Fuel and Technology Choice in Residential End-Use Forecasting: Evaluation and Comparison of Three Models with Respect to Space Heating

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In this paper, we discuss and compare three end-use forecasting models for space heating under similar assumptions for fuel prices, technology characterizations, and energy services demanded. The three models are the Residential Energy Model of Lawrence Berkeley Laboratory, the Residential Energy End-Use Model of the Energy Information Administration and the Residential Energy End-Use Planning System developed for the Electric Power Research Institute. We consider differences in the three modeling frameworks with special reference to technology choices for space heating equipment. We examine the characterization of market shares for space heating equipment, the effects of changing fuel prices on electricity consumption, and the impact of changing the consumer discount rate.

We first caution the reader that differences in the approaches and structures of the models make the results difficult to compare on a strictly numerical basis. However, we can draw some qualitative conclusions from these analyses. Fuel consumption for space heating in the Energy Information Administration model is the most sensitive of the three models to changes in the discount rate. Heat pump market shares and natural gas consumption are both less sensitive to price changes in the Electric Power Research Institute model than in the other two models. The Lawrence Berkeley Laboratory model behaves similarly to the Electric Power Research Institute model for natural gas consumption but not for heat pumps. The characterization of market shares for space heating and the modeling approaches to market penetration of electric heat pumps appear to be two of the main drivers behind these differences. Finally, differences in the characterization of technology choices and in the base-year calibration of the models are an important determinant of the underlying trends in energy consumption.

Introduction

Engineering-economic models of residential energy demand attempt to characterize the long-term structure and patterns of energy consumption in homes. They rely on data regarding the building stock, the technologies available in meeting energy services and historical patterns of energy consumption in homes. Engineering data on the building thermal shell and on energy-using equipment is combined with economic parameters regarding purchase and usage of the equipment. At the national level, these end-use forecasting models facilitate the analysis of energy conservation programs and policy initiatives that are widely applicable and broad in their scope. They have been used to support development of residential building codes and for the analysis of federal appliance standards [U.S. DOE 1989]. Utilities also rely on end-use forecasting models to evaluate the potential for demand-side management programs and to meet regulatory requirements. In this study, we are concerned only with end-use forecasting at the national level.

The upper part of Figure 1 depicts the higher level assumptions and structure common to many residential end-use forecasting models. The household is considered the fundamental unit for energy consumption in these models. The physical housing stock is defined by its thermal properties and energy-using equipment is described by variables such as size and efficiency. Exogenous variables that change over time include a projection of the housing stock, household size, fuel prices and household income. Technology data characterizes the existing and/or future stock of equipment and allows the formulation of functional relationships to use in the forecast. Consumer data describes ownership patterns for equipment and appliances, generally segmented by housing type. Consumer attitudes towards purchases are typically characterized via the discount rate used by consumers in evaluating alternative investments in new or replacement equipment. Market shares are estimated for each technology or fuel in a given end-use or energy service and the models adjust these market shares over time as households purchase equipment.

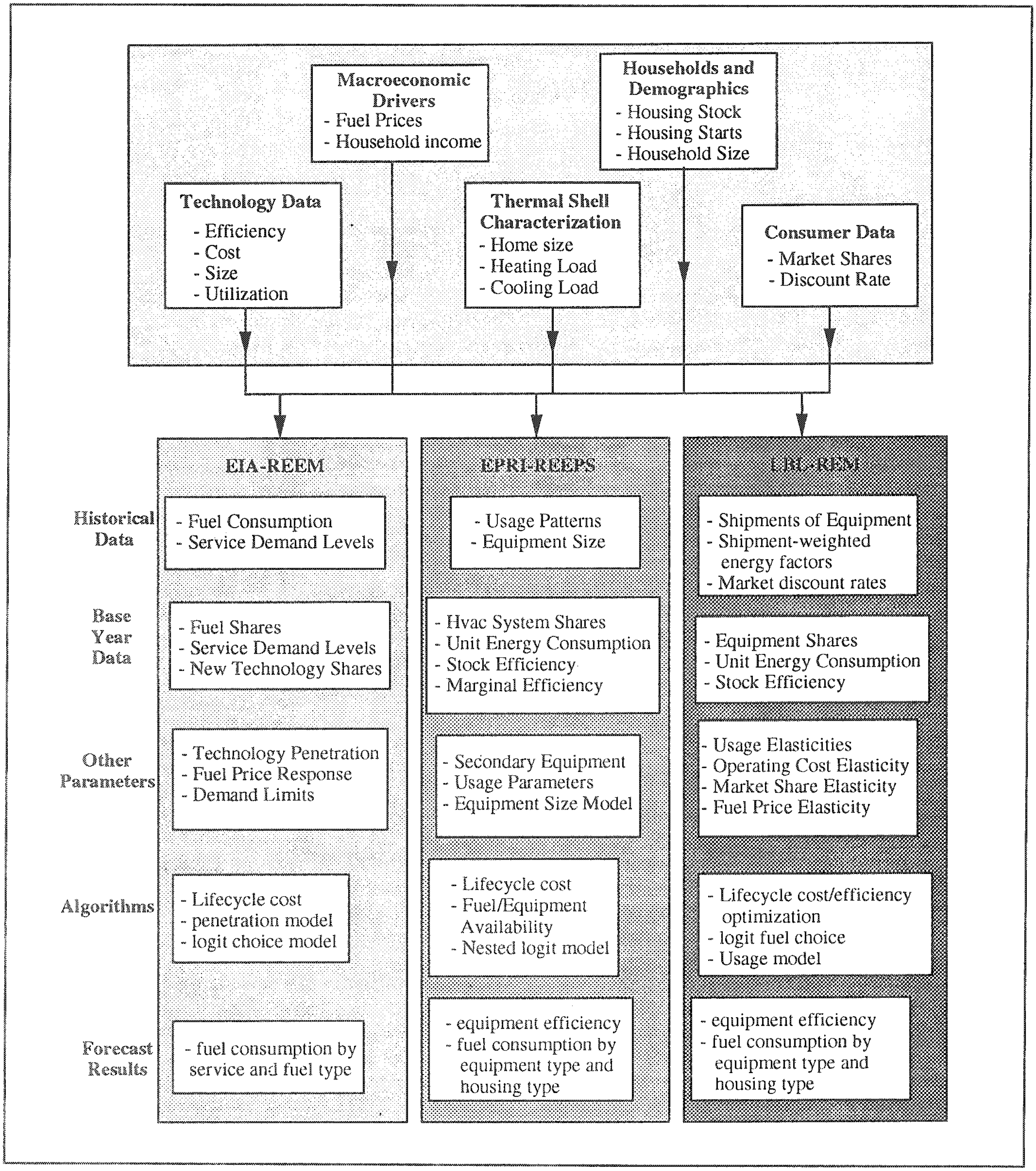

Figure 1. Residential End-use Forecasting Model Structure

The lower level of the diagram shows the three residential end-use forecasting models included in this analysis and shows the differences and similarities across various components. Historical data refers to the means by which the model is calibrated or benchmarked to insure its consistency with historical patterns of energy consumption. Base year data defines a starting point for the model and generally sets the baseline for the stock of equipment and its characteristic features. Model parameters are estimated empirically and/or derived theoretically in order to account for various impacts on final energy consumption. Engineering/cost parameters define relationships among attributes such as equipment efficiency, equipment size and various cost components such as purchase cost or maintenance costs. Economic parameters generally include elasticities or other behavioral parameters which reflect the sensitivity of consumers to changes in key drivers such as fuel prices or household income.

The Energy Information Administration's Residential Energy End-use Model (EIA-REEM) provides an annual forecast of energy demand in residences and also feeds into a multi-sectoral model, which integrates supply and demand models from different sectors to produce a national forecast to the year 2010. The concepts of service demand, service capacity and technology penetration drive the EIA-REEM. Service demand for each end-use drives decisions about replacement and new purchases of equipment up to a specified limit. Unlike the other two models, there is no explicit characterization of the existing stock of equipment, nor is the stock of equipment associated with particular housing characteristics. Instead, estimates of the cost, efficiency, market shares and penetration rates of representative technologies determine equipment purchases based on sensitivity to fuel prices and to the cost of purchasing and operating the equipment. The energy consumed by the new equipment in a given year serves to increment the previous year's fuel totals in order to obtain the new totals. The model includes some regional differentiation of variables such as fuel prices, but for this analysis we assume these variables are the same across all regions [EIA PC-AEO 1990].

The Electric Power Research Institute's Residential Energy End-Use Planning System (EPRI-REEPS) provides the capability to track important characteristics of the equipment stock such as efficiency and size. The EPRI-REEPS model has been used since the early 1980s, first as a tool for national policy analysis and then as an analytical tool for electric utilities to forecast long-term residential energy demand. The newest version of the model, REEPS 2.0, provides a flexible, user-friendly modeling framework in which the user has considerable control over the structure and algorithms to be employed.

For the purposes of this analysis, we have chosen a structure for the REEPS model comparable to the EIA-REEM and LBL-REM. The basic driving variables are analogous to those for LBL-REM, although there are differences in the structure of the market share algorithms, as we will discuss in the next section. We employ here portions of the default structure for REEPS 2.0 as provided by Regional Economic Research (McMenamin et al. 1991).

The Residential Energy Model of Lawrence Berkeley Laboratory (LBL-REM) is actually a modified version of one of the earliest residential end-use forecasting models developed at Oak Ridge National Laboratory (Hirst and Carney 1978). The LBL-REM segments energy consumption by housing type, end-use and fuels, and tracks detailed characteristics of the equipment stock over time. It distinguishes between replacement of equipment in existing houses and purchases of equipment for new houses. The turnover in the housing stock drives changes in energy consumption through replacements of existing equipment and purchases of new equipment based on life-cycle cost. The efficiency of new equipment purchases is determined through an optimization algorithm based on functions which define the relationship between capital cost and average energy consumption. The LBL-REM incorporates an extensive set of elasticities to depict market responses to changes in important economic variables, including own-price and cross-price fuel elasticities, income elasticities, operating cost elasticities, usage elasticities and market share elasticities [McMahon 1987].

The number and configuration of end-uses differ slightly across the three models. The EPRI-REEPS model treats all space conditioning along with thermal shell data in an integrated module and then configures appliance models for each other end-use as desired by the user. The LBL-REM treats central heating, room heating and air conditioning as separate end-uses along with other end-uses such as water heating and cooking, and then sets interaction variables among the end-uses where appropriate. In the versions of the models used here, there were nine end-uses beyond space conditioning in both the LBL-REM and the EPRI-REEPS. The EIA-REEM relies on five end-use categories: heating, cooling, water heating, refrigeration and other.

Given time constraints and the limitations imposed by differences in the end-uses, we focus on space heating in this analysis. Space heating accounts for roughly half of all residential energy use in the U.S. when primary resource energy is considered [RECS 1989]. Furthermore, space heating provides the most interesting point of comparison because each model relies on similar technology configurations, such as heat pumps or gas central heating, but uses a different market share structure to estimate the future trends in new equipment purchases. Choices for air conditioning are potentially important drivers in space heating choices, especially as related to heat pumps. We thus mention air conditioning in the paper as it relates to the modeling algorithms for market shares and technology choices, but we present only the results for space heating.

Assumptions and Methodology

At the aggregate level, the three models are quite similar. Each divides the housing stock similarly and uses the changes in the stock to model the demand for energy services. New homes are tracked separately from old homes in allocating technologies and service levels for energy end-uses. The models all utilize basic information on each type of equipment such as efficiency, size, utilization, average lifetimes and base cost. They also use market share information to define existing patterns of ownership for equipment and appliances. The demand for space conditioning is defined by expected heating and cooling loads for each house type. Finally, and perhaps most significantly for this analysis, each model bases purchase decisions on the life-cycle cost of equipment. The life-cycle cost of equipment is defined as the sum of purchase cost, installation cost and the discounted sum of annual maintenance, operation and fuel costs over the expected lifetime of the equipment.

The structure and methodology for determining future market shares for fuel/technology choices do differ across the three models. The EIA-REEM calculates market shares based on a logit share algorithm for the available technologies, which distinguishes between the heat pump market and other systems so as to account for the dual use of heat pumps for heating and cooling in considering life-cycle cost. The EPRI-REEPS integrates heating and cooling end-uses into a single HVAC module which forecasts market shares using a nested logit model of discrete systems. The LBL-REM model relies on long-term market share elasticities for heating and cooling with respect to key variables such as purchase cost, operating cost and income levels. The LBL-REM algorithm includes a simulation and sample enumeration approach [Wood et al. 1989] for new single-family homes while the multi-family and mobile home calculation uses a more simplified logit model. Another difference particular to the EIA-REEM model is that the consumer is assumed to be "myopic" in the sense that the time horizon for the present value calculation is five years [EIA PC-AEO 1990], so that savings beyond five years are not considered.

Another source of difference in the models is the manner in which they are "calibrated," that is, referenced and/or adjusted to certain criteria in the base year of the analysis. We can distinguish between two broad methods of calibration in end-use forecasting. An "external" calibration adjusts the total energy consumption in the base year to an independently derived aggregate exogenous estimate. The EIA-REEM exhibits such a method of calibration, since it benchmarks the overall fuel consumption totals to the fuel consumption in the State Energy Data Report. [SEDS 1991] An "internal" calibration, such as that used in EPRI-REEPS, relies only on the model inputs themselves and derives calibration constants that make the set of inputs and equations true in the base year. The EPRI-REEPS calibration draws on the four components of total energy consumption for a particular technology: UECs, size, efficiency and usage. The LBL-REM uses elements of both of these two methods in the calibration. The LBL-REM does rely on exogenous historical information, namely the shipments of equipment and appliances, but such data is of course disaggregated for each fuel and end-use and is also used elsewhere in the model. The important general point here is that the term "calibration" in end-use forecasting means something different from one model to another and depends essentially on the structure of the model and on the context in which the model is applied.

We use the same macroeconomic or exogenous inputs to the models, including forecasts of changes in the housing stock, fuel prices and household income. The housing forecast, reference case fuel prices and relative income are shown in Figures 2a-2c, and are taken from the National Energy Strategy [NES 1992]. The year 1987 serves as the base-year for the energy demand forecast in all three models, coinciding with the latest published Residential Energy Consumption Survey (RECS) [EIA-RECS 1989]. We used the RECS in deriving base-year market shares for space heating equipment for existing and new homes for each of the three housing types: single-family, multi-family and mobile homes. We do not consider improvements in the thermal shell in this analysis, due to our focus on space conditioning equipment as well as the fact that the models differ in their representation of thermal shell improvements. The analysis is carried out to 2010 to allow for a reasonable portion of the equipment stock to be replaced during the forecast.

We derive the technology characteristics for space heating equipment from technology parameters in the Energy Information Administration model [EIA PC-AEO 1990] and from the LBL-REM. These technology assumptions were used in all three models, including engineering estimates of average efficiencies and sizes of equipment along with economic data on average purchase costs and

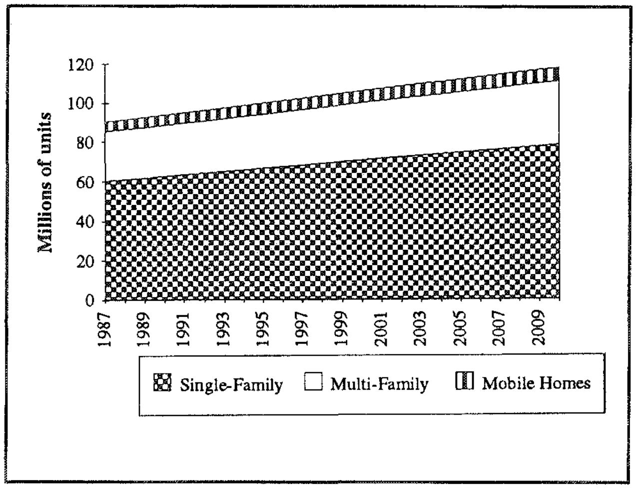

Figure 2a. Housing Stock

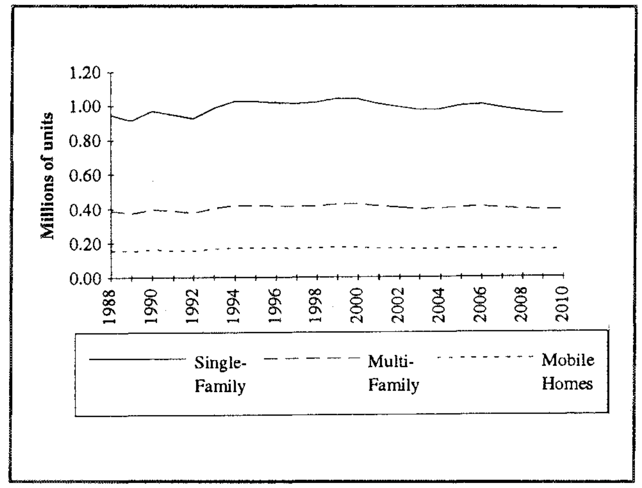

Figure 2b. Housing Starts

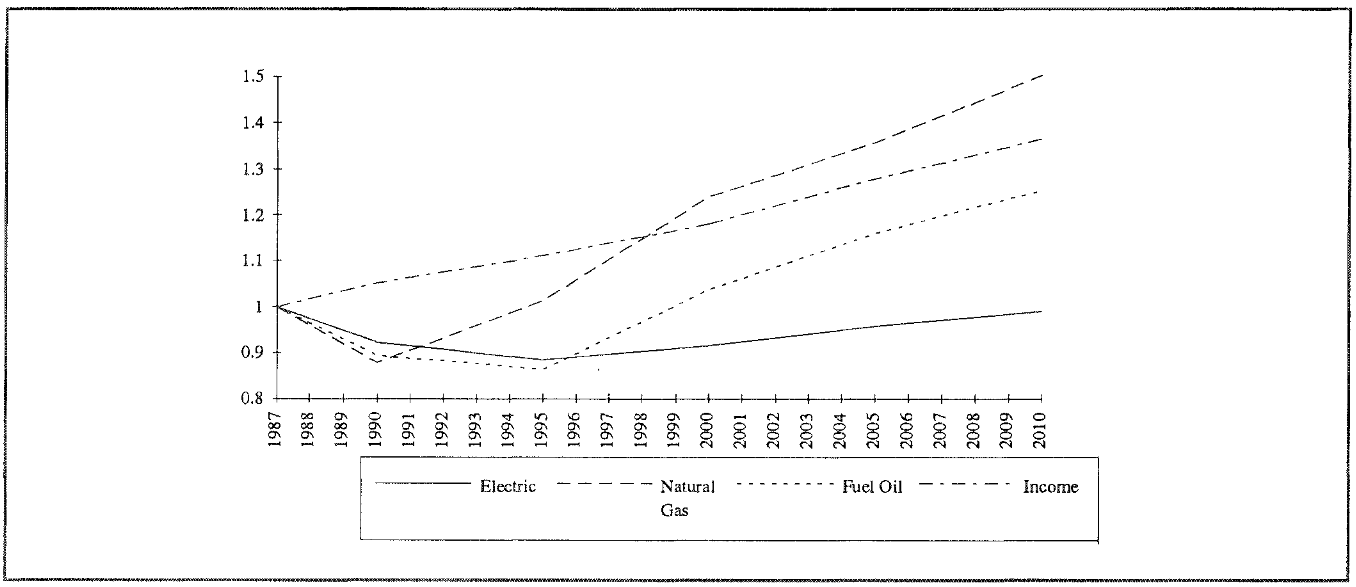

Figure 2c. Prices and Income (1987 = 1.0)

installation costs. The base year Unit Energy Consumption (UECs) values were equivalent for LBL-REM and REEPS. The EIA-REEM does not use UECs, but instead uses the concept of service demand for end-uses based on 1987 levels [EIA-RECS 1987], and uses estimated trends to increment these levels for future years, mainly driven by expected increased demand for cooling. We have not included the effects of appliance/equipment standards on the results since the EIA-REEM model does not offer the capability to model such effects.

It is important to note that many of the differences in structure to which we have alluded above represent both a source of difficulty in the comparison and a point of departure for an understanding of the differences in the results. One of the challenges in comparing the models was thus to find a "lowest common denominator" for which a meaningful comparison could be accomplished without sacrificing the validity of the results. In this light, we chose to focus our analysis on the results for a few important parameters and response variables. The key parameters of interest are those that are important drivers for all three models and indeed, for any residential end-use forecasting model: fuel prices and the consumer discount rate. We choose two types of response variables in assessing changes over time: consumption of electricity and gas for space heating and changes in the market share for heat pumps. These response variables offer useful metrics for two of the main issues in technology choices in residential space heating: the issue of fuel choice between electricity and natural gas, and the issue of market penetration of heat pumps.

Results

The baseline case uses a 20% consumer discount rate and the macroeconomic and fuel price assumptions used in the National Energy Strategy [NES 1992]. The results for the baseline case are shown in Figures 3a-3e. Note that all results for electricity are based on primary energy consumption, using a conversion factor of 11500 Btu fuel per kWh delivered electricity [McMahon 1987]. As Figure 3a shows, the total energy consumption numbers do not match up for the base year. This is primarily due to the fact that each of the models is calibrated or bench-marked differently, as discussed previously. For this reason, it is more useful to consider the changes in each model relative to the respective values for the base year. We use 1990 rather than 1987 for this normalization to make the results easier to interpret and to avoid some of the lagged effects of the differing calibration procedures.

We should add here two caveats in interpreting the results. First, there will be some cases where a lower level of detail may seem desirable in the results. Unfortunately, due to both the nature of the models and their computing environment, such outputs are sometimes not available. For example, if one would like to separate results for new homes from results for existing homes, this can only be done in the case of LBL-REM. Second, the choice of a single discount rate for the purpose of comparing the three models is a departure from the normal use of the LBL-REM model, which customarily relies on distinct discount rates for each fuel/technology choices to reflect the historical purchase patterns for such equipment and calibrate the model accordingly [Ruderman et al 1987].

Figures 3b to 3d show the changes over time for total primary energy, electricity and natural gas in space heating. Primary energy consumption is forecasted to level off by 2010 in EPRI-REEPS, while it increases for LBL-REM and EIA-REEM. Natural Gas consumption is almost level for EIA, but decreases for LBL-REM and REEPS, which seems to make sense given that natural gas prices are increasing while electricity prices are flat over the period. The primary reason why REEPS forecasts yield lower electricity consumption is the predicted market penetration of heat pumps, as shown in Figure 3e. The LBL-REM results converge towards EPRI-REEPS results for natural gas, but towards EIA-REEM results for electricity consumption and heat pump market shares. The EIA-REEM is driven more by fuel shares than by specific technology choices due to the market share algorithm. LBL-REM exhibits this behavior also because its market share algorithm first chooses a fuel and then chooses a technology, so that heat pumps are a share of electric heating. Both models differ in this way from EPRI-REEPS, which treats each feasible combination of heating and cooling as a discrete choice, independent of fuel choice.

Figures 4a to 4e show the results for a case which again uses a discount rate of 20%, but this time uses constant fuel prices. It is interesting to note that the model results generally converge over time except for heat pump market shares, which actually differ little from the previous case. In the case of natural gas, the EPRI-REEPS and LBL-REM track each other nearly identically, while the EIA-REEM results diverge. This suggests that fuel prices are important drivers for fuel shares in all three models, but do not have the same effect on penetration of heat pumps. The base-year calibration and market share algorithms contribute greatly to this difference among the models. The results for heat pump shares demonstrate more clearly the strong impact of discretizing the technology choices in the REEPS model. Heat pump shares continue to increase in EPRI-REEPS while LBL-REM forecasts greater growth in the market for electric resistance heating.

The effect of changing the consumer discount rate is examined in Figures 5a-5c for electricity consumption, natural gas consumption and heat pump shares in 2010. These results are relative to the reference case results for 2010 for which the discount rate was 20% and the NES fuel prices were used. The EIA-REEM forecasts increased heat pump penetration with lower discount rates while LBL-REM forecasts the opposite effect, lower heat pump penetration with lower discount rates. The EIA-REEM uses a set of discrete heat pump technologies in with different efficiencies, while LBL-REM relies on a cost-efficiency curve for heat pumps. Thus, consumers choose the more efficient heat pump in EIA-REEM at lower discount rates, whereas in LBL-REM, all options are positively affected by the lower discount rate. Thus, in LBL-REM, consumers invest in more efficient gas furnaces instead, as the results for natural gas demonstrate. The EPRI-REEPS results are essentially unaffected by changes in the discount rate, which is a direct result of the

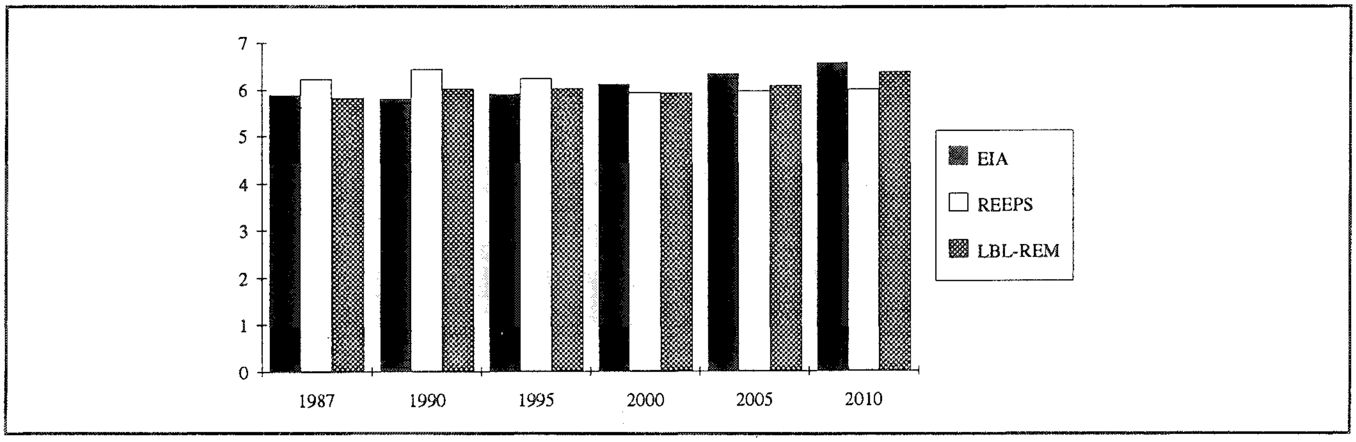

Figure 3a. Total Primary Energy for Residential Space Heating (QBtu)

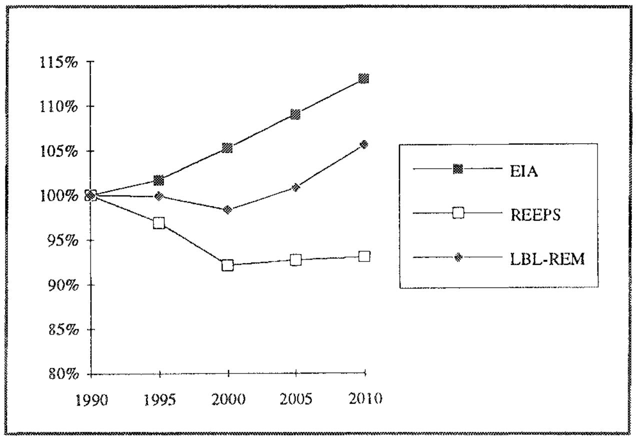

Figure 3b. Primary Residential Energy Consumption for Space Heating (relative to 1990)

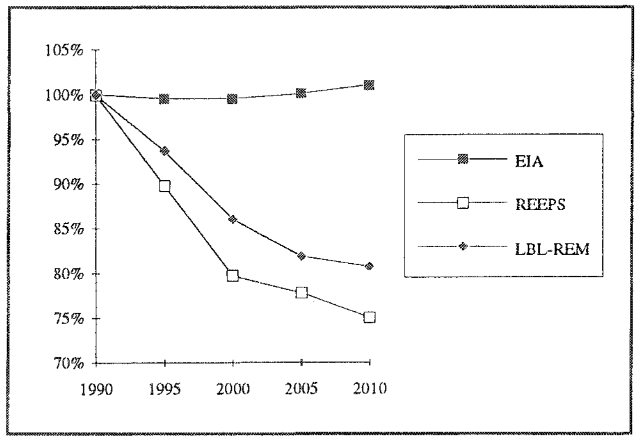

Figure 3c. Residential Natural Gas Consumption for Space Heating (relative to 1990)

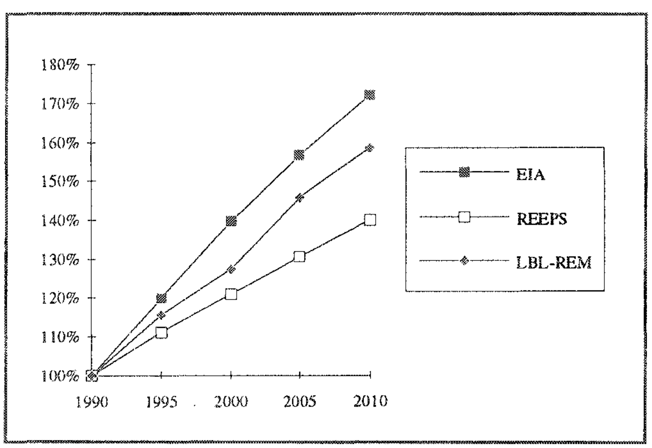

Figure 3d. Residential Electricity Consumption for Space Heating (relative to 1990)

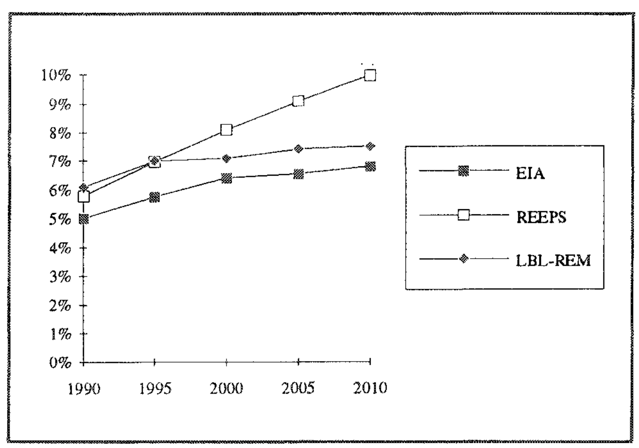

Figure 3e. Electric Heat Pump System Shares for Residential Space Heating (Percentage of all households)

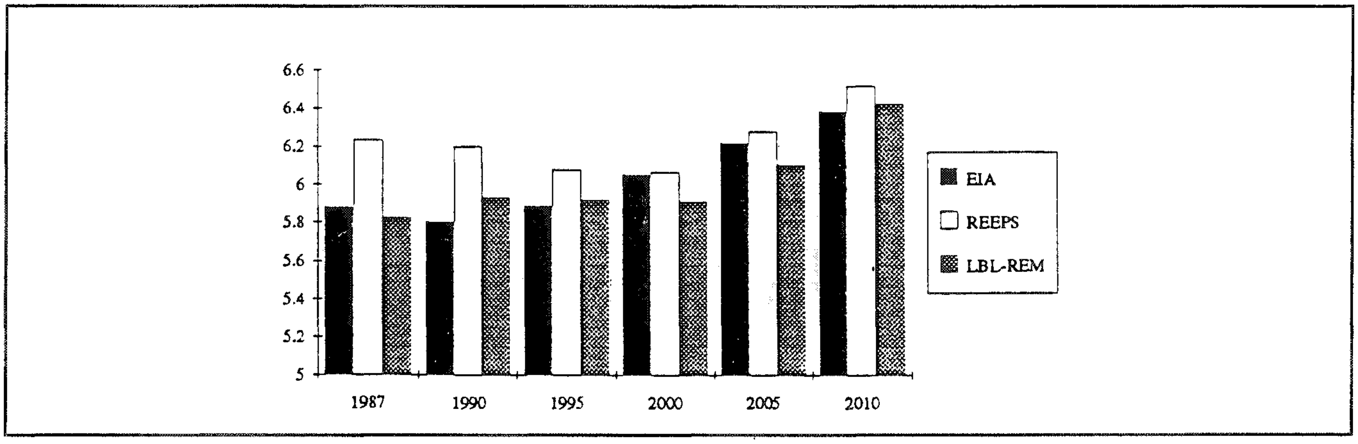

Figure 4a. Total Primary Energy for Residential Space Heating (QBtu) for Constant Energy Prices

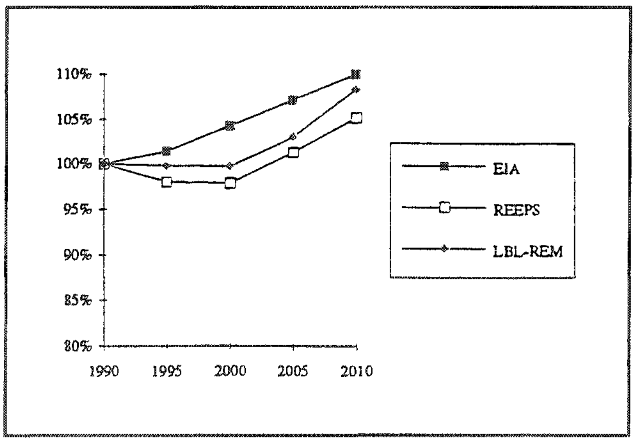

Figure 4b. Primary Residential Energy Consumption for Space Heating (relative to 1990)

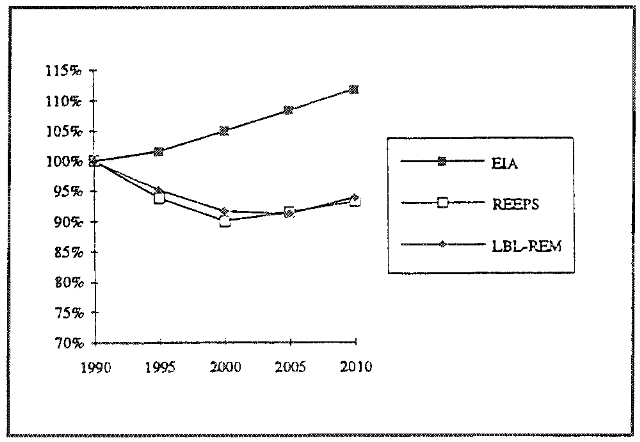

Figure 4c. Residential Natural Gas Consumption for Space Heating (relative to 1990 level)

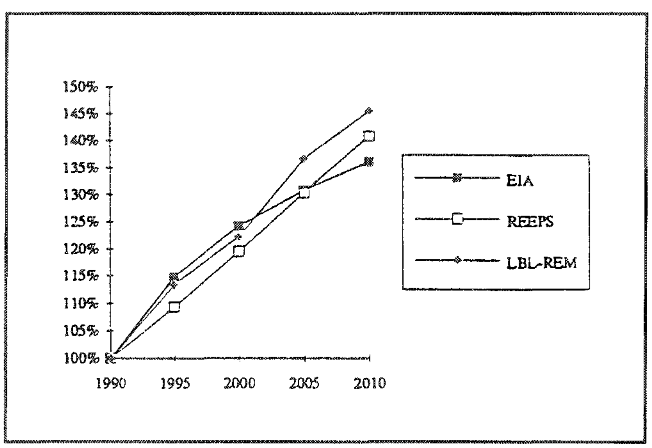

Figure 4d. Residential Electricity Consumption for Space Heating (relative to 1990)

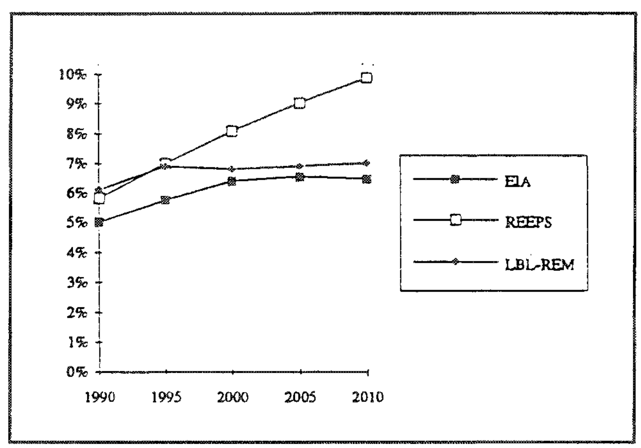

Figure 4e. Electric Heat Pump System Shares for Residential Space Heating (Percentage)

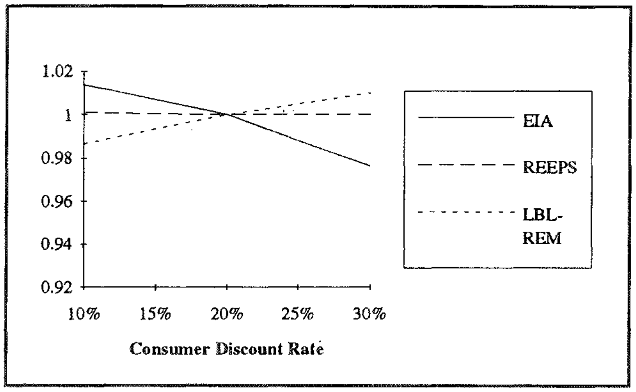

Figure 5a. Electric Heat Pump Market Share Relative to Reference Case

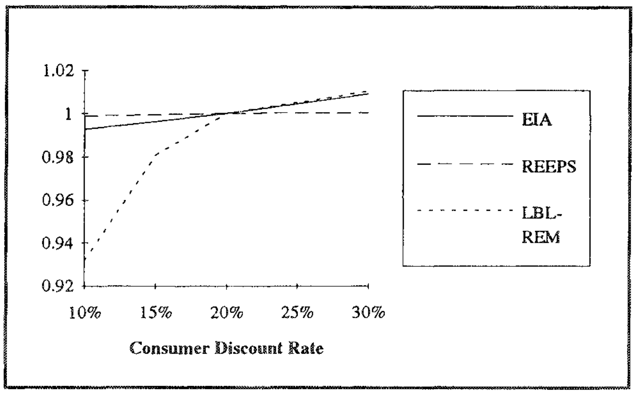

Figure 5b. Natural Gas Consumption in 2010 Relative to Reference Case

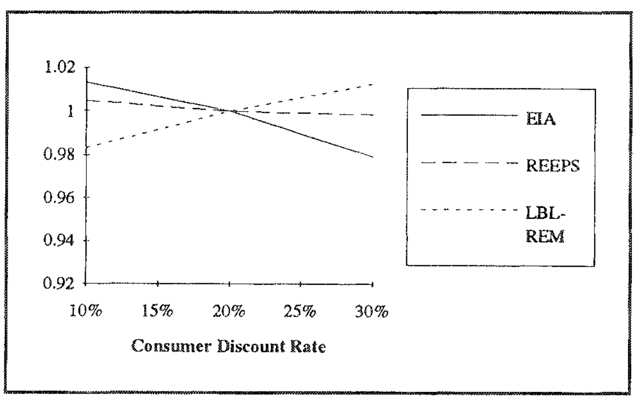

Figure 5c. Electricity Consumption in Electricity Consumption in 2010 Relative Case

system characterization used in REEPS in which discrete systems are chosen rather than fuel and technology combinations.

The effect of increasing electricity prices was also considered for electricity consumption, natural gas consumption and heat pump market shares, as shown in Figures 6a-6c. For natural gas consumption, the EIA model is most sensitive, suggesting the predominance of fuel share effects as opposed to particular technologies. LBL-REM is not as sensitive as the EIA model, but is more sensitive than REEPS. One reason for this is the fact that REEPS has no mechanisms in this framework to employ cross-price elasticities for fuels. Both the EIA-REEM and LBL-REM incorporate cross-price effects in the algorithms for market shares, as discussed previously. LBL-REM is most sensitive to electricity price for heat pump shares. REEPS actually increases the market share for heat pumps slightly with increasing electricity prices due to the effect of switching from other electric technologies to heat pumps.

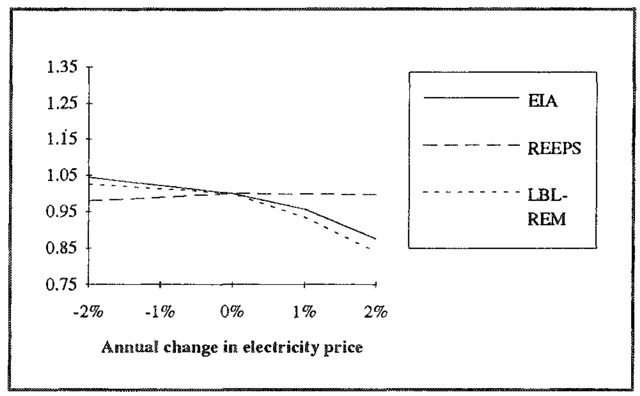

Figure 6a. Electric Heat Pump Market Share Relative to 2010 Relative to Constant Energy Price Case

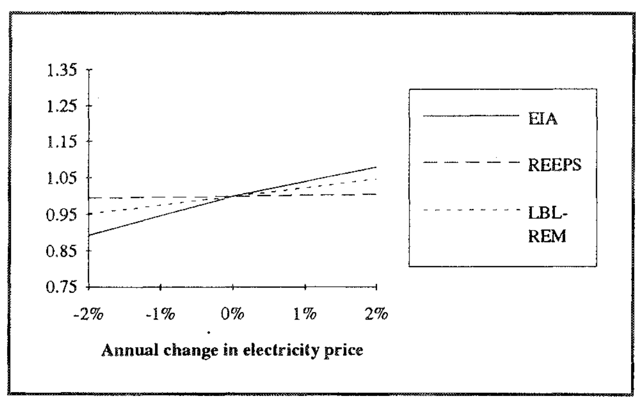

Figure 6b. Natural Gas Consumption Relative to Constant Energy Price Case

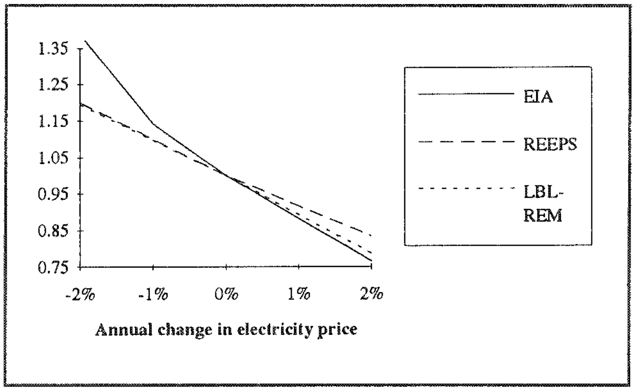

Figure 6c. Electricity Consumption Relative to Constant Energy Price Case

Conclusions

The three residential end-use forecasting models in this analysis share many common driving variables and parameters such as fuel prices, life-cycle cost and the discount rate. The characterization of technologies for space heating are also quite similar across the three models. We employed a common set of exogenous variables as well as a common set of technology and cost data in our analysis with each model. Yet there were some differences in the models for which the data could not be used in the same manner due to differences in structure and in the nature of the algorithms employed. The determination of market shares for these technologies, their respective calibration procedures and their use of different metrics for energy consumption by technology are among the important drivers in the differences in the results.

The results of the analysis suggest that the LBL-REM and EIA-REEM are driven more directly by the shares of particular fuels and the prices of those fuels than is REEPS. On the other hand, REEPS is driven more by technology choices which meet existing levels of demand for heating services at the lowest cost. The heat pump market shares and differences in the efficiency forecasts account for much of the difference in changes over time among the models. The REEPS characterization of the HVAC system yields greater penetration of heat pumps because they satisfy both heating and cooling requirements at a lower total life-cycle cost. The simulation and sample enumeration approach used in LBL-REM incorporates elasticities for other variables as well as life-cycle cost in order to determine market shares and thus yields lower shares for heat pumps.

Since the EPRI-REEPS model predicts a robust market share for heat pumps, changes in the discount rate do not have a large impact on energy consumption. The EIA-REEM and LBL-REM models behave oppositely with respect to changes in the discount rate. The LBL-REM uses a full life-cycle cost calculation for determining efficiency and energy consumption for each fuel/technology while the EIA-REEM chooses among discrete technologies. Lower discount rates thus cause LBL-REM to invest directly in more efficient technologies for a given fuel, while EIA-REEM makes its choice at the higher level between heat pumps and non-heat pump systems. The important point here is that while the three models used the same discount rate, they each use them in a different way. In comparisons across models, it is not enough to choose the same discount rate because one must also consider how the discount rate is used. A more general point is that a "model" actually consists of both algorithms and inputs as well as the relationship between them, so that comparisons across models are constrained by the differences in model structure.

Acknowledgments

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