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Article

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Ingredients for growth: Examining electricity consumption and complementary infrastructure for Small and Medium Enterprises in Kenya

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ABSTRACT

In Kenya, between 2010 and 2015, the number of Small and Medium Enterprises (SMEs) connected to the grid increased by over 60%. Despite this substantial increase, little is known about the behavioural patterns or conditions that contribute to increased electricity consumption among these SMEs. This study addresses the problem through a longitudinal analysis of monthly electricity bills for over 179,000 grid connected SMEs in Kenya. We then leverage multiple publicly available geospatial datasets to estimate how complementary infrastructural variables (such as access to roads, markets, financial services, and macro/micro-economic conditions) correlate with sustained electricity consumption growth by SMEs. Results from our longitudinal analysis indicate that newly electrified SMEs in urban areas have higher median consumption than their older counterparts while in rural areas, more newly connected SMEs appear to have lower median consumption. We find the effects of complementary infrastructure on SME electricity consumption to be more pronounced in rural areas than urban areas. For example, SMEs located in rural neighbourhoods with close proximity to roads, markets or financial service providers are associated with a 10% to 16% increase in electricity consumption while in urban areas, we only observe about a 2% increment in electricity consumption for SMEs within close proximity to roads. All other infrastructural variables are either statistically insignificant or negatively correlated with urban SME electricity consumption.

1. Introduction

The role of Small and Medium Enterprises (SMEs) in enhancing economic development is widely acknowledged by many economists. In sub-Saharan Africa (SSA), SMEs make up more than 90% of all businesses, contribute over 30%–70% of economic activity, and are responsible for 50%–80% of all non-farm employment (Abor and Quartey, 2010; CDC-Ghana, 2012; KNBS, 2016; Berry et al., 2002).

Despite this out-sized influence, the SME sector continues to face a number of infrastructural and regulatory problems. For example, in their report on obstacles to SME growth in SSA, Fjose et al. (2010) singled out two indicators of the World Bank Doing Business (DB)¹ index, namely; access to electricity and finance. Using World Bank Enterprise survey data, they found that electricity was considered the most important infrastructural issue by close to 25% of surveyed businesses, while access to finance was ranked as the second most important impediment by about 18% of the businesses. Likewise, similar studies in South Africa and Kenya concluded that infrastructural factors such

as access to finance, markets, business training as well as poor roads were some of the tightest bottle necks to SME growth (Rogerson, 1997; KNBS, 2016). Thus, to stimulate entrepreneurship, many SSA governments have embarked on large scale grid extension projects with a special emphasis on SME electricity access.

Despite this effort, numerous studies have consistently demonstrated that electrification, while necessary, is not in itself sufficient to trigger SME growth (Peters et al., 2009; Kirubi et al., 2009; de Leon Barido et al., 2017). In fact, these studies have shown that grid extension should always follow (or be followed by) complementary infrastructure or services that augment and support uptake/usage of electricity. Such infrastructure largely comprise of Business Development Services (BDS) and micro-finance services (Peters et al., 2009), infrastructural services such as telecommunications networks, markets, roads, and facilities for social amenities (schools, polytechnics and hospitals) (Kirubi et al., 2009).

In this paper, we perform a large-scale analysis of grid connected SMEs in Kenya with the end goal of understanding how various types

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¹ Doing Business is a World Bank project that ranks countries according to regulatory and infrastructural barriers faced by businesses within that country. Economies are ranked on their ease of doing business, from 1–190.

of complementary infrastructure influences electricity consumption among small businesses. To do this, we rely on large scale electricity consumption data as well as multiple publicly available survey and remotely sensed data.

2. Background and research problem

2.1. Country context

Following a period of un-bundling and deregulation led by the Government of Kenya (GoK) and World Bank in the late 90's, the Kenya Power and Lighting Company (KPLC or Kenya Power) was left as the national electric utility charged with dispatch and distribution of electricity in Kenya (KPLC, 2020; Taneja, 2018). As part of the deregulation reforms, Kenya Power was also partially privatized with 49.9% of shares listed on the Nairobi Stock Exchange while 50.1% of shares remained in the hands of the GoK (Taneja, 2018).

Today (as of the end of June 2020), Kenya Power has grown to include more than 7.5 million customers translating to an electrification rate of more than 73% (KPLC, 2020). These grid-connected customers are categorized into 3 major groups: Residential, Small Commercial, and Large Commercial/Industrial customers. For our analysis, we focus on Kenya Power's Small Commercial (SC) customers who mainly consist of small businesses that range from services-based SMEs such as retail shops, restaurants, schools, health centres, to manufacturing-based SMEs such as foods/beverage packing firms and milling plants.

According to the 2016 Kenya National Bureau of Statistics (KNBS) Micro Small and Medium Establishments survey (KNBS, 2016), of the total 1.56 million enterprises in Kenya, wholesale and retail trade was the largest sector with 57.1% of all licenced SMEs, followed by Manufacturing and Accommodation service sectors with 11.2% and 8.8% respectively. With regards to gross value added however, manufacturing had the highest share at 24.3% followed by wholesale & retail trade at 22.8%. The survey also noted that the percentage of businesses with an electricity connection increased from 33% to 88.9% since the last 1999 survey. For our study, we only use data on formal sector SMEs that are recorded in the Kenya Power data base as Small Commercial (SC) electricity consumers.

2.2. Related work

In SSA, it is important for electric-utilities to understand how rural electrification affects SMEs. This is because targeting electrification towards income generating activities has a potential of raising the demand for electricity and hence support cost recovery efforts of electrifying agencies (Cook, 2011). Indeed, studies in Kenya and India have found evidence of growth in rural SME creation and earnings as a result of rural electrification (Kirubi et al., 2009; Rao, 2013), while in South Africa, (Dinkelman, 2011) observed that the rise in non-farm employment and female participation in the labour force (by releasing women from home production) in some rural areas could be tied to increased rural electrification.

Despite this, extending the grid to previously unelectrified areas does not always mean that businesses will adopt the use of electricity. This rate of adoption/uptake often depends on a variety of pre-existing conditions. For example, in a survey of 650 SMEs in Muranga county (Kenya), (Kariuki, 2014) found that distance to markets and amount of capital invested had the highest effect on the probability of electricity adoption by businesses. Similar, assessments of rural electrification efforts in Rwanda, India and Uganda, observed that any shift in firm investments towards electricity reliant equipment either occurred in flour milling businesses, or in locations that already had a thriving business centre prior to electrification (Lenz et al., 2017; Kooijman-van Dijk, 2012; Neelsen and Peters, 2011). The implication of this being that businesses are more likely to benefit from electrification efforts if they are within close proximity to roads or markets.

Furthermore, for rural electrification to have a meaningful impact, electricity adoption should lead to some productivity gains among SMEs in the community. However, very often in developing countries, most SMEs are subsistence in nature with very little use/need for electricity (de Leon Barido et al., 2017; IFC, 2009; Kooijman-van Dijk, 2012). This is illustrated by previous field studies in rural South Africa and Benin (Matinga and Annegarn, 2013; Peters et al., 2009, 2010) in which the authors observed that much as newly-acquired electricity increased working hours (and by extension profits) for many local shops and bars, there was not any growth in newer, more sophisticated businesses that use power tools. In fact, for most of the businesses, electricity was simply used for lighting.

From the interviews carried out in the 3 studies, two factors were identified as the source of this low uptake in electricity: lack of access to credit facilities as well as lack of knowledge on how to apply these machines. The authors observed that very often firms decide to get connected without having properly developed a business plan for investment in the connection of electric equipment or simply for reasons of convenience related to lighting and radio usage. Like Barnes (2005), they concluded that complementary services such as sensitization, entrepreneurship training, and loan schemes should be carried out by the electrifying agency to support SME formation. This was reaffirmed by Kirubi et al. (2009) who stressed the importance of linking the electrification benefits accrued by SMEs in Mpeketoni town (Kenya) to the existence of other types of infrastructural development, including business support services.

While shining critical light on SME development as a result of electrification, all these studies are either limited in sample size (and as such are difficult to generalize over the whole country), or do not explicitly measure the role that complementary infrastructure plays. Our work aims to fill this gap by leveraging large scale data on monthly SME electricity use, as well as multiple publicly-available remotely sensed datasets to understand the important link between sustained electricity consumption in SMEs and existence of complementary infrastructure.

2.3. Research questions

In this paper, we use a unique, national scale dataset on monthly electricity bills from small commercial electricity customers in Kenya covering the period from 2010 to 2015 to address two core research questions. First, we perform a descriptive analysis of how electricity consumption evolves over time among Kenya's grid connected SMEs, segmenting by connection year and splitting SMEs into rural and urban settings, providing a complementary analysis to Fobi et al. (2018).

Second, we investigate how complementary infrastructure influences electricity consumption and consumption growth for grid connected SMEs in Kenya. Our hypothesis is that SMEs' ability to grow their electricity consumption depends on the availability of complementary services and infrastructure that unlock productive use of power. For example, SMEs may be unable to harness electricity to grow their businesses without access to financial services to access capital and tarmacked roads to access external markets. Another hypothesis is that local population density, electrification rates and economic activity are important to establishing local markets for SMEs. We combine the electricity billing dataset with temporally and spatially resolved datasets on financial service providers (FSPs), road networks, night lights, population, building structures, and electrification rates to study how these factors individually and jointly affect electricity consumption for SMEs in Kenya.

This work has important implications for utilities as well as off-grid electricity providers that often struggle with low consumption from rural customers. Low consumption threatens the sustainability of rural electrification programs. Measuring consumption growth patterns is critical for utilities to plan electricity infrastructure development that supports economic growth in a cost effective manner. Furthermore, by understanding how other infrastructure and services interact to influence electricity use in SMEs, planners and policymakers can ensure that an enabling environment is in place for businesses to fully benefit from electricity access.

Table 1
Summary table of the different data sources and corresponding feature types we extract for use during our analysis.

Data source	Feature types	Year
Kenya Power	SME monthly electricity use (kWh)	2010–2015
Kenya National Electrification Plan - Structures Survey	Number of buildings within 0.5 km of SME	2014
Worldpop (WorldPop, 2020)	Population within 0.5 km of SME	2000–2015
World Bank (WBG, 2017)	Shortest distance to road (km)	2015
Earth Observation Group (Elvidge et al., 2021)	Nighttime illumination	2012–2015
Financial Sector Deepening Trust (FSD)-Kenya (FSD-Kenya, 2015)	Number of financial service providers within 0.5km of SME	2010–2015
Kenya National Bureau of Statistics (KNBS, 2019)	Quarterly County-level GDP per capita (USD)	2013–2015

3. Data and methods

3.1. Description of the data

During our analysis, we relied on a number of publicly available datasets as well as proprietary data provided by Kenya Power. The Kenya Power data includes locations and date of connection for about 3.9 million of Kenya Power's estimated 5 million residential customers as of December 2015, monthly bills (from 2010 to 2015) and locations for over 60% of all grid-connected SMEs, locations and date of commissioning for all Kenya Power's distribution transformers to help estimate locations of missing customers, and finally locations for over 12 million buildings/structures throughout Kenya obtained from human-labelled satellite images used in the development of Kenya's National Electrification Master Plan.

The SME electricity consumption data, which forms the crux of our analysis, contains monthly records for 281,972 customers. After filtering out customers with missing metadata such as GPS locations and dates of connection, we were left with 179,839 customers, approximately 60% of all available SME customers as of the end of 2015.

In addition to the electricity consumption and buildings/structures' location data from Kenya Power, we use publicly-available data on the spatial location of all financial service providers in Kenya as of December 2019 (FSD-Kenya, 2015), all tarmacked roads in Kenya as of 2017 (WBG, 2017), gridded population density data from WorldPop at 100 m spatial resolution (WorldPop, 2020), quarterly county GDP values between 2013–2015 (KNBS, 2019), and lastly, monthly nighttime lights data from the Earth Observation Group. This data consists of nighttime illumination values taken by the VIIRS satellite over Kenya at a spatial resolution of approximately 450 m (Elvidge et al., 2021). A summary of the data and feature types used in this study is shown in Table 1

3.2. Methodology

In order to understand the drivers of electricity consumption among SMEs in Kenya, similar to Fobi et al. (2018), we dis-aggregated the data spatially by their rural–urban location and temporally by the duration since acquiring an electricity connection. We then created a fixed-radius buffer around each SME in order to extract features that were then used in both bivariate and multivariate analyses to provide insight into the determinants of electricity consumption growth among SMEs in Kenya.

3.2.1. Spatial–temporal segmentation

Based on their geographic location, SMEs were segmented into 3 main categories: Urban, Peri-urban, and Rural. The method used follows Fobi et al. (2018) and employs a constrained K-means clustering approach that relies upon high-resolution data on population density, land use classification, and satellite nighttime light intensity.² Using this method, Fobi et al. (2018) developed a Kenya raster file with pixels

² A more detailed description of the method can be found Appendix A of Fobi et al. (2018).

Table 2

This figure shows SME classifications according to urbanization level of our SMEs' location. This segmentation is based on data as of the year 2010, which is the beginning of our study period. The unclassified customers were found to be located on islands in the Indian Ocean as well as Lake Nakuru.

	No. of customers	Percentage (%)
Rural	107952	59.02
Peri-Urban	57243	31.30
Urban	17553	9.60
N/A	146	0.08

clustered into the 3 main categories (Urban, Peri-Urban and Rural). It is this raster file that we use to segment our list of SMEs. Table 2 shows the clustering results from our use of this model and their respective percentage split. 146 customers appear to be unclassified and this is because they were located in uninhabited areas such as Mount Kenya, islands in the Indian Ocean, Lake Nakuru, and others. For the purposes of our analysis, it was decided to consider these as Rural consumers.

Fig. 1 shows the geographic distribution of our SME consumers on a map of Kenya. Customers classified as urban are mainly in the core areas of Nairobi and Mombasa, the two largest cities in Kenya. A few urban areas can be seen in the smaller cities of Kisumu and Nakuru as well. The peri-urban regions generally envelop the urban areas, although other peri-urban areas occur in small towns without “Urban” centres. We decided to combine urban and peri-urban locations since the urban area sample was very small, similar to previous work on residential electricity consumption (Fobi et al., 2018). Hereafter, throughout this paper urban refers to both peri-urban and urban SMEs.

In addition to the spatial segmentation, the study dataset was decomposed by calendar date as well as by duration since acquiring an electricity connection. For the former, billing dates were used to aggregate consumption by calendar month while for the latter, the number of months since an SME got their electricity connection was used. Most of our analysis uses this latter characterization which aims at providing insight into growth of consumption by the duration of SMEs' experience with access to electricity.

3.2.2. Creating fixed-radius buffer and estimation of features

To extract features that influence electricity consumption growth among small businesses, we started by creating a fixed-radius buffer area around each SME. This was premised on the assumption that, unlike large industrial businesses who serve wider areas of Kenya (including exports), SMEs mainly serve customers who are within a neighbouring locale. This fixed radius area is then used as an “economic zone” within which most of the business' operations take place. Our first task therefore was coming up with a reasonable distance for the buffer radius around each SME. To do this, we looked at various studies that sought to understand retail sales while using some measure of geographic proximity of customers and businesses.

The studies employed different metrics to define geographic proximity, ranging from 5 miles to living within the same city as the business (Goolsbee and Klenow, 2002; Bell and Song, 2007; Manchanda et al., 2008; Janakiraman and Niraj, 2011). The most interesting of these however was a more recent National Consumer Survey which found that over 80% of all discretionary spending by households in

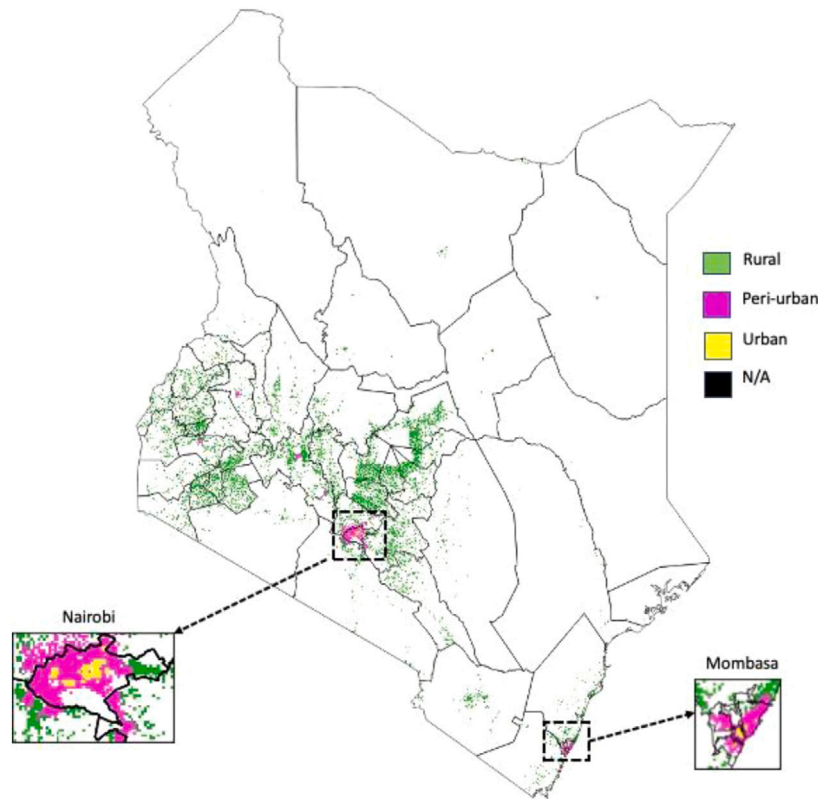


Fig. 1. Shows the segmentation of our SME customers by level of urbanization overlaid on the Kenya map. It can be seen that most of the urban and peri-urban SMEs are located in the higher income Nairobi and Mombasa counties.

the USA was within 20 miles and that over 92% of respondents in the study travelled between 6 to 20 min for purchases (depending on rural-urban location and frequency of shopping) (NCS, 2017). This suggests that, SMEs typically have most of their customers within 6 (at most 20) minutes walking/driving distance (depending on the most prevalent mode of transport in the area³).

Based on this, as well as the authors’ personal experiences, we came up with two key assumptions regarding an appropriate buffer zone radius:

- An effective “economic buffer zone” radius in Kenya means about 5 to 30 min of walking. This implies an estimated distance of 0.5 km to 2 km.
- To keep our model parsimonious, we use the same radius for both rural and urban SMEs.

We initially chose 3 distances as our buffer radii: 0.5 km, 1.5 km, and 2 km. On running tests however, like (Janakiraman and Niraj, 2011), we found very little difference in the output and therefore we only present results for the 0.5 km fixed-radius buffer in this paper. Fig. 2 shows an illustration of this approach for a single SME customer located in an urban area of central Kenya.

Having established a buffer area for each SME, we then are able to extract relevant features such as, the number of buildings within the buffer-zone, population density, average monthly nighttime lights, electrification rate of surrounding buildings, distance to the nearest road and number of financial service providers within the buffer zone. The distribution of each of these features is shown in Fig. 3 and descriptions for each feature are shown below.



Fig. 2. Satellite image showing a typical urban SME and corresponding buffer zone in Laikipia County-Kenya. We create similar buffer zones for every SME with a goal of extracting important features that influence SME electricity consumption growth.

Structure count and population density. The population density and number of neighbouring structures within vicinity of an SME may potentially have impact on its electricity consumption growth. We therefore use the structures and population datasets to determine how many buildings and people are located within 0.5 km of each SME. Both these features are used as proxies for a firm’s access to markets for its goods and services. Fig. 3B&A shows distributions of structure counts and population density within each SME’s buffer zone. We see that as expected, businesses in urban areas have far more structures and people within 0.5 km compared to their counterparts in rural areas. Our

³ 89% of all adult commuting in urban Kenya is walking and “matatus” (privately-operated paratransit) (Deborah Salon, 2019).

initial hypothesis is that population density and/or structure density in the economic buffer zone is indicative of market size for each SME and therefore positively correlated with electricity consumption and growth. We test this hypothesis in both bi-variate and multi-variate settings by using simple line graphs as well as ordinary least squares (OLS) models respectively.

Neighbourhood electrification rate. The rate of household access to electricity services in a business' buffer zone is another potential factor that influences SME electricity consumption growth. Thus, using the structures' location data and the locations of Kenya Power residential customers, we determine the percentage of electrified structures within each SME's buffer region. We considered each residential connection as a single household with all residential connections who share a GPS location considered to be living in a multi-unit building. This number of grid-connected buildings in each SME buffer zone was then divided by the total number of buildings (in a corresponding SME buffer zone) hence providing an indication of neighbourhood electrification levels for each SME. Fig. 3F shows this for rural and urban SMEs by using a Cumulative Density Function (CDF). As expected, generally urban SMEs tend to have a higher percentage of electrified structures in their vicinity.

Access to financial service providers. Access to financial services is another factor that may affect small business activity and, consequently, electricity consumption growth. Therefore, we estimated an SME's access to financial services by using the number of Financial Service Providers (FSPs) within its 0.5 km radius. To do this, we used publicly available data (FSD-Kenya, 2015) on location and starting date of more than 100,000 FSPs in Kenya as of 2019. Our underlying hypothesis was that a business that is located in an area with several FSPs will have more options in terms of access to financial services such as loans, money transfer, insurance services and other financial products. While we recognize that measuring financial inclusion in SMEs would require more data on actual loans, accounts and balance sheets of the FSPs and SMEs themselves (Makina et al., 2015; Ganbold, 2008; Zajd, 2020), we use this as a proxy due to the unavailability of such detailed financial data. Fig. 3C shows this distribution for urban and rural SMEs.

Access to Roads. Based on our literature review, SME access to roads is vital for uptake of electricity services. Using World Bank data on road network in Kenya, we measure each SME's distance to the nearest major road. A distribution of the distance to the nearest major road for each SME is shown by the CDF in Fig. 3D. It can be seen that more than 80% of urban SMEs are within 5 km of a main road while this is true for only about 30% of rural SMEs.

Night lights and Quarterly County GDP. Changes in economic activity are another factor that potentially could affect electricity consumption growth among small businesses. To approximate this, we relied on two datasets: nighttime lights and GDP measurements by the government of Kenya. Building on previous work that has used nighttime lights to approximate national (Henderson et al., 2012; Chen and Nordhaus, 2011) and sub-national (Sutton et al., 2007; Goldblatt et al., 2017) economic activity, we used monthly nighttime illumination data as a proxy for the micro-level economic changes within a 0.5 km radius of each SME, and county GDP (KNBS, 2019) as measured by KNBS to indicate the macroeconomic changes experienced by each SME.

While nighttime lights is a useful tool to understand changes in economic activity, we note however that it suffers from a number of limitations as outlined in the literature. For starters, the VIIRS data exhibit noise in the form of negative light values for some months. Also, we notice some pixels indicating lights even when they are in remote uninhabited locations such as lakes, game reserves etc. To correct for these issues, we converted the negative light values to zero and used an error correction method described in Appendix C to solve the later. Another limitation of nighttime lights for measuring economic activity is that they tend to perform better in more developed countries

Table 3

This figure shows the distribution of our regression data sample based on urban or rural location.

	Number of SMEs	Percentage
Rural	23,601	59%
Urban	16,401	41%

than in low-income countries (Hu and Yao, 2019). In addition to this, nighttime lights are much better at estimating spatial variations in economic activity than temporal ones (Goldblatt et al., 2017; Chen and Nordhaus, 2011) - yet for our particular study, we are interested in both. Despite these challenges, we believe there are very few datasets able to capture changes in micro-economic activity at the scale and granularity required for this study better than the VIIRS nighttime lights data.

3.2.3. Segmenting based on complementary infrastructure

To zoom in further and identify which features influence electricity consumption the most, we segmented the SMEs according to how the mean values for each feature compare with thresholds set in Fig. 3. For instance, based on the distance to a road variable, we split SMEs into "High" or "Low" categories — that is, those with "High" access to roads and those with "Low" access to roads. From Fig. 3D, we see that in urban areas, SMEs that are less than 0.8 km from a road are considered in the "High" category while the rest are in the "Low" category. Similarly in rural areas the threshold is around 8 km. This coding mechanism enables us to create dummy variables for all the other features as well — with an end goal of estimating differences in electricity consumption levels between High–Low categories.

3.2.4. Panel-data Regression

We utilized panel regression analysis to evaluate relationships between complementary infrastructure and electricity use in multivariate settings. This is because when data has both time and cross-section dimensions (as is the case with this dataset), panel data techniques offer the best method of analysis as they allow for the exploitation of both cross-sectional and temporal dimensions to eliminate unobserved heterogeneity in the data (Baltagi, 2008; Idahosa et al., 2017).

Before running the regressions however, we randomly selected a sample from the dataset because carrying out panel data regression on the complete data proved computationally intractable (there were more than 6 million data points). To do this, we used a stratified random sampling method in which we segmented the population by urban–rural location and year of connection to the grid. We then randomly selected a total of 40,002 SC customers on which to run the regression. We also, randomly chose 3 samples on which we ran regression analysis as a robustness check. The results are reported in Appendix E. Table 3 shows a breakdown of the sample by rural–urban locations.

The formulation for our model is given by Eq. (1) below. We went with a log linear model and chose the time variable as the number of months since an SME received a connection (rather than calendar month) because our main aim was to capture how SMEs' electricity consumption matures with each additional month that they are connected to the grid rather than seasonal patterns captured by calendar months.

$$\ln(kWh_{it}) = \beta_0 \ln(ppn_{it}) + \beta_1 \ln(str_i) + \beta_2 \ln(fsp_{it}) + \beta_3 \ln(rd_i) + \beta_4 \ln(NL_{it}) + \beta_5 \ln(GDP_{it}) + \beta_6 \ln(El_{it}) + \gamma_i + \epsilon_{it} \quad (1)$$

Where;

i = individual SME

t = Month after connection

kWh = electricity demand by SME i in month t after connection

ppn = population density

str = structure density within 0.5 km radius of each SME

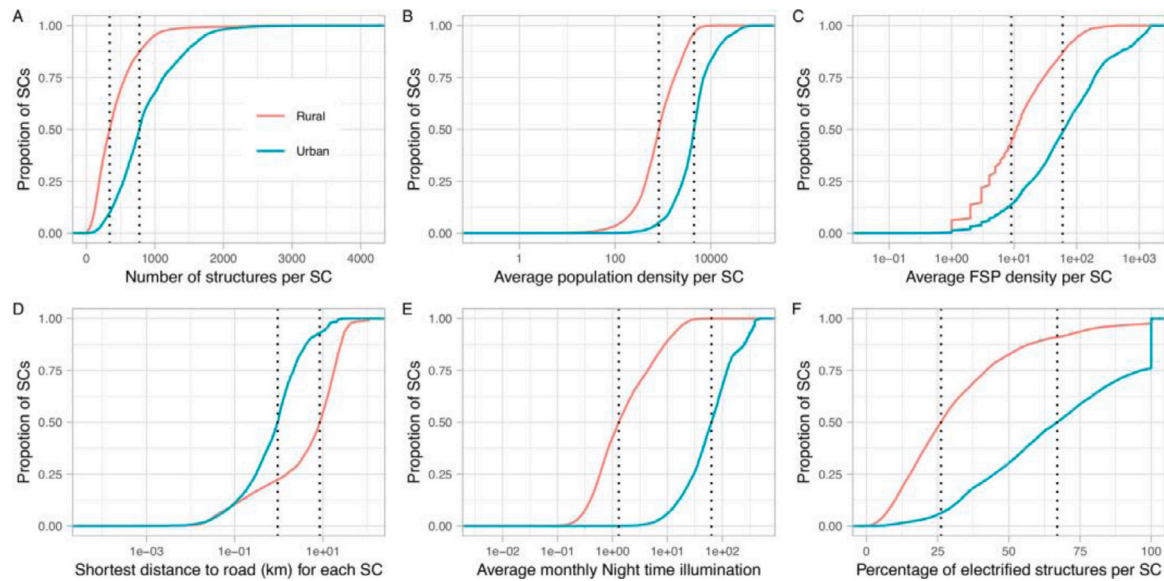


Fig. 3. Cumulative Density graphs showing distributions for different infrastructural features in both rural and urban SMEs. Horizontal dashed lines indicate thresholds at the 50th percentile for either rural or urban distributions. These thresholds are used to segment the rural or urban SMEs as either “High” or “Low”. We then analyse and compare consumption across segments.

rd = distance to nearest road of each SME

NL = average Nighttime lights for each month

GDP = Quarterly GDP as measured by KNBS

Ele = Percentage of electrified structures within 0.5 km of each SME

γ = Individual time invariant fixed effect

ϵ = error

β = regression constants

Using the `plm` library in R, we attempted a number of panel data regression methods to determine the model best suited for our case. First, we ran a Breusch–Pagan Lagrange Multiplier test on the pooled OLS model of the dataset to determine the existence of individual and/or time effects. As expected, the results showed existence of panel effects hence eliminating the need for a pooled OLS model and leading us to either a Fixed Effects (FE) or Random effects (RE) model. Next, we ran a Hausman test to help us choose between a random effects model and fixed effects model. The Hausman test (also commonly referred to as the Durbin–Wu–Hausman test) is a statistical test commonly used in panel data analysis to help choose between FE and RE models (Baltagi, 2008; Wooldridge, 2010). The test determines if there is correlation between idiosyncratic errors and regressors in the model. The null hypothesis is that there is no correlation between the two. Our test resulted in a rejection of the null hypothesis indicating that a FE model was better suited for our data. However, a major drawback of FE models is their inability to estimate the within-effects of time-invariant variables. Because of this, it has been suggested by numerous authors to use RE models (Allison, 2009; Wooldridge, 2010; Schunck, 2013). Despite their usefulness, we felt that RE models given our data and research problem would suffer from heterogeneity bias owing to their implicit exogeneity assumption. To overcome this problem, we opted for the approach suggested by Mundlak (1978) that involves adding cluster means of the time-varying variables to our regression equation. Referred to as the correlated random effects (CRE) method by some econometricians (Wooldridge, 2019), this method has the advantage of being able to control for unobserved heterogeneity in the same way as the FE model while also handling time-invariant variables. For our analysis, we used the CRE implementation in the `plm` library.

Finally, to overcome problems caused by heteroskedasticity and serial correlation in the error terms, we used the Newey–West Heteroskedasticity and Auto-correlation Consistent (HAC) estimator in the

`plm` library to estimate robust standard errors (Newey and West, 1987; Zeileis, 2004; Millo, 2014).

4. Results and discussion

4.1. Descriptive analysis of consumption patterns

4.1.1. Median monthly consumption

In order to get a macro-level view of SME monthly consumption as seen from the utility’s perspective, we start by inspecting median kWh use for each calendar month (between 2010–2015). This shows monthly behaviour of a typical grid connected SME as viewed by KPLC. Fig. 4 shows the monthly consumption for the median customer (solid line) and the inter-quartile range (light blue region) during our study period. We chose the median over mean as our measure of central tendency because monthly bills are distributed in such a way that there is a strong skew towards larger customers and as such, using the mean would bias the result upwards. Also, one should note that for each month, this representative customer is not necessarily the same customer.

Based on Fig. 4, we see that median monthly electricity consumption for KPLC’s SME customers is relatively flat over the study period. The same is true for the inter-quartile range.

4.1.2. Electricity consumption growth with customer maturity

To further tease out more patterns in electricity consumption by SMEs, we decompose the data based on the number of months after each customer received an electricity connection and examine consumption growth over time. Using this approach, we start by graphing monthly electricity consumption against the number of months a customer has had an electricity connection. From Fig. 5, we can see that the median SME consumer’s electricity use increases sharply for the first few months after connection and then gradually tapers off to a slower growth rate. Because of how our input dataset is structured, a cohort of older customers who were connected before 2010 enter the graph at month 60, leading to a sudden increase at that point. However, as noted by Fobi et al. (2018), analysis of the entire cohort of customers may obscure more interesting patterns among different customer segments. We therefore break down consumers further by location and maturity of grid connection.

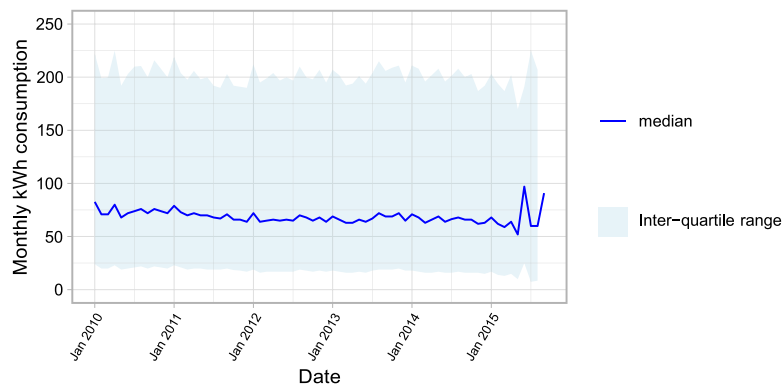


Fig. 4. Monthly electricity consumption of SME customers from Jan-2010 to Dec-2015. The solid line represents the monthly median customer's consumption while the light blue area represents the inter-quartile range of the study dataset.

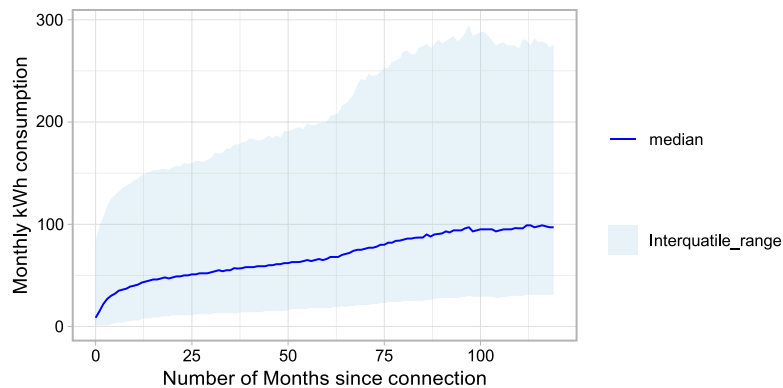


Fig. 5. Monthly SME customer electricity consumption by duration of customer's electricity connection. The solid line represents the monthly median customer consumption while the light blue area represents the interquartile range. Electricity consumption for the whole dataset initially increases sharply followed by continual, though diminishing, growth.

4.1.3. Influence of location on SME electricity consumption

Having seen in Fig. 5 how a typical SME's monthly electricity consumption grows over time, we now segment the SMEs based on their rural–urban location. Plotting the median monthly consumption of our rural–urban clusters against the number of months since connection shows that: (1) each group demonstrates the same characteristic pattern of fast initial growth followed by persistent though slowing growth and (2) as expected, urban SMEs generally have higher monthly consumption than their rural counterparts. This is displayed in Fig. 6.

4.1.4. Influence of year of connection on SME electricity consumption

Thus far, we have seen how the typical SME customer grows their monthly electricity consumption from the first month after receiving an electricity connection. This pattern of growth is consistent across all levels of urbanization and, while this in itself is telling, it does not account for customers who were connected in different years. For example, would newer customers consume less than older customers as was the case for domestic consumers in Fobi et al. (2018)? If the consumption levels are different, by how much would they be different? Would the same pattern in consumption growth be observed for customers connected in different years and if so, how would it compare across rural and urban SMEs? To answer these questions, we segment customers based on the year in which they received a connection. In order to ensure that we can compare consumption of customers with the same age of electricity connection, we consider only customers who received an electricity connection in 2009 or later.

Fig. 7 shows median consumption growth for rural and urban SMEs segmented by their year of connection respectively. From the two graphs, we make two observations. First, urban SMEs still have higher median monthly consumption than their rural counterparts regardless of their year of connection. For instance, rural SMEs have a peak of

less than 50 kWh while urban SMEs connected in 2009 (with the least consumption in the urban cluster) peak at about 70 kWh. Second, while rural SMEs generally follow the same pattern observed by Fobi et al. (2018) in residential grid connected customers,⁴ this is reversed when it comes to urban SMEs where more recently connected SMEs tend to have higher median consumption than their older counterparts. Reasons for the behaviour are many and varied. One reason could be organic grid extension that normally happens in urban places as opposed to rural grid extensions that are as a result of government electrification policy, or perhaps the economy was better in urban areas during the study period leading to growth in the size of urban businesses and their monthly kWh consumption as a result. Also, another competing hypothesis is that complementary infrastructure such as roads, markets and FSPs are more developed in urban areas, leading to expansion in businesses and electricity consumption (as laid out in the literature⁵).

In the next section, we test out some of these hypotheses by relying on both descriptive as well as regression-based statistical methods.

4.2. Which infrastructural variables are associated with SME electricity demand?

Following the results in Section 4.1.4, we sought to better understand reasons for the observed behaviour in both urban as well as rural SMEs and, in the process, answer the specific research question: *Which*

⁴ See Figure 7 from Fobi et al. (2018).

⁵ Most of the literature surveyed in Section 2.2 concluded that electricity was a necessary but not sufficient condition for growth. The impact of electrification on SMEs very often than not depended on existence of other complementary infrastructure.

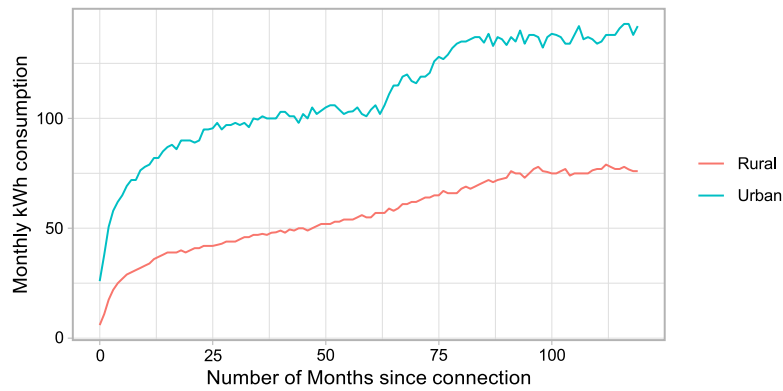


Fig. 6. Shows median electricity consumption growth for urban vs rural SMEs with each month after connection. We see that as expected, urban SMEs consistently use more electricity than their rural counterparts.

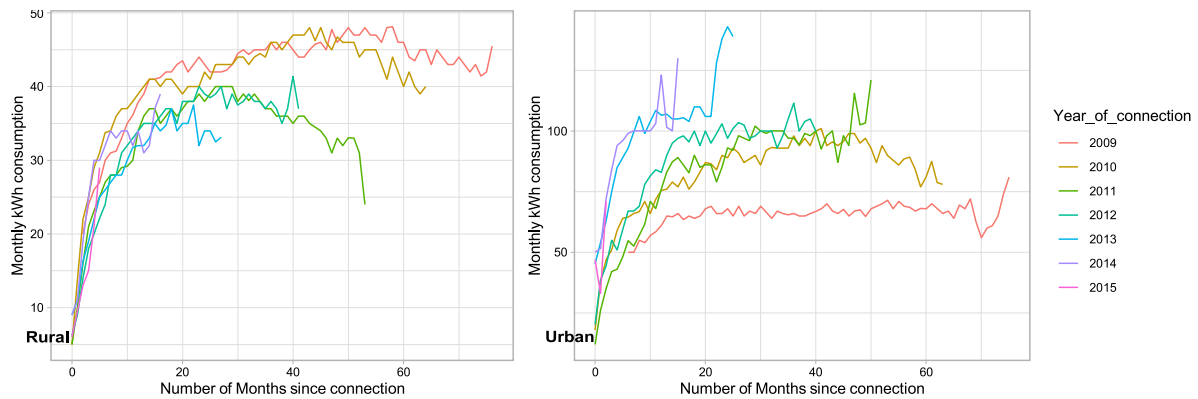


Fig. 7. This figure shows rural and urban SME median electricity consumption growth based on which year they were connected to the grid. We see that among rural SMEs, there is declining electricity consumption with newly connected SMEs tending to peak at lower values while this pattern is reversed for urban SMEs where newly connected SMEs peak at higher levels.

combination of infrastructural variables help explain long term electricity consumption growth among SMEs in rural–urban Kenya? To do this, we analysed the influence of the complementary infrastructure features mined in Section 3.2.2 on electricity consumption growth in both a multivariate as well as bi-variate setting (both methods are described in the methodology Sections 3.2.4 and 3.2.2). In this section, we present the results obtained for the multivariate case while the bi-variate analysis results can be found in Appendix A.

We first estimated our model by using rural–urban dummy variables in order to get a cross-sectional comparison between urban and rural electricity consumption. From Table 4, we see that Urban SMEs have about 4% higher average electricity consumption than their rural counterparts based on the statistically significant *dummy (Urban)* coefficient. This is in line with the results in Fig. 6 of our bi-variate analysis. In addition to this, we observe that population density, electrification rate and distance to tarmacked roads are the only variables that behave as hypothesized in Section 3.2.2. All the other variables appear to be negatively correlated with SME electricity consumption growth. Our main suspicion for this behaviour is because of the pooled regression that combines urban and rural SMEs. In the next chapter, we separate the regressions by urban or rural location of SMEs in order to get a better understanding of the relationship between the various infrastructure variables and SME electricity consumption growth

4.2.1. Separating rural–urban regressions

In pooling urban and rural SMEs together for a single regression, we miss out on some idiosyncratic behaviour that might be due to an SME’s rural–urban location. To overcome this, we ran two separate regressions for rural and urban SMEs. In these regressions, we also

Table 4

Shows summary of a pooled regression with an urban–rural dummy variable. *Dummy(Urban)* represents the percentage difference in average consumption between rural and urban SMEs. This result indicates that after controlling for infrastructural effects, urban SMEs consume about 4% more electricity than their rural counterparts.

	(kWhs)
FSP_density	-0.117*** (0.022)
population	0.052*** (0.018)
Night_Lights	-0.001 (0.003)
GDP	-0.067*** (0.005)
Electrification	0.043*** (0.007)
structs_density	-0.029*** (0.009)
Distance to road	-0.025*** (0.005)
dummy(Urban)	0.046*** (0.018)
Constant	-0.095*** (0.006)
Observations	770,796

Note: *p<0.1; **p<0.05; ***p<0.01.

included *Year of connection* as a dummy variable in order to test for the effect of newer vs. older SME grid connections (in the manner shown by Fig. 7). Results from our panel regression model are presented using separate columns for both rural and urban SMEs in Table 5.

The first major observation from Table 5 is that effects from the “Year of connection” dummy variables depart from what was observed in Fig. 7 regarding the influence duration of connection has on SME electricity demand. We observe that in both rural and urban areas, newly connected SMEs consistently consume less electricity than their older counterparts. Also, having split our regression analysis by urban–rural location of SMEs, a clearer picture of how complementary infrastructure affects SME electricity consumption starts to emerge. For example, in rural areas, we notice that growth in the neighbourhood population, electrification rates, and access to tarmacked roads have the strongest positive correlations with monthly SME electricity use. Each percentage increase in the respective variables corresponds to about 6%, 2.5% and 2.3% rise in SME electricity use respectively. As we initially hypothesized, the three variables could potentially indicate an SMEs access to markets (population and roads) as well as the quality of those markets (electrification) hence the positive correlation with electricity consumption.

In urban areas, micro-economic activity (as measured by nighttime lights) and closeness to tarmacked roads appear to have the strongest positive correlation with electricity consumption given their elasticities of 2%–6%. This is not surprising given that businesses generally thrive as part of an economy and also need access to external markets through robust road networks. Population and neighbourhood electrification rates on the other hand showed no statistically significant relationship with monthly SME electricity consumption.

In addition to this, the regression model showed some surprising counter-intuitive results. For starters, county GDP appears to still be negatively correlated with SME electricity demand in both rural and urban areas. Our suspicion for this is that because the GDP data is at a much lower spatial resolution (county level) than our SME data, it results in some bias in the regression. Also, structure density in both urban and rural areas showed negative correlation with SME electricity demand. This result in our view is primarily due to a combination of 3 main factors. First, most manufacturing or service-based SMEs such as, schools, hotels, churches etc — with a high energy intensity are almost always located in remote places with very few buildings. Secondly, more densely populated/built places in urban areas correspond with informal settlements that tend to have smaller businesses, resulting in reduced electricity use. Finally, the time invariant nature of these variables could also be factor in this behaviour. In the next section, we segment the data based on the methodology in Section 3.2.3 to get a better understanding of which complementary infrastructure have the highest influence on SME electricity use and also mitigate any effects from the time invariant nature of some of our explanatory variables.

4.2.2. Segmenting by complementary infrastructure

To determine the type of infrastructure most associated with high electricity consumption, we segmented the SMEs based on complementary infrastructure variables according to the methodology described in Section 3.2.3, and ran regression analysis accordingly.

Table 6 shows results from our regression model for SMEs located in urban areas. It strongly suggests that variations in structure count are the main infrastructure variable associated with a substantial difference in SME electricity consumption in urban areas while all other variables either have a small difference in consumption between high–low categories or are altogether statistically insignificant. In other words, SMEs in high structure density locations consume about 11% less electricity than those in low structure density areas while businesses that are close to roads (about 5 km), or in high nighttime light areas consume approximately 4% and 1% more electricity than their opposite counterparts. Electrification rates and population density show no statistically significant difference in SME electricity consumption between their respective high–low subgroups. This finding corroborates our hypothesis in Section 4.2.1 about the influence of informal settlements in urban areas that lead to lower electricity consumption of SMEs located in high structure density areas.

Table 5

Shows separate regression results for urban and rural SMEs with the year of connection to the grid as a dummy variable. In the table, each year of connection variable represents the percentage difference in electricity consumption when compared to the base year of 2009. For example, the Year of connection (2010) row suggests that urban SMEs that were connected to the grid in 2010 on average use 6% less electricity than corresponding urban SMEs who got connected in 2009 while their rural counterparts use 11% less electricity than corresponding 2009 rural SMEs.

	(Urban)	(Rural)
FSP_density	−0.153*** (0.015)	−0.128*** (0.013)
population	0.011 (0.030)	0.060*** (0.010)
Night_Lights	0.018*** (0.006)	−0.004 (0.002)
GDP	−0.028*** (0.006)	−0.075*** (0.003)
Electrification	0.011 (0.014)	0.025*** (0.006)
structs_density	−0.046*** (0.015)	−0.040*** (0.008)
Distance to road	−0.065*** (0.012)	−0.023*** (0.005)
Year of connection (2010)	−0.063** (0.029)	−0.116*** (0.019)
Year of connection (2011)	−0.150*** (0.030)	−0.208*** (0.018)
Year of connection (2012)	−0.216*** (0.029)	−0.211*** (0.018)
Year of connection (2013)	−0.167*** (0.035)	−0.221*** (0.023)
Year of connection (2014)	−0.236*** (0.030)	−0.338*** (0.020)
Year of connection (2015)	−0.509*** (0.041)	−0.515*** (0.026)
Constant	0.213*** (0.026)	0.003 (0.008)
Observations	233,055	537,741

Note: *p<0.1; **p<0.05; ***p<0.01.

Furthermore, our results indicate that unlike urban SMEs, rural SME electricity consumption is generally linked to complementary infrastructure. We see that across the board, all infrastructure variables have an upward effect on SME electricity consumption. The most important of these infrastructure include: (1) neighbourhood electrification rate, (2) structure count and (3) access to tarmacked roads — in that specific order. For instance according to Table 7, SMEs located in highly electrified neighbourhoods use almost 14% more electricity than those in less electrified locations. Similarly, there appears to be an 10% increase in average electricity consumption for SMEs located in high structure count areas while average electricity consumption also increases by almost 6% for SMEs located in areas closer to roads. Our interpretation of this result is that since high electrification rates in rural areas can be associated with affluent neighbourhoods, it follows that SMEs in highly electrified neighbourhoods will have higher electricity consumption than those in less electrified places. Similarly, both structure count (as an indicator of local market size) and proximity to tarmacked roads (access to external markets) are strong indicators of SME electricity consumption levels.

From the analysis so far, a few major conclusions can be drawn to assist in electrification policies for both Kenya Power and other utilities in similar settings. (1) The number of financial service providers and nighttime light conditions in an area have a very minimal effect on SME electricity demand potential (about 1%–2% additional electricity consumption) and 2), during rural electrification, easy access to roads, and the structure count of an area are the most likely factors to

influence SME electricity demand (since electrification rate is obviously not applicable). During the process of grid extension, the utility should therefore divert more resources to identifying such areas, or actually build roads in tandem with the grid infrastructure as a way of boosting SME electricity demand.

In the next section, we attempt to get at what combination of infrastructural variables best explain SME electricity consumption growth. For example, do businesses in high structure density locations with close proximity to roads consume more electricity, or does the number of financial service providers have a stronger effect in high population density vs low population density areas etc. Answering this would help KPLC optimize electrification resources by targeting areas that have better combinations of infrastructural conditions that indicate higher potential demand for electricity.

4.2.3. Analysis of interaction effects

Having seen which complementary infrastructure variables are associated with increased consumption among SMEs in rural and urban settings, we then performed pairwise interactions between some key variables to understand which particular combination of complementary infrastructure correspond with high SME electricity consumption levels. This approach is important because it answers some interesting questions for the government or electricity utility interested in understanding how deep the relationship between infrastructure and electricity consumption is. For example, what is the effect of being closer to a road in areas that are high population vs. low population, high structure count vs. low structure count, or how does the influence of FSP density vary in areas that are closer to roads vs. those that are far away from roads?

From Table 8, we see that in urban areas, the most important interactions involve population density, structure density, access to roads, and FSP density. We observe that SMEs in areas with a combination of high population and high structure density, or high FSP and high structure density are likely to consume about 10%–13% less electricity than their respective base cases (columns 4 and 5 of Table 8). This still points to the influence of informal settlements where often we have densely populated/built neighbourhoods with lots of M-Pesa⁶kiosks. Businesses in such areas are likely to be smaller and as such consume less electricity.

Looking at the interaction between access to roads and population/FSP density, we see that the effect of being close to a tarmacked road only correlates with increased SME electricity consumption in low population and low FSP areas. This is shown by the 4% increase in electricity consumption (columns 2 and 3 of Table 8) for SMEs in these locations. This tells us that while more energy intensive SMEs are most likely located in uninhabited areas (as hypothesized in Section 4.2.2), being close to a road often correlates with a slight increase in average electricity consumption.

In rural areas, there is significantly more interaction between the various infrastructure variables as shown in Table 9. Based on the results, we see that structure density is the strongest indicator of increased SME electricity consumption in rural areas. Businesses located in high structure density neighbourhoods are likely to consume over 16% more electricity than the base case regardless of whether the neighbourhood is close to a road or not. In the same way, businesses in high structure density locations are likely to consume 8%–11% more electricity regardless of population density or FSP density. This suggests that structure density in rural areas is the biggest indicator of how economically active a community is. Thus the government of Kenya and KPLC could identify such locations as areas of potential growth.

⁶ M-Pesa is a mobile banking service that allows users to store and transfer money through their mobile phones. M-Pesa was introduced in Kenya as an alternative way for the population of the country to have access to financial services.

Also, we observe that the effect of high population on SME electricity consumption is insignificant in far from road and low structure density areas, but quite strong in places with high structure density or closer to tarmacked roads (columns 3 and 4). This suggests that in rural areas, a high population alone is not enough. The community needs to have several buildings and access to tarmacked roads for population density to have any meaningful correlation with increased SME electricity demand.

Finally, access to financial services also has a stronger effect on SME electricity demand when paired with other complementary infrastructure variables such as access to roads and access to markets as measured by population density or structure density. It can be seen that while SMEs in high FSP density but far from road locations consume about the same electricity as the base case, improved access to roads increases this to about 9%. In the same way, increase in the neighbourhood structure or population density corresponds with about 11% and 2% additional consumption for those SMEs located in high FSP communities.

From the interactions we have seen, a number of conclusions can be drawn: (1) In rural areas, the effect of complementary infrastructure on SME electricity consumption is very strong. This is especially true for structure density which does not need to be paired with other variables in order to have an upward effect on SME electricity consumption. (2) there is a good case to be made for how extension of roads could potentially boost SME electricity consumption by targeting places with high population density, (3) The influence of FSP density in rural areas is stronger in places with access to roads and local markets, and (4) generally, access to roads or FSPs makes very little difference for urban SME electricity consumption growth. Instead, there is a downward effect of population density and number of buildings for most urban SMEs.

5. Conclusions and policy implications

In this paper, we sought to investigate electricity demand growth among SMEs in Kenya and in the process develop an understanding of the enabling environments that lead to sustained growth in electricity use among SMEs. We intend that our findings be valuable for energy policy makers in Kenya and other countries in similar settings. Our analysis of electricity consumption patterns indicates that as SMEs mature after connecting to the grid, electricity consumption generally trends upwards in both rural and urban areas. However, segmenting the data by year of connection reveals that more recently connected urban SMEs noticeably consume more than their older urban counterparts while in rural areas, the pattern is opposite: recently connected SMEs have lower consumption than their older rural counterparts. This leads to a number of implications for Kenya Power's future electrification policies. For example, a utility focused on measures to enhance revenues may favour urban customers even more than is often already the case. Further, the progressively eroding consumption plateaus among newer cohorts of rural SME customers challenges recovery of infrastructure and operating costs from expanding rural grid connectivity. Thus, while SMEs are no doubt critical to rural economies as a whole, they are likely not sufficient by themselves to cross subsidize the large pool of rural residential electricity customers. At some extent, this may further limit the boundary from the existing grid of where it makes financial sense to continue grid extension instead of encouraging alternative distributed electrification techniques like minigrids and solar home systems.

Regarding the influence of complementary infrastructure on SME electricity demand, our results indicate a significant difference in the way urban SMEs respond to infrastructure when compared with rural SMEs. In urban areas for example, there was limited correlation between complementary infrastructure and SME electricity consumption growth while among rural SMEs, complementary infrastructure appeared to have more correlation. Neighbourhood electrification rates,

Table 6

Shows regression results for urban SMEs after segmenting infrastructural variables into high or low based on the thresholds set in Section 3.2.3. Each column represents a separate regression in which we include a high–low dummy variable. For example, in column 4, the regression includes a dummy variable in which SMEs are categorized as having ‘High’ or ‘Low’ access to roads. The dummy (High) coefficients in this case represent our main variable of interest and they can be interpreted as the percentage difference in electricity consumption of the High category compared to the reference Low category e.g, the coefficient under column 4 indicates that urban SMEs with higher access to roads consume 4% more electricity than those with lower access to roads. Similarly, column 6 tells us that urban SMEs in locations with a high structure density consume 11% less electricity than those in low structure density neighbourhoods.

	Urban					
	Electrification (1)	Night_Lights (2)	FSP_density (3)	Access to road (4)	population (5)	structs_density (6)
Main variable:						
dummy (High)	0.009 (0.015)	0.010** (0.004)	-0.026*** (0.007)	0.041*** (0.015)	-0.015* (0.008)	-0.117*** (0.007)
Controls:						
Electrification		0.015 (0.011)	0.026** (0.011)	0.020* (0.011)	0.017 (0.011)	-0.004 (0.011)
Night_Lights	0.018*** (0.006)		0.014** (0.006)	0.018*** (0.006)	0.018*** (0.006)	0.018*** (0.006)
FSP_density	-0.153*** (0.015)	-0.151*** (0.015)		-0.153*** (0.015)	-0.154*** (0.015)	-0.153*** (0.015)
Distance to road	-0.044*** (0.011)	-0.044*** (0.011)	-0.045*** (0.011)		-0.043*** (0.011)	-0.041*** (0.011)
population	0.011 (0.030)	0.010 (0.030)	-0.006 (0.030)	0.011 (0.030)		0.011 (0.030)
structs_density	-0.100*** (0.011)	-0.103*** (0.011)	-0.099*** (0.012)	-0.103*** (0.012)	-0.098*** (0.012)	
GDP	-0.028*** (0.006)	-0.026*** (0.006)	-0.059*** (0.005)	-0.028*** (0.006)	-0.026*** (0.006)	-0.028*** (0.006)
Constant	0.173*** (0.014)	0.162*** (0.013)	0.172*** (0.013)	0.171*** (0.014)	0.172*** (0.013)	0.171*** (0.014)
Observations	233,055	233,055	233,055	233,055	233,055	233,055

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 7

Shows High–Low dummy variable regressions for rural SMEs. Similar to Table 6, the dummy (High) coefficients represent our main variable of interest while all the other variables are used mainly as controls. For example, column 6 can be interpreted as rural SMEs in high structure density locations consume 10% more electricity than those in low structure density areas. Similarly, column 1 indicates that SMEs in highly electrified neighbourhoods consume 14% more electricity than those in places with low electrification rates.

	Rural					
	Electrification (1)	Night_Lights (2)	FSP_density (3)	Access to road (4)	population (5)	structs_density (6)
Main variable:						
dummy (High)	0.145*** (0.011)	0.009*** (0.003)	0.022*** (0.007)	0.067*** (0.011)	0.029*** (0.011)	0.107*** (0.011)
Controls:						
Electrification		0.086*** (0.006)	0.083*** (0.006)	0.091*** (0.006)	0.084*** (0.006)	0.078*** (0.005)
Night_Lights	-0.004 (0.002)		-0.004* (0.002)	-0.004 (0.002)	-0.004 (0.002)	-0.004 (0.002)
FSP_density	-0.128*** (0.013)	-0.127*** (0.013)		-0.128*** (0.013)	-0.123*** (0.013)	-0.128*** (0.013)
Distance to road	-0.044*** (0.005)	-0.040*** (0.005)	-0.041*** (0.005)		-0.040*** (0.005)	-0.035*** (0.005)
population	0.060*** (0.010)	0.058*** (0.010)	0.047*** (0.010)	0.060*** (0.010)		0.060*** (0.010)
structs_density	0.033*** (0.005)	0.016*** (0.006)	0.014** (0.006)	0.020*** (0.006)	0.010* (0.006)	
GDP	-0.075*** (0.003)	-0.077*** (0.003)	-0.088*** (0.003)	-0.075*** (0.003)	-0.071*** (0.003)	-0.075*** (0.003)
Constant	-0.212*** (0.008)	-0.125*** (0.006)	-0.134*** (0.007)	-0.161*** (0.007)	-0.137*** (0.007)	-0.181*** (0.008)
Observations	537,741	537,741	537,741	537,741	537,741	537,741

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 8

Shows pairwise interactions between various infrastructure variables among urban SMEs. Each column represents a separate regression in which pairwise interactions were tested. For example, column 1 shows a regression in which the interaction between structure density and access to road was measured while still controlling for all other infrastructure variables. We use the high–low dummy variables previously used as it makes for easier interpretation. The first coefficient of column 1 can be interpreted as; SMEs in locations that have high structure density and easier access to roads consume 5% less electricity than those SMEs located in low structure density areas that far from roads (low–low base case).

	Urban					
	structs_density & Access_to_roads (1)	FSP_density & Access_to_roads (2)	population & Access_to_roads (3)	population & structs_density (4)	FSP_density & structs_density (5)	FSP_density & population (6)
(High–High)	–0.057** (0.023)	0.018 (0.020)	0.026 (0.020)	–0.128*** (0.017)	–0.134*** (0.018)	–0.029* (0.018)
(High–Low)	–0.155*** (0.021)	–0.024 (0.016)	–0.014 (0.017)	–0.015 (0.018)	–0.007 (0.021)	–0.001 (0.016)
(Low–High)	0.001 (0.023)	0.043** (0.021)	0.042** (0.019)	–0.108*** (0.019)	–0.097*** (0.021)	0.013 (0.017)
Constant	0.190*** (0.018)	0.176*** (0.018)	0.175*** (0.018)	0.176*** (0.017)	0.170*** (0.018)	0.167*** (0.017)
Observations	233,055	233,055	233,055	233,055	233,055	233,055

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 9

Shows pairwise interactions between various infrastructure variables among rural SMEs. Similar to Table 8, each column represents a separate regression in which pairwise interactions were tested. In this case, the first coefficient of column 1 can be interpreted as; rural SMEs in locations that have high structure density and easier access to roads consume 16.5% more electricity than those SMEs located in low structure density areas that are far away from roads (low–low base case).

	Rural					
	structs_density & Access_to_roads (1)	FSP_density & Access_to_roads (2)	population & Access_to_roads (3)	population & structs_density (4)	FSP_density & structs_density (5)	FSP_density & population (6)
(High–High)	0.165*** (0.015)	0.093*** (0.017)	0.097*** (0.015)	0.115*** (0.012)	0.113*** (0.014)	0.048*** (0.015)
(High–Low)	0.162*** (0.015)	0.026 (0.017)	0.027** (0.012)	0.017 (0.013)	–0.005 (0.017)	0.029** (0.014)
(Low–High)	0.111*** (0.016)	0.071*** (0.016)	0.063*** (0.014)	0.095*** (0.016)	0.085*** (0.017)	0.035** (0.014)
Constant	–0.241*** (0.011)	–0.179*** (0.014)	–0.178*** (0.011)	–0.186*** (0.009)	–0.181*** (0.011)	–0.152*** (0.012)
Observations	537,741	537,741	537,741	537,741	537,741	537,741

Note: *p<0.1; **p<0.05; ***p<0.01.

structure count and access to roads were among the strongest correlates to SME electricity consumption growth in rural areas. This finding calls for different electricity system planning expectations from rural settings as compared to urban and peri-urban settings.

Finally, using a mixture of dummy variables and pairwise interactions for our regression model, we came up with a number of findings for Urban and rural SMEs. In rural areas, a high structure density corresponds with higher electricity consumption for SMEs regardless of proximity to roads or population density. However, SMEs in densely populated areas only increased their electricity consumption when the same area had a high structure density or was close to a main road. This shows that high population density should most likely be combined with other infrastructural variables like roads and FSPs to have any upward effects on rural SME electricity consumption. Another implication of this observation is that government or KPLC could potentially unlock business activity in these high population/structure density areas by extending tarmacked roads and as a result increase electricity demand. In addition, we see that increase in access to financial services (as measured by number of financial service providers in

the neighbourhood) also favours SMEs that are closer to roads, in highly built neighbourhoods or are located in highly populated areas. Thus government could also potentially boost SME electricity consumption in targeted rural communities through a number of fiscal measures that encourage extension of financial service providers for example business development centres, micro-finance institutions et cetera.

Taken in total, our findings shed light on key differences in complementary infrastructure effects between urban and rural SMEs, not only showing unexpectedly opposite effects, but also characterizing the relative strength of various types of complementary infrastructure. We believe these findings, based on datasets of unprecedented scale for low and low–middle income settings, are applicable to other settings seeking to grow their electricity access footprint and their SME-led economies, enhancing lives and livelihoods in turn.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Bivariate analysis

Access to roads. We segment the SME dataset based on proximity to a tarmacked road and plot ensuing median monthly kWh used against number of months since connection as we did earlier in Section 4.1.4. Looking at the graphs in Fig. A.8, we see that SMEs which are closer to tarmacked roads in rural areas use consistently more electricity than those that are far away (which makes sense based on Table 5). In urban areas however, the result is more mixed with far-from-road SMEs starting off lower and then surpassing those near-to-road SMEs after about a year.

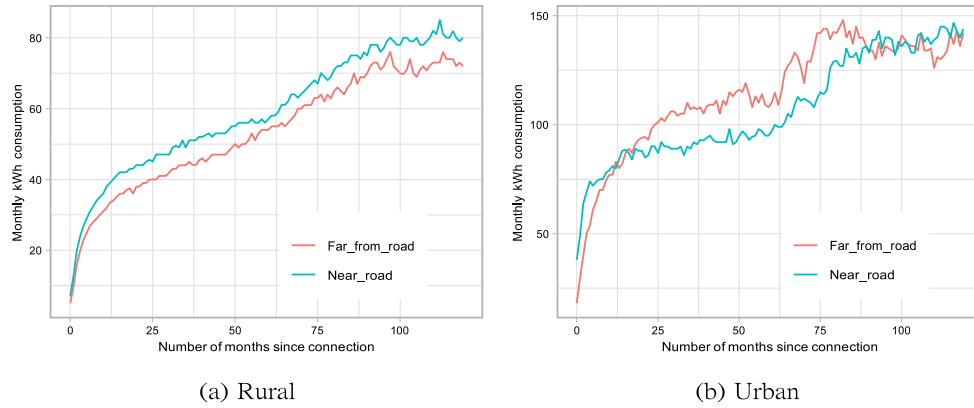


Fig. A.8. Shows median electricity consumption growth as a function of number of months since connection for SMEs that are far from a road vs those that are near a road in rural and urban areas respectively.

Structures and population density. To shed some light on the bivariate relationship between electricity consumption and access to markets, we segment the SMEs on these two features to get Figs. A.9 (a) and (b). From these, we see that both population and structure density have similar effects on electricity consumption growth in urban as well as rural SMEs. Businesses located in more densely-populated or built up neighbourhoods have higher monthly electricity demand in rural areas while in urban areas the reverse is true. Our preliminary hypothesis for this behaviour in urban areas was that more densely populated/built places in urban areas correspond with informal settlements that tend to have more residents with lower incomes resulting in reduced electricity use.

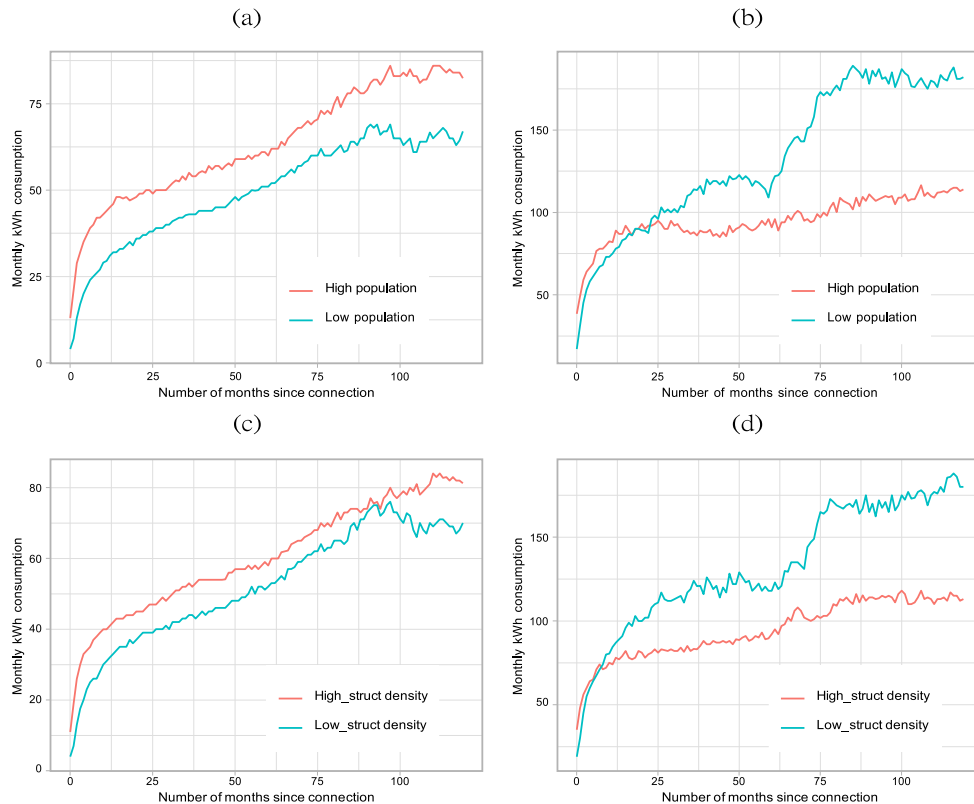


Fig. A.9. Compares median electricity consumption growth between SCs in high population vs low population density neighbourhoods as well as SCs in high vs low structure/building density neighbourhoods. The graphs (a) and (c) correspond to rural SCs while (b) and (d) correspond to urban SCs.

Access to financial services. Continuing with this approach, we assess how a firm’s access to financial services (as measured by the number of nearby FSPs) relates with their electricity use. Fig. A.10 shows the bi-variate case after segmenting based on the number of FSPs within 0.5 km of an SME as specified in Section 3.2.2. From the results, it can be observed that (1) there is a clear distinction in monthly consumption between SMEs in

areas with a low and high density of FSPs for both rural and urban locations, and (2) like the case for proximity to roads and access to markets, in rural areas, SMEs located in areas with a high density of FSP have higher monthly consumption while the reverse is true for urban based SMEs.

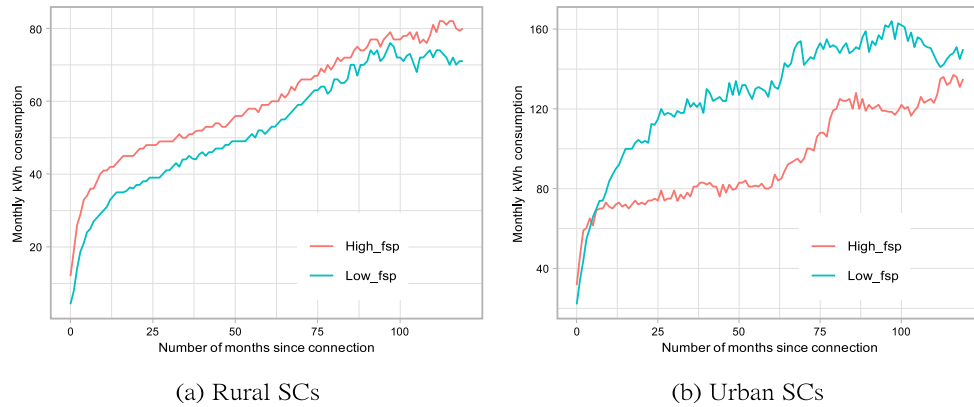


Fig. A.10. Compares median monthly electricity consumption growth between SMEs located in high FSP-density neighbourhood vs those in low FSP-density neighbourhood for rural and urban areas respectively.

Neighbourhood electrification rate. To understand the influence of residential electrification rates on monthly SME electricity consumption, we split them into those within low and high electricity-access neighbourhoods. Both results from the regression model and line graph indicate that in rural areas, the level of electrification is positively correlated with long-term SME electricity demand while in urban areas, it is the opposite. (see Fig. A.11).

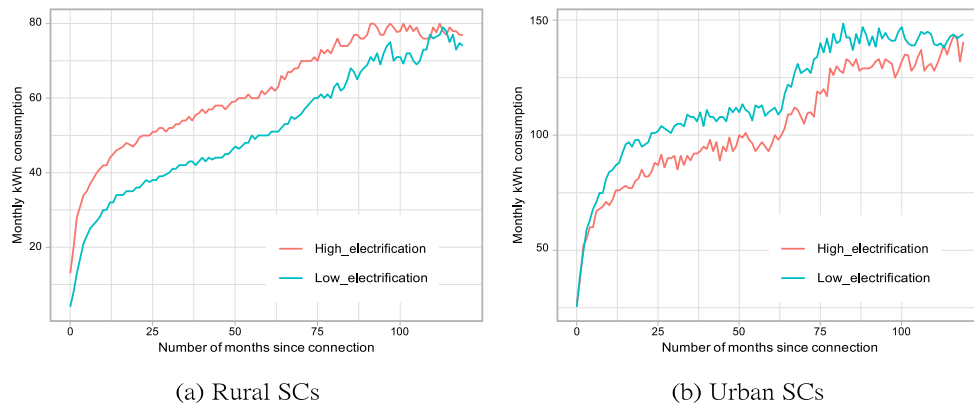


Fig. A.11. Compares median monthly electricity consumption growth between SMEs located in highly electrified neighbourhoods vs those in low electricity access neighbourhoods for rural and urban areas respectively.

Night lights and quarterly county GDP growth. Lastly, we analyse the influence of both micro-and macro-economic conditions as estimated by night-time illumination and quarterly GDP on electricity use for urban as well as rural SMEs. According to Fig. A.12, the relationship between GDP and SME electricity use is stronger in urban areas than rural areas. This could be because the government only measures formal sector GDP which is mainly concentrated in urban areas. The majority of businesses in rural areas are informal in nature and as such may not be captured by official GDP measurements.

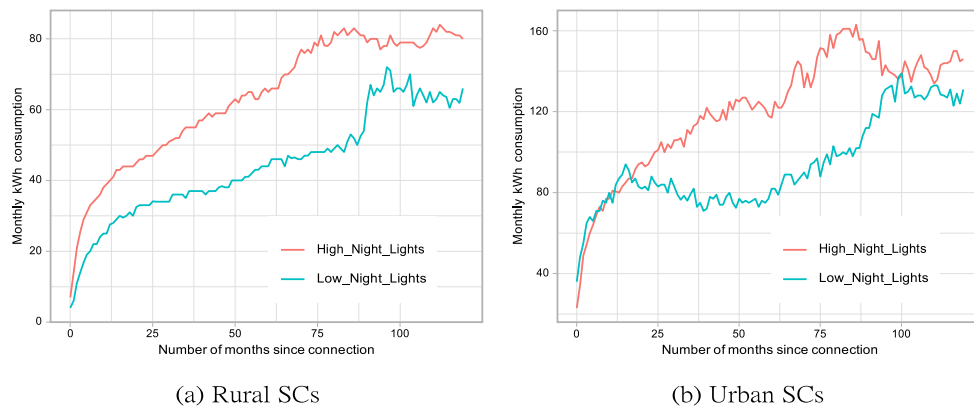


Fig. A.12. Compares median monthly electricity consumption growth between SMEs in highly lit areas vs those in poorly lit areas for rural and urban areas respectively.

A.1. Investigating interactions between features

To tease out further effects that complementary infrastructure have on SME electricity demand, we looked at pairwise interactions between chosen features. Using our already set thresholds in Section 3.2.2, we found the four main features whose interactions had the biggest impact on electricity consumption (with a significant enough sample size) to be population, number of financial service providers, access to roads and electrification rates. We in turn examine each of these for rural and urban SMEs. In addition to the graph indicating growth in monthly median electricity consumption, we include a dotted line plot that shows the sample size in each month. This is to help us identify which months of the graph are subject to noise due to limited sample sizes.

A.1.1. Population density and access to roads

From Fig. A.13(a), we see that in rural areas, businesses located in sparsely populated areas that are far from a tarmacked roads consume the least amount of electricity over time as expected. In more densely populated rural areas however, we see that the effect of access to roads is limited so much so that far-from-road SMEs have somewhat similar consumption to those SMEs that are closer to roads. This behaviour would have been missed if we only relied on Fig. A.8 which shows all far-from-road businesses in rural areas having less electricity demand. A likely implication of this is that investing in road extensions to low population rural communities in Kenya could create benefits that lead to increased use of electricity by SMEs in those areas. This effect appears to be less pronounced in high population rural areas.

In urban areas, Fig. A.13(b) shows us that during the first 5 years of connection, only far-from-road SMEs that are located in sparsely populated areas have distinct electricity consumption growth. All the others have very similar electricity use patterns. Only after the 60th month when older SMEs kick in do we see clear separation between the 4 groups. This could be because the sample sizes get smaller resulting in more noise, or it suggests that the interaction effect of population density on road access gets stronger as SMEs spend more time on the grid. A general take away from this is that there is no added advantage of being closer to a road in urban areas. Instead, being in more remote locations (far from roads and population centres) seems to boost a business' electricity consumption.

A.1.2. Population density and number of surrounding structures

The interaction between population density and structure density offers a number of interesting observations for both urban as well as rural SMEs. In rural areas, Fig. A.14(a) shows that electricity consumption growth is mostly influenced by population density with very little effect from structure density. In urban areas (Fig. A.14(b)), we see that the influence of structure density on electricity consumption is not necessarily homogeneous across all SMEs. Instead, we observe that businesses in high-population, high-structure density areas have the smallest median monthly kWh consumption while low-population, low-structure density neighbourhood SMEs have the highest. This makes sense because, high-population and structure-density neighbourhoods in urban areas tend to be informal settlements in which businesses are smaller and as such consume less electricity while low-population, low-structure density locations are mostly free-trade areas that contain manufacturing SMEs. Finally, we see that until the 60th month, when older SMEs kick in and sample sizes get smaller, high-population, low-structure density SMEs and their low-population, high-structure density counterparts have almost identical electricity consumption growth. This could be because high-population, low-structure density neighbourhoods suggest multi-unit apartment blocks while low-population, high-structure density areas imply down-town business districts. These two locations most of the time contain similar services-based businesses such as restaurants, retail and trade.

A.1.3. Number of financial service providers and access to roads

We looked at how interactions between access to FSPs and roads also influence electricity consumption growth among grid connected small business in Fig. A.15. In rural areas, SMEs that are in low fsp-density neighbourhoods and far from tarmacked roads experience the least electricity use as expected while SMEs in low fsp-density neighbourhoods but closer to roads experience the same electricity consumption levels as their high fsp-density counterparts. This would suggest that access to roads is very important for SME electricity consumption growth in rural areas such that by extending roads to fsp-sparse areas, SME electricity consumption could be potentially increased over the long-term.

A.1.4. Number of financial service providers and electrification rate

Finally, Fig. A.16(a) and (b) shows the influence neighbourhood access to financial services has on SME electricity consumption growth within the context of neighbourhood electricity access rates. For rural areas, we observe that in high electricity-access neighbourhoods, FSP-density does not make much difference on SME electricity consumption growth while in low electricity-access neighbourhoods, high FSP-density is linked to higher SME electricity use. In urban areas however, we see that median SME electricity consumption is mostly split on FSP-density with neighbourhood electricity-access rates having making very little difference on SME electricity consumption. This suggests that the rate of electricity access in an SME's neighbourhood has more influence electricity consumption than it does in urban areas. This makes sense because electricity access is a better measure of income in rural households than urban ones.

From the interactions we look at, a number of conclusions can be drawn: (1) there is a good case to be made for how access to roads could potentially boost SME electricity consumption in low population-density and low FSP-density rural communities, (2) generally, access to roads or FSPs makes very little difference for urban SME electricity consumption growth. Instead, the combinations between population and number of buildings seem to explain SME consumption the best.

Appendix B. Checking for multicollinearity

See Table B.10.

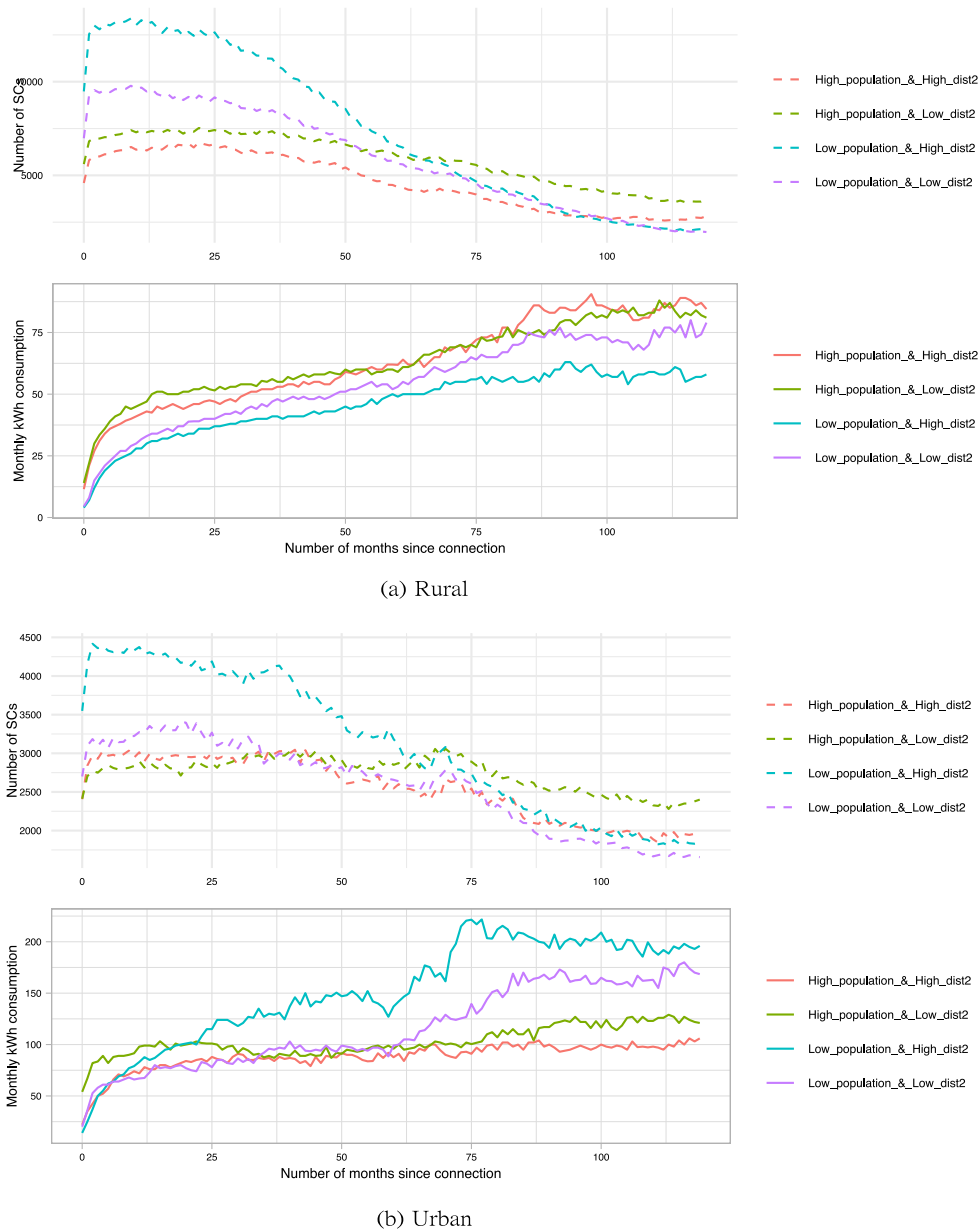


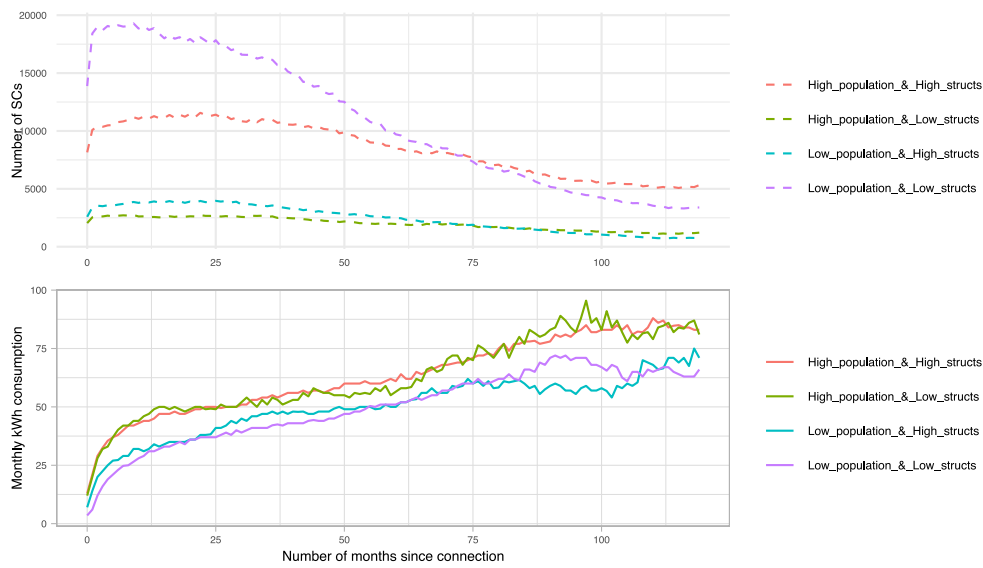
Fig. A.13. Shows monthly median electricity consumption growth and sample sizes of SMEs in each month. The graphs show interaction effects between population density and access to roads.

Appendix C. Night lights correction method

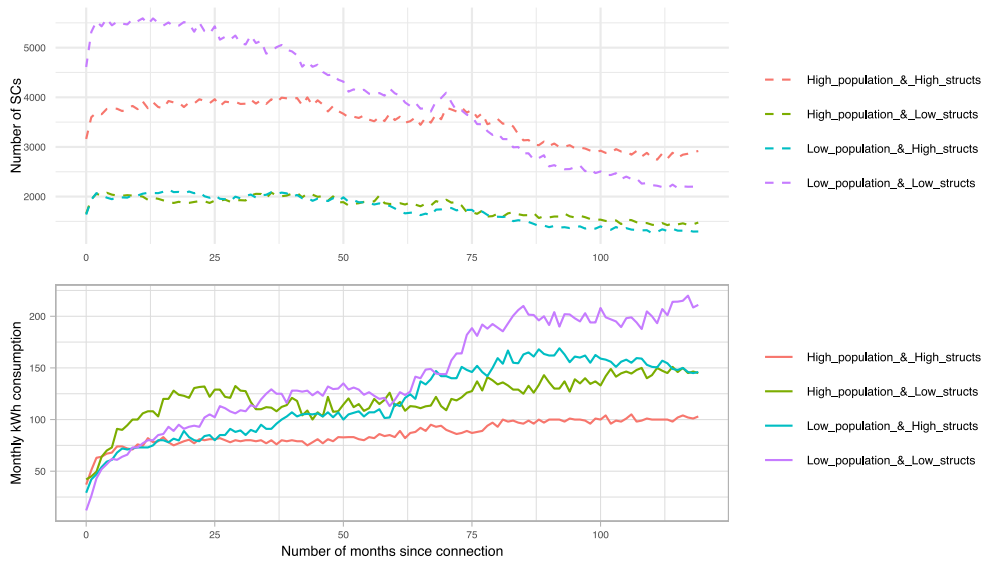
Because of the noise exhibited in the VIIRS nighttime dataset, we noticed that some pixels had values despite being in un-inhabited places e.g. lakes, game reserves etc. This effected was compounded when we aggregated night lights by county as shown in Fig. C.18. It can be seen that the larger, un-inhabited counties of Turkana, Marsabit etc. in northern Kenya appear to have the highest values of total night lights in spite the fact that they are the least lit in reality as shown by Fig. C.17. This is because of their massive sizes when compared to the smaller, busier and more populous Nairobi or Mombasa. In order to identify noisy pixels, we used the structures dataset to determine the number of buildings in each pixel of the nighttime lights raster file and then calculated for each pixel the average light intensity for a single year. With this, we were able to identify and set to zero pixels that had no buildings within them while also showing very small average nighttime lights (less than 0.125). We assumed these to be noise and all the other pixels we left as they were. Fig. C.19 shows total county night lights after our correction method.

Appendix D. Fixed effects panel regression

See Table D.11.



(a) Rural

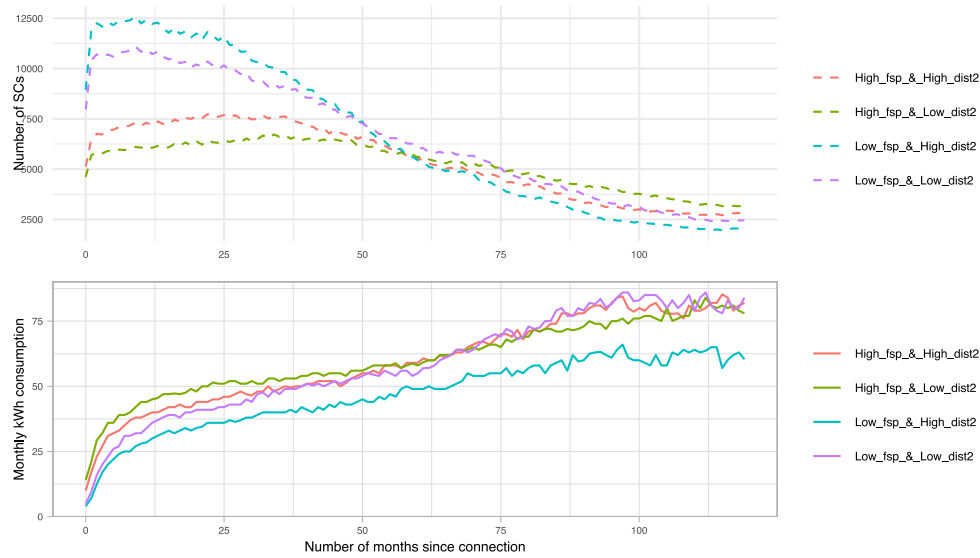


(b) Urban

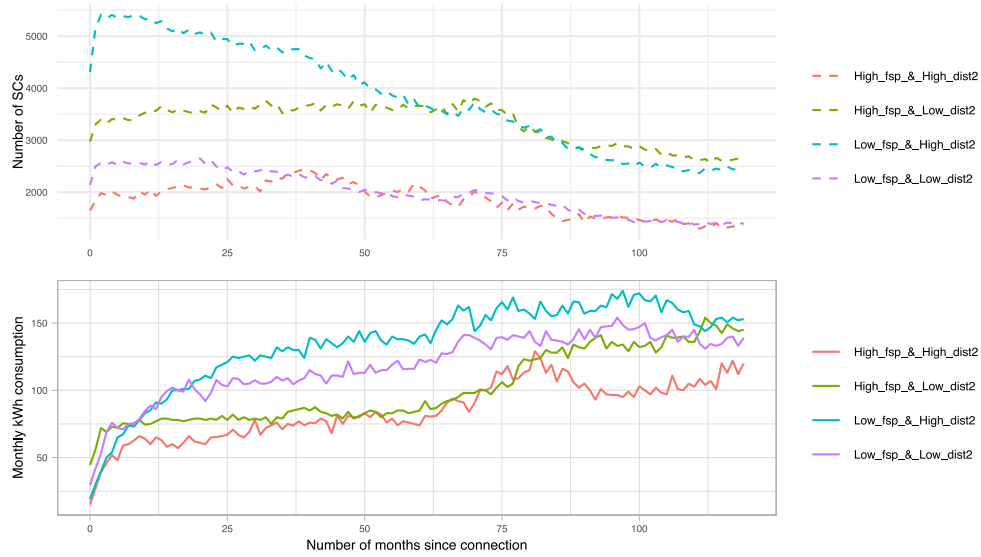
Fig. A.14. Shows monthly median electricity consumption growth and sample sizes of SMEs in each month. The graphs show interaction effects between population density and structure density.

Appendix E. Robustness check

See Table E.12.

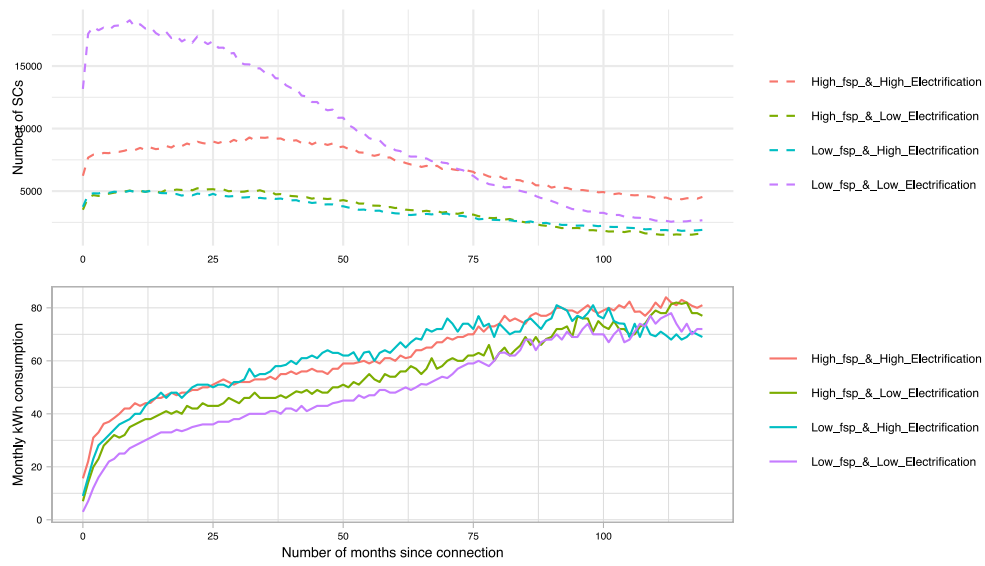


(a) Rural

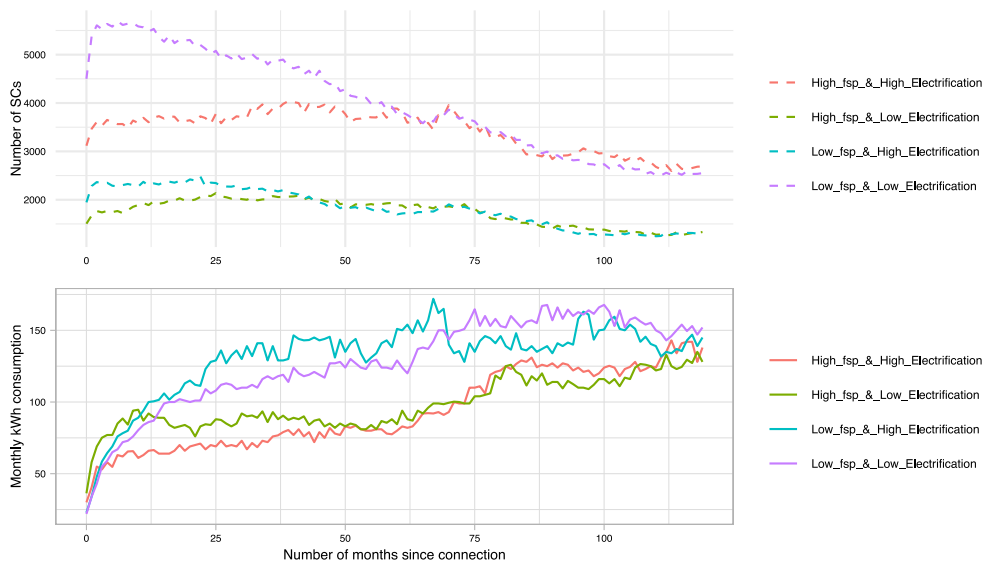


(b) Urban

Fig. A.15. Shows monthly median electricity consumption growth and sample sizes of SMEs in each month. The graphs show interaction effects between FSP-density and access to roads.



(a) Rural



(b) Urban

Fig. A.16. The graphs show interaction effects between FSP-density and neighbourhood electricity access.

Table B.10

Checks for multicollinearity between population and nighttime lights by dropping either one and running the regression. Results show very little difference with [Table 5](#).

	<i>Dropping Night lights</i>		<i>Dropping population</i>	
	(Urban)	(Rural)	(Urban)	(Rural)
fsp	0.011* (0.007)	-0.026** (0.011)	0.009 (0.007)	-0.027** (0.011)
population	-0.080*** (0.028)	-0.040 (0.046)		
Night_Lights			0.002 (0.004)	-0.008 (0.009)
GDP	0.050*** (0.013)	-0.026* (0.014)	0.040*** (0.013)	-0.027** (0.013)
Electrification	0.005 (0.015)	0.079*** (0.010)	0.016 (0.015)	0.069*** (0.010)
total_structs	-0.034*** (0.012)	0.051*** (0.016)	-0.032*** (0.010)	0.036*** (0.013)
min_dist2_road	0.009 (0.051)	-0.024*** (0.007)	-0.017 (0.052)	-0.022*** (0.007)
Year_of_connection2010	0.309*** (0.050)	0.065** (0.029)	0.310*** (0.050)	0.063** (0.029)
Year_of_connection2011	0.309*** (0.050)	-0.039 (0.027)	0.309*** (0.050)	-0.036 (0.027)
Year_of_connection2012	0.350*** (0.048)	-0.037 (0.027)	0.348*** (0.048)	-0.035 (0.027)
Year_of_connection2013	0.373*** (0.051)	-0.026 (0.029)	0.374*** (0.051)	-0.027 (0.029)
Year_of_connection2014	0.234*** (0.047)	-0.108*** (0.027)	0.235*** (0.047)	-0.110*** (0.027)
Year_of_connection2015	0.037 (0.051)	-0.280*** (0.028)	0.037 (0.051)	-0.284*** (0.028)
Constant	-0.013 (0.047)	-0.029 (0.023)	-0.018 (0.047)	0.030 (0.024)

Note: *p<0.1; **p<0.05; ***p<0.01.

Table D.11

Showing Fixed Effects regression results for urban and rural SMEs.

	<i>Fixed Effects regression model</i>	
	(Urban)	(Rural)
fsp	0.011 (0.007)	-0.025** (0.011)
population	-0.082*** (0.028)	-0.040 (0.045)
Night_Lights	0.003 (0.004)	-0.007 (0.009)
GDP	0.048*** (0.013)	-0.024* (0.014)

Note: *p<0.1; **p<0.05; ***p<0.01.

It can be seen that coefficients and standard errors for the time-varying variables are similar with those obtained using the CRE model in [Table 5](#).

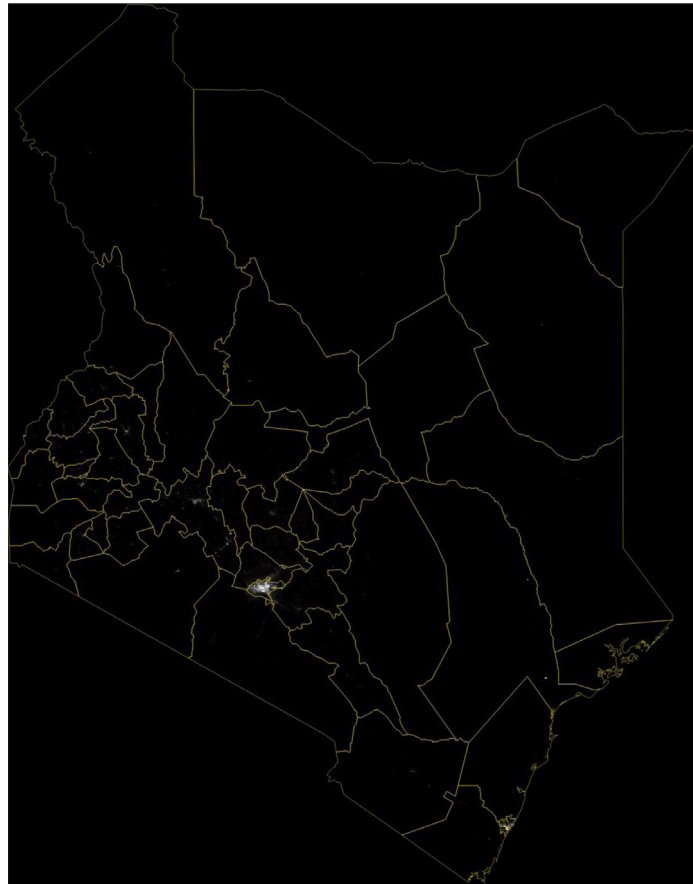


Fig. C.17. Shows the original VIIRS nighttime lights for Kenyan counties in April 2017.

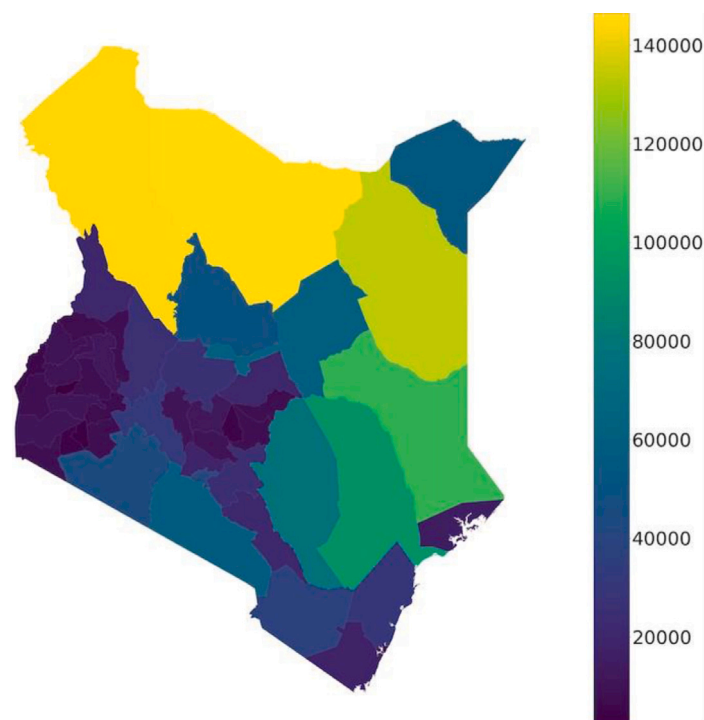


Fig. C.18. Shows April 2017 night lights summed over counties in Kenya. We see that owing to noise, the larger semi-arid, uninhabited counties have the highest values of night lights.

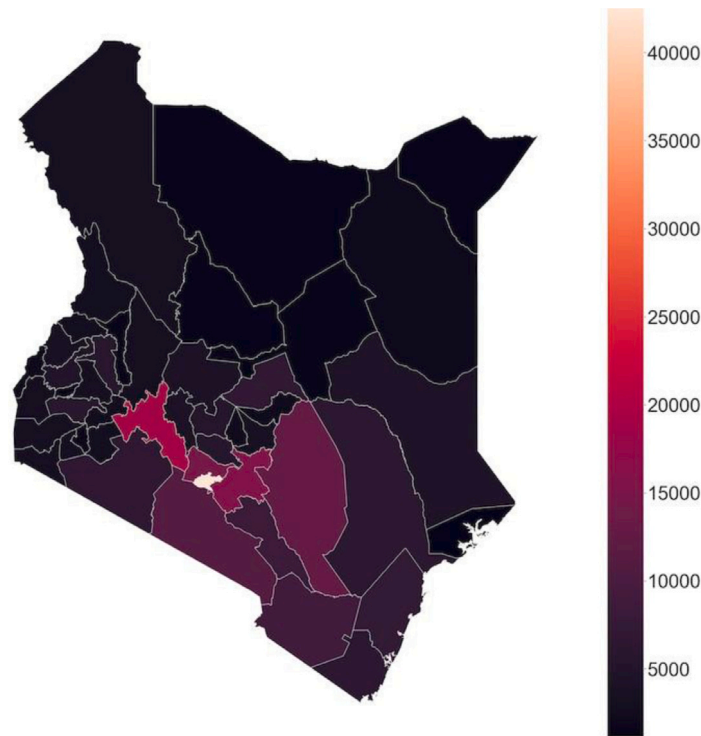


Fig. C.19. After correcting for noisy pixels, we see that total county night lights better reflects reality.

Table E.12

Shows separate regressions for urban–rural SMEs using 3 randomly selected samples. There is very little difference in the results.

	Sample 1:		Sample 2:		Sample 3:	
	(Urban)	(Rural)	(Urban)	(Rural)	(Urban)	(Rural)
FSP_density	-0.138*** (0.013)	-0.281*** (0.012)	-0.154*** (0.013)	-0.257*** (0.012)	-0.174*** (0.013)	-0.230*** (0.012)
population	0.042 (0.028)	-0.066*** (0.010)	-0.007 (0.027)	-0.030*** (0.010)	-0.005 (0.028)	-0.057*** (0.010)
Night_Lights	0.005 (0.006)	-0.016*** (0.002)	0.003 (0.006)	-0.016*** (0.002)	0.001 (0.006)	-0.016*** (0.002)
Electrification	-0.013 (0.014)	0.020*** (0.006)	-0.016 (0.014)	0.018*** (0.006)	0.022 (0.014)	0.013** (0.006)
structs_density	-0.061*** (0.015)	-0.045*** (0.007)	-0.052*** (0.015)	-0.052*** (0.007)	-0.057*** (0.015)	-0.043*** (0.007)
Distance to road	-0.080*** (0.012)	-0.024*** (0.005)	-0.089*** (0.012)	-0.028*** (0.005)	-0.075*** (0.012)	-0.031*** (0.005)
Year of connection(2010)	-0.096*** (0.030)	-0.111*** (0.019)	-0.092*** (0.030)	-0.136*** (0.019)	-0.098*** (0.030)	-0.127*** (0.019)
Year of connection(2011)	-0.134*** (0.030)	-0.236*** (0.018)	-0.119*** (0.030)	-0.223*** (0.018)	-0.142*** (0.030)	-0.197*** (0.018)
Year of connection(2012)	-0.154*** (0.029)	-0.228*** (0.018)	-0.198*** (0.029)	-0.207*** (0.018)	-0.165*** (0.029)	-0.231*** (0.018)
Year of connection(2013)	-0.128*** (0.036)	-0.258*** (0.023)	-0.123*** (0.036)	-0.228*** (0.023)	-0.091** (0.036)	-0.245*** (0.023)
Year of connection(2014)	-0.212*** (0.030)	-0.285*** (0.020)	-0.195*** (0.030)	-0.337*** (0.020)	-0.206*** (0.030)	-0.333*** (0.020)
Year of connection(2015)	-0.475*** (0.042)	-0.503*** (0.026)	-0.541*** (0.042)	-0.529*** (0.026)	-0.512*** (0.042)	-0.539*** (0.026)
Constant	0.203*** (0.026)	0.007 (0.008)	0.194*** (0.026)	0.011 (0.008)	0.194*** (0.026)	0.009 (0.008)

Note: *p<0.1; **p<0.05; ***p<0.01.

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