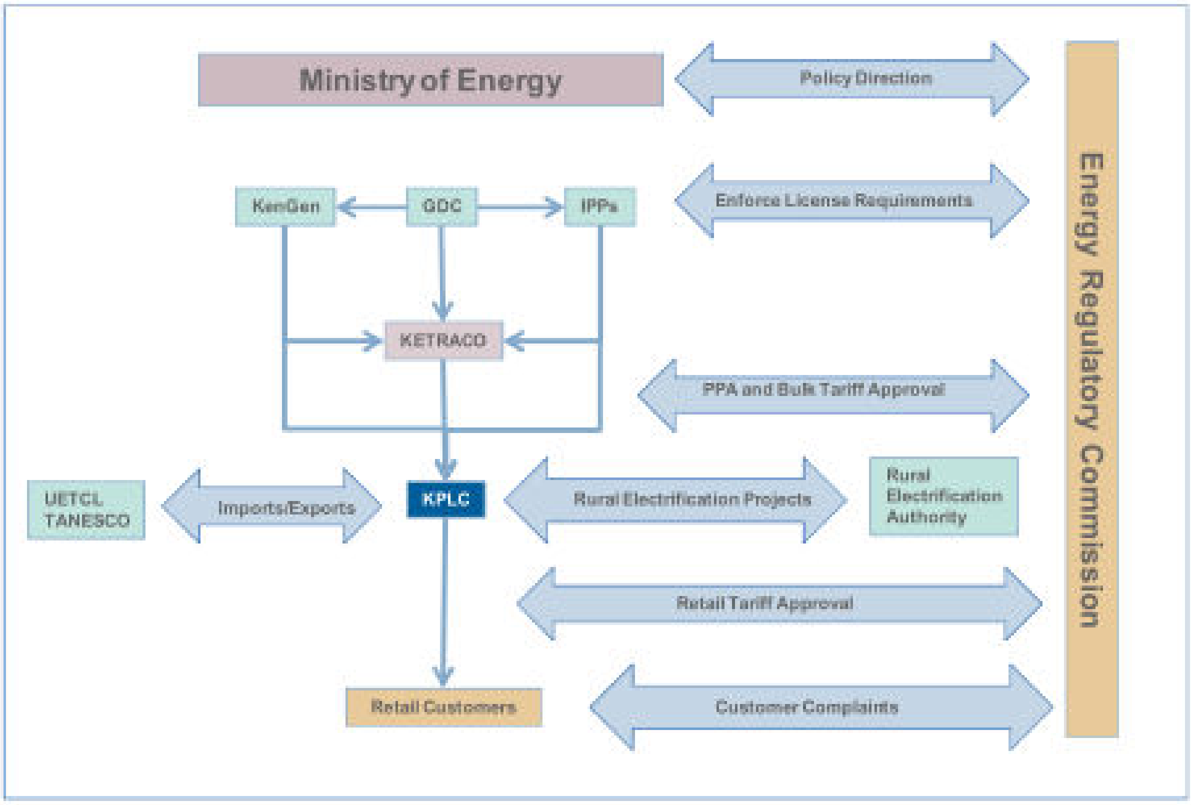
Something happened. The 2013 master plan expected an ambitious investment of 300 new substations that were due for completion in 2017. Two major modern transmission lines (400 kV) were built between Mombassa and Nairobi, and between Lake Turkana and Suswa in center of Kenya. After the nomination of Dr. Chumo in 2014, KPLC's governance also put a strong focus on the improvement of reliability. With further research on their effective completion, one of those events could be exploited as a quasi-natural experiment for an *expost* evaluation, extending the present study with an external validity check.

[34] http://www.doingbusiness.org
[35] https://data.worldbank.org/indicator/EG.ELC.ACCS.ZS?locations=KE

Another way for further research would be to explore the role of households' individual characteristics with respect to their preference for reliability, relying on (Lee et al., forthcoming) specification. The Afrobarometer survey contains variables such as occupation, pay job, self-employed, education level, gender, race language, age. I did not include them in the equation because of time constraint and also because the identification strategy focused on identifying the role of reliability: those factors are obviously correlated with wealth or poverty, and would have introduced collinearity in the estimation. However, in a prospective approach of building a tool for policy enforcement, introducing those characteristics in a predictive model while controlling by poverty and sensitivity to reliability would help KPLC or the REA to prioritize an action plan, by contacting first those unconnected households which might have the highest likelihood to connect to the grid. However, such a tool would raise other delicate questions such as the equality of access to electricity, and the indispensable growth of investment in capacity and grid quality that would be necessary to accompany this induced acceleration of connections' growth.

Annexes

A.1 Main actors of electricity sector in Kenya



Source : (Parsons Brinckerhoff, 2013)

A.2 Main questions used from Afrobarometer survey

A.3 Access to electricity in sampled unit

THE FOLLOWING QUESTIONS ARE TO BE FILLED IN CONJUNCTION WITH THE FIELD SUPERVISOR

EA-SVC. Are the following services present in the primary sampling unit / enumeration area?	Yes	No	Can't determine
A. Electricity grid that most houses could access	1	0	9
B. Piped water system that most houses could access	1	0	9
C. Sewage system that most houses could access	1	0	9
D. Cell phone service	1	0	9

A.4 Outages in unit as observed by interviewed household between 2010 and 2014

94. *[Interviewer: If it is 100% clear that there is no electricity supply to the home, e.g., in an unserved rural area, do not ask the question of the respondent. Just select 0=No electricity supply and continue to the next question.]* **Do you have an electric connection to your home from the mains?**

No mains electric supply or connection to the home	0
[If yes] **How often is electricity actually available?**	
Never	1
Occasionally	2
About half of the time	3
Most of the time	4
All of the time	5
Don't know *[Do not read]*	9

A.5 Proportion of households observing the availability of electricity service

	Rate of outages, as measured by the proportion of households in a district answering about the observed level of power availability (Never, Occasionally, About half of the time, Most of the time, All of the time)					
Availability	Never (0%)	Occasionally (1%-25%)	About half of the time (26%-50%)	Most of the time (51%-75%)	All of the time (76%-100%)	Total
Outages intensity	1:Total (100%)	2:Serious (99%-76%)	3:Partial (75%-51%)	4:Occasional (50%-26%)	5:None (25%-0%)	
District						
Baringo Central	0	8,3	16,7	75	0	100
Borabu	0	0	40	60	0	100
Bungoma East	33,3	0	66,7	0	0	100
Bungoma South	0	0	25	50	25	100
Bungoma West	0	0	100	0	0	100
Buret	0	28,6	14,3	57,1	0	100
Busia	0	0	0	100	0	100
Butere	0	0	0	100	0	100
Eldoret East	0	0	0	81,8	18,2	100
Eldoret West	0	0	14,3	85,7	0	100
Embu	0	0	0	87,5	12,5	100
Emuhaya	0	66,7	0	33,3	0	100
Garissa	0	0	0	71,4	28,6	100
Gatanga	0	0	50	50	0	100
Gatundu	0	7,7	0	46,2	46,2	100
Githunguri	0	7,1	7,1	42,9	42,9	100
Gucha South	0	100	0	0	0	100
Homa Bay	50	50	0	0	0	100
Igembe	4,8	9,5	0	47,6	38,1	100
Ijara	33,3	0	0	66,7	0	100
Imenti North	0	0	0	70,6	29,4	100
Imenti South	0	0	0	83,3	16,7	100
Kajiado Central	14,3	14,3	0	57,1	14,3	100
Kajiado North	0	5	15	75	5	100
Kakamega Central	0	0	40	60	0	100
Kaloleni	0	0	8,3	91,7	0	100
Kangundo	0	25	0	75	0	100
Kericho	0	6,3	18,8	62,5	12,5	100
Kiambu	0	0	0	78,6	21,4	100
Kibwezi	0	0	25	75	0	100
Kikuyu	0	0	4,5	36,4	59,1	100
Kilifi	0	0	0	0	100	100
Kilindini	0	0	7,1	92,9	0	100

	Rate of outages, as measured by the proportion of households in a district answering about the observed level of power availability (Never, Occasionally, About half of the time, Most of the time, All of the time)					
Availability	Never (0%)	Occasionally (1%-25%)	About half of the time (26%-50%)	Most of the time (51%-75%)	All of the time (76%-100%)	Total
Outages intensity	1:Total (100%)	2:Serious (99%-76%)	3:Partial (75%-51%)	4:Occasional (50%-26%)	5:None (25%-0%)	
District						
Kissi Central	0	16,7	0	83,3	0	100
Kissi South	0	0	0	100	0	100
Kisumu East	0	16,7	0	83,3	0	100
Kitui	0	28,6	14,3	57,1	0	100
Kwanza	66,7	0	33,3	0	0	100
Lagdera	50	0	0	50	0	100
Laikipia East	0	42,9	0	28,6	28,6	100
Laikipia West	50	50	0	0	0	100
Lari	0	12,5	12,5	50	25	100
Limuru	0	0	0	25	75	100
Loitoktok	0	50	0	50	0	100
Lugari	0	0	100	0	0	100
Maara	0	14,3	0	71,4	14,3	100
Machakos	5	15	10	60	10	100
Makueni	11,1	22,2	22,2	44,4	0	100
Malindi	0	9,1	9,1	81,8	0	100
Mandera Central	100	0	0	0	0	100
Manga	0	0	100	0	0	100
Marakwet	0	0	50	50	0	100
Masaba	0	20	40	40	0	100
Mbeere	0	20	0	80	0	100
Meru Central	0	0	0	60	40	100
Meru South	0	20	0	20	60	100
Migori	0	33,3	0	66,7	0	100
Molo	0	0	0	0	100	100
Mombasa	0	0	5,9	94,1	0	100
Msambweni	0	0	0	87,5	12,5	100
Mumias	33,3	0	33,3	33,3	0	100
Muranga North	0	0	7,1	28,6	64,3	100
Muranga South	0	0	0	50	50	100
Mutomo	0	0	0	100	0	100
Mwingi	0	0	0	100	0	100
Nairobi East	9,8	4,9	13,4	46,3	25,6	100
Nairobi North	0	9,9	1,4	73,2	15,5	100

	Rate of outages, as measured by the proportion of households in a district answering about the observed level of power availability (Never, Occasionally, About half of the time, Most of the time, All of the time)					
Availability	Never (0%)	Occasionally (1%-25%)	About half of the time (26%-50%)	Most of the time (51%-75%)	All of the time (76%-100%)	Total
Outages intensity	1:Total (100%)	2:Serious (99%-76%)	3:Partial (75%-51%)	4:Occasional (50%-26%)	5:None (25%-0%)	
District						
Nakuru North	14,3	28,6	28,6	28,6	0	100
Nandi Central	0	0	0	70	30	100
Nandi South	100	0	0	0	0	100
Narok North	0	12,5	12,5	62,5	12,5	100
Nyamira	0	10	60	30	0	100
Nyandarua North	0	9,1	0	63,6	27,3	100
Nyandarua South	5,3	10,5	0	73,7	10,5	100
Nyando	0	0	33,3	66,7	0	100
Nyeri North	0	0	0	40	60	100
Nyeri South	0	7,7	0	46,2	46,2	100
Nzaui	50	50	0	0	0	100
Pokot North	100	0	0	0	0	100
Rarieda	0	50	0	50	0	100
Rongo	0	0	0	100	0	100
Ruiru	0	0	14,3	35,7	50	100
Samia	0	50	0	50	0	100
Siaya	0	100	0	0	0	100
Taita	0	0	0	100	0	100
Taveta	100	0	0	0	0	100
Teso South	0	20	0	80	0	100
Tharaka	0	0	40	40	20	100
Thika West	0	0	0	58,3	41,7	100
Tigania	0	0	0	71,4	28,6	100
Trans Nzoia West	0	0	16,7	50	33,3	100
Turkana Central	40	20	0	40	0	100
Wajir East	50	0	0	25	25	100
Wareng	0	0	0	100	0	100
West Pokot	100	0	0	0	0	100
Westlands	4,2	12,5	8,3	41,7	33,3	100
Yatta	0	0	0	0	100	100
Total	4	8,5	7,9	59	20,5	100

A.6 Assessment of lightning as an instrument

Causes of outages	Potentially enough correlated with outages (through transmission lines)	Exclusion restriction at individual connection nodes	Relevance
Lightning	Yes. a/ Lightning is attracted by the height of metallic pylons b/ There is a strong zone effect. A local surge caused by a lightning strike will let automated circuit-breakers to cut the line, avoiding over-voltage propagation toward next grid sections. Then, the local shortage creates a sudden barrier to power supply in sections where it occurred, carrying forward electrical flow to next grid sections, eventually generating an over-load that can itself trigger a new cut from automated balancing. A local outage might thus trigger a wider blackout, due to a chain-reaction at light-speed, making impossible any human intervention like deriving the excess flow or reducing power generation. To sum-up, automated balancing after a lightning strike on local point into the electrical grid might trigger a reverse tide effect, spreading the initial outage on large areas.	Yes. Lightning might strike directly individual external features of connection (boxes, cases, final atmospheric cables). But the probability of a strike on individual nodes (small, numerous and dispersed across space) might be small in front of the probability of a strike on high metallic grid features (pylons, HV-lines, transformers or LV-lines). Partial correlation of lightning with a lower number of connections might thus be small enough in front of correlation of lightning with outages.	Yes. Lightning meets exclusion restriction assumption and is enough correlated with outages.

A.7 Main components of the MCA's first axis (poverty index)

Category	Coord1	Contrib1	Contrib/Mass	N	CO2
use mobile : Never	2.81	7.4%	7.9	180	0.63
roof : Thatch or grass	2.55	8.9%	6.5	263	0.68
mobile : No, don't own	2.39	10.5%	5.7	354	0.68
sanit : No latrine	2.28	1.4%	5.2	50	0.50
use mobile : A few times a month	2.24	1.5%	5.0	56	0.50
roof : Tiles	-2.60	2.4%	6.7	69	0.57
sanit : Inside the house	-2.63	10.1%	6.9	280	0.52
water : Inside the house	-2.80	10.6%	7.9	258	0.52
shelter : Flat in a block of flats	-3.00	5.2%	9.0	111	0.44
roof : Concrete	-3.14	2.3%	9.9	44	0.41
roof : missing	-3.43	2.0%	11.8	33	0.38

A.8 Number of clusters and accuracy of estimates

Clustered robust standard error converges toward the true standard error when the number of groups tends to infinity (Arellano, 1987). In practice, a minimal number of clusters ensures such a convergence. It has been estimated between 42 by (Angrist and Pischke, 2008) and 50 by (Kezdi, 2003) who has tabulated the bias with Monte-Carlo simulations. Bias is slightly reduced close to zero as soon as the number of clusters is over 50, while to the opposite, a too small number of groups yields over-estimated standard errors.

In this article, all estimations have been clustered with 90 districts, a sufficient number to ensure convergence of standard error toward its true value, yielding thus accurate estimates for further inference.

A.9 Selection process of 2SLS model (3 instruments)

Estimations were organized in four classes of equations, introducing the Uncertainty Index (bSev), control by poverty index (cSev) and interaction of both indexes (iSev). The last class of equations (eSev) corresponds to an extended definition of uncertainty, introducing the last level ("always available") apart from the uncertainty index. For each class of equation, the 4 possible levels (q) of uncertainty are tested (and 3 for the eSev class), defining a whole set of 15 estimated equations.

Class denomination	Set of tested indicators
bSev	CO(q)
cSev	CO(q) + control by the poverty index
iSev	CO(q) + control + interaction
eSev	CO(q) + control + interaction + outages of last uncertainty level (4)

The three first (12 models) were diagnosed all together. The last class was used to estimate the extended model for simulations.

The following set of backward-decision tests has been applied to diagnose the instrumentation.

Are instruments strong enough?	Stock-Yogo < 30% F > 6 with p < 1%
Are estimates of outages significant, even if the instruments were weak?	Anderson-Rubin test (p <1%)
Is the model correctly identified?	Endogeneity test (p < 5%)
	Under-identification test (p < 5%)
	Over-identification Hansen test (p > 10%)
Does instrumentation bring a significant difference in estimates?	Hausman test (p < 5%)

Using a Monte-Carlo simulation, (Staiger and Stock, 1997) have tabulated the bias between finite distance estimation and asymptotic value[36]: it converges more or less the same for a F-value of 10 with one instrument than a F-value of 5 with 4 instruments. With 3 instruments, the usual rules-of-thumb (10) can thus be relaxed to 6, while keeping the objective of a p-value below 1%.

When i.i.d assumption is dropped, the test by (Stock and Yogo, 2005) compares the Kleibergen-Paap statistic with tabulated values, according to the number of endogenous and exogenous variables. If instruments were to be weak (Stock-Yogo null hypothesis), the *relative bias* would be not much greater than X% as the biased obtained from OLS, where X is the number reported in column "SY :KP" (*maximal relative bias*).

[36] In (Staiger and Stock, 1997), Table1, p 574

Table 12: Selection process of 2SLS model (3 instruments)

IV (2SLS) estimation of connection, Variance : robust cluster by districts.
b : simple OLS of uncertainty.
c : adds poverty index as control
i : adds the interaction of uncertainty and poverty
e : extension with the next uncertainty level (not included in the identification diagnosis)

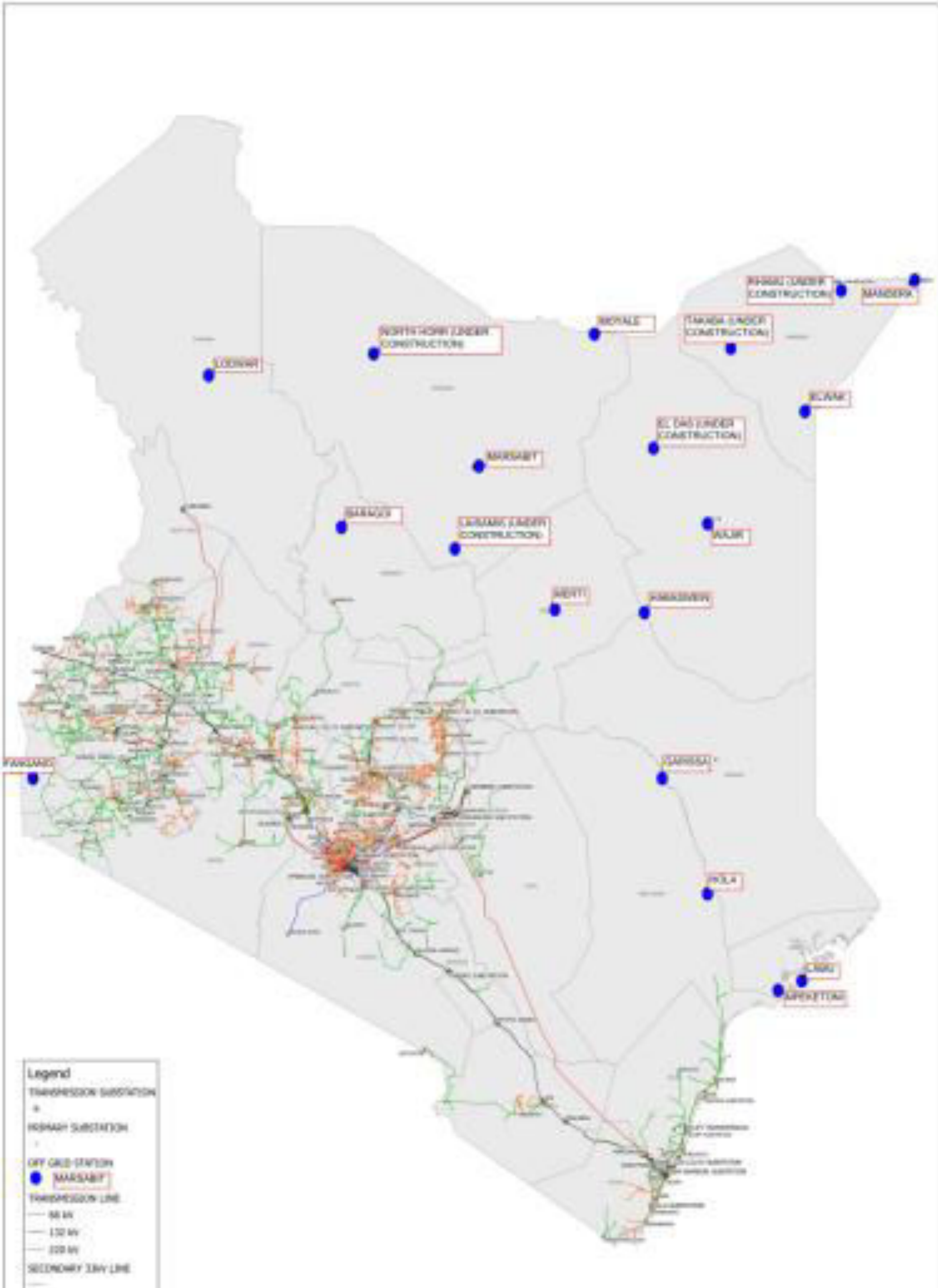
Model	Endog (chi2)	Endog (p)	F First	(p)	Underid (p)	Hansen (p)	SY:KP	A-R (p)	Haus.(p)	N	Clus.
bSev1iv	0.2	0.628	4.0	0.010	0.100	0.001	100	0.000	0.130	1669	90
bSev2iv	6.4	0.011	9.8	0.000	0.004	0.061	10	0.000	0.011	1669	90
bSev3iv	9.4	0.002	14.7	0.000	0.001	0.318	5	0.000	0.003	1669	90
bSev4iv	13.4	0.000	6.7	0.000	0.002	0.908	20	0.000	0.002	1669	90
cSev1iv	0.3	0.608	3.4	0.022	0.153	0.000	100	0.000	0.769	1669	90
cSev2iv	3.1	0.076	8.8	0.000	0.004	0.011	20	0.000	0.079	1669	90
cSev3iv	7.6	0.006	12.9	0.000	0.001	0.128	10	0.000	0.009	1669	90
cSev4iv	13.3	0.000	5.6	0.002	0.004	0.877	30	0.000	0.014	1669	90
iSev1iv	0.3	0.586	2.3	0.043	0.267	0.005	100	0.000	0.830	1669	90
iSev2iv	1.8	0.184	5.3	0.000	0.023	0.019	100	0.000	0.115	1669	90
iSev3iv	5.8	0.016	6.7	0.000	0.004	0.092	30	0.000	0.020	1669	90
iSev4iv	12.3	0.000	3.4	0.005	0.018	0.376	100	0.000	0.041	1669	90
eSev1iv	0.1	0.765	2.4	0.034	0.345	0.008	100	0.000	0.998	1669	90
eSev2iv	2.3	0.127	5.9	0.000	0.024	0.031	100	0.000	0.139	1669	90
eSev3iv	5.9	0.015	5.4	0.000	0.001	0.155	30	0.000	0.057	1669	90

Model bSev3iv yields the best estimation, with Large Uncertainty Index. However, this equation includes only outages, without control for poverty and its interaction with unreliability. One thus switches to another equation, provided that vector of tests still holds.

Introducing poverty index, model cSev3iv yields a satisfactory Stock-Yogo threshold (10), whereas all other tests remain very close. Then, introducing interaction term, model iSev3iv yields a weaker Stock-Yogo threshold (30) but still acceptable. The lower F in first-stage (6.7) is only due to a larger number of instrumented variables (2). This F-value remains above the targeted threshold (6) with an acceptable p-value (0.000). Anderson-Rubin test also ensures that the model provides estimates that would remain robust if instruments were weak. All second-order tests remain acceptable. Equation (iSev3iv) is thus retained as the preferred instrumented estimation in 2LS framework.

A.10 Kenya’s electrical grid

A.11 Transmission lines, distribution lines and off-grid generators



Source : (Parsons Brinckerhoff, 2013)

A.12 Transmission lines, and power pants, by types of energy

Source : Africa-energy.com

A.13 Initial setting of margins analysis and average predictions

Stata provides a powerful analytic feature –margins- which allows to compute directly marginal effect of each predictor on dependent variable, also taking into account interactions. By default, average values of variables in sample are the referral values for margins computation at mean of other variables.

Table 13 checks that the global prediction (AAP = 57.4%) equals the average proportion of connected household in estimation sample (57.4% in Table 4). Adjusting for means of predictors in sample yields a very close estimate (APM = 56.2%). The margins analysis has thus been based on the deviation from this referral prediction.

Table 13: Connection's likelihood (IVREG) - Predictions of third uncertainty's outages

	Adjusted Average Prediction	Adjusted Prediction at Means
Constant	0.574***	0.562***
	(0.027)	(0.030)
Observations	1669	1669

Adjusted predictions : margins of connection. SE in parenthesis
Instrumented variables : Large Uncertainty Index, Large Uncertainty Index # Poverty index.
Excluded Instruments : Lightning, Lightning by neighbors, WCP, instruments interacted with poverty index.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Definitions and acronyms:

Adjusted Average Prediction (AAP): adjusted prediction, taking into account interaction terms.

Adjusted Prediction at Means (APM): adjusted prediction as above, computed at means of other variables in sample.

Average Marginal Effect (AME): marginal effect computed with observed values of variables in sample.

Marginal Effect (ME): marginal effect at different referral level of outages and poverty (at means, median or deciles). With a linear model, AME and ME at means are equals. Thus, only AMEs are reported in section 5.

A.14 Extended model for global simulation and extended margins

There might be an additional effect of less frequent outages (level 4: occasional), which is assessed by extending the preferred specification with equation below:

$$Connection_i = a_0 + \mathrm{a}_1.CO_d(3) + \mathrm{a}_2.poverty_i + \mathrm{a}_3.CO_d(3)x\, poverty_i + roi_d\,(4) + \mathrm{u_i}$$

Different strategies have been unsuccessfully tried to instrument variable roi(4) in the 2SLS estimation, but the backward-decision criteria failed (result not shown). An explanation could be the inability to affect three instruments separately to endogenous variables. Therefore, the next level of outages is introduced as a control in preferred specification, defining the "extension" models' class e. Third level of uncertainty remains the most relevant with respect to robustness of instrumentation: equation eSev3iv passes successfully all tests (Table 12 in A.9).

Table 14: Marginal effects of extended outages (Extended IVREG)

	Marginal effect Preferred	Extended	Point estimates Preferred	Extended
Large Outages' Uncertainty	-0.824***	-1.289***	-0.806***	-1.289***
	(0.168)	(0.318)	(0.167)	(0.318)
Poverty	-0.485***	-0.465***	-0.615***	-0.465***
	(0.059)	(0.067)	(0.103)	(0.067)
Occasional outages		-0.835**		-0.835**
		(0.289)		(0.289)
Large Outages' Uncertainty x Poverty			0.479	
			(0.330)	
Constant			0.762***	
			(0.061)	
Observations	1669	1669	1669	1669
Clusters			90	
AIC	.	.	2070.7	.

Average marginal effects : margins of connection. SE in parenthesis
Instrumented variables : Large Uncertainty Index, Large Uncertainty Index # Poverty index.
Excluded Instruments : Lightning, Lightning by neighbors, WCP, instruments interacted with poverty index.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Chapter TWO : Impact of Decentralized Electrification Projects on Sustainable Development: A Meta-Analysis[37]

Abstract

This paper is the first product of a project which aims at building a Collaborative Smart Mapping of Mini-grid Action (CoSMMA), whose principal objective is to identify best practices of Decentralized Electrification Projects (DEP).

Using evaluations of 403 projects, from published research papers, we built a pilot CoSMMA which proves its feasibility. Its relevance is demonstrated by a meta-analysis, which reveals the principal characteristics of DEP with positive impacts on sustainable development.

Five main characteristics were considered: project objective, technology (source of energy), system capacity, decision level (from local to country level), geographic location. When searching for best practices, technology and capacity must be considered together, because the chosen technology may constrain the supplied power. We find that the most popular projects, which are based on Solar Home Systems (SHS) are the most effective; but we also show that the efficiency of SHS for development may be constrained by their limited capacity. We find a non-linear growing relationship between capacity and the probability of positive impacts: micro-grids allow filling the gap of energy access. Mini-grids, of larger size, especially hybrid systems which use solar source of energy along with fuel or renewable, have larger positive impacts, beyond access to energy, because they combine the benefits of sustainability and flexibility.

We attempted to study the nature of effects resulting from DEP. Descriptive data suggest that positive impacts are more likely for some natures of effects than others. Decentralized electrification projects have a more positive impact on Information and communication, Basic Access and Housework than on Economic Transformation, Financial transformation, Security, or even on Energy. However, this pilot CoSMMA does not contain enough information to model the probability of positive impact for all natures of effects, because some types of effects have not been studied frequently enough in the existing literature. Environmental effects, for instance, have been rarely measured scientifically. We could isolate some key factors of success of DEP for their impact on education. In terms of decision level, we find that both top-down and bottom-up approaches have advantages, with the observation of a U-shaped curve for the influence of the decision level on the probability of obtaining positive impacts

[37] This chapter is a joint work with Pr. Jean-Claude Berthélémy, University Paris 1 Panthéon- Sorbonne, Centre d'Economie de la Sorbonne (CES), Programme Director at FERDI - France.

on education. Geographical location matters, as it is very often the key to system feasibility. We find that DEP are more effective for education in Latin America, than in Asia and in Africa.

Finally, we attempted to broaden our information set by including expert data, which was entered into the CoSMMA meta-analysis. We define expert data as observed effects that are not supported by heterogeneous samples, whereas the evaluations based on scientific data were supported by heterogeneous samples, eventually allowing for statistical tests of significance. The expert data may be valid, but our attempt to include it in the analysis failed at this stage. The determinants of unproven favorable effects appear to be quite different from the determinants of positive impacts in our meta-analysis, and using expert data would imply merging both, which would blur the conclusions.

JEL : L94, O13, O18, O22

Keywords : Decentralized electrification, sustainable development, impact assessment, meta-analysis.

Introduction: The CoSMMA project

Decentralized Electrification Projects (DEP) are booming in developing countries as a response to the deficiencies of on-grid electrification in many parts of the developing world, particularly in rural areas. Technological progress in renewable sources of energy also offers new possibilities of delivering electricity to households. This evolution potentially has a lot of promise for sustainable development in developing countries, but it may be curbed by a lack of visibility of what works and what does not work, which may in turn become an obstacle to financing such projects.

This paper is part of a project to build a collaborative database on decentralized electrification, named CoSMMA (Collaborative Smart Mapping of Mini-grid Action), with the objective of identifying best practices from the point of view of sustainable development: we seek at identifying the project characteristics that maximize the chance of positive impacts on sustainable development.

To this end, DEP are described in the CoSMMA in several dimensions:

- Basic technical characteristics of the project, such as the energy source and the capacity of the system delivering electrical power;
- Project objective and expected impacts;
- Ex-post evaluated effects.

Additional types of information include the conditions of evaluation and document sources.

At the current stage of our project, we have built a pilot CoSMMA, with the objective of testing its feasibility and proving its relevance. We used information on 403 DEP available in published research papers, which we analyzed and coded into variables describing the projects and their effects. This information was gathered by a structured search from 4 principal academic sources - Academic Search Premier, Business Source Complete, EconLit, and GreenFILE. The information was then processed through a meta-analysis regression, whose results shape the core of this paper.

Our principal tool is a multi-probit meta-regression, which shows which factors led to which effects of DEP on sustainable development. We also attempt to break down the analysis by nature of effects, but at this stage the available information limits our analysis. Only a few types of effects of DEP have been sufficiently explored in the papers registered in the CoSMMA to allow uncovering their specific determinants. Finally, we attempted to enlarge the data base used in the meta-regression by including so-called expert data (i.e. evaluations provided by experts but not supported by heterogeneous statistical samples). However, we were unsuccessful in this attempt, because statistically proven effects and unproven effects appear to have quite different determinants.

In section 1, we develop in more detail our research question and relate it to the existing literature. In section 2 we document our sources of data and methods used to build the CoSMMA and we report descriptive statistics on project characteristics and project effects registered in the CoSMMA. In section 3, we describe the econometric methodology used to perform our meta-analysis. In section 4, we discuss our empirical results and their possible extensions. Section 5 is devoted to a discussion of the possible bias that could affect our results; section 6 concludes and proposes some possible areas for further research.

1. Research question and literature review

1.1. Definition of DEP

Defining decentralized electrification is not simple, because many field practitioners and scientists refer to decentralized project as an obvious notion, although to the best of our knowledge, no clear criteria has been established so far.

CoSMMA is limited to off-grid or individual solutions, with no connection to the national grid. Our definition also includes a size limitation: any project above 100 MW cannot be considered as decentralized, because it could be involved in clearing price exchanges (Dillig et al., 2016) .

1.2. The need to identify best practice of DEP

A variety of DEP projects have been implemented and evaluated so far, with a focus on solar Nano solutions, the so-called SHS (Solar Home Systems). This focus comes from a convergence of interest between funders and developers, as they offer a low-commitment solution for the funder, and a low-cost market test for the developer. This focus does not imply that SHS represent the best practice in terms of positive impact on sustainable development. Institutions working in the sector frequently face the reality of economic or technical failures (Ikejemba et al., 2017). Defaults are also repeatedly reported by NGOs promoting DEP, with estimates of default rates commonly being above one third. Clarifying the question of DEP performance and identifying the best practices is thus important.

The development of DEP faces three major challenges:

- Because projects are not connected to the grid, they show a large heterogeneity of economic and technical design;
- So far, no unified framework of knowledge and data on DEP can offer a complete vision on the variety of field experiments, and qualify their ability to yield sustainable favorable impacts;

- There is no clear consensus on the types of effects that matter and the primary types of impacts that a DEP should address first.

In this study, "best practice" is defined as the project characteristics that produce significant favorable effects on sustainable development. Significant favorable effects are also called "positive impacts" in this study.

1.3. The potential contribution of a meta-analysis

Identifying best practices in DEP requires an innovative methodology, because the focus on energy in Sustainable Development Goals (SDG) is recent. Few DEP have been assessed in a rigorous evaluation framework, although many observations of DEP effects are available in other areas of research. Using these observations is complex given their heterogeneity, however it can provide an approach to delivering an early assessment of DEP strategic choices.

A meta-analysis adds to the understanding of a phenomena by combining results obtained by researchers using a variety of data and methods (Stanley, 2001). In conducting a meta-analysis with published results for DEP effects, we expect, like(Carré et al., 2015), to have more robust conclusions than a mere review of separate regressions. Using a systematic selection from research databases, a meta-analysis avoids the classic pitfalls of a literature review, which could be unbalanced due to selection bias, or reflect the beliefs of authors who might tend to reject papers that run against their convictions (Stanley, 2001).

To the best of our knowledge, this study is the first meta-analysis which attempts to relate DEP characteristics to their impact on sustainable development, and hence which addresses clearly the question of best practices in decentralized electrification.

In order to base our contribution on previous literature, we review below two branches of research: first we consider what has been proposed so far in terms of mapping DEP effects. Second, we analyze the methodological references for meta-analysis.

1.4. Previous mapping of DEP effects

To the best of our knowledge, there is no previous study which proposes a complete mapping of DEP effects in developing countries. Several studies have been done with more specific research questions, as shown in Table 15. The CoSMMA offers an original contribution, mapping a wide scope of DEP effects in developing countries with observed data.

Special attention must be paid to (SE4ALL, 2017) and (Katre et al., 2019).

(SE4ALL, 2017), *Why wait?*, was the first study to assess the effects of access to electrical appliances in developing countries on SDG, using the multi-tier framework defined by (ESMAP, 2015). There was a similarity with our objectives, although CoSMMA covers more countries (72) and indicators (793). Furthermore, by considering all effects published by researchers, our analysis does not make any preconceived assumption about which impact should be evaluated first or might be expected to arise initially.

(Katre et al., 2019) propose a complete comprehensive scorecard for DEP evaluation which was tested on 24 villages in India. Using observed or reported effects of DEP, we are able to feed a large database with observational or experimental data, covering 2,712 effects over 156 dimensions.[38]

Table 15 - Previous studies adressing a mapping of the socio-economic effects of electricity

Reference	Converging feature	Differentiating feature
(Kanagawa and Nakata, 2008)	Socio-economic impact of access	Macro study, no project
(Hayn et al., 2014)	Socio-demographic factors	In Europe
(Bell et al., 2015)	Electricity effect on sociability	131 customers in United Kingdom
(Marszal-Pomianowska et al., 2016)	35 electrical appliances	In Denmark. Looking at the impact of appliances on the system, not on socio-economic household behaviors
(Thopil and Pouris, 2015)	Externalities on environment, health and employment, in South Africa	1 country, 3 types of effects, 9 indicators
(Holtorf et al., 2015)	Consider success criteria of SHS	Technology constrained (SHS only) No data (a comprehensive framework)
(SE4ALL, 2017)	Quantify the access dividends according to the multi-tier framework of appliances. Relate tiers of appliances and research on effects	3 countries (Bangladesh, Ethiopia, Kenya), 21 indicators
(Katre et al., 2019)	Build a scorecard relating tiers of appliances with dimensions of yielded effects.	Calibration made with Field data from 24 villages in India.

1.5. Previous meta-analyses

Frequently used in medical studies, meta-analyses were popularized in social science (Carré et al., 2015), and were widely used as a quantitative method of research synthesis to calibrate structural models, examine patterns of publication bias, and explain differences in the results of individual studies (http://meta-analysis.cz/).

[38] Some data are experimental, yielded by evaluations of DEPs in a natural experiment (Randomized Control Trial) or in quasi-natural experiment conditions (DiD).

In a seminal work, (Stanley, 2001) provides clear and comprehensive advice on the steps to follow and pitfalls to avoid, when conducing a meta-analysis that "*employs conventional statistical methods and criteria to summarize and evaluate empirical economics*". We follow this methodology, especially in the important step of defining the objective of the meta-analysis.

(Doucouliagos and Paldam, 2009) conducted a referral meta-analysis for development economics, in which they assessed the publication bias in aid effectiveness evaluation. They used 97 research papers on aid effectiveness, from 4 databases. Their main research questions were to determine whether aid increases accumulation in the recipient country, and if so, by how much? The spirit of our research question is similar to this approach because we are examining whether the theoretical favorable effects of DEP on sustainable development have been proven by the literature.

However, classical meta-analyses like these, address only one parameter of interest at a time (aid effectiveness in (Doucouliagos and Paldam, 2009), Ricardian equivalence in (Stanley, 2001)), and usually a continuous parameter. We propose an original extension to these classic approaches, by testing simultaneously a relatively large number of categorical parameters.

To clarify to what extent our study fills a gap, we investigated 4 sources specialized in conducting international meta-analysis, a website http://meta-analysis.cz/ and reviews of Journal of Economic literature, Journal of economic perspective, Journal of economic surveys.

As shown in Table 16 there is no meta-analysis about access to electricity ("electrification"). Our research shows that our paper is the first meta-analysis on electrification effects.

We found 12 meta-analyses about "electricity", which proves the growing importance of the electricity economics field, as each meta-analysis is based on a populated set of underlying studies. Those studies address topics so different from CoSMMA, that we can hardly use them as reference, but we can highlight 2 findings:

- Meta-analyses about electricity economics are feasible;
- CoSMMA fills a gap in off-grid electrification assessment.

It is worth noting that 6 of the existing meta-analyses are about USA electricity economics, 2 about developing countries, and 1 about renewable electricity.

Several literature reviews about energy economics were also investigated. Table 17 shows the number of articles reviewed. These numbers are small compared to the number of papers populating the CoSMMA (125).

Table 16 - Review of literature or meta-analysis about electricity economics (as of Oct 12th 2018)

Review	Key words	Response/reference	Title	Qualification with respect to CoSMMA objectives
Journal of Economic Literature	"electrification"	0		
Journal of Economic Perspectives	"electrification"	0		
Journal of Economic Surveys	"electrification"	2. Of which, responses to consider : 0		Off-topic: railroad electrification and cliometrics
http://meta-analysis.cz/		(Havranek et al., 2018)	*Does Daylight Saving Save Electricity? A Meta-Analysis*	Off-topic and reverse causality: the authors study the impact of daylight saving time on electricity consumption (44 studies)
Journal of Economic Literature	"electricity"	(Zheng and Kahn, 2013)	*Understanding China's Urban Pollution Dynamics*	Off-topic: on-grid analysis and only one dimension studied. Underlying studies unclear (an assembly of datasets). Authors study the impact of electricity consumption on environmental externalities, notably air quality
Journal of Economic Perspectives	"electricity"	8		
		(Joskow, 2003)	*Creating a Smarter U.S. Electricity Grid*	Off-topic: US
		(Davis, 2012)	*Prospects for Nuclear Power*	Off-topic: US, Nuclear Power
		(Borenstein, 2012)	*The Private and Public Economics of Renewable Electricity Generation*	The author aims to evaluate the pricing of (positive) externalities from renewable electricity generation. Off-topic: Discussion in the literature.
		(Wolfram et al., 2012)	*How Will Energy Demand Develop in the Developing World?*	Off-topic: Impact of growing energy demand on the grid
		(Borenstein, 2002)	*The Trouble With Electricity Markets: Understanding California's Restructuring Disaster*	Off-topic: US
		(Bazelon and Smetters, 1999)	*Discounting Inside the Washington D.C. Beltway*	Off-topic: US
		(Winston, 1998)	*U.S. Industry Adjustment to Economic Deregulation*	Off-topic: US
		(Joskow, 1997)	*Restructuring, Competition and Regulatory Reform in the U.S. Electricity Sector*	Off-topic: US
Journal of Economic Surveys	"meta-analysis electricity"	18. Of which, responses to consider: 2	*Note: retrieved papers strongly orthogonal to our research (i.e. not in electricity economics field) are not shown.*	
		(Stern, 2012)	*Interfuel Substitution: A Meta-Analysis*	Off-topic: underlying studies are macro-economics The author studies inter-fuel substitutability (47 studies)
		(Heshmati, 2014)	*Demand, Customer Base-Line and Demand Response in the Electricity Market: A Survey*	The authors study models used in the literature to evaluate the demand for electricity (and its impact on reliability)

Table 17 – Listed studies in electricity economics (as of 12th Oct 2018)

Reference	Number of listed studies
(Praktiknjo et al., 2011)	16
(Jamasb et al., 2017)	18
(Bonan et al., 2014)	20
(Brenneman and Kerf, 2002)	40[39]
(Peters and Sievert, 2015)	9
(Thopil and Pouris, 2015)	15
(van Gevelt, 2014)	90

2. Sources of data

2.1. Methods used to build the CoSMMA

Research papers used to document DEP in the CoSMMA were taken from 4 economic research academic databases: Academic Search Premier, Business Source Complete, EconLit, GreenFILE.

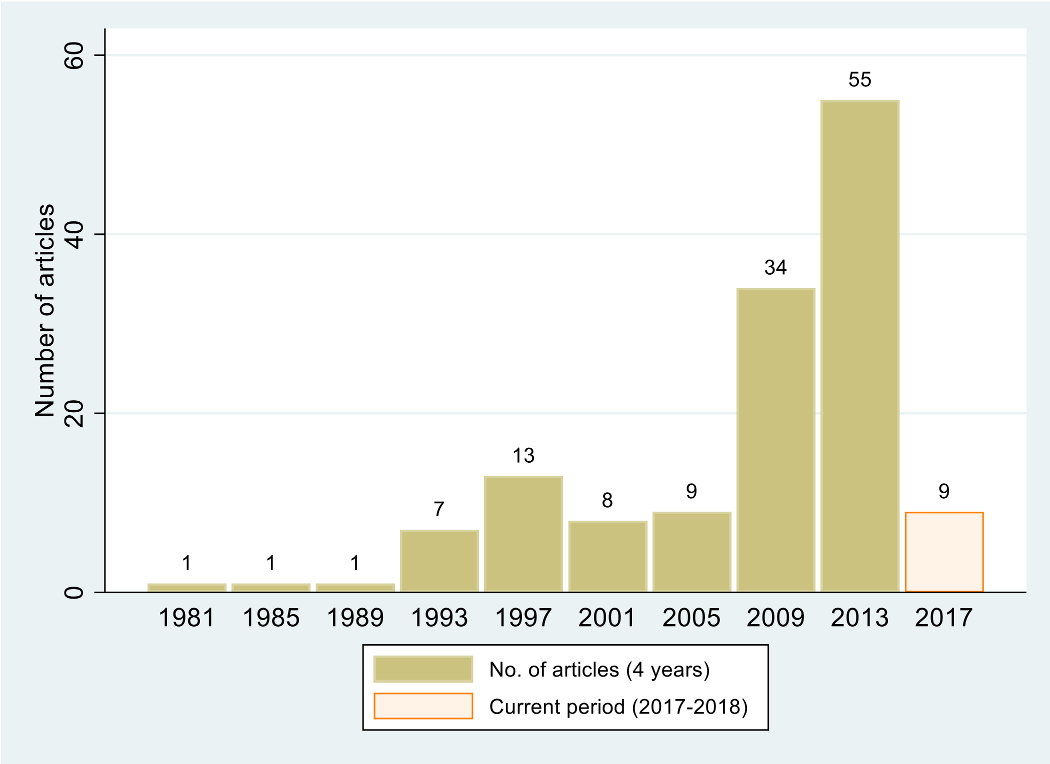
The studies on the impact of electrification show a wide scope of methodologies, data, and projects. Following (Stanley, 2001), "*differences in quality, data or methods do not provide a valid justification for omitting studies. Rather, such differences provide the underlying rationale for doing a meta-regression analysis in the first place*."

A systematic collection of research papers was made, with no *ex-ante* exclusion, but the topic relevance (Stanley, 2001): "*after reducing the sample of studies to those that contain some relevant empirical estimate, test or finding*". Off-topic studies (e.g. electrification of railways), macroeconomic studies, studies focused only on potential and barriers, *ex-ante* cost/benefit analyses, or technical feasibility studies were not used for the CoSMMA. Papers with a developed country in title were excluded. Only papers with a publication date later than 1980 were selected. This time span was set to avoid missing any important precursor publications about decentralized electrification. However, because the growing interest in decentralized electrification is recent, papers before 1990 are scarce (see Figure 8).

Publication conditions were also checked. Documents had to use a common language (English) and be peer-reviewed, or designed for such a process (e.g. working papers of research institutions). A few economic reports (from financing institutions or companies) were included because they had been through a quality control process before public dissemination. They represent 7% of the current primary sources of the CoSMMA.

[39] Only papers about the impacts of energy are counted. Papers about the impact on growth are not counted.

Figure 8 - Number of papers by publication period (4 years)



A key sentence containing words usually used to analyze decentralized electrification projects was defined and parsed through EBSCO for the 4 databases. Keywords were automatically reweighted by a smart text mining function in EBSCO. Some variants were also used. Finally 6 main queries were defined which gave 6 sets of documents, called "packs". For the most complex queries, a common set of additional keywords was used in order to limit the study more closely to decentralized electrification projects.

Reweighted queries were saved to keep track of the search, allowing for possible external replication.

Being keyword-based and systematic, this methodical sampling aims to define a neutral collection of papers, which is not influenced by the researcher's knowledge or a specific direction of research. The keyword-based sampling approach provides a random selection of papers related to the DEP effectiveness field of research. However, the ability of an algorithm to fit accurately to a field of research cannot be guaranteed, and so *ex-post* human checks were performed on the EBSCO selection results. Possible duplicates were eliminated, and a final check of the application of *ex-ante* selection criteria was made (e.g. residual macroeconomic studies or other off-topic papers were eliminated).

Within each of the 6 packs, keywords defined specific branches. Inside each branch, some articles with large bibliography were used to define sub-branches, in which some of the papers quoted in the bibliography of the head article were collected as well. However, the bibliographies of initial articles were used with parsimony, because too many papers from sub-branches could have introduced a bias toward the past into the meta-analysis, and also a direction bias: at a given point in time, a researcher can only cite previously published papers, and papers strongly related to his or her own research direction.

For reasons related to the research project's origin, 32 articles were used in addition, following a classic approach based on research about the econometric evaluation of decentralized electrification. These articles did not duplicate the EBSCO extraction. They constitute an additional pack in the meta-base. Additional papers (from sub-branches or historical pack) are 18% of all collected papers.

The inclusion criteria applied to project characteristics are presented in Table 18 below. Note that the number of exclusions results from the simultaneous application of criteria, and the number of exclusions is thus not the total number resulting from each individual criterion.

After this selection process, the dataset ready for statistical analysis contains 2,484 effects from 112 unique papers[40] and 332 evaluated projects.

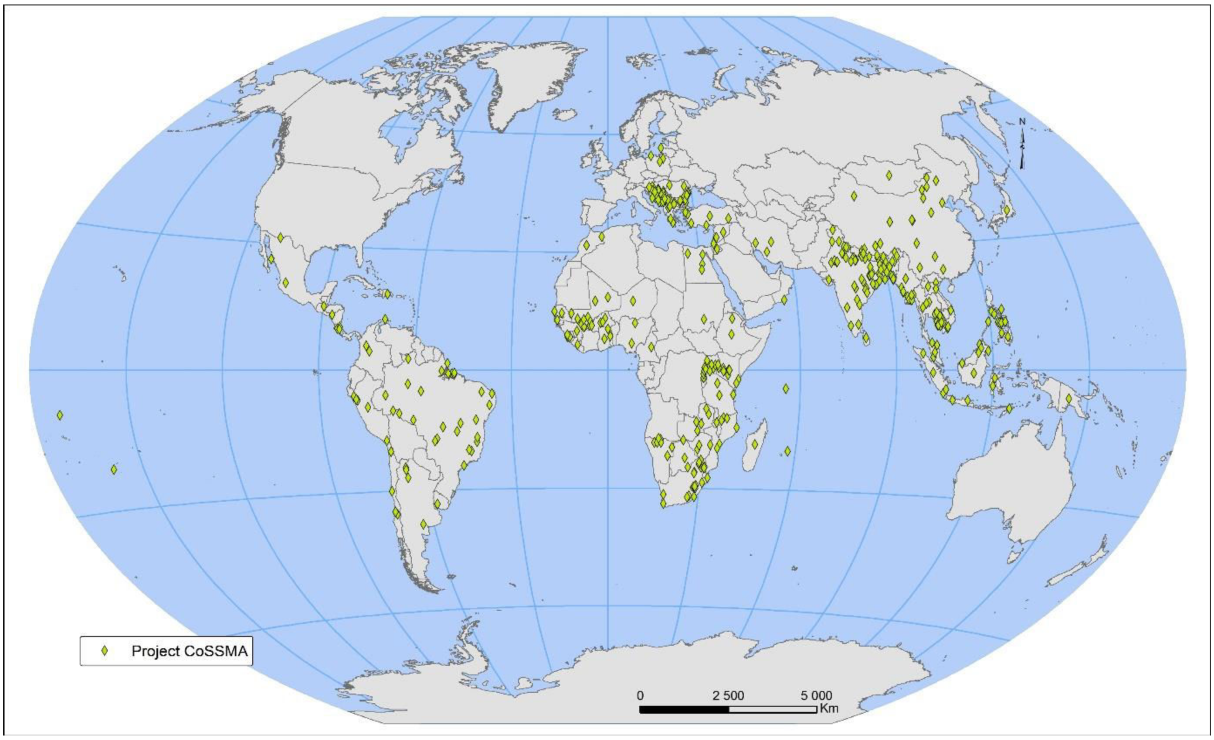
Table 18 - Project inclusion criteria

Projects in sample must :	Initial number of observations in CoSMMA: 2,712 effects	Number of excluded observations
be operative (or eventually have been operative)	Commission date is known and before 2018. Defaulted projects are accepted.	107
not be in OECD and must have an understandable continental location	Effects from projects in OECD countries or with unclear continental location ("worldwide" studies) are excluded	36
deliver capacity below 100 MW	Application of (Dillig et al., 2016) criteria : projects with capacity below 100 MW cannot be involved in balancing, nor in market exchanges nor in clearing	2
use a clear specified technology	Effects from imprecise technology (existing energy mix)	81
be deployed in rural area	Effects from projects in urban area are excluded	0
be evaluated with samples of normal size	Samples with observation number larger than the 99% quantile of this number were excluded. The threshold was 352,800 observations	2
	Number in large sample: 2,484 observations	Total number of deleted observations (effects): 228

Figure 9 shows the geographical distribution of DEP registered in the CoSMMA, showing that CoSMMA is based on a wide variety of experiences.

[40] Articles are counted based on title. A specific attention was paid at collection time to avoid including two versions of the same paper at different time periods. We kept the newest one.

Figure 9 Map of DEP registered in CoSMMA



2.2. Descriptive statistics

The CoSMMA covers a variety of evaluations, from well-identified econometric estimations to mere descriptive observations.

Annex A.1 lists the various methods used by authors for effects' estimation. About a third of reported effects were submitted to statistical tests by their authors, with an econometric model. Some of the estimations made with methods that do not allow for inference, still use statistics with variance, which could have been used for testing. Therefore, we built another criterion than the presence of statistical test : this criterion is based on the heterogeneity of samples supporting estimations.

We call scientific data those effects estimated with heterogeneous samples. We call the remaining expert data. For reasons explained later, our conclusions from the meta-analysis are based only on scientific data. For this reason, we restrict at this stage our description of CoSMMA data to the sub-sample of scientific data.

Annex A.2 describes the distribution of project objective, technology, system size, decision level, and continent over the subset of scientific data. The vast majority of DEP is dedicated to access. Solar electricity is the dominant technology (75% of effects) and other sources are mainly renewables. Fuel systems account only for 4.1% of the sub-sample.

Our classification of systems' capacity is based on the following definitions:

- Nano: < 1 kW
- Micro: 1 to 100 kW
- Mini: 100 kW to 100 MW

More than 73% effects arise from Nano systems, which in fact are mostly solar based: the most frequent systems are SHS.

The most frequent decision levels are at country and province levels or at local level (municipality). This corresponds to two vastly different approaches: top down or bottom up.

As for geographical distribution, approx. 50% of projects are in Africa, approx. 40% are in Asia, and 10% are in Latin America.

Annex A.3 describes the distribution of effects by direction and significance. Effects are qualified as favorable to sustainable development when they make a socio-economic indicator better-off (e.g., they increase energy availability, develop income generating activities, save time for households, improve health or education, or reduce environmental damage). Effects are qualified as unfavorable when they cause a prejudice to economic development.[41]

About 2/3 of effects are favorable and 1/3 are unfavorable (with a small proportion of inconclusive studies; second table in Annex A.3). This ratio of 2 to 1 corresponds to anecdotal evidence reported by NGOs on their success rates with DEP. However, the most striking observation is that whatever the direction, 4/5 of effects are unproven, either because statistical tests could not reject the assumption that the estimate is insignificant, or because those effects were estimated without any test. Only about 20% of reported effects are proven, and this proportion is a much higher for favorable effects than for unfavorable effects. As a consequence, out of the sample of 1,416 effects measured with scientific data, only 208 are proven favorable effects, which we call henceforth "positive impacts", and 71 are proven unfavorable effects, which we call "negative impacts".

Annex A.4 shows the distribution of characteristics associated with positive impacts. Comparing this distribution with the distribution of observed effects in Annex A.2 gives a primary assessment of where the best practices are. From this comparison, we observe relatively more positive impacts in projects using hybrid technology with renewables and less positive impacts in projects using hybrid technology with fuel. There are also a few more solar-based projects with positive impact than in the full sample. We observe also relatively more positive impacts from projects based on Nano size systems. The proportion of positive impacts is the highest at provincial decision level. Finally, there are more positive impacts in Africa than in Asia. These descriptive conclusions may however be

[41] Both directions were manually qualified for each effect -and are excludable- whichever the mathematical sign: increasing the household's income is favorable; decreasing indoor air pollution is favorable; increasing GreenHouse Gas emission is unfavorable; decreasing the probability of women's work is unfavorable. All effects were submitted to an economic judgment, with double check.

misleading, because the different characteristics considered one by one are actually correlated. For instance, most solar systems are SHS of Nano size. We will show in section 4 that the predominance of hybrid and renewable technologies is confirmed by a multivariate analysis, but that Nano size systems are not best practice, and that the provincial decision level is not as effective as the country decision level. As for geographical considerations, the multivariate analysis will not confirm the better performance of Africa than Asia suggested by simple descriptive statistics.

3. Methodology for a meta-analysis of DEP impacts

3.1. Objects of the meta-analysis

Because our meta-analysis does not use directly data from the field, it is important to define what the objects of the analysis are. As pointed out by (Glass, 1977) : *"the design of a study is a complex judgmental process that produces as many different studies as there are researchers and settings in which they work".*

The objects of this meta-analysis are the effects of DEP observed from previous published evaluation studies, which used experimental or observational data. An evaluation study of electrification project is a document that:

- Describes the characteristics of the project
- Describes the general purpose of the project
- Documents or measures the effects of the project

3.2. Source of heterogeneity across control variables

A meta-study aims at exploiting the variance along a common dimension across a set of various studies; but because each research is unique, it seems paradoxical to pretend to identify a common dimension from all the features that make every study unique. As noted by (Stanley, 2001), "*because [...] most studies entail a unique combination of techniques, independent variables, data, time periods and other research choices, not every study characteristic can be coded and analyzed. Nor should a researcher wish to do so. Variation due to minor modeling choices may be treated as part of the random study-to-study background.*"

To achieve this separation between genuine sources of heterogeneity and heterogeneity that arises from modeling choices, we attempted to establish a clear distinction between the measured phenomenon (effects of a DEP), and the conditions of measurement performed to capture this phenomenon (estimation methods, number of observations).

Some meta-analyses capture the number of observations, others capture the T-statistic (Doucouliagos and Paldam, 2006) or standard error (Havranek et al., 2015), some even include the date of collection, which gives a panel of studies (Havranek et al., 2018).

First, in this study, we controlled for the number of observations (N) when it was available. A clear distinction is made between using scientific data (N>1) and studies using expert data (N ≤ 1), as illustrated in Table 19. Annex A.6 provides a more detailed vision of meta-data in CoSMMA, crossing the size of samples with estimation methods of effects.

Table 19 - Scientific vs. Expert data

Denomination	Type	Number of obs. (N)	Frequency
Scientific data	Quantified effect with variance	N > 1	1,416
Expert data	Quantified effect without variance	N = 1	226
Expert data	Documented effect from Research	N = 0	769
Expert data	Unmeasured effect	N = 0	73
Total			2,484

The use of expert data merits a specific discussion. The classical meta-analysis framework relies on two main equations (Doucouliagos and Paldam, 2006) :

- A meta-regression, which explains the interest parameter, controlling for samples' size used by authors ;
- A meta-significance testing, which assesses the relevance of statistical tests used by authors, and notably can diagnose the publication bias that arises from using large samples' size, as in (Hanousek et al., 2011).

(Havranek et al., 2018) follow an intermediate approach, relating the interest parameter with its standard error, in order to assess the publication bias. However, their dataset include some observations without samples' size or standard error, which dramatically reduces the numbers of observations kept in the final regression.

As shown by the dataset used in (Havranek et al., 2018), the absence of statistical tests in some studies, though infrequent, is not an obstacle to conducting a rigorous meta-regression, although it might be expected that introducing too high a proportion of studies without significance testing could weaken the ability to arrive at conclusions. (Carré et al., 2015) also conducted a meta-regression using data without variance of the estimates, which confirmed that the methodology is feasible with expert data. They introduced a dummy for the quality level of observations.

In this study, we initially conducted a baseline meta-regression using scientific data only, reproducing the classical meta-analysis framework. Then we introduced expert data in an attempt to enlarge the estimation sample. However, as discussed later, this attempt was inconclusive, because we observed large differences in best practice revealed by regressions that separate proven and unproven effects, and by regressions mixing them.

Our approach is original because we qualify the nature of meta-data: indeed, we do not expect the same contribution to support conclusion according to the quality of observations. As show from authors above, classical meta-analyses are delimited to scientific data with variance. Our approach proceeds in two stages, building a clear distinction between data with variance (scientific data) and data without variance (expert data). Our contribution arises from introducing a large subset of expert data, exploiting the large number of effects provided by CoSMMA.

Second, we controlled for the methodology of evaluation (Annex A.1). A large variety of research methodologies has been used by researchers to gather evidence of DEPs effects, from the least sophisticated ones (citing others' results) to the most advanced ones (robust econometric evaluations which permit statistical inference).

Third, we controlled for the time lag between the year of implementation of the system and the year of publication of its evaluation. This time lag may reflect the short term vs. long term nature of effects, but may also reflect other factors such as the difficulty to collect data which relies on the memory of survey respondents.

3.3. Specification and estimation strategy

As noted by (Stanley, 2001), "*the independent variables -often called "moderator variables"- are those study characteristics that are thought to be consequential*". In this meta-analysis, project specifications are expected to be the essential channel of DEP impact. First, this is in line with our objective of exploring best practices in DEP. Second, DEP show highly different characteristics, because in decentralized electricity there is no grid providing standards of balancing, demand response, or interconnection. Third, the heterogeneity of DEP characteristics is also higher across projects chosen for research evaluation, because evaluated projects are often the most innovative ones, either in terms of technological features or in terms of socio-economic environment and organizational features.

The outcome variable is the direction of the effect of a DEP, which is a categorical variable; we aim at exploring the determinants of the probability of observing favorable effects. Basically, we could consider a dichotomous outcome, i.e. whether evaluated DEP had favorable effects on sustainable development or not. However, given the large number of studies reporting unproven directions of the effects (Annex A.3, second table), our set of information would be too fuzzy in the absence of a distinction between proven and unproven conclusions. In an attempt to avoid this shortcoming, we considered 3 distinct categories of coupling significance and directions of effects (Annex A.3, first table), such as proven favorable and unproven favorable effects are separated.[42]

[42] As shown by comparing first and second table in Annex A.3, inconclusive direction accounts for less than 2% of scientific effects and were thus aggregated with the "indeterminate" case. Due to the asymmetry of statistical tests, unproven tests do not prove that the effect does not exist, they can only conclude that no conclusion was possible. Therefore, those effects remain "indeterminate", and could be proven in the future

The baseline estimation links a set of project characteristics and of controls by the evaluation's conditions to the probability of achieving a given outcome. The possible outcomes are defined by the combination of the direction of the effects (favorable or unfavorable) and their significance (proven or unproven). The parameters are estimated with a multi-probit estimator, which yields simultaneously all equations, one for each possible outcome.

Equation 3 : Probability of multiple outcomes of socio-economic effect as a function of DEP characteristics

$$P(\text{outcome}_{ip} = k) = \text{constant} + c.\text{EvalCond}_{ip} + s.\text{ProjectSpec}_{p} + \text{error-term}_{ip}$$

Where:

- p is a project
- i is an observed or reported effect
- outcome = k is one of 3 possible outcomes : proven favorable, proven unfavorable, indeterminate.
- EvalCond_{ip} is a vector of control variables defined by the evaluation's conditions ;
- ProjectSpec_{p} is a vector of a project's specifications

This equation provides an assessment of best practices by evaluating *s*, a vector of parameters which describes the influence of project specifications (*ProjectSpec*) on the probability of obtaining a positive impact (*P(outcome = proven favorable)*), after controlling for conditions of evaluation in underlying studies (*EvalCond*). Although our interest is focused on the positive impact outcome, estimating the full set of parameters associated with all 3 outcomes in a multi-probit regression provides a way to enrich our diagnosis, because estimating the determinant of other outcomes conveys information about the DEP characteristics that limit their ability to have positive impacts.

Most of the variables in the vector ProjectSpec are categorical. We consider 5 different types of characteristics:

- Project objective : the main economic approach : access, time limited feature, or increasing existing capacity ;
- Technology: the sources of energy and technics used to produce electricity ;
- System capacity: electric power available for connected users ;
- Organization: decision level - from local to country or multi-country, at which the DEP was conceived ;
- Geographical location.

The variance estimator uses clusters by effects' type, at the second level of a specific nomenclature we built to classify observed effects.

with other evaluation conditions.

Researchers used 1,909 variables that we allocated into 793 indicators (E3), 156 dimensions (E2) and 15 natures of effects (E1) (Annex A.5). At the aggregated level (E1), we combined SDG with some specific categories, as shown in Table 22: some natures of effects are directly related with SDG, but researchers may also measure some extended natures of effects, which brings a broader comprehensive scope of effects of decentralized electrification.

Using the dimensions of nomenclature is a relevant choice for clustering the estimation of estimates' variance, for the two following reasons.

First, dimensions are numerous, and the larger the number of clusters, the higher the chance to correct the Moulton problem, which would result into an over-estimated precision of estimates (Angrist and Pischke, 2008).[43] With 156 dimensions, the second level of effects' type (E2) largely ensures a convergence of estimated standard-error.[44]

However, some dimensions count only one observation. Using the nomenclature at level E1 would make lose the benefit of a large number of categories. We then compared our estimated variance of estimators with two pure algorithmic approaches: a bootstrap and a jackknife (*comparison not shown*). The structure of significance is closely similar: this supports the choice of our cluster, because using the dimensions of the effects' nomenclature is as robust as using a pure algorithmic procedure, but in addition it supports more comprehensive arguments, as described below.

Second, authors might specialize differently by type of estimated effects: e.g., some researchers may focus on estimating health effect, while others will dedicate more attention on economic transformations. Because there could be a convergence of evaluation methodologies by type of estimated effects, heteroscedasticity could happen across effect types, ie. different distributions of variance of estimated effects could occur according to the effect type. For instance, most of environment effects have been estimated with descriptive statistics, while impacts on education concentrate a large share of Randomized Control Trials (RCT) and Difference-in –Difference (DiD). Therefore, clustering by effect type will correct for the various specialization of researchers and uneven variance of estimates according to the type of effect.

3.4. Excluding outliers

In the same way as controls were introduced ex-ante in the estimation strategy, some essential robustness checks were performed before the estimation, to exclude the worst cases that could have spoiled the estimation. These checks correspond to the last criteria in Table 18.

[43] The Moulton problem refers to the risk of over-estimating the precision of estimation by ignoring intra-class correlation: standard-error would be underestimated if they are not corrected for the intra-class correlation. The Moulton factor measures the ratio between the true variance of the estimated coefficient, and the conventional variance in OLS setting; it is congruent to the number of groups multiplied by intra-correlation.

[44] According to (Angrist and Pischke, 2008) the minimum number of clusters ensuring the convergence of estimates' variance should be 42.

The most atypical observations were excluded from the estimation sample, because they could have a too high influence on the meta-estimation, and hide other more frequent relationships. Atypical data appear from uncheckable errors during the collection process, or due to abnormal observations at the extreme end of the variables' distributions. Therefore, observations above the 99% quantile of their distribution were dropped.

4. Which characteristics of electricity projects yield positive impacts on sustainable development?

Table 20 shows the role of characteristics in project effectiveness, after controlling for the conditions of evaluation. This table presents the average marginal effects (AME) of the probability of generating distinct outcomes. As variables of interest are categorical, estimated AME represent the difference between the probability that a given category generates the outcome and the probability associated with a reference category, which is denoted as "ref. =". Columns 1 to 3 show estimated coefficients on scientific data. Column 4 to 6 show estimated coefficients on a restricted sample without effects on energy (i.e. excluding Energy and Basic Access in Table 22).

Then below, we discuss the role of project objective, source of energy, system capacity, decision level, and location.

Table 20 – Effectiveness characteristics of DEP - Average Marginal Effects (AME)

	All types of effects			excl. effects on energy outcomes		
	(1)	(2)	(3)	(4)	(5)	(6)
Effects are :	Proven - Favorable	Proven - Unfavorable	Indeterminate	Proven - Favorable	Proven - Unfavorable	Indeterminate
No. of Observations (N)	-0.000	0.000	0.000	-0.000	0.000	0.000
Delay of evaluation	0.029	-0.015	-0.014	0.027	-0.014	-0.013
Method (ref. = Simple econometrics)						
Identification	0.440***	-0.862***	0.422***	0.365$^{*\circ\circ}$	-0.873***	0.508***
Econometrics without inference	0.000	0.000	0.000	0.000	0.000	0.000
No inference	-0.006	-0.947***	0.953***	-0.010	-0.970***	0.980***
Project objective (ref. = Access)						
Access	0.000	0.000	0.000	0.000	0.000	0.000
Time limited	-0.010	0.000	0.010	-0.019	0.002	0.018
Capacity	0.013	0.024	-0.037	-0.004	0.041	-0.037
Technology : (ref. = Hydro)						
Hydropower source	0.000	0.000	0.000	0.000	0.000	0.000
Solar	0.146***	0.068°°°	-0.214°°°	0.136***	0.096°°°	-0.233***
Hybrid with Fossil fuel	0.128	0.049	-0.178	0.114	0.096	-0.210
Hybrid renewables	-0.001	0.543***	-0.542***	0.012	0.617°°°	-0.630°°°
Biomass (and related tech.)	-0.002	0.537***	-0.535***	0.005	0.611°°	-0.616°°°
Fossil Fuels	-0.003	-0.017°°°	0.020°°°	0.004	-0.004°°°	0.000
Capacity : (ref. = Nano)						
Nano: $<1 kW$	0.000	0.000	0.000	0.000	0.000	0.000
Micro: 1 to 100 kW	0.310°°	-0.082°°°	-0.228°	0.489***	-0.100°°°	-0.389$^{**\circ}$
Mini: 100 kW to 100 MW	0.370***	-0.048°°°	-0.322***	0.493***	-0.070$^{**\circ}$	-0.423***
Program Decision Level (ref. = Local)						
Country	-0.022	0.085	-0.062	0.004	0.086	-0.091
Province	0.014	0.019	-0.033	0.019	-0.040	0.021
County	-0.048	0.085	-0.037	-0.036	0.165	-0.129
District	0.016	-0.015	-0.001	0.066	-0.063	-0.003
Local	0.000	0.000	0.000	0.000	0.000	0.000
Geographical Area (ref. = Asia)						
Africa	0.035	0.042	-0.076	0.055	-0.024	-0.031
Asia	0.000	0.000	0.000	0.000	0.000	0.000
Lat. America	-0.073	0.128	-0.055	-0.074	0.222*	-0.148
Total N in Mprobit	1416	1416	1416	964	964	964
Obs. Number of outcome	208	71	1137	134	68	762

*Average Marginal Effect of Multinomial probit regression. LHS : Proven - Favorable, Proven - Unfavorable, Indeterminate. Subset of 1416 scientific data : evaluation samples with variance (N>1). Ref =: Reference category. Estimates controlled by : Number of observations in evaluation samples (N), Delay of evaluation, Method of evaluation. Values hold as observed in meta-sample. Coefficients tell the difference in percentage points from the prediction of referral category. Variance : cluster by E2en : effect type. The variance-covariance matrix is estimated all at once for all three equations. * p<0.05, ** p<0.01, *** p<0.001. ° : significance level is not achieved with bootstrap estimator of variance. + : significance level occurs only with bootstrap estimator.*

4.1. Role of project objective

All evaluated DEP can be sorted by the main project's objective: access to electricity, delivering time limited access or increasing capacity of existing power supply. However, the project objective is never significant *per se*, neither for favorable impact, nor for unfavorable impact or indeterminate effects. The lack of significance tells something important about the independence between the project objective and its effectiveness: achieving a positive impact for development is not a matter of objective but of the means' alignment to achieve such a performance. Other physical features of project design might thus be the relevant determinants of its success or failure.

4.2. Role of source of energy

Many different sources of energy can be utilized in DEP, with different unit costs, intermittence, reliability, or maintenance requirements. At this stage we can only measure the average performance of the different sources, and we cannot compare them because in practice performance is conditioned by many other factors such as geography.

We chose as reference hydroelectric power projects, which were historically among the first DEP based on renewable energy deployed in developing countries. Small Hydroelectric Power (SHP) were considered as feasible answer to electricity needs with a theoretical potential for impacts (UNIDO, 2010). The literature shows a genuine know-how of rural electricity development with hydro power : 400,000 villages have been electrified using SHP systems in China (NRGExpert, 2013) (UNIDO, 2010), which shows the referral role of hydropower technology for the development of electricity.

Solar power based on photovoltaic panels is by far the most popular technology for DEP and proves to be the best practice of decentralized electrification. Solar technology has significant higher chance of generating positive impact than hydropower projects (+14.6 pp, Table 20, col 1), and this result is robust to the exclusion of energy effects (Table 20, col 4). It is worth noting that effects of solar-based DEP are relatively well known, with significant lower probability of indeterminate impacts (-21.4 pp, col 3). Hybrid solar projects with fossil fuel may also have higher chance of positive impact (+12.8pp, col 1), although the significance of this large effect could not be established.

Other technologies do not bring significant difference with respect to hydropower projects.

In particular, fossil fuel technologies do not show a probability of positive impact significantly different from that of hydropower projects. However, fossil fuels technologies have lower probability of causing negative impacts than hydroelectric power projects (-1.7 pp, Table 20, col 2), which is robust to the exclusion of energy effects (types, costs and basic access). This result suggests that flexibility could play a mitigation role. Although strong environmental negative impacts could be expected from diesel generators, they are highly mobile and have the capacity to fill a missing link in energy supply networks. Notably, they provide short term solutions in emergency situations. On the opposite, hydroelectric power projects are highly constrained by the resource location and the topography of hydrological basins, which can also increase the cost of local power lines due to mountainous terrain and distance to local populations. The benefits of flexibility could thus counter balance the negative effects of fuel technologies, by delivering missing energy to populations: actually, 78% of effects observed with fossil fuel projects are related to the Energy & Basic Access effect types. In comparison, renewable technologies cover a much broader scope of other socio-economic and environmental effects, with 70% of effects appearing in all types but Energy & Basic Access.

The effects of DEP using fossil fuels, either alone or included in hybrid solutions, suggest the underlying role of availability too. This is because the results show that fuel technology is not *per se* a factor of positive impacts, but could improve the probability of success of hybrid solar projects. Although the availability of electricity service does not directly appear as a key factor of impacts, it could be at work in the performance DEP using fuel. In fact, the insignificant estimates could just come from a lower attention of research, because researchers do most frequently assess the impact of access than the impact of availability. Chapter one has shown the important role of availability on the households' decision to pay for a connection to national grid. Availability may also underlie the probability of success of DEP, which would demand more research.

Biomass technology and Hybrid renewables show significantly higher risks of negative impacts (+53.7 pp and +54.3 pp, Table 20, col. 2), without any significant positive impact. However, this negative result does not hold on the restricted sample with a bootstrap estimation (Table 20, col. 5), and is thus only related to energy effects. As a matter of fact, the dependence of biomass or renewable energy solutions on the local availability of energy sources could limit their ability to provide a cost-effective response to energy demand.Hybrid renewables could also be affected by the cost of CAPEX combining several types of technologies. However, this result suffers from a lack of methods or observations, because both technologies report only indeterminate effect; therefore, a more demanding computation of significance shows no significant result with bootstrap estimator.[45]

4.3. Role of system capacity

As reference we use the Nano system capacity, which is mostly associated with SHS.

All projects larger than Nano capacity have higher chance of generating positive impacts, showing a non-linear growing relationship between capacity and the probability of positive impacts: Micro-grids

[45] Some coefficient can be estimated despite the lack of observation, because the Mprobit computes a variance-covariance matrix for all three equations simultaneously. Using demanding methods of significance assessment (numerous clusters and bootstrap) avoids the pitfall of concluding on fragile coefficients.

have significantly +31 pp higher probability of generating positive impacts than Nano systems, and the probability is +37 pp higher for Mini-grids (Table 20, col. 1). Conversely, micro (resp. mini) grids have lower risks of generating negative impacts (-8.2, resp. -4.8 pp, Table 20, col. 2). All these results are robust to the exclusion of energy effects (Table 20, col. 4), and the non-linear growing relationship with capacity is even stronger with other socio-economic effects.

The difficulty for Nano capacity solutions to bring positive impacts may come from the observation that many projects based on Nano systems fail, because they do not generate enough new income to cover their cost (Roche and Blanchard, 2018). However, this result may also occur from the lack of accurate evaluations of such projects: as shown by Table 20, col 3, effects of Nano projects have a significantly higher probability of remaining unproven than those of other project capacity.

4.4. Role of project decision level

DEP can be decided at many different levels, from the local to the country level (or even the multi-country level, which we aggregated with the country level, due to lack of sufficient number of observations of multi-country projects).

The level of project decision could have different types of consequences. On the one hand, a locally decided project might take population needs better into account; it might also be based on a governance structure attentive to promoting cooperation in resource management, thereby preventing the emergence of free-riding issues. On the other hand, projects decided at country level, or at multi-country level, could benefit from a higher degree of expertise, experience, and scalability. Economies of scale in knowledge accumulation and a higher level of expertise can help to find, at least from a technical point of view, the most efficient solutions; public management and supervision systems provide country authorities with accurate feedback from the field, which can be used to identify good and bad practices in the project cycle.

The combination of these two sets or arguments suggests that both bottom-up approaches and top-down approaches can trigger positive impacts, which may lead to a U-shaped relationship between the level of decision and the probability of obtaining positive impacts. However, considering all types of projects and all natures of effects together, we could not verify this assumption with the global sample: taking the local level as reference, no decision level proved to be significantly more or less efficient.

4.5. Role of location

Location is considered at the scale of continents and introduced as a broad control of project context, using Asia as the reference location, due to its long experience in developing rural electricity based on DEP.

An important issue of DEP deployment is to know whether the local context can alter the effectiveness of technical features. Addressing this question, for small geographic areas would be affected by many unobservable variables, which have been identified in the literature as important factors. Factors like distance to raw material, cost of resource transportation, light intensity, solar incidence, wind speed, cost of local power line extension according to the morphology of terrain, and population density may influence the total costs of production and/or system performance. We do not mean that these geographical factors are unimportant, they are important, but we cannot disentangle them from other unobservable factors that affect the outcome of DEP.

Continental location gives some information about the area of economic influence. Experts and engineers may have different training and experience on different continents, and these differences might lead to various practices in electrification projects. However, our model does not find significant differences between projects across various continents.

4.6. Significant pairs of technology and capacity

Table 21 shows the most contrasted interactions of system technology and capacity, by replacing the variables technology and capacity from Table 20 with their interaction. Only interactions with more than 30 observations were kept, and only the most contrasted pairs are shown. A positive value means that the interaction on the left has a higher probability of impact than the one on the right.

The four highest positive contrasts are obtained when comparing Nano solar projects to more efficient combinations of technology and capacity. Compared to Nano solar projects, the most efficient practices are Micro hybrid renewables projects (+37.8 pp), Mini hybrid with fossil fuel (+38.3 pp), Micro hydropower projects (+38.2 pp), and Micro solar projects (+32.6 pp). As shown by the separated effects in Table 20, the solar technology solar *per se* has the highest chance of positive impact; but solar projects are less efficient when the power is delivered through Nano systems (i.e. in SHS), as compared to other combinations of capacity and technology. The lower probability of positive impacts is due to the capacity limitation of Nano solar projects: a too low supplied power does not permit access to all types of electrical appliances.

Half of the biggest contrasts involve hybrid projects: deploying a hybrid mini-grid with fuel or a hybrid micro-grid with renewables has higher chance of generating positive impacts than a Nano solar solution. This result shows that hybrid systems reach higher socio-economic efficiency than other combinations of technology and capacity, and the reason could be their ability to combine the benefits of sustainability, flexibility and availability.

Table 21 – AME of impacts - Highest Significant Pairwise Comparisons

	Pairwise delta	p-value
Hybrid renewables Micro 1 to 100 kW vs Solar Nano <1 kW	0.378	0.000
Hybrid with Fossil Mini 100 kW to 100 vs Solar Nano <1 kW	0.383	0.000
Solar Micro 1 to 100 kW vs Solar Nano <1 kW	0.326	0.006
Solar Nano <1 kW vs Hydropower source Micro 1 to 100 kW	-0.382	0.000

Estimation from Table 20 replacing capacity and technology by their interaction. Subset of scientific data. Interactions with less than 30 observations were dropped.Only the most substantial and significant interactions are shown: delta > 20 pp, pvalue < 5%. Values hold as observed in sample.

4.7. Factors of success by nature of effects

Table 22 compares the distribution of effects and positive impacts observed with scientific data over the nature of effects.

The highest concentration of effects (col 2) is for Energy and is even higher considering Basic Access. Education and Health concentrate large shares of effects. The lowest concentrations are observed for Migration and Community. Noteworthy, the low number of scientific measurements of effects on environment may be due to the recent emphasis in development policies on this core aspect of sustainable development. Observations are also relatively fewer than expected for Economic transformation, perhaps due to the concentration of observations on SHS, which do not target productive uses of electricity.

Table 22 - Distribution of effects and positive impacts by nature of effects (with scientific data)

	Effects		Positive Impacts		
	(1) Freq.	(2) Pct	(3) Freq.	(4) Pct	(5) Row pct
Energy (type, costs & faults)	306	21,6	22	10,6	7%
Education (O4)	250	17,7	42	20,2	17%
Health (O3)	210	14,8	30	14,4	14%
Basic Access (O7)	146	10,3	52	25,0	36%
Economic transformation (O8)	108	7,6	4	1,9	4%
Usable time & leisure	61	4,3	9	4,3	15%
Information & communication	60	4,2	22	10,6	37%
Income & living conditions (O1)	55	3,9	8	3,8	15%
Security (O16)	49	3,5	4	1,9	8%
Environment (O13)	41	2,9			
Gender (O5)	39	2,8	6	2,9	15%
Housework	39	2,8	8	3,8	21%
Financial transformation	28	2,0	1	0,5	4%
Community (O11)	20	1,4			
Migration	4	0,3			
Total	1416	100	208	100	15%

Comparing the distribution of positive impacts (col 4) with the distribution of effects (col 2) suggests which nature of effects are the most likely to be observed from the success of DEP (col 5). Information and communication, Basic Access and Housework are the most likely nature of effects to occur from deploying a DEP: the proportion of positive impacts in observed effects is respectively 37%, 35% and 21%. Positive impacts have lower chance to be reached in Economic Transformation (4%), Financial transformation (4%), Energy (7%), and Security (8%). For the other natures of effects the proportion of positive impacts is close to the average (15%).

The distribution of positive impacts by nature of effects (col 3) shows that identifying factors of positive impacts by various natures of effects is constrained by the small number of available observations for most of the natures: only three natures of effects have more than 30 positive impacts in the CoSMMA.

Table 23 estimates which project characteristics predict the probability of positive impacts by nature of effect. For each type of effects, only observations with effects of this type were selected, thereby defining separated multi-probit estimations. However, due to the restriction to 30 positive impacts and the peculiar heterogeneity of impacts in each nature of effects, estimates could be computed only for Education. Only coefficients of the probability of positive impacts are shown. Due to the limited number of observations, the set of controls was restricted to essential controls, the number of observations (N) and the method of estimation.

Table 23 - AME - Impacts - scientific data - separated regressions by subset of Effect Type

	(1) Education (O4)
No. of Observations (N)	-0.001***
Method (ref. = Simple econometrics)	
Identification	0.000
Econometrics without inference	0.000
No inference	0.000
Project objective (ref. = Access)	
Access	0.000
Time limited	0.136***
Increase capacity	0.074
Technology : (ref. = Hydro)	
Hydropower source	0.000
Solar	-0.309
Hybrid with Fossil fuel	-0.023
Hybrid renewables	0.379
Biomass (and related tech.)	0.507*
Capacity : (ref. = Nano)	
Nano: $<1 kW$	0.000
Micro: 1 to 100 kW	-0.141***
Mini: 100 kW to 100 MW	-0.114**
Program Decision Level (ref. = Local)	
Country	0.158***
Province	-0.320***
County	-0.087
District	0.060
Local	0.000
Geographical Area (ref. = Asia)	
Africa	-0.558***
Asia	0.000
Lat. America	0.157**
Total N in Mprobit	250
Obs. Number of outcome	42

*Average Marginal Effect of Multinomial probit regression. LHS : Only Proven - Favorable is shown. Equations computed for nature of effects with > 30 positive impacts and estimable variance matrix. Subsets by nature of effect, among scientific data (evaluation samples with variance : N>1). Ref =: Reference category. Estimates controlled by : Number of observations in evaluation samples (N), Method of evaluation. Values hold as observed in meta-sample. Coefficients tell the difference in percentage points from the prediction of referral category. Variance : cluster by E2en : effect type. The Variance-Covariance matrix is estimated all at once for all three equations. * p<0.05, ** p<0.01, *** p<0.001.*

DEP have significant higher probability of positive impact on education if they deliver time limited service (+13.6 pp, Table 23). And this objective could also be more efficient than increasing capacity. The reason may be related to the timing of electricity consumption, which is limited to the homework time of children, or the time-limited need for electricity in school.

Technology does not appear as a significant feature for positive impacts on education, excepting Biomass. However, as explained for Table 20, the lack of observation let the significance of this coefficient be dubious.

The most efficient DEP for education are Nano system, which have higher probability of positive impacts than micro-grids (+14.1 pp) or mini-grids (+11.4 pp). Therefore, the growing relationship with capacity found in Table 20 might rather come from other natures of effects. The performance of Nano systems for education may be due to the mobility of small electricity devices in off-grid area, allowing the delivery of low consumption appliances for homework (e.g. lighting).

The U-shaped relationship that we expected in section 4.4 occurs between the level of decision and the probability of positive impacts on education, which suggests that governance levels play differentiated roles according to the natures of effects.

Taking the local level as reference, we observe that the highest probability of obtaining positive impacts is achieved at the country (or multi-country) level (+15.8 pp). On the opposite, the minimum probability is significantly reached at province level (-32.0 pp). Then, the closer the decision level comes to the local level, the higher the probability of a positive impact.

Although the beneficial role of countries and the counter-productive role of provinces are significant, the country and district levels are not, and there is a positive sign associated with the district's role. These limits raise some doubts about the complete significance and U-shaped pattern of the curve. In addition, the higher efficiency at country level could also be biased, because country or multi-country programs may have more resources to implement ex-post evaluations. As a matter of fact, the probability of obtaining indeterminate effect is significantly lower at country level than at local level (-18.4 pp, *table not shown*): the higher probability of positive impacts at country level could thus result from a higher probability of conclusive evaluation. There could also be some unobservable factors correlated with province decision level, such as a higher exposure to corruption risk, and actually, the province level is also exposed to higher indetermination (+0.29.8 pp, *table not shown*). However, the opposition between significant minimum and maximum strongly suggests that both top-down and bottom-up approaches plays a role for the efficiency of DEP on education.

The most successful projects for education were in Latin America (+15.7 pp), while DEP in Africa have a significantly lower chance of positive impacts on education than in Asia (-55.8 pp). This result could be correlated with unobservable cultural or organizational factors that DEP design cannot capture.

4.8. Extending knowledge of effects with expert data

Given the shortage of information based on scientific data, it is tempting to try to expand our information base with expert data. Expert Data (ED) has two levels of data quality: effects that rely on observations without variance (N=1) (i.e. without confidence interval), and effects that are solely documented from other research papers, or simply mentioned in institutional reports (N=0). Table 24 shows the estimation including ED in the estimation sample. Due to the large number of missing values on samples' size (N), this controlled was relaxed.

Including ED in the estimation does not allow the separation of proven outcomes from unproven outcomes, because ED do not provide confidence intervals (see Annex A.6). Hence the use of ED, which enlarges the observation sample, limits the precision of the model because the precision of some effects' estimates in research articles is unknown. This modifies the results.

Table 24 - AME- with expert data (N >= 0)

Effects are :	Favorable	Unfavorable	Unknown direction
Delay of evaluation	0.002	-0.002	0.000
Method (ref. = Simple econometrics)			
Identification	0.237	0.077	-0.315*
Econometrics without inference	0.000	0.000	0.000
No inference	0.280	0.064	-0.344**
No measurement	0.382	-0.068	-0.314**
Project objective (ref. = Access)			
Access	0.000	0.000	0.000
Time limited	-0.563***	0.579***	-0.016
Capacity	-0.002	-0.031	0.033
Technology : (ref. = Hydro) :			
Wind	-0.288**	0.152*	0.137
Geothermal Tidal	0.099	-0.134***	0.035
Hydropower source	0.000	0.000	0.000
Solar	-0.130**	0.111*	0.019*
Hybrid with Fossil fuel	-0.049	0.033	0.017
Hybrid renewables	-0.057	0.042	0.015
Biomass (and related tech.)	-0.086	0.060	0.026
Fossil Fuels	-0.043	0.058	-0.015
Power : (ref. = Nano)			
Nano: $<1 kW$	0.000	0.000	0.000
Micro: 1 to 100 kW	-0.090*	0.071	0.019
Mini: 100 kW to 100 MW	-0.060	0.009	0.050*
Program Decision Level (ref. = Local) :			
Country	-0.050	0.068*	-0.018
Province	-0.097*	0.127***	-0.031
County	-0.340*	0.373*	-0.033*
District	0.094*	-0.054	-0.040*
Local	0.000	0.000	0.000
Geographical Area (ref. = Asia) :			
Other non-OECD	0.242***	-0.199***	-0.042*
Africa	-0.039	0.049	-0.011
Asia	0.000	0.000	0.000
Lat. America	-0.008	0.047	-0.039*
Europe non-OECD	-0.748***	-0.129**	0.877***
Total N in Mprobit	2447	2447	2447
Obs. Number of outcome	1796	559	92

Average Marginal Effect of Multinomial probit regression. LHS : Ifav3 : Unfavorable Favorable Unknown_direction. Subset of 2447 scientific data : evaluation samples with variance (N>1).Ref =: Reference category. Estimates controlled by : Delay of evaluation, Method of evaluation. Values hold as observed in meta-sample. Coefficients tell the difference in percentage points from the prediction of referral category. Variance : cluster by E2en : effect type. The Variance-Covariance matrix is estimated all at once for all three equations. p<0.05, ** p<0.01, *** p<0.001*

Indeed, merging proven and unproven favorable effects hides the specific information provided by proven favorable effects (positive impacts). In our data, unproven favorable effects are more numerous (1588 versus 208), and a more detailed analysis using all five cases described in Annex A.3 shown that proven and unproven favorable effects have different explanatory factors (*model not shown*). As a result, comparing favorable effects of Table 24 (col 1) with Expert Data included, and positive impacts restricted to scientific data in Table 20 (col 1), the unproven favorable effects dominate in Table 24, and lead to a totally different picture of DEP effectiveness. The positive sign of some estimation conditions confirms that estimates with no measurement have higher chance to conclude on favorable effects (Table 24, col1).

According to the inclusion of Expert Data, DEP would have much higher chance of positive impacts if they would pursue the objective of access to electricity instead of time limited service (+56.3 pp, Table 24, col1). Increasing capacity would not have different effect than bringing access to households.

Solar technology would be beaten by most alternatives, except Wind (whose parameter could not be estimated in Table 20). The most effective technologies for development would be hydroelectric generators, and maybe geothermal systems (whose parameter could not be estimated in Table 20, and is not significant despite large magnitude).

Nano solutions would be a significantly better choice than Micro-grids (+9.0 pp, col 1) and would have almost a similar performance to Mini-grids.

Local decisions (whether from municipalities or districts) would be more efficient than any other level (col 1), and decision at the level of country, province or county would bring more unfavorable effects (col 2).

These results are in contrast to the conclusions reached from Table 20. They are however fragile, as the significance of parameters is very sensitive to sample changes: when estimated on the sub-sample of scientific data, parameters associated with sources of energy and decision level become non-significant (*table not shown*).

5. Discussion

5.1. Possible selection bias

Comparing the role of identification methods for favorable and unfavorable impacts shows that authors tend to use robust methods to identify favorable impacts, much more than unfavorable impacts: in Table 20 (col 1 and col 2), there is higher chance to prove positive impacts with a robust method than with simple econometrics (+44.0 pp); and there is much lower chance to prove unfavorable impacts (-86.2 pp) with the same robust methods. This result suggests that the estimation of the probability of positive impacts in our model could be affected by a publication bias.

The selection procedure with EBSCO ensures that no bias from a focus in search of a specific research frontier, which would result in a narrowly oriented selection of papers, remains. However, some selection bias could still occur.

First of all, impacts of DEP can be evaluated only under 3 conditions:

- Effects arise from implemented projects
- Researchers tested these effects
- Effects were measured with observed data with heterogeneity.

Effects are not observable if researchers have not considered evaluating them: some effects were not considered relevant, or not of interest, at the time of evaluation, or not surveyed due to budget constraints on the collection of field data. This might be the case for environmental effects, which are rarely measured with field data in the papers entered in the CoSMMA. Some effects are only documented from other pieces of research, or quantified without any sample of observations. In both cases, the significance of an effect is not computable, and whether the reported effect is an evidence of impact remains unknown. Our results suggest that evaluations without statistical tests may lead to conclusions at odds with conclusions obtained from evaluations with statistical tests. Resolving this issue is beyond the scope of this paper, but future developments of the CoSMMA, whose aim is to broaden the scope and depth of DEP evaluations, could contribute to the solution.

In addition, research on DEP impacts can be affected by publication bias, because research publications are driven by the need to show innovation and tend to favor significant positive results. However, in our case, the relatively small proportion of positive impacts reported in evaluations suggests that this publication bias may be limited.

The publication bias can nonetheless be magnified by the possible lack of independence of the project assessor. Organizations implementing funded projects need to demonstrate *ex-post* that positive impacts occur, and might be tempted to resort to assessors dedicated to showing positive impacts. This may explain why a large proportion of papers that we have collected in the CoSMMA report favorable effects without providing scientific evidence in support of their conclusions. At this stage of development of the CoSMMA, our choice of using evaluations based on scientific data, and not on expert data, is the only way to deal with this issue and identify best practice.

Finally, sample size could also be the origin of a publication bias. The cost of field evaluations puts a budget constraint on the sample size that researchers might be able to collect: as a result, small studies with limited samples might show significant effects only for those studies with the largest magnitude effects. The reason for this is that the critical size sample is a convex decreasing function of the magnitude of the assessed effect (Châtelain, 2010).

5.2. Cycle between funding and evaluation

Because projects are risky, donors or lenders tend to commit funds to new projects that show comparable specifications to previous successful projects, especially when they have defined risk management policies based on project characteristics. Publication bias might therefore sustain conservative commitment strategies, repeating the funding of the same type of projects as those which have shown large effects with small samples. In the absence of any third-party evaluations of electrification projects, the cycle of decision/evaluation/judgment could continue unabated. There could be a virtuous/vicious circle between publication bias and project commitment, each nurturing the other, a cycle that is all but random.

6. Concluding remarks

This research is the first step of the CosMMA project, towards a better understanding of the potential contribution of DEP to sustainable development, with the aim of identifying best practice. In this pilot CoSMMA we have assembled a database of the characteristics of 403 DEP and their effects on sustainable development.

The results of our meta-regression highlight the roles of energy source and system capacity. There is clearly a trade-off between the choice of new sources of renewable energy, especially solar energy, and system capacity. Solutions relying on solar energy alone bring positive impacts, but these impacts are reduced because solar electricity is mainly delivered through Nano systems, whose positive impacts are much less frequent than positive impacts of larger systems such as Mini-grids. Hybrid systems may provide an interesting compromise, because they can be larger than SHSs, and also help to solve other technical issues such as intermittence. Our results also suggest the role of organizational characteristics, as evidenced by the U-shaped curve describing the influence of the decision level for impacts on education.

So far, we have been able to use only scientific data, and not expert data, for lack of comparable precision of data provided by experts and data reported in econometric research. As a consequence, the sample size available for meta-analysis is smaller than what we have in the CoSMMA, which limits the breadth of our exercise. In particular, data limitations prevented us from exploring systematically the different natures of effects of DEP. In particular, we could not reach any conclusions in many fields that are critical for sustainable development, such as environment, health, or economic transformation. Also, we could not assess the best practices related to Energy, because despite the large number of reported effects, only few were proven so far. Hopefully, the fast development of DEP may remove these limitations in the future.

One possible direction for further research could be related to the assessment of different uses of electricity. The CoSMMA project could sustain further studies to measure which uses of electricity matter in terms of economic development, based on the proven effects of DEP. As a result, developers of electrification projects could size the system capacity according to the socio-economic conditions of targeted off-grid area. Being optimized for their expected economic use, DEP might increase their survival probability.

Measuring the latent demand for electricity uses is important because the development path of electrical appliances that was followed by households in advanced countries cannot be replicated today in developing countries. European consumers started to buy fridges during the 1950's and mobile phones in the 2000's. In contrast, African households have reached a 60% equipment rate in mobile phones in the last 5 years, but rarely own a fridge. It is thus crucial to further analyze what will be the household preferences for electrical appliances.

Our meta-analysis of DEP effects gives a preliminary contribution to the measurement of latent demand for electricity, because positive impacts of electrification may be considered as proxies of electricity uses in developing countries.

In addition, our meta-analysis emphasizes which project characteristics have the highest probability of achieving positive impacts on sustainable development, and this should help developers to relate project design to expected electricity uses.

Presenting best practices of decentralized electrification may both encourage better sizing of projects, and also provide first indications for further research on latent demand for electrical appliances of decentralized electricity.

Annexes

A.1 Methods used by research to evaluate DEP effects

	Groups of Methods		
	Freq	Pct	Cumpct
Identification	721	29.0	29.0
Econometrics without inference	30	1.2	30.2
No inference	891	35.9	66.1
No measurement	842	33.9	100.0
Total	2484	100.0	

Source : Estimation sample from CoSMMA

A.2 Distributions of characteristics over scientific data

	Project's objective		
	Freq	Pct	Cumpct
Access	1189	84.0	84.0
Time limited	77	5.4	89.4
Capacity	150	10.6	100.0
Total	1416	100.0	

	Technology		
	Freq	Pct	Cumpct
Hydropower source	62	4.4	4.4
Solar	1129	79.7	84.1
Hybrid with Fossil fuel	88	6.2	90.3
Hybrid renewables	45	3.2	93.5
Biomass (and related tech.)	34	2.4	95.9
Fossil Fuels	58	4.1	100.0
Total	1416	100.0	

	System Capacity		
	Freq	Pct	Cumpct
Nano: $<1 kW$	1038	73.3	73.3
Micro: 1 to 100 kW	266	18.8	92.1
Mini: 100 kW to 100 MW	112	7.9	100.0
Total	1416	100.0	

	Decision Level		
	Freq	Pct	Cumpct
Country	494	34.9	34.9
Province	376	26.6	61.4
County	141	10.0	71.4
District	63	4.4	75.8
Local	342	24.2	100.0
Total	1416	100.0	

	Continent		
	Freq	Pct	Cumpct
Africa	672	47.5	47.5
Asia	606	42.8	90.3
Lat. America	138	9.7	100.0
Total	1416	100.0	

Source : subset of scientific data from estimation sample from CoSMMA

A.3 Distribution of effects by direction and significance of effects

	Significance and direction of effects		
	Freq	Pct	Cumpct
Proven - Favorable	208	14.7	14.7
Proven - Unfavorable	71	5.0	19.7
Indeterminate	1137	80.3	100.0
Total	1416	100.0	

	Significance and direction of effects (5 cases)		
	Freq	Pct	Cumpct
Proven - Favorable	208	14.7	16.6
Proven - Unfavorable	71	5.0	21.6
Inconclusive direction	27	1.9	1.9
Unproven - Favorable	765	54.0	75.6
Unproven - Unfavorable	345	24.4	100.0
Total	1416	100.0	

Source : subset of scientific data from estimation sample from CoSMMA

A.4 Distributions of explanatory variables in the subset of positive impacts

	Project's objective		
	Freq	Pct	Cumpct
Access	172	82.7	82.7
Time limited	6	2.9	85.6
Capacity	30	14.4	100.0
Total	208	100.0	

	Technology		
	Freq	Pct	Cumpct
Hydropower source	5	2.4	2.4
Solar	197	94.7	97.1
Hybrid with Fossil fuel	6	2.9	100.0
Total	208	100.0	

	System Capacity		
	Freq	Pct	Cumpct
Nano: $<1 kW$	198	95.2	95.2
Micro: 1 to 100 kW	4	1.9	97.1
Mini: 100 kW to 100 MW	6	2.9	100.0
Total	208	100.0	

	Decision Level		
	Freq	Pct	Cumpct
Country	48	23.1	23.1
Province	98	47.1	70.2
County	16	7.7	77.9
District	6	2.9	80.8
Local	40	19.2	100.0
Total	208	100.0	

	Continent		
	Freq	Pct	Cumpct
Africa	116	55.8	55.8
Asia	66	31.7	87.5
Lat. America	26	12.5	100.0
Total	208	100.0	

A.5 Nomenclature of effects: dimensions by natures of effects

Basic Uses

	E2en - Dimension Freq	Pct	Cumpct
Lighting(quantity)	44	23.8	23.8
Use of Kerosene	30	16.2	40.0
Lighting(quality)	27	14.6	54.6
Consumer Satisfaction	19	10.3	64.9
Use of Batteries	19	10.3	75.1
Mobile Phone Charging	12	6.5	81.6
Use of Candles	11	5.9	87.6
Calibration of Electricity Use	8	4.3	91.9
Use of Coal	4	2.2	94.1
Use of Wood	3	1.6	95.7
Electrical appliances	2	1.1	96.8
Production Activities	2	1.1	97.8
Access to Electricity	1	0.5	98.4
Electrical Asset (possession)	1	0.5	98.9
Electricity Demand	1	0.5	99.5
Use of Fuel	1	0.5	100.0
Total	185	100.0	

Community

	E2en - Dimension Freq	Pct	Cumpct
Social Cohesion	32	39.0	39.0
Personal Development	12	14.6	53.7
Decompartmentalisation	7	8.5	62.2
Institutional Resources	6	7.3	69.5
Social Acceptance	6	7.3	76.8
Infrastructures	5	6.1	82.9
Poverty	5	6.1	89.0
Quality of Life	4	4.9	93.9
Night time activities	2	2.4	96.3
Consumer Satisfaction	1	1.2	97.6
Socioeconomic Aspects	1	1.2	98.8
TV	1	1.2	100.0
Total	82	100.0	

Economic transformation

	E2en - Dimension Freq	Pct	Cumpct
Production Activities	43	17.6	17.6
Support Systems for Agricultural Output	25	10.2	27.9
Training	23	9.4	37.3
Hours of Work	22	9.0	46.3
Employment as Paid Employee	21	8.6	54.9
Revenues	19	7.8	62.7
Productivity	15	6.1	68.9
Setting up New Businesses	12	4.9	73.8
Electrical Asset (possession)	11	4.5	78.3
Night time activities	11	4.5	82.8
Participation	11	4.5	87.3
Productive asset	8	3.3	90.6
Non-electric asset	6	2.5	93.0
Infrastructures	4	1.6	94.7
Working Conditions	4	1.6	96.3
Access to Financial Services	2	0.8	97.1
Impact on Orders	2	0.8	98.0
Access to Financing	1	0.4	98.4
Agricultural Asset	1	0.4	98.8
National Revenue	1	0.4	99.2
Personal Development	1	0.4	99.6
Structural Unemployment	1	0.4	100.0
Total	244	100.0	

Education

	E2en - Dimension Freq	Pct	Cumpct
Results	156	44.7	44.7
Study activities	44	12.6	57.3
Night time activities	40	11.5	68.8
Education Resources	32	9.2	77.9
School enrolment	24	6.9	84.8
Education Quality	23	6.6	91.4
Attendance	15	4.3	95.7
Study conditions	11	3.2	98.9
Education Expenses	3	0.9	99.7
Training	1	0.3	100.0
Total	349	100.0	

Energy

	E2en - Dimension Freq	Pct	Cumpct
Default	91	11.4	11.4
No data	91	11.4	22.8
Cost of Energy	86	10.8	33.6
Calibration of Electricity Use	84	10.5	44.1
Value	59	7.4	51.5
Reliability of Electricity Service	33	4.1	55.6
Operational Costs - OPEX	32	4.0	59.6
Energy Expenses	29	3.6	63.3
Socioeconomic Aspects	27	3.4	66.7
Energy Production	25	3.1	69.8
Balancing	21	2.6	72.4
Price Competitiveness of Electricity	21	2.6	75.1
Total Cost	20	2.5	77.6
Upfront Costs - CAPEX	18	2.3	79.8
Access to Electricity	17	2.1	82.0
Consumer Satisfaction	17	2.1	84.1
Energy Mix Composition	15	1.9	86.0
Use of Electricity	14	1.8	87.7
Use of Kerosene	12	1.5	89.2
Access	9	1.1	90.4
Sale of Energy	9	1.1	91.5
Energy Market	7	0.9	92.4
General Externalities	7	0.9	93.2
Energy Efficiency	6	0.8	94.0
Use of Batteries	6	0.8	94.7
Use of Candles	6	0.8	95.5
Means of Production	5	0.6	96.1
Use of Fuel	5	0.6	96.7
Electrical appliances	4	0.5	97.2
Energy Dependence	4	0.5	97.7
Security of Supply	4	0.5	98.2
Use of Wood	3	0.4	98.6
Energy Storage	2	0.3	98.9
Personal Development	2	0.3	99.1
Complete Cost	1	0.1	99.2
E3 to specify	1	0.1	99.4
Electricity Demand	1	0.1	99.5
Financial Risks	1	0.1	99.6
Lighting (quantity)	1	0.1	99.7
Use of Coal	1	0.1	99.9
Use of Gas	1	0.1	100.0
Total	798	100.0	

Environment

	E2en - Dimension Freq	Pct	Cumpct
Atmospheric Pollution	84	37.8	37.8
Environmental Performance	54	24.3	62.2
Energy Transition	25	11.3	73.4
Environmental Externalities	21	9.5	82.9
Ex-Ante Environmental Impact	8	3.6	86.5
Soil Fertility	6	2.7	89.2
Deforestation	5	2.3	91.4
Waste	5	2.3	93.7
Noise Pollution	4	1.8	95.5
Biofuels	3	1.4	96.8
Soil Pollution	3	1.4	98.2
Biodiversity	2	0.9	99.1
Energy Storage	2	0.9	100.0
Total	222	100.0	

Financial transformation

	E2en - Dimension Freq	Pct	Cumpct
Debt Structure	24	41.4	41.4
Savings	15	25.9	67.2
Access to Financing	7	12.1	79.3
Value	6	10.3	89.7
Financial Risks	4	6.9	96.6
Access to Financial Services	1	1.7	98.3
National Debt	1	1.7	100.0
Total	58	100.0	

Gender

	E2en - Dimension Freq	Pct	Cumpct
Independence	39	48.1	48.1
Fertility	15	18.5	66.7
Living Conditions	14	17.3	84.0
Time Budget	7	8.6	92.6
Housework	6	7.4	100.0
Total	81	100.0	

Health

	E2en - Dimension Freq	Pct	Cumpct
Respiratory Risk	76	24.3	24.3
Disease Prevention	27	8.6	32.9
Gastrointestinal Risk	24	7.7	40.6
Food Security	17	5.4	46.0
General Risk	17	5.4	51.4
Indoor Air Pollution	17	5.4	56.9
Ophthalmology Risk	16	5.1	62.0
Cerebrovascular Risk	15	4.8	66.8
Health Facilities	15	4.8	71.6
Access to Healthcare	12	3.8	75.4
Burns Risk	12	3.8	79.2
Refrigeration	12	3.8	83.1
ENT Risk	9	2.9	85.9
Infection Risk	9	2.9	88.8
Cardiac Risk	6	1.9	90.7
Electrical Asset (possession)	5	1.6	92.3
Childcare	4	1.3	93.6
Dermatology Risk	3	1.0	94.6
Longevity	3	1.0	95.5
Unexpected Health Risk	3	1.0	96.5
Health Expenses	2	0.6	97.1
Hepatic Risk	2	0.6	97.8
Night time activities	2	0.6	98.4
Absenteeism	1	0.3	98.7
Childhood Risk	1	0.3	99.0
Cost of Health Risks	1	0.3	99.4
Public Health Externalities	1	0.3	99.7
Water Pollution	1	0.3	100.0
Total	313	100.0	

Housework

	E2en - Dimension Freq	Pct	Cumpct
Collecting Water & Energy	13	26.5	26.5
Housework Conditions	8	16.3	42.9
Night time activities	7	14.3	57.1
Time Spent on Housework	7	14.3	71.4
Meal Preparation	5	10.2	81.6
Housework & Laundry	4	8.2	89.8
Weaving	4	8.2	98.0
Cooking Method	1	2.0	100.0
Total	49	100.0	

Income & living conditions

	E2en - Dimension Freq	Pct	Cumpct
Revenues	28	30.1	30.1
Consumption Expenses	18	19.4	49.5
Quality of Life	16	17.2	66.7
Poverty	8	8.6	75.3
Financial Risks	5	5.4	80.6
Debt Structure	4	4.3	84.9
Electrical appliances	4	4.3	89.2
Energy Expenses	2	2.2	91.4
National Revenue	2	2.2	93.5
Electrical Asset (possession)	1	1.1	94.6
Food Security	1	1.1	95.7
Leisure Consumption	1	1.1	96.8
Radio	1	1.1	97.8
Telephone	1	1.1	98.9
Value	1	1.1	100.0
Total	93	100.0	

Information & communication

	E2en - Dimension Freq	Pct	Cumpct
Electrical Asset (possession)	25	28.1	28.1
Radio	23	25.8	53.9
Access to Information	17	19.1	73.0
TV	10	11.2	84.3
Mobile phone use	6	6.7	91.0
Communications	2	2.2	93.3
Internet	2	2.2	95.5
Lighting(quality)	2	2.2	97.8
Electrical appliances	1	1.1	98.9
Telephone	1	1.1	100.0
Total	89	100.0	

Migration

	E2en - Dimension Freq	Pct	Cumpct
Urban migration	5	45.5	45.5
Rural immigration	4	36.4	81.8
Demographics	1	9.1	90.9
Migration flows	1	9.1	100.0
Total	11	100.0	

Security

	E2en - Dimension Freq	Pct	Cumpct
Night time Security	26	46.4	46.4
Crime	14	25.0	71.4
Vandalism	6	10.7	82.1
Fire risk	3	5.4	87.5
Security of Public Spaces	3	5.4	92.9
Burns Risk	2	3.6	96.4
Security of Supply	2	3.6	100.0
Total	56	100.0	

Usable time & leisure

	E2en - Dimension Freq	Pct	Cumpct
Daily routines (getting up/going to bed)	24	29.3	29.3
Availability	14	17.1	46.3
Night time activities	11	13.4	59.8
Time Budget	10	12.2	72.0
Type of Leisure Activity	7	8.5	80.5
Daily activities (bath, meals, rest)	6	7.3	87.8
Leisure Conditions	5	6.1	93.9
Time for oneself	4	4.9	98.8
Electrical Asset (possession)	1	1.2	100.0
Total	82	100.0	

A.6 Type of meta-data in CoSMMA

$\hat{\beta}$: estimated parameter

$\hat{V}(\hat{\beta})$: variance estimator of estimated parameter

$W\{\hat{\beta}, \hat{V}(\hat{\beta})\}$: critical region associated with parameter and its variance : a statistical test does exist.

		Method of estimation		
Name of meta-data	Number of observations in estimation sample (N)	Identification (econometrics allowing for inference)	Simple econometrics	No inference
Scientific data	N > 1	$W\{\hat{\beta}, \hat{V}(\hat{\beta})\}$	$W\{\hat{\beta}, \hat{V}(\hat{\beta})\}$	$\hat{\beta}, \hat{V}(\hat{\beta})$
Expert data	N = 1			$\hat{\beta}$
Expert data	N = 0			Citation of $\hat{\beta}$
Expert data	N = 0			unknown $\hat{\beta}$

Chapter THREE: Impact of various practices of Decentralized Electricity in Developing Countries

Abstract

Evaluating the complete performance of decentralized electrification needs to take into account the combination between practices and the nature of effects. This study proposes a performance assessment of Decentralized Electrification Projects (DEP) in developing countries as to their contribution of achieving Sustainable Development Goals, using a typology of projects that extends the exploration of the Collaborative Smart Mapping on Mini-grids Action (CoSMMA) database.

With data on 497 Production Units, a classification sorts the main practices of decentralized electrification, which allows evaluating their probability of positive impact and describing the natures of positive impacts by project types. An extension looks at the determinants of the nature of favorable effects observed with individual SHS.

DEP for Productive Uses and Utilities have +39.4 percentage point higher probability of achieving positive impacts than individual SHS. Then come Micro-grids for access in remote areas (+10.9 pp). Modern private mini-grids and Individual SHS achieve similar performance.

The probability of positive impacts increases with the capacity of Individual SHS, and the relationship is stronger for socio-economic effects beyond access to electricity and cost of energy. This result stresses the importance of increasing electricity power to achieve economic development. The increasing relationship could be linked with favorable effects of on Information and communication. However, some natures of favorable effects on Health and Usable time and leisure have higher chance of being observed with Nano systems. Micro-grids for access in remote areas are also more likely to succeed with reduced capacity.

The study confirms a non-linear relationship of the role of DEP governance for their performance for economic development. For Micro-grids in remote areas, the duality of local and global governance exists only for other socio-economic effects. For Individual SHS, the combination of bottom-up and top-down approaches mainly exists for impacts on the 7th SDG. The complex role of governance depends on the combination of DEP practices and natures of effects, which suggest possible specializations of decision levels with respect to the main expected uses of supplied electricity.

Individual SHS and Micro-grids in remote areas are the only practices of decentralized electrification for which some positive impacts have been proven so far. The former are associated with positive impacts mainly on education, and the latter mainly on information and communication.

According to expert data, private mini-grids and projects for productive use and utilities would have positive effects on economic transformation or the environment. However, these benefits have never been proven with scientific data. Beyond the lack of proven favorable effects, the use of expert data could blur the results, as invariant statistics or citations can be called as *ad hoc* arguments in support of the project objective. The final mapping shows the practices and natures of effects that require more identification of DEP impacts.

JEL :, L94, O13, O18, O22, Q01

Keywords : Decentralized electrification, sustainable development, impact assessment, classification, typology, off-grid projects

Introduction

Practices of decentralized electrification are very diverse, involving multiple combinations of primary sources of energy, technologies, sizing, governance choices and range of appliances. Mostly using renewable resources, Decentralized Electrification Projects (DEP) are notably constrained by the local conditions of electricity production and cannot expect any balancing support from central grid, which limits the supplied power in terms of capacity and availability. Patterns of electricity service and connected users might thus be very different from one project to another, reflecting the rationing of supply. On another hand, the funding of DEP largely involves development aid, government subsidies or private donations, for which those projects must show proven favorable effects for sustainable development (“*positive impacts”*). How to avoid wasting financial resources while waiting for the positive effects of projects that offer only a limited service offer? This question requires to clarify which types of projects ("*practices*") can achieve the Sustainable Development Goals.

The rapid growth of standalone systems and mini-grids offers a feasible opportunity to assess the relationship between the design of DEP and the achievement of positive impacts. Using meta-data from the Collaborative Smart Mapping on Mini-grids Action (CoSMMA) database, this study extends the assessment of the probability of positive impacts by various practices of decentralized electrification, relying on a typology of projects computed with statistical classification. Performance of practices is measured by the achievement of Sustainable Development Goals, and then analyzed by natures of effects.

Estimating the probability of positive impact by projects’ type provides a robustness check of the main results found in chapter 2, and allows exploring some practices of decentralized electrification as the main channel of the probability of positive impacts. Then the study presents which natures of positive impacts have been proven so far for some practices. In addition, profiles of favorable effects help isolate those natures of effects that were only reported with expert data but have not been proven so far. Finally, an extension looks at the determinants of the nature of favorable effects observed with individual SHS, providing clues as to the possible determinants of the natures of impacts.

This study contributes to the literature on DEP evaluation by bringing a first empirical typology of practices of decentralized electrification. It is also the first study that explores several practices of decentralized electrification as the channel of the probability of positive impacts on economic development. Finally, it brings a comprehensive vision of to date knowledge on the natures of impacts of decentralized practices, thereby separating proven favorable effects from those effects that will require more research to be qualified as impacts.

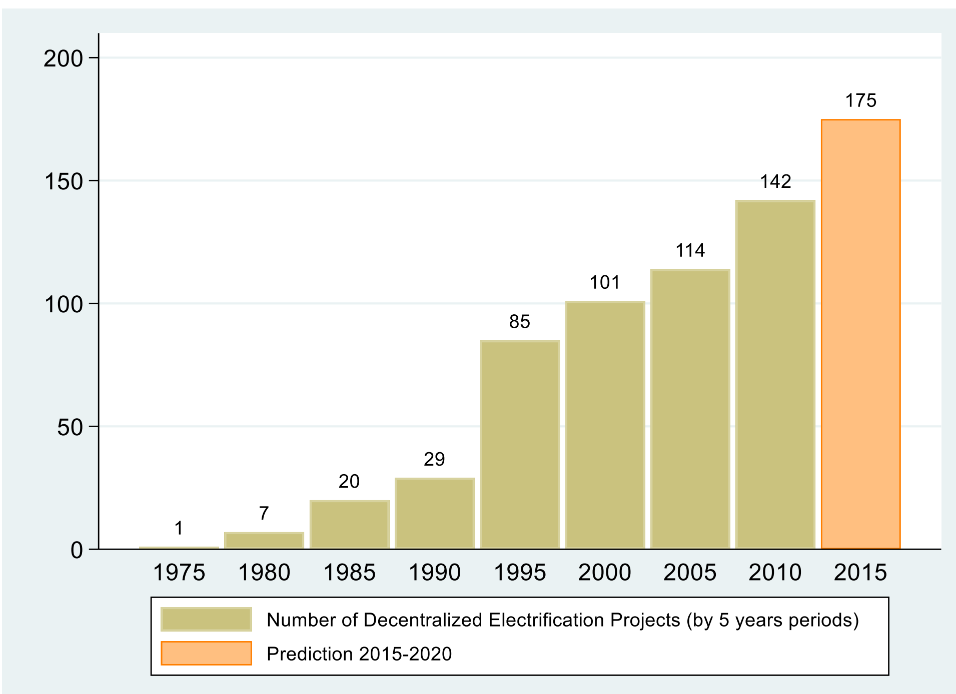
Section 1 sets the research question. Section 2 explores the previous literature. Section 3 presents the data, indicators, and some key descriptive statistics. Section 4 exposes the methodological corpus of the study: definitions, qualification, assumptions and classification. Section 5 presents the results. Finally, section 6 concludes.

1. Which practices of decentralized electrification lead to sustainable development?

1.1. Which practices are efficient for sustainable development?

Commissions of DEP in developing countries are catching up (Figure 10). Nonetheless, as DEP are spreading out, reports on default also arise. As shown in Annex A.5 of chapter 2 (table Energy), faults and defaults occur at first rank of energy outcomes of DEP, and personal information from the field let think that those observations might be under-evaluated. In these conditions, it is important to assess which DEP are successful for economic development.

Figure 10: Number of off-grid projects in developing countries in CoSMMA



But DEP have long been very diverse, even in the history of advanced countries. In 1907, six different companies operated in Paris with distinct area and norms, and still three in 1930.[46] The electricity grid

[46] http://www.mege-paris.org/

unified only under the pressure of nationalization in 1946; the decision to converge toward a unique technical norm (radial tri-phase) was taken in 1960, and only achieved in 1993. This case shows that the equivalence between unified grid and homogeneous service of electricity has not always been obvious. The convergence toward unified electrical grid was slow and did not result from natural equilibrium, needing instead a strong involvement of the State in the design of energy economics. The electricity market has long been anything but a "*natural monopoly*", but a coexistence of various decentralized solutions, which is also today the typical state of electricity supply in developing countries, where many heterogeneous electricity systems and services operate in parallel with the national grid. In these conditions, the contribution of off-grid systems to improving economic welfare could differ according to the type of decentralized practices of electrification.

The heterogeneity of DEP is in fact consubstantial with their market, because they address a large variety of communities, densities of population or distances to the national grid, where mini-grids can bring relevant solutions for electrification, with lower costs than national grid: the so-called "triangle of mini-grids" (ESMAP, 2017). Mini-grids could also bring earlier economic development, by accelerating the pace of access to modern energy in those areas.

Assessing the performance of DEP for economic development is important because the policy maker that takes commitment of supporting rural electrification with off-grids systems backed on large scale policies mobilizes resource for long duration, while the access to financial resource is constrained in many developing countries. Actually, DEP frequently receive funding from stakeholders who support SDG, and therefore projects are deemed to show proven favorable impacts achieving these goals.

Supporting the path of electrification with DEP is indeed a strategic choice. But this choice can be riskier than a national grid following normative technical design and compliant scheme of governance, because DEP design is much more variable and less constrained by standards and regulation. The performance of DEP for development could significantly depend on projects' design. Avoiding a waste of resource need thus to clarify which practices have the highest probability of positive impacts.

1.2. Which natures of impacts occur from efficient practices of decentralized electrification?

Going one step further, assessing the nature of impacts matters when it comes to the quality of electricity service delivered by mini-grids. Sizing an electrical system in a development perspective needs in fact to take into account the cost of infrastructure (CAPEX), the number of connected people as also the "*electrification dividends*" (SE4ALL, 2017) . The latter introduces the range of socio-economic effects of electricity as key parameter for DEP success. In other words, for a given target of people to connect, the ideal DEP should achieve the highest contribution for sustainable development, with the lowest use of capital; and therefore, it should be sized by the range of expected appliances, and not only by expected LCOE or EROI, because appliances are the channels for impacts. Beyond the probability of impact, the pattern of achieved impacts can provide a finer vision of the quality of electricity service, because the range and type of appliances is mostly conditional to capacity, availability and reliability of the service.

Additionally, most of DEP are power-limited projects, and many projects *exante* restrict the scope of electricity distribution to specific buildings, like family farms; or public utilities like schools or dispensaries; or some targeted productive activities of the community. As a matter of fact, many DEP distribute a specific service of electricity, in relationship with the project's design that was tailored to exploit a local resource. As a result, some DEP will not yield some peculiar effects, because they have not been designed for. For instance, including batteries in a Solar Home System (SHS) project will allow reading at night, while in the absence of battery the project will rather deliver electricity for water pumping.

The constrained supply raises the question of which primary goals for economic development should be targeted first by DEP: which electrical uses should they favor with the highest probability of positive impacts? Answering this question goes beyond the feasible research objective of this paper, but the study can bring a first contribution by describing which projects' patterns led to which patterns of impacts.

2. Literature review

2.1. Measuring performances of mini-grids: state-of-the-art

To the best of my knowledge, (Katre and Tozzi, 2018) offer the most advanced framework for the assessment of mini-grids' performance. This framework is based on a scorecard with 5 dimensions, and a breakdown in 10 measures and 37 indicators. (Katre et al., 2019) applied this framework on 24 solar mini-grids in Indian villages, notably using users' payment as a measurement of affordability.

My study differs from (Katre et al., 2019) on several points.

First, I built an evaluation of performance which is supervised by the achievement of SDG, as projects in the meta-analysis were evaluated from researchers in the perspective of their contribution to economic development.

Second, my empirical evaluation relies on much larger collection of data. With 403 programs, the nomenclature of effects groups 1,909 measurements made by previous researchers. This nomenclature was built from a bottom-up approach, instead of top-down approach. Unfortunately, I achieved the first version of this work one year before the publication of (Katre and Tozzi, 2018). The revision of the nomenclature in 2019 then intended to be closer to the one of UN's Sustainable Development Goals.

Third, using a measure of performance based on unpaid bills was not feasible at large scale, due to the lack of daily management data on projects. Thus, I focused on the two first dimensions of the assessment, capacity and availability of the service.

2.2. Multi-criteria analysis of electrical systems

Some authors already used multi-criteria classifications in electricity economics, building typologies of systems, however not in a development perspective. Multi-criteria analyses were used by energy economists in order to solve a variety of challenges (Table 25) related with systems' performance or optimization. However, those approaches are not statistical (K. et al., 2017), or they deal only with techno-economic issues (Omran, 2010), (Sachs and Sawodny, 2016), or they classify only theoretical cases derived from investments scenarios (Ajayi and Olamide, 2014)

Table 25: Multi-criteria analysis of electrical systems

Authors	Application of multi-criteria analysis
(K. et al., 2017)	Economic performances of PV systems in India
(Omran, 2010)	Technical performances of connected PV systems
(Sachs and Sawodny, 2016)	Optimization of load profiles for hybrid off-grid systems
(Ajayi and Olamide, 2014)	Optimal locations of power plants in Nigeria according to resource type and location

I use a multi-criteria assessment that has already been applied for the classification of the performance of electrical systems, including the most recent off-grid systems, but I innovate by measuring the economic performance of projects for development and grouping projects according to their initial characteristics

3. Data, indicators and descriptive statistics

3.1. Extending CoSMMA data with electricity production units

Data on DEP originate from the Collaborative Smart Mapping of Mini-grids Action (CoSMMA) meta-base, as described in chapter 2. The initial dataset of 2,712 effects was extended during summer 2018 by a lean survey with the objective of covering a broader scope of projects' characteristics. A complimentary questionnaire was sent to the community of authors, who were already identified at the first stage of data collection. From this extension, thirty new variables were added in the study (Annex A.1), according to a maximal rate of missing values below 30%.

Because the extension of CoSMMA focused on projects' characteristics, a new dataset was designed and contains 619 Production Units (PU) with geographical coordinates. Where the PU's coordinates could not be collected, the coordinates of the smallest administrative unit encompassing the PU were imputed.

Some electrification programs may deploy several PU. In some rare cases, deployed PU may be very far away from each other. However, some abnormal high distance could just result from measurement error at the time of reading and imputing data from the articles. Therefore, the farthest PU in a group were assigned to a new specific project identifier; in each group, a statistical cutoff was set at the 95% quantile in order to qualify which PU had to be separated from the other ones (Annex A.2). However, such cases remain rare (7 programs).

After applying the inclusion criteria presented in chapter 2 (Table 18), the estimation sample contains 2,484 effects, to which corresponds an equivalent dataset of 497 production units of electricity, from 332 electrification programs. 419 PU supplied power to households, and 78 supplied power to utilities (clinics, schools,...) or productive uses (shops, farms, business, ...) (Table 26). More descriptive statistics are shown in Annex A.3.

Table 26: Structure of estimation sample

	Count	**Units**
Estimation sample contains :	497	Production Units of electricity
from :	332	Programs of decentralized electrification
evaluated by :	112	Peer-reviewed articles
in :	56	Countries
generating :	2,484	Effects
and :	208	Favorable proven impacts ("*positive impacts*")

3.2. External databases for contextual variables

External databases enrich the information on the context of DEP deployment (Table 27). Those databases allow getting more information on governance, radiation conditions for solar projects, distance to the nearest port as a proxy for an arbitrage to diesel cost, and population density.

Table 27: External databases used in this study

EXTERNAL DATABASE	**INDICATEUR**
(RISE and SE4All, 2017)	**GLOBAL Score of governance**
(RISE and SE4All, 2017)	**EXISTENCE of National Program**
(RISE and SE4All, 2017)	**LEGAL framework for Mini-Grids operation**
(RISE and SE4All, 2017)	**ABILITY to charge cost-reflective tariffs**
(RISE and SE4All, 2017)	**FINANCIAL incentives**
(RISE and SE4All, 2017)	**STANDARDS and quality**
(LARC POWER, 2018)	**All Sky Insolation Incident on a Horizontal Surface (kW-hr/m^2/day)**
(LARC POWER, 2018)	**Normalized Clear Sky Insolation Clearness Index (dimensionless)**
(LARC POWER, 2018)	**Direct Normal Radiation (kW-hr/m^2/day)**
(LARC POWER, 2018)	**Insolation Clearness Index (dimensionless)**
(LARC POWER, 2018)	**Daylight Hours (hours)**
(WFPGeoNode, 2017)	**Distance to the nearest port**
(Goodman et al., 2019) : AIDATA	**Area population density**

3.3. Key Indicators definitions

3.3.1. Indicator of projects' group

Practices of decentralized electricity are described by a typology of DEP, which is built from a statistical classification that separates projects into six groups. The detailed methodology of the classification will be presented in section 4, and the detailed interpretation of groups well be shown in section 5. The classification let three main practices of decentralized electrification appear in developing countries: Micro-grids for access in remote areas, individual SHS and private mini-grids (Table 28). Three more specific groups of projects are presented in Annex A.4.

Table 28: Most frequent types of DEP

Group No.	Number of units	Typical DEP	Modal date	Most likely capacity	Most likely observed MTF level and typical appliances
1	121	Micro-grids for access in remote areas	2007	Micro	Level 1 of MTF. Water pumping and basic appliances: lighting, phone charging, radio.
2	102	Individual SHS	1997	Nano	Level 2 of MTF. Mostly small appliances: lighting, phone charging, radio, and TV.
3	115	Modern private Mini-Grids	2006	Micro Mini	Level 2 of MTF. All appliances can be plugged. Some appliances are exclusive: microwave ovens, toasters, hair dryers, washing machines and printers. Some appliances are largely over-represented: televisions, computers, fans, air coolers, refrigerators, freezers, food processors, water pumps, iron, space heaters, water cleaners, and electric cookers.

3.3.2. Distance to the nearest port

At time of the project's commitment, there could be a trade-off between exploiting a local renewable primary source of energy, and routing fuel by road or train.

Fueled off-grid generators are easy and quick to install, and might deliver immediate answer to some population's needs, especially at time of emergency. Or they might help demonstrate the involvement of State with public utilities in sensitive areas. For instance, in Garissa, the Kenyan government ordered a 3.4MW off-grid fuel generator by the British company Aggreko in 2006[47], because outages could

[47] https://constructionreviewonline.com/2016/05/kengen-gets-a-ten-year-aggreko-power-deal/ , http://www.kengen.co.ke/content/thermal-power-plant

emphasize political risks, while the city is already exposed to the attacks of Shebab tribes. The same company, Aggreko also addresses emergency needs related to drought in Kenya (60 MW in Naivasha, 80 MW in Embakassi)[48], and actually intervenes for comparable needs in many developing countries with off-grid systems bellow 100 MW.[49]

For fueled supplied systems, the distance to the nearest port matters, due to the need of importing fuel. Actually, refineries are scarce across the world, and even discovering large oil reserves in a country, as it has been the case in Lokichar basin in Kenya in 2012[50], does not prevent from re-importing fuel through its harbor(s), or the neighbor's one(s).

The constraint of using refined fuel and then transport it inside the continent could dramatically increase the running cost of fuel-supplied generators, the high price of which has already been measured by previous research (Comello et al., 2017), (Foster and Steinbuks, 2009). Diesel generators may also suffer from high price-volatility, with serious impediments for economic development (Shah, 2009). The price of diesel might thus be an important incentive as to a technological arbitrage at design time by projects' developers.

Obviously, the cost of capital also plays a significant role in this arbitrage. In a TOTEX approach, projects may be sorted between those with low CAPEX and high OPEX due to diesel cost on one side, and those with higher CAPEX but low OPEX because they consume a free renewable resource, on the other side. However, the data on projects cost in CoSMMA suffered from many measurement errors and could not be used to date. Therefore, only the OPEX dimension of arbitrage is captured, using the distance to the nearest port as a proxy of the cost of fuel in remote off-grid area.

Using the external database (WFPGeoNode, 2017), I computed the spherical distance from each PU to the nearest harbor, using the `–geonear–` package in Stata.

3.3.3. Simplified Multi-Tier Framework: a measure of quality of electricity service

(ESMAP, 2015) brings an exhaustive framework for the assessment of delivered electricity service by mini-grids. The Multi-Tier Framework (MTF) combines several key dimensions compounding the electricity service, with distinct frameworks for households or productive uses. For instance, the MTF for households combines seven dimensions: peak capacity, availability, reliability[51], quality of power[52],

[48] https://www.power-technology.com/contractors/gensets/aggreko/pressreleases/press34-4/
[49] http://ppi.worldbank.org/snapshots/sponsor/aggreko-plc-46
[50] https://www.reuters.com/article/us-kenya-oil/kenya-says-crude-oil-capacity-insufficient-for-refinery-idUSKCN1Q80JZ
[51] Number or duration of disruptions per week
[52] Voltage stability

affordability, legality[53], safety. The Framework for productive uses combines the first five dimensions. Each dimension is valued from level 0 to 5, according to some criteria related with the dimension. This provides a score for each dimension. Then, the MTF is defined as the minimum of all scores across dimensions.

In this study, I compute a simplified empirical application of the MTF with available data in CoSMMA. This simplified MTF indicator provides an index of the quality of electricity service, combining capacity and availability, which are derived from data on total capacity, technology and known uses of supplied power. Annex A.5 gives more details on the MTF implementation.

Table 29 shows that 56.5% of effects occur from projects at Tier1 of availability, and 43.5% from projects at Tier 2. In fact, 29.8% of effects occur from low-capacity and low-availability projects (7.7 + 22.1): almost a third of DEP supply only limited electricity service.

Table 29: Distribution of effects and positive impacts by capacity and availability

Capacity per user	Availability				All effects			Availability				Proven favorable	
	1	1	2	2	Total	Total		1	1	2	2	Total	Total
	No.	Cell %	No.	Cell %	No.	Cell %		No.	Cell %	No.	Cell %	No.	Cell %
0 : Min 0W[54]	192	7.7	202	8.1	394	15.9		23	11.1	20	9.6	43	20.7
1 : Min 3W	550	22.1	71	2.9	621	25.0		120	57.7	2	1.0	122	58.7
2 : Min 50W	260	10.5	411	16.5	671	27.0		34	16.3	0	0.0	34	16.3
3 : Min 200W	341	13.7	294	11.8	635	25.6		0	0.0	2	1.0	2	1.0
4 : Min 800W	31	1.2	35	1.4	66	2.7		0	0.0	2	1.0	2	1.0
5 : Min 2000W	4	0.2	49	2.0	53	2.1		0	0.0	5	2.4	5	2.4
n.c	26	1.0	18	0.7	44	1.8							
Total	1404	56.5	1080	43.5	2484	100.0		177	85.1	31	14.9	208	100.0

However, those projects are associated with positive impacts: focusing on proven favorable effects (Table 29, right) low-capacity and low-availability projects contribute to 68.8% of all proven impacts (11.1+57.7). However, this high frequency could arise from a publication bias, because researchers may have focused on deploying pilot projects in order to demonstrate favorable effects.

[53] Available channels of payment

[54] Projects in Tier 0 ("Min 0W") typically correspond to projects based on bulbs' distribution and deserve a specific level for their tiny contribution to electrification: "*Access to lighting using stand-alone devices requires separate attention. Many of these devices do not meet the Tier 1 threshold, but may yet contribute significantly to improved access*" (ESMAP, 2015).

Combining both dimensions, the achievement of electricity service is very different according to the type of users (Figure 11). Most of projects addressing households' needs belong to Tier 1 of MTF, which is mainly due to the low capacity allocated to users in solar pilot projects. Not surprisingly, productive uses and utilities require electricity at higher levels, with a large share of projects being at Tier2, and none at Tier 0 (Figure 11, right). This observation suggests that productive uses or utilities could be relevant drivers for impact of mini-grids.

Figure 11 : Distribution of MTF by user type (# of Production Units, in sample)

4. Methodology for a qualification of decentralized electrification practices

4.1. Definitions

In this study, I call a "practice" a combination of choices relative to:

- a set of technologies exploiting one or several primary resource;
- a place where the generator produces electricity;
- a set of economic features relative to project objective, funding, decision level, deployment level, belonging to a program;
- a quality level of electricity service measured by the MTF indicator;
- a range of electrical appliances.

Practices are observed through deployed projects on the field, and data on projects are collected in CoSMMA through the evaluations published by researchers in peer-reviewed articles.

4.2. Qualifying effectiveness

Chapter 2 measured the probability that DEP deliver positive impact for economic development. This chapter now wants to qualify the effectiveness of decentralized electrification practices by their ability of achieving various development goals.

The global approach of qualification is the following. First, I built groups of similar projects with a statistical classification. Second, I exploit two measurements over groups of similar projects:

- using Equation 3 from chapter 2, the probability of positive impact by groups checks the robustness of results found in Table 20;
- the distribution of nature of effects by groups provides a descriptive exploration of practices achievement regarding the nature of impact, with available data so far.

The effectiveness of DEP could be measured by the distance between the range of expected impacts and observed effects. However, this approach is not feasible because expected impacts on economic development are mostly not communicated by developers, or simply not taken into account. Also, because impact evaluations by researchers focus on some peculiar types of effects, they would not consider all possible *ex-ante* projects' expectations at the time of *ex-post* evaluation. The collection of metadata on the expected impacts therefore suffers from a double selection bias, missing a large part of the true information.

Another way to proceed is to check the range of achieved development goals, as defined by the UN's Sustainable Development Goals (SDG). I use the nomenclature we built for chapter 2, which extends SDG with some additional nature of effects that were also evaluated by researchers.

As shown by Table 30, DEP effects on Energy dimension (typically effects on costs of energy), and Basic Access (mostly lighting, use of kerosene), counts for 35.9 percent of observed effects and 35.6 percent of positive impacts, which shows the extent to which the 7th SDG has already been measured. Therefore, the measurement of practices effectiveness will be separated between all effects and effects with neither Energy nor Basic Access. I call this second set of effects "*other socio-economic effects*".

Table 30: Effects of DEP by nature of effects and type of measurements

E1enjn - Groups of effects (rev. JCB)	**All effects**		**Favorable effects**		**Effects with scientific data**		**Proven favorable effects**	
Energy (type, costs & faults)	715	28,8	439	24,3	306	21,6	22	10,6
Education (O4)	304	12,2	194	10,7	250	17,7	42	20,2
Health (O3)	292	11,8	224	12,4	210	14,8	30	14,4
Economic transformation (O8)	227	9,1	204	11,3	108	7,6	4	1,9
Environment (O13)	198	8,0	142	7,9	41	2,9		
Basic Access (O7)	177	7,1	152	8,4	146	10,3	52	25,0
Income & living conditions (O1)	88	3,5	68	3,8	55	3,9	8	3,8
Information & communication	85	3,4	81	4,5	60	4,2	22	10,6
Community (O11)	81	3,3	64	3,5	20	1,4		
Usable time & leisure	81	3,3	62	3,4	61	4,3	9	4,3
Gender (O5)	78	3,1	62	3,4	39	2,8	6	2,9
Security (O16)	56	2,3	34	1,9	49	3,5	4	1,9
Financial transformation	48	1,9	45	2,5	28	2,0	1	0,5
Housework	47	1,9	30	1,7	39	2,8	8	3,8
Migration	7	0,3	7	0,4	4	0,3		
Total	2484	100,0	1808	100,0	1416	100,0	208	100,0

The achievement of development goal is measured by descriptive statistics at the aggregated level of groups of similar projects, each group being qualified by the distribution of effects by nature of effects, which I call "*profile of achieved development goals*".

However, the distribution of effects by their natures can be altered by a selection bias, because researchers might focus on some peculiar effects at various stages of the evaluation (data collection, estimation, publication).Section 4.4 will enter into a more detailed discussion about the risk arising from selection bias.

4.3. Assumptions

Qualifying DEP effectiveness relies on three assumptions which underlie the assessment.

4.3.1. Permanent Perfect Balancing let DEP effects be fully observable (H1)

First, **decentralized generators deliver reliable electricity** (H1), ie. balancing is constantly perfect, without any outage, which means that supply permanently equals demand whatever the latter's inelasticity. This assumption relies on the fact that mini-grids are mostly deployed in delimited areas with a predefined range of connected users, which ease the expectation of local peak-load.

Indeed, the wide branch of literature dedicated to DEP feasibility spends a large effort on sizing systems under reliability constraint: the capacity of a preconfigured system is set such as the maximal delivered power would always exceed the expected aggregated peak-load for a target population. Typical and recent works include (not exhaustively) : (Shahzad et al., 2017), (Shaw, 2017), (Adaramola et al., 2017), (Phurailatpam et al., 2018), (Sen and Bhattacharyya, 2014), (Hafez and Bhattacharya, 2012). In fact, the reliability constraint is so strong, that many calibration of DEP tend to over-size the system capacity (Blodgett et al., 2017). Due to the lack of support from any national grid, the trend to over-size DEP capacity makes this assumption (H1) enough credible. In addition, off-grid projects rarely expect any local grid extension after deployment; therefore, the optimality of project's sizing can be considered to be kept once the project is running on daily basis.

The assumption of permanent perfect balancing supports an important econometric feature: no censorship of observed effects could occur from significant number of unreliable projects that would have been subject to severe random outages. In other word, effects of DEP are fully observable at the generator's output; if any alteration of observation occurs, it does not come from the system's operation. In the computation of simplified MTF, this assumption also means that the reliability dimension achieves always level 5, which consequently allowed computing power by users by dividing the total system's capacity by the number of connected users (see Annex A.5).

4.3.2. Uneven heterogeneity of decentralized electrification projects (H2)

Second, **projects are unevenly heterogeneous** (H2).

Although electron is a homogenous object, the electricity service can be heterogeneous, mainly because projects address differently the range of users' needs under capacity constraint. In addition, the local nature of DEP exacerbates the differentiation across projects. This simple assumption of heterogeneity underlay the estimation of probability of favorable impacts in chapter 2. The heterogeneity of DEP can be easily checked with a simple look at the distribution of production units along key projects' characteristics in Annex A.6.

In chapter 2, we implicitly assumed that projects were distributed along a common law of probability. However, there could be a convergence of expertise according to the type of projects, with spill-overs across some practices that would not spread toward other types of practices. This means that heterogeneity of projects could vary according to the type of project, and what was assumed to be a single common law could in fact results from the composition of several laws of probability by groups of projects.

Modeling the probability of positive impact by groups of similar projects should overcome this form of heteroscedasticity. Assumption H2 thus supports the choice for a statistical classification that aims at grouping similar practices among a population of heterogeneous projects, by separating dissimilar projects from each other and grouping the most similar projects together.

In chapter 2, we also made some initial checks to avoid including the most atypical projects in estimation sample. However, due to the convergence of projects' expertise, there could be some small groups of atypical projects, which threaten the robustness of estimates. Using a classification also helps isolating those groups of most similar projects, still keeping enough heterogeneity within other groups to estimate a multi-probit model.

4.3.3. The range of appliances constrains the scope of observable effects' types (H3)

Third, **the range of possible appliances constrains the scope of observable effect** (H3)**.** This assumption is obvious because the range of appliances is constrained by supplied power, and DEP deliver limited capacity. However, it has important implication about the measurement of DEP effectiveness, as soon as effectiveness is qualified by the nature of observed effects.

Because electrical appliances support electricity uses, electrification effects depends on the list of devices that can be plugged on the system: possible appliances are the channel through which electrification projects can deliver socio-economic impacts. Therefore, assumption H3 implies that the variety of achieved effects could simply depend on which practice was designed and deployed. The classification introduces thus appliances as active variables of groups' computation, and aims at showing which peculiar associations exist between appliances patterns and effects patterns.

As explained in chapter 2, the limited set of data prevents from estimating a probability of positive impact by natures of effect. However, assumption H3 makes relevant to check empirically the extent to which profiles of achieved impacts change according to practices. Due to the limited set of proven favorable effects, the relationship between various natures of positive impacts and various practices will be only described by measuring the distribution of effects over the natures of positive impacts, for each group of project derived from the classification.

In fact, assumption H3 further implies that there is not a unique optimal practice of providing decentralized electricity for economic development. At this stage, it is important to stress that I assess several practices of decentralized electrification, and do not try to prove the existence of a unique best practice: in an empirical approach, it is practically not feasible to prove that a unique optimum could exist without previous theoretical support. My approach is rather a statistical exploration of the DEP meta-base, supervised by a characterization of performance driven by SDG achievement, which at best can compare practices by an empirical ranking. The theoretical idea behind may eventually be related with the surplus of producers and consumers, this surplus being maximal when various segments of supply allow addressing all segments of demand differently, which means a variety of supply's contents.

4.3.4. Homology of appliances or selection bias of effects?

Linking all assumptions, full observability of effects, changing heterogeneity according to groups of projects and delimited scope of possible effects implies that some effects of some practices cannot be observed because they cannot occur. This is due to the lack of some appliances in some projects, which therefore cannot achieve some peculiar development goals. This is known as the homology problem, which typically occurs when building a typology. As noticed by (Gower, 1971): "*The taxonomist has the problem of deciding whether a character occurring in one group of organisms also occurs in another group; this is the so-called homology problem. A missing character should not be confused with missing information because it is known that the character definitely does not exist*". The homology problem can be solved by using the specific Gower dissimilarity measurement in the classification design, which I will describe more in detail in section 4.4.

However, in the case of a meta-analysis, solving the homology problem of appliances cannot avoid a discussion with respect to the selection bias of measured effects, which could bring higher threat to the qualification of DEP effectiveness.

On the one hand, some appliances cannot occur in some groups of DEP because those groups gather projects that do not allow some peculiar electrical appliances. Assumption H3 implies that the homology problem also affect the observability of effects.

On the other hand, some projects' effects are only known through observations made by researchers on projects. Observing some nature of effects may be affected by a selection bias because researchers may have initially selected those projects that were deemed to yield the highest probability of favorable impacts. However, the large number of unproven effects in the database shows that this risk remains limited. But there is still a risk of selection bias at evaluation time, because researchers tend to observe and evaluate a selection of nature of effects which have the highest chance to be proven and published, and they will rarely evaluate the complete scope of SDG. This risk of publication bias do much more affect the range of nature of effects that were collected into CoSMMA than a possible selection of practices by researchers, because the latter rather depends on less flexible constraints like priorities of sponsors, organization and budgets of research.

When qualifying DEP effectiveness by natures of effects, one needs to diagnose to which extent some missing natures of effects arise from homology or from publication bias. Publication bias is usually solved by a meta-significance testing which would be suited for the simple probability of impact, but does not bring a solution to the selection bias over the range of natures of effects, which is more complex. In addition, solving the antagonism between both issues goes far beyond the objective of this paper. But one must keep in mind that both phenomena do exist. A part of the answer could be that homology is conditional to selection bias: homology occurs due to the true lack of appliances in some projects, but it can be completely solved only once the magnitude of selection bias of some natures of effect is known.

4.4. Classification of DEP for households

4.4.1. General features of the classification

I built the typology of DEP addressing households' needs with a Hierarchical Cluster Analysis. The classification groups projects according to their distance from each other. The distance is computed at the level of PU because projects' characteristics may be differentiated across PU of the same project. Projects that do not report differentiated observations across multiple PU are weighted by construction, in the proportion of the number of units. However, for further simplification, I will keep the terminology "projects".

Variables are separated between active variables (Annex A.6) and supplementary variables (Annex A.7). All dimensions characterizing a practice are selected as active variables, along which distance between projects is computed according to a specific metric. Groups are then qualified by descriptive statistics of active variables. Environment variables are added as supplementary variables in order to help qualify the groups.

I chose the number of groups based on the Calinski-F (Milligan and Cooper, 1985) and a heuristic judgement on the reasonable number of groups for further analysis. I did not consider atypical groups with strictly less than 5 individuals. This is an interesting feature of a classification: it can rapidly coalesce outliers in specific groups that do not deserve more attention. Those observations would thus not affect the estimation of coefficients when applying Equation 3 on well-populated groups, which will strengthen the robustness of estimates.

4.4.2. Measurement of the classification

Computing the classification consists in finding the most heterogeneous groups of most homogenous projects, using a multidimensional measurement of similarity (or dissimilarity) between projects. Groups' formation is optimized according to the Ward criterion, which maximizes the variance between groups and minimizes the variance within groups. Therefore, the most similar (or the least different) projects are grouped together.

The question of homology arises about missing appliances. For the range of collected electrical appliances during the lean survey, I assume that authors reported an exact answer about what could be plugged or not down the generator of the project. Hence, missing values bring true information about the absence of some appliances. Therefore, I compute a Gower's dissimilarity matrix between PU with the set of active variables, and then I perform a hierarchical cluster analysis on this dissimilarity matrix, using the Ward criterion. [55]

The Gower dissimilarity measure was made to solve the homology problem in biological taxonomies (Gower, 1971), and thus keeps missing values as true information for the classification. This interesting feature avoids computing a multiple-imputation to deal with the missing values issue -as for instance in (Basagaña et al., 2013)- a method which is actually not seen as reliable approach in first intention by some practitioners (Wagstaff, 2004).

In this study, data on DEP are observed with both numerical and categorical variables. The Gower dissimilarity measure also allows taking into account such a mix of numerical and categorical variables.

4.4.3. Choosing the number of groups in Ward classification

Some projects could be affected by a measurement error along active variables. Hence, one must assess to which extend such measurement error could affect the groups' computation.

In fact, at each step of a hierarchical grouping, a project is linked with the closest similar[56] project. Therefore, if a falsely measured observation is taken as reference, its influence in the group will decrease as long as new "normal" individuals will be added to the group. If only few projects are aggregated with a poorly measured project, they will collectively define an atypical group, which help characterizing other "normal" groups that will more consistently fit with the spherical multi-normal assumption.[57]

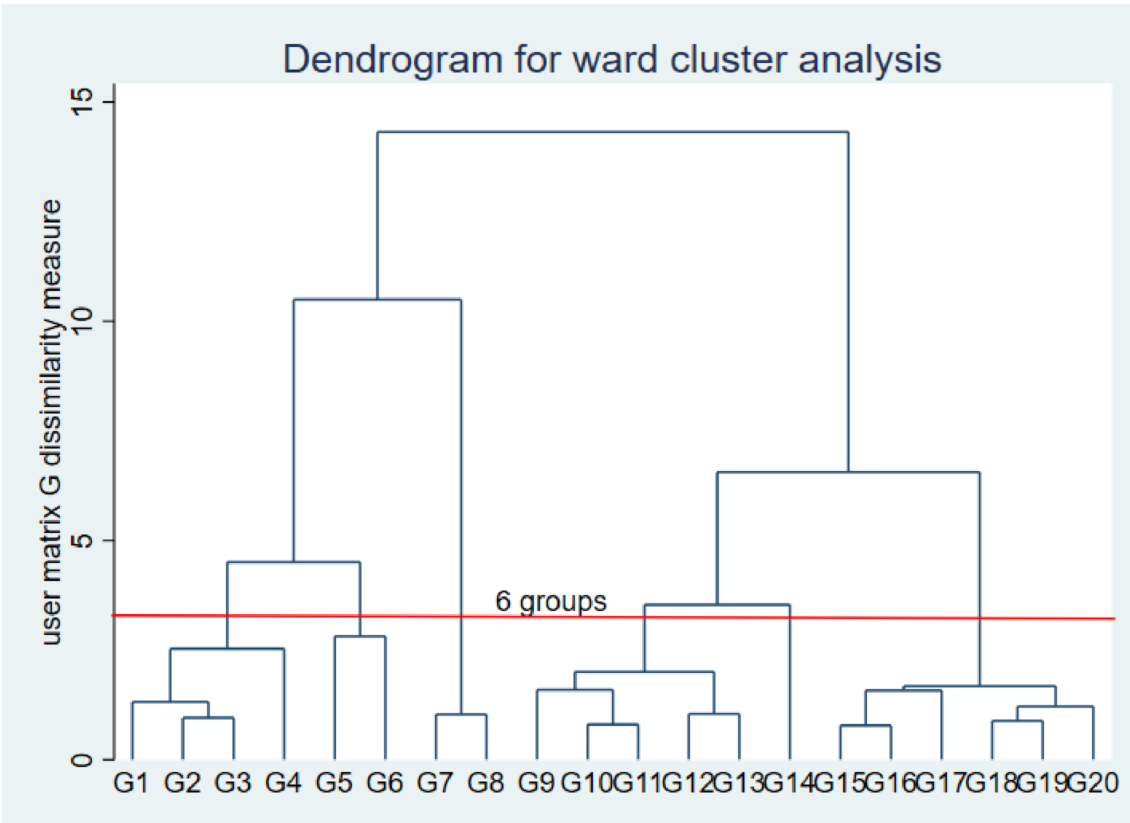
[55] In the individual approach with `-cluster-`, missing values would be excluded, like in a regression. With `-clustermat-`, the hierarchical clustering methods can be applied on a user-supplied dissimilarity matrix. Here, the dissimilarity matrix his obtained with Gower dissimilarity measurement.

[56] Or least dissimilar

[57] According to (Kaufman and Rousseeuw, 2009), Ward is rather suited for spherical groups following a multi-normal distribution

Based on the Calinski-F of Ward classification (Annex A.8) and heuristic judgement, I set a cut-off at 6 groups (Figure 12). The Ward classification renders a clear distinction between 3 main well-populated groups, and 3 groups with specific projects (Annex A.8)

Figure 12: Dendrogram of DEP for households in Ward classification



5. Results: effectiveness by groups of project

5.1. Main groups of DEP for households

This section describes the three most populated groups of projects. All corresponding graphs are in Annex A.9, where all cited percentages can be found. Groups are qualified by over-representation or under-representation of active variables with respect to the sample's profile. All graphs display the sample's profile for comparison.

5.1.1. Group1: Micro-grids for access in remote areas

Group 1 gathers off-grid systems (100%) which are most frequently deployed over Africa (55% versus 32% in the whole sample), far away from the nearest harbor (520 km) and in relatively dense areas of population. Typical installation delivers micro-capacity (+18 pp), rarely uses batteries, uses biomass almost twice more frequently than other projects (39% versus 21%), and uses solar technology almost twice less frequently (29% versus 48%). Those projects were more likely decided at the province level (36% versus 20%), or at the country level (47%) focusing on access objective (+9 pp), but were deployed only at the local level, over a group of localities (67%) or at spot locations (26%). Those projects do most likely benefit from development aid (+28 pp), three quarters of them receiving such aid.

Three quarters also deliver a low-level of electricity service with a MTF indicator bellow level 1, which could be correlated with less frequent use of batteries and thus, a higher risk of outages. A large share of those systems is used for water pumping (43%), but otherwise, they allow only a limited range of basic appliances: lighting, phone charging and radio.

The use of appliances that need more power is anecdotal: computers, fans, refrigerators, rice cookers, irons, space heaters, water cleaners, electric cookers are largely under-represented. Other appliances do not occur.

5.1.2. Group 2: Individual Solar Home Systems

Group 2 gathers all individual systems (100%), which are mostly solar projects (86% + 5% hybrid renewables) in Asia and Africa, mostly delivering less than 1 kW (84%) and up to 100 kW (16%). Installed in area with relatively high level of radiation, they also make the highest use of batteries (+16 pp). Deployed on single spot location (93%) or over a group of localities (6%), they were decided at the country level (66%) or province level (16%), and they benefit more frequently from development aid (+14 pp). They deliver time-limited formula twice more frequently than other projects (12% versus 6%).

Those projects deliver a good standard of electricity service, with 46% of systems being qualified at level 2 of MTF (+8 pp), which could be correlated with more frequent use of batteries that increase the availability of the service. However, individual SHS allow only a limited range of small appliances that often comes with kits: lighting, phone charging, radio, or TV are over-represented, sometimes largely.

Appliances that need more power like computers, fans, air coolers, refrigerators, water pumps, rice cookers, irons, space heaters, vacuum cleaners, water cleaners, electric cookers are under-represented, sometimes largely. Other appliances do not occur.

5.1.3. Group 3: Modern private mini-grids

Group 3 gathers micro-grids (56%; +10pp) and mini-grids (31%; +6pp) in Asia (+13pp) and Latin America (+3 pp), which less likely benefit from development aid (-9 pp), and were most frequently commissioned in 2006. They cover a group of localities (80%, +21 pp), addressing mainly the access issue (85%). Benefiting from the highest level of radiation, they operate in remote area (542 km) with a combination of two dominant technologies, solar (59%) and hydro (22%), and they less frequently use batteries (-9 pp). Decisions at the district level are almost twice higher frequent than in other groups (11% versus 6%), however most of those projects were committed at the country level (59%) or at the province (18%) level.

Such projects deliver the highest level of electricity service, with 53% of systems being qualified at level 2 of the MTF indicator even though the use of batteries is less frequent than in other projects. All appliances can be plugged, including some advanced ones that cannot be found in other groups of projects like microwave ovens, toasters, hair dryers, washing machines and printers, ie. the most consuming ones. Some appliances are notably over-represented like televisions, computers, fans, air coolers, refrigerators, freezers, food processors, water pumps, iron, space heaters, water cleaners, and electric cookers.

5.1.4. Observable positive impacts by groups of projects

Although only 36% of effects of Micro-grids for access in remote areas were measured with scientific data, 10% could be qualified as proven favorable impacts. With lower number of scientific observations, these projects could nonetheless contribute to a better understanding of electrification practices.

Individual SHS concentrate the highest rate of scientific data (88%) and proven favorable impacts (15%). Because they concentrate the largest number of effects, they might drive a part of the results found in chapter 2, which motivated to disentangle the analysis by groups of projects.

Modern private mini-grids (group 3) are recent and show a higher delay of evaluation (8.8 years), which can explain why they report only a low rate of scientific data (32%) and only one favorable impact. Almost all effects of those modern private mini-grids are just observed or could not be proven so far.

In specific groups (Annex A.4), scientific data count less than 21% of measured effect, and scientists could not conclude about any positive impact.

If anything, this meta-study shows that individual SHS played the role of demonstrators they were expected to play. It also shows the scarcity of proven impacts of other practices, and notably the need for future impact evaluations on recent mini-grids.

5.2. Best practices for impacts

Table 31 shows a synthetic assessment of best practices, estimating the probability of positive impacts according to practices, and controlling by the conditions of evaluation. Table 31 uses the same model as in chapter 2, Table 20, but replaces detailed projects characteristics by projects types. Because the classification recombined those characteristics to achieve groups of projects, Table 31 just provides a more synthetic vision of practices' impact. This allows for qualifying their relative performance.

Estimates were not computed on groups with less than 30 scientific effects, and thus specific groups were excluded. In addition to practices for households, a seventh group gathers all DEP addressing Productive Uses and Utilities.

DEP for Productive Uses and Utilities are the most likely of achieving positive impacts, with +39.4 pp higher probability than individual SHS (col. 1). Then come Micro-grids for access in remote areas (+10.9 pp, col1). Modern private mini-grids and individual SHS achieve similar performance.

The relative order of performance between practices is not changed for other socio-economic effects. In fact, DEP for Productive Uses and Utilities and Micro-grids in remote areas have even higher probability of success excluding Energy and Basic Access effects. However, this synthetic approach does not allow seeing what mechanisms of reconfiguration could be at work in each group when one goes from all the effects to the other socio-economic effects.

Table 31: Best Practices of DEP

	All types of effects			excl. effects on energy outcomes		
	(1)	(2)	(3)	(4)	(5)	(6)
Effects are :	Proven - Favorable	Proven - Unfavorable	Indeterminate	Proven - Favorable	Proven - Unfavorable	Indeterminate
No. of Observations (N)	-0.000	0.000	-0.000	-0.000	0.000	-0.000
Delay of evaluation	0.015	-0.007	-0.008	0.017	-0.008	-0.009
Method (ref. = Simple econometrics)						
Identification	0.356***	0.079	-0.435***	0.312***	0.067	-0.379***
Econometrics without inference	0.000	0.000	0.000	0.000	0.000	0.000
No inference	-0.041*	-0.071***	0.112***	-0.019***	-0.071***	0.090***
Practice (ref. = Individual SHS)						
Micro-Grids in remote areas	0.109**	-0.020	-0.089**	0.129*	-0.050	-0.079
Individual SHS	0.000	0.000	0.000	0.000	0.000	0.000
Modern private mini-grids	0.042	0.300	-0.342***	0.320	0.123	-0.443***
DEP for Productive Uses and Utilities	0.394***	-0.053**	-0.341***	0.517***	-0.075**	-0.442***
Total N in Mprobit	1390	1390	1390	948	948	948
Obs. Number of outcome	208	71	1111	134	68	746

Average Marginal Effect of Multinomial probit regression. LHS : Proven - Favorable, Proven - Unfavorable, Indeterminate. Subset of 1390 scientific data : evaluation samples with variance (N>1). Practices with less than 30 scientific data are excluded. Ref =: Reference category.
Estimates controlled by : Number of observations in evaluation samples (N), Delay of evaluation, Method of evaluation. Values hold as observed in meta-sample. Coefficients tell the difference in percentage points from the prediction of referral category. Variance : cluster by E2en : effect type. The Variance-Covariance matrix is estimated all at once for all three equations. $p<0.05$, ** $p<0.01$, *** $p<0.001$.*

5.3. Factors of positive impact by practices

Table 32 estimates the factors of the probability of positive impact for the two main practices, using the same model as in Table 20. Therefore, it provides a robustness check of the results found in chapter 2. Although the classification intents to minimize the variance within each group, some groups still present enough heterogeneity in order to estimate the probability of positive impact. However, only the two first groups of projects had enough data for this analysis; but both groups gather 78% of 1,416 effects shown in Table 20.

Estimates were not computed on groups with less than 30 measured effects with scientific data, or less than 30 positive impacts. Groups 5 and 6 together contain only 26 measured effects with scientific data

(Annex A.10), and group 4 does not contain any effect with scientific data; even grouping them altogether could not gather enough scientific observations. Group 3 contains only one proven positive impact, and Group 7 only two, which is insufficient to disaggregate the estimate into more detailed factors. In order to ease the constraints due to data limitation, the control by delay of evaluation was released in the estimation. Some coefficients could not be estimated because the corresponding category does not exist in this group: for instance, group2 concentrates a high share of solar system (86%); when it comes to proven favorable effect, no other technology is associated with positive impacts in this group.

Micro-grids in remote areas (group 1) have significantly higher chance of positive impact when they target access rather than capacity (+27.0 pp, col1). However, this relationship does not hold on the restricted sample without energy effects. Further, even though the coefficient is not significant, it turns to be positive for capacity projects (+26.6 pp, col3). Micro-grids in remote areas are thus more successful when they favor access to energy (including basic form of access).

Micro-grids in remote areas also show a significant decreasing relationship with capacity: Nano project have higher probability of impact than micro (+ 24.3 pp) or mini (+22.7 pp) grids. This peculiarity could come from a correlation with technology: mini-grids of this group contain a large number of biomass DEP, which are associated with a high concentration of indeterminate impacts (Table 20), leading to predict a lower probability of positive impacts.[58] Therefore, we find we find that the efficiency of this practice decreases with the system's capacity.

The increasing relationship of performance with capacity shown in chapter 2 (Table 20) comes from the group of Individual SHS (group 2): micro-grids in this group have significantly much higher chance of impact (+60.5 pp) than Nano capacity systems. Because this practice has the biggest weigh, concentrating the largest share of effects measured with scientific data (66%), the relationship also appeared in Table 20 with all types of projects. The growing relationship is even stronger on the restricted sample without energy effects (+73.8 pp, col4), which stresses the importance of increasing power, in order to yield socio-economic effects beyond the initial access to electricity. Looking at group 1 projects on the restricted sample, the decreasing relationship does not hold for Micro-grids in remote areas; and even though insignificant, the estimate becomes positive, which also suggests the need for power in this practice, when it comes to other impacts than access to energy.

The U-shaped relationship of DEP governance that we found in chapter 2 for their performance on education may more specifically depend on the combination of practices and the nature of effects.

[58] See note 45 in chapter 2

For Individual SHS, a U-shaped relationship appears clearer than in Table 23, with the same significant minimum at the province level (-32.4 pp, col 2) and a non-linear U-shaped curve of other estimates: although not significant, they decrease from the local level down to the province level, then we find a positive coefficient at the country level. The U-shaped curve is weaker on the restricted sample (col 4), which means that the combination of bottom-up and top-down approaches mainly exists for impacts on energy.

Micro-grids in remote areas show a contrasted role of governance, as the U-shaped relationship exists only for socio-economic effects excluding energy (col 3). Including effects on energy, the governance rather follows an inverted U-shaped curve. Starting from local level as reference, the maximum significant probability of positive impact is reached at the province level (+22.2 pp, col 1), then the country level achieves a positive but smaller significant difference (+6.2 pp). Because these projects were designed for access and supported by national programs, country and province levels of decision played a more significant role for Energy and Basic Access than local levels.

This contrast shows an interesting result: even for projects where global governance plays a decisive role for energy access, the ability to achieve other goals than the 7th SDG, is related with the mix between local and global decisions.

The role of governance follows thus complex determinants, which depend on the combination of DEP practices and natures of effects. These results suggest possible specializations of decision levels with respect to the main expected uses of supplied electricity.

Continental location plays a significant role only for Individual SHS. The practice is more successful in Latin America than in Asia (+8.5 pp, col2) but much less in Africa (-34.7 pp). Further, this contrast is strengthened on socio-economic effects without energy (col 4).

Table 32: Factors of positive impact by project types (scientific data)

	All types of effects		excl. effects on energy outcomes	
	(1)	(2)	(3)	(4)
	Group 1	Group 2	Group 1	Group 2
No. of Observations (N)	-0.000	-0.000**	0.000	-0.000***
Method (ref. = Simple econometrics)				
Identification	0.000	0.000	0.000	0.000
Econometrics without inference	0.000	0.000	0.000	0.000
No inference	0.000	0.000	0.000	0.000
Project objective (ref. = Access)				
Access	0.000	0.000	0.000	0.000
Capacity	-0.270***	0.033	0.266	0.024
Time limited		-0.017		-0.023
Technology : (ref. = Hydro)				
Hydropower source	0.000	0.000	0.000	0.000
Solar	-0.022	0.000	-0.116	0.000
Hybrid with Fossil fuel	-0.230		-0.387***	
Hybrid renewables	-0.249	0.000	0.038	0.000
Fossil Fuels	-0.189	0.000	-0.023	0.000
Capacity : (ref. = Nano)				
Nano: $<1 kW$	0.000	0.000	0.000	0.000
Micro: 1 to 100 kW	-0.243***	0.605***	0.302	0.738***
Mini: 100 kW to 100 MW	-0.227***		-0.252***	
Program Decision Level (ref. = Local)				
Country	0.062**	0.055	-0.110	0.034
Province	0.222***	-0.324***	-0.316**	-0.392***
County		-0.047		-0.023
District	0.003	-0.000	-0.019	0.030
Local	0.000	0.000	0.000	0.000
Geographical Area (ref. = Asia)				
Africa	0.067	-0.347***	0.033	-0.386***
Asia	0.000	0.000	0.000	0.000
Lat. America		0.085*		0.122**
Total N in Mprobit	159	944	98	679
Obs. Number of outcome	46	159	27	104

*Average Marginal Effect of Multinomial probit regression. LHS : Only Proven - Favorable equation is shown. Ref =: Reference category. Subsets by groups of projects with measured effects with scientific data (evaluation samples with variance: N>1).Equations are computed only for groups of projects with more than 30 positive impacts and more than 30 measured effects with scientific data. Group 1 : Micro-grids in remote areas. Group 2 : Individual SHS. Estimates controlled by: Number of observations in evaluation samples (N), Method of evaluation. Values hold as observed in meta-sample. Coefficients tell the difference in percentage points from the prediction of referral category. Variance: cluster by E2en : effect type. The Variance-Covariance matrix is estimated all at once for all three equations. * p<0.05, ** p<0.01, *** p<0.001.*

5.4. Profiles of achieved development goals by practices

Table 33 show the profiles of achieved development goals, as measured by the highest frequent nature of favorable effects (col 1) and positive impacts (col 3), and by over-represented natures of favorable effects (col 2) and impacts (col 4). Favorable effects are reported both with expert data and scientific data, whereas positive impacts are proven with scientific data. Correspondent graphs are in Annex A.11. In all groups, effects on Energy and Basic Access are the most frequent; therefore, Table 33 considers only other socio-economic effects. Natures of effects with less than 20 observations and over-representations with less than 2 pp are not considered.

Table 33 : Dominant natures of effects and positive impacts by project types

Group No.	Num ber of units	Typical DEP	Modal nature of favorable effects (1)	Most likely natures of favorable effects (2)	Modal nature of positive impact (3)	Most likely natures of positive impact (4)
1	121	Micro-grids for access in remote areas	Environment	Environment, Information & Communication, Community, Gender, Income & living conditions	Information & Communication	Information & Communication, Usable time & leisure, Income & living conditions, Gender, Security
2	102	Individual SHS	Health	Health, Education, Usable time & leisure	Education	Education, Health
3	115	Modern private Mini-Grids	Economic transformation	Economic transformation, Community	nc	nc
5	25	Private hybrid micro-grids in Latin America	Economic transformations	Economic transformation, Income & living conditions, Migration, Financial transformations	nc	nc
7	78	Productive uses and Utilities	Environment	Environment, Economic transformations	nc	nc

Modal nature of favorable effects (resp. impacts): most frequent nature of favorable effect (resp. impacts) (excluding energy outcomes). Most likely natures of favorable effects (resp. impacts): over-represented natures of favorable effects (resp. impacts) with respect to the global distribution.

Micro-grids in remote areas and Individual SHS are the only types of DEP for which some natures of positive impacts have been proven so far (Table 33, col. 3 and 4).

Micro-grids in remote areas have positive impacts mainly on Information and communication (33%), and have also higher chance of achieving positive impacts on Usable time and leisure, Income and living conditions, Gender and Security (col. 4). Including expert data, they were also expected to achieve favorable effects on Environment and Community (col. 2), but no proven impact of this nature has been established to date.

Individual SHS have positive impacts mainly on Education (36%) and have also higher chance of achieving positive impacts on Health. Both natures of effect were expected by expert data (col. 1 and 2). Individual SHS could also have favorable effect on Usable time and leisure, which however remains unproven.

Other types of DEP could not prove any positive impact with scientific data, but some natures of effect were expected by expert data. For instance, private mini-grids expect favorable effects on Economic transformation, but this benefit could not be proven so far. DEP for Productive uses & Utilities may have mainly favorable effects on Environment, and should also have higher chance of achieving favorable effects on Economic transformation, but those observations were never turned to evidences.

Going one step further, Table 34 explores which are the significant factors of the natures of favorable effects with Individual SHS. However, mixing expert and scientific data, it cannot disentangle the determinant of positive impacts. As a matter of fact, the lack of data does not allow estimating the probability of proven favorable effects by natures of effects. Therefore, Table 34 can only provide clues about the determinants of the nature of favorable effects.

Provided the project objective is to bring access to electricity, Individual SHS have significantly higher chance of showing favorable effects on Education, Information and communication, Economic transformation, and Usable time and leisure. However, it looks dubious that the type of achievement could be supported by the project objective. Chapter 2 shown that project objective has in fact no significant role on achieving proven impacts (Table 20), which is confirmed for Individual SHS in Table 32.Therefore, this finding in Table 34 shows how expert data could blur the results, because citation or invariant statistics may be called as *ad hoc* arguments supporting the objective. This finding stresses the need for more econometric evaluations. It means also that project objective is an important control for other projects' dimensions when taking into account expert data.

Table 32 showed the increasing relationship of the probability of positive impacts with the capacity of Individual SHS capacity. This relationship could in fact come from favorable effects on Information and communication (Table 34, col 3). To the opposite, there is higher chance of observing favorable effects on Health and Usable time and leisure with Nano SHS.

The role of decision level for Individual SHS looks very complex once taking into account distinct natures of effects. The U-shaped curve could come from favorable effects on Usable time and Leisure, and to a lesser extent on Economic Transformation, up to the province level. However, some peculiar levels of decision could be significantly more or less effective according to the nature of achieved effect: the district level could be significantly more effective for Education, but less for Health which looks to be better driven at county level. The bottom up approach, favoring local level instead of country level, could be more effective for Health and Economic transformation. These results confirm the assumption that possible specializations of governance levels could exist according to the nature of Development Goal.

The role of location is also contrasted. The less effective African projects (Table 32) could be only those achieving effects on Information and communication (Table 34, col 3), whereas no significant bonus of Latin American project can be found, once adding Expert Data. Asian projects might be significantly more effective for Health than those in Latin America (col. 1).

Table 34 : Probability of observing a nature of effect with favorable effects from Individual SHS

	(1) Health (O3)	(2) Education (O4)	(3) Information & communication	(4) Economic transformation (O8)	(5) Usable time & leisure
No. of Observations (N)	0.000	0.000	0.000	-0.000	0.000
Delay of evaluation	0.030**	0.002	-0.046*	0.009	0.005
Method (ref. = Simple econometrics)					
Identification	0.000	0.000	0.000	0.000	0.000
Econometrics without inference	0.000	0.000	0.000	0.000	0.000
No inference	0.000	0.000	0.000	0.000	0.000
Project objective (ref. = Access)					
Access	0.000	0.000	0.000	0.000	0.000
Time limited	-0.272	-0.330**	-0.096***	0.798***	-0.100*
Increase capacity	0.050	-0.043	0.002	-0.004	-0.005
Technology : (ref. = Hydro) :					
Hydropower source	0.000	0.000	0.000	0.000	0.000
Solar	0.000	0.000	0.000	0.000	0.000
Hybrid renewables	0.000	0.000	0.000	0.000	0.000
Capacity : (ref. = Nano)					
Nano: $<1 kW$	0.000	0.000	0.000	0.000	0.000
Micro: 1 to 100 kW	-0.352***	-0.061	0.564***	-0.045	-0.106*
Program Decision Level (ref. = Local) :					
Country	-0.238*	0.275	0.306	-0.253**	-0.090
Province	0.086	0.215	0.056	-0.263*	-0.095
County	0.389*	0.090	-0.006	-0.285**	-0.189*
District	-0.339**	0.748***	0.065	-0.284**	-0.189*
Local	0.000	0.000	0.000	0.000	0.000
Geographical Area (ref. = Asia) :					
Africa	-0.206	0.196	-0.129***	0.055	0.084
Asia	0.000	0.000	0.000	0.000	0.000
Lat. America	-0.435***	-0.104	0.440	0.002	0.097
Total N in Mprobit	331	331	331	331	331
Obs. Number of outcome	116	113	33	36	33

Average Marginal Effect of Multinomial probit regression. Ref =: Reference category.
LHS : Probability of achieving a favorable effect on Health (O3), Education (O4), Economic transformation (O8), Information & communication, Usable time & leisure.
Subset of all data (expert and scientific data) from projects group 2 (Individual SHS)
*Only natures of effects with more than 30 observations were selected. Effects on Energy and Basic Access are excluded. Estimates controlled by : Number of observations in evaluation samples (N), Delay of evaluation, Method of evaluation. Values hold as observed in meta-sample. Coefficients tell the difference in percentage points from the prediction of referral category. Variance : cluster by E2en : effect type. The Variance-Covariance matrix is estimated all at once for all equations. * p<0.05, ** p<0.01, *** p<0.001.*

5.5. Extended qualification of practices: governance environment

Extending the exploration of DEP in CoSMMA, this section presents salient facts on project types, looking at governance environment and the risk of default.

5.5.1. Micro-grids for access in remote areas

Micro-grids in remote areas were deployed with large support of a national program (74% with RISE score above 66%), benefiting from favorable legal framework (54% with index above 66%), substantive financial incentives (46% with index above 66%) and a large ability to charge cost-reflective tariffs (75%). This support was largely driven by independent regulation agencies (+9 pp), and the highest implication of rural electrification agencies (+18 pp). As seen before in Table 32, this large favorable governance environment translated into positive impacts for access to energy with top-down approach, however delivering projects with only low standards and quality (54% below 43% score).

5.5.2. Individual SHS

Individual SHS were frequently deployed in countries with a national program for decentralized electrification and have 66% higher chance of benefiting from financial incentives. They are more likely supported by independent regulation agencies (+11 pp) than rural electrification agencies (+6 pp).

Projects of group 2 are the oldest ones, with a modal date in 1997. Although the observations of defaults may be largely under-estimated in CoSMMA, individual SHS concentrate the highest rate of defaults (12%), three times higher than the global rate. In fact, with the longest delay of observation, individual SHS could support further research on the causes of DEP defaults, as a research extension on best practices.

5.5.3. Modern private Mini Grids

Projects of group 3 were less likely installed in countries with favorable legal framework for mini-grids (-5 pp above 75% score), do less likely benefit from incentives (+5 pp below 50 % RISE score), but they do show higher standards and quality (+10 pp above 86% RISE score). Those projects receive less support from independent regulation agencies (- 2pp) and are notably twice less frequently supported by rural electrification agencies.

6. Concluding remarks: assessing the natures of effects open new needs for evaluation

This study achieved an extended analysis of CoSMMA prototype. With a sample of 497 geo-localized off-grid production units in 56 developing countries yielding 2,484 socio-economic effects, it built a classification of projects that supported the identification of best practices of decentralized electrification, the estimation of the probability of positive impact by main practices, and the description of main natures of impact of these practices. Finally, the study proposed a first attempt to explore the determinants of some natures of favorable effects by Individual SHS. This attempt extended the analysis up to the limits of analytical feasibility with current volume of data, because the latter did not allow going one step further by isolating the determinants of proven impacts with scientific data. Extending the scope of evaluated projects would support better knowledge on the proven contribution to economic development by some practices, which remain insufficiently evaluated so far.

In terms of probability of positive impacts, DEP for Productive Uses and Utilities and Micro-grids for access in remote areas appeared as the best practices of decentralized electrification, whereas Modern private mini-grids and Individual SHS achieve lower performance for economic development.

However, evaluating the performance of DEP is more complex than just ranking practices and needs to take into account the combination between the type of project and the nature of effects. Individual SHS and Micro-grids in remote areas are the only practices with enough proven favorable effects allowing a breakdown of the probability of positive impacts, and for which various natures of positive impacts have been proven so far. A complete evaluation of known practices would need more data in order to estimate the probability of all natures of impacts by practices.

For Individual SHS, the probability of positive impacts increases with capacity, which becomes stronger for socio-economic effects beyond the 7^{th} SDG. This result stresses the importance of increasing power to achieve SDG beyond the initial access to electricity. The increasing benefit of capacity could arise through specific favorable effects of Individual SHS on Information and communication. Taking in consideration other natures of effects like Health and Usable time and leisure, there is higher chance of observing favorable effects with Nano SHS. Micro-grids in remote areas have also higher chance of success with smaller capacity.

The study also confirms a non-linear relationship between the role of DEP governance and their performance for economic development, which was found in chapter 2 for the impact of DEP on education. For Micro-grids in remote areas, the duality of local and global governance exists only for other socio-economic effects. For Individual SHS, the combination of bottom-up and top-down approaches mainly exists for impacts on the 7^{th} SDG.

The complex role of governance depends on the combination of DEP practices and natures of effects, which suggest possible specializations of decision levels with respect to the main expected uses of supplied electricity. More research is encouraged to assess the possible differentiation of expertise by decision-level at the time of project commitment.

Individual SHS report positive impacts mainly on Education, and may also have higher chance of achieving positive impacts on Health. Micro-grids in remote areas report positive impacts mainly on

Information and communication, and may also have higher chance of achieving positive impacts on Usable time and leisure, Income and living conditions, Gender and Security.

Other types of DEP could not prove any positive impact with scientific data, but some natures of effect were expected by expert data. Private mini-grids and projects for productive uses and utilities expected favorable effects on Economic transformation or Environment, but these benefits have never been proven. However, expert data could blur the results because citations or invariant statistics may be called as *ad hoc* arguments supporting the project objective.

The lack of proven favorable effects cannot be compensated by expert data, which again advocates for more econometric evaluations. Therefore, any extension of CoSMMA should focus only on scientific data. The final mapping in Table 33 shows the practices and natures of effects that requires deeper attention and more identification of DEP impacts.

Annexes

A.1 Variables added from Lean Survey 2018

Only variables with less than 30% missing values are shown.

Q29	The project is deployed as part of a multi-projects program
Q83.	Type of appliances (as observed) : 24 dummies of electrical appliances
Q147	The project is financed by a financing program for development aid
N5	Independence note
R2	Rural electrification agency
R3	Independent regulation agency
Q114a	Availability of Pay-As-You-Go

A.2 Recodification of some projects' IDs based on a statistical rule

Some electrification programs deploy multiple production units, some of which being very far away from each other. Notably, some international programs can have a unique name corresponding to a brand, and a common source of funding, while various projects might be managed by various teams at different locations. Because we did not track a fine distinction between programs and projects during data collection in CoSMMA, I used a statistical approach to identify units belonging to the same cluster, hence defining a common project ID: units that are statistically too far away from other units of the same program (IP2) were assigned to a distinct project identifier (IPJ2) than those belonging to the program's geographical kernel of production units.

First, I computed the nearest neighbor of each UP within a given program. The nearest neighbor is obtained with -*geonear*- Stata procedure, yielding the geodesic distance to the closest neighbor. Second, I set a cutoff at the 95% decile of the closest-distance variable, which is estimated on the complete sample.

Identifying the closest neighbor of each unit suffices to qualify the farthest unit with a statistical rule: if the minimum distance to other units is considered "*too far away*", all other distances will be as well. Because several units can be far away from the program's kernel, I preferred a statistical rule than a minimax criterion (excluding only the highest minimum)

As a result, the logical data model is as follow:

1 program → 1:n project(s) → 1:n PU(s) (production unit(s))

A.3 Distribution of production units along key characteristics

P6g2 - Technology	Freq.	Percent	Cum.
Wind	23	4,63	4,63
Geothermal and Tidal	7	1,41	6,04
Hydropower source	67	13,48	19,52
Solar	232	46,68	66,20
Hybrid with Fossil fuel	17	3,42	69,62
Hybrid renewables	22	4,43	74,05
Biomass (and related tech.)	110	22,13	96,18
Fossil Fuels	19	3,82	100,00
Total	**497**	**100,00**	

P3n2 - Project capacity	Freq.	Percent	Cum.
Nano: $<1 kW$	123	24,75	24,75
Micro: 1 to 100 kW	231	46,48	71,23
Mini: 100 kW to 100 MW	143	28,77	100,00
Total	**497**	**100,00**	

P11n2 - Program Decision Level	Freq.	Percent	Cum.
Country	290	58,35	58,35
Province	92	18,51	76,86
County	10	2,01	78,87
District	28	5,63	84,50
Local	77	15,49	99,99
Total	**497**	**100,00**	

P12n - Project Deployment Level	Freq.	Percent	Cum.
Country	9	1,81	1,81
Province	13	2,62	4,43
County	1	0,20	4,63
District	19	3,82	8,45
Group of localities	289	58,15	66,60
Spot	166	33,40	100,00
Total	**497**	**100,00**	

MTF - simplified Multi-Tier Framework	Freq.	Percent	Cum.
0	27	5,43	5,43
1	274	55,13	60,56
2	196	39,44	100,00
Total	**497**	**100,00**	

P4n - Network status	Freq.	Percent	Cum.
Off-grid	387	77,87	77,87
Individual	110	22,13	100,00
Total	**497**	**100,00**	

Igrappe - Part of a multi-projects program	Freq.	Percent	Cum.
0	75	15,09	15,09
1	422	84,91	100,00
Total	**497**	**100,00**	

Q147 - The project is financed by a financing Program for development aid	Freq.	Percent	Cum.
0	121	24,35	24,35
1	262	52,72	77,07
.	114	22,94	100,01
Total	**497**	**100,00**	

A.4 Groups of specific projects

Three groups of specific projects appeared from the classification, which separate wind farms in non-OECD Europe, hybrid projects in Latin America, and biomass projects in Asia.

Group No.	Number of units	Specific DEP	Modal date	Most likely capacity	Most likely observed MTF level and typical appliances
4	31	Local renewable projects in non-OECD Europe	2012	Intensive occurrence of Mini	Levels 1 and 2 of MTF Unknown appliances.
5	25	Private hybrid micro-grids in Latin America	2003	Micro	Intensive occurrence of level 0 of MTF. 50/50 levels 1 and 2. Lighting, phone charging, radio, TV, computer, air cooler, refrigerator, freezer, food-processor, water pump, rice cooker, air conditioning, electric cooker, are over-represented.
6	25	Asian biomass and wind projects	2010	Mini	Intensive occurrence of level 0 and 1 of MTF. Limited range of appliances: lighting, phone charging, fans, water pumps, space heaters.

6.1.1. Group 4: local renewable projects in non-OECD Europe

Group 4 gathers recent mini-grids above 100 kW (97%) in non-OECD Europe (97%). Designed for capacity issues (94%), they make an intensive use of wind technology, six times more frequently than in other groups, and to a lesser extent they use hydraulic (+7 pp) or geothermal resource (10%, six times more frequently). Those projects are committed by local communities (81%), almost five times more frequently than in other groups. To the opposite of other electrification projects, they are mostly stand-alone, being rarely part of multiple units program (87% do not). Appliances are unknown. No scientific observations were collected on those projects.

6.1.2. Group 5: Private hybrid micro-grids in Latin America

Group 5 gathers micro-grids (88%) in Latin America (100%) in the farthest remote area (665 km) and least populated area. Suffering from the lowest level of radiation, they use intensively hybrid technology (36%), four times more frequently than in other groups of projects. They also make intensive use of biomass (40%), twice more than in other groups of projects.

Although they mostly address access issue (92%), they may also deliver most frequently time limited service (+2 pp). Those projects are all part of multiple units program and were all decided at the country level; they do not receive any development aid, neither any support from rural agency. Conversely, all those projects were operated under the supervision of a regulation agency.

Although all of these projects are using batteries (100%), this group shows the highest concentration of low quality electricity service, with 20% of projects achieving only level 0 of the MTF; otherwise there is a fifty/fifty distribution between level 1 and 2. This heterogeneous quality of electricity service leads to a wide but incomplete scope of observable appliances, including some consuming ones. Lighting, phone charging, radio, TV, computer, air cooler, refrigerator, freezer, food-processor, water pump, rice cooker, air conditioning, electric cooker, are over-represented.

Only 21% of effects from group 5 projects were measured with scientific data, but none could be proven as positive impact.

6.1.3. Group 6: Asian biomass and wind project

Group 6 gathers exclusively Asian off-grid projects for energy access (100%), producing electricity with either biomass (84%) or wind (16%) in area with the highest density of population. Half of the projects are micro-grids and the other half are mini-grids. Half were decided locally, and half at the country level. This group could thus result from a too small number of defined clusters in classification, but the small number of projects and positive impacts did not motivate to split this group into more detailed sub-groups.

These projects deliver only low quality electricity service, all projects being below the level 1 of MTF. In fact, they are used for a limited range of appliances: lighting, phone charging, fans, water pumps, space heaters are over-represented, some of them largely. Plugin radios or TV is scare. Other appliances are not observed.

Scientific data are on these projects are scarce (11%) and no effect could be proven as a positive impact.

A.5 Simplified MTF implementation with CoSMMA

(ESMAP, 2015) defines a Multi-Tier Framework which delivers a synthetic indicator about the mini-grid's response to economic needs, according to the type of users: productive uses or households. This indicator combines capacity, availability, reliability, quality and affordability for all types of users; the framework is extended with legality and safety for systems addressing households.

I compute a restricted MTF, limited to capacity and availability vectors, following (ESMAP, 2015) table 6.10[59] for households, and table ES.6 for productive activities and utilities.

6.1.4. Capacity Vector

For each project, capacity is a 6-levels categorical variable which is obtained by a set of hierarchical rules combining specific uses, appliances, technology and targeted users if observed; or by the ratio of power by user if observed.

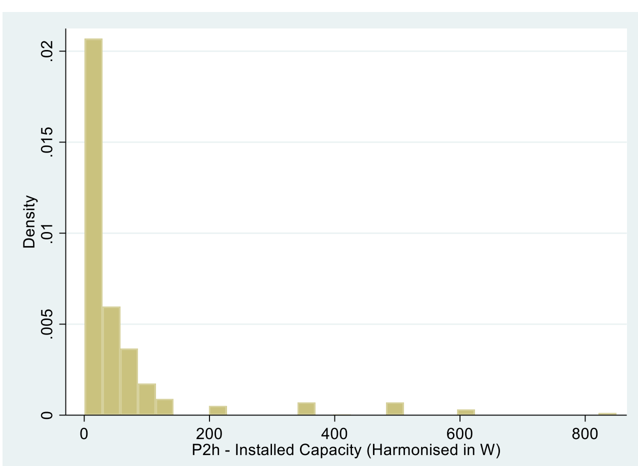
[59] Or ES.1

If some specific combinations of services or appliances are known, the category of capacity vector is given by these combinations, following table 6.10 in (ESMAP, 2015). Using the nomenclature of effects in CoSMMA, I detect if some projects' effects are related with specific services, like (not public) lighting, air conditioning, mobile phone use or charging. I could not differentiate lighting according to luminescence (Tier 1 = 1000 lmhr/day max); hence, I applied a conservative rule, assigning all lighting uses to Tier 1. Then, I detect the type of appliances as described in table 6.2 of (ESMAP, 2015), and allocate them to the corresponding Tier, as described in table 6.11 of (ESMAP, 2015). This detection is based both on the effects' indicators in CoSMMA (E3en) and the set of dummies on appliances (Q83.), which were purposely codified following the grid of uses in table 6.2.

If pre-defined specific combinations are not observable, capacity vector results from cutting the quantitative power by user, following defined cutoffs in table 6.10 of (ESMAP, 2015). Power by user is obtained by dividing total quantitative capacity of the system (P2h) by the number of connected users (P13), assuming Permanent Perfect Balancing (assumption H1). Because I only observe total capacity in CoSMMA, assuming perfect balancing is needed to allow dividing it by the number of users. This assumptions also means that all DEP in CoSMMA achieved the highest level of reliability vector in MTF ("*level 5 : no reliability issue, or little (or no) impact*").

Power by user is computed only if total capacity is greater than 200W. If total capacity (P2h) is strictly bellow 200W, it is considered to be an individual capacity, mainly the capacity of distributed bulbs to households. The threshold value (200 W) was statistically checked with a zoom on capacity bellow 1000W (Figure 13). In some cases, total capacity was only codified in categorical variable (P3); the latter was then used as a proxy for quantitative capacity, using the central value of the class.

Figure 13 : Distribution of installed capacity bellow 1000W (# of effects)



Finally, the denominator of power by user could also have been affected by a measurement error, because target population (P13n) was sometimes confused with country population -which was however justified in some cases for national programs. In order to compute a robust value of the ratio, only observations below the 90% quantile of target population were kept, filtering extremely high observations. I checked that the chosen quantile did not lead to exclude any proven favorable impacts (208) from the final computation of the MTF.

I follow a similar approach for productive uses, following table ES.6 of (ESMAP, 2015). Instead of services and appliances, categories of capacity are defined by the type of technology. Otherwise, quantitative power by user is retained.

6.1.5. Availability Vector

Because CoSMMA does not contain any information about the duration of supplied power, I'm using a proxy, based on the type of system and the presence of batteries. I'm computing a two-case indicator for availability, the same way for all types of users.

Because most of systems in CoSMMA are based on renewable sources, they are exposed to intermittence, at least to some degree. Default value for availability is thus set to the lowest Tier. However, because it cannot be assumed that systems are never available, the default value for availability is assigned to Tier 1 (and not 0).

Then, availability is assigned to Tier 2 if:
- the technology is one of the following :
    - Fossil fuels
    - Hydropower and Other Energy, incl. Foss
    - Cogeneration
    - Biofuels
    - Solar and Other Energy, incl. Fossil Fuels
    - Hydropower source
    - Geothermal energy
- the project uses solar technology and there are some batteries (Q49) deployed as part of the project.

6.1.6. Combining capacity and availability

Finally, as defined in (ESMAP, 2015), the MTF is computed as the lowest level achieved among all criteria, hence, the minimum of capacity and availability in this simplified application.

In a first step, MTF was computed at effects' level, because the computation needed information about uses that are approximated by observed effects. Therefore, some Production Units might report several values of the MTF. In that case, the highest value of MTF was then retained, considering the highest level of uses allowed by the generator.

A.6 Lists of active variables in classification of DEP for households

variable name	Active variables
P7g	P7g - Continent
P4n	P4n - Network status
P12n	P12n - Project Deployment Level
Q83a	Q83a - Type of appliances (as observed) : Task lighting
Q83b	Q83b - Type of appliances (as observed) : Multipoint General lighting
Q83c	Q83c - Type of appliances (as observed) : Phone charging
Q83d	Q83d - Type of appliances (as observed) : Radio
Q83e	Q83e - Type of appliances (as observed) : Television
Q83f	Q83f - Type of appliances (as observed) : Computer
Q83g	Q83g - Type of appliances (as observed) : Printer
Q83h	Q83h - Type of appliances (as observed) : Fan
Q83i	Q83i - Type of appliances (as observed) : Air Cooler
Q83j	Q83j - Type of appliances (as observed) : Refrigerator (continuous load)
Q83k	Q83k - Type of appliances (as observed) : Freezer (continuous load)
Q83l	Q83l - Type of appliances (as observed) : Food processor
Q83m	Q83m - Type of appliances (as observed) : Water Pump
Q83n	Q83n - Type of appliances (as observed) : Rice Cooker
Q83o	Q83o - Type of appliances (as observed) : Washing machine
Q83p	Q83p - Type of appliances (as observed) : Iron
Q83q	Q83q - Type of appliances (as observed) : Hair dryer
Q83r	Q83r - Type of appliances (as observed) : Toaster
Q83s	Q83s - Type of appliances (as observed) : Microwave oven
Q83t	Q83t - Type of appliances (as observed) : Air conditioner (continuous load)
Q83u	Q83u - Type of appliances (as observed) : Space heater (continuous load)
Q83v	Q83v - Type of appliances (as observed) : Vacuum cleaner
Q83w	Q83w - Type of appliances (as observed) : Water cleaner
Q83x	Q83x - Type of appliances (as observed) : Electric cooker
Q114a	Q114a - Availability of Pay-As-You Go
Q147	Q147 - The project is financed by a financing Program for development aid
MTF	MTF - simplified Multi-Tier Framework
P6g2	P6g2 - Technology
P11n2	P11n2 - Program Decision Level
P3n2	P3n2 - Project size
P21b2	P21b2 - Project type (larger groups)
Igrappe	Igrappe - Part of a multi-projects program
P15n	P15n - Commissioning Date
Dnearestport	Dnearestport - Distance to nearest port
LTMoyDNR	Direct Normal Radiation (kW-hr/m^2/day)
density2010_q95	robust population density, 2010 (<95%)

A.7 Lists of supplementary variables in classification of DEP for households

variable name	Supplementary variables
N5	N5 - Independence note
R2	R2 - Rural electrification agency
R3	R3 - Independent regulation agency
Q49	Q49 - Installation of storage equipment required for project: batteries
mExinat	Governance Score (RISE) - Existence of national program
mLegal	Governance Score (RISE) - Legal framework for minigrids operation
mAbil	Governance Score (RISE) - Ability to charge cost-reflective tariffs
mFina	Governance Score (RISE) - Financial incentives
mStan	Governance Score (RISE) - Standards and quality
D8g	D8g - No. of Citations (after 2 years)
Idef	Idef - Closed project

A.8 Calinski-F and Groups composition in the Ward classification of DEP for households

Large value of Calinski/Harabasz pseudo-F indicates more distinct clustering. The stopping rule needs a heuristic judgment with a balance between the highest pseudo-F as possible, and achieving comprehensive groups.

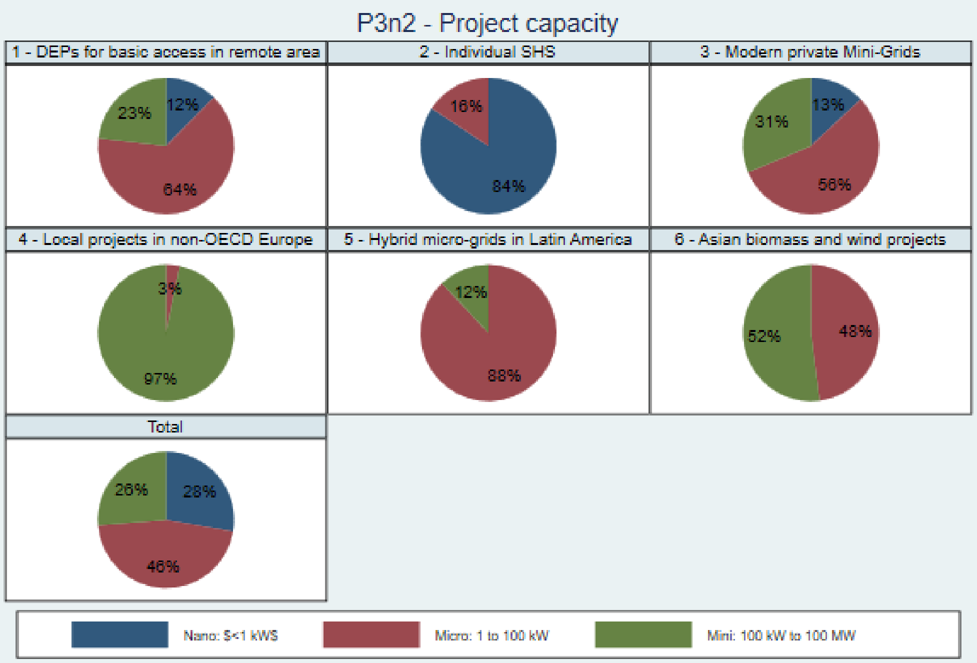
Number of clusters	Calinski/ Harabasz pseudo-F
2	2.81
3	13.59
4	9.13
5	7.65
6	10.34
7	8.63
8	10.77
9	9.58
10	8.53
11	8.63
12	7.89
13	8.11
14	7.64
15	7.30

No. of group (Ward)	Freq.	Percent	Cum.
1	121	28,88	28,88
2	102	24,34	53,22
3	115	27,45	80,67
4	31	7,40	88,07
5	25	5,97	94,04
6	25	5,97	100,01
Total	**419**	**100,00**	

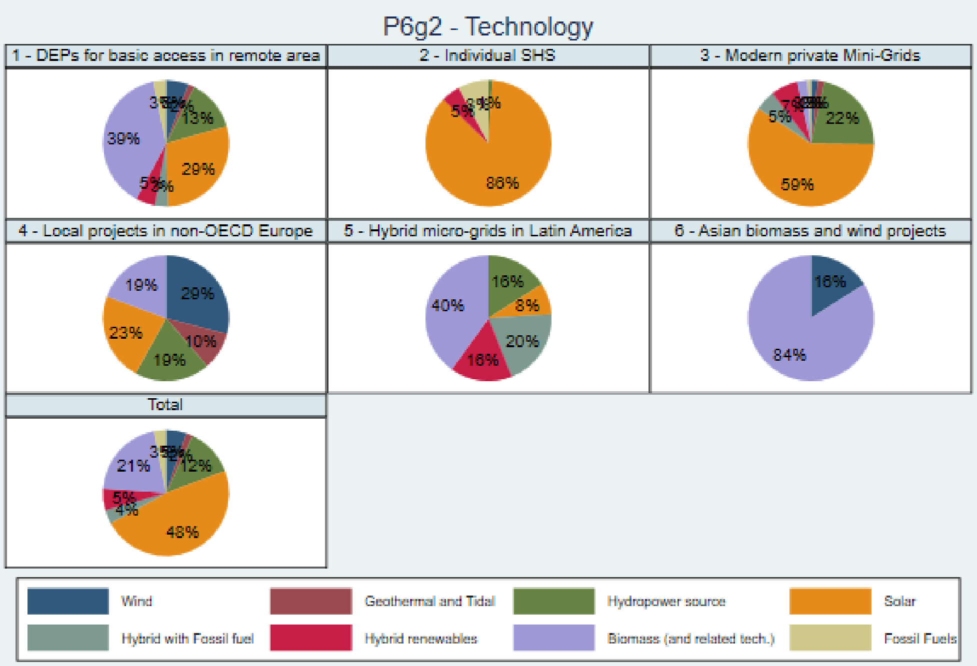
A.9 Classification of DEP for households: a selection of statistics by groups

For all pie charts, percentages in groups must be compared to the global profile in sample, with sub-graph "Total".

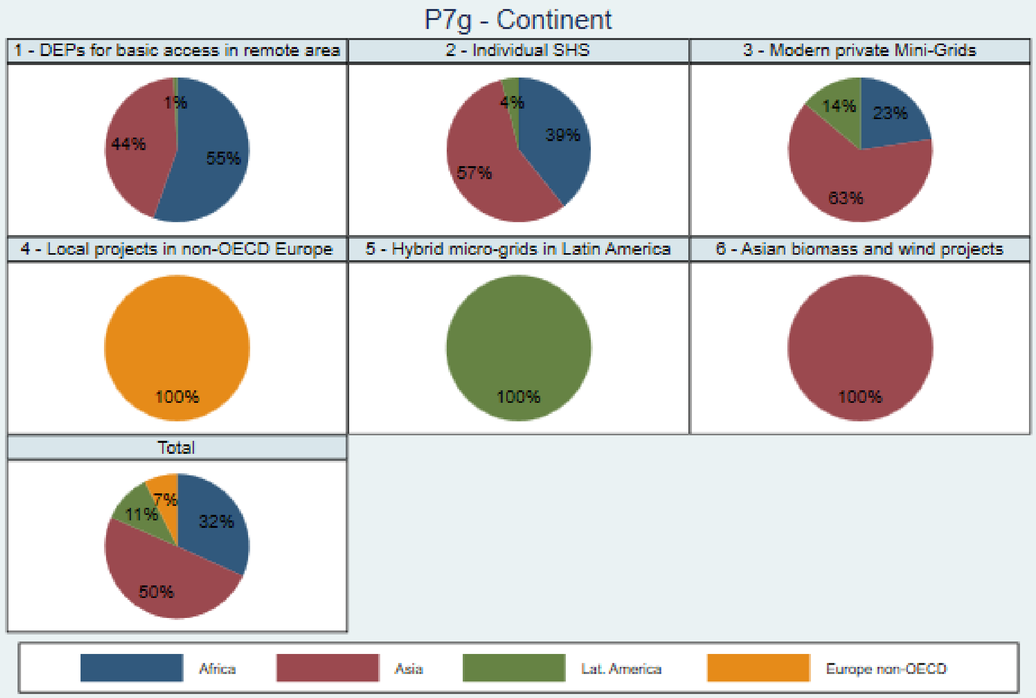
➢ Project design



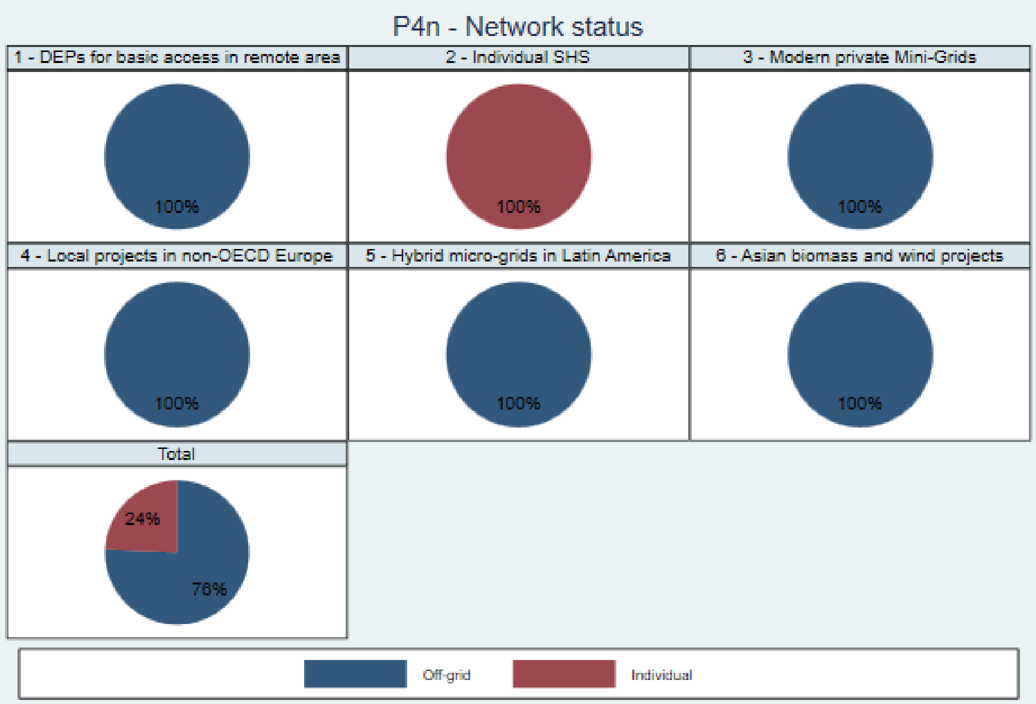
Groups characterized by active variables of classification. Linkage : ward_gp



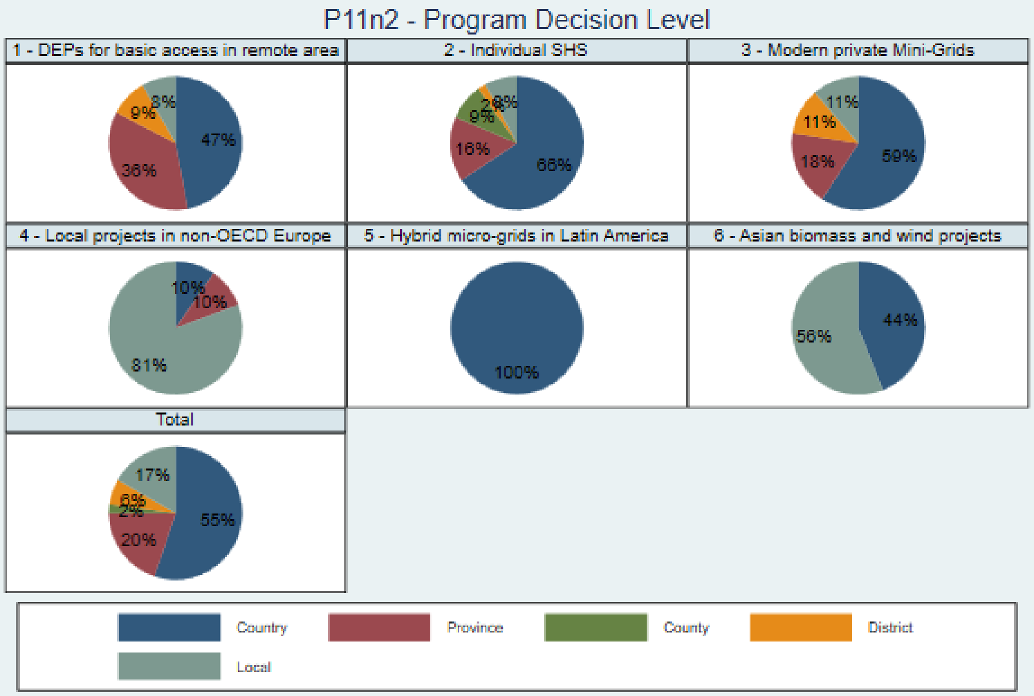
Groups characterized by active variables of classification. Linkage : ward_gp



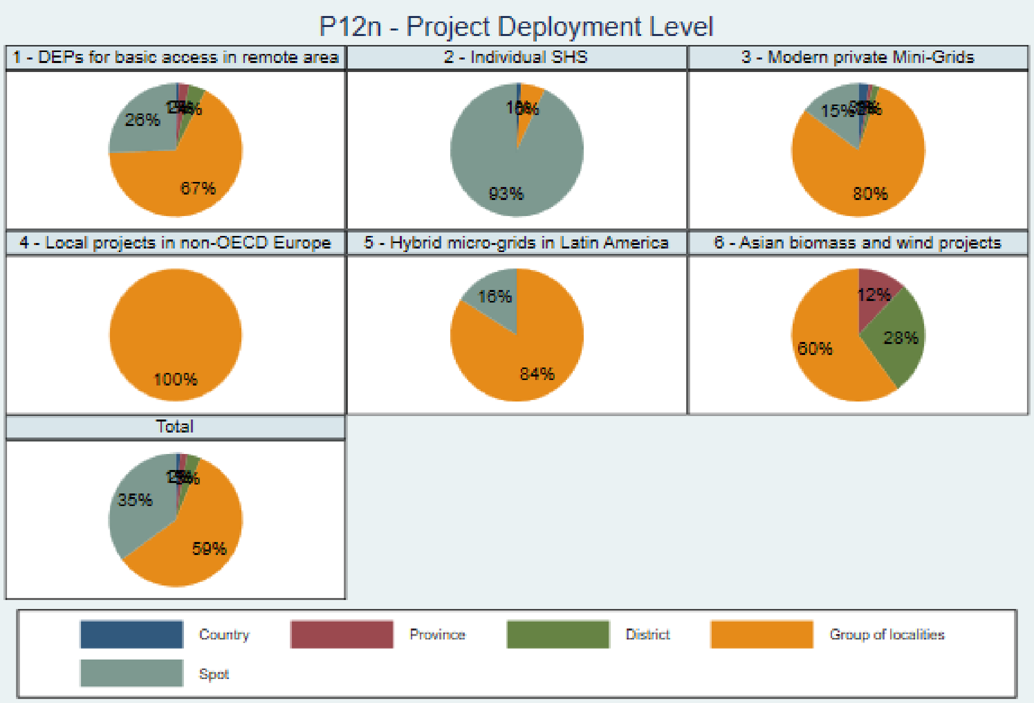
Groups characterized by active variables of classification. Linkage : ward_gp



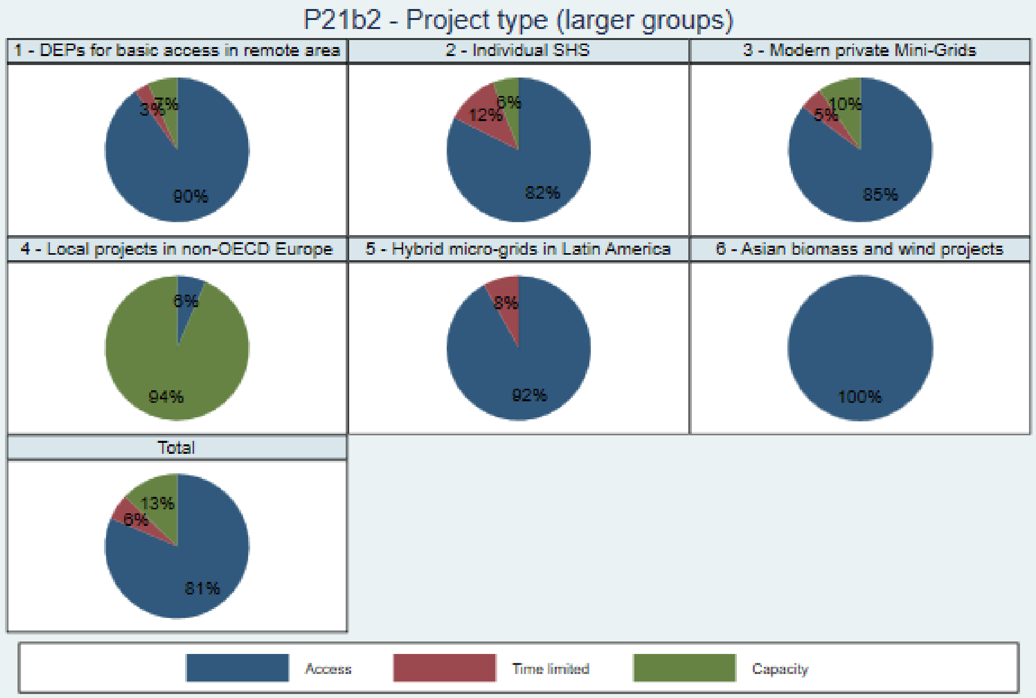
Groups characterized by active variables of classification. Linkage : ward_gp



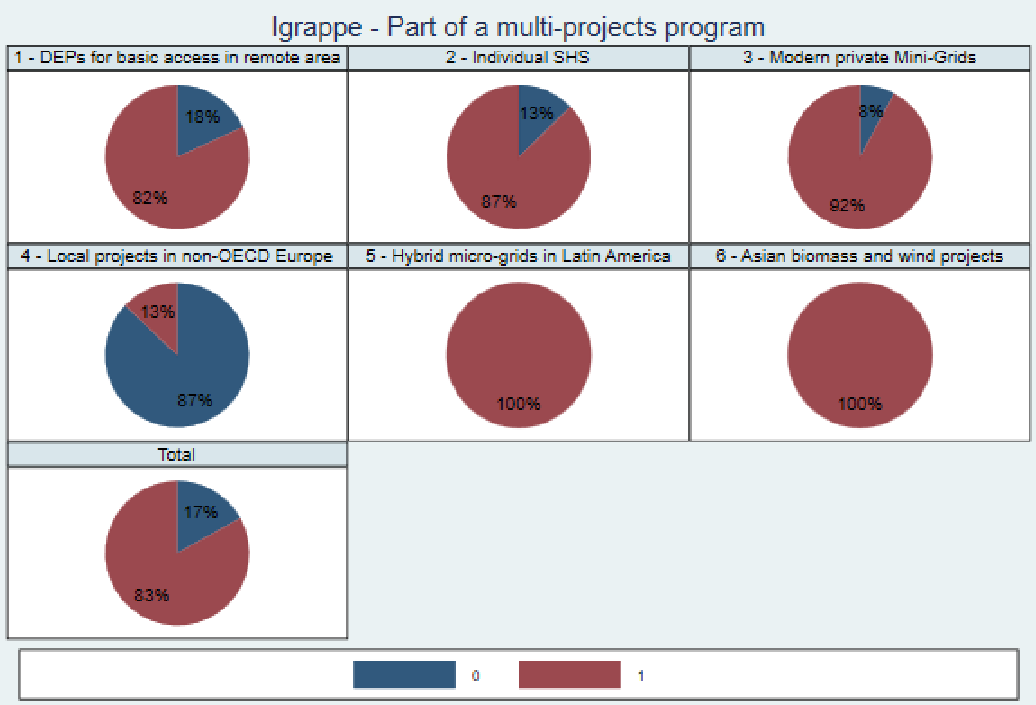
Groups characterized by active variables of classification. Linkage : ward_gp



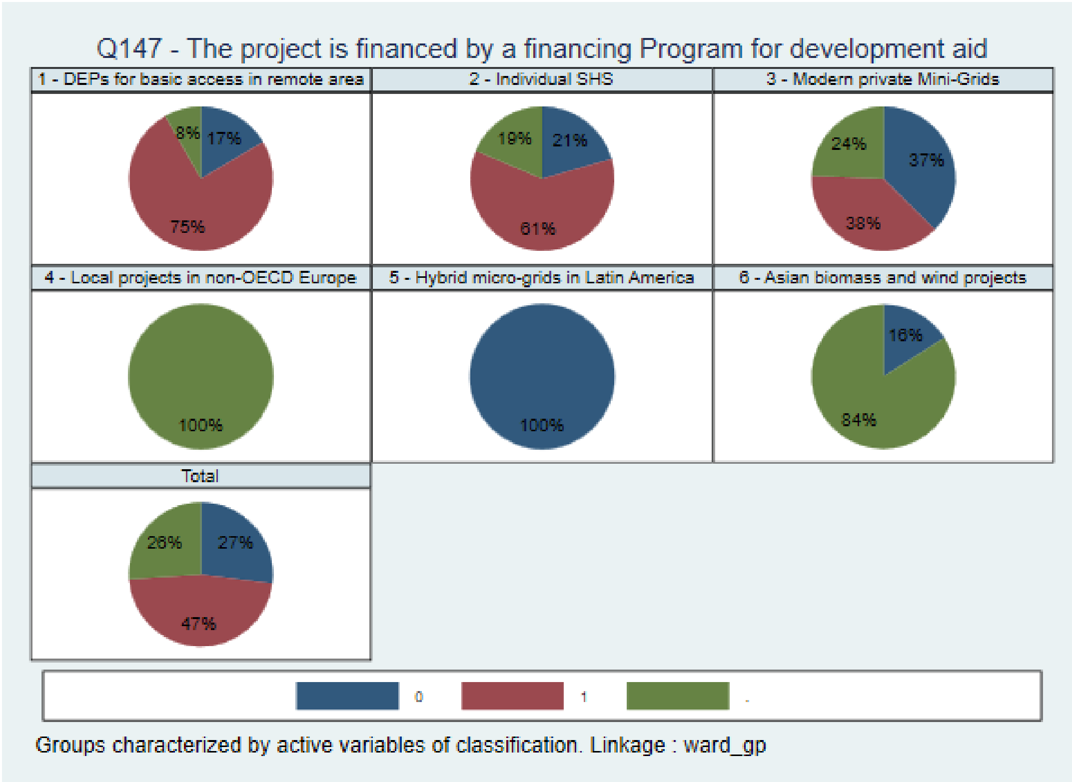
Groups characterized by active variables of classification. Linkage : ward_gp

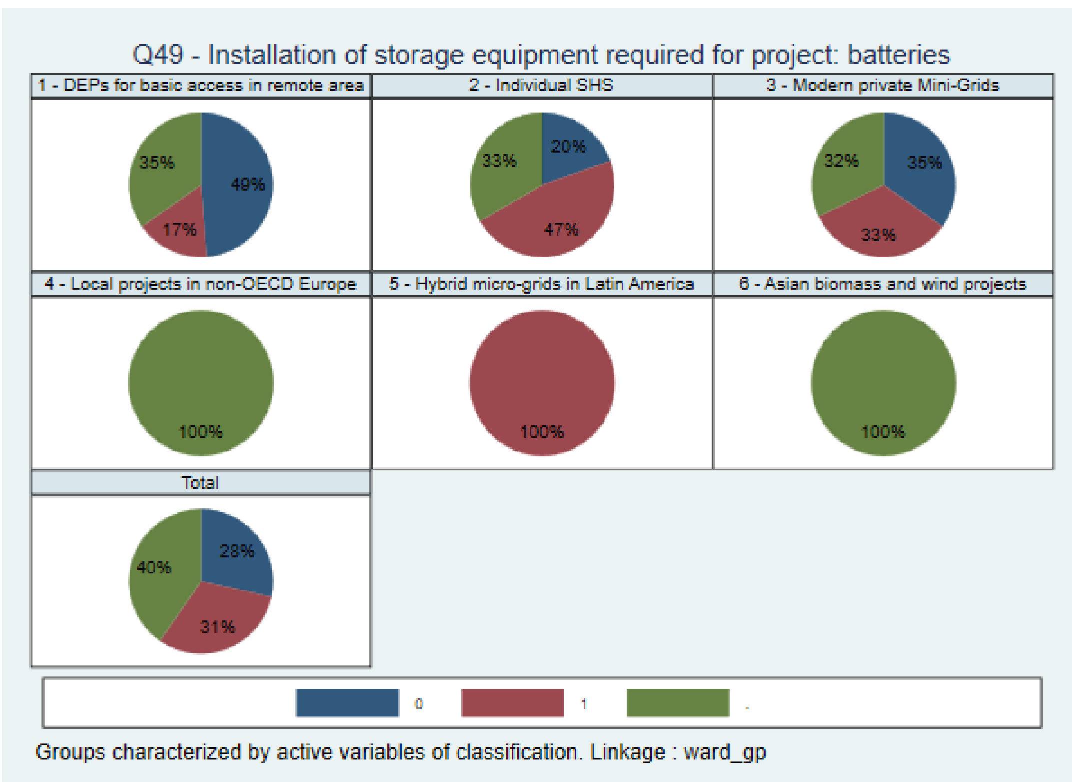


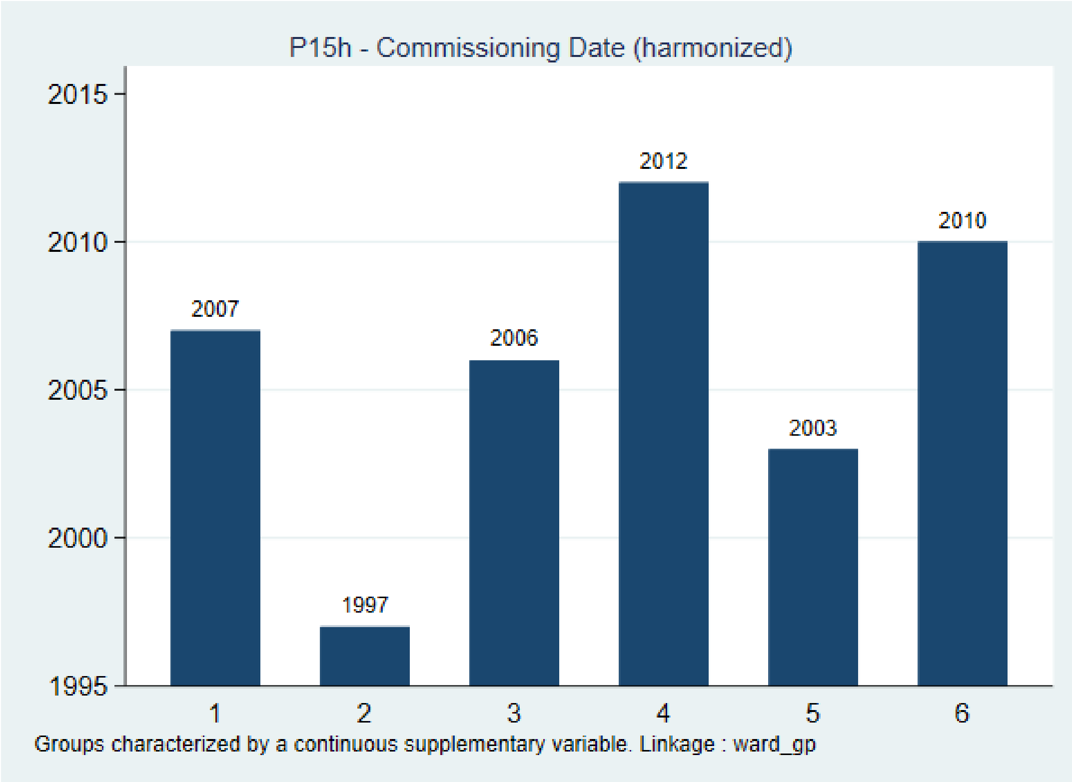
Groups characterized by active variables of classification. Linkage : ward_gp



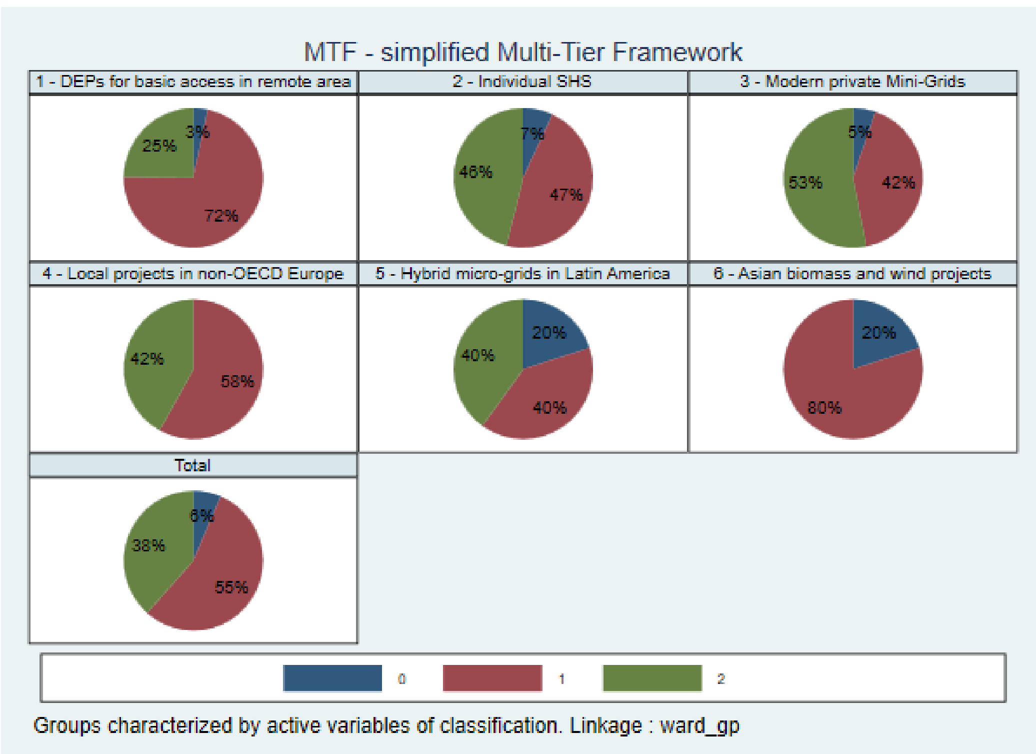
Groups characterized by active variables of classification. Linkage : ward_gp


Q147 - The project is financed by a financing Program for development aid
1 - DEPs for basic access in remote area
8%
17%
75%
2 - Individual SHS
19%
21%
61%
3 - Modern private Mini-Grids
24%
37%
38%
4 - Local projects in non-OECD Europe
100%
5 - Hybrid micro-grids in Latin America
100%
6 - Asian biomass and wind projects
16%
84%
Total
26%
27%
47%
0
1
.
Groups characterized by active variables of classification. Linkage : ward_gp

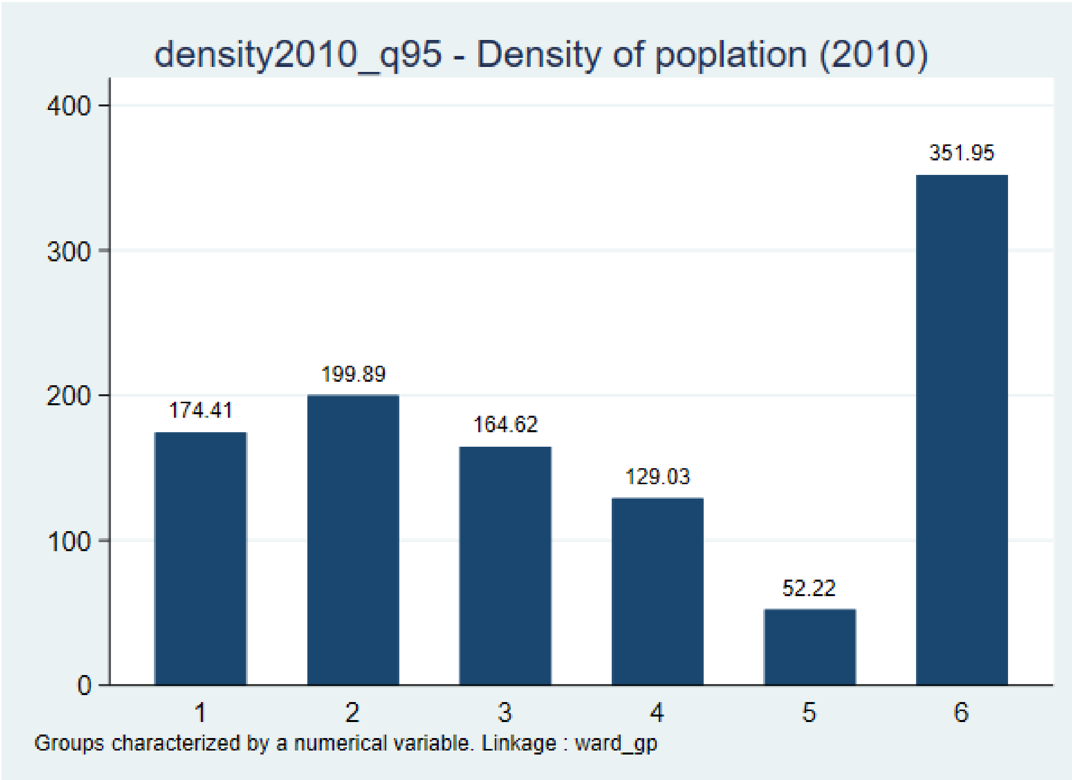

Q49 - Installation of storage equipment required for project: batteries
1 - DEPs for basic access in remote area
35%
49%
17%
2 - Individual SHS
33%
20%
47%
3 - Modern private Mini-Grids
32%
35%
33%
4 - Local projects in non-OECD Europe
100%
5 - Hybrid micro-grids in Latin America
100%
6 - Asian biomass and wind projects
100%
Total
40%
28%
31%
0
1
.
Groups characterized by active variables of classification. Linkage : ward_gp

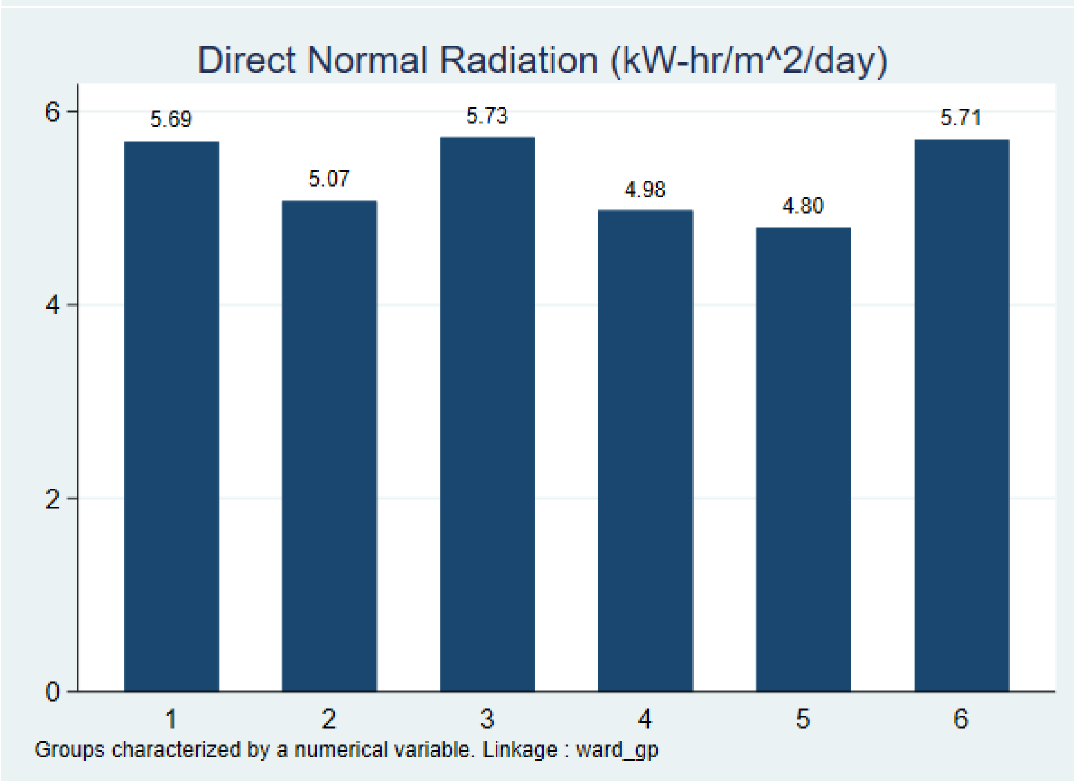


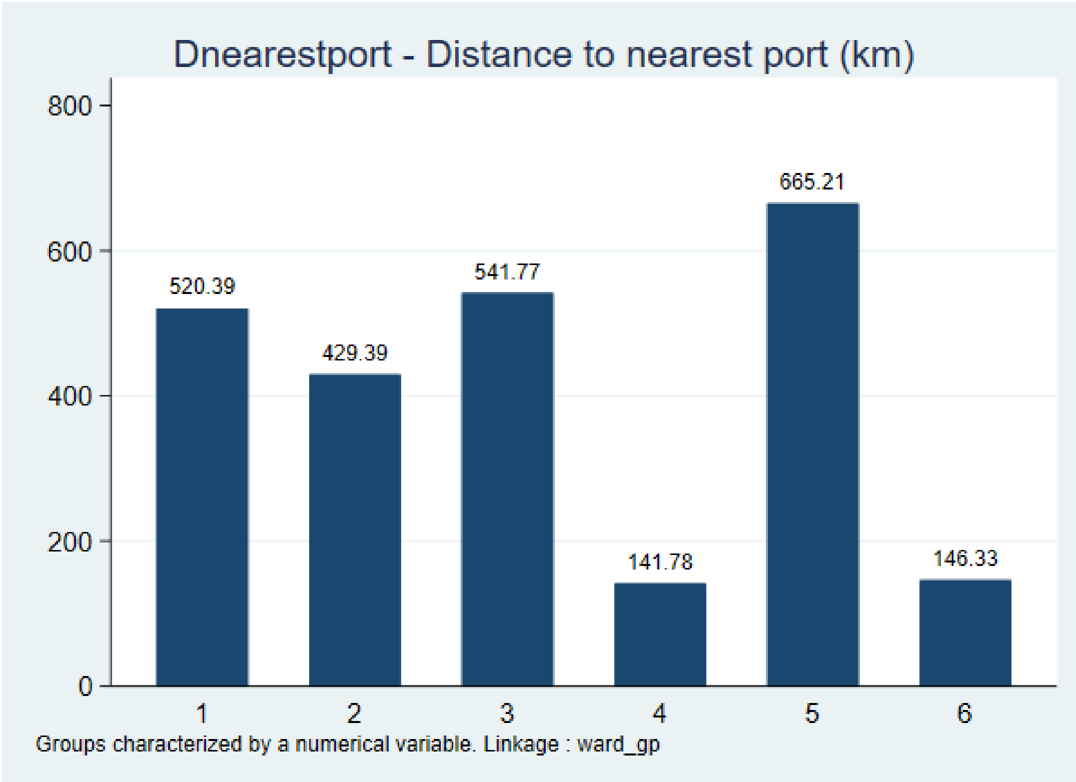
➢ Quality the electricity service: simplified MTF indicator



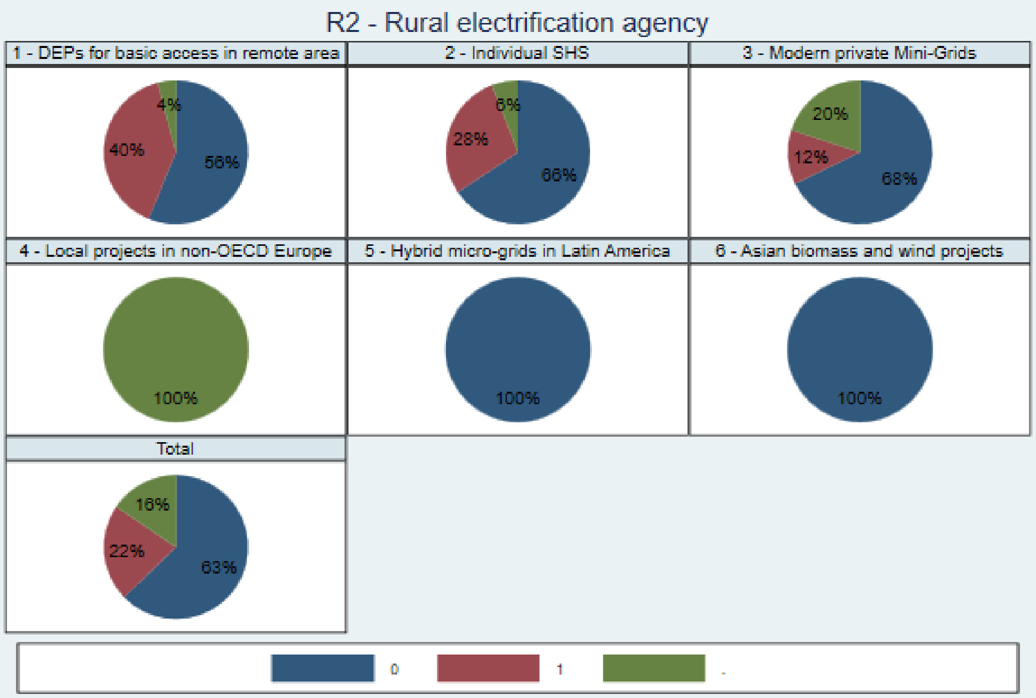
- Location context



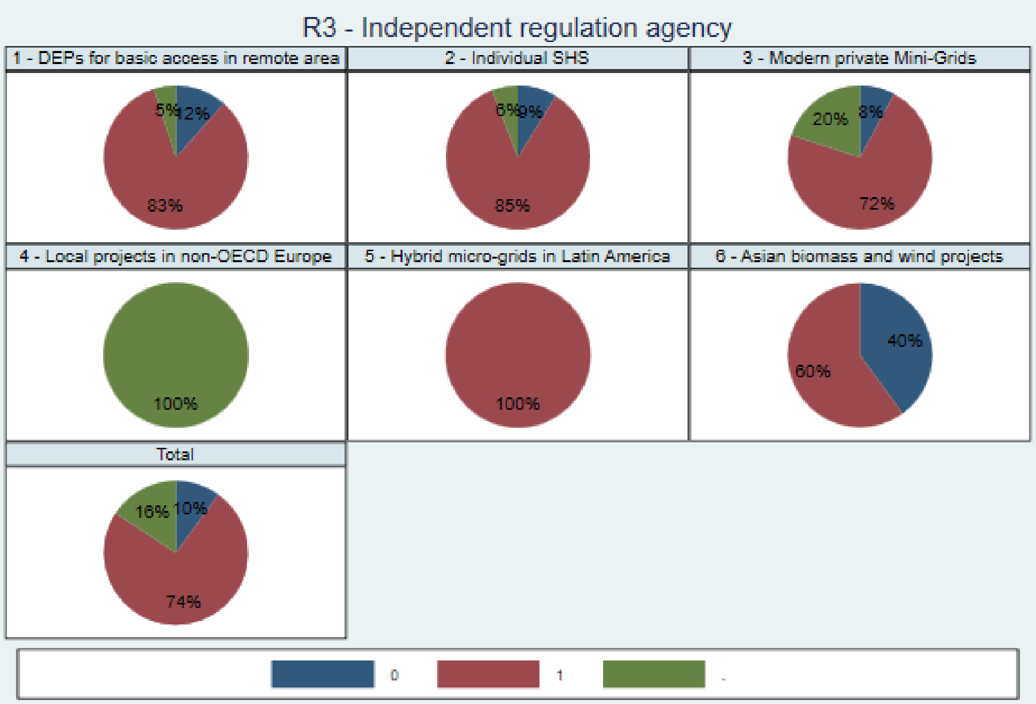



Dnearestport - Distance to nearest port (km)
800
600
400
200
0
520.39
429.39
541.77
141.78
665.21
146.33
1
2
3
4
5
6
Groups characterized by a numerical variable. Linkage : ward_gp

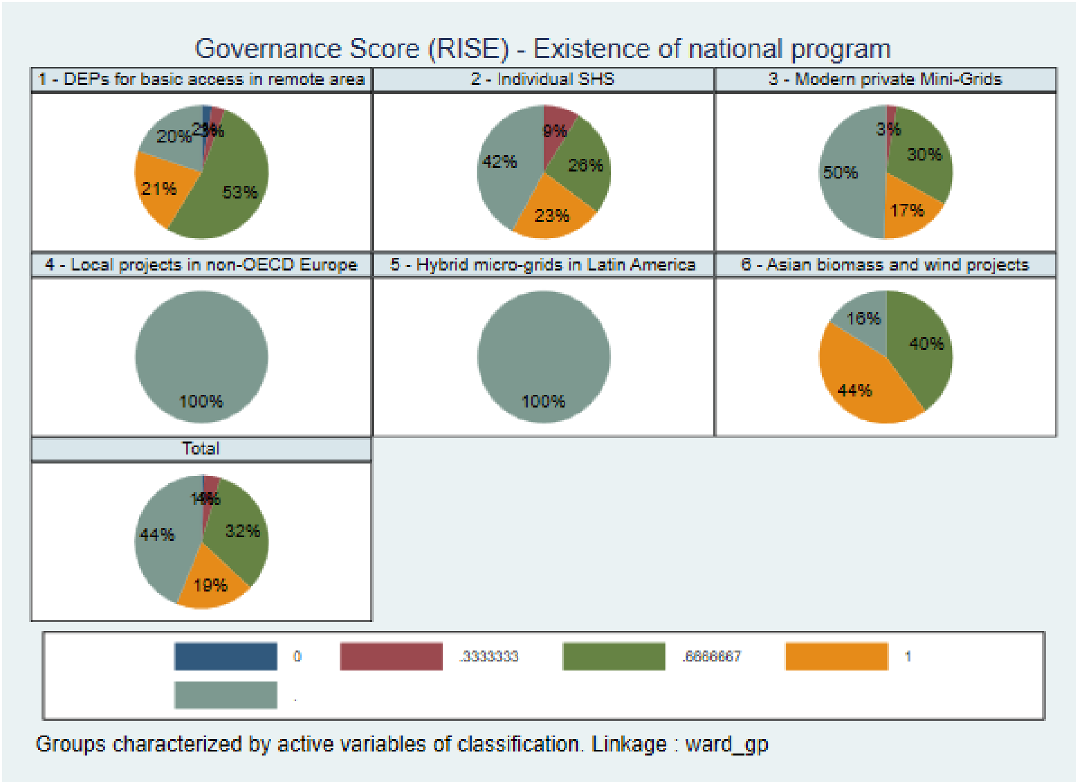
- Governance design and regulation context

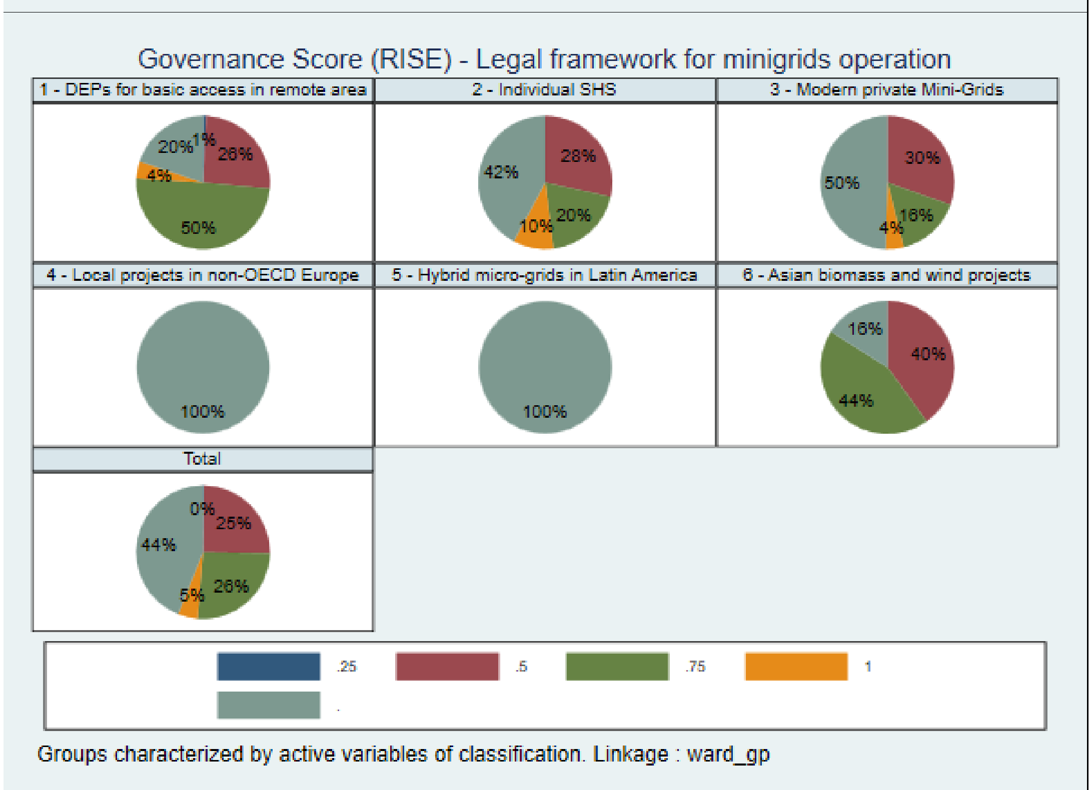


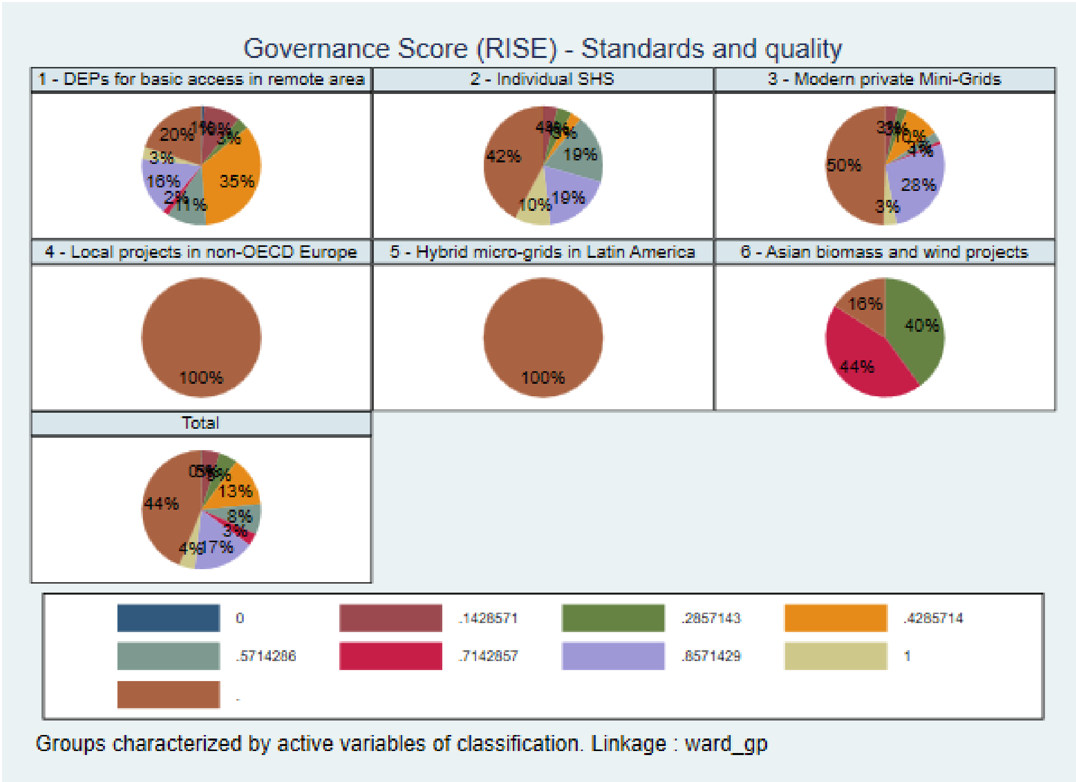
Groups characterized by active variables of classification. Linkage : ward_gp



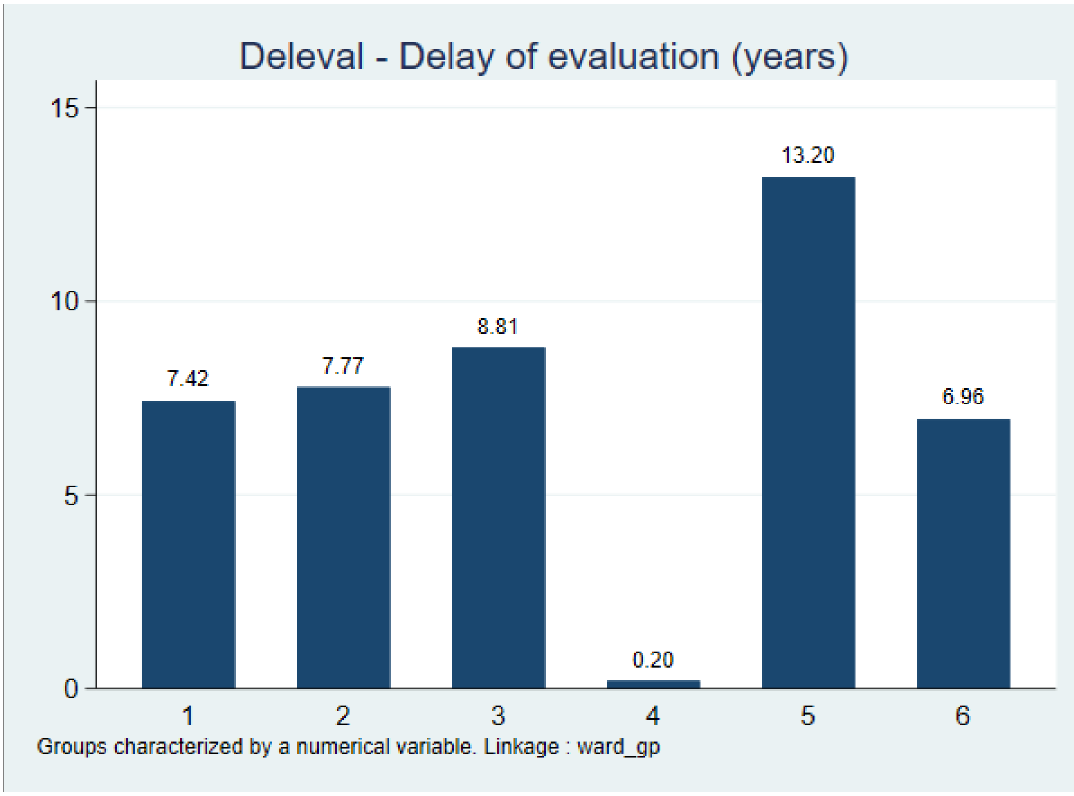
Groups characterized by active variables of classification. Linkage : ward_gp


Governance Score (RISE) - Existence of national program
1 - DEPs for basic access in remote area
2 - Individual SHS
3 - Modern private Mini-Grids
4 - Local projects in non-OECD Europe
5 - Hybrid micro-grids in Latin America
6 - Asian biomass and wind projects
Total
20%
21%
53%
42%
9%
26%
23%
50%
3%
30%
17%
100%
100%
16%
40%
44%
44%
32%
19%
0
.3333333
.6666667
1
.
Groups characterized by active variables of classification. Linkage : ward_gp

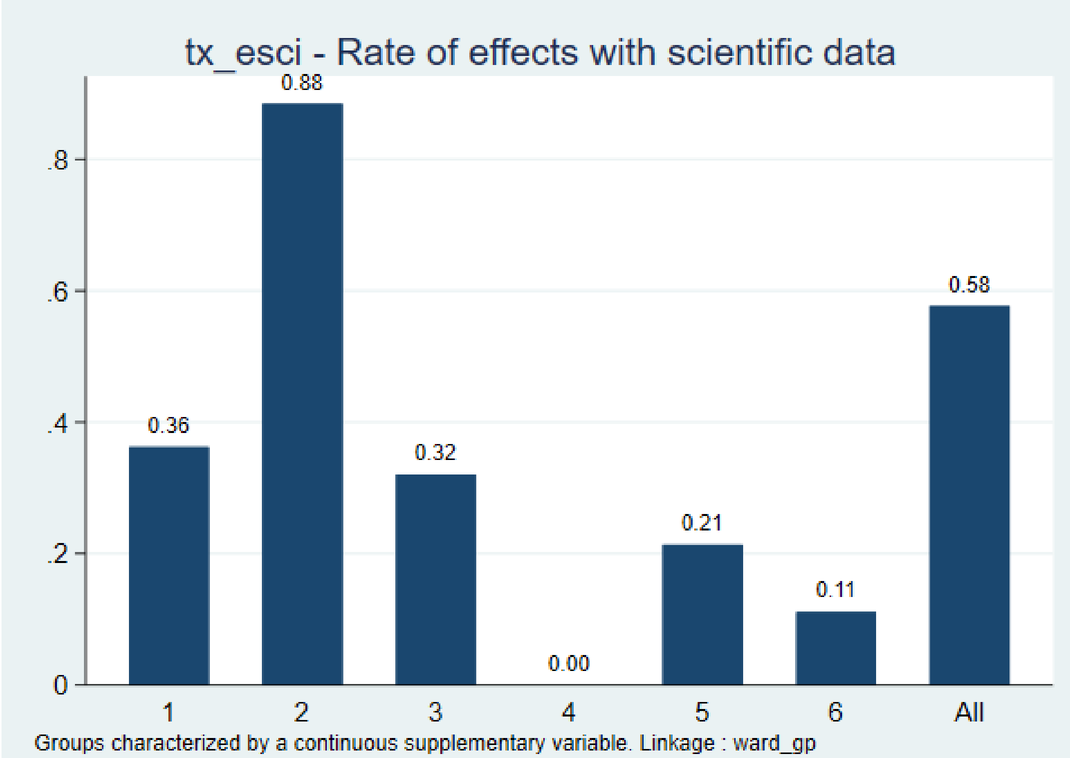

Governance Score (RISE) - Legal framework for minigrids operation
1 - DEPs for basic access in remote area
2 - Individual SHS
3 - Modern private Mini-Grids
4 - Local projects in non-OECD Europe
5 - Hybrid micro-grids in Latin America
6 - Asian biomass and wind projects
Total
20%
1%
26%
4%
50%
42%
28%
20%
10%
50%
30%
16%
4%
100%
100%
16%
40%
44%
0%
25%
44%
26%
5%
.25
.5
.75
1
.
Groups characterized by active variables of classification. Linkage : ward_gp

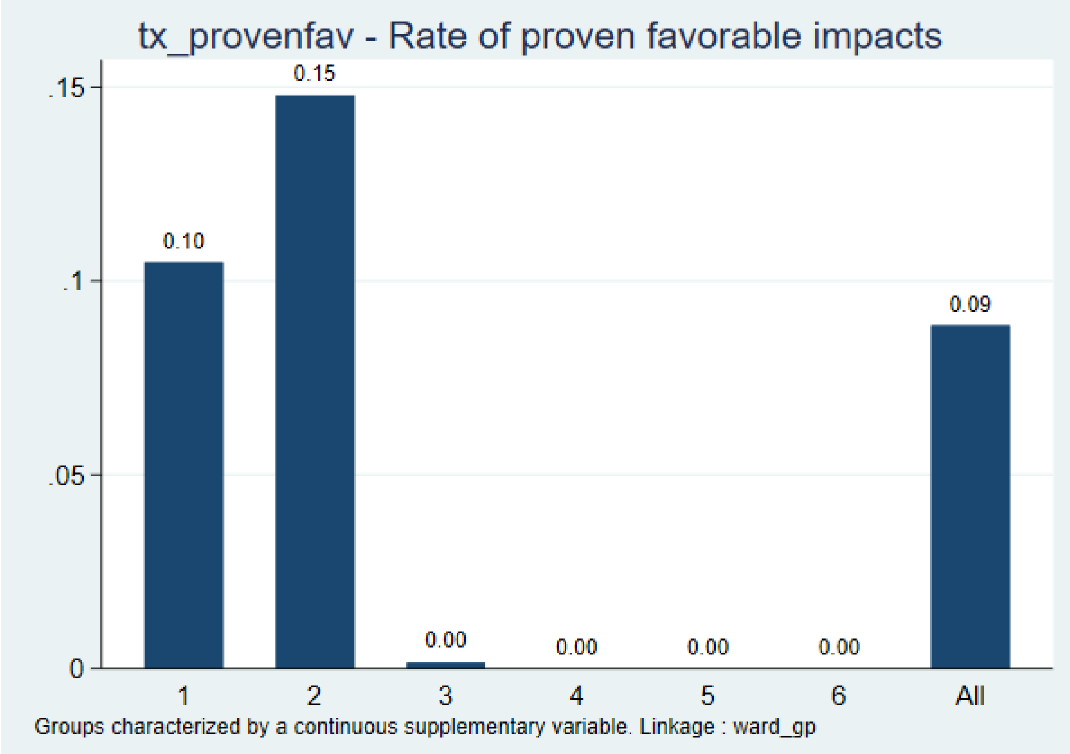

Governance Score (RISE) - Standards and quality
1 - DEPs for basic access in remote area
2 - Individual SHS
3 - Modern private Mini-Grids
4 - Local projects in non-OECD Europe
5 - Hybrid micro-grids in Latin America
6 - Asian biomass and wind projects
Total
35%
20%
16%
11%
3%
42%
19%
19%
10%
50%
28%
3%
100%
100%
40%
44%
16%
44%
17%
13%
8%
3%
4%
0
.1428571
.2857143
.4285714
.5714286
.7142857
.8571429
1
Groups characterized by active variables of classification. Linkage : ward_gp

➢ Evaluation context and outcomes



- Measurements of effects and proven favorable impacts



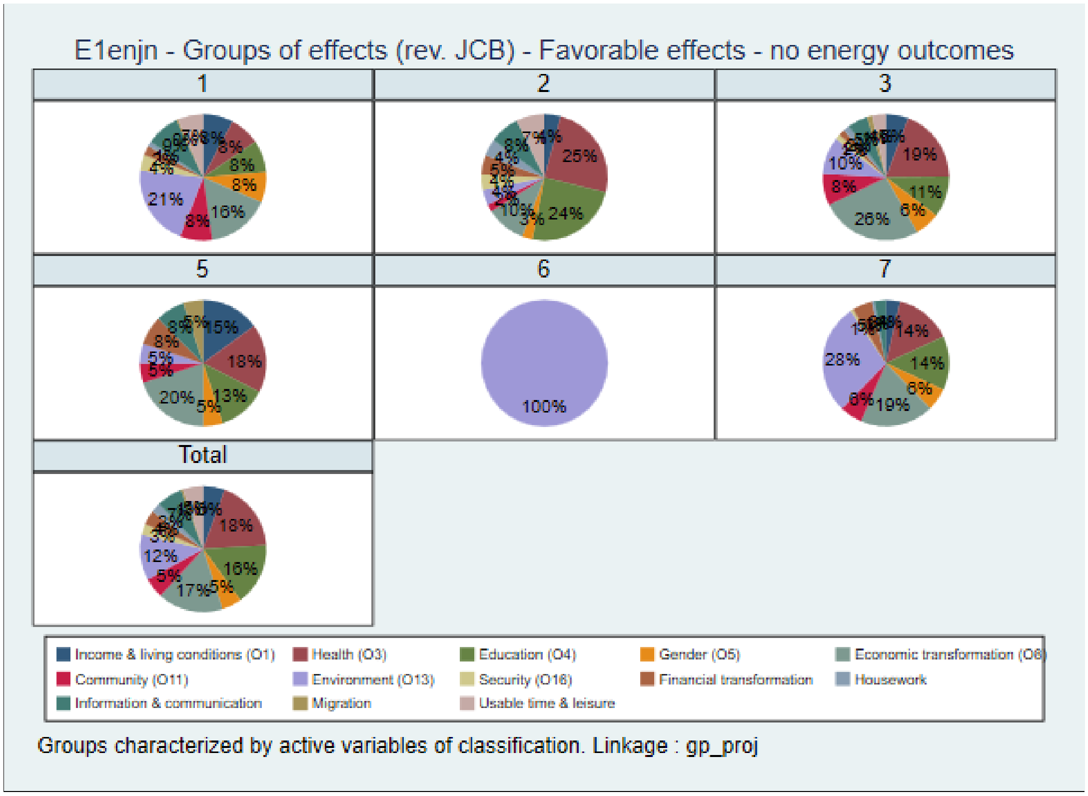


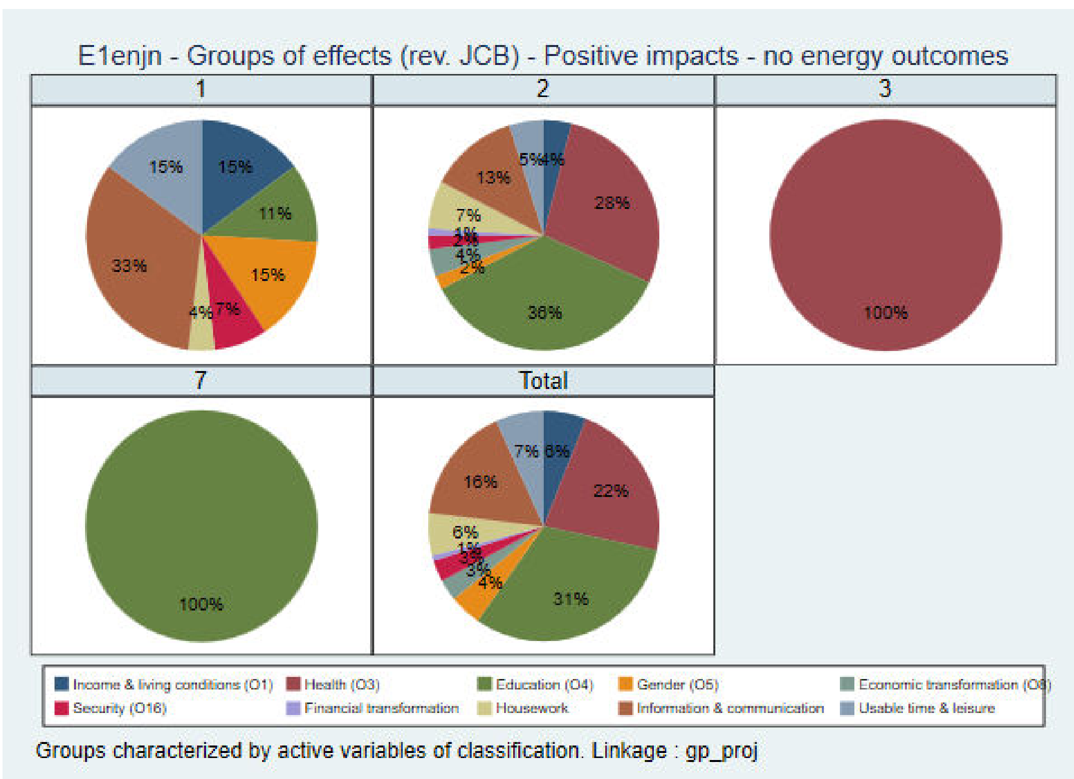
A.10 Distribution of effects with scientific data and positive impact by groups of projects

	Distribution of measured effects with scientific data among groups of projects		
	Freq	Pct	Cumpct
1	159	11.2	11.2
2	944	66.7	77.9
3	203	14.3	92.2
5	22	1.6	93.8
6	4	0.3	94.1
7	84	5.9	100.0
Total	1416	100.0	

	Distribution of positive impacts among groups of projects		
	Freq	Pct	Cumpct
1	46	22.1	22.1
2	159	76.4	98.6
3	1	0.5	99.0
7	2	1.0	100.0
Total	208	100.0	

A.11 Nature of effects, favorable effects and impacts by groups





➢ Conclusion

In this thesis, I explored important issues for electrification policies: the main determinant of demand for grid electricity; the probability that decentralized supply achieves positive impacts for economic development; the determinant of success in various practices of decentralized electrification; and as far as possible, the natures of impacts that can be expected by types of projects.

The first chapter explored the role of reliability of electricity service as an important determinant of effective electrification: permanent availability of electricity supports long term households' expectations of availability, and thus their decision to effectively use the supplied electricity by national grid, in the areas where it is accessible.

Because it is observable, a reliable service decreases uncertainty, which in turn increases the trust of households for long term availability of the electricity service. In fact, reliability is not the same kind of connection's determinant as wealth, building quality, or distance to the distribution grid: it does not only tell something about the economic or technical feasibility of connection, but also it is a context factor that can be directly and permanently seen by everybody. Therefore, reliability sends a long-term signal about the commitment of the electricity supply chain to produce, transport and distribute power without interruption. Providing a reliable electricity service is an essential requirement for sustainable electrification because the long-term trust in the service could help unconnected households to overcome the cost of connection barrier, as they could expect more benefits from the permanent power supply than damages related to outages. Additional research should then demonstrate to which extent the support of governance and regulation can preserve households' trust by improving the grid's quality on long term.

But reliability is not a sufficient condition. I have shown that households are not myopic to the price-to-quality ratio of electricity service. However, the poorest households are the least sensitive to the reliability of electricity service, which is more a concern for the wealthiest households. This paradox can be explained by the changing nature of electricity service, according to the wealth level. While the demand for electricity by the wealthiest households tends to be inelastic, electricity remains a luxury service for the poorest households, thereby highly substitutable, moreover in an uncertain context.

This paradox raises new questions about the content of demand: what do households expect from using electricity? How would they consume electricity in a way that they would not accept anymore to give up this form of energy? In the perspective of these questions, a first indispensable step must check whether using electricity brings any favorable effects for households' welfare. Seeming rather trivial, it turns out that this question has been rarely explored before. The recent introduction of access to electricity in

Sustainable Development Goals (SDG) raises a research duty, in order to clarify which evidences are known about the benefits of electrification.

The second chapter, co-written with Pr. Jean-Claude Berthélémy, assessed the probability of positive impacts of decentralized supply. As a first result, this meta-analysis showed the scarcity of scientific evidences of decentralized electrification's benefits for sustainable development. Nevertheless, our large meta-data collection and our methodology allowed us to conclude about some key factors of success. Scientific evidences did not need to be numerous, provided that the identification methodology used by researchers supported statistical inference or external validity.

With limited meta-data, we could thus demonstrate the role of key factors of Decentralized Electrification Projects (DEP): capacity, technology and governance.

The meta-study shows a growing relationship between capacity and the probability of achieving positive impacts. This result brings evidence that limited capacity of some electrification projects can act as a barrier to development. Electricity-based development may therefore require projects that exceed a critical size, as the range of electrical appliances and their hidden interactions may be more important than simply connecting small electrical devices. However, calibrating critical capacity threshold with respect to development objectives remains complex, and opens rich path for future research.

Among existing projects, there is a trade-off between technology and capacity. Solutions based on solar energy have the highest chance of positive impacts. However, in practice, solar electricity is frequently delivered through Solar Home Systems (SHS) with very low capacity, which decreases the chance of projects' success. Therefore, hybrid systems of larger capacity, supplementing solar energy with fuel or renewables, have higher probability of positive impacts. The combination of technologies also brings flexibility and availability in a resource-constrained environment, which fills a missing link and avoids interruptions of power. The study thus shows the importance of transition choices in off-grid areas. However, clarifying the exit conditions for operators at time of the grid's arrival remains an important question for future regulation frameworks.

As an important contribution, the second chapter also showed a U-shaped curve of the governance's role for the impact of DEP on education: global and local powers are key factors of success. The reasons for this are many-fold. Decisions at multi-countries or national level convey cross-expertise across similar projects. They also bring supervision benefits, avoiding the occurrence of obvious failures of design or management. Finally, they can achieve imbrication gains in the sense that local projects benefit from global support. Conversely, local governance supports inclusive choices that may favor the adoption by households and lower the risk of hidden passengers, which in turn increases the probability of success.

The third chapter extended the exploration of the nature of effects of decentralized electrification. It separated the determinants of the probability of positive impact according to distinct practices and showed which natures of impacts were most likely observed by practices. An extension looked at the determinants of the nature of favorable effects observed with Individual SHS.

The various practices of decentralized electrification do not achieve the same level of performance for sustainable development. Decentralized projects for Productive Uses and Utilities, and Micro-grids for access in remote areas are the most efficient practices. Individual SHS and private mini-grids are less efficient. The difference of efficiency occurs from different determinants of positive impacts along practices.

The probability of positive impacts increases with capacity of Individual SHS, notably for other natures of effects than access to electricity or cost of energy, which could be linked with favorable effects on Information and communication. Nevertheless, Micro-grids for remote areas have significantly higher chance of positive impact with smaller capacity, which could come from favorable effects on Health and Usable time and leisure. This chapter thus found that the growing role of capacity found in chapter 2 is actually driven by Individual SHS, which is the most frequent practice and relies on the most effective technology.

This chapter also showed the non-linear role of governance. For Individual SHS, the combination of bottom-up and top-down approaches mainly exists for impacts on the 7^{th} SDG. For Micro-grids in remote areas the combination of local and global governance plays a significant role for other socio-economic effects. The role of DEP governance for impacts is complex and depends on the combination of DEP practices and natures of effects. Specializations by decision levels on the potential uses of electricity could be at work at the time of project engagement, which would require further research to highlight this channel.

Finally, the third chapter explored the natures of effects by various practices. Micro-grids for remote areas have mainly positive impacts on Information and communication, and Individual SHS on Health and Education. Private Micro-grids and projects for Productive Uses and Utilities could favor Economic transformations or be favorable to Environment, but such natures of effects have not been proven so far.

In fact, scientific knowledge about the natures of impacts did not achieve the same degree of completeness according to various practices. The meta-data could be sorted between scientific evidences (identified coefficient, statistics with variance) and expert observations (citations, simple figure) on favorable effects. Some natures of effects could be proven as positive impacts with scientific data, but others were just expected by expert data. The latter can only provide clues as to the nature of unidentified impacts, because they may be just invoked as *ad hoc* arguments supporting the project objective. Expert data may even blur some results, and thus do not compensate the lack of proven favorable effects with scientific data.

The final mapping relates practices and natures of effects, showing which ones require more impact evaluation. This mapping aims at contributing to a consistent agenda of future research on proven benefits of decentralized electrification.

Obviously, positive impacts on Energy (substitution types and costs) and Basic Access are largely known, as well as benefits for Health and Education which are supported by many proofs. However, Basic Access can trigger induced demand higher than the expected demand: future feasibility studies should take into account the induced growing peak-load by unexpected novel uses of electricity, in order to predict the optimal scalability of the system at local level.

Other natures of effects and their implications have been even less explored. Economic transformations were frequently addressed but never proven, and no study has ever showed how economic transformations induced by decentralized electrification might interact with other development goals in complex chains of interactions. Assessing aggregation effects, spill-overs toward unconnected users, retro-feedbacks for projects' developers, or virtuous cycles, would open many complex extensions for future research.

Effects on environment are not numerous and remain largely unproven, because many studies were done in the perspective of pollution reallocation through the Clean Development Mechanism. However, some previous non-polluting countries have turned into strongly polluting areas as they were developing. Serious action to achieve the Paris Agreement cannot only count on volatile marked-to-market features that keep the poorest countries into poverty traps of energy, distributing Nano individual devices to the population in exchange of large polluting plants in advanced and emerging countries. There is a need for more scientific evidences of environmental benefits of larger decentralized systems. Future research should evaluate to which extent renewable off-grid systems contribute to a low-carbon path of economic development, by answering to the need for electricity of local populations, with a light footprint on environment. Kenya offers a unique case, which combines a wide range of renewable resources, while meeting the growing demand for electricity and enhancing the reliability of service. It could be a case study, even for advanced countries facing the urgency of the energy transition.

Some other recent and urgent research topics remain unexplored: to which extend does decentralized electricity support women entrepreneurship? Does decentralized electrification contribute to increase the number of stayers among candidates for migration? To which extend does decentralized access to electricity contribute to peace keeping in troubled area?

Collecting evaluations of projects in a collaborative effort of supervision is in the interest of the community of mini-grids' developers. CoSMMA may help support a Special Purpose Vehicle (SPV) that would gather projects with similar risks and performances in a common portfolio: such financial instrument could then leverage the access to funding of small electrification projects considered all together; but such structuration demands finer knowledge on projects' benefits, which is where CoSMMA can bring the highest value.

In this perspective, a research extension on predictive performance of projects is encouraged to be done. Each new decentralized electricity project entering into the collaborative meta-base could be individually evaluated *exante*, according to its distance to existing projects in the typology of practices. Such predictive classification would then provide an estimation about each new project's chance of achieving sustainable development goals. Using predicted performance for economic development in the SPV, such initiative could accelerate the funding of projects at larger scale, providing support for the scalability of decentralized electrification.

Bibliography

Adaramola, M.S., Quansah, D.A., Agelin-Chaab, M., Paul, S.S., 2017. Multipurpose renewable energy resources based hybrid energy system for remote community in northern Ghana. Sustain. Energy Technol. Assess. 22, 161–170. https://doi.org/10.1016/j.seta.2017.02.011

Afrobarometer, 2014. Afrobarometer.

Aguirre, J., 2014. Impact of Rural Electrification on Education: A Case Study from Peru. Mimeo, Research Center, Universidad del Pacfico (Peru) and Department of Economics, Universidad de San Andrés (Argentina).

Ajayi, K.T., Olamide, O.O., 2014. Multi-criteria Analysis of Power Plants in Nigeria. Glob. Sci. Technol. J. 2, 1–22.

Aklin, M., Cheng, C., Urpelainen, J., Ganesan, K., Jain, A., 2016. Factors affecting household satisfaction with electricity supply in rural India. Nat. Energy 1, 16170. https://doi.org/10.1038/nenergy.2016.170

Alby, P., Dethier, J.-J., Straub, S., 2010. Firms operating under infrastructure and credit constraints in developing countries: The case of power generators. World Bank Policy Res. Work. Pap. Ser. Vol.

Allcott, H., Collard-Wexler, A., O'Connell, S.D., 2016. How Do Electricity Shortages Affect Industry? Evidence from India. Am. Econ. Rev. 106, 587–624. https://doi.org/10.1257/aer.20140389

Andersen, T.B., Dalgaard, C.-J., 2013. Power outages and economic growth in Africa. Energy Econ. 38, 19–23. https://doi.org/10.1016/j.eneco.2013.02.016

Angrist, J.D., Pischke, J.-S., 2008. Mostly harmless econometrics: An empiricist's companion. Princeton university press.

Arellano, M., 1987. Computing Robust Standard Errors for Within-Groups Estimators. Oxf. Bull. Econ. Stat. 49, 431–434.

Arnold, J.M., Mattoo, A., Narciso, G., 2006. Services inputs and firm productivity in Sub-Saharan Africa: Evidence from firm-level data. World Bank Policy Res. Work. Pap.

Arráiz, I., Calero, C., 2015a. From Candles to Light: The Impact of Rural Electrification. Inter-American Development Bank.

Arráiz, I., Calero, C., 2015b. From Candles to Light: The Impact of Rural Electrification. Inter-American Development Bank.

Basagaña, X., Barrera-Gómez, J., Benet, M., Antó, J.M., Garcia-Aymerich, J., 2013. A Framework for Multiple Imputation in Cluster Analysis. Am. J. Epidemiol. 177, 718–725. https://doi.org/10.1093/aje/kws289

Bazelon, C., Smetters, K., 1999. Discounting Inside the Washington D.C. Beltway. J. Econ. Perspect. 13, 213–228. https://doi.org/10.1257/jep.13.4.213

Bell, S., Judson, E., Bulkeley, H., Powells, G., Capova, K.A., Lynch, D., 2015. Sociality and electricity in the United Kingdom: The influence of household dynamics on everyday consumption. Energy Res. Soc. Sci. 9, 98–106. https://doi.org/10.1016/j.erss.2015.08.027

Belsley, D.A., 2004. Regression diagnostics: identifying influential data and sources of collinearity, Wiley series in probability and statistics. Wiley-Interscience, Hoboken, N.J.

Bernard, T., Torero, M., 2015. Social Interaction Effects and Connection to Electricity: Experimental Evidence from Rural Ethiopia. Econ. Dev. Cult. Change 63, 459–484.

Berthélémy, J.-C., 2016. Mini-grids as an Application of Elinor Ostrom's Theses on Polycentric Governance as a Way to Cope with the Tragedy of the Commons. Rev. Econ. Dév.

Blodgett, C., Dauenhauer, P., Louie, H., Kickham, L., 2017. Accuracy of energy-use surveys in predicting rural mini-grid user consumption. Energy Sustain. Dev. 41, 88–105.

https://doi.org/10.1016/j.esd.2017.08.002
Bonan, J., Pareglio, S., Tavoni, M., 2014. Access to modern energy: a review of impact evaluations.
Booysen, F., van der Berg, S., Burger, R., Maltitz, M. von, Rand, G. du, 2008. Using an Asset Index to Assess Trends in Poverty in Seven Sub-Saharan African Countries. World Dev. 36, 1113–1130. https://doi.org/10.1016/j.worlddev.2007.10.008
Borenstein, S., 2012. The Private and Public Economics of Renewable Electricity Generation. J. Econ. Perspect. 26, 67–92. https://doi.org/10.1257/jep.26.1.67
Borenstein, S., 2002. The Trouble With Electricity Markets: Understanding California's Restructuring Disaster. J. Econ. Perspect. 16, 191–211. https://doi.org/10.1257/0895330027175
Brenneman, A., Kerf, M., 2002. Infrastructure & Poverty Linkages. Lit. Rev. World Bank Wash. DC.
Carré, E., Couppey-Soubeyran, J., Dehmej, S., 2015. La coordination entre politique monétaire et politique macroprudentielle. Que disent les modèles dsge ? Rev. Économique 66, 541–572. https://doi.org/10.3917/reco.663.0541
Chakravorty, U., Kyle, E., Ravago, M.-L., 2016. Lighting up the last mile: The benefits and costs of extending electricity to the rural poor.
Chakravorty, U., Pelli, M., Ural Marchand, B., 2014. Does the quality of electricity matter? Evidence from rural India. J. Econ. Behav. Organ. 107, 228–247. https://doi.org/10.1016/j.jebo.2014.04.011
Chaplin, D., Mamun, A., Protik, A., Schurrer, J., Vohra, D., Bos, K., Burak, H., Meyer, L., Dumitrescu, A., Ksoll, C., 2017. Grid Electricity Expansion in Tanzania by MCC: Findings from a Rigorous Impact Evaluation. Rep. Submitt. Millenn. Chall. Corp. Wash. DC Math. Policy Res.
Châtelain, J.-B., 2010. Comment bien régresser: La statistique peut-elle se passer d'artefacts?, in: Séminaire Probabilismes. pp. 1–38.
Comello, S.D., Reichelstein, S.J., Sahoo, A., Schmidt, T.S., 2017. Enabling Mini-Grid Development in Rural India. World Dev. 93, 94–107. https://doi.org/10.1016/j.worlddev.2016.12.029
CRA, 2011. Kenya County Facts Sheet.
Davis, Chmieliauskas, Dijkema, Nikolic, 2015. Enipedia Database [WWW Document]. Enipedia. URL http://enipedia.tudelft.nl
Davis, L.W., 2012. Prospects for Nuclear Power. J. Econ. Perspect. 26, 49–66. https://doi.org/10.1257/jep.26.1.49
Deaton, A., 2010. Instruments, randomization, and learning about development. J. Econ. Lit. 48, 424–455.
Diboma, B.S., Tamo Tatietse, T., 2013. Power interruption costs to industries in Cameroon. Energy Policy 62, 582–592. https://doi.org/10.1016/j.enpol.2013.07.014
Dillig, M., Jung, M., Karl, J., 2016. The impact of renewables on electricity prices in Germany – An estimation based on historic spot prices in the years 2011–2013. Renew. Sustain. Energy Rev. 57, 7–15. https://doi.org/10.1016/j.rser.2015.12.003
Dinkelman, T., 2011. The Effects of Rural Electrification on Employment: New Evidence from South Africa. Am. Econ. Rev. 101, 3078–3108. https://doi.org/10.1257/aer.101.7.3078
Doucouliagos, H., Paldam, M., 2009. The aid effectiveness literature: The sad results of 40 years of research. J. Econ. Surv. 23, 433–461.
Doucouliagos, H., Paldam, M., 2006. Aid effectiveness on accumulation: A meta study. Kyklos 59, 227–254.
Eberhard, A., Gratwick, K., 2005. The Kenyan IPP Experience 41.
ESMAP, 2018. TRACKING SDG7: THE ENERGY PROGRESS REPORT Highlights 2018.
ESMAP, 2017. State of Electricity Access Report 2017. World Bank, Energy Sector Management Assistance Program (ESMAP).
ESMAP, 2015. BEYOND CONNECTIONS Energy Access Redefined - Technical Report (No. 008/15).

Fisher-Vanden, K., Mansur, E.T., Wang, Q. (Juliana), 2015. Electricity shortages and firm productivity: Evidence from China's industrial firms. J. Dev. Econ. 114, 172–188. https://doi.org/10.1016/j.jdeveco.2015.01.002
Foster, V., Steinbuks, J., 2009. Paying the price for unreliable power supplies: in-house generation of electricity by firms in Africa. World Bank Policy Res. Work. Pap. Ser. Vol.
Glass, G.V., 1977. 9: integrating findings: the meta-analysis of research. Rev. Res. Educ. 5, 351–379.
Gonzalez-Eiras, M., Rossi, M.A., 2007. The impact of electricity sector privatization on public health.
Goodman, S., BenYishay, A., Lv, Z., Runfola, D., 2019. GeoQuery: Integrating HPC systems and public web-based geospatial data tools. Comput. Geosci. 122, 103–112. https://doi.org/10.1016/j.cageo.2018.10.009
Gower, J.C., 1971. A General Coefficient of Similarity and Some of Its Properties. Biometrics 27, 857. https://doi.org/10.2307/2528823
Hafez, O., Bhattacharya, K., 2012. Optimal planning and design of a renewable energy based supply system for microgrids. Renew. Energy 45, 7–15. https://doi.org/10.1016/j.renene.2012.01.087
Hanousek, J., Kočenda, E., Maurel, M., 2011. Direct and indirect effects of FDI in emerging European markets: A survey and meta-analysis. Econ. Syst. 35, 301–322. https://doi.org/10.1016/j.ecosys.2010.11.006
Harish, S.M., Morgan, G.M., Subrahmanian, E., 2014. When does unreliable grid supply become unacceptable policy? Costs of power supply and outages in rural India. Energy Policy 68, 158–169. https://doi.org/10.1016/j.enpol.2014.01.037
Havranek, T., Herman, D., Irsova, Z., 2018. Does Daylight Saving Save Electricity? A Meta-Analysis. Energy J. 39.
Havranek, T., Horvath, R., Irsova, Z., Rusnak, M., 2015. Cross-country heterogeneity in intertemporal substitution. J. Int. Econ. 96, 100–118.
Hayn, M., Bertsch, V., Fichtner, W., 2014. Electricity load profiles in Europe: The importance of household segmentation. Energy Res. Soc. Sci. 3, 30–45. https://doi.org/10.1016/j.erss.2014.07.002
Heshmati, A., 2014. Demand, Customer Base-Line and Demand Response in the Electricity Market: A Survey. J. Econ. Surv. 28, 862–888. https://doi.org/10.1111/joes.12033
Holtorf, H., Urmee, T., Calais, M., Pryor, T., 2015. A model to evaluate the success of Solar Home Systems. Renew. Sustain. Energy Rev. 50, 245–255. https://doi.org/10.1016/j.rser.2015.05.015
Ikejemba, E.C.X., Mpuan, P.B., Schuur, P.C., Van Hillegersberg, J., 2017. The empirical reality & sustainable management failures of renewable energy projects in Sub-Saharan Africa (part 1 of 2). Renew. Energy 102, 234–240. https://doi.org/10.1016/j.renene.2016.10.037
Jamasb, T., Nepal, R., Timilsina, G.R., 2017. A Quarter Century Effort Yet to Come of Age: A Survey of Electricity Sector Reform in Developing Countries. Energy J. 38. https://doi.org/10.5547/01956574.38.3.tjam
Joskow, P., 2003. Electricity Sector Restructuring and Competition: Lessons Learned. Cuad. Econ. 40, 548–558.
Joskow, P.L., 1997. Restructuring, Competition and Regulatory Reform in the U.S. Electricity Sector. J. Econ. Perspect. 11, 119–138. https://doi.org/10.1257/jep.11.3.119
K., P., Govindarajan, U., K. Ramachandaramurthy, V., T., S.O.S., 2017. Multiple Criteria Decision Making (MCDM) Based Economic Analysis of Solar PV System with Respect to Performance Investigation for Indian Market. Sustainability 9, 820. https://doi.org/10.3390/su9050820
Kanagawa, M., Nakata, T., 2008. Assessment of access to electricity and the socio-economic impacts in rural areas of developing countries. Energy Policy 36, 2016–2029. https://doi.org/10.1016/j.enpol.2008.01.041

Kaseke, N., 2011. An estimate of the cost of electricity outages in Zimbabwe. Port Elisabeth.
Katre, A., Tozzi, A., 2018. Assessing the Sustainability of Decentralized Renewable Energy Systems: A Comprehensive Framework with Analytical Methods. Sustainability 10, 1058. https://doi.org/10.3390/su10041058
Katre, A., Tozzi, A., Bhattacharyya, S., 2019. Sustainability of community-owned mini-grids: evidence from India. Energy Sustain. Soc. 9. https://doi.org/10.1186/s13705-018-0185-9
Kaufman, L., Rousseeuw, P.J., 2009. Finding Groups in Data: An Introduction to Cluster Analysis. John Wiley & Sons.
Kezdi, G., 2003. Robust standard error estimation in fixed-effects panel models. Available SSRN 596988.
Khandker, S.R., Samad, H.A., Ali, R., Barnes, D.F., 2014. Who Benefits Most from Rural Electrification? Evidence in India. Energy J. 35. https://doi.org/10.5547/01956574.35.2.4
Kirubi, C., Jacobson, A., Kammen, D.M., Mills, A., 2009. Community-Based Electric Micro-Grids Can Contribute to Rural Development: Evidence from Kenya. World Dev. 37, 1208–1221. https://doi.org/10.1016/j.worlddev.2008.11.005
Kjolle, G.H., Samdal, K., Singh, B., Kvitastein, O.A., 2008. Customer Costs Related to Interruptions and Voltage Problems: Methodology and Results. IEEE Trans. Power Syst. 23, 1030–1038. https://doi.org/10.1109/TPWRS.2008.922227
KPLC, 2016. Causes of outages [WWW Document]. Kenya Power. URL http://www.kplc.co.ke/content/item/554/outages-and-weather
KPLC, 2014. Annual Report.
KPLC, 2009. Annual Report.
Küfeoğlu, S., Lehtonen, M., 2015. Comparison of different models for estimating the residential sector customer interruption costs. Electr. Power Syst. Res. 122, 50–55. https://doi.org/10.1016/j.epsr.2014.12.026
LARC POWER, N., 2018. POWER Data. NASA Langley Research Center (LaRC) POWER Project, Hampton, VA (USA).
Lee, K., Brewer, E., Christiano, C., Meyo, F., Miguel, E., Podolsky, M., Rosa, J., Wolfram, C., 2014. Barriers to Electrification for" Under Grid" Households in Rural Kenya. NBER Working Paper, 30.
Lee, K., Miguel, E., Wolfram, C., forthcoming. Experimental Evidence on the Economics of Rural Electrification. J. Polit. Econ.
Lipscomb, M., Mobarak, A.M., Barham, T., 2012. Development Effects of Electrification: Evidence from the Topographic Placement of Hydropower Plants in Brazil.
Marszal-Pomianowska, A., Heiselberg, P., Kalyanova Larsen, O., 2016. Household electricity demand profiles – A high-resolution load model to facilitate modelling of energy flexible buildings. Energy 103, 487–501. https://doi.org/10.1016/j.energy.2016.02.159
Martins, J., 2005. The Impact of the Use of Energy Sources on the Quality of Life of Poor Communities. Soc. Indic. Res. 72, 373–402.
Matungwa, B., 2014. An analysis of PV solar electrification on rural livelihood transformation. University of Oslo.
Mensah, J.T., 2016. Bring Back our Light: Power Outages and Industrial Performance in Sub-Saharan Africa.
Milligan, G.W., Cooper, M.C., 1985. An examination of procedures for determining the number of clusters in a data set. Psychometrika 50, 159–179.
Moulton, B.R., 1990. An Illustration of a Pitfall in Estimating the Effects of Aggregate Variables on Micro Units. Rev. Econ. Stat. 72, 334. https://doi.org/10.2307/2109724
Nordman, E.E., 2014. Energy transitions in Kenya’s tea sector: A wind energy assessment. Renew. Energy 68, 505–514. https://doi.org/10.1016/j.renene.2014.02.031

NRGExpert, 2013. Renewable Energy and the Global Recession 2008-2013. Glob. Renew. Rep. 1–596.
Omran, W., 2010. Performance analysis of grid-connected photovoltaic systems.
Oseni, M.O., Pollitt, M.G., 2015. A firm-level analysis of outage loss differentials and self-generation: Evidence from African business enterprises. Energy Econ. 52, 277–286. https://doi.org/10.1016/j.eneco.2015.11.008
Palmer, W.C., 1965. Moisture variability and Drought severity. National Academies.
Parsons Brinckerhoff, 2013. Kenya Distribution Master Plan.
Pasha, H.A., Ghaus, A., Malik, S., 1989. The economic cost of power outages in the industrial sector of Pakistan. Energy Econ. 11, 301–318.
Peters, J., Sievert, M., 2015. Impacts of Rural Electrification Revisited: The African Context.
Phurailatpam, C., Rajpurohit, B.S., Wang, L., 2018. Planning and optimization of autonomous DC microgrids for rural and urban applications in India. Renew. Sustain. Energy Rev. 82, 194–204. https://doi.org/10.1016/j.rser.2017.09.022
Praktiknjo, A.J., Hähnel, A., Erdmann, G., 2011. Assessing energy supply security: Outage costs in private households. Energy Policy 39, 7825–7833. https://doi.org/10.1016/j.enpol.2011.09.028
Reichl, J., Schmidthaler, M., Schneider, F., 2013. The value of supply security: The costs of power outages to Austrian households, firms and the public sector. Energy Econ. 36, 256–261. https://doi.org/10.1016/j.eneco.2012.08.044
RISE, SE4All, 2017. RISE - Regulatory Indicators for Sustainable Energy. The WorldBank Group.
Roche, O.M., Blanchard, R.E., 2018. Design of a solar energy centre for providing lighting and income-generating activities for off-grid rural communities in Kenya. Renew. Energy 118, 685–694. https://doi.org/10.1016/j.renene.2017.11.053
Rogers, E.M., 2003. Diffusion of innovations. Free Press, New York etc, Etats-Unis d’Amérique, Royaume-Uni de Grande-Bretagne et d’Irlande du Nord, Canada.
Rud, J.P., 2012. Electricity provision and industrial development: Evidence from India. J. Dev. Econ. 97, 352–367. https://doi.org/10.1016/j.jdeveco.2011.06.010
Sachs, J., Sawodny, O., 2016. Multi-objective three stage design optimization for island microgrids. Appl. Energy 165, 789–800. https://doi.org/10.1016/j.apenergy.2015.12.059
SE4ALL, 2017. Why wait ? Seizing the energy access dividend. SE4ALL.
Sen, R., Bhattacharyya, S.C., 2014. Off-grid electricity generation with renewable energy technologies in India: An application of HOMER. Renew. Energy 62, 388–398. https://doi.org/10.1016/j.renene.2013.07.028
Shah, T., 2009. Taming the Anarchy: Groundwater Governance in South Asia, 2009th ed.
Shah, T., 2007. Crop per drop of diesel? Energy squeeze on India’s smallholder irrigation. Econ. Polit. Wkly. 4002–4009.
Shahzad, M.K., Zahid, A., ur Rashid, T., Rehan, M.A., Ali, M., Ahmad, M., 2017. Techno-economic feasibility analysis of a solar-biomass off grid system for the electrification of remote rural areas in Pakistan using HOMER software. Renew. Energy 106, 264–273. https://doi.org/10.1016/j.renene.2017.01.033
Shaw, C.T., 2017. Assessing Feasibility of Fostering Productive Energy Use of Swarm Electrified Microgrids in Rural Communities in Developing Countries (Master’s Thesis). Universitat Politècnica de Catalunya.
Smith, M.G., Urpelainen, J., 2016. Rural electrification and groundwater pumps in India: Evidence from the 1982–1999 period. Resour. Energy Econ. 45, 31–45. https://doi.org/10.1016/j.reseneeco.2016.05.004
Squires, T., 2015. The Impact of Access to Electricity on Education: Evidence from Honduras.
Staiger, D., Stock, J.H., 1997. Instrumental Variables Regression with Weak Instruments. Econometrica

65, 557. https://doi.org/10.2307/2171753
Stanley, T.D., 2001. Wheat from Chaff: Meta-Analysis as Quantitative Literature Review. J. Econ. Perspect. 15, 131–150.
Stern, D.I., 2012. Interfuel Substitution: A Meta-Analysis. J. Econ. Surv. 26, 307–331. https://doi.org/10.1111/j.1467-6419.2010.00646.x
Stock, J.H., Yogo, M., 2005. Testing for weak instruments in linear IV regression. Identif. Inference Econom. Models Essays Honor Thomas Rothenberg.
Thopil, G.A., Pouris, A., 2015. Aggregation and internalisation of electricity externalities in South Africa. Energy 82, 501–511. https://doi.org/10.1016/j.energy.2015.01.059
UNIDO, E.G., 2010. UNIDO Projects for the Promotion of Small Hydro Power for Productive Use.
Van de Walle, D.P., Ravallion, M., Mendiratta, V., Koolwal, G.B., 2013. Long-term impacts of household electrification in rural India. World Bank Policy Res. Work. Pap.
van Gevelt, T., 2014. Off-grid energy provision in rural areas: a review of the academic literature.
Wagstaff, K., 2004. Clustering with missing values: No imputation required, in: Classification, Clustering, and Data Mining Applications. Springer, pp. 649–658.
WFPGeoNode, 2017. Global Ports.
Williams, R., 2012. Using the margins command to estimate and interpret adjusted predictions and marginal effects. Stata J. 12, 308–331.
Willis, K.G., Garrod, G.D., 1997. Electricity supply reliability: Estimating the value of lost load. Energy Policy 25, 97–103.
Winston, C., 1998. U.S. Industry Adjustment to Economic Deregulation. J. Econ. Perspect. 12, 89–110. https://doi.org/10.1257/jep.12.3.89
Wolfram, C., Shelef, O., Gertler, P., 2012. How Will Energy Demand Develop in the Developing World? J. Econ. Perspect. 26, 119–138. https://doi.org/10.1257/jep.26.1.119
Zachariadis, T., Poullikkas, A., 2012. The costs of power outages: A case study from Cyprus. Energy Policy 51, 630–641. https://doi.org/10.1016/j.enpol.2012.09.015
Zheng, S., Kahn, M.E., 2013. Understanding China's Urban Pollution Dynamics. J. Econ. Lit. 51, 731–772. https://doi.org/10.1257/jel.51.3.731
Zhou, P., Hankins, M., 2015. Sustainable Energy for All Investment Prospectus for Kenya.

Résumé

En 2018, environ un milliard de personnes vivaient sans électricité. Or l'extension des réseaux est confrontée à de nombreux défis qui compromettent la soutenabilité de l'électrification traditionnelle. Les Projets d'Electrification Décentralisée (PED) offrent désormais des solutions réalistes pour un accès à l'électricité hors réseau dans les pays en développement.

Cette thèse explore le rôle de la demande de fiabilité du service d'électricité comme déterminant d'une extension durable du réseau, et l'efficacité de l'offre d'électricité décentralisée pour l'atteinte des objectifs du développement durable.

Avec des données sur les coupures observées par les ménages au Kenya, le premier chapitre établit la préférence des ménages pour la fiabilité du service d'électricité, laquelle pourrait constituer le levier majeur d'une extension efficace du réseau.

Dans le deuxième chapitre, une méta-analyse consolidant 112 évaluations de projets décentralisés montre que la technologie, la capacité et la gouvernance supportent les choix de conception les plus déterminants pour atteindre les objectifs du développement durable.

Le troisième chapitre explore la gamme d'objectifs atteints par les pratiques de l'électrification décentralisée. Les plus efficaces sont celles qui adressent les utilisations productives et les services publics, ainsi que les micro-réseaux dans les zones éloignées, qui ont des impacts positifs sur l'information et la communication. La probabilité d'impacts positifs augmente avec la capacité des systèmes solaires individuels, qui favorisent la santé et l'éducation.

Mots-clés: fiabilité, coupures, Kenya, variable instrumentale, électrification décentralisée, développement durable, évaluation d'impact, méta-analyse, typologie, hors réseau

Abstract

By 2018, about one billion people were living without electricity. The extension of electrical grids is facing many challenges that jeopardize the sustainability of traditional electrification. Decentralized Electrification Projects (DEP) now offer feasible solutions for off-grid access to electricity in developing countries.

This thesis explores the role of the demand for reliability of the electricity service as a determinant of sustainable extension of the electrical grid, and the efficiency of electricity supply by DEP to achieve the sustainable development goals.

With data on outages observed by households in Kenya, the first chapter establishes the households' preference for the reliability of electricity service, which could be the major lever for effective network expansion.

In the second chapter, a meta-analysis consolidating 112 decentralized project evaluations shows that technology, capacity and governance support the design choices that are most critical to achieving the sustainable development goals.

The third chapter explores the range of objectives achieved by decentralized electrification practices. The most effective are those that address productive uses and public services, as well as micro-networks in remote areas, which have positive impacts on information and communication. The likelihood of positive impacts increases with the capacity of solar home systems, which favor health and education.

Keywords : Reliability, outages, Kenya, instrumental variable, decentralized electrification, sustainable development, impact evaluation, meta-analysis, typology, off-grid