

Is access enough? Low use and large price response for electricity in central Ghana

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Abstract

Investments in electricity access have increased remarkably in the past decades in low- and middle-income countries (LMICs). The underlying foundation for these investments is the promise that connecting households and businesses to the grid can stimulate economic development. This, however, relies on the assumption that people will indeed use electricity at productive levels after they get connected. We use seven years of monthly data from urban prepaid meters in central Ghana to show that both residential and commercial accounts use very little electricity post-connection, with virtually no increase in consumption over time. We then explore whether electricity prices can be a tool to promote use. We leverage ten policy-induced price changes in both up and down directions to estimate price elasticities of -0.28 and -0.26 for residential and commercial demand, respectively. These numbers are an order of magnitude higher than previously estimated in the literature in LMICs. We also uncover strong heterogeneities in these elasticities: they are increasing in residential and decreasing in commercial consumption. Targeting electricity subsidies to specific consumption brackets of different types of customers may prove useful to incentivize clean energy transitions and economic growth in LMICs.

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1 Introduction

Access to affordable and clean energy is one of the United Nation's Social Development Goals to promote worldwide sustainable development by the year 2030. As such, governments and international organizations working in developing countries have prioritized investments in electricity access and use in the past few decades. In 2019 alone, the International Energy Agency reports \$10.3 billion in investments in electricity access across the globe (Cozzi et al., 2022). In the same document, the authors estimate the need for \$30.2 billion until 2030 for universal electricity access, with \$19.6 billion going to sub-Saharan Africa (SSA). These investments have produced remarkable results. Between 2000 and 2020, the world's population with electricity access increased from 78% to 90%. In the same period, the increase in SSA was from 26% to 48% of the population connected to the grid (World Bank Web).

Investments in electricity access are grounded in the promise that connecting people to the grid and promoting electricity use generates economic growth and increases welfare. After being connected, individuals can substitute away from fuels that rely on biomass combustion (predominantly firewood and charcoal) towards electricity, a cleaner and more efficient alternative. At the household-level, research has reported electricity access improving outcomes in health and women's education and employment (Barron and Torero, 2017; Khandker et al., 2013; Dinkelman, 2011). For firms, reliable electricity supply was linked to increases in overall total factor productivity and labor allocation, making both small- and large-scale firms more productive (Fried and Lagakos, 2021; Hardy and McCasland, 2019).

Yet the positive evidence for the role of electrification in economic development has been challenged by recent studies. Figure ??, borrowed from Lee et al. (2020), depicts the current state of the literature. Taking labor supply as an example, the authors show that while earlier studies found positive and significant impacts of electrification on employment, recent papers using modern causal-inference approaches found none or negligible effects. This leaves us with a puzzle. It is unclear whether investments in electricity access can actually stimulate development.

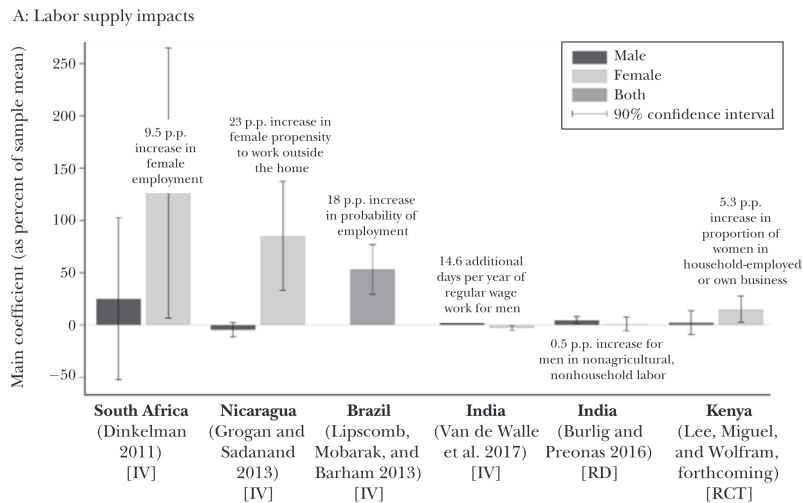


Figure 1: Estimates of the Impact of Rural Electrification (Lee et al., 2020)

This paper focuses on a foundational point that grounds investments and research around electricity access: *electricity use is a necessary condition for large-scale investments in electricity access to impact economic development outcomes.* If individuals and businesses do not adapt their lifestyle and production functions to using electricity, then electricity access will not lead to economic growth, and the marginal dollar spent on electricity infrastructure is either better employed elsewhere or needs to be complemented with incentives to promote and sustain its consumption.

So far most of the literature has focused on the impact of “last mile” electrification. That is, bringing electricity to remote, mostly rural communities. Little is known about urban electricity consumers in low-income settings, especially in the long-term. In this paper, we use meter-level data from over 75,000 residential and commercial prepaid accounts in central Ghana between 2012 and 2019 to investigate “the necessary condition” that rationalizes investments in electricity access. We begin by asking two questions: (i) How much electricity do households and small businesses actually use? And (ii) how does their electricity use evolve over time? We find that residential electricity consumption is low and shows little temporal evolution. The median household in central Ghana takes roughly six years with a prepaid meter to move from a monthly average of 87kWh to 100kWh. The average household moves from 110kWh to 119kWh per month. During the same period, while commercial accounts are expected to be

leading productive uses of electricity to drive economic growth, their consumption is lower and more stagnant than households'. The median commercial account consumes an average of 67kWh per month at the end of their first year with a prepaid meter. The average commercial account consumes 166kWh. Both commercial statistics show virtually no increase in consumption despite Ghana's per-capita GDP increasing 41% and annual GDP growth averaging 5.7% in the seven years of our data (Figures 10 and 11 in Appendix A).

For comparison, the average American household consumed 820kWh per month in 2020 (U.S. Energy Information Administration, 2021). The 13kWh increase in monthly use that we observe for the median Ghanaian household in six years is equivalent to increasing daily consumption by one light bulb for six hours. Alternatively, it can keep an average-size refrigerator powered for two days of the month.

This low and stagnant use of electricity triggers the second part of this paper. We ask: how effective are price policies in promoting electricity use by households and firms?¹ Electricity tariffs are oftentimes (contentiously) subsidized in LMICs. The literature has documented that heavy subsidies can force state-owned utility companies to operate on a loss (Khanna and Rao, 2009), hindering their ability to invest in infrastructure and new technologies. This, in turn, can negatively affect power reliability (McRae, 2015), productivity, and growth (Fried and Lagakos, 2021). But if lower electricity prices also increase consumption, especially among low or recently-connected users, they may help unlock paths of increasing electricity use over time. The pros of subsidizing electricity may then offset the cons. In this context, we estimate causally-identified residential and commercial price elasticities of demand for grid-electricity in central Ghana. These elasticities are important both because they support current policy decisions around clean energy use in SSA, as well as for their novelty in the literature.

In 2022, Ghana's Public Utilities Regulatory Commission (PURC), the government body responsible for setting country-wide utility prices, implemented a tariff reform that lowered prices relative to inflation and, for the first time in history, set commercial tariffs below residential ones. PURC was explicit about its intention of using electricity tariffs as a mean to promote economic growth. In their press release, PURC mentioned "the role of small and medium scale enterprises in the country's economic develop-

¹The underlying assumption here is that electricity is indeed a more efficient, welfare improving technology, so it is desirable for society to promote its use.

ment, [and] in particular, the creation and/or preservation of jobs and livelihoods” as reasons for lowering commercial prices relative to residential ones (PURC, 2022). Well-identified price elasticities are key parameters to rationalize these decisions.

While several studies estimated different elasticities of electricity demand (price, income, property value, etc.) in LMIC, only a few have done so for commercial accounts². What distinguishes our contribution is the combination of (a) a 7-year monthly panel of direct, meter-level observations of consumption across ten policy-induced price changes in both up and down directions, (b) the simultaneous observation of commercial and residential accounts in the same economic environment, (c) a sample of predominantly low-use customers relative to other studies, which most closely approximates recently-connected customers across the developing world, (d) our ability to disaggregate residential and commercial elasticities by different consumption levels, and finally, (e) the application of modern causal identification techniques that were not feasible or available in previous studies.

We follow Saez et al. (2012) and Ito (2014) to estimate short-term residential and commercial price elasticities using “simulated instruments” for marginal prices. The instrument is customer-month specific and uses each customers’ consumption history to help predict the price change they experience when a new tariff schedule is implemented. Our final estimates are price elasticities of -0.28 for households and -0.26 for businesses, which are an order of magnitude higher than what was found in previous studies. We also reveal important heterogeneity in these numbers. Residential elasticities are increasing in consumption while commercial ones are decreasing. Households in the lowest quartile of consumption are the least price sensitive, with an elasticity of -0.18. In the third quartile, residential elasticities are much higher, at -0.39. Commercial accounts change from -0.32 for the lowest to -0.15 for the highest users. This suggests that subsidies on electricity prices would be more effective at increasing use if targeted to high-use households or low-use commercial enterprises. The latest is precisely the strategy implemented by PURC’s reform in 2022.

Finally, residential electricity use is positively correlated with household income. So we view the heterogeneity in residential elasticity in agreement with studies that estimated a similar increase in the income

²See Khanna and Rao (2009) for a review and Jack and Smith (2020) and Khanna and Rowe (2021) for more recent papers that estimated residential price elasticities of demand in Cape Town and New Dheli, respectively.

elasticity of electricity demand with country-level data (Brenton, 1997) and in the property-value elasticity of electricity demand with individual data (Jack and Smith, 2015). We are not aware of other studies that disaggregated commercial price elasticities. We complement our analysis with descriptive statistics on the acquisition of durable, residential electrical appliances. High-income households are likely to own more electrical appliances, and thus enjoy more margins for price adaptation than low-income ones. They have more choices of appliances to turn off and on. We explore a three-wave panel dataset with households from our study region to show the levels and temporal evolution of appliance ownership. The average household owns few appliances, and similarly to electricity use itself, there is little increase in appliance acquisition over time. We infer that the small price response of low users comes, at least in part, from the fact that they have very few appliances, and thus cannot adjust their consumption in either direction.

Broadly, this paper contributes to the literature on the impact of electricity infrastructure on economic development in LMICs (Dinkelman, 2011; Lipscomb et al., 2013; Lee et al., 2020; Burlig and Preonas, 2022; Foster et al., 2023). Our contributions are twofold. First, by observing consumption directly at the meter-level, we show that electricity use is low and has virtually no upward trend over time for households and businesses in central Ghana. This makes it unlikely that electricity use could significantly impact socioeconomic outcomes. This result contributes to a puzzle that has recently emerged in the literature, with later studies departing from earlier ones in finding none or minimal effects of electrification on a wide range of measurements.

Secondly, we contribute to the literature focused on estimating demand curves for electricity in LMICs (Jack and Smith, 2020; Khanna and Rowe, 2021; Khanna and Rao, 2009). This informs debates on whether price incentives and subsidies can effectively promote electricity use and clean energy in developing countries. Our contribution comes from estimating residential and commercial elasticities for the same population over multiple years and price changes with modern causal identification. Given the low levels of electricity use in our sample, our estimates approximate the elasticity of households and businesses who are currently being electrified by electricity access programs around the world.

2 Conceptual Framework

This section develops the conceptual framework we use to guide our study. We borrow from Khanna and Rao (2009), as they provide a simple understanding of how electricity (in kWh units) enters both households' utility and firms' production functions. kWh is a special good to study. One component of its demand follows the usual utility maximization problem in economics: it is a function of income and prices. A second component of the demand is a function of the technology that households and firms have access to. These are durable goods that expand the frontier in which agents can choose to use electricity.

We take the demand for electricity to be derived from household and firm productions. Residential demand comes from households purchasing durable goods that are used as inputs to the production of lighting, cooking, heating, etc. We define the following utility function:

$$U = U(E(R, K), X; T), \quad (1)$$

where E is the electrical service produced by a capital stock of appliances K used at a rate R , X is the outside consumption, and T defines households' endogenous preferences. Optimal E^* is thus determined by choices of K and R , while taking as given the prices of E , K and X and a fixed level of income Y . We can turn to the firm's problem if we substitute U for a production function F of a marketable output (which we can also call) Y .

The solution for both the household and firm (henceforth called, the agent) is a two-stage process. Agents first minimize the cost of producing E , then maximize their objective function with a fixed E^* . The demand functions for R and K become

$$R = R(P_E, Y; T) \quad (2)$$

$$K = K(P_E, P_K, Y; T) \quad (3)$$

with P_E and P_K being the price of electricity and electrical appliances, respectively. Note that in this static

version, agents have $\frac{\delta R}{\delta P_E} < 0$ and $\frac{\delta K}{\delta P_E} = 0$. Agents respond to an increase in electricity price by lowering the rate of stock use. And also $\frac{\delta R}{\delta Y} > 0$ and $\frac{\delta K}{\delta Y} > 0$. Agents increase the rate and stock of energy-using assets as income/production increases.

Since we don't observe R and K , in our empirical work we specify electricity consumption directly from input prices and other available observable characteristics:

$$E = E^*(P_E, P_K, Y; T). \quad (4)$$

Assuming a linear relationship, in our analyses on the long-term evolution of electricity use, we proceed with approximating the following equation:

$$E_t^* = \alpha + \beta_P P_E + \beta_Y Y + \beta_K K + \phi T. \quad (5)$$

For our short term elasticity estimations, we disregard changes in capital, which take longer to realize, and assume quasilinear utility and production functions in electricity, which yields no income/production effects. In a log specification, this translates to

$$\ln E_t^* = \alpha + \beta_P \ln P_E + \phi T, \quad (6)$$

which we approximate empirically with our simulated instrument approach.

3 Setting and Data

3.1 Ghana and the Bono East Region

The Ghanaian Government has led a remarkable effort expanding the electricity grid across the country in the past two decades, reaching nearly 90% of its population (Figure 8 in Appendix A). This sets Ghana in a uniquely special position for a study on longer-term electricity use after grid-connection in SSA.

Also, as in many LMICs, the electricity sector in the country is operated by public utility companies. In our study setting, the Bono East Region in central Ghana, electricity is provided by the Northern Electricity Distribution Company (NEDCo). NEDCo is the sole supplier of grid-electricity in the central and northern parts of the country.

The Bono East Region is representative of fast-growing urban populations in the interiors of sub-Saharan Africa following a rural-exodus trend. Between the 2010 and 2020 Ghanaian Censuses, the Bono East urban population grew by 77% while the rural population grew 4% (Ghana Statistical Service, 2021). These numbers reveal a pattern that is not unique to our study region and reinforce the importance of studies on clean energy consumption in urban areas of the African continent.

3.2 Data

3.2.1 Electricity Consumption

Our main analyses use a panel of meter-level electricity purchases in the Bono East region from 2012 to 2019, with more than 50,000 residential and 16,000 commercial prepaid meters. In a prepaid meter system, customers purchase kWh ahead of their usage, creating a positive balance with the utility company. Customers lower their balance as they use electricity. When their balance is depleted, the power goes out until the next purchase. The marginal kWh is priced based on the sum of kWh purchased within the month of each purchase.

While what we observe are electricity *purchases* on each meter, we treat these data as electricity *consumption*. This requires the assumption that households and businesses do not use their meters as “savings accounts” for their money. In other words, we assume that people do not choose to top up their meters beyond what they plan to use as a way to save money in the form of electricity with the utility company. This is by all means reasonable in our setting.

We argue that our data is unique in the sense that the literature still lacks knowledge on electricity consumption and price elasticity estimates in low-use settings. To illustrate this point, we note that the median monthly consumption in the sample studied by Jack and Smith (2020) in Cape Town was 450kWh.

In New Delhi, (Khanna and Rao, 2009)'s median customer used 200kWh. In our setting, the median customer uses 90kWh. 200kWh and 450kWh represent the 85th and 98th percentiles of consumption in our data, respectively³.

Note that we do not necessarily observe the first date when a NEDCo customer was connected to the grid. In fact, the majority of the structures we follow were previously connected to postpaid meters. We observe customers from when they first received a prepaid meter. From then on, we track all purchases made on each meter. Our unit of analyses are the residential and commercial structures to which the meters in our data are connected. We do not observe if or when different households or businesses move in and out of each structure.

From discussions with NEDCo's management team, we learned that decisions to transitioning customers from post to prepaid meters were institutional and happened in different waves of prepaid meter procurements. Different municipalities were assigned different quota of prepaid meters in different points in time. Municipality managers then decided which postpaid meters to substitute for prepaid ones. By and large, this choice was made on the basis of fieldwork convenience. Specific customers or groups of customers could not privately select themselves into receiving prepaid meters.

It is also worth noting the prevalence of "meter-sharing" in our setting: when multiple households or business share the same meter and thus are counted as one, single customer for the electricity company. Meter-sharing is illegal and not identified in the data. So we cannot control for it in our analysis. However, we know it exists. In February 2021, we conducted a questionnaire-based data collection with 250 small-business owners in Techiman, the capital of the Bono East Region. Forty-five percent of business owners reported sharing their residential and 26% share their commercial meter with independent neighbors. Sixteen percent mentioned that they use the same residential meter for their business and residence. While these numbers are not representative, they give us a sense for the order of magnitude of meter-sharing in our sample.

We take this with caution in the interpretation of our results. The levels and temporal evolution of elec-

³The sample in India is also particularly different than ours in the sense that their meters are postpaid, which implies a very different relationship between the utility company and its customer, default rates are much higher, and the Indian culture has a culturally inherited understanding of electricity "as a right" rather than a marketable good (see Burgess et al. (2020)).

tricity use become upper-bounds for individual households and businesses. The interpretation of price elasticities are a bit more nuanced. On one hand, we can take them on their face value, since they are calculated for the average meter, and ultimately this is the policy-relevant estimate. On the other hand, intra-household dynamics can generate “free-riding” and lower price responses for utilities if consumption is not fully observable by all members and costs are not shared proportionately to use (Jack et al., 2023). This could be the case intra-structures (in addition to intra-households) sharing a meter, which biases our elasticity estimates towards less price-sensitive responses.

3.2.2 Country-wide tariffs

We complement historical consumption data with the history of electricity tariffs in Ghana. Electricity and water tariffs in the country are determined by the Public Utilities Regulatory Commission (PURC). PURC implements two types of price changes. Major Tariff Reviews (MTRs) restructure the entire tariff schedule and happen once every three to five years. Within MTRs, PURC predetermines Automatic Adjustment Formulas (AAFs), which adjust tariffs quarterly following macroeconomic parameters. The temporal evolution of electricity tariffs is plotted in Figure (9) in Appendix (A). In the span of our data, our sample goes through three MTRs and seven AAF adjustments. The first two MTRs were in October 2013 and December 2015 and increased prices by 79% and 59%, respectively. The third MTR was in March 2018 and lowered prices by 18%. All AAF adjustments increased prices, ranging between 2% and 12% in nominal terms.

3.2.3 Household-level questionnaire

We also use the Ghana Socioeconomic Panel Survey (GSPS) to shed light on households’ acquisition of electrical appliances. The GSPS is a public, three-wave panel that tracked households for almost ten years. Instead of using its national reach, we focus our analyses on households interviewed in urban enumeration areas of the Bono East region, so we can directly relate the insights coming from these data to the electricity customers in our sample. These are a total of 195 households. The GSPS data is not

linked to the electricity consumption dataset. It serves the purpose of providing descriptive statistics for the general population where our electricity data from NEDCo is included.

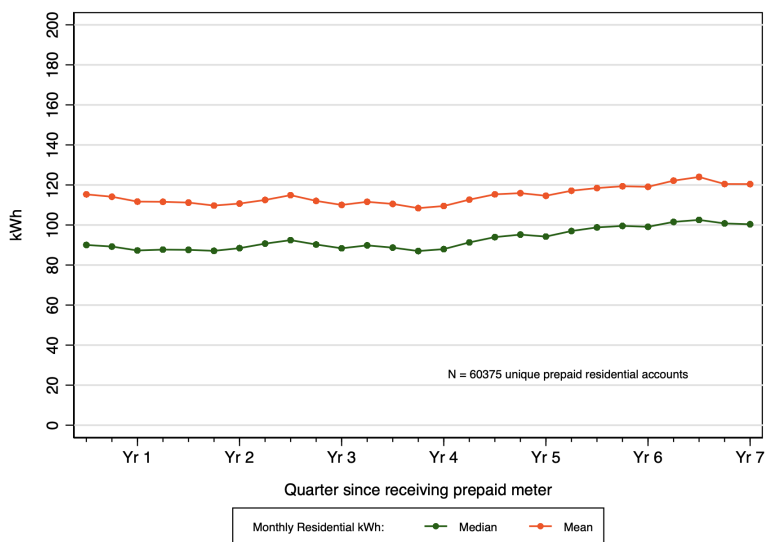
4 The evolution of electricity consumption

The motivating fact driving this paper are the extremely low levels and temporal evolution of monthly average electricity use in our sample. Also interesting is that commercial accounts use less electricity than residential ones and show nearly no evolution in time. This data is depicted in Figure (2). The two panels plot the quarterly evolution of average monthly kWh consumption since the first electricity purchase for residential and commercial accounts, respectively. Green dots are the median values in the distribution. Orange dots are the means. The graph excludes the first three months of consumption with prepaid meters, as behavior in that period can be dominated by customers “learning” how to use the new meter. Table (5) in Appendix A provides descriptive statistics. At the end of the first year with their prepaid meter, residential customers use 87 kWh. Six years later, 100kWh. This increase is equivalent to adding three light bulbs to the home and using them for six hours per day. Commercial accounts move from 68kWh after their first year to 71kWh at the end of their seventh year.

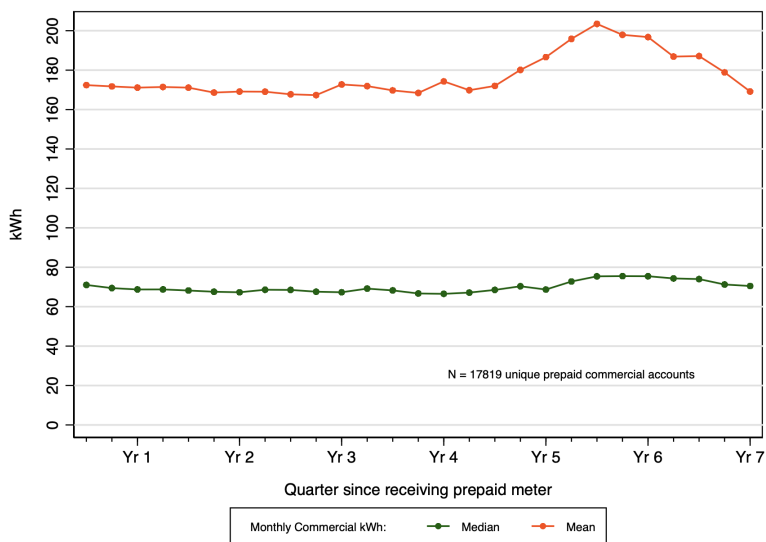
We improve on this work by estimating a linear regression following Equation 5 to inspect correlations between time-with-meter and electricity use. We estimate the following equation:

$$kwh_{im} = \beta_1 Months_{im} + \mathbf{X}^T \Phi + \eta_i + \zeta_{sc} + u_{im}, \quad (7)$$

where kwh_{im} is the amount of kWh that account i consumed in month m . At each calendar month m , $Months_{im}$ counts the number of months since customer i 's first prepaid purchase. \mathbf{X} takes on a series of controls, including each customer's marginal price, any subsidies or charges that were applied to their account, lags for the consumption in the past three consecutive months, and annual GDP growth in Ghana. We also include fixed effects for meter numbers, captured by η , and for semester-of-entry-by-city, capture by ζ , to control for different “cohorts” of customers across all cities in the data. The coefficient of interest is β_1 , which gives us the correlation between how long the customer has had a prepaid meter



(a) Residential



(b) Commercial

Figure 2: Electricity consumption since receiving a prepaid meter

Notes. (1) Outcome: Monthly electricity consumption per quarter after first prepaid payment.

and their monthly kWh consumption, everything else equal.

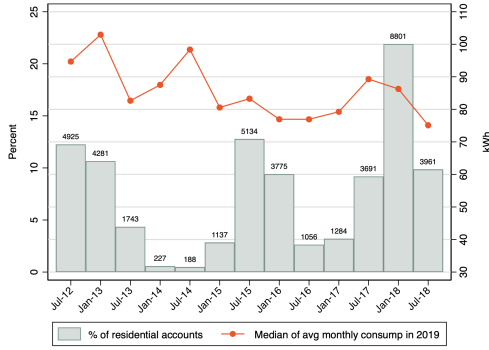
This analysis validates the intuition from Figure (2). Table (1) presents the regression results. Columns (1) and (3) show estimates for a simpler version of Equation (7), without any of the control variables in \mathbf{X} . Columns (2) and (4) present results for the main specification. The point estimate for the correlation of time-with-meter and kWh for residential accounts is 0.091. The interpretation for this estimate is that all else equal within meter, its location and the semester it started, subsidies and charges, GDP growth, and past consumption, then on average, an extra calendar month is associated with an increase in residential electricity consumption by 0.091kWh. Over a year, this means an increase of 1.1kWh. For commercial accounts, the coefficient from our preferred estimation shows an increase of 0.272kWh with an extra month. Over an year, this means an increase of 3.26kWh. These results are well in-line with the trends coming from the descriptive statistics of the data. By any economic interpretation, they are essentially null results: having time with the meter does not prompt residential or commercial accounts to using more electricity.

Table 1: The role of time in electricity use.

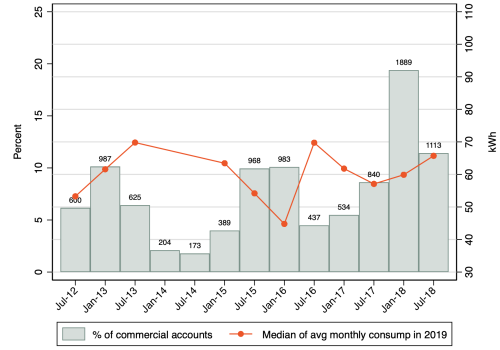
	Residential		Commercial	
	(1)	(2)	(3)	(4)
Months since first payment	0.073*** (0.002)	0.091*** (0.002)	-0.030*** (0.009)	0.272*** (0.011)
R2	0.60	0.75	0.80	0.88
N: ID-Month	2,225,100	1,978,192	552,887	482,198
N: Unique Accs.	52679	52679	16383	16383
Avg kWh	126	126	250	250
SE Cluster	Robust	Robust	Robust	Robust
Controls	No	Yes	No	Yes

Notes. (1) The outcome is monthly kWh consumption by the electricity account.

The statistic on time-with-meter pulls together accounts starting at different points in time. This may mask the evolution of different cohorts of customers. For example, it could be the case that early adopters of prepaid meters were fundamentally different in their consumption than late adopters. Hence our use of fixed effects for semester-of-entry-by-city. Figure (3) develops on this point by aggregating customers



(a) Residential



(b) Commercial

Figure 3: Average consumption in 2019 by semester of entry

Notes. (1) Outcome: Median of average kWh consumption in 2019. (2) The left vertical axis plots the percentage of accounts from each semester in the data. The right vertical axis plots average kWh consumption in 2019. The number above each bar shows the actual number of accounts in each semester.

by the semester when their first prepayment happened and plotting their average electricity consumption in 2019. This division creates “cohorts” of customers based on when they entered the data and fixes the analysis to observing the consumption of these cohorts in a fixed point in time, 2019. The results are displayed in Figure (2) and validate the lessons from above.⁴

We conclude this analysis estimating the following regression, to investigate time-with-meter correlations with monthly average consumption in 2019:

$$AvgkWh2019_i = \beta_1 Months_i + \zeta_{cs} + u_i. \quad (8)$$

The predicted variable $AvgkWh2019_i$ is each account i 's average monthly consumption in 2019. $Months_i$ counts the number of months between customer i 's first prepaid purchase and January 2019. ζ_{sc} are city-semester fixed effects controlling for the city and semester when each customer entered the data. The coefficient of interest is β_1 , which estimates the correlation between consumption in 2019 and time-with-meter after controlling for the location of the account.

⁴For robustness, in Appendix (A) we plot the same figures fixing the year in 2018. The interpretation remains.

Table (2) presents the results. Columns (1) and (3) show estimations without the control for city. Our preferred estimations are in Columns (2) and (4), which we interpret as an extra month with a prepaid meter being associated with an increase of 0.289kWh and a decrease of 0.031kWh on average consumption in 2019, holding locations and cohorts fixed, for residential and commercial accounts, respectively. The coefficient for commercial accounts is not statistically significant at conventional levels. As above, although the residential coefficient is significantly different from zero, it is not economically relevant. This analysis reinforces our argument that time connected to the grid does not appear to have an effect on households' and business' use of electricity. This helps us answer the first set of questions in this paper and contributes to deconstructing the argument that providing electricity access in low-income settings can by itself trigger productive levels of electricity use over time.

Table 2: The role of time in electricity use: 2019.

	Residential		Commercial	
	(1)	(2)	(3)	(4)
Months since first payment	0.242*** (0.014)	0.289*** (0.039)	0.213** (0.084)	-0.031 (0.215)
R2	0.01	0.05	0.00	0.10
N: ID-Month	43,670	43,670	11,595	11,595
N: Unique Accs.	45357	45357	12183	12183
Avg kWh	91	91	109	109
SE Cluster	Robust	Robust	Robust	Robust
Controls	No	Yes	No	Yes

Notes. (1) The outcome is monthly kWh consumption by the electricity account in the year of 2019.

5 Short-term elasticities

Having shown no evolution in electricity use over time, the objective of this section is to estimate consumers' price elasticity of demand for grid electricity with the purpose of understanding whether price-based policy instruments can spur demand. We follow Ito (2014) and Saez et al. (2012), and assume a quasilinear form for the utility function in Equation (6): agents have utility $u(E_t, x_t)$, where for each month t , E_t is electricity consumption in kWh and x_t is an outside basket of goods. Taking the difference

of logs of consumption in each time t , we seek to estimate

$$\Delta \ln(E_{it}) = \alpha + \beta_P \Delta \ln(P_{it}) + \eta_{it}, \quad (9)$$

where E_{it} identifies monthly prepaid purchases of kWh for customer i in month t , and $\Delta \ln(E_{it}) = \ln(E_{it}) - \ln(E_{i,t-12})$, with $t-12$ being the same billing month but in the previous year⁵. P represents the marginal price paid by the customer in each month, and $\eta_{it} = \epsilon_{it} - \epsilon_{i,t-12}$ is an idiosyncratic error term. In this formulation, β_P seeks to identify the price elasticity of demand with respect to the marginal price of electricity.

This is a linear equation and can be estimated with an ordinary least-squared regression. However, in such regression, β_P would not identify the desired price elasticity. Electricity in Ghana (and in most of the world) is priced with an increasing-block tariff schedule. The more electricity the customer uses, the higher the marginal price of the electricity unit. It follows that marginal prices are a function of consumption and correlated with unobserved shocks to the error term η_{it} in the regression.

To resolve this endogeneity, we use what is known as a “simulated instrument.” This type of instrument has been mostly used and discussed in the context of nonlinear taxation (Saez et al., 2012; Blomquist and Selin, 2008) but also by Ito (2014) to study electricity consumption. For any consumption level \tilde{E}_{it} , the instrument isolates changes in the price of electricity induced by exogenous policy decisions. Mathematically, this works as follows, with superscript I denoting the instrumental variable:

$$\Delta \ln(P_{it})^I = \ln(P_t(\tilde{E}_{i,t-6})) - \ln(P_{t-12}(\tilde{E}_{i,t-6})). \quad (10)$$

The instrument is operationalized by taking the difference of log-price experienced by each customer i in months t and $t-12$ had the consumption in both months been the same as what it was in $t-6$, their equidistant month.

⁵Going back a whole year in the comparison is important because it accounts for seasonality in electricity consumption, which we do observe in the data

5.1 Threats to exogeneity

For this instrument to identify the causal effect of a change in prices in a change in consumption, it needs to satisfy standard instrumental variable assumptions: relevance and exogeneity. Relevance requires that the instrumental variable is correlated with the endogenous variable, the marginal price of electricity. This is easily satisfied in our setting. Exogeneity requires that the instrument only affects consumption through its relationship with marginal price. This is achieved by using $t - 6$ as the reference month.

We need the consumption level used by the instrument, $\tilde{E}_{i,t-6}$, to be uncorrelated with the error term from the second-stage regression: $\eta_{it} = \epsilon_{it} - \epsilon_{i,t-12}$. Earlier studies using this instrument operationalized this instrument with the base-year consumption $E_{i,t-12}$ instead of $x_{i,t-6}$. This presents a “mean-reversion” challenge. As mentioned by Blomquist and Selin (2008), using $E_{i,t-12}$ carries the assumption that consumption in $t - 12$ correlates equally with ϵ_{it} and $\epsilon_{i,t-12}$. If this is not true (the more likely scenario given mean-reversion in consumption following transitory shocks in $t - 12$), then $E_{i,t-12}$ is more correlated $\epsilon_{i,t-12}$ and thus with the error term η_{it} . We follow the more recent literature cited above and use the midpoint $t - 6$ as the reference consumption month.

Ito (2014) also mentions that the simulated instrument may fail the exogeneity criterion if high and low electricity users have different consumption paths over time. We follow his econometric structure and add decile-by-time dummies to the estimation equation. This brings a flexible, non-parametric control function for confounding factors associated with the distribution of consumption levels.

Finally, the estimation to retrieve the price elasticities uses a two-stage least squares regression of consumption on marginal prices, instrumenting for the price variable, adding a flexible function $f_t(E_{i,t-6})$ to control for distributional changes in consumption, and other observable characteristics:

$$\begin{aligned} \text{First Stage: } \Delta \ln(P_{it}) &= \alpha \Delta \ln(P_{it})^I + f_t(E_{i,t-6}) + \mathbf{X}^T \omega + u_{it} \\ \text{Second Stage: } \Delta \ln(E_{it}) &= \beta_P \widehat{\Delta \ln(P_{it})} + f_t(E_{i,t-6}) + \mathbf{X}^T \gamma + \eta_{it}, \end{aligned} \tag{11}$$

where $f_t(E_{i,t-6})$ are decile-by-time fixed-effects in $t - 6$ consumption. For each decile $j \in \{1, \dots, 10\}$, we have $f_t(E_{i,t-6}) = \sum_{j=1}^9 \theta_{tj} \cdot 1\{E_{j,t-6} < E_{i,t-6} \leq E_{j+1,t-6}\}$. As before, the vector \mathbf{X} holds government subsidies

that were put in place at different levels of electricity purchases in different points in time, as well as three lags of consumption, and the total sum of charges applied to each electricity purchase. The coefficient of interest is β_P , which identifies the price elasticities of demand for grid electricity. The data is a monthly panel, so the identified elasticity is also monthly.

5.2 Results

Tables (3) and (4) show estimation results for residential and commercial accounts, respectively. The first-stage regressions in Column (1) show strong correlations between the instrument and the instrumented variable for both user types. The estimated coefficients are 0.955 for residential and 0.993 for commercial accounts. These coefficients are high and may raise suspicions on the validity of the instrument. If the instrument is too correlated with the endogenous variable, then it may fail the exogeneity assumption.

In our case, the high correlation comes from two features of our setting. Price brackets have only four pricing levels. So after a price change, most consumers still stay on their original bracket, which causes old and new prices to be more correlated than if customers were switching brackets often. Secondly, and possibly most important, the instrument leverages the panel feature of the data. Since the data is monthly and prices changes are few, the majority of observations are identical: 70% of residential and 88% of commercial accounts have the exact same values for the true and instrumented price. It is thus natural that after adding controls to the regression, the endogenous and instrumental variables will be highly correlated.

The estimated elasticities are -0.282 for residential and -0.262 for commercial accounts, displayed in columns (3) of their respective tables. To put these numbers in perspective, a reduction of 40% in residential (commercial) electricity prices would lead to an increase of 14kWh (13kWh) per month, on average. This is essentially the increase in consumption that we observe residential accounts reaching after six years with their prepaid meter. This provides hope for the possibility of using price tools to spur electricity demand.

Our residential elasticities are also an order of magnitude higher than what has been previously estimated in the literature. Jack and Smith (2020) estimated an elasticity of -0.121 with prepaid customers in South Africa. The short-run elasticities in Khanna and Rowe (2021) are smaller and range between -0.013 and -0.04, but the authors observe a large increase in arrears and defaults, which attenuates price responses. We are not aware of causally identified commercial electricity elasticities for low-income settings in the literature.

We also estimate the same regression splitting the sample by quartiles of the distribution of average electricity consumption. The estimates for each quartile are displayed in Columns (4) to (7). Residential elasticities increase with consumption. For example, residential accounts in the first quartile of consumption consume an average of 55kWh per month and have an estimated elasticity of -0.18. Households in the fourth quartile average 231kWh and have an elasticity of -0.3. Commercial elasticities, on the other hand, decrease with consumption. In the first commercial quartile, average consumption is 31kWh and the elasticity is -0.32. On the fourth commercial quartile, average consumption is 782kWh and the elasticity is -0.15.

One intuitive explanation for the heterogeneity in residential accounts is that households with higher consumption are most likely those who have already acquired more appliances and thus have more margins of adaptation. We show descriptive statistics on the acquisition of durable, residential electrical goods in the next section. For businesses, it is intuitive to think that high users are also the ones that have adapted their production functions to electrified machines. Because of that, firms that use higher levels of electricity become more dependent on it and thus more price inelastic. Meanwhile, shops that use low levels of electricity may do so for not-core activities, and hence be more able to adjust their use according to price. We do not have data on shop acquisition of durable goods so cannot further explore this hypothesis.

Table 3: Price elasticities of electricity consumption for residential accounts.

	1st Stage	2nd Stage		Q1	Q2	Q3	Q4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS
$\Delta \ln MP_{it}^I$	0.955*** (0.002)						
$\Delta \ln MP_{it}$		0.796*** (0.001)	-0.282*** (0.008)	-0.180*** (0.012)	-0.312*** (0.015)	-0.385*** (0.017)	-0.302*** (0.021)
N: ID-Month	1,510,198	1,509,263	1,509,263	303,807	402,303	425,780	376,959
N: Unique Accs.	52679	52679	52679	16847	12843	11638	11351
Avg kWh	126	126	126	55	89	129	231
FE: Loc-Mon	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Decile-Mon	No	Yes	Yes	Yes	Yes	Yes	Yes
SE Cluster	Robust	Robust	Robust	Robust	Robust	Robust	Robust
F-stat	57536						

Notes. The 2SLS specification instruments for marginal prices. Column (1) reports the 2SLS first-stage. Column (2) shows the main regression specification without instrumenting for marginal price. Columns (3) to (7) report 2SLS estimations.

Table 4: Price elasticities of electricity consumption for commercial accounts.

	1st Stage	2nd Stage		Q1	Q2	Q3	Q4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS
$\Delta \ln MP_{it}^I$	0.993*** (0.001)						
$\Delta \ln MP_{it}$		-0.021** (0.011)	-0.262*** (0.016)	-0.322*** (0.026)	-0.289*** (0.027)	-0.307*** (0.033)	-0.151*** (0.044)
N: ID-Month	347,162	350,927	346,650	66,957	92,352	97,708	89,051
N: Unique Accs.	16383	16383	16383	5042	3967	3781	3594
Avg kWh	250	250	250	31	63	122	782
FE: Loc-Mon	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Decile-Mon	No	No	Yes	Yes	Yes	Yes	Yes
SE Cluster	Robust	Robust	Robust	Robust	Robust	Robust	Robust
F-stat	157742						

Notes. The 2SLS specification instruments for marginal prices. Column (1) reports the 2SLS first-stage. Column (2) shows the main regression specification without instrumenting for marginal price. Columns (3) to (7) report 2SLS estimations.

6 Durables acquisition

In this section we leverage four waves of panel data from the Ghana Socioeconomic Panel (GSPS) to study household's acquisition of durable, electrical goods. The insight from this data is simple. Households in central Ghana have few and low energy-demanding appliances. Similarly to electricity consumption, there has been little evolution in appliance acquisition. In 2009, 47% of households owned a TV. This number increased to 69% in 2018. However, ownership is still low for larger and more energy-intensive goods, such as refrigerators and air-conditioners. The percentage of the GSPS sample with refrigerators in 2009 was 36%. This number increased to 41% in 2018. Air-conditioner ownership has remained close to zero during the time-window of this data.

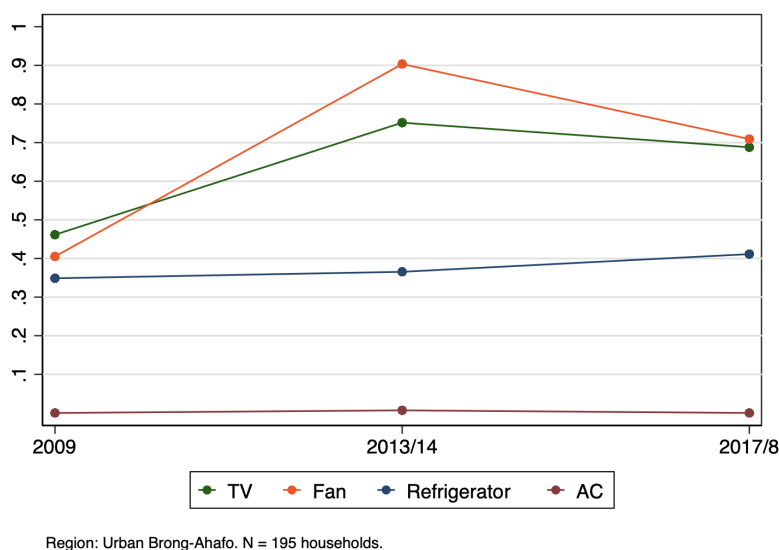


Figure 4: Percentage of population with each type of appliance

Notes. Outcome: Ownership of electrical appliances (percent of population). (2) Source: GSPS.

We can relate these results with the evidence and discussion put forth by Gertler et al. (2016): the acquisition of energy-using assets does not happen linearly (gradually) with income over time. Instead, households purchase electrical appliances after income reaches some context-specific threshold, especially in the presence of credit constraints. The low levels and flat evolution of ownership of larger energy-using

assets suggest that urban, central Ghanaian households are below such income threshold. Clearly, with few appliances, households are constrained to using low levels of electricity. Furthermore, the model we developed above in the conceptual framework teaches us that changes in electricity prices do not affect the stock of electrical appliances in the short term. It follows that households with fewer appliances are the most constrained and thus less able to adapt their consumption, which is confirmed in our elasticity estimations. All in all, one lesson coming from this data is that even after many years being connected to the grid, most households in our study region have not acquired enough electrical appliances to have electricity consumption change their overall lifestyle.

7 Conclusion

This paper looks at the temporal evolution and price sensitivity of electricity use among households and businesses in central Ghana. We observe residential and commercial accounts' monthly consumption for up to seven years. While most of the literature on electrification has focused on rural areas in LMICs, we offer results from a setting that is representative of fast-growing urban areas of SSA, where most of electricity customers reside.

Our first result is that residential and commercial customers use remarkably small amounts of electricity, and their consumption does not increase with time. This is important for two reasons. First, it provides a general insight to global efforts focused on expanding electricity access: connecting households and businesses to the grid does not appear to trigger a process that changes lifestyle and productivity. Second, this result speaks to a contentious literature studying whether infrastructure investments in electricity spur economic development and growth in LMICs. Observing increasing electricity use over time after agents get connected to the grid is a necessary condition for electricity infrastructure projects to impact economic growth. By any economic standard, the levels of electricity use that we observe in our data cannot qualify as transformational enough to meaningfully impact economic growth by itself.

We then estimate price elasticities of electricity demand for households and businesses to assess whether subsidies on electricity tariffs can be useful to spur electricity use. Prices incentives are the primary tool

that governments can leverage to incentivize clean energy transitions. We estimate similar and relatively large elasticities for residential and commercial accounts. More importantly, we reveal a large heterogeneity in our estimations across consumption levels. Residential elasticities increase with consumption, while commercial elasticities decrease. Low residential users are half as responsive and high users; and low commercial users are twice more responsive than high users. To the extent that subsidies on tariffs can ultimately lower profits and hurt the performance of state-owned distribution companies, our results highlights the importance of targeting subsidies to different consumption brackets to make them more effective. We conclude by showing that households' acquisition of durable, electrical appliances over time is very low in our study region, which also contributes to the low levels of electricity use and small price responses by low users.

References

- M. Barron and M. Torero. Household electrification and indoor air pollution. *Journal of Environmental Economics and Management*, 86:81–92, Nov. 2017. ISSN 00950696. doi: 10.1016/j.jeem.2017.07.007. URL <https://linkinghub.elsevier.com/retrieve/pii/S0095069617304825>.
- S. Blomquist and H. Selin. Hourly Wage Rate and Taxable Labor Income Responsiveness to Changes in Marginal Tax Rates. *Working Paper 2018:16*, 2008.
- P. Brenton. Estimates of the demand for energy using cross-country consumption data. *Applied Economics*, 29(7):851–859, July 1997. ISSN 0003-6846, 1466-4283. doi: 10.1080/000368497326507. URL <https://www.tandfonline.com/doi/full/10.1080/000368497326507>.
- R. Burgess, M. Greenstone, N. Ryan, and A. Sudarshan. The Consequences of Treating Electricity as a Right. *Journal of Economic Perspectives*, 34(1):145–169, Feb. 2020. ISSN 0895-3309. doi: 10.1257/jep.34.1.145. URL <https://pubs.aeaweb.org/doi/10.1257/jep.34.1.145>.
- F. Burlig and L. Preonas. Out of the darkness and into the light? Development effects of rural electrification. *Journal of Political Economy*, forthcoming, page 42, 2022.
- L. Cozzi, D. Wetzel, G. Tonolo, and J. Hyppolite II. For the first time in decades, the number of people without access to electricity is set to increase in 2022, 2022. URL <https://www.iea.org/commentaries/for-the-first-time-in-decades-the-number-of-people-without-access-to-electricity-is-set-to-increase>.
- T. Dinkelman. The Effects of Rural Electrification on Employment: New Evidence from South Africa. *American Economic Review*, 101(7):3078–3108, Dec. 2011. ISSN 0002-8282. doi: 10.1257/aer.101.7.3078. URL <https://pubs.aeaweb.org/doi/10.1257/aer.101.7.3078>.
- V. Foster, N. Gorgulu, S. Straub, and M. Vagliasindi. The Impact of Infrastructure on Development Outcomes: A Qualitative Review of Four Decades of Literature. *World Bank Group*, (Policy Research Working Paper 10343), 2023.
- S. Fried and D. Lagakos. Electricity and Firm Productivity: A General-Equilibrium Approach. *Working Paper*, page 57, 2021.

- P. J. Gertler, O. Shelef, C. D. Wolfram, and A. Fuchs. The Demand for Energy-Using Assets among the World's Rising Middle Classes. *American Economic Review*, 106(6):1366–1401, June 2016. ISSN 0002-8282. doi: 10.1257/aer.20131455. URL <https://pubs.aeaweb.org/doi/10.1257/aer.20131455>.
- Ghana Statistical Service. Ghana 2021 Population and Housing Census, General Report, Volume 3A. Technical report, Ghana Statistical Service, 2021.
- M. Hardy and J. McCasland. Lights Off, Lights On: The Effects of Electricity Shortages on Small Firms. *The World Bank Economic Review*, page 15, 2019.
- K. Ito. Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing. *American Economic Review*, 104(2):537–563, Feb. 2014. ISSN 0002-8282. doi: 10.1257/aer.104.2.537. URL <https://pubs.aeaweb.org/doi/10.1257/aer.104.2.537>.
- B. K. Jack and G. Smith. Pay as You Go: Prepaid Metering and Electricity Expenditures in South Africa. *American Economic Review: Papers and Proceedings*, 105(5):237–241, May 2015. ISSN 0002-8282. doi: 10.1257/aer.p20151096. URL <https://pubs.aeaweb.org/doi/10.1257/aer.p20151096>.
- B. K. Jack, S. Jayachandran, F. Malagutti, and S. Rao. Environmental externalities and free-riding in the household. 2023.
- K. Jack and G. Smith. Charging Ahead: Prepaid Metering, Electricity Use, and Utility Revenue. *American Economic Journal: Applied Economics*, 12(2):134–168, Apr. 2020. ISSN 1945-7782, 1945-7790. doi: 10.1257/app.20180155. URL <https://pubs.aeaweb.org/doi/10.1257/app.20180155>.
- S. R. Khandker, D. F. Barnes, and H. A. Samad. Welfare Impacts of Rural Electrification: A Panel Data Analysis from Vietnam. *Economic Development and Cultural Change*, 61(3):659–692, Apr. 2013. ISSN 0013-0079, 1539-2988. doi: 10.1086/669262. URL <https://www.journals.uchicago.edu/doi/10.1086/669262>.
- M. Khanna and N. D. Rao. Supply and Demand of Electricity in the Developing World. *Annual Review of Resource Economics*, 1:567–596, 2009. ISSN 1941-1340, 1941-1359. doi: 10.

- 1146/annurev.resource.050708.144230. URL <https://www.annualreviews.org/doi/10.1146/annurev.resource.050708.144230>.
- S. Khanna and K. Rowe. Short- and Long-Run Consumption and Non-Payment Responses to Retail Electricity Prices in India. 2021. khanna_rowe_2021.
- K. Lee, E. Miguel, and C. Wolfram. Does Household Electrification Supercharge Economic Development? *Journal of Economic Perspectives*, 34(1):122–144, Feb. 2020. ISSN 0895-3309. doi: 10.1257/jep.34.1.122. URL <https://pubs.aeaweb.org/doi/10.1257/jep.34.1.122>.
- M. Lipscomb, A. M. Mobarak, and T. Barham. Development Effects of Electrification: Evidence from the Topographic Placement of Hydropower Plants in Brazil. *American Economic Journal: Applied Economics*, 5(2):200–231, Jan. 2013. ISSN 1945-7782, 1945-7790. doi: 10.1257/app.5.2.200. URL <https://pubs.aeaweb.org/doi/10.1257/app.5.2.200>.
- S. McRae. Infrastructure Quality and the Subsidy Trap. *American Economic Review*, 105(1):35–66, Jan. 2015. ISSN 0002-8282. doi: 10.1257/aer.20110572. URL <https://pubs.aeaweb.org/doi/10.1257/aer.20110572>.
- PURC. Press Release: 2022-2025 Multi-Year Tariff Review for Natural Gas, Electricity and Water Services, 2022.
- E. Saez, J. B. Slemrod, and S. H. Giertz. The Elasticity of Taxable Income with Respect to Marginal Tax Rates: A Critical Review. *Journal of Economic Literature*, 50:3–50, 2012. doi: 10.1257/jel.50.1.3.
- U.S. Energy Information Administration. Residential energy consumption survey (recs) data. <https://www.eia.gov/consumption/residential/data/2020/index.php?view=microdata>, 2021. Accessed on May 14, 2023.
- World Bank Web. World bank - electricity access (% of population). <https://data.worldbank.org/indicator/EG.ELC.ACCS.ZS?locations=ZG>. Accessed: July 5, 2023.

Appendix

A Tables and Figures

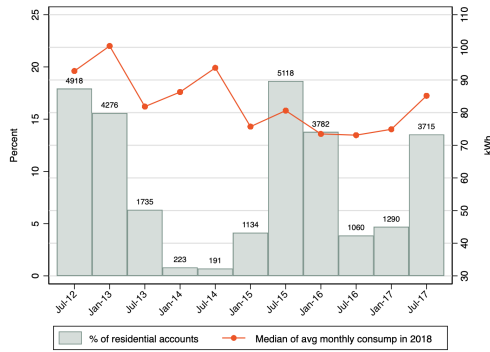
A.1 Tables

Table 5: Consumption since prepaid meter

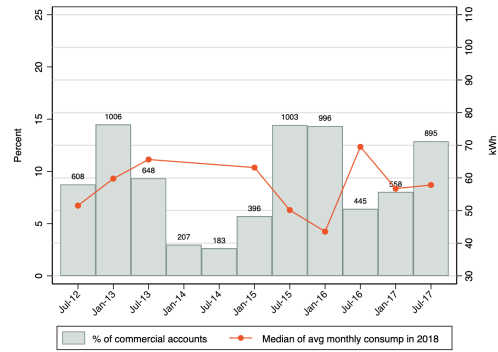
	Residential								Commercial							
	P50	Mean	SD	Min	P10	P90	Max	N	P50	Mean	SD	Min	P10	P90	Max	N
Yr-1	87.3	111.7	(79.4)	18.4	43.9	217.6	1579.3	47183	68.7	171.1	(306.1)	5.4	20.3	416.4	3630.9	13427
Yr-2	88.4	110.7	(75.0)	18.6	44.5	212.1	940.6	43975	67.3	169.1	(309.2)	5.5	20.3	401.4	3390.7	11521
Yr-3	88.4	110.0	(74.3)	17.6	44.5	210.5	576.8	30276	67.3	172.7	(321.6)	5.5	20.4	414.3	3522.6	8014
Yr-4	88.0	109.5	(72.7)	19.6	44	208.0	582.4	25622	66.5	174.3	(333.2)	5.9	20.8	399.8	3571.0	6354
Yr-5	94.2	114.6	(73.3)	20.8	49.8	214.9	515.3	17754	68.7	186.6	(349.4)	5.5	20.8	440.7	3357.3	4127
Yr-6	99.1	119.1	(75.4)	21.6	48.2	224.4	514.1	12551	75.4	196.8	(356.2)	5.5	21.2	475.0	3299.7	2847
Yr-7	100.4	120.4	(75.7)	22.8	48.9	223.9	520.8	11175	70.5	169.2	(295.5)	5.4	20.5	405.4	2741.7	2194
Yr-8	99.5	120.9	(76.1)	22.8	50	225.3	517.2	4324	59	135.4	(222.2)	5.5	15.8	337.6	2659.5	568
Yr-9	110.0	130.7	(81.4)	22.8	50	239.6	494.9	678	71.4	144.1	(216.8)	5.4	21.6	379.9	1434.7	115

A.2 Figures

A.2.1 Consumption in 2018



(a) Residential



(b) Commercial

Figure 5: Average consumption in 2018 by semester of entry

Notes. (1) Outcome: Median of average kWh consumption in 2019. (2) This analysis excludes 415 commercial accounts created in 2014 (N = 415) due to them being high outliers with unknown explanation. (3) The left vertical axis plots the percentage of accounts from each semester in the data. The right vertical axis plots average kWh consumption in 2018. The number above each bar shows the actual number of accounts in each semester.

A.2.2 No Bunching Around Tariff Changes

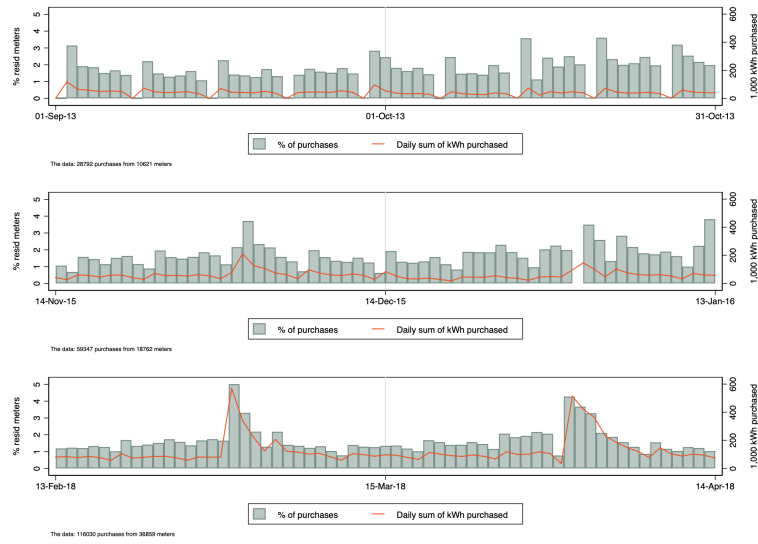


Figure 6: Electricity purchases 30 days before and after price changes (Residential)

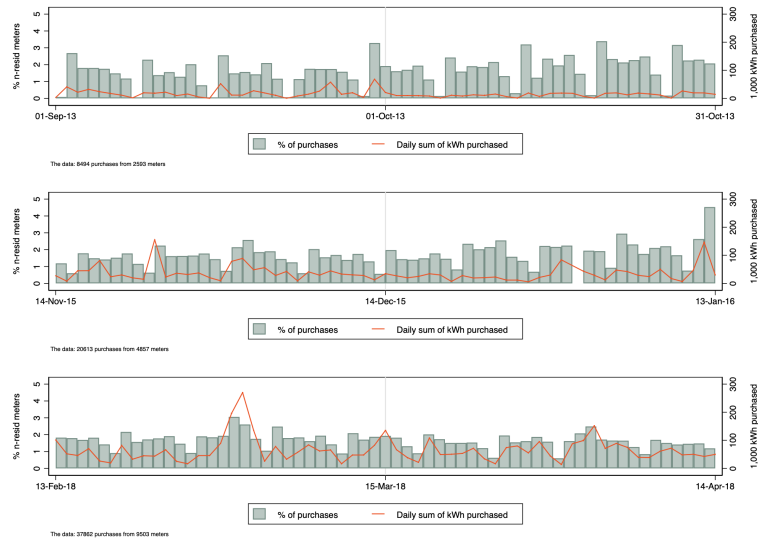


Figure 7: Electricity purchases 30 days before and after price changes (Commercial)

A.2.3 Electricity Access

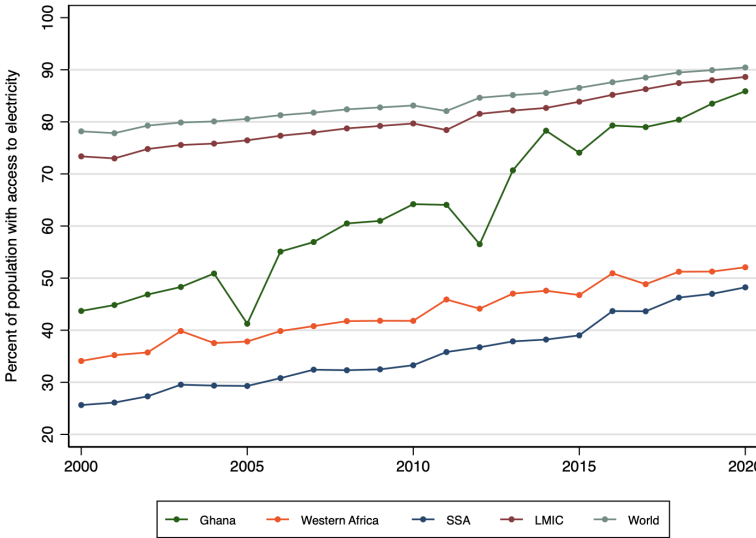


Figure 8: Percentage of population with access to electricity over time
 Notes. (1) Outcome: Access to electricity (percent of population). (2) Source: World Bank.

A.2.4 Electricity tariffs

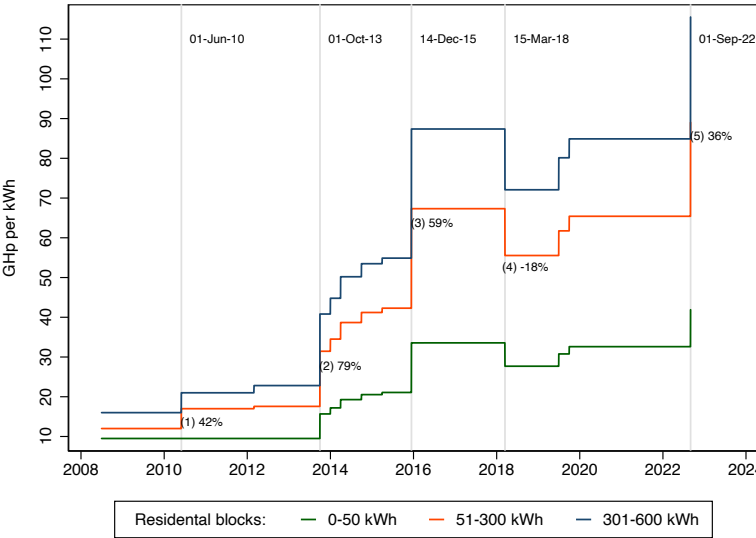


Figure 9: Temporal evolution of electricity tariffs in Ghana

Notes. (1) The timing of Major Tariff Reviews (MTRs) are marked with gray vertical lines. (2) Percentage numbers show the percentage change imposed by each Major Tariff Review. (3) Source: PURC.

A.2.5 Growth

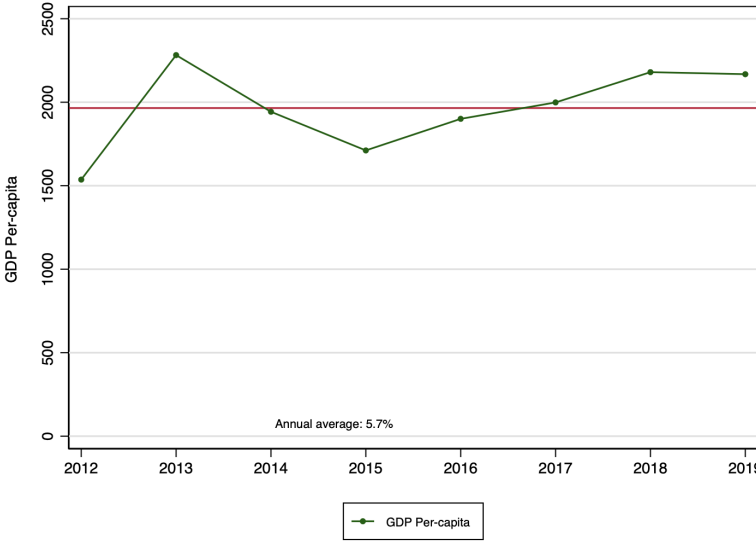


Figure 10: GDP Growth

Notes. (1) Outcome: GDP per-capita. (2) Source: World Bank.

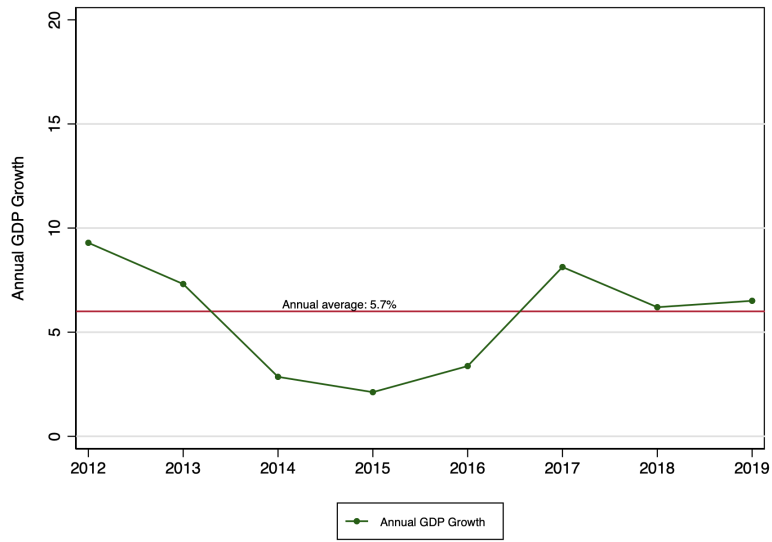


Figure 11: GDP Growth

Notes. (1) Outcome: Annual GDP Growth. (2) Source: World Bank.

IGC

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