Income, Inequality and Population Growth Household Electricity Demand

Miguel Poblete-Cazenave, Shonali Pachauri
PRELIMINARY VERSION - DO NOT CITE OR DISTRIBUTE

September 19, 2018

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 assume constant elasticities of demand. Here we use a simulation-based structural estimation approach employing micro-data from household surveys for three developing nations to estimate responsiveness of electricity demand 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. We use our estimated model along with information on the current and projected future distribution of income and population in each nation to estimate the total latent electricity demand of achieving universal access to electricity services. Our results confirm that neglecting heterogeneity in individual behavior and responses can result in biased demand estimates.

1 Microeconomic Analysis

1.1 Model

The basic idea behind this model is that there are two channels for the income effect in the demand for electricity. First, it comes directly through the budget constraint, as households with higher income can afford more electricity given its price. Second, indirectly, households with higher income can afford expensive electrical appliances that will increase the demand for electricity. In that sense, we have to model, first, the probability that a household buys an appliance, and, second, what is the demand for electricity given how many of the appliances the household has.

Similar to [Dubin and McFadden, 1984], electricity consumption is assumed to be of the form:

$$x_1 = \beta_0 + \beta_1 p_1 + \beta_2 p_2 + \beta_3 w + \beta_4 \left(y - \rho \sum_{j=1}^{m} K_j \delta_j + \sum_{j=1}^{m} \frac{\beta_{4+j}}{\beta_4} \delta_j \right)$$

in which consumption depends on the price of electricity p_1, the price of alternative fuels p_2, household size w, income y minus investment cost $\rho \sum_{j=1}^{m} K_j$ and dummies for appliances δ_j.

Country	Dataset	Years	No. of Obs*
Brazil	Pesquisa de Orçamentos Familiares (POF)	2008-2009	42,154 (54,621)
Ghana	Ghana Living Standards Survey (GLSS)	2012-2013	6,819 (16,772)
India	National Sample Survey (NSS)	2011-2012	81,976 (101,662)

* Number of observations per household after data cleaning (original sample size in parentheses).

Table 1: Datasets Used by Country

I assume that δ_j distributes logit over income per capita and that the choice of appliance j is independent of the choice of other appliances when controlling by income per capita:

$$\mathbb{E}(\delta_j) = \frac{exp(\gamma_{1j} + \gamma_{2j}\frac{y}{w})}{1 + exp(\gamma_{1j} + \gamma_{2j}\frac{y}{w})}$$

Also following [Dubin and McFadden, 1984], consumption of other energy sources is:

$$x_2 = \frac{\beta_2}{\beta_4}(\alpha - 1) + \frac{\alpha}{\beta_4}\left(\beta_0 + \frac{\beta_1}{\beta_4}\right)\frac{1}{p_2} + \frac{\alpha\beta_1}{\beta_4}\frac{p_1}{p_2} + \frac{\alpha}{p_2}\left[y - \rho\sum_{j=1}^{m} K_j\delta_j + \sum_{j=1}^{m}\frac{\beta_{4+j}}{\beta_4}\delta_j\right]$$

1.2 Data

I estimate the model for three countries representatives of three developing regions of the world: Brazil, Ghana and India.

I use the following variables in all the datasets:

- Monthly Household Electricity Consumption
- Monthly Household Electricity Expenditure
- Monthly Household Overall Expenditure
- Household Size

In the case of Brazil and India, values for Monthly Household Electricity Consumption are also obtained directly from the Data. For the case of Ghana, this variable was imputed by taking the values for electricity expenditure and dividing by the electricity tariff[1].

A preliminary analysis was done on the available set of electric appliances in the datasets to test whether they are significant in terms of explaining electricity consumption of the household. After this analysis, the following assets were selected in each country:

- Brazil: Fridge, Small Appliances, Stove, Washing Machine, Dryer, Air Conditioner, Sewing Machine, PC, Microwave, Dishwasher
- Ghana: TV, Fan, Air Conditioner, Washing Machine, Fridge, PC, Small Appliances, Microwave
- India: TV, Music Equipment, Fan, Air Conditioner, Sewing Machine, Washing Machine, Fridge, PC

[1] http://www.purc.com.gh/purc/sites/default/files/approved_electricity_and_water_tariffs_2013.pdf

1.3 Estimation

We follow a simulation-based structural estimation approach mainly for two reasons. First, the difficulty of obtaining valid instruments that can be used as an exclusion restriction over a set of different databases corresponding to different countries. Second, it allow us to do straightforward policy simulations.

We do a two-step estimation. On the first step, we estimate the γs separately using a logit regression. Additionally we estimate non-parametrically the distribution of household size over income quintiles.

On the second step, we use Indirect Inference [Gourieroux et al., 1993] to estimate α and the βs. This because from the data we observe p_1, but not p_2 nor $\rho \sum_{j=1}^{m} K_j \delta_j$, in particular ρ and K_j. Therefore we simulate p_2, ρ and K_j. To do that, we additionally assume that richer households pay more for other fuel sources (as richer households prefer cleaner, more expensive fuels) and for their appliances (either because they buy better quality or higher quantities), and that they have different discount rates, therefore:

$$p_2 = \zeta_0 + \zeta_1 \frac{y}{w}$$
$$\rho = \rho_0 + \rho_1 \frac{y}{w}$$
$$K_j = \eta_{0j} + \eta_{1j} \frac{y}{w}$$

where the ζs, ρs and ηs are also to be estimated. In particular the η_js are estimated directly from the sample for the cases where there are observations available, that is, for the households that bought the appliance during the survey period. On the other hand, the ρs and ζs are estimated jointly with the other parameters of the estimation.

The following auxiliary models are used in the estimation:

- Electricity consumption over other fuels expenditure household size, total household consumption and dummies for the appliances
- Electricity expenditure over household size, total household consumption and dummies for the appliances
- Other fuels expenditure over household size, total household consumption and dummies for the appliances

Additionally, we match mean household electricity consumption by income quintiles.

Indirect Inference works as follows. First, the auxiliary models and the selected moments are estimated from the data. Second, using initial parameter guesses, the model is run and a simulated data is obtained. Then, the same auxiliary models and moments are estimated from the simulated data. A distance factor is calculated by adding the square difference between the estimated parameters from the auxiliary moments in the data and the simulation weighted by the inverse of the variance of the estimated parameter. The process is iterated for new tries of the unknown parameters until the distance is minimized.

We estimate two different models, one where all households face the same unique electricity price (henceforth Model 1), and one where the price of electricity also rises with income (Model 2). Prices for both models are estimated, the first using the sample mean as a super-consistent estimator, and the second using a linear regression of electricity price vs household income per capita. Both estimated models are able to closely follow the electricity consumption patters by levels of household income as can be seen in Tables 2, 3 and 4. We can also see that for Brazil and Ghana the model with increasing prices of electricity provides a closer fit than the model with a single price, whereas we see the opposite for India. Nevertheless the results for both models are fairly similar, supporting the argument that the effect of the assumed price structure is minimal.

We calculate elasticities as the percentage change in electricity consumption over the percentage change in average income between different percentiles of the population. In particular, we divide the population into 20 subgroups in order to provide a richer profile of elasticities. Figures 1a, 1b and 1c show the results of these calculations. As we expected, the model is able to provide insights that cannot be clearly and directly observed in the data, namely, that there is a faster increase in elasticity at lower income levels, but then it tends to stabilize as we reach the higher income levels.

As a second approach, we created a pooled dataset consistent of data from the three countries. To control for within-country differences, we added some country fixed effects to the estimation of the appliance choices and the energy consumption. The choice set of appliances was selected considering only the available options in all the datasets, and therefore, differs from the ones in the single country models. In particular, the options available are:

- Fridge, Washing Machine, TV, Music Equipment, Radio, Air Conditioner, Fan, PC, Video Equipment

Finally, to account for differences in the income levels of the countries in the sample, we expanded the categorization of income from quintiles to deciles.

Table 5 shows that the fit of the model with increasing prices by income provide a much better fit to the empirical observations. This is not surprising as it is what we observed for the cases of Brazil and India, who dominate the sample. Nevertheless, it is important to acknowledge the important differences in the income distribution of the different countries. Indeed, in Brazil, the limit for a household to be included in the higher income decile is three times higher than the limit in Ghana and India. This distorts the picture of the income elasticity in the pooled data as, having the same level of income, households who could be considered rich in India and Ghana, would only be average in Brazil.

Notes:
Model 1: Electricity price increasing by income per capita $p_1 = \lambda_0 + \lambda_1 \frac{y}{w}$
Model 2: Single electricity price p_1 (sample average)

Notes: Elasticity defined as the percentage increase in the average electricity consumption over the percentage increase in average household income (separated in deciles)

	Data	Model 1	Model 2
1st Quintile	92.1	101.3	100.1
2nd Quintile	113.6	111.5	111.2
3rd Quintile	138.2	122.6	122.8
4th Quintile	167.3	140.8	143.3
5th Quintile	227.1	194.7	199.7
Model Fit		13,446.042	13,700.736

Table 2: Brazil: Average Monthly Electricity Consumption per Household by Income Quintile (kWh)

	Data	Model 1	Model 2
1st Quintile	45.6	35.2	41.1
2nd Quintile	59.8	49.1	52.0
3rd Quintile	68.6	61.5	61.3
4th Quintile	82.3	77.4	72.8
5th Quintile	111.2	119.4	101.2
Model Fit		3,250.641	2,285.066

Table 3: Ghana: Average Monthly Electricity Consumption per Household by Income Quintile (kWh)

2 Simulations

2.1 Electricity Access to All

The first simulation consists of giving electricity access to every household in our sample of countries. To do that, we simulate a subsample of households with similar characteristics as the households that do not have electricity in the datasets, namely, income and household size, in a similar manner as done for the estimation. Figure 2 shows the differences in the income distributions of the households who currently have electricity access in the sample and the ones who don't. Immediately noticeable is the fact that the households who do not possess access are poorer than the ones who have access, and therefore, we can expect that their electricity consumption would be lower.

Effectively, in our simulations we find that the electricity consumption per capita is lower in all cases and for both model specifications, as can be seen in Figure 3. Now, in terms of total electricity consumption the picture differs by countries not only because of the different levels of consumption and income per capita, but also for the differences in levels of current access: in the Brazilian sample only around 8% households do no possess electricity access, while this figure is around 18% for India and around 47% for the case of Ghana. The simulation results can be seen graphically in Figure 4.

As a comparison, we estimate the growth in total electricity consumption using our model and using the standard method of a single value for the income elasticity (i.e. energy consumption increases linearly with income). The results in Table 6 show significant differences between the estimates of our models and the estimates using the standard approach. For the case of

	Data	Model 1	Model 2
1st Quintile	42.1	47.2	46.5
2nd Quintile	55.0	54.9	56.5
3rd Quintile	66.7	63.5	65.6
4th Quintile	84.5	76.6	78.1
5th Quintile	126.2	117.1	115.2
Model Fit		27,417.718	29,695.612

Table 4: India: Average Monthly Electricity Consumption per Household by Income Quintile (kWh)

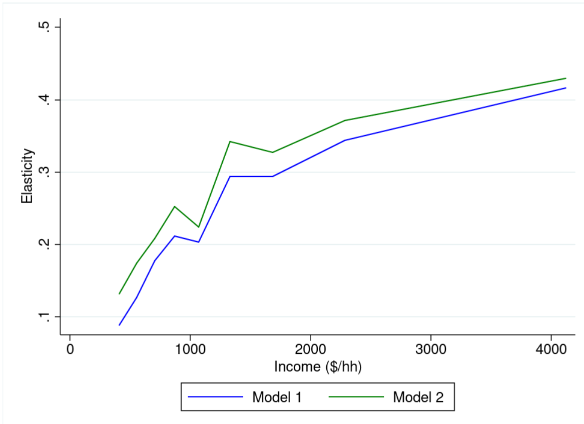
	Data	Model 1	Model 2
1st Decile	36.2	46.9	38.3
2nd Decile	47.3	60.4	49.0
3rd Decile	55.9	68.6	56.8
4th Decile	67.0	74.9	63.9
5th Decile	80.4	81.3	72.7
6th Decile	96.8	88.4	82.5
7th Decile	112.3	96.3	95.5
8th Decile	138.5	107.6	113.9
9th Decile	165.3	126.6	144.1
10th Decile	204.4	191.4	247.0
Model Fit		49,790.777	78,769.680

Table 5: Pooled Data: Average Monthly Electricity Consumption per Household by Income Decile (kWh)

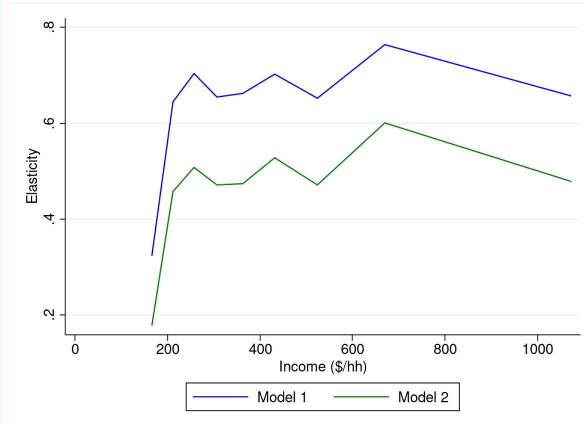
Brazil and Ghana, a single income elasticity overestimates the increase in energy consumption compared to our models, which is in line with what we could intuitively expect. However, for the case of India, our models estimate a higher consumption than the standard method. This can be attributed to the fact that in India, for idiosyncratic reasons, households with higher levels of income are composed by a much higher number of individuals than in most countries, as can be seen in Figures 8 to 10 in the Appendix. Therefore, for this particular case, per capita measures tend to underestimate the energy consumption of high income households.

2.2 Full Access by 2030

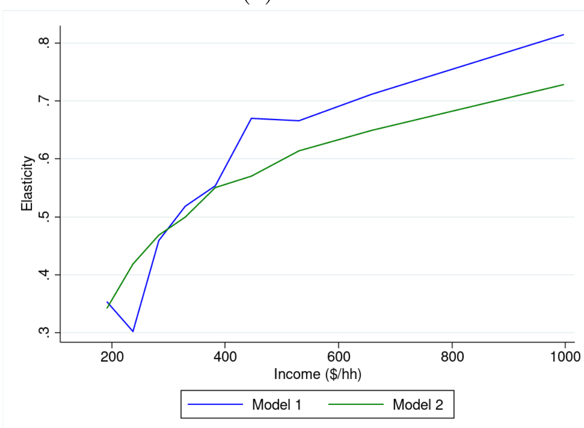
We use the GDP projections of the SSP2 from [Cuaresma, 2017] and the Inequality projections from [Rao et al., 2018] to explore scenarios of electricity consumption for the year 2030, assuming full electricity access for the population. The three cases are very distinct. For the case of Brazil, given that the electricity access is close to complete and that the projected increase in GDP per capita is a mere 5% (figure 5a), there are no significant changes in electricity consumption per capita (figures 6a and 6b) and the increase in total electricity consumption is mainly due to population increase (figure 7a). For the case of Ghana, the increase in GDP per capita is slightly higher (6.5%, fig 5b), but given that most of the population that has no access belongs to the lower tails of the income distribution, the pattern of electricity consumption per capita remains basically the same (figs 6c and 6d). However,



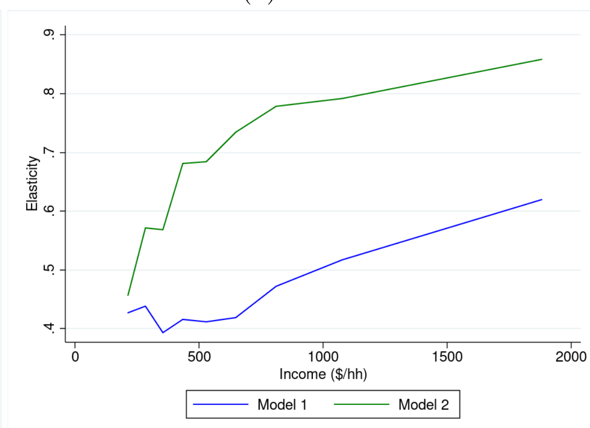
(a) Brazil



(b) Ghana



(c) India

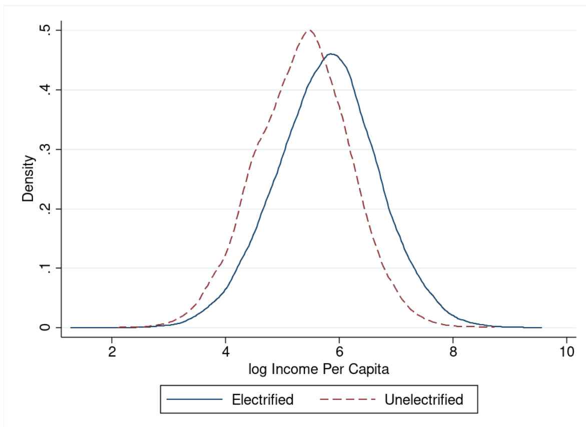


(d) Pooled Data

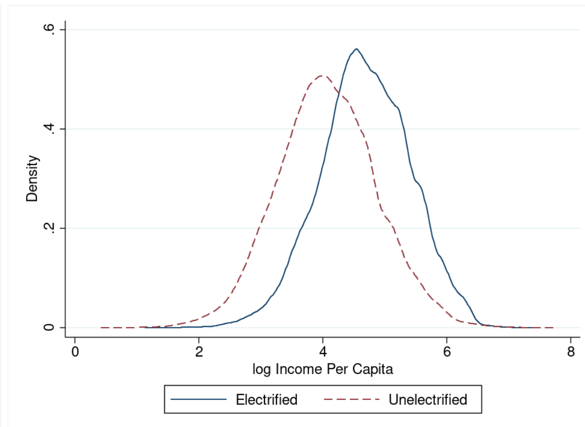
Figure 1: Elasticity by Income (2010 USD)

there are significant increases in total energy consumption (fig 7b). Finally, for the case of India, there is a significant increase in GDP per capita (17.4%, fig 5c), which creates a shift of the distribution of electricity consumption per capita (figs 6e and 6f) and also a shift of the total energy consumption towards higher levels of income (fig 7c).

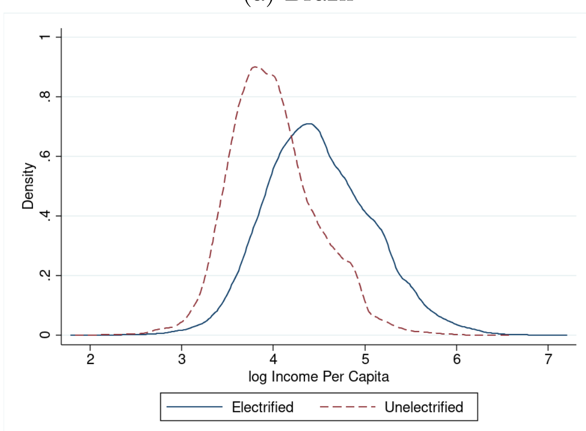
In Table 7 we compare the growth in electricity consumption form 1990 to 2010 to our projections in the case of full energy access by 2030. Again, we can see three very distinct patterns. For the case of Brazil, projected consumption growth is relatively small, as there is currently almost full electricity access, and therefore the growth is purely driven by income and population growth. For the case of India, the expected growth is smaller than in the previous 20 year period, but still substantial, as there is yet need to improve electricity access. For the case of Ghana, the projected consumption growth is immense, as about half of the current population does not have access, besides the expected growth in average income and population.



(a) Brazil



(b) Ghana

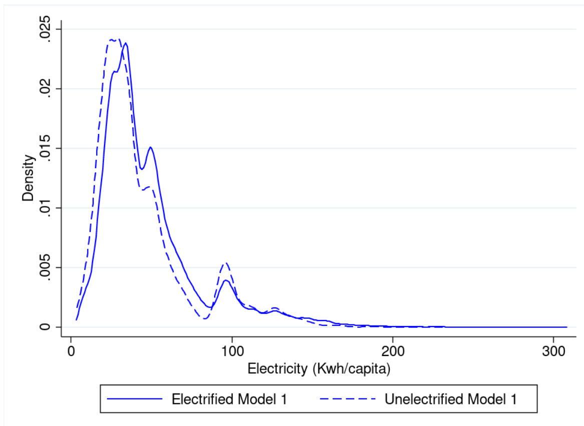


(c) India

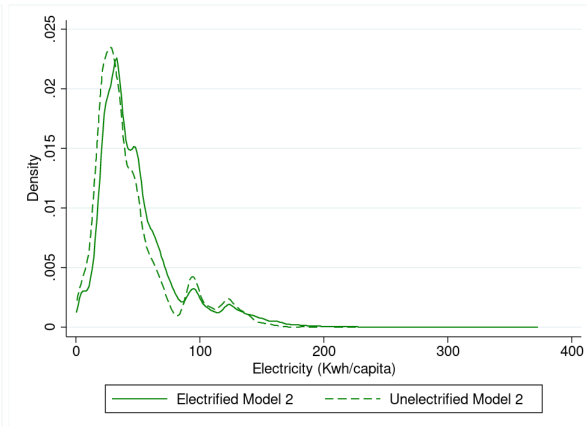
Figure 2: Income per Capita Distribution, Households among Electrified and Unelectrified

	Brazil	Ghana	India
Normal Elasticity	10.9%	96.6%	8.9%
Log Elasticity	10.3%	91.5%	8.4%
Model 1	7.6%	69.8%	15.3%
Model 2	7.5%	76.5%	16.0%

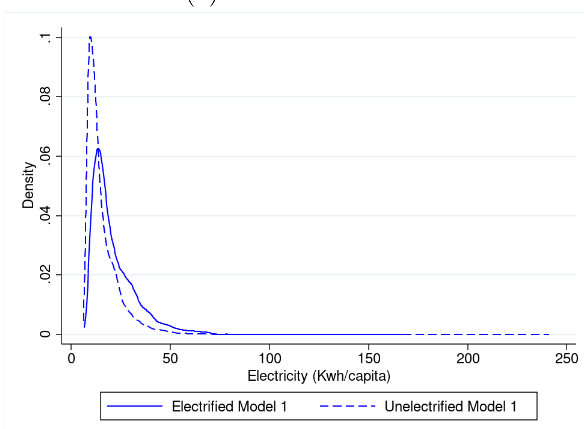
Table 6: Total Electricity Consumption Growth Towards Full Electricity Access: Constant Income per Capita Elasticities vs Proposed Models



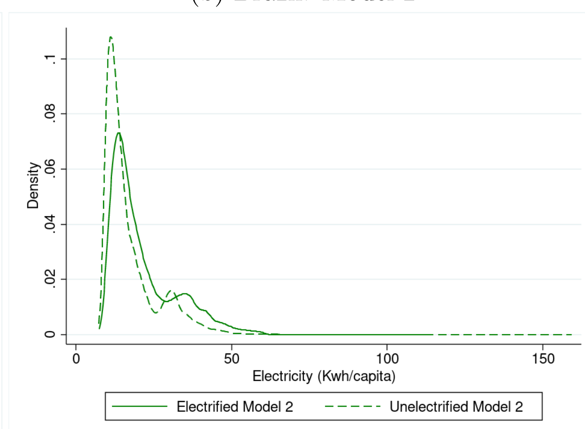
(a) Brazil: Model 1



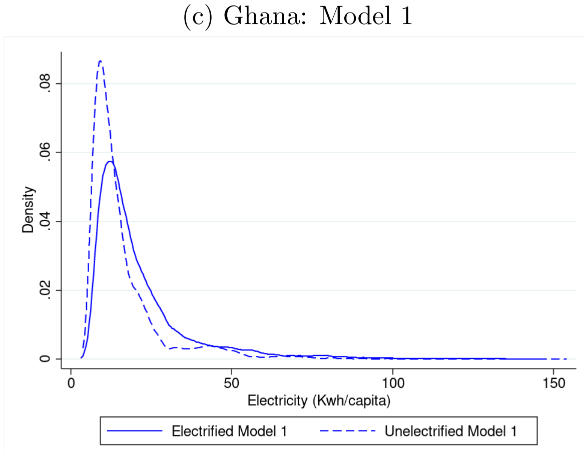
(b) Brazil: Model 2



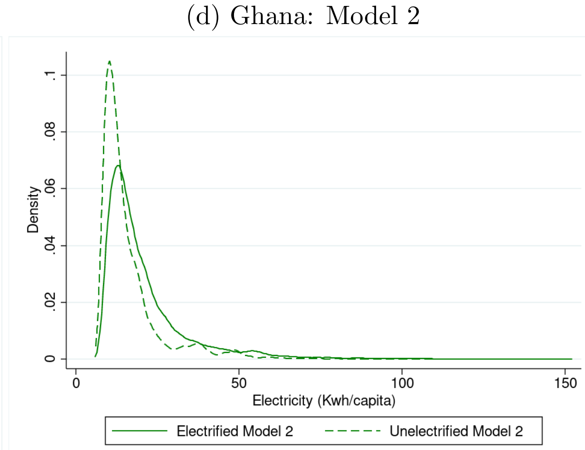
(c) Ghana: Model 1



(d) Ghana: Model 2

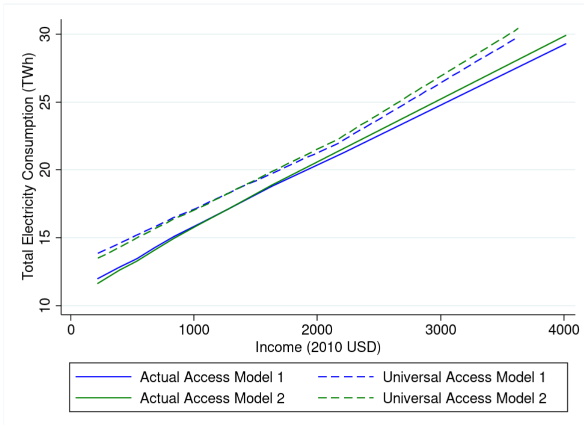


(e) India: Model 1

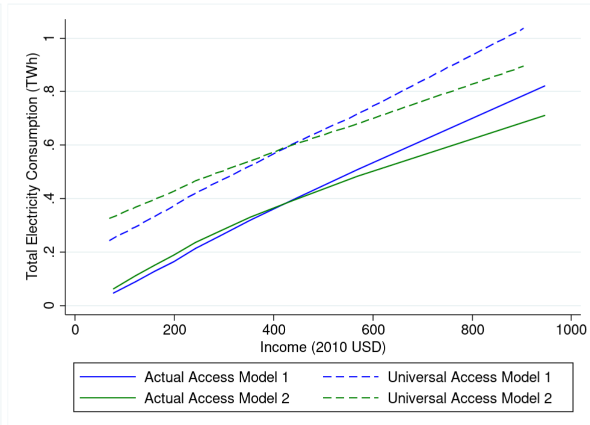


(f) India: Model 2

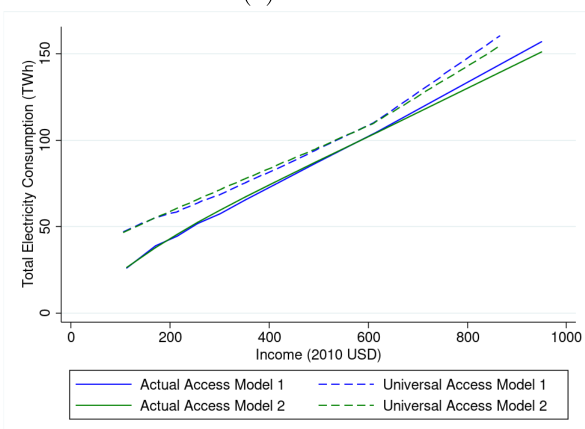
Figure 3: Distribution of Electricity Consumption per Capita, Households among Electrified and Unelectrified



(a) Brazil



(b) Ghana

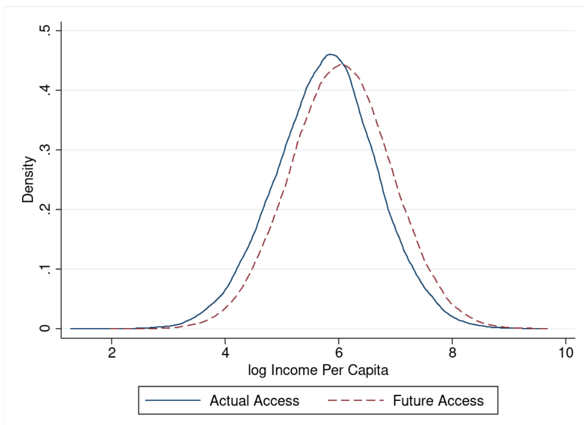


(c) India

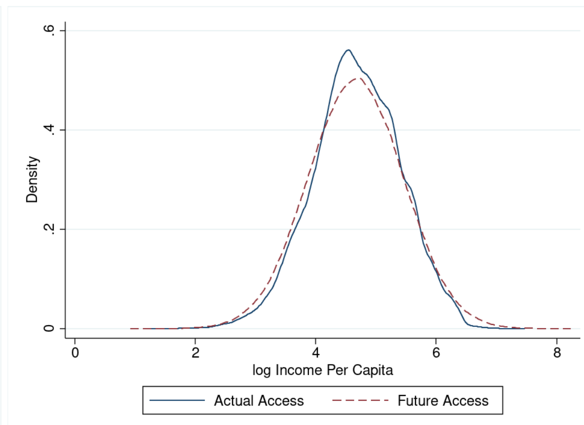
Figure 4: Total Electricity Consumption by Household Income, Current and Universal levels of Electricity Access

	Brazil	Ghana	India
1990-2010	122.9%	202.5%	382.6%
2010-2030 Model 1	34.1%	173.1%	270.5%
2010-2030 Model 2	35.0%	169.0%	246.6%
2010-2030 - Just Income - Model 1	16.9%	35.5%	215.8%
2010-2030 - Just Income - Model 2	18.1%	21.8%	202.1%
2010-2030 - Just Pop - Model 1	13.5%	97.8%	26.5%
2010-2030 - Just Pop - Model 2	13.9%	91.9%	27.2%

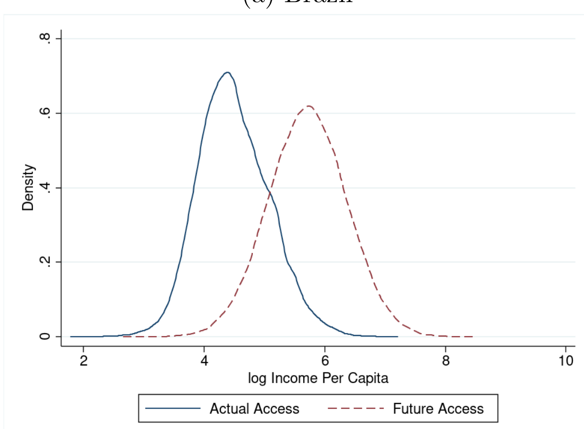
Table 7: Total Electricity Consumption Growth: 1990 to 2010 (IEA) and 2010 to 2030 (Projected from Our Models)



(a) Brazil

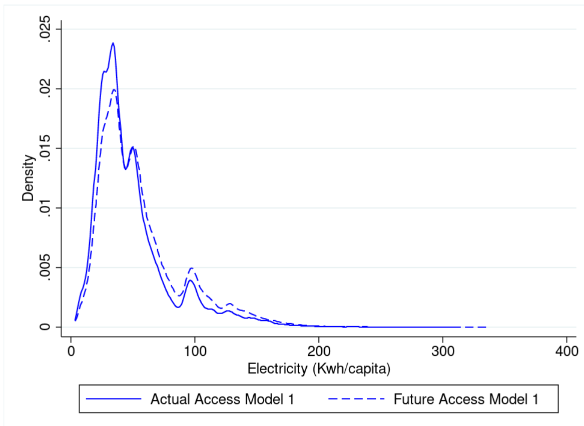


(b) Ghana

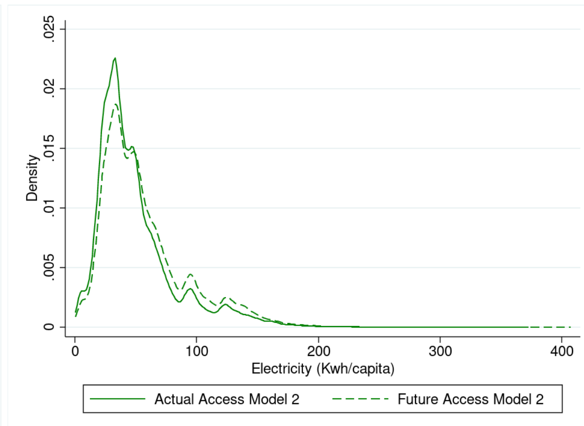


(c) India

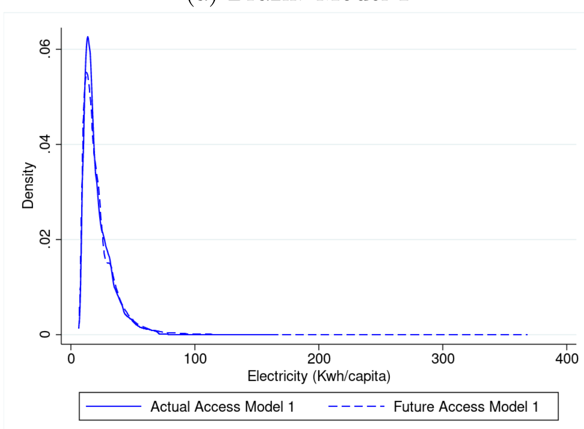
Figure 5: Income per Capita Distribution, Households with Access in the Respective Samples and Future Projections for 2030



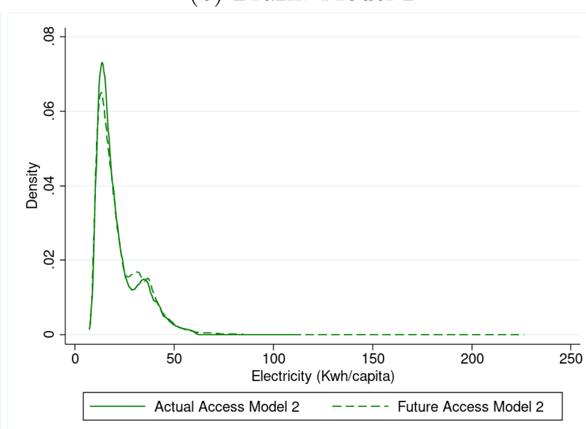
(a) Brazil: Model 1



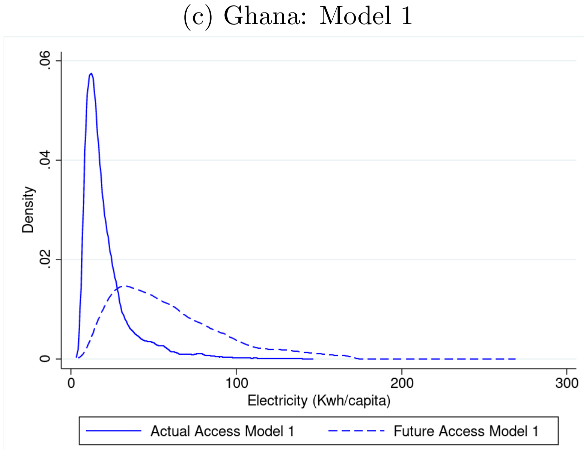
(b) Brazil: Model 2



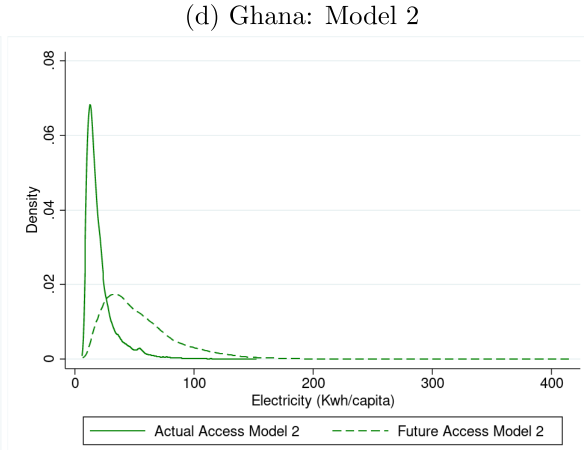
(c) Ghana: Model 1



(d) Ghana: Model 2

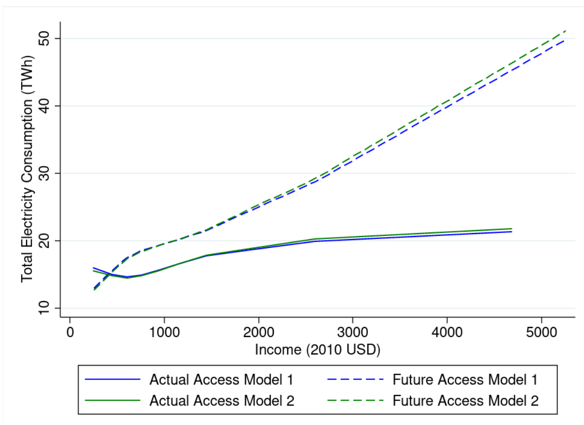


(e) India: Model 1

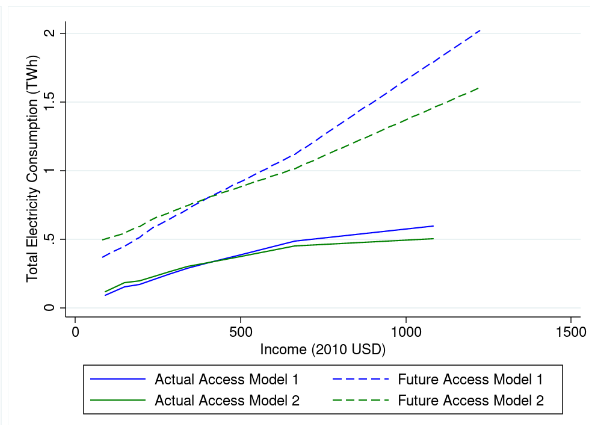


(f) India: Model 2

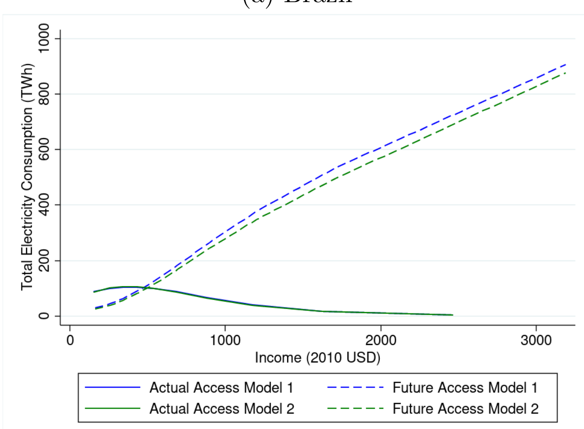
Figure 6: Distribution of Electricity Consumption per Capita, Households with Access in the Respective Samples and Future Projections for 2030



(a) Brazil



(b) Ghana



(c) India

Figure 7: Total Electricity Consumption by Household Income, Current and Projected Future levels of Electricity Access

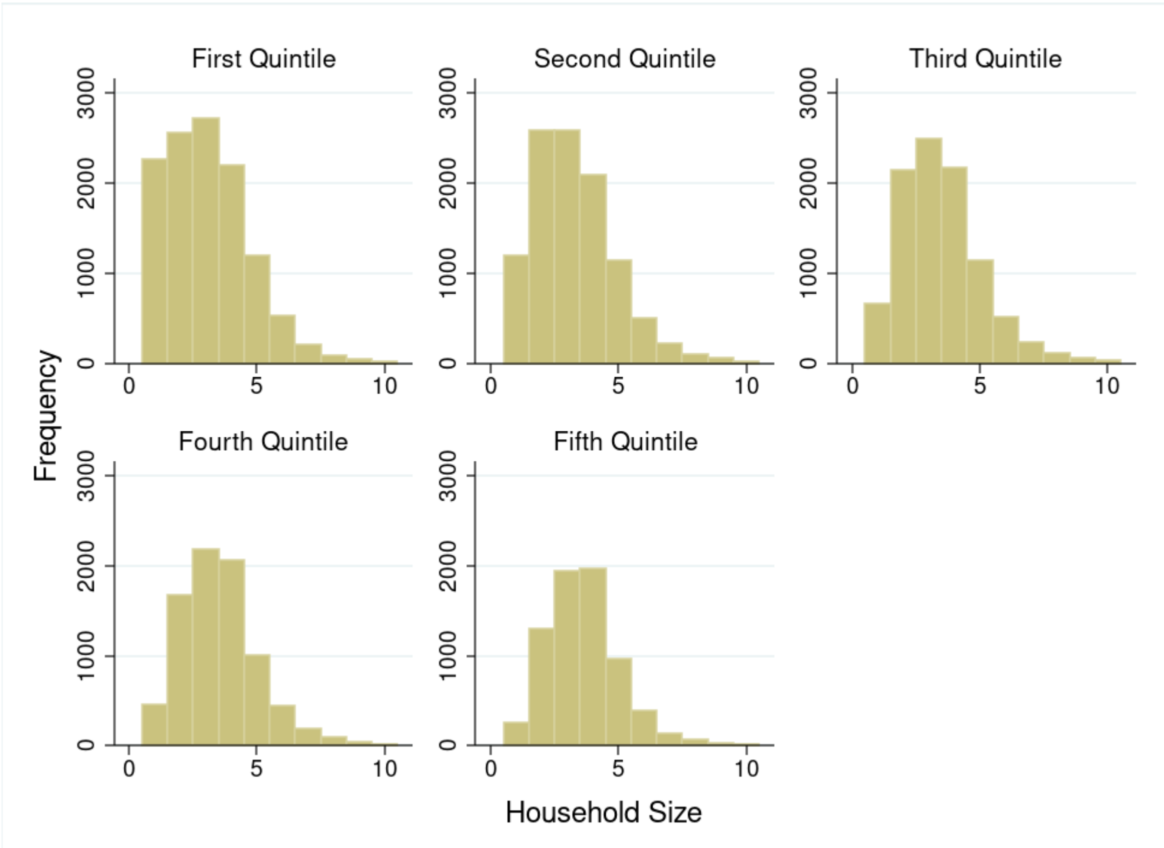


Figure 8: Brazil: Household Size Distribution

References

[Cuaresma, 2017] Cuaresma, J. C. (2017). Income projections for climate change research: A framework based on human capital dynamics. *Global Environmental Change*, 42:226 – 236.

[Dubin and McFadden, 1984] Dubin, J. A. and McFadden, D. (1984). An econometric analysis of residential electric appliance holdings and consumption. *Econometrica*, 52(2):345–62.

[Gourieroux et al., 1993] Gourieroux, C., Monfort, A., and Renault, E. (1993). Indirect inference. *Journal of Applied Econometrics*, 8(S):S85–118.

[Rao et al., 2018] Rao, N. D., Sauer, P., Gidden, M., and Riahi, K. (2018). Income inequality projections for the shared socioeconomic pathways (SSPs). *Futures*.

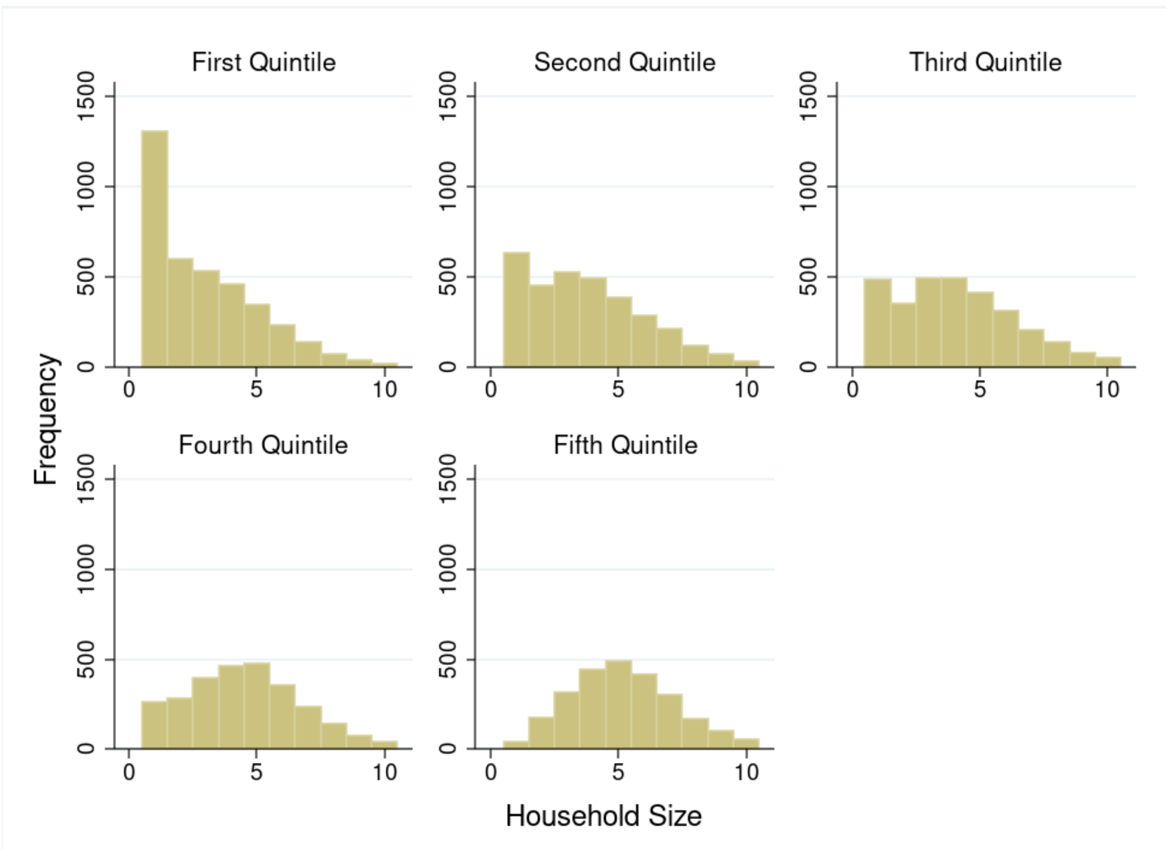


Figure 9: Ghana: Household Size Distribution

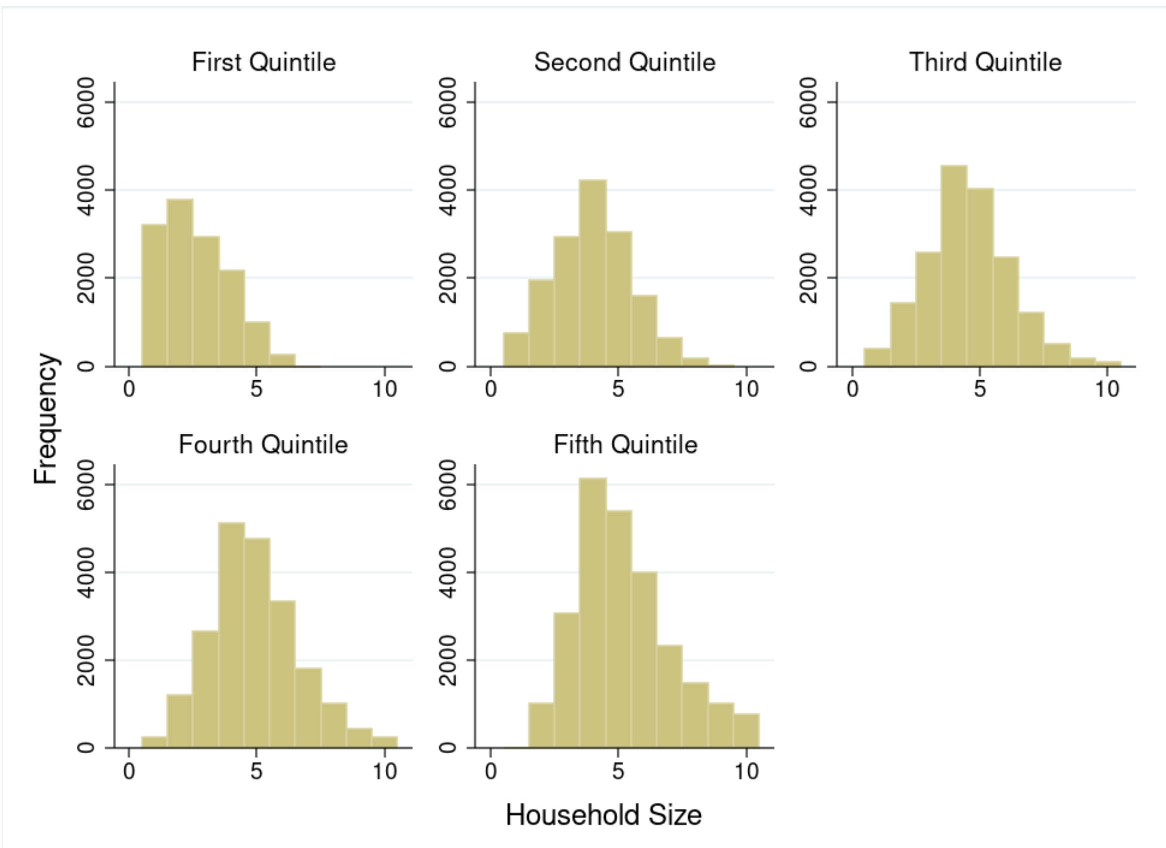


Figure 10: India: Household Size Distribution