A simulation-based estimation model of household electricity demand and appliance ownership

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Abstract

Understanding how electricity demand is likely to rise once households gain access to it is important to policy makers and planners alike. Current approaches to estimate the latent demand of unelectrified populations usually assume constant elasticity of demand. Here we use a simulation-based structural estimation approach, employing micro-data from household surveys for four developing nations, to estimate responsiveness of electricity demand and appliance ownership to income considering changes both on the intensive and extensive margin. We find significant heterogeneity in household response to income changes, which suggest that assuming a non-varying elasticity can result in biased estimates of demand. Our results confirm that neglecting heterogeneity in individual behavior and responses can result in biased demand estimates.

1 Introduction

The ownership of household appliances and equipment determines the demand for electricity and fuels in residences around the globe. For households that still lack access to electricity or are newly electrified, understanding what demand will be once they connect and how it will grow is important for planning purposes. Such latent demand is rarely estimated because of the challenges involved in doing so. Residential electricity demand projections for power sector planning in developing countries typically involve assumptions about average electricity use per consumer or estimate this applying constant average income elasticity of demand estimates (van Ruijven et al., 2012; Pachauri et al., 2013; Kemausuor et al., 2014; Mentis et al., 2017; Dagnachew et al., 2018). However, evidence from studies using microdata shows that such average estimates mask vast heterogeneity poorly explained by statistical methods. Household energy demand can vary tremendously across incomes, climates, seasons and regions even within nations (Pachauri and Jiang, 2008; Zeyringer et al., 2015; Zhou and Teng, 2013).

There is a large body of literature that focuses on electricity demand estimation, but studies estimating household electricity demand in developing countries remain scarce. In some part, this is the result of a lack of adequate data. Many studies estimate the relationship between per capita income and residential electricity using aggregate time series or panel data. Recent examples of such work still largely assume a linear relationship between income and electricity use (Liu et al., 2016). Yet, there is evidence that the linearity assumption is in question and there maybe biases associated with estimates that use aggregate data (Lescaroux, 2012; Halvorsen and Larsen, 2013). Studies using micro household level data have adopted a largely econometric approach using either parametric or non-parametric methods (Filippini and Pachauri, 2004; de Fátima S.R. Arthur et al., 2012; Zhou and Teng, 2013). Electricity demand models that do not account for changes in appliance ownership are likely to provide imprecise estimates of electricity demand, particularly in developing countries where the ownership of appliances is currently limited.

Few studies have focused on estimating household electricity demand in still electrifying regions using household level microdata. Existing literature has focused largely on the relationship between household income and the adoption of specific electrical appliances that are expected to drive household electricity demand growth (Wolfram et al., 2012; Auffhammer and Wolfram, 2014; Gertler et al., 2016; Rao and Ummel, 2017; McNeil and Letschert, 2010; Dhanaraj et al., 2018). These studies find that while income is a key predictor of appliance ownership, there is still considerable variation by income level and non-income drivers matter as well. Especially, the quality and reliability of electricity supply can be important to explaining appliance ownership (Samad and Zhang, 2018; Dang et al., 2019). Recent research also suggests that the sensitivity of energy demand to income or price changes can vary significantly between high and low energy consumers and spenders (Blundell et al., 2017; Harold et al., 2017; Wolfram et al., 2012).

Studies like those of Wolfram et al. (2012) and Gertler et al. (2016) suggest that, as the income of the poor rises, their demand for electricity is likely to increase substantially along the extensive margin as they buy electric appliances for the first time. However recent evidence from studies such as those by Dhanaraj et al. (2018); Rao and Ummel (2017) suggests that appliance diffusion can remain low despite rising incomes, if appliances are too expensive to afford or electric supply remains unreliable. A recent study from Kenya also corroborates these findings by providing evidence that many newly-connected customers only consume limited amounts of electricity, which means that built capacity may remain underutilized (Taneja, 2018). This also implies that in many instances, households that are officially counted as having access to electricity actually enjoy very few modern energy services.

In this study we contribute to the literature on the empirical estimation of electricity demand in developing countries by developing a model of household electricity demand using micro-data from representative national surveys for a subset of countries representing different regions of the Global South. For the selected countries, from a few percent to a quarter of the population still lack access to electricity. We contribute to the literature in two aspects. First, to the best of our knowledge, this is the first paper that uses a simulation-based structural estimation approach, employing micro survey data, to estimate responsiveness of electricity demand to income considering changes both on the intensive and extensive margin, and accounting for non-linearity in the relationship between income and demand. Second we apply the model to test the implications for electricity demand of different socio-economic futures and policy scenarios regarding the achievement of the United Nation's 2030 Agenda for sustainable development, specifically goal 7 on universal access to sustainable, reliable and affordable modern energy by 2030.

The rest of the paper is organized as follows. In the next section, we discuss the model, data and estimation procedures to calculate electricity demand employing micro data. In Section 3 we present results of our estimations employing the estimated parameters from our model for a set of different socio-economic scenarios that also distinguish between those where universal access to electricity is achieved by 2030 in accordance with the UN 2030 Agenda, and others where the goal is not achieved. Finally, in Section 4 we conclude by summarizing our key results and discuss some implications of the research for policy.

2 Modeling Approach

The main objective of our modeling approach is not to attempt to match the empirical data as closely as possible (for those purposes, other tools may be more appropriate, see Rovenskaya et al. 2019; Poblete-Cazenave et al. 2020), but to create a model of explicit behavioral responses to assess different policy scenarios, where the channels of causality are clearly identified. We consider two channels by which income can affect the demand for electricity. First, is directly through the budget constraint, as households with higher income can afford more electricity. Second, is indirectly, as households with higher income can afford more electrical appliances, the ownership and use of which increase the demand for electricity. To capture both these effects, we first model the probability that a household buys an appliance, and second, model the demand for electricity given the number of appliances the household owns.

Our methodology builds on the classic model of Dubin and McFadden (1984), but with several deviations, as our objective goes beyond the pure econometric analysis of the effect of appliance ownership and household characteristics on the demand for electricity and other fuels. Our approach is similar to that of Dubin and McFadden's in that the consumption of electricity and other fuels is determined by the choice of a set of appliances, within the framework of an indirect utility maximization model. However, it differs in that we follow a simulation-based approach, which allows us to model the ownership of a larger set of appliances and estimate the associated fuel and electricity demands on a variety of counterfactual and future scenarios, such as the ones we present in Section 3.

The model is defined as follows: consider the indirect utility function:

$$u = V(\bar{y}, p_1, p_2, s, w, \nu)$$

A household of observable characteristics w and other unobservable characteristics ν will choose a bundle of consumption $\{x_1, x_2, \bar{y}\}$ and appliances $s = i$ given prices p_1 and p_2 as long as:

$$U_i > U_j, \forall i \neq j$$

In particular, in terms of a choice model, the probability that a portfolio i is chosen is:

$$P_i(\nu_i : V_i > V_j,\ \forall i \neq j)$$

A simple, linear functional form/maximization problem that is consistent with these properties is:

$$\max U = \ln\left(\alpha_0 + \frac{\alpha_1}{\alpha_4} + \alpha_1 p_1 + \alpha_2 p_2 + \alpha_3 w + \alpha_4 \bar{y} + \nu_i\right) e^{\alpha_4 p_1} - \alpha \ln p_2$$

$$\text{s.t.} \qquad \bar{y} = y - \rho \sum_{j=1}^{m} K_j \delta_j + \sum_{j=1}^{m} \frac{\alpha_{4+j}}{\alpha_4} \delta_j$$

where the αs are preference parameters, K_j is the price of appliance j and δ_j is a dummy variable representing the ownership of appliance j. Hence, as an outcome of this maximization problem, the household chooses the set of appliances and electricity consumption in such a way that fuel consumption is a function of the explanatory variables we are interested in. In particular, to derive the demand for electricity x_1, we use Roy's identity:

$$x_1 = -\frac{\frac{\partial U}{\partial p_1}}{\frac{\partial U}{\partial y}} = \alpha_0 + \alpha_1 p_1 + \alpha_2 p_2 + \alpha_3 w + \alpha_4 \left(y - \rho \sum_{j=1}^{m} K_j \delta_j + \sum_{j=1}^{m} \frac{\alpha_{4+j}}{\alpha_4} \delta_j\right) + \nu_i$$

Then, to make it such that the demand x_i is consistently and asymptotically efficiently explained with the explanatory variables we select, we need that:

$$\mathbb{E}(\nu_i) = 0$$
$$\text{Var}(\nu_i) = \sigma^2_{\nu_i} < \infty$$

For that, we can use either a likelihood or a method of moments estimator. Here we use the latter. In this case, we have to make sure that:

$$\mathbb{E}\left(x_i - \left[\alpha_0 + \alpha_1 p_1 + \alpha_2 p_2 + \alpha_3 w + \alpha_4 \left(y - \rho\sum_{j=1}^{m} K_j\delta_j + \sum_{j=1}^{m}\frac{\alpha_{4+j}}{\alpha_4}\delta_j\right)\right]\right) = 0$$
$$Var\left(x_i - \left[\alpha_0 + \alpha_1 p_1 + \alpha_2 p_2 + \alpha_3 w + \alpha_4 \left(y - \rho\sum_{j=1}^{m} K_j\delta_j + \sum_{j=1}^{m}\frac{\alpha_{4+j}}{\alpha_4}\delta_j\right)\right]\right) = \sigma^2_{\nu_i}$$

If the problem is well defined and we have enough data, we know this will hold. But in our case, we have several cases with missing observations. Let's say, for example, we don't know what the cost of a refrigerator f is for every household in the sample. What we can do, is use a simulator sf such that:

$$\mu_{sf} \to \mathbb{E}(K_{sf}) = \mathbb{E}(K_f)$$
$$\sigma^2_{sf} \to Var(K_{sf}) = Var(K_f)$$

and estimate the parameters of interest using a random draw of a distribution with mean μ_{sf} and variance σ^2_{sf}. In this case, this is straightforward, as we can obtain consistent estimators of μ_{sf} and σ^2_{sf} using the empirical distribution for the households where we have information. We only need to be careful to use a large number of draws, such that the simulated mean $\bar{\mu}_{sf} \to \mu_{sf}$ and variance $\bar{\sigma}^2_{sf} \to \sigma^2_{sf}$. Using a similar logic for the variables of interest we create our "simulated" data. In particular, first we estimate the asymptotic distributions and simulators of the appliances:

- The demand for space cooling options is done using a multinomial logit on the following alternatives: no space cooling, only AC, only fan, both AC and fan
- The demand for water heating, space heating and main cooking device options are done using multinomial logit on: no device, electric device, gas device, kerosene device, solid biomass device
- The demand for refrigerators and freezers are modeled jointly, as also the demand for washing machines and dryers
- The demand for all remaining appliances is modeled independently using a simple logit

Then we simulate the remaining variables and the model is estimated using a "simulated" method of moments estimator, which is done as follows:

- Start by estimating the income, household size and rural/urban joint distribution
- Estimate distributions for other household characteristics, depending on the aforementioned variables
- Get N random draws of these estimated distributions, to represent N simulated households
- Using the estimated parameters from the discrete choice models, simulate the appliance uptake by end use for the households in the simulated sample
- Give an initial guess for the unknown preferences parameters (i.e. αs), calculate the household demands according to these parameter guesses

- Use a minimization algorithm to find the preference parameters that approximate as closely as possible the simulated moment conditions to the empirical moments

Specifically, we use Indirect Inference (Gourieroux et al., 1993) as our simulated method of moment estimator, as, first, it allows us to better capture the joint effect of the household characteristics and appliance ownership on electricity consumption, and second, it arises naturally from the original linear model developed by Dubin and McFadden (1984). We use the following auxiliary models:

- Two linear regressions (separate urban/rural) of log electricity expenditure over prices, expenditure on other fuels, household characteristics and dummies for appliances
- Mean electricity consumption and consumption of other fuels for different urban/rural quintiles
- Percentage of people with non-zero electricity consumption and of people with non-zero consumption of other alternative fuels

In the following, we present details of the data sets we employ to apply the model and some key results and insights gained from the analysis.

3 Model Results and Scenarios

3.1 Data and Estimation

We test our model by applying it to data from four developing countries with different realities: Ghana, Guatemala, India and South Africa. All of these nations have not yet achieved universal electrification, and fall within the lower-middle income category of the World Bank's income classification. Nevertheless, they have different historical backgrounds, and

Country	Dataset	Years
Ghana	Ghana Living Standards Survey (GLSS)	2012-2013
Guatemala	Encuesta Nacional de Condiciones de Vida (ENCOVI)	2014
India	India Human Development Survey (IHDS)	2011-2012
	National Sample Survey (NSS)	2011-2012
South Africa	Living Conditions Survey (LCS)	2014-2015

Table 1: Household Surveys Used

therefore, different institutional frameworks, as well as very different climates. Therefore, both the supply and the demand of fuels vary greatly among them. For example, while Ghana and Guatemala are closer to tropical areas and, therefore, may require space cooling, South Africa and India also have much cooler regions in their territories, so require space heating as well.

We use different data sources for these countries (Table 1), to create the estimation datasets which are described in Tables A1 and A2. For these datasets, we employ variables related to fuel consumption, household characteristics and appliances, which can be found in the aforementioned tables. Additionally, we impute climate information from Beck et al. (2018). We use the level of regional disaggregation on climate for each country that is provided in this data set.

We visually display the match from our simulation-based estimation to the empirical survey data in Figure 2 and numerically in Table 2. We can see that the model does a good job in replicating the pattern and, partially, the dispersion of electricity consumption by income, save some anomalies that can be observed in the empirical data. For example, in the cases of Ghana and South Africa, block electricity tariffs create peak points of consumption that are not replicated by the model, basically because our simulated dataset purposefully does not include these tariffs[1]. Additionally, there is a big peak in electricity consumption at the beginning of the distribution in South Africa, which can be explained by current public policies that provide free electricity up to a certain threshold to poor households, something that is also not part of our modelling approach. Nevertheless, it is extremely interesting to highlight the wide variance of the joint distribution of electricity consumption and income, something that most modelling approaches based on matching aggregate statistics cannot capture. These wide variances also bias our simulated means for the case of Ghana and India, where electricity consumption is relatively high even for households that are around middle levels of the income distribution.

	Mean		Std.Dev	
	Data	Sim	Data	Sim
Ghana	1663.9	1780.6	3316.7	1288.9
Guatemala	1125.0	1125.0	1180.6	513.9
India	1272.2	1413.9	1486.1	1061.1
South Africa	2969.4	2977.8	3091.7	2763.9

Table 2: Mean and Standard Deviation of Annual Household Electricity Consumption (KWh): Data vs Model Simulation

3.2 Appliance Ownership and End-Use Service Shares

The importance of taking into account appliance ownership in such behavioral demand models is also reflected in the differences we observe in appliance uptake over income across the different countries. Our analysis of appliance ownership patterns are similar to patterns observed in other studies (Chunekar and Sreenivas, 2019; Twerefou and Abeney, 2020). As we can see in Figure 1, appliance diffusion is much less responsive to income in Guatemala than in the other countries. Also, the rate of adoption/diffusion varies widely

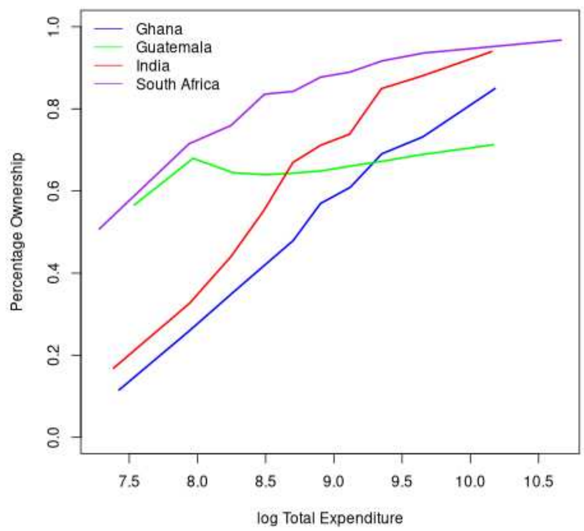
[1] As the model is designed to assess future policy scenarios, we decided not to include time-specific electricity tariff schedules.

by country, appliance type, and income level. This evidence is in line with results from prior research that point to the non-linear relationship between appliance adoption and income (see e.g. (Gertler et al., 2016)). This is another reason supporting the argument against using point estimates of income elasticity for the purposes of electricity demand estimation and projection.

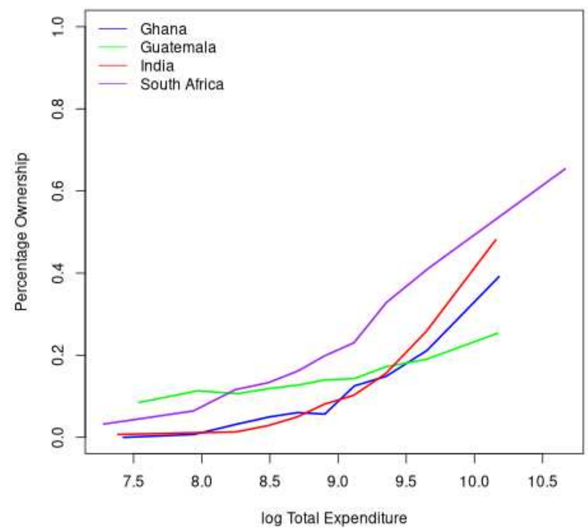
We apply the model to analyze the distribution of electricity consumption by end use. To do so, we distinguish five end use groupings: thermal comfort (space cooling and water and space heating), food preservation and preparation (stoves, fridges and freezers), clothes maintenance (washing, drying, ironing), entertainment and fun (televisions, music equipment, computers), and others. As we see in Table 3, the share of each group of appliances in total electricity use varies widely by income level and household location. Some key patterns are evident from our analysis. First, we find that the share of electricity use in appliances in the food group rises steeply for households in the top income quintile in almost all countries. This is because refrigerators are aspired for among households that can afford these, but also because high income households increasingly use electric cookstoves. This is particularly true in South Africa, which is an exceptional case, as government programs in this country incentivize electric cooking through the free basic electricity policy. A consequence of this relatively high adoption of electric cooking is that inequalities in electricity use are much lower in South Africa.

For all countries, we find consistently that the share of electricity used in entertainment appliances is the largest of the total of the five groups we distinguish, and this share does not vary widely across income levels. We also observe an increase in the share of electricity use in the clothes group, as richer households are able to afford the convenience of owning their own washing machines and dryers, as opposed to doing laundry by hand or using

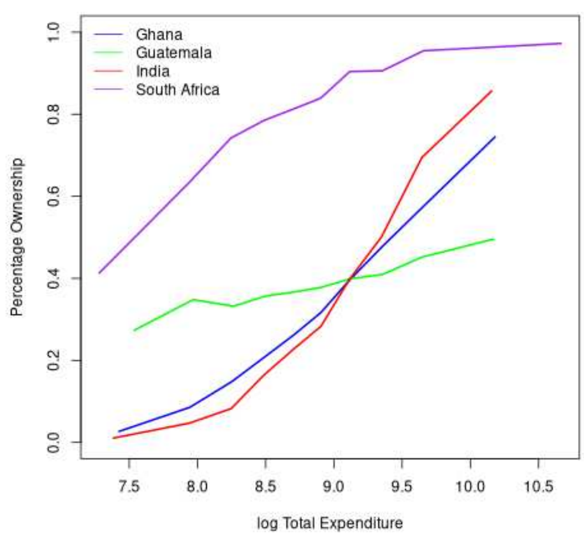
(a) Television



(b) Computer



(c) Refrigerator



(d) Washing Machine

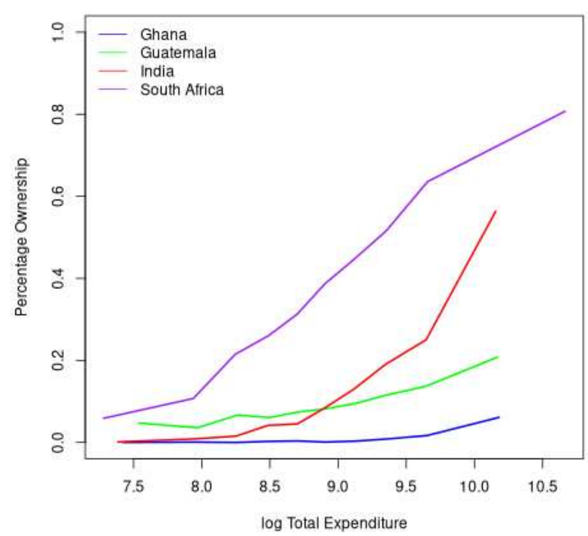


Figure 1: Diffusion of appliances by income in different countries

communal laundry services. Appliances for thermal comfort use about a quarter of total electricity use in the larger nations of India and South Africa that include regions that require cooling and heating. However, it is important to acknowledge that the appliances considered in this category are not the same across all countries, still, they represent the most basic needs in terms of thermal comfort given differences in climate and levels of affluence. The biggest missing component is space cooling in South Africa, which, if anything, would increase even more the already large share of thermal comfort in total electricity consumption. The full list of appliances for which data are available in each of the country surveys is presented in Table A2.

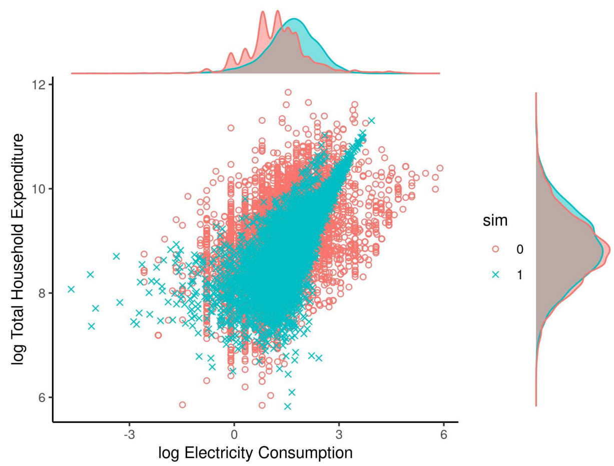
3.3 Scenarios

The biggest advantage of our modeling approach is that it lends itself to the assessment of policy scenarios. As we use a specific choice model where households decide on both appliance ownership and energy use based on the prices they face, their income and other important socio-economic characteristics, we can estimate the behavioral responses to changes in some of these relevant variables. We therefore simulate a variety of scenarios considering future developments in population by age, sex, and education (KC and Lutz, 2017), income growth and distribution (Cuaresma, 2017; Rao et al., 2018), urbanization (Jiang and O'Neill, 2017), and energy prices (Fricko et al., 2017) following the narratives of the Shared Socioeconomic Pathways (SSPs) (Riahi et al., 2017) (see Table A3). We consider a business as usual future of demographic and socio-economic change following the narrative of the SSP2 scenario, but consider sensitivities under the SSP1 (higher growth) and SSP3 (lower growth) scenarios. Building on this, we then consider two alternative policy scenarios: the first where we assume universal access to electricity by 2030 in line with the UN 2030 Agenda goals (referred to as universal access scenario), and the second, where electricity access is modeled as a logit function of income, urbanization, house characteristics and regional zones, in such a way that households with higher income, in urban areas and of better housing characteristics have a higher probability of being in an electrified area,

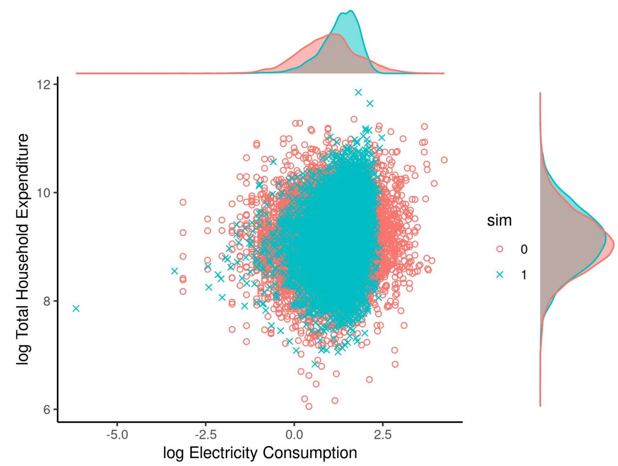
Country	Location	Quintile	Thermal Comfort	Food	Clothes	Entertainment	Other
Ghana	Rural	1	11.57	2.31	7.55	31.17	47.40
		2	10.24	5.61	7.98	36.71	39.46
		3	13.17	5.94	11.96	39.52	29.41
		4	14.88	8.45	13.57	40.36	22.73
		5	15.84	12.15	16.14	38.51	17.36
	Urban	1	9.10	8.85	22.89	37.15	22.01
		2	8.73	12.66	27.05	36.52	15.04
		3	8.56	14.94	28.63	35.28	12.59
		4	7.93	16.43	31.12	33.84	10.68
		5	6.92	21.12	30.82	32.01	9.12
Guatemala	Rural	1	2.50	11.10	11.48	39.38	35.55
		2	2.08	12.36	12.18	38.33	35.06
		3	3.09	11.35	13.37	37.77	34.42
		4	3.05	12.03	14.00	36.67	34.25
		5	3.00	13.27	14.77	36.49	32.47
	Urban	1	3.01	16.15	18.96	33.97	27.92
		2	3.60	16.59	19.95	33.00	26.86
		3	2.85	17.20	20.53	32.90	26.51
		4	2.86	17.12	21.39	32.98	25.64
		5	3.34	16.31	23.14	32.25	24.95
India	Rural	1	27.70	1.02	0.39	33.48	37.42
		2	28.54	2.31	0.34	38.17	30.63
		3	26.92	3.69	0.56	42.00	26.82
		4	24.91	5.60	1.48	45.75	22.26
		5	22.41	10.44	2.92	46.40	17.82
	Urban	1	26.93	5.24	0.79	43.72	23.32
		2	24.33	9.13	1.75	43.60	21.19
		3	21.32	13.22	3.36	43.64	18.45
		4	18.86	16.15	4.98	43.05	16.96
		5	13.30	19.11	9.69	44.36	13.54
South Africa	Rural	1	29.16	22.93	1.85	28.80	17.26
		2	25.84	25.41	1.93	31.52	15.29
		3	25.30	26.45	4.47	30.81	12.98
		4	25.72	25.95	4.84	31.35	12.13
		5	26.24	25.50	7.72	29.39	11.15
	Urban	1	37.57	21.51	2.19	26.66	12.07
		2	35.23	22.29	4.79	27.14	10.55
		3	33.98	22.33	7.00	27.16	9.52
		4	31.05	21.19	9.31	28.60	9.85
		5	29.52	19.15	11.41	29.36	10.55

Table 3: Estimated Percentage of Total Electricity Consumption of Appliances by Appliance Group in the Base Year

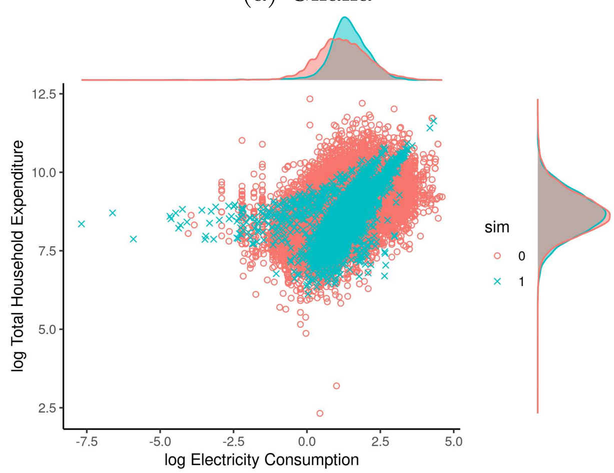
but still universal access is not achieved by 2030 (referred to as the no new access policy scenario). Nevertheless, it is important to note that our model allows for the possibility that households living in electrified areas may choose not to use electricity, because they cannot afford it and other fuels satisfy their needs at lower expense.



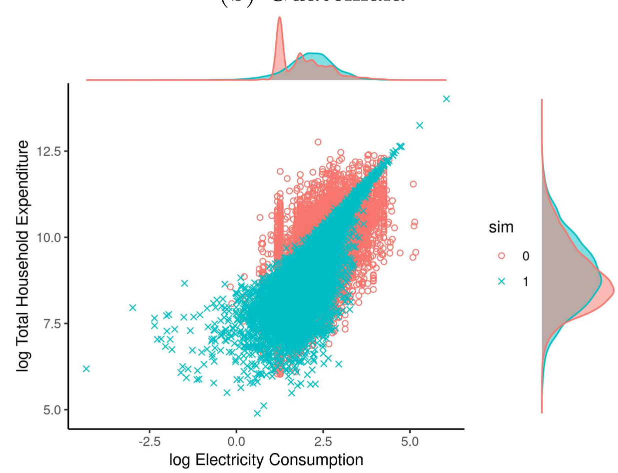
(a) Ghana



(b) Guatemala



(c) India



(d) South Africa

Figure 2: Distribution of log Household Expenditure vs log Electricity Consumption: Data vs Simulation

Indeed, as shown in the summary of the scenario results in Table 4, even under the universal access scenario, in almost all countries there is a small percentage of the population that chooses not to use electricity. It is also interesting to note that we estimate a lower average electricity consumption per capita for individuals that use electricity under the universal access scenario. This is because in the no new access policy scenario, households with lower income, whose capacity to afford electricity and appliances is more limited, don't have access to electricity. This can be noticed visually in Figure 3, where the distributions of electricity consumption in the universal access scenario are to the left of the distribution in the no new access policy scenario.

Our estimates of average and total electricity consumption in 2030 for India and South Africa are similar in magnitude to other estimates in the literature (de la Rue du Can et al., 2019; Agency, 2020). The share of different end-uses in total household electricity use estimated for 2030 reflect the relationship of end-use shares and income for the individual nations presented already in Table 3. These are, in turn, related to estimates of appliance ownership in 2030 that are presented in Table 5. As estimated in other studies, we find a rapid increase in ownership of appliances with increasing urbanization and income growth over time.

Another interesting feature of our model is that it allows us to perform analysis of scenarios at various levels of disaggregation relative to the respective household characteristics that are included. For example, as mentioned above, our model includes the effect of different climatic zones and urbanization on appliance uptake and energy demand. In Figures A1 to A4 we generate maps of average electricity consumption for the different countries in our study. There are three levels of spatial disaggregation included: first, as mentioned previously, we identify different climatic zones according to the Köppen-Geiger climate classification (Beck et al., 2018), then we ascribe to each region/subregion (Hijmans, 2012) the modal climatic zone, and finally, we find the average electricity consumption for individuals in rural and urban areas (Lloyd et al., 2017) at different levels of income. To simplify the presentation of the income effects, we aggregate the population by income

Country	Scenario	% Population using electricity	Mean Elec Cons PerCap If Using Elec (KWh)	Total Elec Cons (billion KWh)
Ghana	No New Access	69.02	558.3	13.85
	Universal Access	98.55	475.0	16.82
Guatemala	No New Access	82.42	175.0	2.94
	Universal Access	99.37	163.9	3.32
India	No New Access	88.95	341.7	464.56
	Universal Access	100.00	336.1	513.78
South Africa	No New Access	95.60	961.1	53.83
	Universal Access	99.62	938.9	54.80

		Percentage by End Use				
Country	Scenario	Entertainment	Thermal comfort	Food	Clothes	Other
Ghana	No New Access	33.30	8.08	19.31	28.18	11.13
	Universal Access	34.60	7.66	17.82	27.20	12.72
Guatemala	No New Access	33.99	3.13	16.12	20.67	26.10
	Universal Access	34.37	3.17	15.49	20.39	26.57
India	No New Access	46.33	15.42	15.87	8.15	14.22
	Universal Access	46.41	15.90	15.42	7.62	14.65
South Africa	No New Access	28.96	30.37	20.54	9.50	10.63
	Universal Access	29.02	30.18	20.56	9.52	10.72

Table 4: Shares and quantities of electricity use in 2030 under access policy scenarios

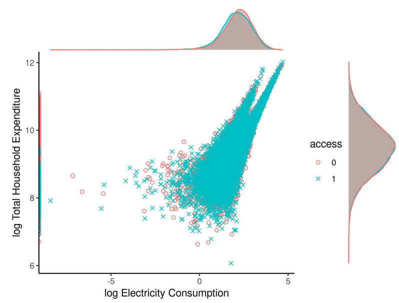
quintiles. We deliberately keep the thresholds for belonging to a particular quintile fixed at the level in the base year, as it allows us to see the transitions of households from lower to higher levels of income over time. This means that, as average incomes rise, the number of individuals in lower quintiles diminishes, while the number of individuals in higher income quintiles increases, changing the average behavior of individuals in each quintile. For example, in the case of India, we can see that in future scenarios, the average electricity consumption of households in the top quintile is lower than in the base year. This is because, by keeping the income thresholds constant, households that belong to the highest quintile in the base year, belong to the second highest quintile of the future distribution (i.e., the income distribution of this quintile gets more skewed to the left).

We also analyze the variation in the cooling and heating needs of households under the different scenarios. Here, we focus solely on India, as it is the only country in our sample

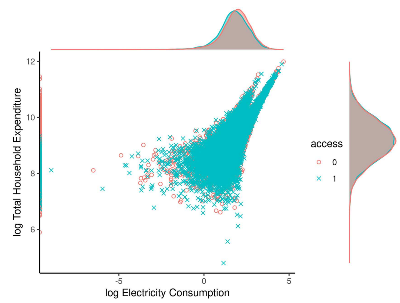
			Television	Computer	Refrigerator	Washing Machine
Ghana	No New Access	Rural	34.6%	5.7%	18.6%	0.2%
		Urban	75.9%	23.1%	57.0%	3.1%
	Universal Access	Rural	61.9%	9.7%	23.3%	0.5%
		Urban	86.3%	24.9%	62.0%	3.2%
Guatemala	No New Access	Rural	50.6%	6.6%	27.3%	2.9%
		Urban	82.6%	30.1%	59.8%	24.0%
	Universal Access	Rural	70.9%	8.4%	35.4%	4.5%
		Urban	88.5%	32.3%	63.2%	26.1%
India	No New Access	Rural	79.5%	19.4%	52.5%	22.8%
		Urban	96.9%	59.4%	88.1%	64.5%
	Universal Access	Rural	91.5%	21.6%	57.1%	23.2%
		Urban	99.1%	61.4%	90.1%	66.0%
South Africa	No New Access	Rural	81.8%	22.4%	80.3%	30.1%
		Urban	90.6%	45.0%	88.8%	61.4%
	Universal Access	Rural	86.0%	21.7%	83.1%	31.8%
		Urban	93.0%	45.6%	91.8%	61.5%

Table 5: Appliances diffusion on the different electricity access scenarios

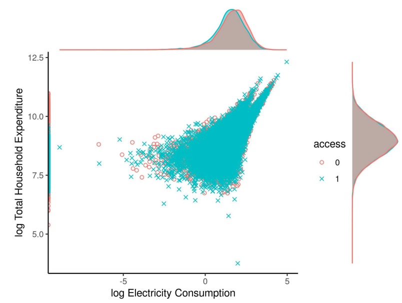
where we have information on the ownership of both cooling and heating appliances. The interpretation of our results requires special attention, as these reflect both the direct and indirect effects of income growth in interaction with climate under the different scenarios, some of which may seem contradictory. For example, higher income growth implies that households can spend more money on appliances and fuels. But also, that more efficient appliances and fuels become affordable. Moreover, a higher income level allows households to live in dwellings that are better insulated to avoid energy losses. These effects explain what we see in Figure 4. As expected, households residing in urban areas in zones with more extreme climates have higher demands for cooling and heating. However, the scenarios with lower income growth have higher energy needs because households in these scenarios live in poorer quality buildings and own appliances and fuels with very low efficiency performance. This explains the comparatively larger demand for space and water heating in the SSP3 scenario. For simplicity, we assume here that the climate remains unchanged till 2030. However, future work could use the model to explore how electricity demand for thermal comfort changes in response to different climate impact scenarios, as



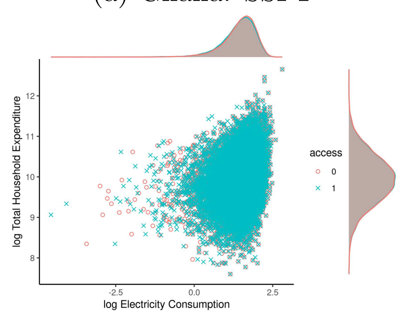
(a) Ghana: SSP1



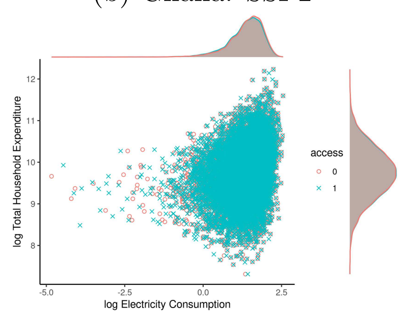
(b) Ghana: SSP2



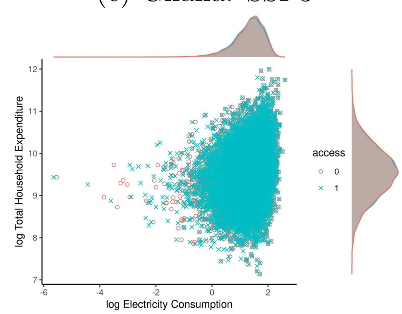
(c) Ghana: SSP3



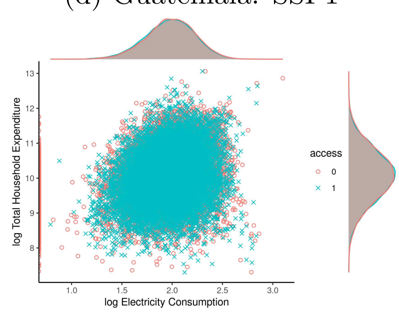
(d) Guatemala: SSP1



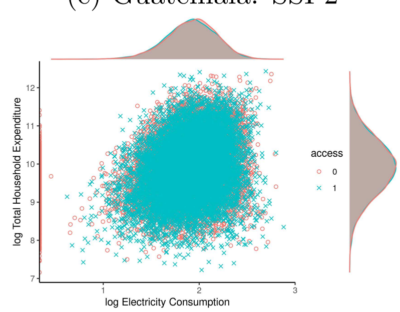
(e) Guatemala: SSP2



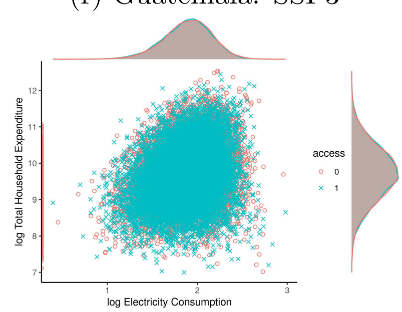
(f) Guatemala: SSP3



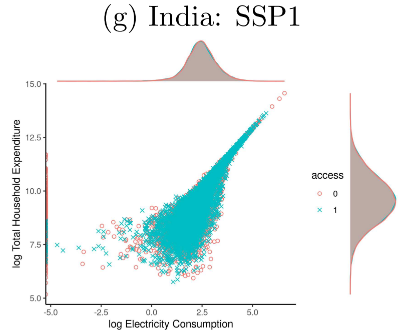
(g) India: SSP1



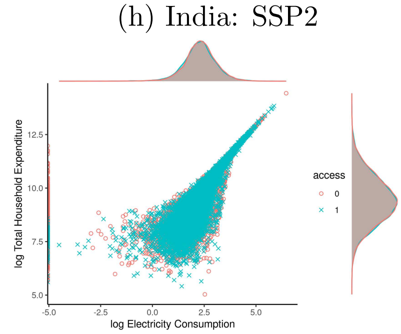
(h) India: SSP2



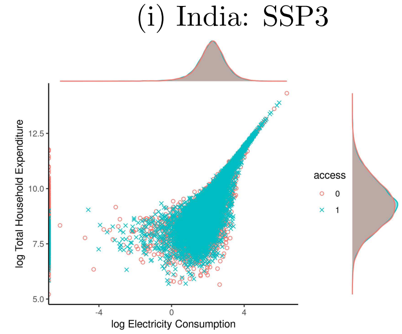
(i) India: SSP3



(j) South Africa: SSP1



(k) South Africa: SSP2



(l) South Africa: SSP3

Figure 3: Distribution of log Household Expenditure vs log Electricity Consumption: Universal Access vs No New Access Policy Scenarios in 2030

well as to analyze how socio-economic and demographic changes interact with climatic change to determine thermal electricity demands.

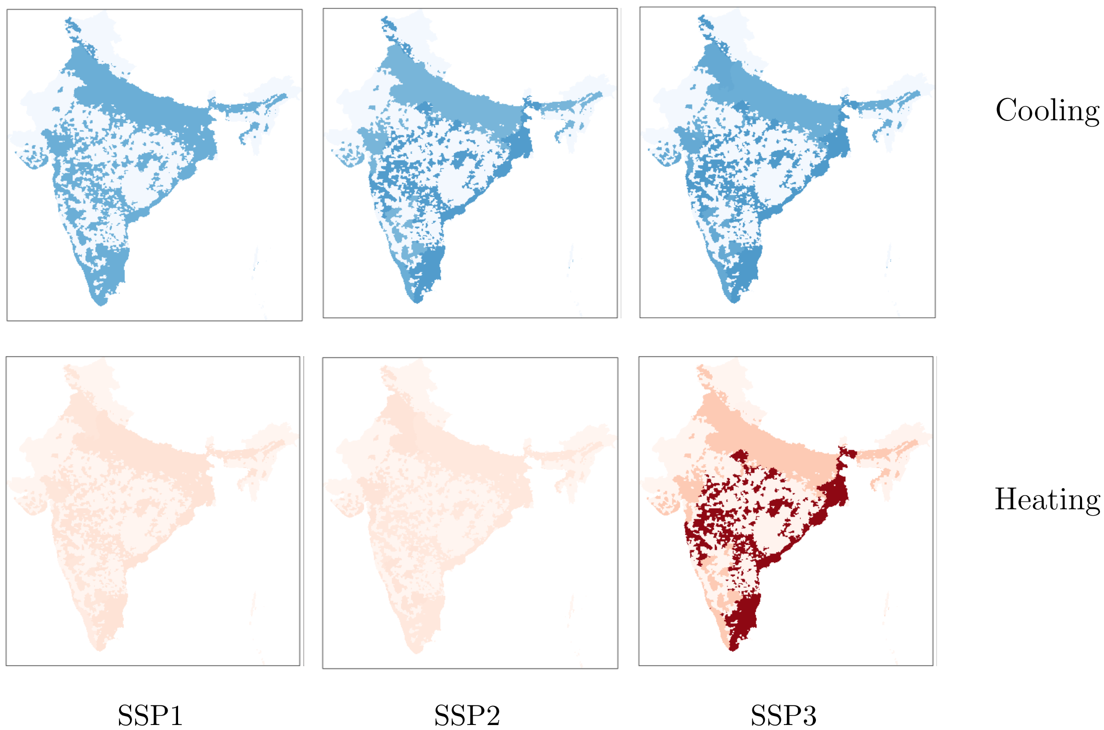


Figure 4: India: Mean Electricity Consumption at urban and rural areas in different climatic zones by quintile for different scenarios

4 Conclusions and Discussion

Estimating appliance and electricity demand in countries that have not as yet achieved universal access to electric services is important for policy makers and planners alike. Here we develop a simulation-based estimation model to analyze changes in electricity demand considering the effect of income on both the intensive and extensive margin. The model is applied to micro-data from nationally representative surveys from four countries that represent different regions of the Global South, with varying climates, incomes and extents of electricity access. We find that our model closely approximates observed patterns in the micro survey data. The utility of the model is tested by applying it to scenarios exploring differences in future income and population size and distribution. We find that appliance and electricity demand under different future scenarios change in line with expected behavioral responses. In other words, in futures with high income growth and urbanization, we estimate higher electricity demand compared to futures with lower income growth and urbanization even though population growth is higher in such scenarios. In scenarios where we consider policies that achieve universal access to electricity by 2030, total electricity demand is higher than in no access policy futures. However, low-income households with access to electricity pull the average per capita electricity demand lower compared to the average in scenarios where low-income households do not get access to electricity.

We find the level of adoption of electrical appliances varies significantly by country, appliance type and income. In all four of the countries we studied, we find that the share of electricity used in appliances for entertainment is the highest compared to all other end-use services and remains relatively unchanged as incomes rise. This is also consistent with our finding that the ownership of televisions is high and more equitably distributed across populations in comparison to the ownership of other major white goods. The share of electricity used in appliances for food preservation and preparation as well as for the maintenance of clothes rises significantly with income as people are able to afford more expensive appliances that provide greater convenience and comfort. Finally, we observe interesting shifts in the electricity demand for appliances that provide thermal comfort because while higher incomes allow households to afford more cooling and heating appliances, they also allow households to shift from less efficient fuels and appliances to more efficient electric appliances and to afford better and more insulated housing.

Our model contributes to the literature in many regards. First, it is not a purely statistical model, and therefore, it explicitly considers several channels or drivers that are relevant in explaining household behavior regarding electricity consumption. Additionally, the use of simulated data allows us to model some of these drivers jointly. For example, income may not only affect demand directly through the budget constraint and indirectly through appliance ownership, but also through other household characteristics that are related to income, such as the number of individuals in a household or the probability of owning vs renting a dwelling, or living in a shack or more efficient dwelling. In this way our approach of creating simulated data sets provides the flexibility of representing different realities and simulate demand under future scenarios, policy changes and to carry out counterfactual experiments. Finally, as this model is not calibrated, but estimated, the behavioral parameters of the model are such that our simulated data set is able to mimic the empirical reality for a wide variety of variables and drivers at the same time.

The model developed here provides a useful tool to assess how appliance and electricity demand change under alternative future scenarios but is not without limitations. The most critical limitation is actually the counterpart of its biggest strength. As the model is completely driven by empirical data, it is not able to estimate the effect of things that are not captured by the data. For example, due to our data limitations, we cannot estimate the effect of air cooling appliances on the electricity consumption of South Africa, as the survey does not include information on the ownership of cooling appliances. Additionally, the estimation is time intensive and a full estimation round including bootstrapping can take days to finish, depending on the available computing power. Finally, as with every structural econometric model, it is, by construction, constrained by the behavioral model. Assuming that the choice model is an appropriate representation of the behavior of households is a strong assumption of the approach.

Our results suggest that there are significant differences in the extent to which different appliances contribute to total electricity demand depending on income and climate. An important policy implication of this work is that the demand for electric services in developing and emerging countries will rise with income but making access to these electric services more equitable requires improving the availability and affordability of efficient appliances, in addition to improving the reliability, affordability and extent of electricity access. Additionally, it can be used to help policy makers in deciding appropriate levels of subsidies to achieve certain purposes. For example, as we can see in the case of South Africa, giving low income households certain levels of electricity for free can certainly help to reduce energy poverty. Nevertheless, unless the cost of certain appliances is also subsidized (for example, electric cookstoves or thermal comfort equipment), households may still not be able to afford these and, instead, continue to use inefficient fuels and equipment that harm their health and the environment.

Estimates and forecasts of the growth of residential or household electricity demand in developing countries are an important input to utility and electricity sector planning. They signal what the appropriate scale of investments in electric infrastructure expansion might be. Approaches such as the one developed in this work, can be used to significantly improve future estimates of demand and aid in integrated energy planning.

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Appendix

	Ghana	Guatemala	India	South Africa
Electricity consumption	3.616	3.091	3.720	8.672
Price of Electricity	29.401	90.718	38.669	42.637
Consumption of other fuels	13.990	48.115	13.650	0.785
Avg Price of Other Fuels	25.967	22.902	20.124	56.245
Total Household Expenditure	7,321.098	10,312.320	6,828.443	11,659.210
Household Size	4.091	4.752	4.857	3.803
Urban	0.483	0.455	0.359	0.608
Age of household Head	44.041	46.347	49.715	49.217
Rented dwelling	0.488	0.098	0.062	0.176
Number of rooms in dwelling	1.756	2.298	2.739	4.437
Single family dwelling	0.250	0.983	0.386	0.935
Informal dwelling	0.355	0.064	0.021	0.096
Walls or roof of light material	0.943	0.844	0.315	0.974
Climate Zone Am		0.066		
Climate Zone Aw	0.065	0.104	0.074	
Climate Zone BWh	0.935	0.461	0.326	
Climate Zone BWk			0.015	0.058
Climate Zone BSh				0.115
Climate Zone BSk			0.280	0.209
Climate Zone Csa				0.220
Climate Zone Csb			0.009	
Climate Zone Cwb			0.284	
Climate Zone Cwc		0.369	0.004	0.398
Climate Zone ET			0.008	

Note: Sample averages for each country, fuel values in GJ, monetary values in 2010USD

Table A1: Fuel consumption, prices and household characteristics per country in the empirical sample

	Ghana	Guatemala	India	South Africa
Air Conditioner	0.007		0.023	
Fan	0.406	0.094	0.758	
Water Heater (any fuel)	0.007			
Electric Water Heater		0.007		0.808
Gas Water Heater		0.060		
Kerosene Water Heater				0.033
Firewood Water Heater				0.131
Electric Space Heating				0.440
Gas Space Heating			0.072	
Kerosene Space Heating			0.180	0.078
Firewood Space Heating			0.201	0.157
Electric Stove	0.007	0.010	0.010	0.793
Gas Stove	0.226	0.216	0.368	0.030
Kerosene Stove	0.011			0.034
Charcoal Stove	0.272			
Firewood Stove	0.521	0.764	0.617	0.13
Kerosene Lightning	0.028		0.562	
Television	0.496	0.701	0.664	0.830
Personal computer	0.089	0.145	0.077	0.236
Music equipment	0.628	0.362	0.281	0.645
Refrigerator	0.267	0.401	0.294	0.742
Freezer	0.048			0.316
Electric kettle	0.048			
Vacuum Cleaner	0.004	0.005		0.144
Washing Machine	0.006	0.089	0.107	0.377
Dryer		0.009		0.108
Iron	0.373	0.453		

Note: Sample averages for each country of dummies representing appliance ownership per household

Table A2: Appliance ownership per country in the empirical sample

		SSP1	SSP2	SSP3
Ghana	Population	37.6%	47.3%	56.3%
	GDP	181.4%	133.1%	103.2%
	Urban Share	32.5%	22.2%	8.8%
	Bio Price	-17.9%	-8.2%	-1.1%
	Gas Price	18.2%	-2.7%	34.6%
	Elec Price	9.2%	14.2%	29.6%
Guatemala	Population	30.1%	41.8%	59.3%
	GDP	164.6%	135.3%	115.7%
	Urban Share	32.9%	22.9%	8.8%
	Bio Price	35.7%	55.7%	2.2%
	Gas Price	18.1%	26.5%	37.9%
	Elec Price	35.8%	25.3%	45.7%
India	Population	19.1%	24.8%	31.0%
	GDP	448.9%	407.4%	359.6%
	Urban Share	64.4%	38.6%	11.3%
	Bio Price	189.9%	243.4%	34.2%
	Gas Price	14.8%	-6.5%	14.6%
	Elec Price	-13.9%	74.7%	105.6%
South Africa	Population	16.6%	16.9%	13.7%
	GDP	128.4%	105.4%	80.1%
	Urban Share	21.8%	15.9%	5.7%
	Bio Price	-17.9%	-8.2%	-1.1%
	Gas Price	18.2%	-2.7%	34.6%
	Elec Price	9.2%	14.2%	29.6%

Table A3: Percentage changes from base year by country and SSP scenario

Figure A1: Ghana: Mean Electricity Consumption at urban and rural areas in different climatic zones by quintile for different scenarios

Figure A2: Guatemala: Mean Electricity Consumption at urban and rural areas in different climatic zones by quintile for different scenarios

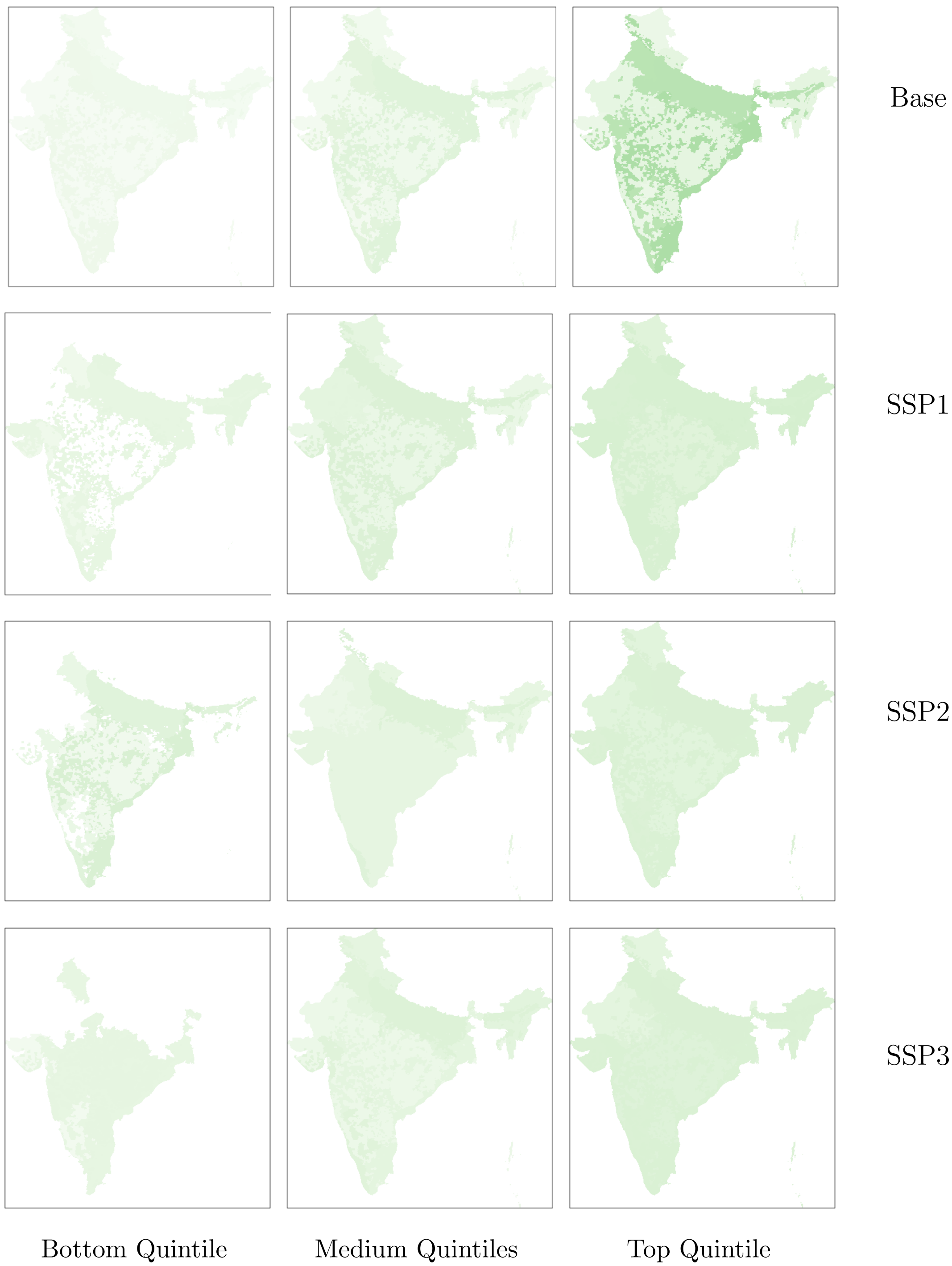

Figure A3: India: Mean Electricity Consumption at urban and rural areas in different climatic zones by quintile for different scenarios

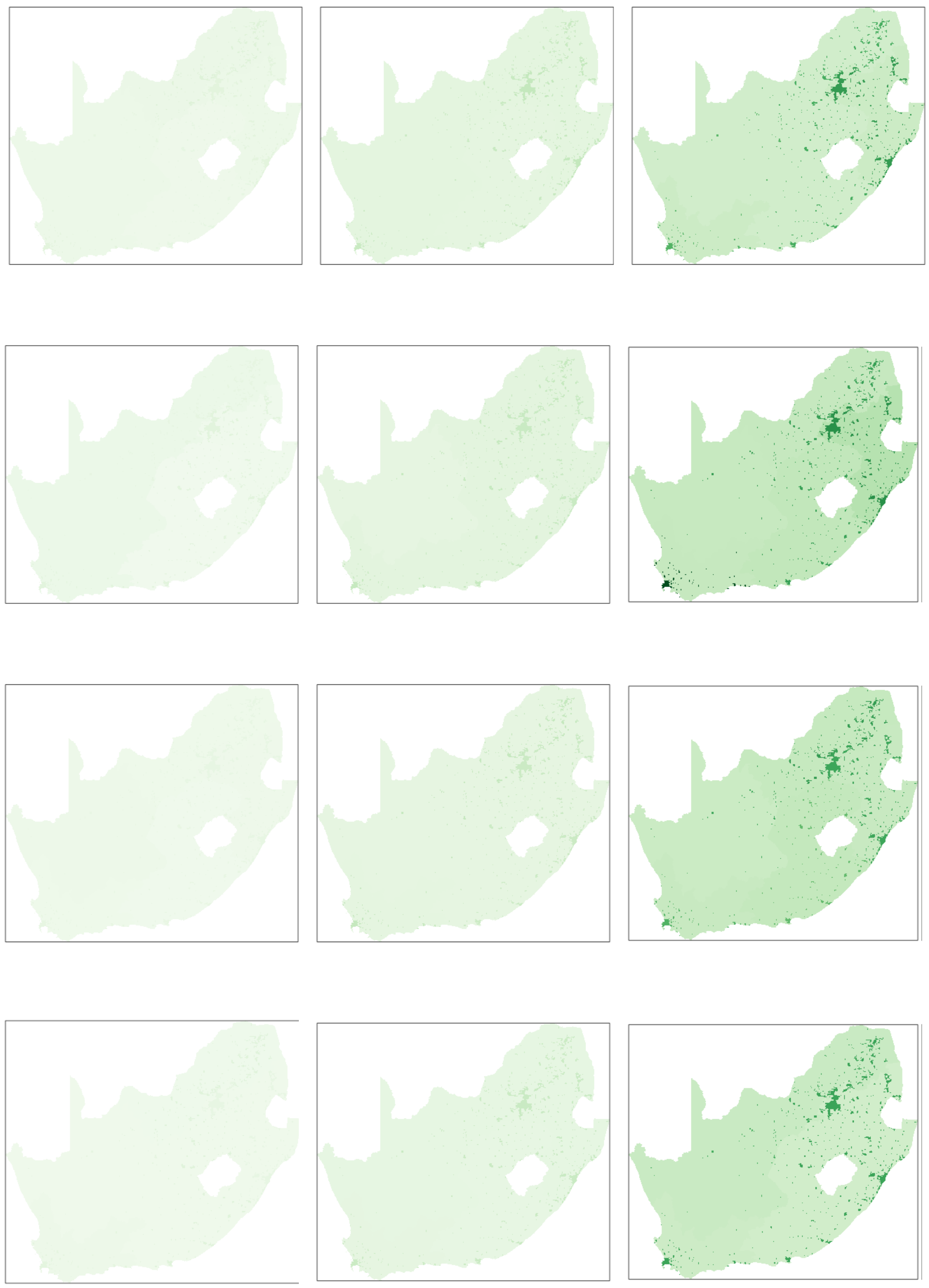

Figure A4: South Africa: Mean Electricity Consumption at urban and rural areas in different climatic zones by quintile for different scenarios