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White goods for white people? Drivers of electric appliance growth in emerging economies

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ABSTRACT

Will everybody want and have a refrigerator, television and washing machine as incomes rise? Considerable uncertainty surrounds the likely increase in energy consumption and carbon emissions from rising incomes among the world's poor. We examine drivers of and predict appliance ownership using machine learning and other techniques with household survey data in India, South Africa and Brazil. Televisions and refrigerators are consistently preferred over washing machines. Income is still the predominant driver of aggregate penetration levels, but its influence differs by appliance and by region. The affordability of appliances, wealth, race and religion together, among other household characteristics, help explain the heterogeneity in appliance ownership at lower income levels. Understanding non-income drivers can be helpful to identify barriers to appliance uptake and to better forecast near term residential energy demand growth within countries.

1. Introduction

Will everybody want and have a refrigerator and washing machine as incomes rise? Considerable uncertainty surrounds the energy consumption and carbon emissions from rising incomes among the world's poor [1]. Besides heating and cooling buildings, household electronics, primarily televisions, and 'white goods' – large electrical household appliances – increasingly drive household electricity demand growth [2]. Residential electricity demand in non-OECD countries, which is currently slightly lower than OECD countries, is expected to grow faster and exceed OECD countries' demand by up to 25 percent in 2030, reaching over 1000 Terawatt-hours [3]. Global climate and energy demand scenarios typically adopt average national GDP as the primary determinant of household electricity demand in countries, while some also consider relevant societal trends, such as urbanization and electrification [3–6]. In effect, the current thinking is based on the assumption that all households globally at a certain income level would have the same appliances. But these assumptions have not been empirically validated on a systematic basis. Using micro (household survey) data in three emerging economies, Brazil, South Africa and India,[1] we show this assumption oversimplifies reality. While income is the dominant driver in the long run, market access, affordability, and wealth together better explain ownership, which differ considerably at similar income levels within and across these countries and for different appliances. Policies to improve energy efficiency and equitable access to decent living conditions can be better designed with such knowledge of market barriers and household preferences.

The lessons from the study of household cooking choices and electrification suggest that household conditions matter, and exhibit heterogeneity across and within countries [7,8]. We attempt to systematically understand the drivers of appliance uptake in major emerging economies, taking into account both internal and external household characteristics. We study televisions, refrigerators and washing machines. Televisions, while not strictly speaking 'white goods', are similar from an energy perspective, being capital intensive consumer durables with high electricity consumption. Other white goods, such as ovens and tumble dryers are not as prevalent in developing countries. Using nationally sampled household survey data from India, Brazil and S. Africa, this paper asks: is rising income alone sufficient to explain the rate and extent of electrical appliance penetration in emerging

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[1] Micro data for China were unavailable.

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economies? How do acquisition trends differ across these countries and why? What implications do these trends have for future energy demand projections? This paper contains a number of novelties. We consider additional drivers besides income and demographic characteristics, including: market conditions, such as appliance prices and electricity reliability, where available; social and cultural factors such as race and religion; and wealth-related indicators, such as dwelling quality and automobile ownership. We develop a standardized household consumption micro-dataset across the three countries and two points in time. We apply machine learning algorithms to identify and visualize influential drivers from the set available in surveys; and we assess ownership prediction accuracy with and without these additional drivers.

We find that beyond a certain threshold of income, it is likely that most households would purchase televisions and refrigerators, though fewer would purchase washing machines. There are, however, likely to be many differences in the interim transition paths in countries, which will be influenced by many non-income factors, not least appliances prices. If with technological change appliance prices show dramatic changes over time or differences between regions, so would the affordability of appliances, and the speed and trajectories of appliance penetration. Other influential non-income drivers include wealth and race – black households are less likely than white and colored people to own washing machines, ceteris paribus. Within countries, especially at lower income levels, appliance ownership varies greatly with these factors, though at an aggregate level the improvement in prediction of total appliance penetration is modest.

The rest of the paper is organized as follows: in Section 2 we discuss the state of knowledge; in Section 3 we discuss data; in Section 4 we illustrate appliance acquisition trends, and the possible role of non-income factors; in Section 5 we present a quantitative analysis to test the influence of household characteristics on appliance ownership; and in Section 6 we discuss the results and policy implications.

2. What we know

Earlier work examined drivers of residential energy use, including space conditioning and transport, and highlighted the importance of energy prices, dwelling type and technology evolution, in addition to income and climate [9,10]. It is clear from the literature, though, that different appliances have very different rates of penetration over time, whose causes are still not well understood. There is much evidence to suggest that televisions are the first and most widely acquired appliance [3,10,11]. Studies of India seem to reveal a hierarchy in the order in which further goods are acquired [5], but, as we discuss later, this may be particular to India.

Empirical research on appliance diffusion has largely focused on explaining or predicting appliance stock based on broad societal trends, while very few examine determinants of appliance ownership at a household level. In industrialized countries, Howarth et al. [12] examine the drivers of residential energy evolution in OECD countries and show that the growth of appliance stock slowed from the sixties to the seventies. However, Bayus [13] in an extensive examination of home appliance diffusion rates over several decades in the US shows that diffusion rates show no pattern with time. In contrast, Bowden and Offer [14] show that different types of appliances do indeed have different diffusion rates.

More recently, many studies describe the growth of appliances in emerging economies, particularly in urban India and China, and extrapolate these trends [3,15,16], often with the goal of estimating energy growth or efficiency potential. However, these studies typically do not formally examine household-level drivers of appliance acquisition, other than household size. A subset of these studies focus on the (positive) income elasticity of appliance acquisition to illustrate the relationship between patterns of income and energy growth [17,18].

Macro approaches to estimate future appliance penetration use logistic curves driven by income, electrification and urbanization [4,5,19,20]. However, these estimates do not comprehensively explain historical appliance diffusion, nor do they attempt to examine household-specific factors, in part because of their focus on appliance stock, and not the extent of household penetration. Conspicuously absent is affordability of appliances, which depend on income and appliance prices, among other factors.[2] The US Energy Information Administration's NEMS model does consider prices, but in appliance-specific payback periods that don't incorporate household-specific preferences for white goods [21].

Among the few studies of household-level determinants, O'Doherty et al. [22] examine the determinants of the total stock of appliances in Ireland to determine energy savings potential. They find that most household characteristics are significant, but home type and age are the most important non-income determinants. Leahy and Lyon [23] in a later study also find that household characteristics influence appliances ownership, but also find that the total stock significantly influences total energy use. In a study of rural China, Rong and Yao [24] quantitatively assess drivers of appliance acquisition, and finds that besides income, more education, female members and public services increase the likelihood of appliance ownership. Kemmler [8] examines predictors of electricity access uptake in India, and finds a number of household conditions influence access. Matsumoto [25] examines and confirms the influence of household size and composition on appliance usage in Japan for different types of appliances. Across all these articles, we find no consideration of social or cultural factors. Appliance prices are accounted for by Zhao and Yang, but not in combination with income as an expenditure share.

In summary, most studies examine macro trends, ignoring within-country heterogeneity. Consequently, not much is understood about the rate and extent of diffusion of different appliances in different countries, particularly in the developing world. While the saturation of televisions and mobile phones may seem inevitable, and possibly predictable with rising income, the same may not be the case for other appliances, such as refrigerators or washing machines.

3. Data

We have constructed a dataset from publicly available nationally representative household survey data and other sources on household characteristics, appliance ownership, national average appliance prices, and consumption expenditure. The dataset includes: India, using the India Human Development Surveys (IHDS) of 2004–05 and 2010–11 (41, 554 and 42, 152 households); Brazil, using the Consumer Expenditure Surveys (POF) of 2002–03 and 2008–09 (48,470 and 55,970 households); and S. Africa, using the Income and Expenditure Surveys of 2005–06 and 2010–11 (21,144 and 25,328 households). We select the IHDS over the often used Indian NSS (National Sample Survey) because the IHDS has more appliances and a question on electricity reliability. All three surveys collect information on household consumption expenditure, and include data on appliances and energy consumption, general demographics and other household characteristics. The Brazil and S. Africa surveys have a question on race, which include common categories of white and black, and different defi-

[2] Electricity prices also influence operating costs, as do the need for and cost of credit, though whether these factors drive appliance acquisition is not known.

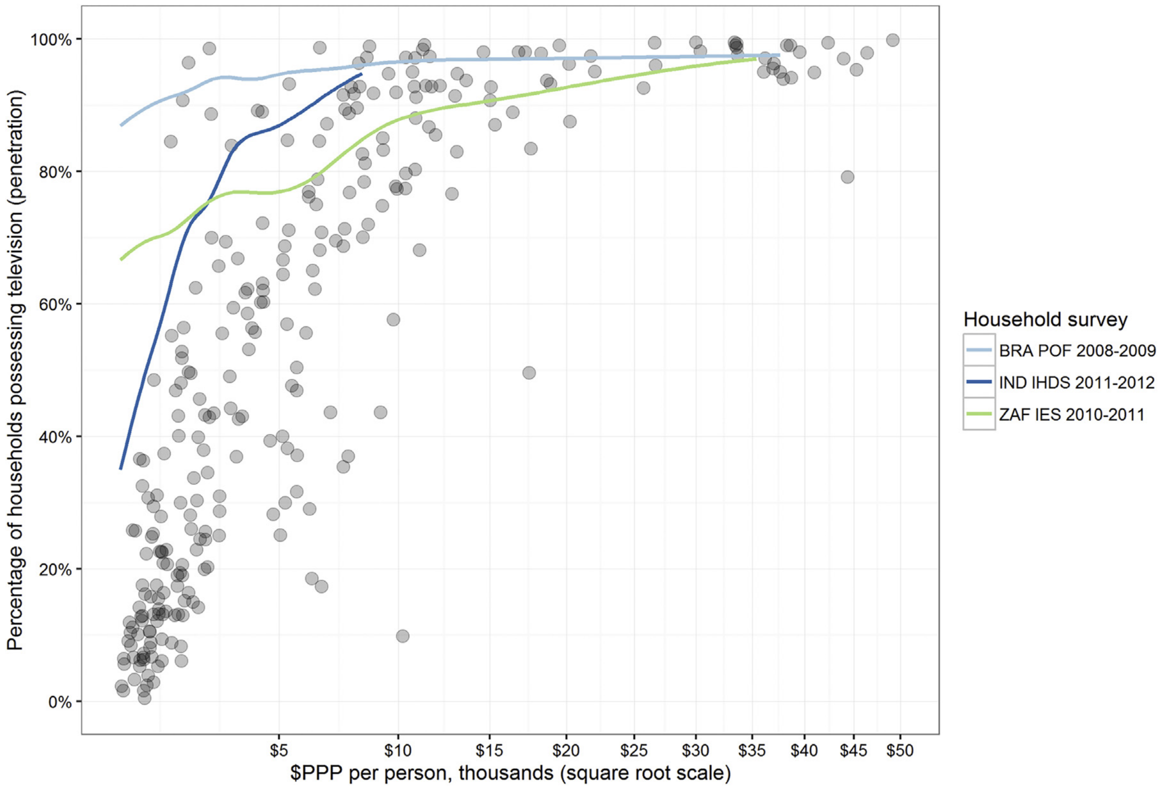

Fig. 1. Television penetration vs income, national average vs within-country. Gray circles show average penetration by GDP per cap for all countries; lines show within-country penetration by household expenditure per cap for Brazil, India and S. Africa.

nitions for other colored people. In the IHDS, the related question is on religion, and includes Hinduism, Christianity, Islam, Buddhism, Sikhism, Zoroastrianism, Jainism and others. In addition, we obtained average national, annual appliance prices and market volumes for different product types for each country from Euromonitor International. Euromonitor surveys retailers across the respective countries to obtain end-use prices for different products. Notably, the prices are built from actual prices paid by households, weighted by the share of product models sold at different prices by different suppliers. However, they only provide a single national average price for each product. Note that in the subsequent analysis we use only appliance prices and not total operating costs of appliances. Given the high discount rates typical of low-income consumers [26], as would be typical in emerging economies, and of buyers of white goods in general [27], the upfront cost dominates decision-making.

The data were interpreted and processed to create a common platform of variables and units across countries and years. This process included: converting all monetary values to purchasing power parity (PPP) 2010 dollars; creating new indicators for potential explanatory variables, such as an affordability metric (share of appliance price in annual per capital expenditure), head-of-household years of schooling, and dwelling quality. We construct dwelling quality using a set of five housing-related variables common across surveys: roof material, wall material, floor material, toilet type, and water source. Response values are survey-specific, but we categorize each as either modern (1) or traditional (0). We did have to exercise some judgment in categorizing dwelling quality, because different materials and housing types exist in the three countries. However, our focus was on distinguishing solid from weak construction, which was straightforward. The dwelling quality index is the mean value across the binary variables, multiplied by five. A value of five indicates a household with modern dwelling features for all available housing variables. Table 2 shows some of the descriptive statistics of key variables examined by country. The last three variables – dwelling quality, number of rooms and automobile ownership – represent proxies for wealth.

4. Appliance acquisition trends

As discussed in Section 2, the common base of understanding today is that appliance penetration[3] would differ by income in the same manner across and within countries. One would expect that at similar income levels in different countries, one should see similar penetration levels, after adjusting for electricity access and urban/rural location. In Fig. 1 we plot national television penetration for countries versus average GDP per capita (PPP-adjusted) for a set of 314 country-year combinations. We then overlay the *within-country* relationship between penetration and per-capita expenditure as observed in Brazil, India and S. Africa.[4] Several observations are noteworthy. First, among countries there is significant variation in penetration at a given income level, which implies

[3] By penetration we mean the share of households that have *at least one* appliance, instead of average number of units per household. The former does not provide an indication of the total stock, while the latter masks the penetration, since multiple ownership among the rich can hide no ownership among the poor. The literature tends to focus on stock, due in part to the concern for energy use and emissions.

[4] Household expenditure is only about 60% of GDP in our selected countries. In order to present country- and household-level data on a single *x*-axis, we divide each household's expenditure by the share of household final consumption expenditure in GDP. Even though all three countries have different levels of urbanization and electrification, we don't know the average income of electrified households, so we are unable to present the data for only electrified households, or controlling for urban/rural. Nevertheless, for the micro data, we see the same pattern with electrified households alone. Similarly, if we adjust the national averages for electrification rates, assuming that electrified households have the same average income as the national average, the pattern and variance is the same.

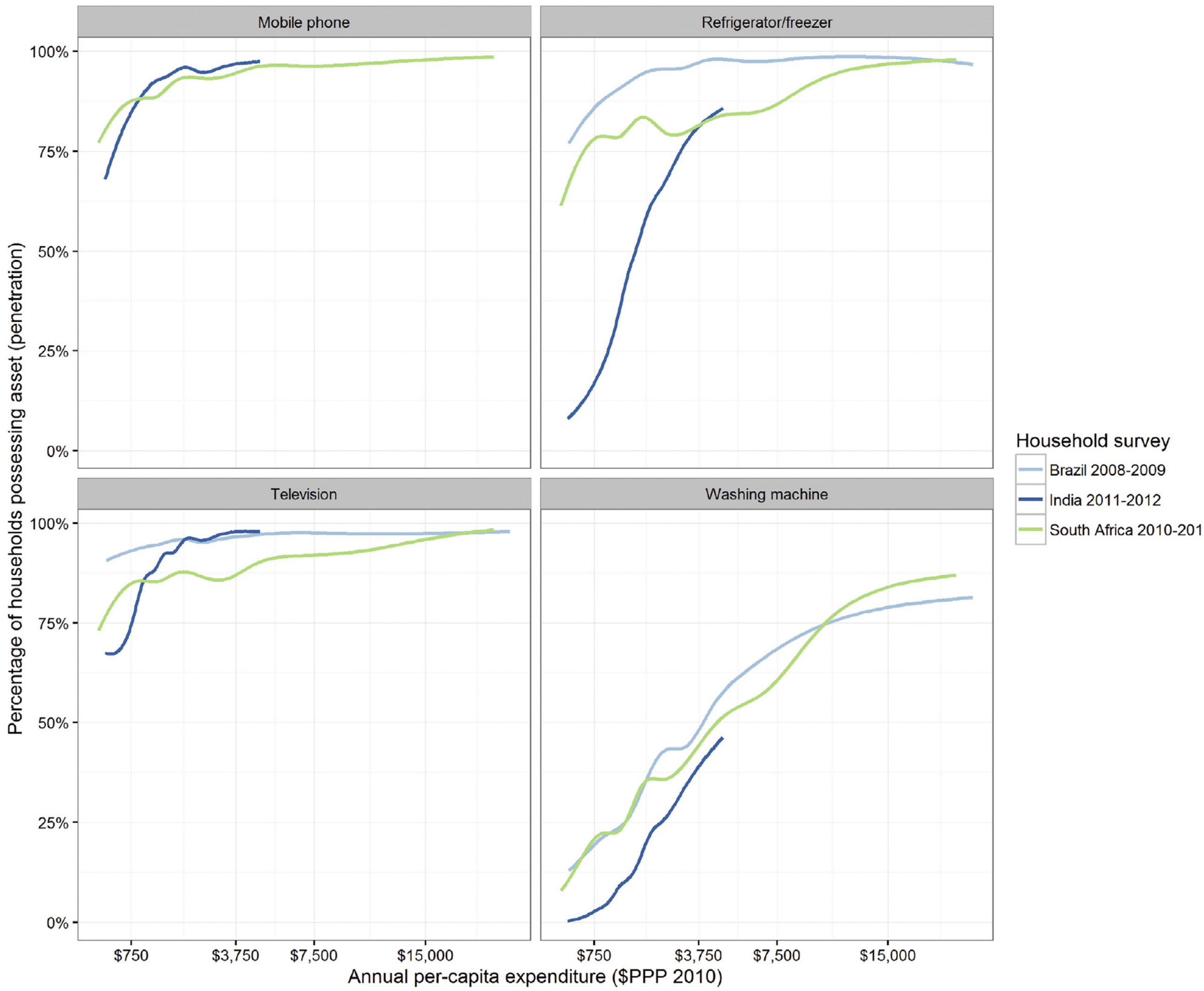

Fig. 2. Appliance penetration by household expenditure level among electrified households in urban areas of IN, BRA and ZAF, 2009–2012. Data are truncated (left) at PPP$750/cap/yr and (right) at 97.5 percentile.

country-specific factors matter. Second, we see clearly the heterogeneity *within* the three countries in the relationship of television penetration to income, and that the three curves differ in shape from each other, and from the implied shape for national averages.

4.1. Not all high income household own washing machines

An implicit assumption in literature is that all households would eventually own white goods, assuming real incomes keep rising. Below we show the rate of penetration for white goods and mobile phones in select EU countries, including two of the poorest countries in Central Europe, Armenia and Albania, for which data were available (Table 1). We show data for mobile phones as a point of comparison, since it has had the fastest and broadest proliferation of any device in history.[5]

The data among developed countries show that saturation levels typically reach over 90%, but with exceptions. Almost all households have televisions, even in Albania/Armenia. Among the emerging economies, television ownership seems to already approach saturation in urban Brazil and China, despite high urban poverty. The same observation applies to refrigerators. It is noteworthy that although washing machines are also owned by over 95% of the non-poor EU countries shown and Japan, they are owned by only 82% of US households.

Looking at micro data (Fig. 2) reveals that in S. Africa and Brazil different appliances reach saturation at different income levels, and at different levels of penetration. Washing machine penetration appears to plateau at ∼80%, while refrigerators, like televisions, reach close to 100% penetration among high income households in both countries (Fig. 3).

4.2. Income effects differ by region and appliance type

Above we show that appliances saturate at different penetration levels. Here we describe trends with income changes, both across households and over time. At very low incomes, very high shares of households have refrigerators in Brazil, fewer have them in S. Africa, and significantly fewer in India. This isn't explained just by price, as prices in Brazil are not particularly low (Fig. 4). While prices in India are highest, there is no demand for even the cheaper small refrigerators (<140 l) that are prevalent is in South Africa, presumably among the poorer population.

We also see that the shapes of the penetration curves differ by country for televisions and refrigerators, but appear similar for

[5] International Telecommunication Union (ITU). ICT facts and figures. Available at: https://www.itu.int/en/ITU-D/Statistics/Documents/facts/ICTFactsFigures2015.pdf

Table 1
Household appliance penetration in select industrialized and emerging economies, various years (2009–12).

Country	Income per cap (2010 $PPP)	Electricity access	Television	Mobile phone	Refrigerator	Washing machines
US	48,374	100	98.7	93	99.8	82
UK	35,855	100	100	92	100	97
Germany	39,612	100	100	>90	99	96
France	35,867	100	100	89	100	100
Japan	33,741	100	100	93	100	100
Albania	9298	100	98.9	94.1	94.8	NA
Armenia	6376	99.8	98.7	86.9	78	39–49
Urban China	NA	>95	95	100	83.3	81.8
Urban India	10,713	97	87.9	91.1	46.9	17.3
Urban Brazil	24,093	99.8	95.9	NA	94.9	49.3
Urban S. Africa	25,149	91.7	84.0	92.1	78.7	44.1

Sources: National statistics, Statista 2014, Euromonitor 2009, Demographic and Health Surveys. For India, Brazil and S. Africa sources, see Data section in text.

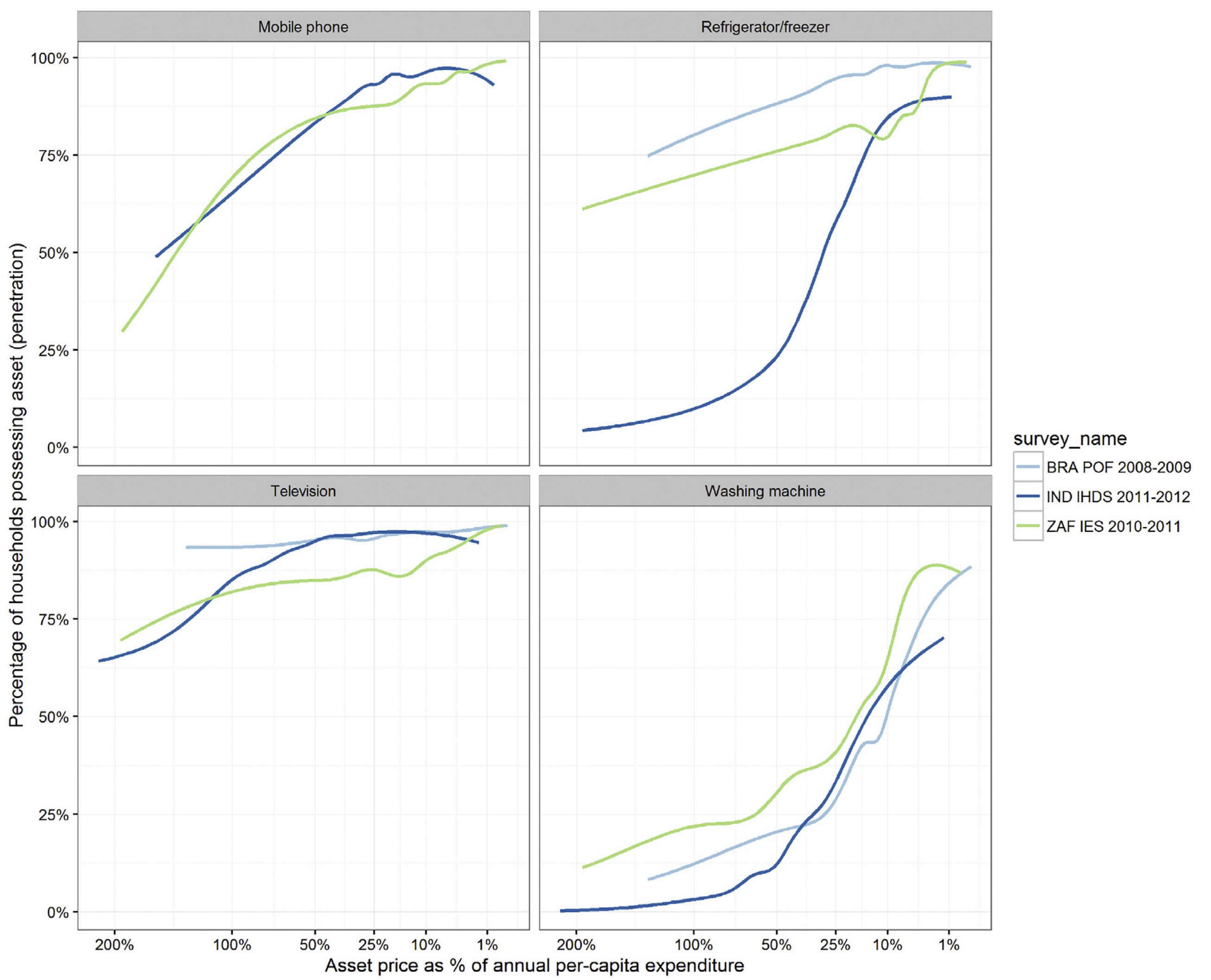

Fig. 3. Appliance penetration levels by affordability (appliance price (national avg)/per cap expenditure) among electrified households in urban areas of IN, BRA and ZAF, 2009–2012. Data are truncated to 2.5 and 97.5 percentile. Values to the left may be exaggerated to the extent the poor pay below-average prices.

washing machines. In India, for instance, televisions and refrigerators seem to exhibit a tipping point in per capita expenditure, above which ownership increases steeply. Whereas in S. Africa, penetration is more (and in Brazil almost completely) income-inelastic.

Changes in penetration levels over time also differ by appliance and by region (Fig. 5). In the 5–10 year period between surveys, in India, despite decreasing prices, the uptake of fridges has been higher at higher income levels than at lower income levels, while in Brazil and S. Africa, the uptake has been greater at lower income levels compared to middle income levels (penetration is already saturated at the highest income levels). Absolute changes have been lowest in India, higher in Brazil and highest in SA, which can't be explained by price changes (Fig. 4). That is, prices have declined more considerably in India, where uptake (in relative terms) has been slowest.

In sum, in the three countries these appliances become widely owned at different levels of income, and exhibit different patterns of ownership at lower income levels. There are, therefore,

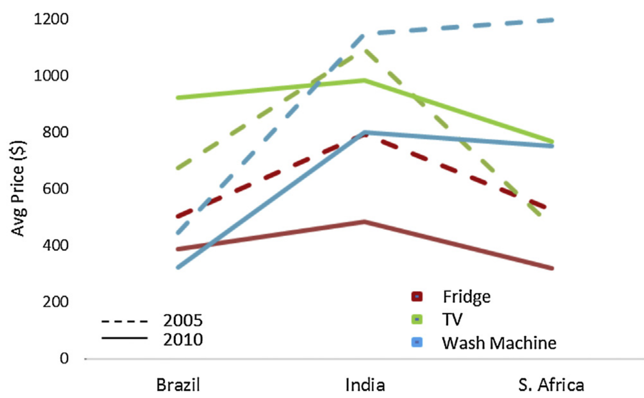

Fig. 4. Appliance prices (2005, 2010) and type (2010). Source: Euromonitor International.

drivers other than income that influence when and how households acquire these appliances.

4.3. Affordability explains some regional differences

Income is intended to be a proxy for affordability, but fails to account for different prices. Upfront purchase costs matter for low-income households, as they may not have the capital to purchase large appliances, or lack the credit to buy financing. In Fig. 3, we show the penetration levels by affordability, which we define as the appliance price divided by per capita household expenditure. Note that these are national annual average prices, so they only differentiate affordability between countries and across time. Prices are generally highest in India on a purchasing power parity (PPP) basis, and lowest in S. Africa for televisions and fridges, but lowest in Brazil for washing machines (Fig. 4).[6] Comparisons of household adoption across countries on the basis of expenditure shares are therefore more appropriate, and those on the basis of income can be misleading. For example, because prices are generally higher in India, the income penetration curves underestimate Indian households' propensity to own these appliances (the curves shift left in Fig. 3 relative to Fig. 2).

Saturation levels of appliances in the three countries when measured against affordability rather than income are more similar. On an income basis, televisions and refrigerators saturate urban households in Brazil at under $5K, but not until $15K in S. Africa. In contrast, as a rule of thumb, it seems that in all regions appliances attain full saturation when appliance costs are close to 1 percent of per capita expenditure.[7]

It is also revealing that many households are willing to pay prices for appliances that exceed their per capita annual expenditure. More households in all regions are willing to pay over a 100 percent of their total expenditure on televisions than on refrigerators, washing machines or even mobile phones.[8] Furthermore, penetration levels are lower for washing machines at all affordability levels in all three regions. Note that this is despite the fact that washing machines are relatively cheaper than televisions in all cases, and by far in India. However, the relative penetration of televisions and refrigerators differs by region. Only in India does there appear to be a clear ordering in penetration levels between refrigerators and televisions at all affordability levels (see also Fig. 5).

Given the different saturation levels for washing machines vis-à-vis refrigerators and televisions as well, these data provide further evidence that households across regions place lower priority on washing machines. Household preferences beyond price and income considerations seem to explain this preference ordering.

5. Quantitative analysis – Methods

In order to understand the relative influence of income and other drivers of appliance uptake by households, we conducted quantitative econometric analysis on our household survey data using two estimation methods. The first, which would represent the state of the art, is a traditional logistic (or logit) model, while the second uses a machine learning algorithm (boosted regression trees (BRT)). With both models, we predict appliance ownership for each of the three appliances (television, refrigerator and washing machines) for each country, pooling both survey periods, and only including households with electricity access. Below, we first describe the machine learning algorithm and the rationale for its use, then discuss the results and their implications.

Conventional logit models have the limitation of being restricted to a particular functional form, and require a priori specification of covariates. With the BRT model, both constraints are relaxed. One can include a 'kitchen sink' of variables, which the algorithm analyzes to determine those that have the strongest influence on appliance ownership, including through nonlinear relationships and complex interaction effects. The use of such a flexible approach is advantageous since there is comparatively little theoretical understanding of people's decision-making around appliances.

BRT is a tree-based, ensemble machine learning technique, similar to the popular random forests,[9] that uses gradient boosting to build an ensemble of decision trees that are sequentially fit to remaining model residuals.[10] The optimal number of trees is typically determined via n-fold cross-validation, so as to maximize the resulting model's expected out-of-sample performance. Elith et al. [28] provide an excellent review of the BRT technique and applications. We employ the BRT implementation in the R programming language *gbm* package.[11]

We know of very few cases of machine learning being employed in energy research. Kuan and White [29] compared the performance of logit models, neural networks and regression trees in predicting appliance ownership in the US. They found that logit out-performed regression trees for in-sample predictions, but regression trees outperformed the others for out-of-sample predictions.[12] More recently, we found only one research group using similar techniques to understand drivers of urban energy use [30,31].

In order to separate the effect of model choice from the influence of a richer set of covariates, we run both estimation methods (logit and BRT) with a 'sparse' and 'rich' set of covariates (predictor/independent variables). The 'sparse' specification includes just income and urbanization – that is, covariates commonly used in past literature on appliance penetration. The 'rich' specification includes a broad set of potential covariates common to all of the

[6] Part of these differences stem from differences in the predominant technology sold in each market, which is another factor deserving attention that we leave for future research.

[7] We tried formally testing for saturation, but were unable as data for top incomes are poorly sampled.

[8] Note that because we use national average prices, the extent to which the poor are willing to pay may be overstated – anecdotally, it is known that the poor buy inexpensive imported televisions that are probably not accounted for in the Euromonitor data.

[9] http://link.springer.com/article/10.1023%2FA%3A1010933404324.

[10] https://statweb.stanford.edu/~jhf/ftp/trebst.pdf.

[11] Greg Ridgeway with contributions from others (2015). gbm: Generalized Boosted Regression Models. R package version 2.1.1. (https://CRAN.R-project.org/package=gbm)

[12] This is not surprising since maximum likelihood (ML) techniques regularly employ cross-validation to prevent over-fitting and explicitly maximize out-of-sample performance, while conventional modeling techniques are prone to overspecification.

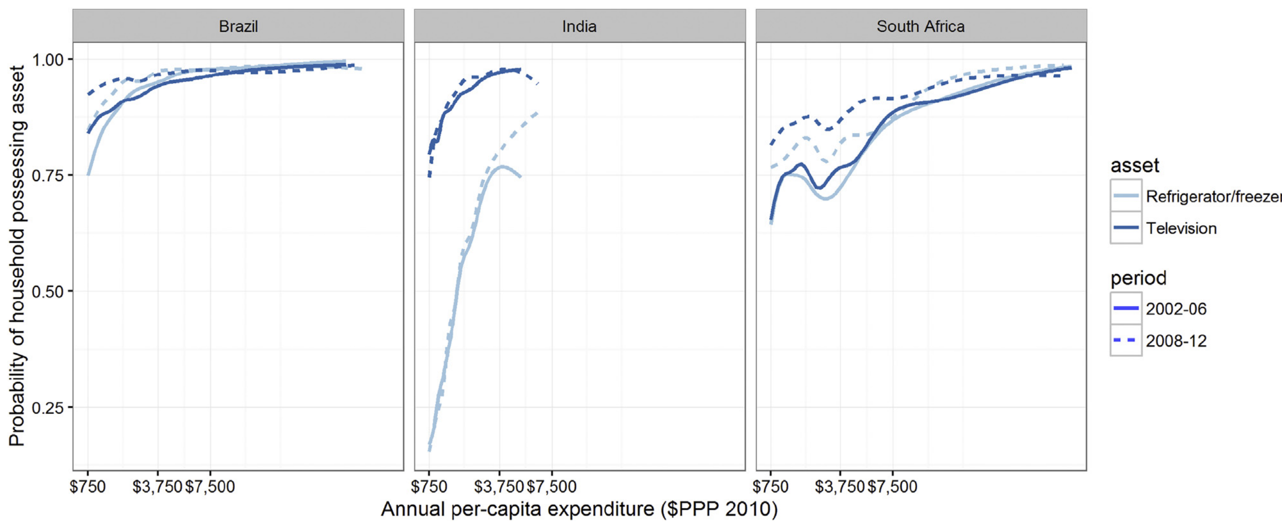

Fig. 5. Appliance penetration over time, by per capita expenditure. The periods shown include different years for each country. For actual years of each survey, see Data section.

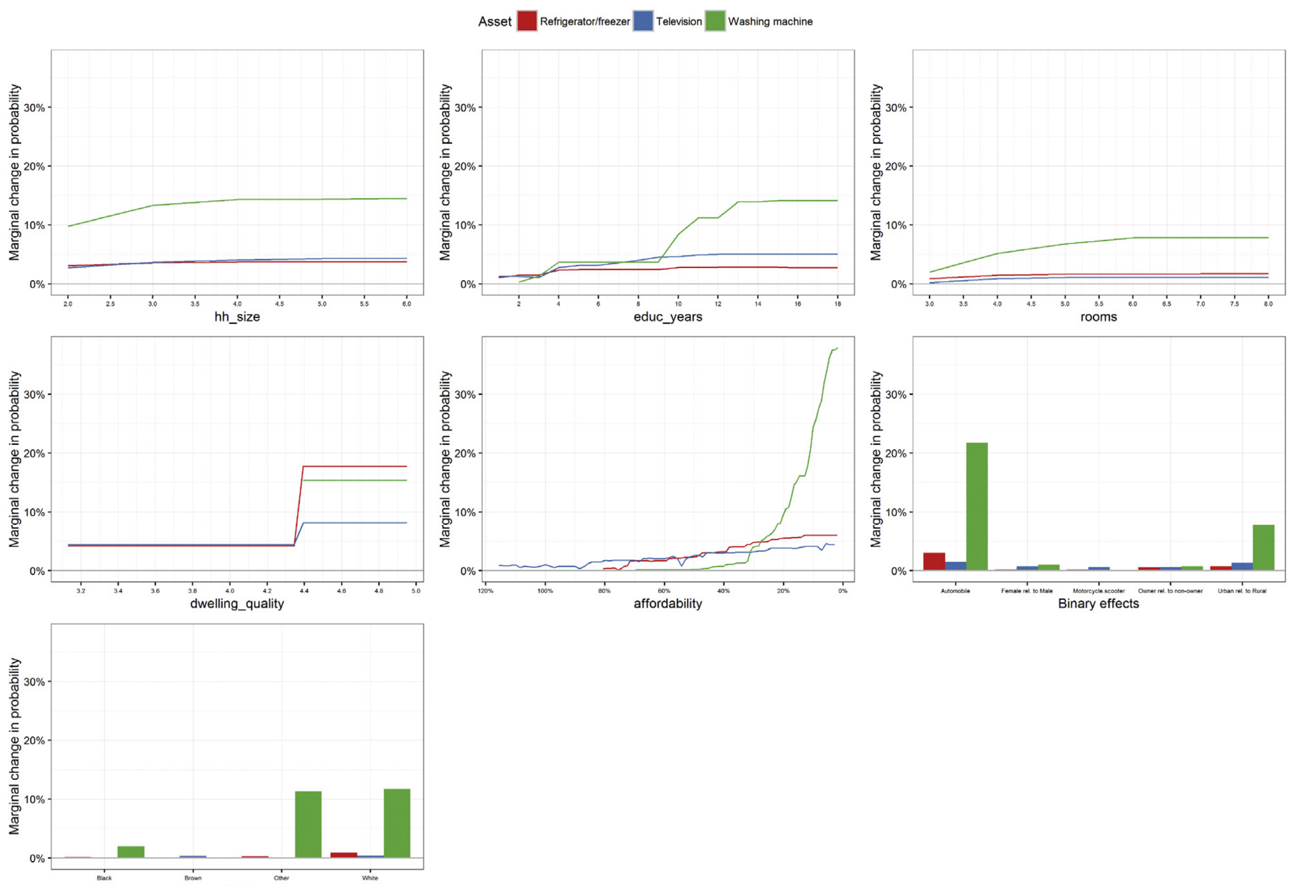

Fig. 6. Marginal effects of relevant covariates in Boosted Regression Tree (BRT) models, Brazil.

country surveys. This set includes the aforementioned affordability metric instead of income, which additionally accounts for appliance price, and therefore captures changes in affordability over time within each country. Data on electricity reliability were available, and therefore included, only for India. For social/cultural factors, we used race for Brazil and S. Africa, and religion for India. Other covariates include age (of the head of household (HoH)), urban/rural, dwelling quality (see Data section), vehicle ownership, household size, education (of the HoH), number of rooms, male/female HoH, and home rental/own. We fit the 'rich' BRT model using all available common covariates, a subset of which was deemed to have non-zero influence. This influential subset was used to fit the 'rich' logit model.

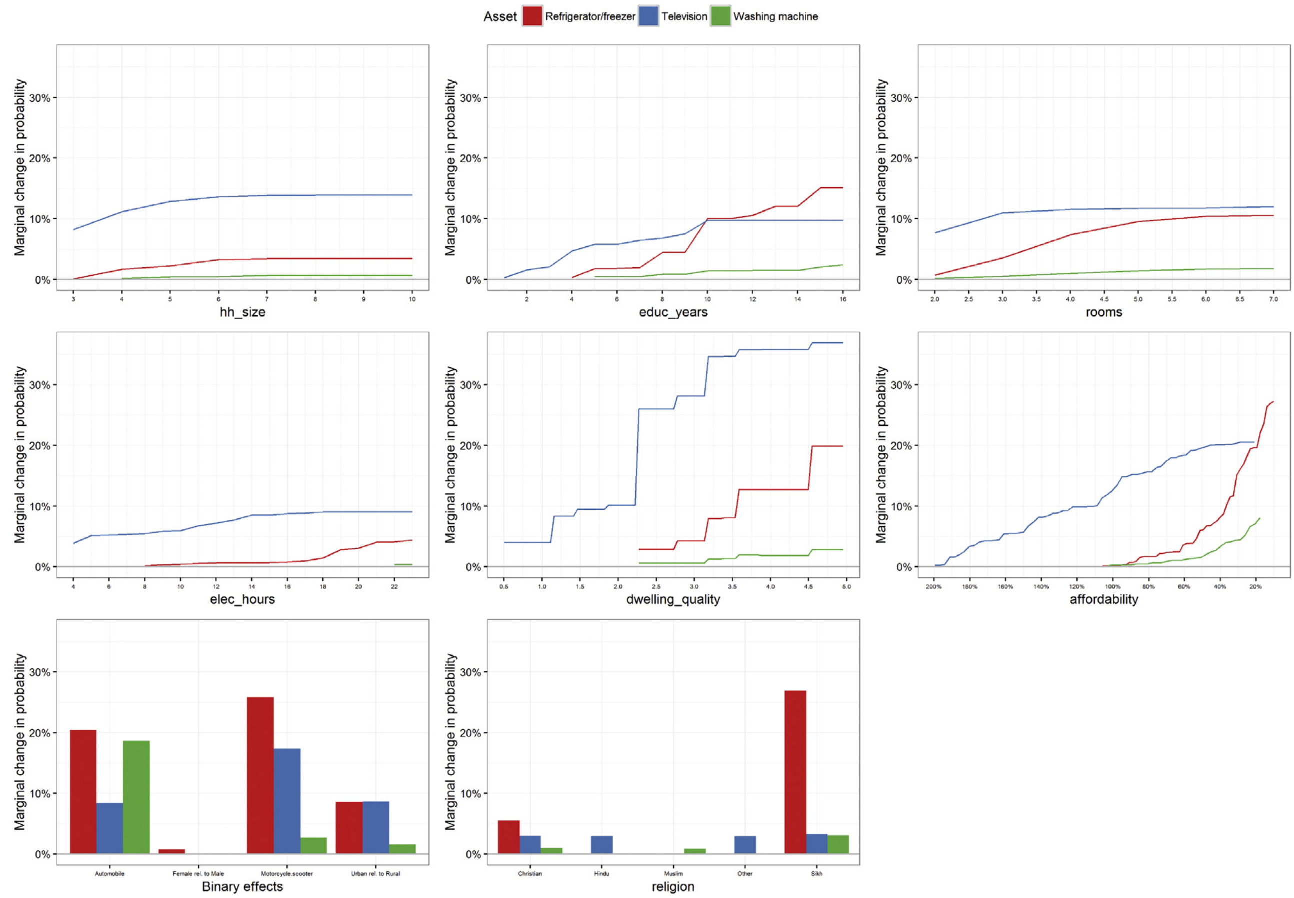

Fig. 7. Marginal effects of relevant covariates in Boosted Regression Tree (BRT) models, India.

6. Quantitative results

Overall, the prediction accuracy for aggregate appliance penetration is quite strong in all the models (See Supplemental Information). The difference in prediction accuracy from the richness of covariates exceeds that from model choice. The value of the BRT model was more in identifying the set of influential variables to include in the logit model in the first place. Across surveys and models, the difference between predicted penetration rates and actuals is within 6 percentage points. A rich model that accounts for household characteristics better predicts appliance ownership than one based on just income and location (urban/rural) alone.[13] However, the benefit of a rich set of explanatory variables is modest – the magnitude of the improvement in prediction is, on average, within two percentage points of the prediction accuracy with the sparse models. At the same time, the marginal propensity of ownership increases by up to 30% for a number of factors related to wealth, culture and other household characteristics. These results likely reflect the fact that the influence of these other factors is higher at lower income levels, where the contribution to overall penetration is relatively low.

6.1. Regional differences in the income effect

The analysis confirms that although income is still the strongest predictor, its influence differs by region and appliance. The income effect is strongest in India, since it is the poorest and has the lowest penetration for all appliances. According to the logit model, for an increase in annual income of PPP$1000 per cap in India, the odds of owning a television increase by 52% and that of owning a refrigerator increase 30%, and that of owning a washing machine increase by about 18%.[14] The same income change has no effect on television ownership in S. Africa and Brazil, and a trivial increase in Brazil and S. Africa for both washing machines and refrigerators. However, noting that Brazil and S. Africa have four times the average income as India, a comparison between the odds of ownership between the 25th and 75th percentile of the population is more informative.[15] For television, odds increase by 43% in both countries; for refrigerators, ~60% in Brazil and 216 percent in S. Africa; and for washing machines ~60% in S. Africa but 288% in Brazil.

In summary, there are clear differences in the elasticity of adoption to changes in income across countries. But there are further differences in the absolute levels of penetration. Some of these differences are explained by heterogeneity in non-income household characteristics. This is discussed next.

6.2. Marginal effects of non-income drivers

The importance of non-income factors is understated when examining aggregate penetration. That is, if one were interested in ‘who’ has particular appliances (for those that are not owned by

[13] A model with only income (and not urban/rural) has marginally different predictions.

[14] The change in probability associated with a change in odds is contingent on the initial probability. Probability changes are usually smaller. For a change in odds of 5 and 50 percent, the maximum change in probability is ~1 and ~10 percentage points respectively.

[15] For India, an income change of $1000 per cap does, coincidentally, correspond approximately to the difference between the 25th and 75th percentile.

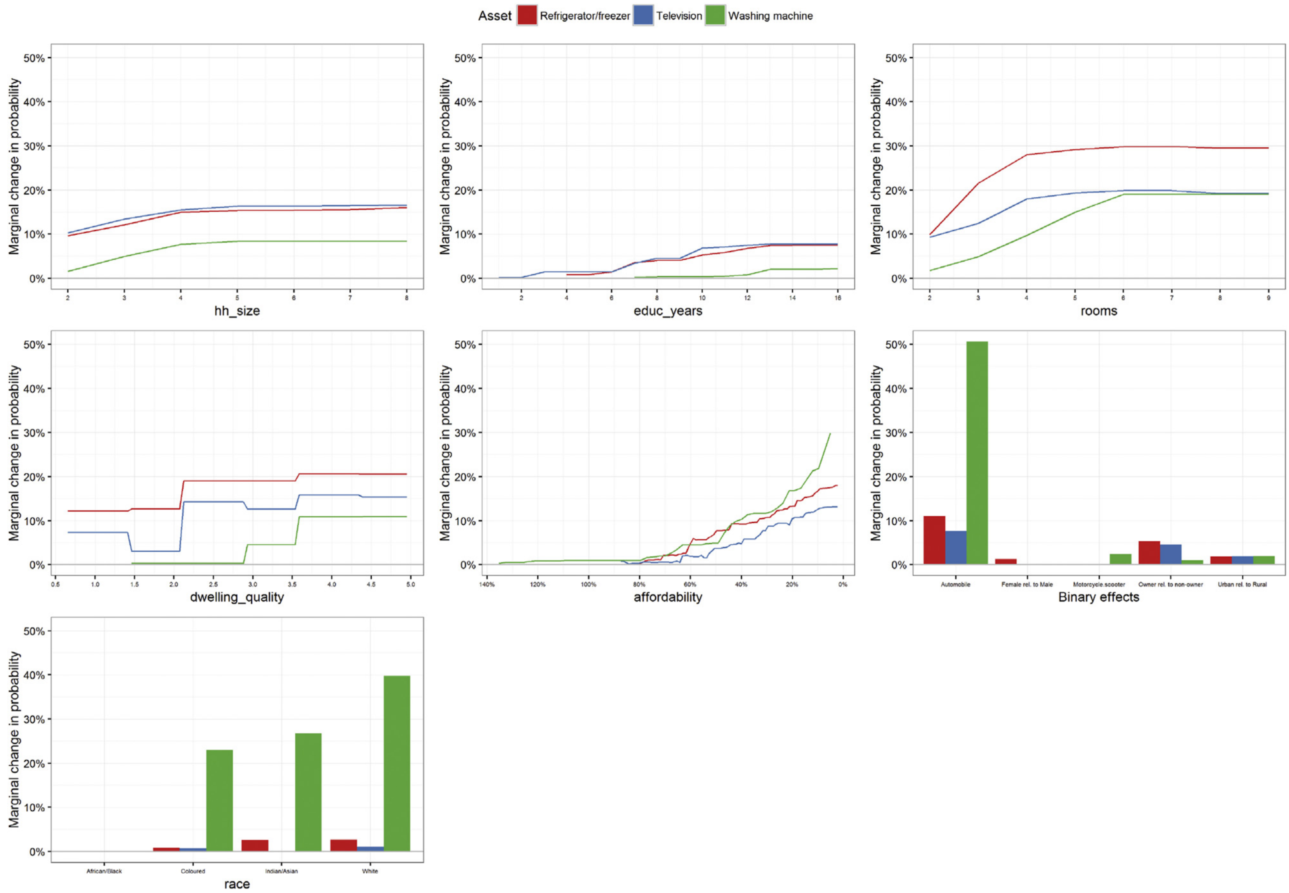

Fig. 8. Marginal effects of relevant covariates in Boosted Regression Tree (BRT) models, South Africa.

all households), rather than just 'how many' households have these appliances, additional covariates become more important.

The rich model reveals some of the household characteristics that may explain this heterogeneous behavior. The marginal effects of these variables are shown by country in Figs. 6–8. In Brazil and S. Africa, indicators of wealth and race seem to strongly influence ownership. The possession of automobiles and the quality and size of the dwelling, both have a strong effect, to different degrees in each country. This could reflect households' ability to get credit, or the availability of communal laundry facilities (for example, suburban homes vs apartment buildings). In India a similar effect is seen for refrigerator ownership – as reflected in the ownership of either motorcycles or cars, and dwelling quality. The effect of better electricity supply is relatively small, and only at average availability higher than 18 h day (which makes sense, given the benefit of having one is fairly low if the refrigerator is off for more than a few hours in hot weather). The effect of dwelling quality is particularly strong for televisions in India.

The influence of race/ethnicity (controlling for all other factors) is particularly interesting – in both S. Africa and Brazil, being colored or white (over being black) has a strong marginal effect on washing machine ownership (Figs. 6–8). In S. Africa, the increase in marginal probability of ownership for being white is higher than that for increased affordability. It is possible that the influence of race reflects household cultural preferences or external market conditions, such as differential access to markets for credit, or for appliances themselves. In India, cultural preferences related to religion may play a role in refrigerator ownership (Fig. 7). In India, there is a smaller, albeit noticeable, effect of religion on refrigerator ownership – wherein Sikhs have a higher chance of owning one. This may have to do with the fact that Sikhs are known for a high consumption of milk products.[16] The relative importance of these findings differs by country, since Sikhs comprise less than 1% of the population, blacks comprise 9% in Brazil, and blacks comprise 79% in S. Africa. Nevertheless, these findings are illustrative of the importance of non-economic factors.

Otherwise, ceteris paribus, urban, more populous, larger, more educated, and better quality homes, are likely to have more appliances. These findings are consistent with those of previous studies. However, our results show that the influence of many of these drivers is gradual over broad segments of the population, rather than having 'tipping points', as in the case of affordability. That is, the marginal probability of ownership increases steadily from below and through the mean levels for the population (see Table 2), and flatten out thereafter. This may explain why the aggregate prediction rates do not shift so significantly in the rich model. However, for any given set of households at a particular income level, the combination of all these marginal effects would make the predicted ownership far more accurate with the rich model than the sparse one.

7. Conclusions

We have examined patterns of ownership of televisions, refrigerators and washing machines in India, Brazil and South Africa using household-level survey data. This study for the first time provides quantitative evidence on a hierarchy of preferences among

[16] Based on our calculations of milk product consumption in the Indian NSS 2011–12, Sikhs consume more than all other religious groups, and more than double that of the predominant groups with higher populations.

Table 2
Descriptive statistics of key covariates by country/survey (for urban households with electricity access only).

	India		*S. Africa*		*Brazil*	
	04–05	11–12	05–06	10–11	02–03	08–09
Expend per cap	1542 *1553*	2191 *2240*	6928 *12,106*	7210 *11,320*	5704 *9435*	6516 *12,621*
Years of education	8.1 *5.1*	7.9 *5.0*	9.7 *4.0*	9.8 *3.8*	6.2 *4.6*	10.7 *2.9*
Household size	4.9 *2.1*	4.7 *2.2*	3.5 *2.3*	3.6 *2.2*	3.6 *1.8*	3.2 *1.6*
Age of HoH	46.1 *12.9*	50.0 *12.8*	42.0 *15.0*	45.7 *14.6*	45.9 *15.3*	47.7 *15.6*
Dwelling quality	4.0 *1.1*	4.2 *1.0*	3.9 *1.4*	4.1 *1.1*	4.8 *0.8*	5.0 *0.3*
Number of rooms	2.6 *1.5*	2.8 *1.6*	4.4 *2.3*	4.5 *2.5*	4.6 *1.9*	4.7 *1.8*
Automobile Owners (%)	3.7	7.5	26.5	39.8	32.3	35.3

Figures in italics show standard deviations. Expenditures in $PPP2010. HoH: Head of household.

electric appliances. If developing economies exhibit the same patterns as we observe in our sample, eventually most households will have televisions and refrigerators, but, a lower share would likely have washing machines.

As with previous studies, we find that household characteristics, including of the physical house, and of inhabitants' demographic characteristics, have an influence on appliance ownership. However, in addition we identify new factors related to affordability, wealth and identity, some of which may be particular to developing economies. Affordability of appliances, defined as their expenditure share, provides a more comparable metric for cross-country comparison than does just income. Indicators of wealth, such as ownership of vehicles or home size and quality, also influence purchases. Surprisingly, race (color) seems to play a distinct role in both Brazil and South Africa in explaining washing machine ownership, while religion was found to play a role in refrigerator ownership in India. These differences could reflect cultural preferences, or differences in market access. This merits further exploration. The technology and size of appliances that are purchased in countries also differ in ways that are related to, but not exclusively explained by, affordability, but which have not been explored in detail in this study.

Affordability may be the most salient insight from this study to incorporate in future demand projections. Forecasts of appliance uptake based on macroeconomic trends alone may be inaccurate to the extent that appliance price trajectories diverge over space and time. Incorporating other factors into long-term forecasts of energy demand would be challenging, and possibly less useful, given the uncertainty in their predictive value and in the ability to project trends at a global scale.

These results are one step toward better understanding the roles of market barriers and household behavior in appliance uptake in developing countries. These insights can inform the design of energy efficiency and equitable access policies and forecast near term residential energy demand growth.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at http://dx.doi.org/10.1016/j.erss.2017.03.005.

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