Title

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Modeling diffusion of electrical appliances in the residential sector

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Disclaimer

1. Introduction

This paper presents a methodology for modeling residential appliance uptake as a function of root macroeconomic variables. While such a determination is an interesting result in itself, the results presented will provide the energy community with a foundation for further analysis, specifically in the development of bottom-up energy demand forecasts, and related projections of greenhouse gas emissions related to energy consumption[1].

Energy consumption is responsible for 70% of greenhouse gas (GHG) emissions (Price, S. de la Rue du Can et al. 2006), but the energy consumption situation is by no means static, nor is it easily predictable. To date, emissions have been dominated by industrialized countries, whose energy consumption is relatively well understood. This situation is changing, however. Due to its rapid economic expansion in the past decades, China recently overtook the United States as the world's largest emitter of greenhouse gases. Providing policymakers with a set of alternatives to head off a potential catastrophe, therefore, demands a serious effort to model future energy consumption which includes the developing world. This report describes the methodology and results of a global model of appliance diffusion – an important step in forecasting electricity consumption in the residential sector.

Most global and long-term projections of energy consumption take a top-down approach, correlating consumption growth to macroeconomic trends. The model utilized by EIA's International Energy Outlook, called the World Energy Projection System (WEPS), for example, forecasts total energy consumption according to region-specific elasticities, which relate growth in GDP to growth in energy consumption. The World Energy Outlook (WEO) developed by the International Energy Agency takes a more detailed approach, projecting residential energy consumption with an econometric model of consumption at the household level. In the recent versions of the model (International Energy Agency 2004), a strong effort was made to include more sector and regional detail to modeled projections. This implied an econometric forecasting of residential consumption by end use and fuel. This effort seems to have concentrated on OECD countries, where detailed data is most readily available, with the possible addition of emphasis in major developing countries (Russia, China, India and Brazil).The methodology presented in this paper provides the possibility for a bottom-up, end use level global model that could be incorporated into the next generation of emissions scenario models. There are two main advantages of such an approach. First, an end-use level diffusion model may more accurately capture the structure of energy demand growth by predicting the uptake of energy intensive products instead of assuming a direct relationship between economic activity and energy demand. Second, the ability to

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[1] Such an analysis is the subject of a forthcoming article by the authors.

mitigate energy-related emissions through efficiency depends on the technologies of individual end uses. Efficiency-related savings is a function both of the baseline energy consumption (base load and efficiency), and the availability of high-efficiency alternatives. A consumption forecast at the level of individual end use equipment therefore allows for the construction of detailed efficiency scenarios, where efficiency improvement can be characterized as easily achievable or highly aggressive, based on the cost-effectiveness and availability of specific technologies[2].

2. Diffusion Modeling

The residential electricity subsector is particularly well-described by appliance diffusion modeling, since household electricity consumption is largely determined by the ownership of individual appliances. Furthermore, this method is particularly useful in charting the impact of economic growth on energy consumption in developing countries. In many developing countries, per-household electricity is low, especially since many households do not have access to electricity. Furthermore, many households that are connected to the grid utilize electric power only for lighting, or perhaps a television or audio player. In the model described here, we describe ownership of electric appliances in the residential sector according to an econometric diffusion model. The objective of the model is to allow bottom-up forecasting of electricity consumption by combining ownership forecasts with predictions of baseline energy consumption and efficiency trends for each appliance type[3].

Economic and demographic parameters by country are taken from other publicly available sources. These are: household size – UN Human Settlement Program (UN-HABITAT); population and urbanization – UNDESA.

The development of an econometric model of appliance diffusion serves two purposes. First, as the paper will demonstrate it, it allows for interpolation of diffusion rates for countries where data is unavailable. Second, using the model parameters determined in this paper combined with forecast of the the main drivers – wealth, urbanization and electrification, it provides a basis for electricity consumption projections from a bottom-up perspective. A basic premise of the approach is that as economies develop, households will choose to purchase and use electricity consuming products in order of desirability and affordability.

The poorest of electrified households will use electricity for lighting only, followed closely by a television. The diffusion rate for both of these end uses closely follows electrification rates, and many households of even moderate income may have more than one television. A refrigerator represents the first major consumption hurdle, because it is a major purchase for low-income households, and also a major electricity consumer. As incomes rise, washing machines become more common, but even though

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[2] Another study by the authors (McNeil, Letschert et al. 2006) has demonstrated the potential for combining diffusion-based energy forecasting with technology parameters to generate a detailed efficiency scenarios, in that case for refrigerators.

[3] The results of that combination will be detailed in a forthcoming report.

this appliance may be less expensive than a refrigerator, washing machine diffusion rates are consistently lower than refrigerator rates, because it is considered more of a luxury. These appliances cover most of the ‘major’ end uses that low and middle income households purchase and use. Electric dryers and dishwashers are common only in well-developed economies. Even then, their ownership is not universal, and their contribution to electricity consumption is relatively low (about 4.5% in Europe, weighted average). Electric space heating is uncommon in developing countries[4]. Four major end uses – refrigerators, washing machines televisions and lighting represent the bulk of electricity consumption. Less important, but significant are small appliances and electronic devices.

Finally, the evidence suggests that air conditioning could be quite an important end use in developing countries in the future. Although air conditioning is already an important end use in the services sector of many developing countries, it remains rare in households. This is changing, however, as incomes rise in hot and humid regions. Therefore, air conditioning is a highly dynamic end use that deserves detailed study, both in terms of economic growth, and climate considerations.

The first step in any econometric analysis is to gather all available data in order to determine the parameters of a theoretical model which then can be used for interpolation or forecasting. We gathered appliance ownership data from diverse sources. Principal sources were demographic and health surveys (DHS 2008). These surveys tend to focus on developing countries, and while they are not specifically energy-focused, they often include inventories of appliances as an indicator of living standards. Other sources are the World Bank (World Bank 2008), the IEA (particularly for industrialized countries) and national census surveys. Using this data, we modeled diffusion econometrically for four major products: refrigerators, washing machines, televisions, and air conditioners[5]. The task of modeling diffusion for these four products was to correlate diffusion rates in different countries with macroeconomic driver variables determined for the years in which the diffusion rate was measured. The importance of each variable was then determined using linear regression analysis. The driver variables chosen and the results of the regression analysis are detailed in the following sections.

1.1. Driver Variables

In order to provide an accurate estimate of appliance diffusion for a wide range of countries, ‘driver’ variables should be available for the entire world, at the country level if possible. Therefore, we limited consideration to the primary macroeconomic variables of income, electrification and urbanization, in addition to a climate variable which does not change in time to model air conditioning diffusion. Inevitably, these macroeconomic variables show a high degree of correlation. Nevertheless, our analysis shows that they each independently yield significant resolving power to describe the current distribution

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[4] The exception is China, where electric heat pumps are becoming common in more temperate regions.

[5] Since lighting electricity consumption depends not only on the number of fixtures, but also the type of fixture/lamp and usage patterns, and because data sources covering these parameters are more scarce, modeling of household lighting is quite distinct from appliance ownership and not covered here. A model of lighting use has been developed by the authors, however, and can be found in (McNeil, Letschert et al. 2008).

of appliance ownership in many countries, for the appliances studied.

2.1.1. Household Income

The most obvious determining variable for national average appliance ownership is average household income, which is approximated by Gross Domestic Product (GDP) per household. GDP data are provided in per capita terms, but major appliances are generally purchased at the household level. Therefore, we calculated household income by multiplying per capita GDP by household size. Household size is estimated by the United Nations (UN Habitat). In order to more accurately relate income to ability to purchase appliances, household GDP was corrected for Purchase Power Parity (PPP). The PPP factor adjusts currency market exchange rates (MER) by taking into account the difference in prices for a given basket of goods. We consider that the disposable income will be related to the cost of living, although we recognize that this factor may overcompensate in some cases, since white good prices may be more consistent across countries compared to other products, especially if they are imported.

2.1.2. Electrification and Urbanization Rates

Electrification rates are taken primarily from the IEA's World Energy Outlook 2002 (2000 data), and World Energy Outlook 2006 (2005 data). In addition, data for some countries not covered by WEO were taken from demographic health surveys[6]. Availability of electricity is an important dynamic in developing country regions. Countries in North America, Europe and the Former Soviet Union are assumed to be totally electrified. Urbanization rates were available from UNDESA.

2.1.3. Air Conditioner Climate Variable

Modeling of air conditioner diffusion is similar to that of the other products, but with the main difference that air conditioners are not only a relatively expensive product, but their utility is climate dependent. This means that in some very wealthy regions, such as northern Europe, air conditioner use remains low, even though air conditioners are generally affordable. On the other hand, in tropical developing countries, air conditioners might be considered among the most desirable appliances, but their high cost continues to categorize them as a luxury item.

The initial approach in developing an econometric model for air conditioning saturation was to follow the method used for other appliances, that is, to combine macroeconomic variables – income, urbanization and electrification – with a climate variable (Cooling Degree Days) into a single linear regression in order to determine the role of each. Modeling of air conditioner ownership using a single regression over CDD and income is complicated by the correlation in these two variables. This is because the warmest countries are among the poorest, and show very low air conditioner diffusion. Therefore, another approach was taken. Following the example of Henderson (Henderson 2005), we took individual regions in the United States as an example of universal

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[6] Demographic Health Surveys (DHS) have been collected for a wide variety of countries by Macro International. These are available at http://www.measuredhs.com

availability (affordability) of air conditioning. More precisely, we assumed that the diffusion rates in the United States represent the maximum diffusion for a given CDD value. Henderson shows data, including CDD and air conditioner diffusion (including both room units and central systems) for the nine U.S. Census Divisions, plus the four largest states (California, Texas, New York and Florida), as provided by the U.S. Energy Information Administration's Residential Energy Consumption Survey (RECS) for 2001 (USDOE 2001). The data show a clear trend, with the coolest regions (Pacific and California) having diffusion rates of about 40%[7], and the warm, humid regions nearly saturated. Henderson references a study which made a fit to U.S. data based on 39 individual cities (Sailor and Pavlova 2003). The relation is

$$Diff = ClimateMaximum(CDD) = 0.994 - 1.17 \times \exp(-0.00298 \times CDD)$$

In the Sailor study, cooling degree days were based on hourly data, as opposed to the RECS values, which use daily average temperatures to calculate CDD. Therefore, we refit the RECS data using the functional form from Sailor. Because diffusion approaches 100%, and in order to allow for linear transformation, we replaced the constant 0.944 with 1.00. Finally, we recalculated CDD using data from major cities in each region, and removed three regions which appear to show anomalous behavior. The modified RECS data are shown in Figure 1. The two curves produced by refitting the above functional form to the data are very similar, but the R^2 from the regression on corrected data is 0.93 for corrected data, vs. 0.53 from the uncorrected RECS data. We chose to use the former fit which gives a relationship of

$$ClimateMaximum = 1.0 - 0.949 \times \exp(-0.00187 \times CDD)$$

The diffusion model assumes that developing country air conditioner ownership will approach the climate maximum given by the above relationship, but never exceed it. Diffusion is expected to scale with this parameter, according to

$$Diff_c = Availability(I_c) \text{ x } ClimateMaximum\ (CDD_c),$$

ClimateMaximum is a function of national average CDD, and *Availability* represents the affordability of air conditioning to households, and is a function of household income I_c, where c is the country index[8].

2.1.4. Other Impacts on Diffusion

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[7] We take current (2001) U.S. diffusion rates as representative of the maximum desirable level, even though there is some evidence that air conditioner saturation rates may still be increasing due to factors independent of climate, such as decreasing equipment prices and short-term weather patterns (heat waves) that are not captured in average annual CDD.

[8] The determination of CDD for each country is worth mentioning. National CDD is necessarily an approximate measure of climate, due to the climatic variation within countries. National CDD were provided in (Baumert 2003) for 171 countries using daily average temperatures where available. Otherwise, monthly averages were used. In those cases where country CDD was not available, a regional average was used.

As mentioned above, the variables used represent a practical set of macroeconomic drivers for which energy consumption scenarios can be built. They do not represent all conceivable variables that may affect a household's choice of whether to purchase an appliance. For example, appliance size (capacity) is not differentiated in the diffusion model. The size of standard refrigerators, for example, has an influence on their price, and the desirability for owning more than one. The degree of domestic production may also be a factor. Several large developing countries (such as India, China, Mexico and Brazil) possess significant local appliance manufacturers, creating a stronger market awareness and greater affordability of products in these countries. Likewise, a large unorganized appliances sector, or existence of a large market for used imports may make appliances more affordable in some countries. Possibly the most significant determinant of future appliance diffusion rates not captured in the model is *appliance price*. It is widely acknowledged that prices of major appliances, in real terms, are not fixed over time. In fact, appliance prices generally increase more slowly than overall rates of inflation, due to economies of scale that reduce per unit costs and reduction of labor costs as an effect of globalization, etc.. In addition, however, evidence suggests a decrease in manufacturing costs through a process of *technological learning* in which manufacturers continually improve production processes in order to improve quality and reduce costs in a competitive environment (for a discussion of technological learning, see (Newell 2000)). The continual decrease in price of appliances means that they become more affordable to households. Therefore, diffusion rates for a certain income may be higher than indicated by a model determined with current prices. Ideally, modeling of diffusion rates would incorporate appliance trends across time and regions. Unfortunately, this type of data is lacking, especially for developing countries, where it is the most relevant. In order to assess the magnitude of likely effects of appliance prices, we tested the effect of adding a time variable in the model. Because prices are expected to vary monotonically (decreasing) with time, the year in which the saturation data point was taken serves as a proxy for price effect. We found that inclusion of this variable did not improve the fit, nor was the resulting time parameter statistically significant. From this we draw the conclusion that, while price effects are likely, they are not observable given the available data set, and recognize that further studies could improve the reliability of the forecasts if historical price data and projections could be identified.

1.2. Functional Form

The general form of the diffusion relationship follows an S-shaped function. There are various options for modeling this type of relationship. We chose the logistic model, which is appropriate for econometric modeling of a simple binary choice (market share) model (Train 2003). Defined in this way, the equation for refrigerators, washing machines, and televisions is given by:

$$Diff_c = \frac{\alpha}{1+\gamma \exp\left(\beta_{inc} I_c + \beta_{elec} E_c + \beta_{urb} U_c\right)} + \varepsilon \qquad \text{Eq. (1)}$$

In this equation: $Diff_c$ is the diffusion of the appliance for the country c, α is the saturation level, I_c is the household income given by GDP divided by the number of households in the country, U_c is the urbanization rate, E_c is the electrification rate, and ε is the error term.

By definition, the electrification and urbanization range between 0 and 1, while income is unbounded. The denominator in Equation 1 is greater than 1, and the model parameters β are less than or equal to 0. By definition, the logistic function has a maximum of one, at which point saturation is reached. In our model the logistic function is scaled by the parameter α, which is the saturation level. We chose α according to maximum observed diffusion levels of high-income countries. For refrigerators, α is taken to be 1.4, slightly above the current diffusion rate of Australia, which has the highest diffusion rate at 1.26. In the case of washing machines, α is assumed to be 1.0, as there is no added utility afforded to a household by owning more than one washing machine. For televisions, we used 3, just above the current rate in the United States, which is 2.49 (USDOE 2001). For air conditioners, α is defined as each country's *Climate Maximum*, as defined in Section 2.1.3[9]. Once α is defined, the remaining logistic function ranges from zero to one. The logistic diffusion function can be converted to a linear function, allowing linear regression analysis. Rearranging and taking the logarithm of both sides gives:

$$\ln\left(\frac{\alpha}{Diff_c}-1\right)=\ln\gamma+\beta_{inc}I_c+\beta_{elec}E_c+\beta_{urb}U_c+\varepsilon$$

1.3. End Use Regression Analysis

A significant part of the effort in developing the diffusion model was to gather as many diffusion data points as possible for each appliance. In some cases, there were multiple data points for some countries, because surveys were repeated periodically. In these cases, in order to avoid the use of highly correlated data points, we chose to use only the most recent available data from any country. The selection resulted in 64 data points for refrigerators, 27 for washing machines, 46 for televisions and 24 for air conditioners. The most recent data point was from 2007, while the oldest was from 1991. Most of the data were from within the last 10 years.

2.1.5. Refrigerators

Refrigerators were the first appliance studied using econometric diffusion modeling, because they are highly desirable but relatively expensive for low-income households in developing countries. In addition, they account for a significant amount of residential electricity consumption. Table 1 shows the results of the linear regression for refrigerators. With an R^2 of 0.92, refrigerator ownership is very well described by a logistic functional form with income, electrification rate and urbanization as independent variables. Each of these variables is statistically significant. Each parameter also has the

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[9] In practice, wealthy households in warm climates generally own more than one room air conditioner, but we define air conditioner diffusion as the ownership of at least one air conditioner.

expected sign, that is, ownership increases with increasing household income, electrification, or urbanization.

As Figure 2 shows, the countries for which data is available exhibit a wide range of refrigerator diffusion. Refrigerators are still rare in households in many countries, usually below 20% for countries with average PPP adjusted incomes below $10,000 per year. Beyond this income level, ownership rises rapidly. After this, diffusion increase levels off, with only households in the wealthiest countries owning more than one refrigerator. The cluster of data points with relatively low incomes, but high diffusion rates are largely from countries of the former Soviet Union and Eastern Europe, where electrification is universal, and incomes may not reflect purchase ability in the same way as countries in the developing world. Electrification and urbanization rates add additional explanation to diffusion rates. In particular, the close relationship with electrification suggests that most households with access to electricity will purchase a refrigerator if they can afford it.

2.1.6. Washing Machines

Like refrigerators, washing machines are also a highly desirable product, and one of the first appliances purchased by low-income households. Washing machines are generally less expensive than refrigerators, allowing for more rapid uptake as incomes rise. For these reasons, the relationship between income and diffusion for washing machines is similar to that of refrigerators. Electrification is also a statistically significant determinant of washing machine ownership. Urbanization, however, was not found to be a significant variable for this appliance; therefore, we eliminated this variable in the linear regression. The resulting fit has an R^2 of 0.66.

Figure 3 shows the relationship between washing machine diffusion and the two remaining variables. Because there were fewer data points for the washing machine regression than for refrigerators, especially at very low income levels, it is difficult to definitively compare the two appliances, but the income plot suggests that washing machine ownership has a higher income threshold for uptake, but then grows very rapidly, reaching near saturation and then leveling off rapidly at high incomes.

2.1.7. Televisions

Of the appliances studied, televisions are by far the least expensive, and most desirable. Also, it is common for even developing country households to own more than one television. Television ownership closely follows lighting as the second use of electricity in the household. We collected 46 data points for television diffusion for countries with a wide range of incomes. The data is well described by linear regression of the logistic function, which shows an R^2 of 0.85.The parameters describing income and electrification are highly significant, while urbanization is less so (see Table 1).

As expected, television diffusion follows electrification rates closely, indicating that nearly every electrified household has at least one television. At high incomes, diffusion exceeds 100%, and continues growing. Diffusion rates show some sign of saturation at very high incomes, but this leveling is slower than for the other appliances, since households see a marginal utility in owning additional TV sets.

2.1.8. Air Conditioners

As discussed in Section 2.1.3, air conditioner is modeled using separate components, *Availability* and *Climate Maximum*, according to

$$Diff_c = Availability(I_c) \times ClimateMaximum\ (CDD_c)$$

Availability is modeled as a function of household income only. The determination of availability follows the method for other appliances, via linear regression of the variable

$$Availability(I_c) = \frac{Diff_c}{ClimateMaximum(CDD_c)}$$

Availability is then modeled as in Equation. 1, with the coefficients β_{Elec} and β_{Urb} set to zero. A strong relationship can be seen between the derived availability variable and income. In the regression results, shown in Table 1, we can observe that income is a highly significant variable. The R^2 of the fit is 0.69.

Figure 5 shows graphically the relationship between income and air conditioner diffusion. The shape of the income curve is distinct from the other appliances due to the high price of this appliance. Below about $25,000, diffusion remains quite low, but then rises rapidly after this point.

2.4 Model Accuracy

In order to give an indication of the success of the model, we analyzed the difference in modeled diffusion and actual data for each country. Figure 6 presents the distribution of errors for modeling diffusion for each appliance studied. The difference between model and data is a roughly Gaussian distribution centered at zero. There are no significant outliers, and this distribution is roughly symmetrical around zero, indicating that, in terms of this parameter, the model produces generally accurate results with no bias towards either under- or overestimation of average diffusion levels (see Figure 6). The overall accuracy of the model may be estimated according to the root mean squared deviation of all data points,

$$Error = \frac{\sqrt{\sum_{i=1}^{N} [Diff_{Model} - Diff_{Data}]^2}}{N}$$

In this equation, *i* is the country index, and *N* is the number of data points. This calculation gives an error of 1.6% for refrigerators, 3.5% for washing machines, 2.5% for televisions and 3.9% for air conditioners.

3. Model Results

Ownership for major appliances is well-known for industrialized countries, but less so for developing countries. Therefore, we make use of the economic diffusion model to interpolate diffusion rates for countries for which data is not available. For each of the 160 countries, the economic and climate parameters are fed into the model in order to give an estimate of current diffusion. Figure 7 shows the modeled year 2005 diffusion rates for all 4 appliances, for selected countries.

Television ownership follows closely to electrification in the developing country regions, and significantly exceeds one television per household for countries with high electrification rates. Refrigerator diffusion rates are relatively high compared to electrification generally exceeding washing machine ownership rates do to the high desirability of this product. Air conditioning remains a luxury item, showing low ownership rates, except in the United States and Mexico.

4. Conclusions

This report demonstrates an effort to characterize the uptake of major residential appliances, covering a significant percentage of the household electricity use, in every region in the world. The development of the LBNL model is a significant step towards the larger goal of forecasting global energy consumption. There already exists a variety of energy forecasting models; the current method brings a highly disaggregated basis for bottom-up energy forecasting, and efficiency scenario building.

The approach of the model is to provide a high level of detail in terms of individual equipment types, while maintaining enough generality to be applied to many countries and regions. We recognize that the perceived utility and affordability of appliances is not uniform, and that a detailed study focusing on one country or end use may call for a less generic approach. As our statistical analysis shows, however, a model based on only a few generalized parameters is adequate to describe general trends. Perhaps most significantly, the model relies primarily on fundamental macroeconomic and demographic drivers and therefore directly addresses the question of energy consumption growth that will accompany economic growth, particularly in developing countries.

Predicting the size of the stock of individual appliances will allow for an accurate estimate of total energy consumption; in addition, it will provide insight into how much can be done to help minimize energy consumption, and where policy efforts may be most effective. High-efficiency technologies for particular appliances are well-known. Also well-understood are the levels of efficiency which can be achieved with moderate effort, and which require a more aggressive policy. These parameters form the basis of efficiency scenarios which can be combined with the diffusion model to describe alternative energy consumption paths for a particular country, region, or the entire world.

Much of the growth in electricity consumption in the developing world will come from the uptake of refrigerators and washing machines, since markets for these products are not yet saturated, but likely to grow rapidly with economic growth in the next two or three decades. The greatest potential for reduction of consumption might therefore prove to be to maximize the efficiency of these large products now, just ahead of this growth.

Finally, our methodology suggests that air conditioning will become an even more critical end use in the coming decades. Much of the world's population lives in warm climates, but in households that cannot afford an air conditioner. Our model suggests that, in these areas, air conditioning use will rise more rapidly than economic growth, contributing significantly to greenhouse gas emissions, and straining peak electricity supply capacity.

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Tables

Table 1 – Linear Regression Results for Appliances

Refrigerator			ln γ	β_{Inc}	β_{Elec}	β_{Urb}
α	1.4	*Coefficient*	4.84	-1.3E-05	-3.59	-2.24
Observations	64	*Standard Error*	0.197	4.82E-06	0.27	0.59
R^2	0.92	*t-Stat*	24.508	-2.77	-13.42	-3.78
Washing Machine			ln γ	β_{Inc}	β_{Elec}	β_{Urb}
α	1	*Coefficient*	8.91	-3.5E-05	-8.98	
Observations	27	*Standard Error*	1.56	1.43E-05	2.06	
R^2	0.66	*t-Stat*	5.70	-2.44	-4.36	
Television			ln γ	β_{Inc}	β_{Elec}	β_{Urb}
α	3	*Coefficient*	3.701	-2.5E-05	-2.39	
Observations	46	*Standard Error*	0.134	4.96E-06	0.31	
R^2	0.85	*t-Stat*	27.584	-5.07	-7.66	
Air Conditioner			ln γ	β_{Inc}	β_{Elec}	β_{Urb}
α	*ClimateMax*	*Coefficient*	4.843	-6.9E-05		
Observations	24	*Standard Error*	0.503	9.82E-06		
R^2	0.69	*t-Stat*	9.635	-7.04		

Figures

Figure 1 – Air Conditioner Saturation vs. CDD for U.S. Regions

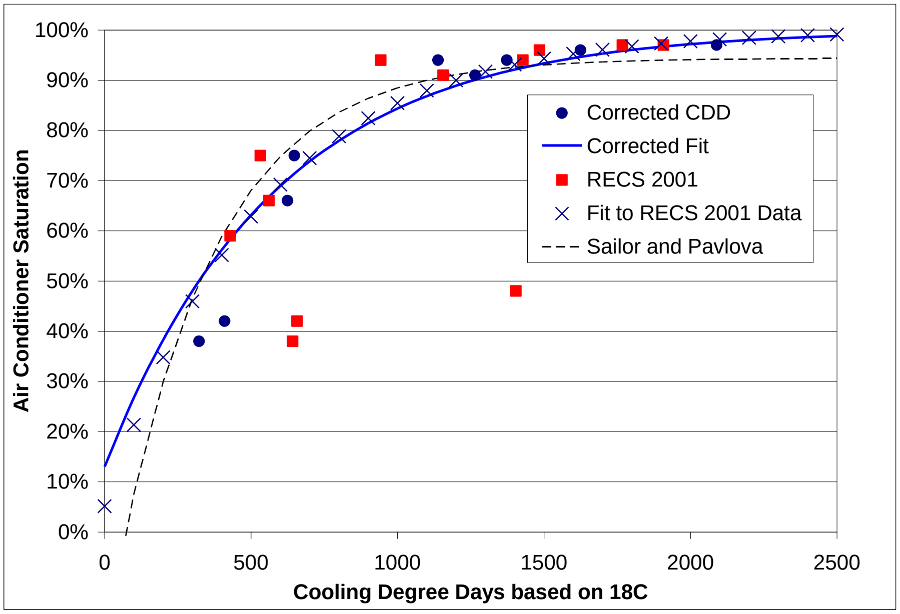

Figure 2 – Linear Regression Results by Variable for Refrigerators

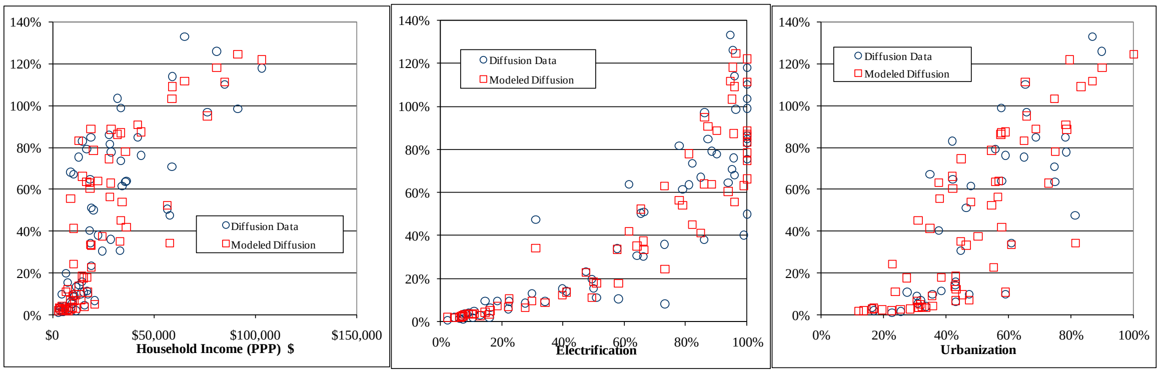

Figure 3 – Linear Regression Results by Variable for Washing Machines

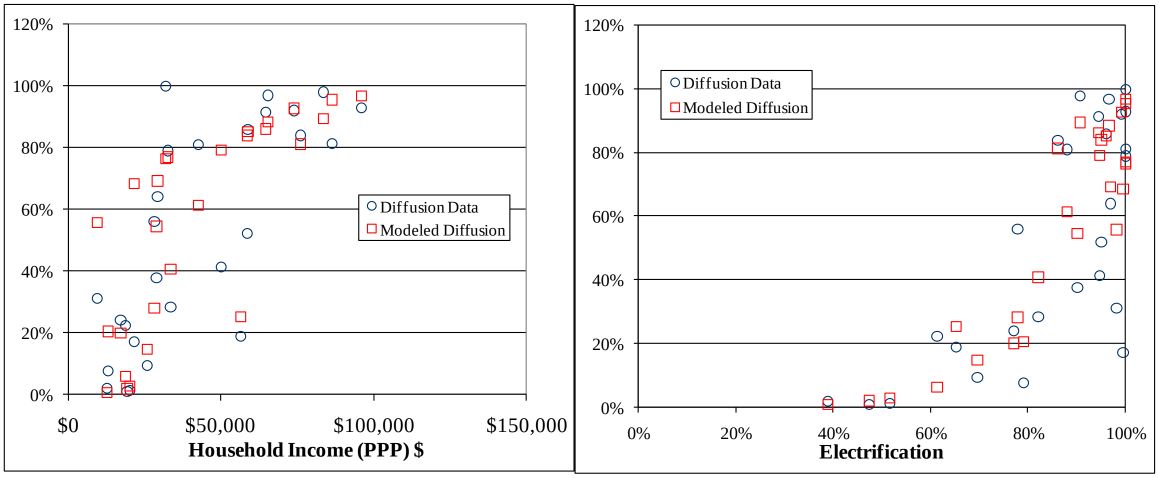

Figure 4 – Linear Regression Results by Variable for Televisions

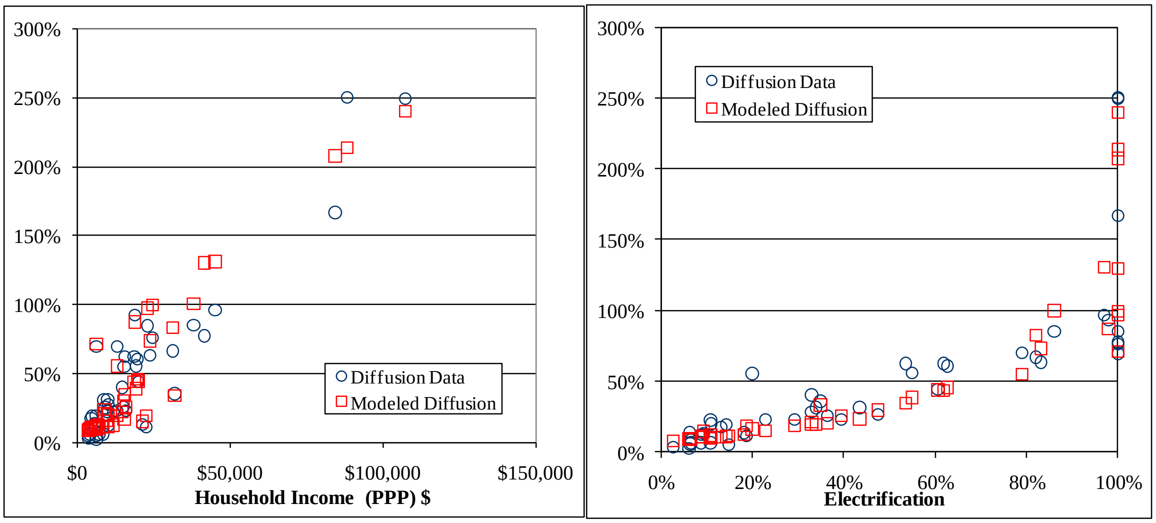

Figure 5 – Air Conditioner Availability vs. Income

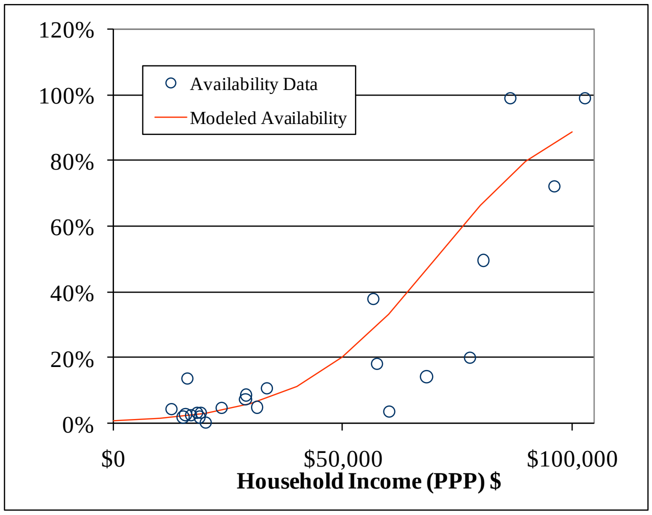

Figure 6 – Difference in Diffusion levels between Model and Data

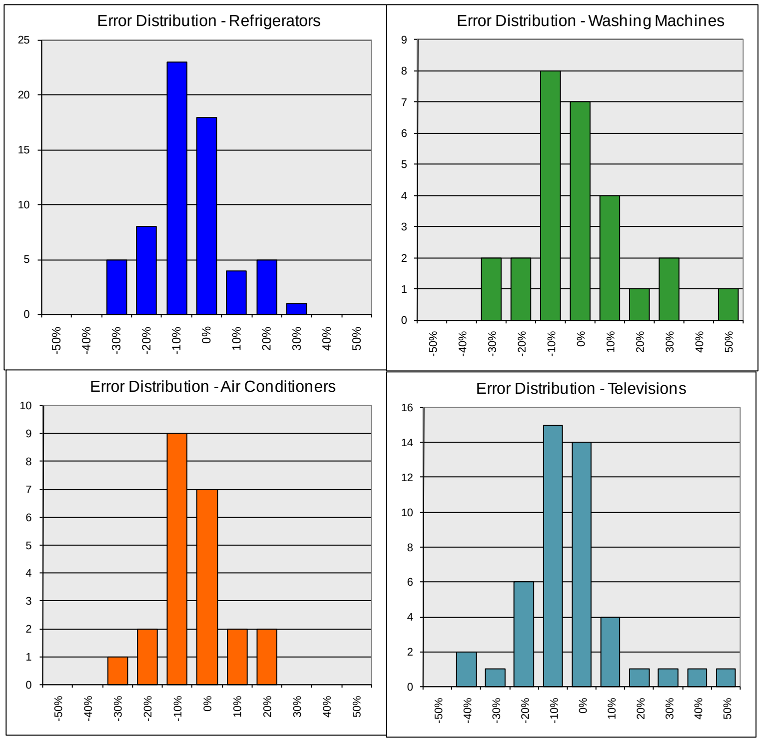

Figure 7 – Diffusion level for major end uses in 2005 – Selected Countries