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Power outages and the decision of under-grid households to connect to the grid

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Abstract

A low power reliability is challenging the electrical grid's extension cost because it's lowering the number of connected households. The quality effect is at least 5% higher than the wealth effect, eventually up to 47%, and emerges as the main hurdle to households' connection.

Addressing the challenge of electrical outages would accelerate *per se* the annual number of new subscribers to the electricity distributor. The intermediate wealthy households would be the more prone to subscribe, provided that the availability of the power would be enhanced. The policy maker should be advised to put a peculiar effort on the technical features that sustain the reliability of power until its final destination.

Keywords : electricity, outages, lightning, grid, transmission and distribution lines, Kenya, poverty, instrumental variable

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

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Introduction

In 2014, 620 million people had no access to electricity in Africa (IEA, 2014). Even connected firms and households suffer severe outages: for instance, 6.3 outages per month occurs in Kenya, each lasting 5.6 hours.¹ The erratic volatility harms the firm's production, while households are exposed to multiple adverse consequences on security, health, education, and employment holding back the human capital accumulation.

In 2012, India suffered the most serious outage ever occurred: a national blackout paralyzed 670 million people for 48 hours. Balancing the response of supply to the volatility of demand is especially fragile, since electricity does hardly store. The ability to permanently supply the maximum consumption (peak-load) is defined as the reliability (NERC, 2011).

This article assesses the impact of reliability on the households' decision to subscribe to electricity. It's related with the stake of the grid's extension cost in a poverty context.

High costs of production and distribution yields heavy billing; meanwhile the lack of capacities makes the occurrence of outages more frequent. Facing both unaffordable connection's cost and unreliable service, the households might be reluctant to subscribe, what lengthens the break-even of new investments and deters in turn the settlement of new capacities or transportation facilities. It looks hard to determine the right starting point for the low-income countries to escape from such a vicious cycle, between the lack of capacities and the lack of subscriptions.

Keeping a full reliability with insufficient capacities is moreover complicated in a growing population context, due to the increasing peak-load. High costs and long delays to build new infrastructures makes the supply's growth slowly responsive, while the grid's extension investments ought to be amortized fast enough by a large number of subscriptions. The households offer the widest customer potential, provided that they pay the monthly fees.

So far, the electricity development has hardly been seen as a priority and the aforementioned issues have been frequently solved by a supply's shortage. But new context's elements are changing the challenges/opportunities balance for Africa, like the strongly decreasing production's cost of renewable energy, the fast equipment's rate of households in mobile

¹ <http://www.enterprisesurveys.org/data/exploreconomies/2013/kenya#infrastructure>

phones, sustaining more regular m-payments and the inclusion of the reliable access to energy for all as the 8th Sustainable Development Goal in 2015.

Kenya is facing such a contrasted evolution. Between 2009 and 2014 the population grew by +14%, while the connected households grew by +218%. As a result, the peak-load grew by +41% as well as the amount of installed capacities (Annex 1). But the production of electricity is costly, scaling from 0.14\$ up to 0.25\$ for diesel plants, and outages are severe: in 2014, 9% of the households report a full unavailability of the power, and 20% report only occasional availability (*Afrobarometer*, 2014). In recent years, the grid has been extended, reaching a coverage rate over 80% in 2/3 of the counties (*Afrobarometer*, 2014). But the lack of connections is pushing up the distribution's marginal cost : evidenced by (Lee et al., 2014), if all the buildings within the distribution's radius of a transformer (600 m) were connected, the median investment per connection would be \$210 instead of currently \$ 2,427. However, as shown above, the growth of the customers' number is much faster than the one of the peak-load, opening opportunities to positively address the challenge of the households' connection: their impact on the grid could be not so heavy while conversely, enhancing the distributed reliability could possibly accelerate the households' subscription, hence reducing the cost of the grid's extension.

Isolating the causal impact of outages on the connections' level faces the risk of a reverse causality. In addition, it is not obvious to disentangle the time dimension of the reliability from its geographical impact on the connections to the grid.

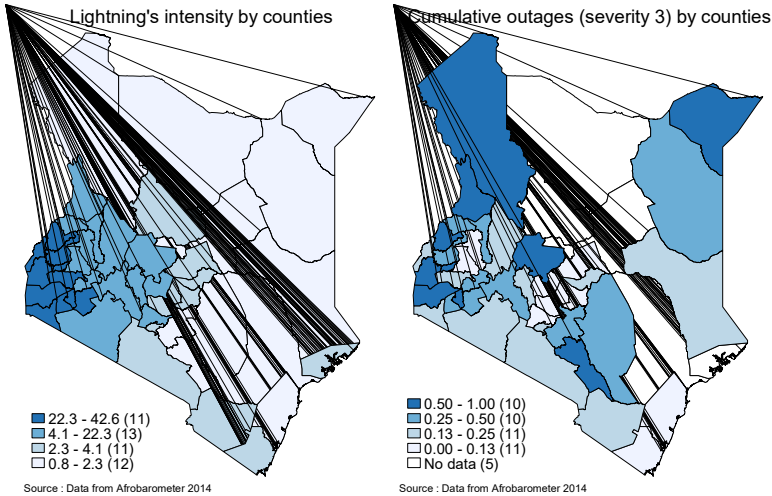
Relying on (Andersen and Dalgaard, 2013), this article uses the lightning intensity as an instrument that has proven to be efficient to solve this peculiar risk, extending meanwhile the previous work at individual level. It also introduces a poverty index in order to compare the impact of the outages to the one of poverty on the connection's level. Exploiting the large share of natural endowments in the Kenyan energy mix, this article introduces the districts' distance to the closest electrical generator as an additional instrument for the outages, under the assumption of a homogenous grid.

The Afrobarometer survey 2014 provides cross-sectional data on the households' assets and their individual exposure to electrical outages in Kenya. The lightning data are sourced from the LIS/OTD Gridded Climatology dataset. The location of to the plants comes from Enipedia, a collaborative database.² From the first, an individual synthetic index of poverty is

² http://enipedia.tudelft.nl/wiki/Kenya/Powerplants#List_of_Power_Plants_in_Kenya_.28limited_to_200.29

computed for each household, as well as the average exposure to outages within a district. From the two others, lightning and distance to the closest plant are aggregated at district level. This article brings the causal evidence by resorting to lightning as an instrumental variable. Under equatorial latitude, Kenya lays among the most exposed countries to storms in the world, with a lightning’s intensity 9 times higher than in France. Compared to other Sub-Saharan countries, Kenya also exhibits a strong heterogeneity of lightning. Intensity and heterogeneity makes the variable a good candidate to instrument the outages, as also suggested by (Map 1).

Map 1: LIGHTNING AND OUTAGES BY COUNTIES



Source : (Afrobarometer, 2014)

Lightning is an external random phenomenon that can causes a variety of direct damages on the electric pylons: thermic, mechanical or electrical shocks. When damaging the grid, it has a strong zone effect making its correlation with the outages much higher than the scarce possibility to damage individual junction’s nodes. Thus, it might be correlated with the connections’ level only through its own correlation with the outages’ occurrence.

To disentangle the past effect of the reliability on the connections’ level, this article uses a cluster estimation combined with the assumption of a homogenous grid. In absence of any bottleneck, the outages suffered in a district might solely but strongly depends on its distance to the closest generator, modulo the capacity of the plant.

Outages have a significant negative impact on the households’ decision to subscribe to electricity: on average, 1 percent point lower reliability in a median district triggers 0.67 percent point less connections. The role of outages in this decision is on average 26% higher

than the one of poverty, from at least 5% in the most conservative estimation in a median district, up to 47% in the wealthiest districts.

The level of outages itself impacts the households' sensitivity. Where the rate of outages is "only" 30%, 1 percent point upgrade of reliability would trigger 1.09 percent point more connections. Where the outages' frequency is too high, the wealth or poverty level of the households has no more effect: they are only responsive to the too low reliability. Conversely, in the poorest western regions of Kenya, the households are not sensitive to outages.

The low reliability has the maximum deterring impact among the households with intermediate wealth, who are the most reluctant to subscribe in presence of outages. For 1 percent point higher reliability, the intermediate wealthy households would be connected 1.28 percent point more.

The remainder of the article is organized as follows. Section I describes the context of the electrification in Kenya. Section II reviews the literature at the starting point of this study. Section III exhibits the data and their origin. Section IV addresses the identification strategy, then section V explains the diagnosis methodology and shows the results, while section VI deals with robustness checks. Finally section VII proposes an extension of the model and section VIII concludes with policy implications and possible advices.

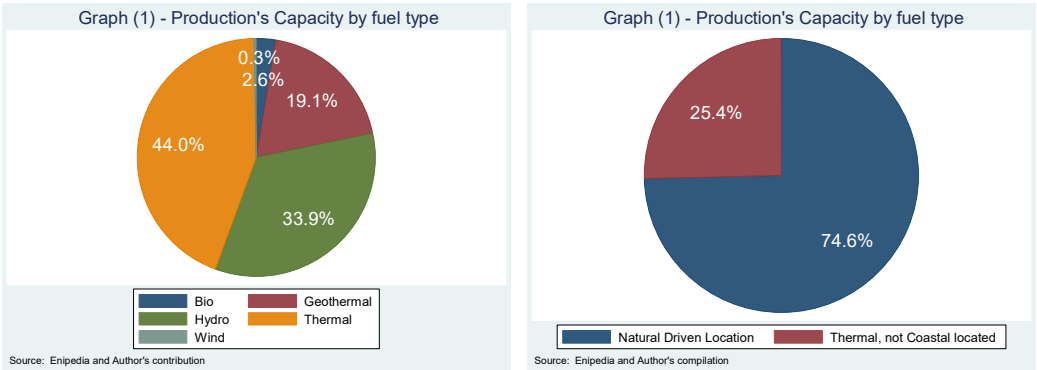
I - Context and issues of electrification in Kenya

The electrical sector in Kenya is organized with a central distributor (KPLC) under a PPP mandate, a public grid manager (KETRACO) and a set of producers, composed by KENGEN, a majority government owned company that produces over 85% of the capacity, and Independent Power Producers (IPP) (Annex 2). A state-owned Special Purpose Vehicle is dedicated to the development of geothermal production (GDC). The Rural Electrification Authority (REA) is a state agency that has launched the *Last Mile Connectivity* project in September 2015, addressing the issue of unconnected under-grid households in rural areas.

As at 2014, electricity produced from the country's natural endowments represents 56% of the capacities (Graph 1, left), with a large share from geothermal origin (19,1%), still growing in 2015 (26,6%). Kenya owns the largest geothermal single plant of the world in Olkaria IV (140 MW), the geothermal industry producing the cheapest electricity of the country: between 0.03\$/KWh and 0.14\$/KWh, the most expensive geothermal plant produces at the same cost as the cheapest diesel plant. The flagship projects in 2016 are the on-going construction of a new geothermal site in Menengai (105 MW ; further 360 MW planned) and the kick-off of a

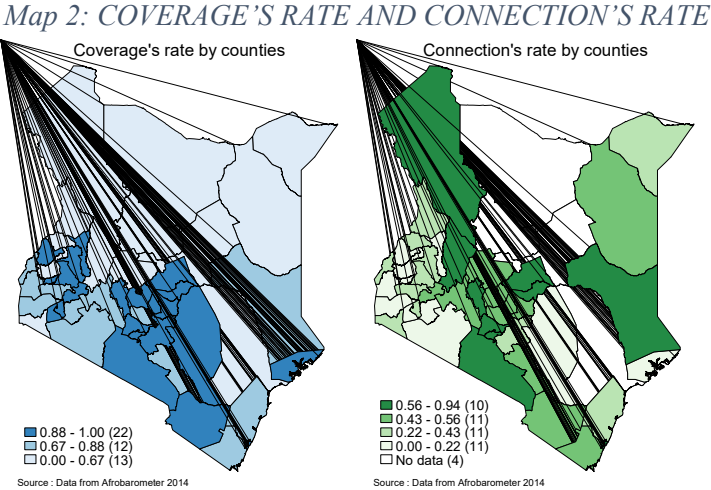
large wind production project close to Lake Turkana (320 MW) (Davis et al., 2015). Two solar plants projects are engaged in Eldoret (2x40 MW, PPA signed) and in Garissa (55 MW).

Graph 1 : PRODUCTION'S CAPACITY BY FUEL TYPE



KPLC had 2 million customers in 2012, 2,7 million in 2014 and should reach 4,3 million in 2016 (KPLC, 2015). The fast growing customer base could be a risk for the reliability, as the electricity crisis in California has illustrated it in the 90's.³ Facing a growing peak load while lacking capacities, KPLC is planning outages to avoid the worst scenario of a national blackout.⁴ A recurrent debate in Kenya points out the distribution's trade-off between firms and households. The historical choice has been to prioritize the reliability for the firms, in order to not deter the foreign investors to operate in Kenya.

But too frequent outages could make the households reluctant to subscribe, for the cost of the service appears too high given its erratic availability. While the grid has been extended most all over the country, the connection's rate remains below 50% in half of the counties (Map 2).



Source : (Afrobarometer, 2014)

³ <http://www.eia.gov/electricity/policies/legislation/california/subsequentevents.html>

⁴ <http://kplc.co.ke/category/view/50/power-interruptions>

As evidenced by (Lee et al., 2014) the lack of connections multiplies the marginal cost of the grid's extension by ten. Therefore, the *Last Mile Connectivity* project entails a special effort for the poorest households, dropping down the fee of connection from KSh35,000 to KSh15,000 (REA, 2015). However, this action plan entails the underlying assumption of an exogenous quality supply. If there is a specific sensitivity to the power reliability, addressing the solely financial issue might not be enough. In other words, would a better power reliability raise the connections' level quicker than the wealth's growth of the households?

II - Related literature

This paper is related with a first strand of literature that has studied the role of the grid's quality on the households' connection. Two factors have been identified, the density of the transmission lines and the proximity to the distribution's transformers. The frequency of outages is commonly used as a measure of the service's quality.

With a panel of 10,000 households from the IHDS database in India (Chakravorty et al., 2014) have shown that the density of the transmission lines facilitates the decision to connect : from an initial level, increasing the density of the cables by one unit increases the grid's connections by 10 percent points. From the Indian case, (Khandker et al., 2014) has also identified the role of transmission and distribution losses on lines.

With a large dataset on geo-tagged structures and residential compounds in Kenya (Lee et al., 2014) have studied the role of the proximity to the closest transformer, distinguishing the access to electricity in a geographical unit from the households' connection. Their work disentangles the impact of the grid's extension from the individual proximity to access nodes. Being the first to introduce the notion of "under-grid" households, they have brought evidences that the wealth effect outweighs the distance to the connection node: within 200 meters, the probability of connection decreases by 20% for the poorest households, who are identified by the walls' quality of the building where they live.⁵

Using the IHDS survey of 2005 (Khandker et al., 2014) have shown that the decision of Indian households to connect to the grid depends both negatively on the price and positively on the quality of the power : an additional available hour of power increases the adoption rate by 2.7%. Villages without power outages have a higher households' access rate (81%) than those with more than 20 hours of outages per day (38%).

⁵ The compounds units are assimilated to households.

As a second strand of literature, the seminal work of (Andersen and Dalgaard, 2013) has brought lightning as an efficient instrumentation to isolate the causal effect of outages on the growth rate, with macroeconomic data on Africa. An increase of + 2.3 outages per month reduces the growth by 1.5 points. Applied to Kenyan data in 2013, such a fail on quality would cost 800 million dollars per year.⁶

This paper aims to extend their work in several ways: first, the study will focus on Kenya, one of the country of their Sub-Saharan sample; second, it will use individual data on households; therefore, it will relate their work with the first strand of literature by studying the outages' impact on the connection's probability. Finally, it will extend the specification, controlling for the poverty level and expanding the set of lightning-based instruments.

This study also relies on the first strand of literature in the following dimensions. First, it will encompass the notion of "under-grid" households, extending the work of (Lee et al., 2014) at the smallest granularity level. Second, while evaluating the impact of the distance to the transformer, (Lee et al., 2014) makes the underlying assumption of an exogenous quality supply, uniform in time or space. This study exploits the heterogeneity of outages between districts to disentangle the specific impact of those last on the connection's decision. Third, while the distance to the transmission lines could be endogenous to the grid's extension, using the lightning intensity as in (Andersen and Dalgaard, 2013) should provide a strong exogenous instrument, independent of the initial electrification level (Chakravorty et al., 2014). Fourth, the study gets one step backward in the causal chain studied by (Khandker et al., 2014): while they instrument the access to electricity as a factor of electrification's benefits, this study intends to establish the causal impact of outages on the connection's decision. Fifth and finally, as (Lee et al., 2014) and (Chakravorty et al., 2014) have suggested the strong role of the distance, respectively to the distribution or to the transmission lines, this study intends to exploit the distance to the generators as an additional instrument.

A third dimension of the literature evaluates the benefits of the electrification for the connected households. (Khandker et al., 2014) have found a reduction of -3.3 hours in the monthly time devoted to the collection of biomass thanks to the reduction of the marginal cost of the lumen. Therefore, electrification has increased the schooling's rate and duration. It has also reduced the consumption of kerosene used in oil lamps by -35%, a major health risk factor. As for the activity outcomes, the access to electricity has contributed to increase the

⁶ <http://databank.worldbank.org/data/home.aspx>

employment's rate of women by + 1.5% and + 17% for that of men, while (Chakravorty et al., 2014) have measured an increase in non-agricultural income by +9%. This study will focus on the interaction effect between outages and poverty on the connection's decision.

III - Data

The data on electrical coverage, connections and outages are provided by the Afrobarometer survey on Kenya, from the questionnaire 2014, round 6. The database contains 2,397 cross-sectional observations on households, segmented by the geographical administrative units of Kenya, counties and districts. The analysis is based on the 1,989 respondent households living in a unit with access to electricity.

The access to electricity is known from the descriptive part of the questionnaire filled by the interviewer. A specific question provides the information on the reliability of the power, with five distinct levels of availability (1 : never, 2 : occasionally, 3 : half the time, 4 : most of the time, 5 : all the time). Since the question also asks to the household whether it owns an electrical connection (0 : no electric supply), there might have been some inconsistent answers with the descriptive part filled by the interviewer. Specific filters have been applied for the computation of the outages' rate (see section IV) to make them consistent.

The lightning intensity is sourced from the LIS/OTD dataset that collects the number of lightning's impacts within 50km² squares. They have been averaged by districts on the 1995-2013 period. Climate controls (altitude, temperature and precipitation) are provided by the geographical database of the FERDI, as well as the distance to Mombasa, weighted by the road's quality. The localization of the generators is provided by the Delft University from its Enipedia collaborative database where the capacity has been supplemented by the author's researches.

IV - Identification strategy

Objective and main specification

This study aims to disentangle the specific impact of outages on connections by first isolating the quality effect, second comparing its magnitude with the wealth effect and third exploring the interaction of both variables.

The general equation below considers the effect of outages (*CO*) on households' connection (*connection*) to the electrical grid. The main variable that could also determine their decision is obviously their wealth that the model ought to control for. To this end, one uses the data on

the households' assets from the Afrobarometer 2014 survey, to compute a composite poverty index (*pov_index*). The potential cross-effect is captured by introducing an interaction term between the outages and the poverty index. Extending the parsimonious specification of (Andersen and Dalgaard, 2013), one considers the general regression model :

$$Connection_i = a_0 + a_1 \cdot CO_u(q) + a_2 \cdot pov_index_i + a_3 \cdot CO_u(q) \times pov_index_i + u_i$$

where, *i* is the household, *u* is the district and *q* is the severity level of the outages.

Variables definitions

Dependent variable

The dependent variable (*connection*) is a dummy that equals 1 for a connected household living in a district with access to electricity. The evaluation exploits the geographical heterogeneity of the connection's rate, spreading from 94% in Nairobi to 0% in Lamu or 4% in Homa Bay.

Poverty index

As in (Booyesen et al., 2008), the poverty index is derived from an MCA of the unconnected assets owned by the household (Table 1). It's the linear combination of the standardized coordinates of the categories on the first axis, weighted by their contribution. It's computed for each household, with positive values for the poorest one.

Table 1 : ACTIVE VARIABLES IN THE MCA

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

The first axis concentrates 54% of the inertia, while the second axis (21%) and the third axis (3,3%) are largely built from missing values of any peculiar categories. Hence, the first axis captures all the meaningful information on the poverty level and can be used confidently as a synthetic composite index. Annex 3 exhibits the main components that contribute positively and negatively to the first axis.

Power reliability index

The power reliability index *CO(q)* is defined by the rate of cumulative outages (*CO*) at successive levels of severity (*q*) in a geographical unit. In a first step, the simple rate of

outages qualifies four severity levels (1 : total, 2 : serious, 3 : partial, 4 : occasional). In a second step, the power reliability index is the rate of cumulated outages for a given severity level. For the sake of simplicity, the same qualification will be used in the study to qualify the cumulated outages; for instance, the accumulation of outages from total to partial frequency will be denominated “partial” severity (Table 2).

Table 2 : POWER RELIABILITY INDEXES BY SEVERITY LEVEL⁷

<i>Severity level</i>	<i>Variable</i>	<i>Frequency of outages in the index</i>	<i>Severity qualification</i>
1	CO1	Total	Total
2	CO2	Total + serious	Serious
3	CO3	Total + serious + partial	Partial
4	CO4	Total + serious + partial + occasional	Occasional

A large part of the empirical work will be dedicated to assess the most relevant level of severity in order to estimate the outages’ effect on the households’ connection.

Due to the low number of observations, some districts report only one connected household. In that case, the observed rate of outage is 100%, at the severity level answered by the household. A filter has been set to keep only the units with at least two connected households.

Neighboring effect

In a context of high connection’s cost and low reliability of the power, subscribing to electricity might also depend on the example of the neighbors, sustaining a diffusion or barrier process. The observed level of connections in 2014 might actually result from a past diffusion or inertia among the households within a unit: it might be much higher in a district than in another one because households have been encouraging each another to subscribe in the first (diffusion) while they have been seeking for mutual confirmation bias to not subscribe in the last (barrier). As identified by (Lee et al., 2014), positive externalities might also be at work, due to economies of scale in the interconnected electrical network.

⁷ As pointed out by (Chakravorty et al., 2014), the word « reliability » has a precise definition in electrical engineering -as defined by (NERC, 2011)- a reason why they prefer to use the term “quality”. However, as clearly stated in the aforementioned reference, the purpose of the standard definition of reliability is “*to maintain interconnection steady-state frequency within defined limits by balancing real power demand and supply in real-time*”. Whether random or planned, outages are clearly a severe breach of the standard definition. From an economic perspective, their occurrence can be used as a synthetic index of this violation to balance supply and demand.

Therefore, the assumption of i.i.d observations can't be hold, leading conversely to assume heteroscedasticity within the units. The neighboring effect will be captured by clustering all the estimations, following (Chakravorty et al., 2014) and (Khandker et al., 2014).

Since the model mixes an individual level variable (the poverty index) and an aggregated variable (the power reliability index), resorting to clusters also solves the Moulton bias (Moulton, 1990). Computing the variance-covariance matrix by clusters corrects the under-estimation of the standard error that would otherwise results from using an aggregated variable. The significance of the coefficients can be then properly diagnosed.

Gradual estimation's Methods

The model will be first estimated by an OLS at districts' level to identify the effect. In the next step, using instrumental variables ought to solve the endogeneity risks. A Probit specification should be then appropriate to estimate the probability of connection and it will also be instrumented. Finally, an extension will be conducted to capture the effect of the next level's severity.

Endogeneity issues and Instrumentation

The evaluation must deal with three econometric risks of endogeneity. First, there is a risk of reverse causality because the growing number of connected households could be itself a cause of outages (see section I). Second, the data are sourced from a field questionnaire and might be distorted by a measurement error.

Third, a major determinant of the connections' level could have been omitted in the specification. The literature suggests three main hurdles (Khandker et al., 2014), (Lee et al., 2014): the high connection's cost, the poor-quality of the building and the unreliability of the service. Since the first barrier is a matter of relative wealth, the poverty index is a suitable proxy. As this last entails the type of shelter, it captures also the second potential omitted variable and can be thus used as a proxy to control for both hurdles together. However, the index being built from an MCA, a robustness check should test for any residual correlation of the shelter's type with the error term. The third hurdle is the effect addressed by this study.

The distance to the closest electrical transformer might also modify the ability to connect to the grid (Lee et al., 2014). This issue is addressed by combining the clustering approach with the sampling delimitation to under-grid households, in districts with access to electricity.

Yet there might be forgotten or unknown, even minor, omitted variables. The only way to deal simultaneously with the three risks of endogeneity is to resort to an instrumental variable.

KPLC identifies seven causes of outages: extreme weather conditions (wind, lightning, rain, floods), contacts of animals with the lines or transformers, growth or fall of the trees, vehicle collisions, vandalism, aging equipment and planned interruptions.⁸ From the detailed qualitative assessment in Annex 4, wind, rain and floods would not meet the exclusion restriction due to their strong zone effect. Animals' contacts, trees' growth and vehicle collisions would easily meet the exclusion restriction, though only providing weak instruments. Vandalism is obviously endogenous to poverty and would thus not be correlated to lower connections only through outages. The age of installations is by definition not random, hence not an exogenous factor.

Finally, only the lightning meets the three requested properties for an instrumentation, being purely random, strongly correlated with the outages' occurrence while acceptably not a direct cause of lower individual connections (see Annex 4). The evaluation exploits the strong heterogeneity of lightning in Kenya, among the highest of the world in the western mountainous provinces while comparable to European level in the eastern regions.

A potential reverse tide effect has also been identified (Annex 4): a power shortage can cause a sudden over-load along the electrical wires that could in turn trigger new outages in the neighbor districts. It is thus necessary to instrument the outages also by the lightning intensity in the surrounding districts.

A third instrument is introduced with the distance of the district's centroid to the closest generator, inversely weighted by the capacity of this last. The lack of capacities feeding the grid plays a key role in the outages' occurrence. Under the assumption of a homogenous grid without any bottleneck, ie with technical features everywhere of the same quality, the ability of KETRACO to saturate it depends solely on the amount of produced electricity. On another hand, the received reliability in connected inhabitations depends in time on the discrepancy between demand and power supply. At a fixed point in time and under the homogenous grid assumption, the outages suffered in a district might solely but strongly depend on its distance to the closest generator, modulo the capacity of the plant.

(Lee et al., 2014) have used the distance to the closest transformer to explain the connection's probability while this study is looking for an instrument of outages. Being at the termination of the grid for the last mile distribution, the transformers are fed by the lines' network and

⁸ <http://www.kplc.co.ke/content/item/554/outages-and-weather>

might undergo themselves the consequence of an upstream tension fall. The two distances play different roles.

The distance to the closest generator meets the instrumentation's requirements because (1) it is both an external and random parameter from the outages, since the plants' location is related with the country's natural endowment (volcano, rivers, lakes, wind and Mombasa harbor on the coast) : as shown in (Graph 1), such plants account for 3/4 of the installed capacities ; (2) the distance to the plant has no influence *per se* on the connection's decision. If the households were to subscribe more because being close to a plant they expect less outages, it is exactly what the instrument ought to captures.

It is computed as the minimum distance among all the generators, weighted by the inverse of the capacity of the closest generator over the total capacity of production. It can be seen as a proxy for the electricity equipment's rate of the district.

V - Empirical diagnosis and results

Assessment methodology

The models are organized in four classes, introducing gradually the effects to be assessed (Annex 5). The first three classes are denominated "foundation" while the fourth is denominated "extension", to be used in section VII. In the foundation assessment, four models per class are defined, given the severity level. The three classes gather 12 models that are presented together for the diagnosis. This last compares the models in order to qualify the best estimation, using the appropriate statistical tests for the estimation's method.

The decision criteria are based on a backward-reading of the tests : the main objective is targeted first, then one checks that the previous test was passed successfully, the antepenultimate also, and so on, until all the tests compounding the decision chain are met. If a test fails, while the first steps were met, one switches to the closest model that met the same initial tests in the decision-chain.

Entry model : OLS at district level

Table 3 shows the assessment of a simple OLS method applied to the three classes base, ctr and i. The backward decision criteria are the lowest AIC (column 6) and the lowest p-value for the Student test of the cumulative outages (column 4). The lowest AIC (1947) leads to retain the model iCO3_reg, where the p-value of CO(3) equals 0.000.

Table 3 : ASSESSMENT OF THE OLS MODELS AT DISTRICTS LEVEL

Model (1)	Outages (2)	Std Error (3)	P value (4)	Adj. R2 (5)	AIC (6)	N (7)	Nb Clusters (8)
base_CO1_reg	-0.413	0.101	0.000	2.1	2354	1669	90
base_CO2_reg	-0.471	0.072	0.000	5.9	2286	1669	90
base_CO3_reg	-0.515	0.068	0.000	8.4	2242	1669	90
base_CO4_reg	-0.591	0.165	0.001	5.1	2302	1669	90
ctr_CO1_reg	-0.142	0.103	0.171	20.2	2014	1669	90
ctr_CO2_reg	-0.273	0.077	0.001	21.8	1979	1669	90
ctr_CO3_reg	-0.313	0.069	0.000	22.8	1957	1669	90
ctr_CO4_reg	-0.339	0.131	0.011	21.5	1985	1669	90
icO1_reg	-0.419	0.117	0.001	21.7	1982	1669	90
icO2_reg	-0.361	0.077	0.000	22.6	1962	1669	90
icO3_reg	-0.362	0.070	0.000	23.3	1947	1669	90
icO4_reg	-0.357	0.138	0.011	21.6	1984	1669	90
dCO1_reg	-0.386	0.098	0.000	23.3	1949	1669	90
dCO2_reg	-0.377	0.079	0.000	23.4	1946	1669	90
dCO3_reg	-0.465	0.126	0.000	23.5	1944	1669	90

In this simple LPM specification (Table 4, column1) both the cumulative outages at partial severity level and the poverty index have a negative coefficient, significant at 0.1% level. Their interaction is also significant, at 1% level. The number of clusters (90) ensures that the standard error converge to its true value, leading to a proper assessment of the estimates' significance (see Annex 6). From the standardized regression, one standard deviation of outages has an impact around the half (-0.099) of the one of poverty (-0.199).

Table 4 : LPM OF CONNECTIONS AT DISTRICTS LEVEL

	Unit values	Standardized values
CO3	-0.362*** (0.070)	
c.CO3#c.pov_index	0.512** (0.184)	
pov_index	-0.735*** (0.070)	
zCO3		-0.099*** (0.020)
c.zCO3#c.zpov_idx		0.051** (0.018)
zpov_idx		-0.199*** (0.015)
Constant	0.637*** (0.036)	0.501*** (0.028)
N	1669	1669
Nb Cluster	90	90
Adj. R ²	0.23	0.23

LHS :
Average marginal effects. SE in parentheses.
Variance : Delta-method delta by

* p<0.05, ** p<0.01, *** p<0.001

This finding is an important result since it confirms the sign found by (Andersen and Dalgaard, 2013) for Sub-Saharan countries as a whole. Their result still holds for Kenya with detailed data on households, opening avenues for field's applications.

The LPM estimation yields accurate estimates, but inconsistent due to the endogeneity issues. As remarkable in Table 3, the coefficient of outages is downward biased in the Base specification (-0.515) compared to the one in the ctr specification (-0.313): the poverty index

would be an omitted variable if not taken in account. The study now turns to assess empirically the instrumentation choice.

Neutralizing the endogeneity risks: assessing the instrumentation quality

Assessment criteria

Table 5 below describes the backward-ordered tests to assess the relevant severity level in the 2SLS method. Annex 13 exhibits their technical application more in depth.

Table 5 : BACKWARD DECISION-CHAIN ON THE INSTRUMENTATION'S QUALITY

Question	Test
Are the instruments strong enough?	Stock-Yogo < 30 F > 6 with p < 1%
Are the estimates of the outages significant, even if the instrument were to be 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 the instrumentation bring a significant difference in estimates?	Hausman test (p < 5%)

Assessment of the 2SLS models

In Table 6, the best specification is the *base_CO3_ivreg* model, meaning that the third level of severity is the best candidate to infer the effect of instrumented outages on connections.

However, it entails only the outages variable, while the study aims to take account for the main potential omitted variable (poverty index) and its interaction with the outages. It would be thus better-off to switch to another equation, provided that the vector of tests will still hold.

Table 6 : ASSESSMENT OF THE 2SLS MODEL AT DISTRICTS LEVEL

Model	Endog (chi2)	Endog (p)	F First	First (p)	Under id° (p)	Hansen	SY : KP	A-R (p)	Haus. (p)	N obs°	N Clus
base_CO1_ivreg	0.0	0.876	0.1	0.883	0.875	0.08	100	0.000	0.647	1669	90
base_CO2_ivreg	13.4	0.000	2.5	0.086	0.157	0.50	100	0.000	0.090	1669	90
base_CO3_ivreg	9.4	0.002	11.2	0.000	0.007	0.22	20	0.000	0.012	1669	90
base_CO4_ivreg	12.5	0.000	9.7	0.000	0.003	0.83	20	0.000	0.003	1669	90
ctr_CO1_ivreg	7.6	0.006	0.2	0.820	0.818	0.54	100	0.000	0.824	1669	90
ctr_CO2_ivreg	14.0	0.000	2.0	0.143	0.206	0.48	100	0.000	0.205	1669	90
ctr_CO3_ivreg	10.8	0.001	10.0	0.000	0.007	0.19	20	0.000	0.018	1669	90
ctr_CO4_ivreg	13.5	0.000	8.2	0.001	0.005	0.74	25	0.000	0.015	1669	90
icO1_ivreg	0.3	0.586	2.3	0.043	0.267	0.01	100	0.000	0.830	1669	90
icO2_ivreg	1.8	0.184	5.3	0.000	0.023	0.02	100	0.000	0.115	1669	90
icO3_ivreg	5.8	0.016	6.7	0.000	0.004	0.09	25	0.000	0.020	1669	90
icO4_ivreg	12.3	0.000	3.4	0.005	0.018	0.38	100	0.000	0.041	1669	90
dCO1_ivreg	0.1	0.765	2.4	0.034	0.345	0.01	100	0.000	0.998	1669	90
dCO2_ivreg	2.3	0.127	5.9	0.000	0.024	0.03	100	0.000	0.139	1669	90
dCO3_ivreg	5.9	0.015	5.4	0.000	0.001	0.16	25	0.000	0.057	1669	90

Introducing the poverty index (*ctr_CO3_ivreg*) yields the same Stock-Yogo threshold (20) as the base model (*base_CO3_ivreg*), with all the other tests being very close to the last.

Introducing further the interaction term (*iCO3_ivreg*) yields a weaker though acceptable Stock-Yogo threshold (25), with also the F of the first-stage being lower (6.7) since now there are two instrumented variables. Still, it's above the targeted threshold (6), with a receivable p-value (0.000). The Anderson-Rubin test ensures that the model provides consistent estimates. All the second-order tests are also receivable.

Passing successfully all the tests, the *iCO3_ivreg* model appears to be robust enough: all the key factors, but the interaction, remain significant at 0.1% level (Table 7). As evidenced from its VIF (6.20), the lower significance of the interaction term is only due to the variance's inflation once stepping from the OLS to the IV estimation.

Table 7 : 2SLS OF CONNECTIONS AT DISTRICTS LEVEL (3 INSTRUMENTS)

	Unit values	Standardized values
CO3	-0.806*** (0.167)	
c.CO3#c.pov_index	0.479 (0.330)	
pov_index	-0.615*** (0.103)	
zCO3		-0.231*** (0.050)
c.zCO3#c.zpov_idx		0.048 (0.033)
zpov_idx		-0.161*** (0.020)
Constant	0.762*** (0.061)	0.502*** (0.031)
N	1669	1669
Nb Clusters	90	90
Kleibergen-Paap Wald rk F	5.97	5.97
Anderson-Rubin	59.9	59.9
pvalue for A-R	0.000	0.000

LHS : connection
 IV (2SLS) estimation SE in parentheses.
 Variance : Robust robust cluster by DISTRICT
 Instrumented variables : CO3 c.CO3#c.pov_index
 Excluded Instruments :
 fdr_moy_DISTRICT fdr_vois_moy_DISTRICT WCP
 c.fdr_moy_DISTRICT#c.pov_index c.fdr_vois_moy_DISTRICT#c.pov_index
 c.WCP#c.pov_index
 Seuils Stock-Yogo : 15.72, 9.48, 6.08, 4.7

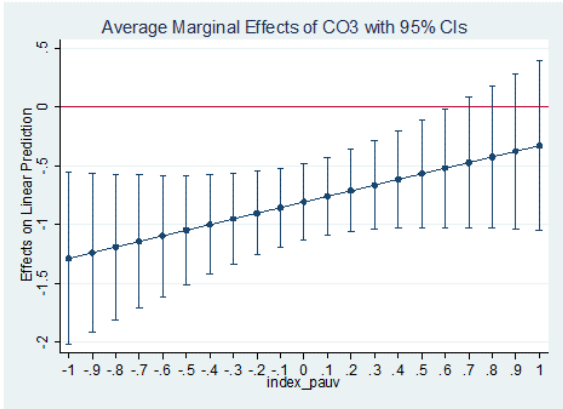
* p<0.05, ** p<0.01, *** p<0.001

In the districts where the rate of cumulative outages is higher, the household are less connected: where the frequency of outages is 1 percent point higher, the households' connections level is -.806 percent point lower. From the standardized regression, the absolute magnitude of the outages' impact on the connections' level (-.231) is 43% higher than the one of the households' poverty (-0.161).

Interacting both effects seems not significant, but the inflated test hides underlying differences in the significance level: while the Z-statistic behind Table 7 tests the distribution of the

coefficient at average level of both terms, the significance of outages in this interaction may indeed be different given the poverty level (Graph 2)

Graph 2: MARGINAL EFFECT OF THE OUTAGES AT POVERTY LEVELS (2SLS)



The marginal effect is the derivative of the connections given the variation of outages: $dc/do = -0.806 + 0.479 \cdot pov_index$. It's negative when $pov_index < 0.806/0.479 = 1.68$. Since $pov_index \in [-1 ; 1]$, the marginal effect of outages is always negative. However, as shown on Graph 3, it's significant only when the poverty level is below 0.6: the outages have no significant impact for the poorest households while they impact negatively the connection's decision of the households with intermediate or higher wealth. The highest the wealth of the households, the more sensitive they are to the frequency of outages.

The linear specification was useful to identify the effect and the relevant severity level of its measurement, to bring the evidence of the impact using instrumental variables, and to get a first idea of the magnitude. However, the LPM does not ensured the predicted level to be a probability belonging to a $[0;1]$ support. The shortcoming is all the more a constraint that the study aims to distinguish the connected from the unconnected households in a readable way, for eventual policy applications.

Non-linear modelling of the connection's likelihood

Probit estimation

For the outcome to be a probability, a Probit estimation is a more suitable method. Here, it's designed to predict the likelihood of the connection, for the dependent variable equals 1 when an individual household is connected to the grid.

Assessment criteria

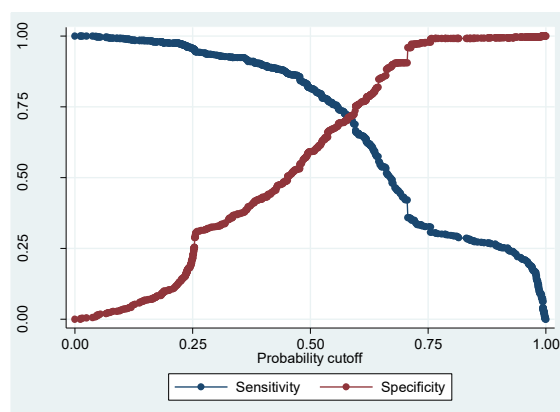
The criteria in Table 8 aim to diagnose the ability of the model to dissociate the connected and unconnected households, ie. to maximize the discriminatory accuracy of the model.

The first criterion is the lowest AIC. The second criterion is the lowest type I error (« T1 err. »), measuring the risk to predict a connection while the household is not connected. The third criterion is the highest specificity (« Id unconnectd ») that measures the exact prediction of unconnected households, ie. the proportion of predicted unconnected households who are effectively unconnected. The fourth criteria is the highest ROC : the area under the ROC curve is a synthetic measurement of the discriminatory accuracy of a probit/logit model. It does not depend on the cut-off, hence it gives an additional assessment, independent of the defined settings for a model's application (see below). The fifth criteria is the smallest p-value of the outages. At this stage, the model should be enough discriminatory: one thus expect the coefficient to be significant. If this test fails, one shall switch to the second-best specification. The sixth criteria is the lowest specification error of the unconnected (« C /- »), that is the proportion of truly connected households among the predicted unconnected households. It gives an expected approximation of the eventual operational cost of the model, since each of this error case would mean an un-efficient cost of inquiry, prospection and commercial effort if the model were to be used on the field.

For a policy application, the model would indeed be better off to minimize the prediction's error of the unconnected households; therefore, the cutoff has been set to 75% in the diagnosis table (Table 8). As shown in Graph 3 such a level maximizes the return to specificity, ie. the ability to identify the unconnected households, at the cost of a lower recognition of the connected household (the sensitivity).⁹ However, one can reasonably expect that the benefit to decrease the marginal cost of the grid's extension by increasing the proportion of recognized unconnected households would be much higher than the usage's cost of the model, measured by this specification error.

⁹ The sensitivity is the proportion of exact predictions of connections, ie. cases of predicted connected households who are effectively connected.

Graph 3: TRADEOFF BETWEEN SPECIFICITY AND SENSITIVITY



Model *iCO3_probit* : power reliability index at third level of severity

Applying the aforementioned criteria, the best specification is achieved with *iCO3* (Table 8). The Probit specification enhances the accuracy of the estimates (Table 9), compared to the OLS (Table 4): they are now all significant at 0.1% level.

Table 8 : ASSESSMENT OF THE PROBIT MODEL AT DISTRICTS LEVEL

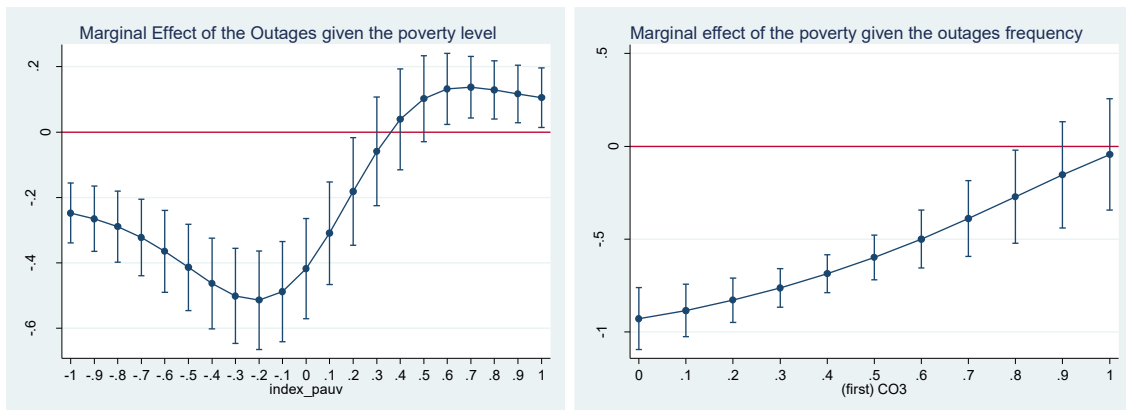
Model	Outages	Std Error	P value	AIC	Tl err.	Id unconctd	ROC	C/-	Nb obs ^o	Nb Clus.
base_CO1	-1.088	0.286	0.000	2245	0.0	100.0	51.7	57.4	1669	90
base_CO2	-1.268	0.222	0.000	2179	0.0	100.0	59.1	57.4	1669	90
base_CO3	-1.375	0.206	0.000	2137	0.0	100.0	64.0	57.4	1669	90
base_CO4	-1.567	0.475	0.001	2194	6.2	93.8	65.4	56.7	1669	90
ctr_CO1	-0.243	0.315	0.440	1870	1.1	98.9	78.7	48.6	1669	90
ctr_CO2	-0.709	0.244	0.004	1843	1.3	98.7	79.0	48.5	1669	90
ctr_CO3	-0.821	0.215	0.000	1827	1.1	98.9	79.3	48.6	1669	90
ctr_CO4	-0.957	0.424	0.024	1844	2.0	98.0	79.3	47.8	1669	90
iCO1	-1.252	0.371	0.001	1824	1.1	98.9	78.5	48.5	1669	90
iCO2	-1.091	0.250	0.000	1814	1.3	98.7	78.6	48.3	1669	90
iCO3	-1.108	0.231	0.000	1800	2.1	97.9	79.1	48.1	1669	90
iCO4	-0.960	0.429	0.025	1845	3.7	96.3	79.3	47.8	1669	90
dCO1	-1.136	0.319	0.000	1798	1.1	98.9	78.9	48.3	1669	90
dCO2	-1.133	0.254	0.000	1803	1.1	98.9	79.2	48.4	1669	90
dCO3	-1.378	0.427	0.001	1798	3.1	96.9	79.3	47.7	1669	90

Table 9 : PROBIT OF THE CONNECTION AT DISTRICTS LEVEL

(1)	
connection	
CO3	-1.108*** (0.231)
c.CO3#c.pov_index	3.111*** (0.694)
pov_index	-3.248*** (0.334)
Constant	0.447*** (0.112)
N	
Nb Clusters	1669
Wald chi2	90
p_value (Wald)	197.8
AIC	0.000
	1800
LHS : connection	
Probit regression. SE in parentheses.	
Variance : cluster by DISTRICT	
* p<0.05, ** p<0.01, *** p<0.001	

The Probit specification brings also a finest evaluation for the marginal effect of the interaction term (Graph 4)

Graph 4: INTERACTED MARGINAL EFFECTS (PROBIT)



As already identified with the linear specification, the poorest household are not sensitive to the quality of the distributed power (poverty index above 0.4, on the left). The highest sensitivity to outages is reached for households with a poverty index equals to -0.2.

Conversely, there is a significant positive wealth effect in the districts where the outages remain under 80% (on the right). In the districts where the households are richer, the likelihood to be connected is higher, provided that the reliability remains below an outages'

rate of 80%. On the opposite, a too extremely low reliability of the power vanished the positive wealth effect of the households.

IV Probit estimation

Though the Probit yields more consistent estimates for a probability outcome, it might be poised by the risks of endogeneity. It is now necessary to instrument the outages the same way as in the linear specification. Stata provides a dedicated procedure `-ivprobit-` that combines the Probit modeling of a likelihood and linear regressions to instrument the endogenous variables. Unfortunately, the available tests to assess the instrumentation's quality are not as much developed as they are in the `-ivreg2-` procedure, because, as recalled by Wooldridge, the diagnosis shall be made in a linear setting.¹⁰

Therefore, the assessment of the instrumentation's quality made above remains, leading to keep the chosen specification *iCO3*. For the sake of consistency, the assessment table (Annex 7) exhibits the key available tests of instrumentation in `-ivprobit-`, to check whether the model still holds while upgrading the method. The AIC and the ROC are also verified, to ensure that the discriminatory capacity of the model still holds.

The diagnosis criteria (Annex 7) are read in the following order:

- Endogeneity Wald test below 1% ;
- Forced Hausman test below 5% ;
- Global Wald test of the specification below 1% ;
- Z-test of the estimates of the first instrument in the first-stage below 1% ;
- ROC among the highest values ;
- AIC among the smallest values.

The *iCO3_ivprobit* specification meets all these ordered criteria but the AIC (1451). Its ROC is the best (77%), proving that this specification remains solid with respect to its discriminatory ability (Annex 7). However, going backward along the chain of tests, the p-value of the lightning is significant at only 9% level, what is not enough for the main instrument to achieve its purpose. Switching to the lowest AIC (-301 for *iCO1*) would provide inconsistent instrumentation with respect to the endogeneity test (0.314), the p-value of lightning (0.666) and the Hausman test (1.000). Switching to the next best AIC (587 for *iCO4*) would also yield a poor instrumentation (Hausman : 8.5% and p-value of lightning :

¹⁰ <http://www.statalist.org/forums/forum/general-stata-discussion/general/1295919-underidentification-and-weak-identification-test-for-ivprobit>

0.854). The risk that the estimates of the instrument would be biased is too high for any specification, yielding a too high risk that the endogenous issues would not be properly tackled in the reduced form.

Looking at the first-stage, Annex 8 indicates that the issue arises from the lightning by neighbor. Though there is no advanced test of over-identification in the IVPROBIT procedure, it looks intuitive that too many linear components in the first-stage regression might actually over-fit the model for a non-linear estimation. One thus keep only the two mainly significant instruments in the *iCO3* specification: the lightning (*fdr_moy_DISTRICT* : 0.090) and the weighted distance to the closest electrical plant (WCP : 0.000).

Reading again the decision criteria (Annex 9), the *iCO3* specification with two instruments appears now to pass successfully all the tests, still showing the best discriminatory ability (ROC : 76.8) while the instrumentation becomes much more consistent (Endogeneity : 0.000, p-value of the lightning in first-stage : 0.006, Hausman : 0.017). The model *iCO3_ivprobit* exhibits accurate estimates at 0.1% level for all the variables in the reduced form (Table 10), with only the excluded instruments being strongly significant in the first-stage (below 1%). Yielding both accurate and unbiased estimates of the outages' impact on the households' connection, it's renamed "scoring grid" and retained as the preferred specification.

Table 10: CONNECTION'S SCORING GRID

	(1)
connection	
CO3	-2.573*** (0.458)
c.CO3#c.pov_index	4.581*** (0.786)
pov_index	-3.026*** (0.331)
Constant	0.797*** (0.153)
CO3	
c.CO3#c.pov_index	1.014*** (0.212)
pov_index	-0.093 (0.062)
fdr_moy_DISTRICT	0.006** (0.002)
WCP	0.011*** (0.003)
c.fdr_moy_DISTRICT#c.pov_index	0.002 (0.003)
c.WCP#c.pov_index	-0.007 (0.005)
Constant	0.094** (0.034)
N	1669
Nb Clusters	90
Wald chi2	250.6
p_value (Wald)	0.000
AIC	1467
LHS : connection CO3	
Probit model with endogenous regressors SE in parentheses.	
Variance : cluster by DISTRICT	
At district level with 2 instruments (lightning, weighted closest pla	
* p<0.05, ** p<0.01, *** p<0.001	

It could be applied to infer the likelihood that any new household out-the-sample would not be connected, provided that the same data could be gathered to feed the scoring grid.

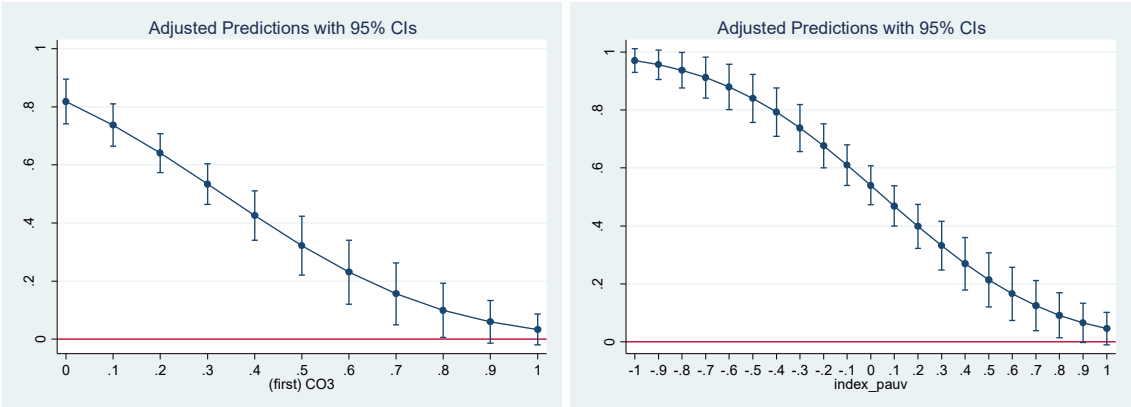
Impact evaluation of the outages on the connection’s decision in a context of poverty

As the model now consistently neutralizes the three risks of endogeneity, it can be confidently used to explore and compare the effects of reliability and poverty. Relying on (Williams, 2012), the study explores the predictions and marginal effects, whether with the observed values of the sample or at different referral levels of the outages and poverty.

Annex 14 checks the initial statistical conditions of this evaluation.

The predicted probability to be connected is not linear, neither in the outages nor in the poverty level (Graph 5). Interestingly, the predicted connection’s probability is not complete given the outages: while the probability to find any connected household is almost 0 when the rate of partial severity outages reaches 100% in a district, it’s up to 80% when the rate of the same severity’s outages is 0. There might be additional occasional outages (4-level severity) that could possibly have a residual effect, deterring the households to subscribe to the grid. This point will be addressed with the “extension“ model (section VII).

Graph 5 : DIRECT EFFECT OF OUTAGES AND POVERTY ON CONNECTION’S PROBABILITY (APM)



One will now explore how the prediction’s change from a referral level, when outages or poverty deviate from their mean or any other referral values in the sample. Graphically, it’s equivalent to assess the slopes of the above prediction at different points (eg. CO3), fixing the other predictor (eg. pov_index) at a specific level (its mean or eventually its median). The marginal effects in Table 11 will all be assessed in absolute value, using eventually the standardized regression for any comparison (table 11, 2nd span).

Table 11 : MARGINAL EFFECTS OF OUTAGES AND POVERTY

VARIABLES	(1) Average Marginal Effect	(2) Marginal Effect at Means	(3) Marginal Effect at Median	(4) Marginal Effect at 1st decile	(5) Marginal Effect at last decile
CO3	-0.673*** (0.102)	-1.079*** (0.188)	-0.994*** (0.162)	-0.076** (0.034)	-0.257*** (0.086)
index_pauv	-0.516*** (0.0806)	-0.703*** (0.112)	-0.814*** (0.116)	-0.044** (0.020)	0.046 (0.121)
Observations	1,669	1,669	1,669	1,669	1,669

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) Average Marginal Effect	(2) Marginal Effect at Means	(3) Marginal Effect at Median	(4) Marginal Effect at 1st decile	(5) Marginal Effect at last decile
zCO3	-0.196*** (0.0296)	-0.304*** (0.052)	-0.281*** (0.045)	-0.028** (0.012)	-0.086*** (0.023)
zpov_idx	-0.178*** (0.0271)	-0.242*** (0.037)	-0.269*** (0.040)	-0.019** (0.008)	-0.021 (0.033)
Observations	1,669	1,669	1,669	1,669	1,669

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

On average, 1 percent point more outages causes 0.673 percent point less connected households. At the average values in sample, 1 percent point more outages causes 1.079 percent point less connected households or 0.994 less in a median district.

Once standardized, the Average Marginal Effect of outages (-0.196) is 10% higher than the solely effect of poverty (-0.178). However, this estimates depends on the fit of outages' and poverty's distributions in the sample to their true distributions in the Kenyan population, hence of the representativeness of the sample. Without any previous adequacy tests (eg. : Kolmogoroff-Smirnoff), the trueness of this estimation is hard to assess. Nonetheless, with 1,669 observations, a normal distribution can be confidently assumed for the poverty index, and so it is in the sample (not shown). Applying the central-limit theorem, its means can be considered as a referral value, already converging to and thus representative of its true value in the population. But outages are not normally distributed over the sample (not shown). It's thus necessary to compare the marginal effects at several referral values of the index.

Comparing districts at average levels of outages and households' poverty (Table 11, column 2), the impact of outages (-0.304) is 26% higher than the one of poverty (-0.242). This result

brings the evidence that the main obstacle to increase subscriptions to the electricity is much more the power reliability than the household's poverty.

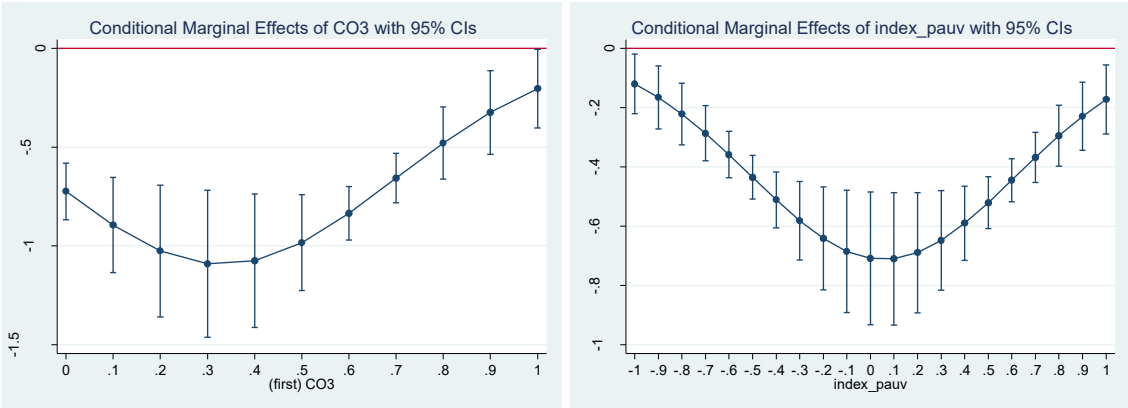
Comparing two median districts would be more robust (Table 11, column 3). In that case, the impact of outages (-0.281) still remains 5% higher than the one of poverty (-0.269), a result to keep as a lower bound.

For two representative districts in the best situation, being respectively in the first decile of the reliability and in the first decile of the poverty index (Table 11, column 4), the impact of outages (-0.028) is 47% higher than the one of poverty (-0.019).

Being now in the worst districts from the last decile, with the highest outages rate and the highest poverty index (Table 11, column 5), the poverty has no more significant impact on the connection's decision. In those districts, the households are only sensitive to the outages (-0.086), but three times less than in the median districts (-0.281).

Beyond the global evaluation, the impact of outages and poverty are not always the same with respect to their own level (Graph 6) or taking into account their interacted effect (Graph 7).

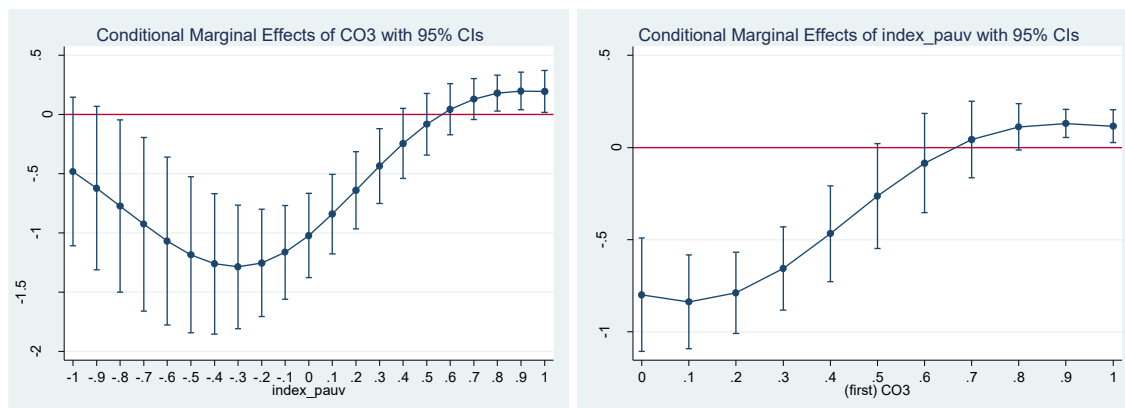
Graph 6 : CONDITIONAL EFFECTS OF OUTAGES AND POVERTY ON THE CONNECTION'S PROBABILITY (MEM)



The marginal effect of outages is of maximum magnitude (in absolute value) in the districts where the rate of partial severity outages reaches 30% (Graph 6, left : -1.09). There, any quality upgrade of the distributed power might have the maximum potential to trigger new subscriptions. On the opposite, in the districts where the partial severity's outages are very frequent (100%), their impact is lower (-0.203), while still significant: there, any reliability upgrade might only have a smooth effect on connections. Since the frequency of outages might be perceived as far too high, the households might be reluctant to believe in any reliability's enhancement. The channel might also surge through the interaction with the poverty level in this kind of districts, as it will be discussed afterward.

The model also captures the role of intermediate wealth (Graph 6, right): the magnitude of the marginal effect is maximum (-0.71) when the poverty index reaches 0, a central level of the index. Among the households with intermediate wealth, being one unit richer (decreasing index, toward the left) has the maximal potential effect to observe more subscriptions. On the opposite, among the richest households ($pov_index = -1$), the wealth effect is much less sensitive (-0.172): for them, any lower level in wealth (increasing poverty index, toward the right) has only a smooth negative marginal effect on the connection's decision. It's also the case among the poorest households (-0.120): for them, being one unit better-off (decreasing poverty index, toward the left) leads to observe only a slightly higher level of connections. The underlying reason of this non-linear wealth effect might also be due to its interaction with the outages intensity.

Graph 7 : INTERACTED EFFECTS OF OUTAGES AND POVERTY ON THE CONNECTION'S PROBABILITY (MEM)



Not only the reliability's impact is not the same way significant according to the level of poverty, but in addition, its magnitude is not linear given the poverty level (Graph 7, left). For a poverty index between 0.4 and 0.7, the outages have no significant impact on the connection's decisions. Above 0.8, the impact is borderline significant and might be considered cautiously. Below -0.9, the outages are neither significant, and since the width of the confidence interval is growing while the index is decreasing, the -0.8 level should also be considered cautiously.

Finally, the outages have a negative significant marginal effect among the households with a poverty index between -0.7 and 0.3, but not substantively of the same intensity: in absolute value, its magnitude is maximum (-1.28) for a poverty index equal to -0.3. The low reliability has the maximum deterring impact among the households with intermediate wealth: in other words, those are the most reluctant to subscribe in presence of outages. Said in positive terms,

for any higher reliability, the intermediate wealthy households would be the most prone to subscribe.

Conversely, in the districts where the rate of partial severity's outages is too high (above 50%), the poverty index is not significant (Graph 7, right). In the districts too much exposed to outages, the wealth or poverty of the households is not the reason why they do not subscribe. On the opposite, in the districts benefiting a higher reliability (outages' rate below 40%) the wealth level contributes to explain the household's decision to subscribe but with a maximum magnitude (-0.837) that is 35% lower than their sensitivity to outages (-1.28).

To sum up : the wealth effects exists only in the districts exposed to a low level of outages, while the low reliability deters at most the unconnected intermediate wealthy households to subscribe. Those last would be the most prone to subscribe for any improvement of the reliability, provided that they're living in a district where the outages are not already too frequent among their neighbors.

VI - Robustness checks

Table 12 controls for the stability of the outages' estimate in the preferred specification (column 1), with respect to potentially omitted variables.

Columns 2 to 5 follow (Andersen and Dalgaard, 2013), with altitude replacing the coastal dummy. As they found, the outages' effect is robust to the inclusion of Altitude, Temperature and Latitude : introduced one at a time, they're not significant and modify only slightly the marginal effect of outages.

The precipitations (column 3) seems to be significantly correlated with a lower level of connections in Kenya. They do not change the direction of the outages' impact, but this omitted variable reduces substantially their magnitude (-0.415), while (Andersen and Dalgaard, 2013) had found them to be insignificant.

Most likely, rainfalls could be partially correlated with the storms, capturing a partial effect of lightning and thus also of the outages. Actually, the western provinces are much more exposed both to rainfalls and lightning than the arid north-eastern regions (Map 1). There is a specific heterogeneity of precipitations in Kenya correlated with lower connections, that was not in the country-level data of (Andersen and Dalgaard, 2013). However, as evidenced from its VIF in the 2SLS settings (1.01), precipitations are fully orthogonal to the hyperplan of the other variables, meaning that their inclusion could well capture the direct area effect on individual connections, as diagnosed in the qualitative causal assessment (Annex 4).

Table 12 : ROBUSTNESS TO ADDITIONAL CONTROLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Outages	-0.673*** (0.102)	-0.673*** (0.102)	-0.415*** (0.094)	-0.682*** (0.104)	-0.641*** (0.120)	-0.389*** (0.107)	-0.586*** (0.166)	-0.643*** (0.155)	-0.576*** (0.103)	-0.268** (0.085)
Poverty index	-0.516*** (0.081)	-0.518*** (0.081)	-0.663*** (0.066)	-0.517*** (0.081)	-0.529*** (0.088)	-0.588*** (0.066)	-0.550*** (0.099)	-0.530*** (0.101)	-0.549*** (0.073)	-0.646*** (0.056)
Altitude		-0.000 (0.000)								
Precipitation			-0.000*** (0.000)							-0.000*** (0.000)
Temperature				0.004 (0.007)						
Latitude					-0.010 (0.016)					
Rural rate						-0.330*** (0.067)				-0.318*** (0.057)
Wghtd dist. Mombasa							-0.000 (0.000)			
Dist. to Mombasa								-0.004 (0.015)		
Dist. to Nairobi									-0.023 (0.020)	
N	1669	1669	1669	1669	1669	1669	1669	1669	1669	1669

Probability of positive outcome (connection)
Average marginal effects SE in parentheses.
ivprobit at district level with 2 instruments
(lightning, weighted closest plant)
Variance : Robust cluster

* p<0.05, ** p<0.01, *** p<0.001

The rural location (Table 12, column 6) is also correlated with a lower connections' level (-0.330), yielding a lower though still negative estimate for outages (-0.389). In 2014, connections to the electrical grid are less likely to be observed in rural districts of Kenya. In a policy perspective, this stake is directly addressed by the REA.

Taking into account both variables together (Table 12, column 10) reduces the marginal effect of outages (-0.268) while still keeping its negative sign. In western rainy Provinces, Kenya has developed a specialization in sugar cane and tea plantations, managed by multinational firms, or Kenyan farms supported by the Kenyan Tea Development Agency (KTDA). In both cases, the transformation requires electricity. But due to the unreliability of the power, the firms produce it from their own installations, with bio-generation or small hydro power generators, selling the remaining excess to the grid, if any. The correlation of the rainfall and rural location with lower connections could simply reflect this peculiar economy in lower connected districts (see Map 2 and Annex 12).

The results of (Khandker et al., 2014) also suggested a possible arbitrage between an electrical connection and the price of kerosene. This last is approximated by the distance to Mombasa weighted by the difficulty of the road (Table 12, column 7), but is neither significant nor it has the expected sign. Turning to absolute distance to the main activity centers in Mombasa and Nairobi (column 8 and 9) is neither significant.

As seen in section IV and also suggested by the results of (Lee et al., 2014), it's needed to check for any residual correlation of the shelter's type with the error term (Annex 10). The

referral category is defined by the non-traditional formal houses, accounting for 73% of the estimation sample. Some types of shelters have a significant residual effect: the traditional huts (11% of the estimation sample) are less connected, while the flats or single room (12% of the sample) are more (0.240 or 0.108). All have only a slight impact on the estimate of the outages' marginal effect (-0.620).

Looking more carefully at the map of the electrical grid (Annex 11) suggests a South-East to North-West development axis that might have left the arid a low-populated North Eastern regions in a lower stage. While the estimation has been clustered by districts, it's worth checking how the model performs in different macro-areas.

Table 13 : ROBUSTNESS TO AREAS FILTERS

	(1) Preferred	(2) Without North	(3) Rift Valley	(4) Nyanza	(5) Western
Outages	-0.673*** (0.102)	-0.699*** (0.112)	0.183 (0.333)	-0.245 (0.152)	-0.257 (0.306)
Poverty	-0.516*** (0.081)	-0.542*** (0.093)	-0.801*** (0.141)	-0.907*** (0.184)	-0.500** (0.190)
N	1669	1629	344	192	104

Probability of positive outcome (connection)
Average marginal effects SE in parentheses.
ivprobit at district level with 2 instruments
(lightning, weighted closest plant)
Variance : Robust cluster

* p<0.05, ** p<0.01, *** p<0.001

Filtering the North-Eastern region (Table 13, column 2) does not change substantially the evaluation. On the opposite, the outages effect disappears in the western regions (Rift Valley, Nyanza, and Western) due to their high level of poverty (see map in Annex 12). As evidenced by the margin analysis (Graph 7, left), the outages have no effect for a too high level of poverty: this vanishing surges from the western parts of the country. In the regions close to Victoria Lake and Uganda, only the poverty deter the households to subscribe, the effect being up to 75% higher in Nyanza (-0.907) as in the whole country (-0.516). The REA should be advised to prioritize the connection's cost reduction in the western regions.

Additional checks have been performed using the `ivvif` procedure incorporated by Roodman in Stata, and a `Dfbeta` with the simple OLS specification. The first allows to compute the variance inflation factor in the 2SLS framework and the second aims to identify the leverage 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. As for the second, 39 households reports a `Dfbeta` with respect to outages over 4.8%, 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, dropping those households from the sample would make the estimate even lower. The evaluated magnitude is thus conservative. As for the poverty index, none of the in-sample households exceed the threshold.

VII - Extending the specification

As pointed out in Section V (Graph 7), there might be an additional effect of less severe outages (level 4 : occasional). This section assesses their introduction in the specification.

$$Connection_i = a_0 + a_1 \cdot CO_u(3) + a_2 \cdot povindex_{index_i} + a_3 \cdot CO_u(3) \times povindex_i + niv4_i + u_i$$

Different strategies have been unsuccessfully tried to instrument the variable niv4 in the 2SLS estimation, but the backward-decision criteria failed (result not shown). An explanation could be the inability to affect the three instruments separately to the endogenous variables.

Therefore, the next level of outages is introduced as a control in the preferred specification (*iCO3_ivreg*), defining the “extension” models' class *d*.

As shown in Table 6, the third level of severity remains the most relevant with respect to the instrumentation's robustness: *dCO3_ivreg* passes successfully all the tests.

Table 14, column 2, displays the margins of *dCO3_ivprobit*, compared to the preferred specification.

Table 14 : EXTENDED EVALUATION TO THE NEXT SEVERITY LEVEL

	(1) Prefered (scoring grid)	(2) Extended
CO3	-0.673*** (0.102)	-0.977*** (0.169)
pov_index	-0.516*** (0.081)	-0.480*** (0.088)
niv4		-0.613*** (0.180)
N	1669	1669

Probability of positive outcome (connection)
Average marginal effects SE in parentheses.
ivprobit at district level with 2 instruments
(lightning, weighted closest plant)
Variance : Robust cluster

* p<0.05, ** p<0.01, *** p<0.001

The marginal effect of the poverty index is going upward (-0.480) compared to the preferred model (-0.516), meaning that the occasional outages were an omitted variable with respect to the poverty. But its omission also made the estimates of the partial severity's outages upward biased (-0.673 instead of -0.977): the preferred specification (column 1) appears thus to be a conservative estimate, still remaining the best instrumented.

Interestingly, the occasional outages have a direct significant negative impact on the connection's probability (-.613), worsening the previous severity level (-0.977). Taking into account all the frequencies of outages, the only impact of the total, serious and partial outages (-0.977) might be impacting the households' connection twice more than their poverty (-0.480). In a policy perspective, this result adds the necessity to solve the occurrence of outages until their smallest severity and to prioritize the action by solving first the most severe ones.

VIII - Policy implication and concluding words

This study has brought evidence that the outages *per se* have a direct negative impact on the subscription's decision, on average 26% higher than the poverty of the households. The expected benefit to act on the supply side would thus be much higher than solely relaxing the demand constraints. Enhancing the reliability would gain most likely the intermediate wealthy household as new customers.

Assuming that these households have a reasonably low likelihood to default on monthly payment, this result provides good reliance to accelerate the pace of connections to the grid in financial safe conditions, hence reducing the marginal cost of its on-going extension. However, supplying a more reliable power would be the pre-requisite to gain those new customers.

In the *Kenya vision 2030* (REPUBLIC OF KENYA, 2015), building new capacities and extending new transmission lines (> 132 kV) or distribution lines (below 66 kV) have been defined as the two first priorities of the development, bringing two main strategic projects: the building of new capacities with a quantified roadmap (5000+ MW in 2016) that KPLC is responsible for and the *Last Mile Connectivity* supervised by the REA.

The last aims to connect 70% households by 2017 by extending the grid of distributions' lines and transformers ; it started September 2015, targeting 314,000 households, within 600 meters of 5,320 selected substations (Chumo, 2015). This project could be advised to identify first the unconnected household with intermediate revenue around the transformers where the power is not too much unreliable: there, the REA could expect the highest rate of new subscriptions. Using the scoring grid of this study could help to target the unconnected households and prioritize the action plan on the field. In addition, if KPLC were to distribute a more reliable power, the quality effect would *per se* accelerate the subscription's rate. Thus, during this first

phase, KETRACO should be advised to set a peculiar monitoring and maintenance on the selected transformers circled by intermediate wealthy households.

As for the first, rising the supply might be not enough to solve the outages challenge because there might be specific bottlenecks within the grid, adding additional risks to the reliability.

On another hand, most of the projects to extend, enhance or build new lines are facing a lack of financing (Zhou and Hankins, 2015), possibly due to their cost, the public status of the grid's manager and the priority set on extending the capacities. Meanwhile, the overwhelming cost of the under-utilized Kenyan grid could be addressed efficiently by raising the quality of the distributed power. In these conditions, the role of KETRACO to enhance or extend the substations' grid that sustains the transmitted tension along the lines should also be enforced: it might be more efficient and less costly to enhance or build new step-up substations, as recently in Mariakani.¹¹

However, this study has made the assumption of a homogenous grid: evaluating the impact of the bottlenecks within the grid would need further researches. Assessing the impact on outages of the districts' distance to the step-up substations could demonstrate further how to relate their implementation with the households' preference for the power reliability.

¹¹ <http://www.ketraco.co.ke/news/2016/Mariakani.html> ;
<http://www.standardmedia.co.ke/business/article/2000189572/how-ketraco-plans-to-end-power-outages-in-kenya>

Annexes

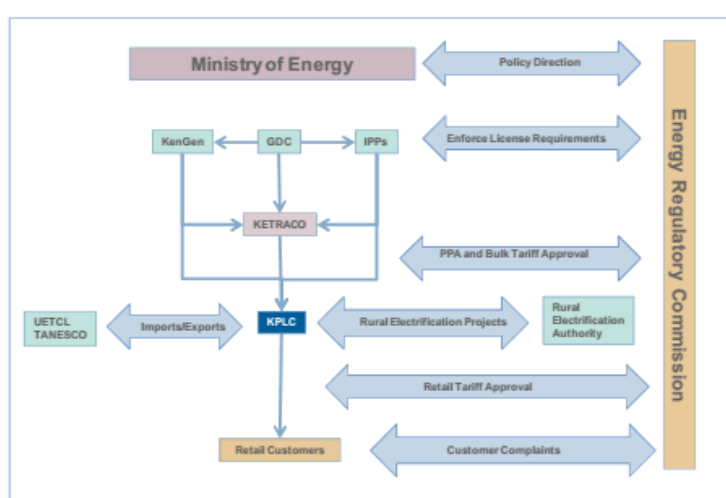
Annex 1: GROWTH OF POPULATION AND ELECTRICAL CAPACITIES IN KENYA

Years	Population ¹² (thousands)	KPLC Customers (thousands)	Peak-Load	Capacity
2009	39,269	1,267	1,044 MW	1,345 MW
2014	44,864	2,766	1,468 MW	1,885 MW
Growth rate	+14%	+218%	+41%	+40%

Sources : World Bank, (KPLC, 2009), (KPLC, 2014)

Annex 2: MAIN ACTORS OF THE ELECTRICITY SECTOR IN KENYA

Figure 2-1: Kenya Electricity Sector



Source : (Zhou and Hankins, 2015)

Annex 3 : MAIN COMPONENTS OF THE MCA'S FIRST AXIS (POVERTY INDEX)

Categories	Coord1	Contrib1	Contrib1 /Mass	Effectives	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:dotm	-3,43	2,0%	11,8	33	0,38

Exhibits of the categories with coordinates outside +/-2 and contribution >1%

¹² <http://databank.worldbank.org/data/home.aspx>

Annex 4: QUALITATIVE ASSESSMENT OF OUTAGES' CAUSES

Causes of outages	Potentially enough correlated with outages (through transmission lines)	Exclusion restriction at individual connection node	Relevance
Wind	Yes (strong zone effect)	Middle : possible correlation with the quality of buildings. The wind might damage fragile building and destroy directly individual nodes of connection.	No (ER not met)
Rain	Yes (strong zone effect)	Middle (see wind)	No (ER not met)
Floods	Yes (strong zone effect)	No because : a/ the flood might damage individual connections on a large area, with higher severity than wind or rain. b/ the flood impairs the access to the building for technicians and repairing electricity of flooded building is dangerous.	No (ER clearly not met)
Contacts of animals	Low : most likely weak	Yes : animals might eventually damage directly the individual nodes of connections, but most likely very scarce.	Low (weakness)
Trees' growth	Low : most likely weak	Yes : one can do the reasonable assumption that households are cutting the trees before they will reach their individual atmospheric line or electrical box.	Low (weakness)
Collisions from vehicles	Middle. Roads are close to low-voltage lines thus there might be more collisions in area where there is more lines and pylons. Might be too scarce to avoid weak instrument.	Yes : the likelihood that collisions on individual connections would be a significant explanation for a lower level of connection is very low.	Low (weakness)
Vandalism	Yes but too much time-varying. Also correlated in space with poverty.	Yes Thief are targeting copper cables, not individual features	No (endogenous to poverty)
Age of features	Yes. Age might imply an increasing likelihood of failures. Specific engineering ageing laws.	Yes : there is no such a policy in <i>Kenya</i> that would give instructions to avoid connections in areas with too old features. On the opposite, the <i>Last Mile Connectivity</i> project aims to target these area, starting sept. 2015 (Chumo, 2015).	No : time varying; ie. not randomly exogenous
Lightning	Yes : a/lightning is attracted by the height of the metallic pylons b/ There is a strong zone effect. A local over-voltage caused by the lightning will trigger the circuit-breakers to cut the line, avoiding the over-voltage to propagate to the next section of the grid. Thus, the local extinction creates a sudden barrier to power supply in its section, reporting the flow to the next sections of the grid, eventually generating an over-load that will itself trigger a new cut from the automated regulation. A local outage might propagate as a wider blackout due to a chain-reaction, at electricity speed, quicker than the ability of human regulators to derive the over-flow or reduce the generation of power. To sum-up, the automated regulation of a lightning impact at a point belonging to the electrical grid might trigger a <i>reverse tide effect</i> .	Yes : Could the lightning directly lower the observed number of connected households ? The lightning might strikes directly individual external features of connection (boxes, cases, final atmospheric cable). But the probability of strikes on individual small nodes (numerous and dispersed across space) might be small in front of the probability of strikes on the large metallic grid's features (pylons, HV-lines, transformers or LV-lines) ? The partial correlation of lightning with a lower number of connection might be small enough in front of the correlation of the lightning with outages met the exclusion restriction.	Yes

Annex 5: CLASSES OF MODELS

Class denomination	Set of tested indicators
<i>Base</i>	CO(p)
<i>ctr</i>	CO(p) + control by the poverty index
<i>i</i>	CO(p) + control + interaction
<i>d</i>	CO(p) + control + interaction + outages of next severity level

Annex 6 : NUMBER OF CLUSTERS AND ACCURACY OF THE ESTIMATES

The 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. This last is slightly reduced close to zero as soon as the number of clusters is over 50 while on the opposite, a too small number of groups yields over-estimated standard errors.

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

Annex 7: ASSESSMENT TABLE OF THE IVPROBIT MODEL (3 INSTRUMENTS)

Model	Endog(p)	First(p)	Haus(p)	CO	Sig(p)	Wald	Wald(p)	AIC	ROC	Tl err	Id Uncon	C/-	N	N Clus
base_CO1	0.559	0.931	0.000	5.681	0.000	33.4	0.000	1015	48.3	14.3	85.7	60.1	1669	90
base_CO2	0.012	0.556	0.000	-3.796	0.000	35.2	0.000	2181	59.1	37.4	62.6	57.5	1669	90
base_CO3	0.001	0.165	0.000	-2.897	0.000	45.0	0.000	2256	64.0	26.2	73.8	52.4	1669	90
base_CO4	0.000	0.759	0.000	-4.484	0.000	39.6	0.000	1083	65.4	18.0	82.0	53.5	1669	90
ctr_CO1	0.143	0.733	0.000	5.715	0.000	71.6	0.000	616	67.5	14.1	85.9	58.8	1669	90
ctr_CO2	0.026	0.616	0.000	-3.581	0.000	93.3	0.000	1803	71.2	26.7	73.3	47.4	1669	90
ctr_CO3	0.001	0.171	0.000	-2.545	0.000	170.7	0.000	1868	76.1	16.2	83.8	44.3	1669	90
ctr_CO4	0.000	0.907	0.000	-4.137	0.000	166.3	0.000	708	74.6	16.2	83.8	48.3	1669	90
icO1	0.314	0.666	1.000	-4.334	0.137	240.5	0.000	-306	76.7	1.5	98.5	48.7	1669	90
icO2	0.002	0.421	1.000	-2.858	0.000	281.5	0.000	1200	76.0	14.1	85.9	46.2	1669	90
icO3	0.000	0.090	0.012	-2.457	0.000	242.2	0.000	1451	77.0	13.5	86.5	45.5	1669	90
icO4	0.000	0.854	0.085	-4.059	0.000	174.7	0.000	587	74.7	16.2	83.8	47.2	1669	90
dCO1	0.474	0.671	1.000	-3.152	0.276	234.8	0.000	-321	78.1	1.8	98.2	48.6	1669	90
dCO2	0.001	0.285	0.515	-2.763	0.000	283.4	0.000	1147	77.0	10.0	90.0	45.5	1669	90
dCO3	0.000	0.363	0.151	-3.620	0.000	238.9	0.000	321	77.8	15.2	84.8	45.4	1669	90

Annex 8: FIRST-STAGE OF ICO3_IVPROBIT WITH 3 INSTRUMENTS

Model iCO3_ivprobit						
Probit model with endogenous regressors		Number of obs	=	1,669		
Log pseudolikelihood = -710.56452		Wald chi2(3)	=	242.22		
		Prob > chi2	=	0.0000		
(Std. Err. adjusted for 90 clusters in DISTRICT)						
		Robust				
		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
branché	CO3	-2.457359	.3937424	-6.24	0.000	-3.22908 -1.685638
	c.CO3#c.index_pauv	4.505792	.74998	6.01	0.000	3.035859 5.975726
	index_pauv	-3.083811	.3327778	-9.27	0.000	-3.736044 -2.431579
	_cons	.7721764	.1468407	5.26	0.000	.4843739 1.059979
CO3	c.CO3#c.index_pauv	1.060837	.197687	5.37	0.000	.6733775 1.448296
	index_pauv	-.1059604	.061013	-1.74	0.082	-.2255436 .0136229
	fdr_moy_DISTRICT	.016673	.0098478	1.69	0.090	-.0026284 .0359743
	fdr_vois_moy_DISTRICT	-.0114784	.0113684	-1.01	0.313	-.03376 .0108031
	WCP	.0112238	.0029317	3.83	0.000	.0054777 .0169698
	c.fdr_moy_DISTRICT#c.index_pauv	-.0298243	.0198899	-1.50	0.134	-.0688078 .0091593
	c.fdr_vois_moy_DISTRICT#c.index_pauv	.0339664	.0217572	1.56	0.118	-.008677 .0766098
	c.WCP#c.index_pauv	-.0073625	.0051512	-1.43	0.153	-.0174587 .0027336
	_cons	.0953864	.033382	2.86	0.004	.0299588 .160814
	/athrho	.4492679	.1184029	3.79	0.000	.2172024 .6813334
	/lnsigma	-1.516662	.0740309	-20.49	0.000	-1.66176 -1.371564
	rho	.4212971	.0973875			.21385 .5923856
	sigma	.2194431	.0162456			.1898046 .2537097
Instrumented: CO3						
Instruments: c.CO3#c.index_pauv index_pauv fdr_moy_DISTRICT fdr_vois_moy_DISTRICT WCP						
c.fdr_moy_DISTRICT#c.index_pauv c.fdr_vois_moy_DISTRICT#c.index_pauv						
c.WCP#c.index_pauv						
Wald test of exogeneity (/athrho = 0): chi2(1) = 14.40 Prob > chi2 = 0.0001						

Annex 9: ASSESSMENT TABLE OF THE IVPROBIT MODEL (2 INSTRUMENTS)

Model	Endog(p)	First(p)	Haus(p)	CO	Sig(p)	Wald	Wald(p)	AIC	ROC	Tl err	Id Uncon	C/-	N	N Clus
base_CO1	0.169	0.781	0.104	-4.158	0.030	4.7	0.030	801	51.7	0.0	100.0	57.4	1669	90
base_CO2	0.000	0.219	0.000	-2.915	0.000	31.8	0.000	1814	59.1	37.4	62.6	57.5	1669	90
base_CO3	0.000	0.005	0.000	-2.708	0.000	47.1	0.000	1956	64.0	25.5	74.5	52.6	1669	90
base_CO4	0.000	0.000	0.000	-4.530	0.000	45.8	0.000	969	65.4	18.0	82.0	53.5	1669	90
ctr_CO1	0.490	0.364	0.724	-1.768	0.455	128.0	0.000	451	78.0	1.1	98.9	48.5	1669	90
ctr_CO2	0.012	0.373	0.026	-2.161	0.000	150.3	0.000	1516	76.6	3.0	97.0	47.6	1669	90
ctr_CO3	0.001	0.006	0.001	-2.154	0.000	171.0	0.000	1654	77.1	13.6	86.4	45.8	1669	90
ctr_CO4	0.000	0.000	0.000	-3.976	0.000	170.4	0.000	658	74.9	14.6	85.4	48.1	1669	90
icO1	0.282	0.608	1.000	-4.639	0.102	239.9	0.000	-300	76.5	1.4	98.6	48.6	1669	90
icO2	0.004	0.291	0.887	-2.944	0.000	281.9	0.000	1203	75.8	14.2	85.8	45.7	1669	90
icO3	0.001	0.006	0.017	-2.573	0.000	250.6	0.000	1467	76.8	14.1	85.9	45.2	1669	90
icO4	0.000	0.001	0.123	-4.033	0.000	174.8	0.000	586	74.8	16.2	83.8	47.2	1669	90
dCO1	0.400	0.460	1.000	-3.570	0.212	243.5	0.000	-313	77.8	1.8	98.2	48.8	1669	90
dCO2	0.002	0.191	0.232	-2.862	0.000	289.1	0.000	1153	76.9	12.4	87.6	45.3	1669	90
dCO3	0.001	0.000	0.089	-3.637	0.000	239.5	0.000	318	77.7	15.2	84.8	45.3	1669	90

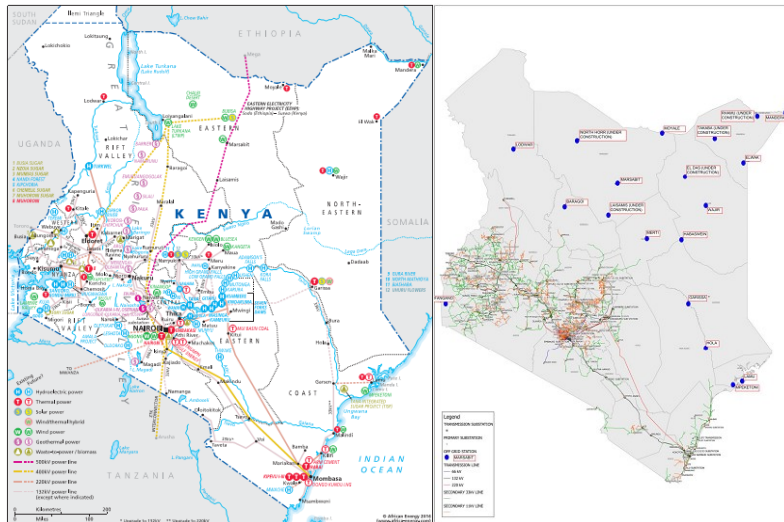
Annex 10: ADDITIONNAL CONTROL BY THE SHELTER'S TYPE

	(1)	(2)
Outages	-0.673*** (0.102)	-0.620*** (0.096)
Poverty index	-0.516*** (0.081)	-0.433*** (0.072)
Non-traditional / formal house		0.000 (.)
Traditional house / hut		-0.113* (0.045)
Temporary structure / shack		-0.023 (0.073)
Flat in a block of flats		0.240** (0.073)
Single room in a larger dwelling structure or backyard		0.108* (0.049)
N	1669	1668

Probability of positive outcome (connection)
 Average marginal effects SE in parentheses.
 ivprobit at district level with 2 instruments
 (lightning, weighted closest plant)
 Variance : Robust cluster

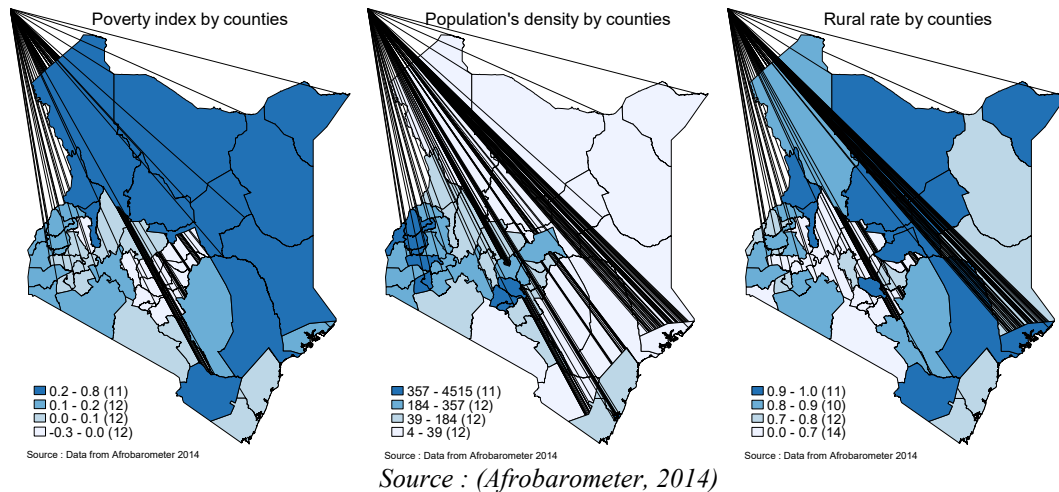
* p<0.05, ** p<0.01, *** p<0.001

Annex 11: KENYA'S ELECTRICAL GRID



*Left : generators and transmission lines (>132 Kv) Right : distribution lines
 Source : (Parsons Brinckerhoff, 2013)*

Annex 12: ADDITIONNAL MAPS ON KENYA



Source : (Afrobarometer, 2014)

Annex 13 : STATISTICAL TESTS USED IN THE ASSESMENT TABLES

The first criterion seeks for the lowest Stock-Yogo threshold answering to the question: are the instruments enough correlated with the outages? Any threshold below a 30% proportion of Wald rejection will be considered as eligible. This test gives only a global clue on the robustness of the instruments since it's designed for the i.i.d assumption (Stock and Yogo, 2005), (Baum and Schaffer, 2007) that is not met here. However, it performs sufficiently in practice to be set as a primary objective.

The second criterion focuses on the first-stage's F: are the instruments enough correlated with the outages? Since the i.i.d assumption is not met, this test complements the previous one. Introducing more than one instrument weakens the F of each excluded variable due to the risk of over-identification. (Staiger and Stock, 1997) suggests a 10 value for one instrument. However, an F lower than 10 does not mean per-se a weaker correlation between the instruments and the explanatory variable, unless it remains strongly significant and above a converging threshold. Using a Monte-Carlo simulation (Staiger and Stock, 1997) have tabulated the bias between the asymptotic value of an estimate and its finite distance estimation for the 2SLS method : it converges more or less the same for an F-value of 10 with one instrument than a F-value of 5 with four instruments, and might be even less.¹³ Thus, with three instruments, the usual assessment threshold can be relaxed to 6, still keeping the objective of a p-value below 1%.

The third criterion is the Anderson-Rubin test (p-value < 1%): are the estimates of outages significant even with weak instruments? It tests the significance of the instrumented estimates, being robust to the presence of weak instruments. Therefore, it doesn't tell whether the instruments are weak but enhance the confidence in the estimates, even if the instruments were to be weak. It's the reason why it comes only in third position in the backward-decision chain, since, if the two first tests will pass successfully, this last should add only a second-order additional check.

The fourth criterion is the endogeneity test (p-value < 5%): were the instrumented outages endogenous? This test is based on the chi2 statistic of the Wooldridge's robust test score. It checks ex-post whether the endogeneity assumption made on outages (and eventually their interaction with poverty) was relevant. If this test fails, the assessed level of severity is not the appropriate indicator to capture the impact of outages on connections.

The fifth criterion is the under-identification test (p-value < 5%): is the equation identified? With clusters, the under-identification test is based on the Kleibergen-Paap rank statistic and its chi2 distribution. It checks only whether the instruments are statistically relevant, ie. correlated with the instrumented variable. However, it is not enough to avoid the bias issue related with weak instrument (Baum and Schaffer, 2007), hence the priority set on the strength of instruments in the decision chain. In fifth position, the under-identification test shall always pass, and is only a second-order check.

The sixth criterion is the over-identification Hansen test (p-value > 10%): in case of multiple instruments, is the model of outages over-identified? It is based on the Hansen J statistic due to the presence of clusters and is robust to this heteroscedasticity assumption. Under the null hypothesis, the statistic $J=0$ and the instruments are jointly uncorrelated with the error term. The null shall thus not be rejected, meaning that the p-value should be the highest as possible. As a joint test, it is useful to check whether the set of instruments is not too large; in the adverse case, their hyperplan would still be correlated with the projection of connections on outages, what would be the opposite of the objective sought by the instrumentation. In penultimate position in the decision chain, the Hansen test has been used for technical monitoring when building the different attempts of modelling, especially when upgrading from one to three instruments.

The seventh criterion is the Hausman test (p-value < 5%): does the instrumentation brings something new compared to a simple OLS? It checks whether the IV estimates are significantly different from the OLS estimates. If the test fails, the instrumentation was ex-post unnecessary. However, it's designed for the i.i.d assumption and is thus denied by Stata in the presence of clusters. The `-force-` option allows to compute it anyway, but since the underlying assumption is violated, the test has been put in the last

¹³ See (Staiger and Stock, 1997), Table 1, page 574, design I, for different setting of external asymptotic parametrization

position of the decision chain. It's used only as an additional information to get a final flavor on the model.

Annex 14 : INITIAL SETTINGS OF THE MARGINS ANALYSIS

In a Probit model, the coefficients measure the change in the Z-score for a one unit change in the predictor, not directly in the estimated probability. Since the model is non-linear, its coefficients are not equal to the partial derivative of the dependent variable, as they are in the LPM. However, Stata provides a powerful analytic feature –*margins*– that allows to compute directly the marginal effect of each predictor on the dependent variable, also taking into account their interaction. Annex Table (1) reminds the average values of the variables in sample that are the reference for the margins, once computed at mean of other variables.

Annex table 1: UNIVARIATE STATISTICS FOR IN-SAMPLE VARIABLES

Variable	Mean	Std. Dev.	Min	Max
branché	.5739964	.4946424	0	1
CO3	.270779	.2795633	0	1
c.CO3#				
c.index_pauv	.0155198	.1119589	-.3526142	.9088469
index_pauv	-.0369804	.3185508	-.8550291	.9900095
fdr_moy_DI~T	9.660998	10.76493	.6178835	43.33413
WCP	9.167813	7.884704	.2562871	47.61148
c.				
fdr_moy_DI~T#				
c.index_pauv	.3073157	3.994223	-28.21505	28.73648
c.WCP#				
c.index_pauv	.4566901	3.985065	-23.96432	37.37938

Std. Dev. not adjusted for clustering

As an initial check, the global prediction (57.3% in Annex Table (2)) equals the average proportion of connected household in the estimation sample (Annex table (1)). Adjusting for the means of the predictors in the sample yields a very close estimate (56.6%), thus the margins analysis is based on the deviation from this referral prediction.

Annex table 2: PREDICTED PROBABILITY TO BE CONNECTED TO THE GRID

VARIABLES	(1) Adjusted Average Prediction	(2) Adjusted Prediction at Means
Constant	0.573*** (0.0236)	0.566*** (0.0345)
Observations	1,669	1,669

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Acronyms:

AAP (Adjusted Average Prediction): prediction, adjusted for the interaction term

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

AME (Average Marginal Effect): marginal effects with the observed values of the sample

ME (Marginal Effect): marginal effect at different referral level of outages and poverty (at means, median on decile).

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