End Use Technology Choice in the National Energy Modeling System (NEMS): An Analysis of the Residential and Commercial Buildings Sectors

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Abstract

The National Energy Modeling System (NEMS) is arguably the most influential energy model in the United States. The U.S. Energy Information Administration uses NEMS to generate the federal government's annual long-term forecast of national energy consumption, as well as to evaluate prospective federal energy policies. NEMS is considered such a standard tool that other models are calibrated to its forecasts, in both government and academic practice. As a result, NEMS has a significant influence over expert opinions of plausible energy futures.

Despite its prominence, NEMS is a massively complicated model whose inner workings receive relatively scant critical attention. This paper presents an in-depth analysis of the manner by which NEMS projects energy demand in the residential and commercial sectors. In particular, we focus on the role of consumers' financial preferences in satisfying projected demand—how consumers choose appliances and other end-use technologies. We identify conceptual issues in the approach the model takes to the same question across both sectors. Running the model with a range of consumer preferences, we estimate the extent to which this issue impacts projected consumption relative to the baseline model forecast for final energy demand in the year 2035. In the residential sector, the impact ranges from a decrease of 0.73 quads (– 6.0%) to an increase of 0.24 quads (+ 2.0%). In the commercial sector, the impact ranges from a decrease of 1.0 quads (– 9.0%) to an increase of 0.99 quads (+ 9.0%).

Keywords: energy models, consumer preferences, behavior, energy forecasting

JEL Codes: Q47, Q48, D14, D23

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1 Introduction

The National Energy Modeling System (NEMS) is arguably the most influential energy model in the United States. The flagship model of the U.S. Energy Information Administration (EIA), NEMS generates official government forecasts of energy supply, demand, technology adoption, and prices; EIA also uses NEMS to evaluate prospective energy and environmental policies. In addition, many academic and private sector researchers use NEMS forecasts as a starting point for supplemental analysis. As a result, NEMS has a profound influence on expert and lay perceptions of U.S. energy futures.

Although NEMS is a key tool in government and academic research, its inner workings remain poorly understood outside of EIA. Because the model needs cost-prohibitive software licenses and older programming tools, the resources required to run NEMS exceed the financial and human resource budgets of many research or consulting groups. Contrary to the hopes of the National Research Council panel that helped EIA develop NEMS, the model user community is small and academic research on the model's function and performance is limited.

Here we present a case study to address part of the gap in the academic literature on NEMS. We investigate the conceptual approach NEMS takes with respect to choosing end-use technologies in the residential and commercial sectors, for which energy consumption in buildings is the principle consideration. Because end-use technology choice has significant impacts on policy-relevant subjects such as energy efficiency and climate policy, understanding the model's conceptual design in these sectors is crucial to informing the results that are used in subsequent policy analysis.

This paper is organized as follows. Section 2 describes the history of NEMS and reviews the available literature on the model's performance and features. Next, Section 3 presents an overview of the model's approach to projecting energy demand in the residential and commercial sectors. We identify key equations and parameters, focusing on the model's approach to end-use technology choice. We develop alternative scenarios designed to explore the full range of plausible input values, and present the results from these model runs in Section 4. We discuss these results in Section 5. Finally, we offer a brief conclusion in Section 6.

2 Theory and Motivation

2.1 The History of NEMS

The NEMS approach to analyzing the energy economy is best understood in the context of its development. NEMS is the third major model developed for the U.S. Department of Energy's national mid-term to long-term forecasting and policy analysis applications. In 1974, the Federal Energy Administration (the organizational precursor to the EIA) developed the Project Independence Evaluation System (PIES) (NRC, 1992, p. 129). PIES operated by combining a set of econometric demand equations with a linear programming model that incorporated supply side constraints (Ahn and Hogan, 1982). Congressional interest in medium-term energy forecasting led to the development of the second major federal government model, the Intermediate Future Forecasting System (IFFS), which was capable of examining near- and medium-term projections in greater detail. IFFS employed a modular structure, with different sub-models for each constituent part of the energy system; an integrating module coordinated the mathematical convergence process to solve the entire system for a single, equilibrium solution (Murphy, 1983, 1993; Murphy et al., 1988). Thus, IFFS can be viewed as an extension of the basic PIES optimization framework, with significantly expanded sectoral details and computational complexity.[1]

In 1990, the U.S. Department of Energy requested the formation of a committee at the National Research Council to study the development of a comprehensive national energy-environment model. After two years of study, that committee produced a series of recommendations that served as the blueprint for the development of NEMS (NRC, 1992). NEMS is a technology-rich energy-economic equilibrium model that is a hybrid of “top-down” and “bottom-up” approaches: the model includes economy-wide general equilibrium effects, but uses a detailed engineering-economic approach to generate energy demand from individual technologies and detailed economic sub-sectors (Gabriel et al., 2001; EIA, 2009a). The model includes thousands of input parameters drawn from EIA energy use surveys, consultants’ reports, and model developers’ expert opinions (for an overview, see EIA, 2009a; also see this paper, Sections 3.2 to 3.4). NEMS is much more complicated than its predecessors, especially in terms of the number of input parameters and structural equations used to forecast energy, economic, and environmental outcomes. Nevertheless, NEMS may be considered philosophically continuous with its predecessors, in the sense that it applies an economic optimization approach to a rich set of input parameters and economic equations.

2.2 How NEMS Is Used

NEMS is a forecasting and analytical tool used by the federal government, academics, and a variety of businesses and other private sector organizations. EIA manages NEMS and uses it to produce official energy forecasts and policy analyses. Outputs from NEMS

[1] Three other energy-modeling systems used by the U.S. Department of Energy for U.S. markets are worth a brief mention (NRC, 1992, Appendix E). First, from 1979-1981, EIA used the Long-Term Energy Analysis Program (LEAP) for forecasts to the year 2020. LEAP was a configuration of the Generalized Equilibrium Modeling System (GEMS), developed by the Stanford Research Institute. Second, EIA also began using the Short-Term Integrated Forecasting System (STIFS) in 1972 to generate two-year energy forecasts. STIFS was eventually replaced by the Regional Short-Term Energy Model (RSTEM), which is in use today. Because the focus in this paper is on policy analysis and long-term forecasting, we do not discuss on STIFS or RSTEM. Third, a model called FOSSIL was developed at Dartmouth College under U.S. DOE sponsorship (Backus and Amlin, 2009). A subsequent version, called FOSSIL2, replaced PIES at EIA for several years. Although the FOSSIL model family is no longer in use at EIA, it served as the basis for the ENERGY 2020 model, which was recently used to evaluate California’s climate policy for the state’s A.B. 32 Scoping Plan (CARB, 2008; Systemic Solutions, Inc., 2008).

drive the long-term forecasts in EIA's Annual Energy Outlook series (e.g., EIA, 2011a), which forms the standard reference scenario used in internal government analysis, as well as throughout private sector and academic work. EIA also uses NEMS to evaluate the impacts of prospective policy changes when government entities—including Congress and any interested part of the Executive Branch—request such analysis (e.g., EIA, 2009b). These two uses make NEMS extremely influential within the federal government.

Because of the model's prevalence, many academic publications use NEMS to evaluate how technological or policy changes might impact the U.S. energy-economy. Examples include a prospective analysis of the impact of a federal renewable portfolio standard on U.S. energy markets (Kydes, 2007); an analysis of polices to reduce oil consumption and greenhouse gas emissions from the U.S. transportation sector (Morrow et al., 2010); the impact of climate and energy policies on the U.S. forest products industry (Brown and Baek, 2010); the effects of climate policy on freshwater withdrawals for thermoelectric power generation (Chandel et al., 2011); and the impacts from the 1990 Clean Air Act Amendments (Luong et al., 1998). Private consulting groups, such as McKinsey & Company, also use the model to explore questions impacting the U.S. energy-economy (Creyts et al., 2007; Choi Granade et al., 2009).

Beyond policy analysis, a handful of papers evaluate the model's performance in particular applications. Some of these studies also present additional model code or modifications to address perceived shortcomings. For example, Hobbs et al. (2001) extensions of the coal sector module are necessary to fully account for modeling the impacts of the 1990 Clean Air Act Amendments; Haq and Easterly (2006) present an overview of various biomass-related extensions to NEMS; Morris et al. (2002) compare NEMS with MARKAL-based models, which are commonly used to study other countries; Illic (2011) discusses how model extensions would be necessary for NEMS to consider smart grid technologies; Chien (2005) discusses the benefits and drawbacks of various energy models from a transportation-oriented model user's perspective.

In addition, a handful of studies have evaluated the retrospective performance of NEMS-based forecasts. All have done so on the basis of model outputs, however, rather than investigation into model inputs (Auffhammer, 2007; EIA, 2012; Fischer et al., 2009; Lady, 2008; Winebrake and Sakva, 2006). Outside of the Kyoto-related papers discussed below, we are aware of only one paper that considers the effect of NEMS structure and inputs on the model's outputs. Kydes (1999) considers the impact of the same parameters we evaluate in this study, but addresses them from the perspective of technological change, rather than as inputs into a conceptual framework under the exclusive oversight and control of model operators.

2.3 NEMS and the Kyoto Debate

NEMS played a key role in the debate over whether or not the U.S. should comply with its Kyoto Protocol greenhouse gas emissions limits. Using NEMS, EIA released a study of the economic impacts of compliance (EIA, 1998). That study found significant compliance costs and emphasized the role of supply-side solutions. Building off prior work from the national laboratories, the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy commissioned a follow-up report from a group of national laboratory scientists (Interlaboratory Working Group, 2000). This report was eventually published in the journal *Energy Policy* (Brown et al., 2001). While the interlaboratory working group used NEMS, they modified the model code and input parameters to address perceived shortcomings, especially with respect to demand-side energy issues. In particular, Koomey et al. (2001) addressed modifications to and results from the residential and commercial buildings sector, raising concerns explored in the present paper.

3 Data and Methods

3.1 Running NEMS

We ran two versions of NEMS during the course of this research, each of which is named after the edition of EIA's Annual Energy Outlook report for which that version of NEMS is employed. Initially, we used the AEO2008 version to explore the model's treatment of consumer decision-making. We then presented our draft results from this earlier model to EIA staff and leadership at an American Statistical Association Committee on Energy Statistics advisory meeting in Washington, D.C. (Cullenward et al., 2009). Prior to the AEO2010 release of NEMS, EIA updated the commercial module parameters which we modify for this study. We use the AEO2010 model to generate the results presented in this paper, in order to match the EIA's current modeling approach.[2]

Despite the changes between the two model versions, the software and hardware requirements for running the model are virtually the same. EIA provided the code and input files for the various versions of NEMS. NEMS is written in FORTRAN and we compiled the code using an Intel compiler. We did not change the source code, and only modified the input files as discussed in Sections 3.3 and 3.4 below.

Running NEMS requires a number of additional software packages beyond the code and input files. The model requires Microsoft Visual Studio and the interface to engaging NEMS is through the UNIX-emulator MKS Toolkit. The model's energy price calculations are computed using the Optimization Modeling Library (OML), available from Ketron Optimization. In addition, NEMS uses a software suite from IHS Global Insight called the Macroeconomic Activity Module (MAM). The MAM includes projections about macroeconomic variables, such as growth in GDP, as well as the relationships between macroeconomic variables, such as the effect of changes in the construction sector on GDP. The IHS macroeconomic software also requires a statistical package called EViews.

We secured a license for the OML, which is necessary to compute any changes to energy prices resulting from changes in the model's baseline assumptions. Because a

[2] Due to budget shortfalls, some of EIA's end use energy consumption surveys were delayed or recalled. As a result, EIA adopted a proprietary database from McGraw-Hill to parameterize the buildings sector forecasting data in the AEO2011 version of NEMS. We lacked funds to acquire the license, but confirmed that the concepts addressed in this paper are unchanged across the 2010 and 2011 model versions (EIA 2011b, p. 30).

license for the MAM is approximately $10,000 per year, however, we could not afford this software. Based on conversations with NEMS modelers at EIA and Lawrence Berkeley National Laboratory, we do not believe that this shortcoming significantly affects our results. In the absence of the IHS license, the macroeconomic forecasts revert to the baseline assumptions, which are included in the software and input packages EIA provided. We believe it is safe to assume that the changes we make to the model, which affect only a small portion of the total economy—and then, only by a small amount—do not have macroeconomic ramifications. However, should our changes have macroeconomic implications, or should future changes to the model have these implications, then the absence of the IHS software would be problematic.

3.2 Generating Energy Demand in NEMS

NEMS projects energy supply, demand, prices, and environmental emissions by region, based on assumptions about the state of the economy, international markets, and energy policies. It is a detailed model of the U.S. energy system, including a determination of both energy supply and demand, integrated into a macroeconomic framework. The model is a modular system composed of distinct parts. There are energy supply and demand modules, and energy conversion modules. Each supply and demand module contains a set of supply and demand curves for the respective segment of the energy system. Operationally, the code attempts to converge to a unique optimization solution.

At the heart of the model is the Integrating Module, which controls the solution algorithm by iteratively calling each NEMS component module in an attempt to achieve energy market equilibrium in each projection year (EIA, 2010). When a NEMS run is initiated, exogenous parameters, such as technological change, population growth, and economic forecasts, are read in as static parameters and represent the baseline expectations through the model's time horizon, calendar year 2035. NEMS uses these parameters to estimate endogenous demand for energy services such as lighting, heating, and cooling.

There are four energy demand modules in NEMS: residential, commercial, industrial, and transportation. We focus only on residential and commercial, as these sectors' primary concern is energy use in buildings, and are thus conceptually similar.

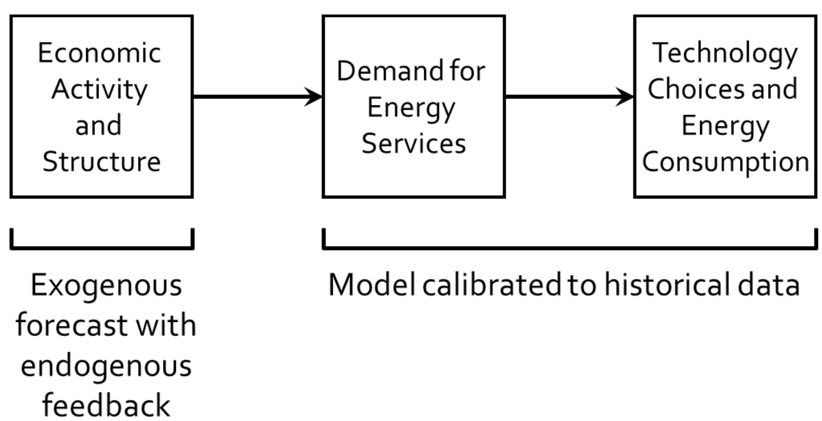

Fig. 1. Generating energy demand in NEMS building sectors

The model's approach to determining energy demand is essentially the same in the commercial and residential building sectors, and is accomplished in two steps. The sectors first determine the demand for energy services based on new and existing building and appliance stocks, and second, apply technologies to meet the demand based on consumer preferences (Fig. 1). Each demand sector module uses macroeconomic inputs to determine the growth of the sector in the given model year. In each sector, the model determines what fraction of the existing building type or square-footage is carried forward, which includes how much is added through new construction and subtracted by demolition. The individual modules also determine what fraction of existing building stock will be remodeled or retrofitted in the current model year based on building and appliance vintage. Once a new stock level is determined, each module forecasts a top-down energy service demand based on the type of building structure and census division. Next, a set of technology choice rules are applied to meet that demand while capturing consumers' preferences on technology parameters, including costs and performance measures. Once these consumer preferences are applied, the modules determine the fraction of energy consumption attributed to different fuels and compute the total energy consumption for the respective sectors.

The process for forecasting energy demand is similar between the two modules; the main structural difference is in how each represents consumer choices.

3.3 Commercial Sector Module

The Commercial Demand Module is essentially a floorspace and appliance stock model. Its purpose is to predict fuel consumption based on a projection of energy service demand in eleven different categories of commercial buildings in different geographical regions. It does this by simulating a constrained lifecycle cost minimization using risk-adjusted time preference premiums to estimate consumer behavior.

Primary inputs to the module include population, historical growth patterns, fuel prices, interest rates, and technology characteristics. Technology characteristics are based on a historical distribution of building floorspace drawn from the 2003 Commercial Buildings Energy Consumption Survey (CBECS). These characteristics include building attrition and growth rates, median construction year and building vintages, and normalized installed capital, operating, and maintenance costs. Technology options, costs, and performance characteristics are drawn from forecasts prepared by Navigant Consulting, Inc.

The key steps in predicting energy consumption in the commercial sector are identified in Fig. 2. This simplified figure omits a few details included within this module, such as onsite energy and co-generation, differences in how energy service demand is computed and principal-agent issues, none of which are affected by the consumer preference issues we describe in this paper. EIA's Commercial Module documentation thoroughly explains how each part of this sector is modeled (EIA, 2010b).

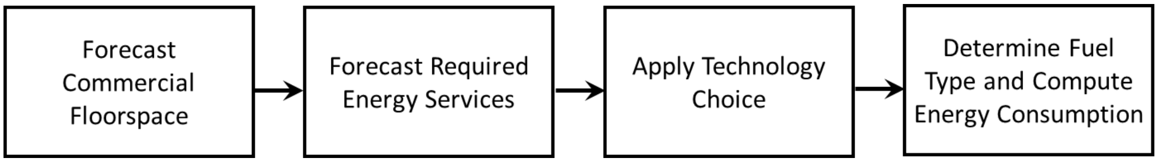

Fig. 2. Key steps to determining energy consumption in NEMS Commercial Demand Module

3.3.1 Floorspace and Energy Use Intensity

The first step in determining energy consumption in a given model year is to project the square-footage of new and surviving commercial buildings in each of nine geographical regions (census divisions) for eleven building types, such as Education, Large and Small Office, Healthcare, and Lodging. This is based on the average lifetime of each building type, ranging from 50-65 years, and the rate of retirement as buildings approach their average lifetime. These rates are the same in each region and constant through the models time horizon. When a model run is initiated, the existing stock, geographic distribution, building usage distribution, and vintage of floorspace are the same as published in the 2003 CBECS. Building shell characteristics for new construction conform at a minimum to the American Society of Heating, Refrigerating and Air-conditioning Engineers (ASHRAE) Standard 90.1-2004.12.

The average efficiency of the existing equipment stock is then calculated for each energy service to match the reported CBECS energy consumption. This floorspace and appliance projection, combined with Energy Use Intensities (EUI) derived from CBECS, provides the energy Service Demand Intensity (SDI) for all building types in each region. SDI is held constant through the forecast period, and the EUI and average equipment efficiencies are computed in each model year such that the SDI is preserved. The SDI is sensitive to inputs such as base year EUIs and equipment efficiencies, building shell efficiencies, short-term price elasticities, rebound effects, and weather.

3.3.2 Consumer Preferences

Once the EUIs have been projected, the model uses estimates of consumer preferences to select which technologies will be used to meet the SDI. The distribution of technologies is chosen with a least-cost model to meet each specific service need. The possible technological choices are narrowed from the total space of technological options, which are provided in an input file.

The model breaks the commercial sector into nine segments based on a combination of three different “decision types” and three different “behavior rules” (Fig. 3). This segmentation is necessary because different end-uses for energy have different costs associated with transitioning from one type of technology to another. For example, changing the fuel type for space heating in a commercial building is an expensive proposition, and thus most buildings that purchase, replace, or retrofit space heating technology will use the same kind of fuel. Similarly, some consumer segments will choose the same category of a certain technology (*e.g.*, overhead fluorescent tube lighting) when buying new, replacement, or retrofitted technology.

All consumers in the model fall into one of these nine categories. All consumers choose the least-cost technology associated with their decision and behavior rules, on the basis of the expected net present value as discussed below.

Behavior Rule	Decision Type: New	Decision Type: Replacement	Decision Type: Retrofit
Least Cost	New Equipment Least Cost	Replacement Equipment Least Cost	Retrofit Decision Least Cost
Same Fuel	New Equipment Same Fuel	Replacement Equipment Same Fuel	Retrofit Decision Same Fuel
Same Technology	New Equipment Same Technology	Replacement Equipment Same Technology	Retrofit Decision Same Technology

Fig. 3. Commercial sector decision types and behavior rules (adapted from Table 7 in EIA, 2010b).

3.3.3 Time Preference Premiums

In order to compare costs across technologies with different capital and operating costs, the model applies risk-adjusted "hurdle" rates to account for consumer preferences about the time-value of money. These discount rates convert the future cash flow associated with a particular technology choice into a net present value calculation, which can be compared across all possible technologies within a segment. (Note that a simple cost-minimization method would, in the absence of segmentation, produce a single representative technology for the entire sector; thus, the combination of segmentation and hurdle rates produces heterogeneity in the model's chosen technologies, which is of course observed in the real world.)

Agents in the commercial sector module lack foresight, so they use current and recent fuel prices to make technology selections. The general expression used within NEMS for determining the annual cost of energy service for a specific technology is shown in Eq. (1), which is simplified form of Equation B-60 from the Commercial Module Documentation (EIA 2010b).

$$\textit{Annualized Cost} = \textit{Cap.Cost}*(\textit{Eff.Hurdle})/(1-(1+\textit{Eff.Hurdle})^{\wedge}\textit{Lifespan}\,) + \textit{Op.Cost}*\textit{Capacity Factor} \qquad (1)$$

As used in the model, the effective hurdle rate is the sum of the Treasury bill rate and a time preference premium. These hurdle rates are used in a way that implies inclusion of all market failures, behavioral issues, information, and transaction costs. Because hurdle rates are applied to all equipment segments in the commercial module at the same time—that is, both existing equipment with remaining useful life, as well as equipment that has failed or ended its useful life—they approximate the barriers facing decisions to retrofit or buy new equipment in a single concept. In other words, the hurdle rate is the discount rate (above the Treasury rate) implied by observed changes to the entire equipment stock. Thus, the discount rate implied by the prevalence of retrofitting will be different than the discount rate implied by new equipment purchases; both will be different than the hurdle rate used in NEMS, which combines retrofitting decisions and new purchases into a single parameter.

Time preference premium rates are read in from external text file ***kprem.txt***. The file contains a time preference premium curve for each major end-use service: space heating, space cooling, hot water heating, ventilation, cooking, lighting, and refrigeration. They range from nearly zero percent to one thousand percent.

When we first reviewed this portion of the code in the AEO2008 release of NEMS, each service had the same curve and all were assumed constant over the entire forecast horizon. In the AEO2010 release, all premiums still begin with the same set of rates used in the AEO2008 through model year 2007, but are then adjusted downward slightly over the next seven years, as shown for space cooling demand in Fig. 4. In 2014, agent discount rates return to the 2009 levels and remain there through 2035.

These changes represent recent improvements to the model. First, the hurdle rates have been updated by EIA to reflect new information about consumer discount rates. This accounts for the overall shift from 2007 to 2009. The other small variations which shift more consumers into lower discount rate categories through 2013 account for the expected effects of the American Recovery and Reinvestment Act, which provided incentives for energy efficiency improvements during this timeframe. The time preference premium curves for other major service demands are similar to the space cooling example, with each service differing slightly; all are constant from 2014 through the remaining model time horizon. Table E1 in the NEMS Commercial Module documentation provides more explicit details of these premiums (EIA, 2010b).

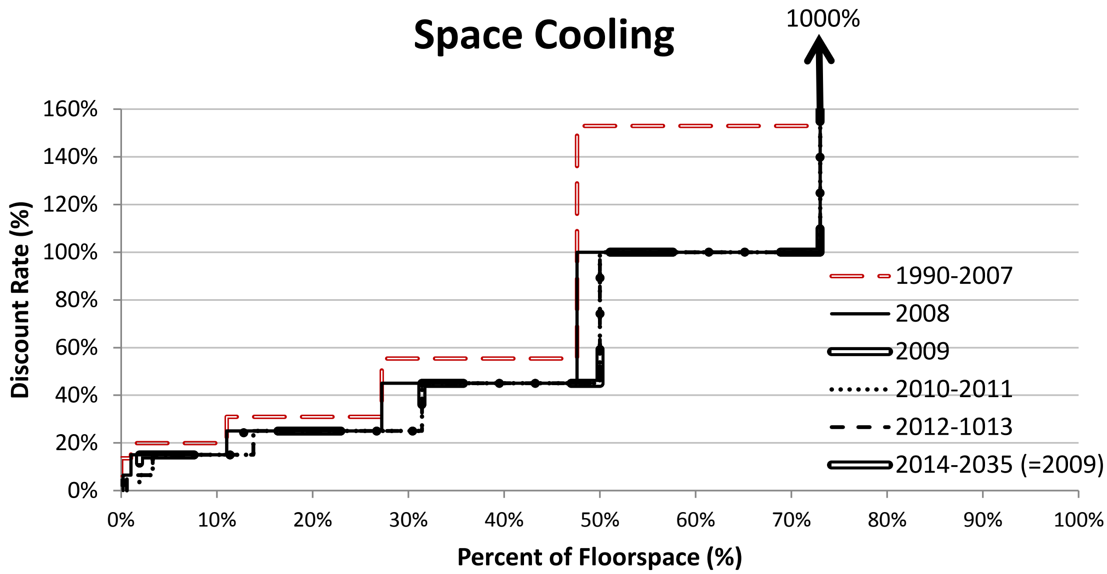

Fig. 4. Commercial time preference premiums for Space Cooling demand

The default premiums are significant: in 2009 (and 2014-2035), agents representing almost 90 percent of all Commercial floorspace have a discount premium of 25 percent or more; half employ a discount rate over 100 percent. Moreover, a quarter of all floorspace is modeled with a premium of 1000 percent, indicating that this percent of the population is unlikely to select efficient technologies, regardless of fuel prices. The small portion of floorspace with zero percent time preference premium represents energy demand from the federal government, which is financed by government debt that is considered risk-free.

Static time preference premiums do not make sense in the context of changing prices or policy interventions. To reflect these concerns, NEMS permits these premiums to fall in response to rising prices (see equation B-59 in EIA, 2010b). If the hurdle rate is above 15 percent, the portion that rate falls in proportion to the ratio of the current year's prices to the base year's prices, raised to the – 0.5 power. To give a sense of the effect, energy prices would need to rise by a factor of four to reduce the hurdle rates by a factor of two.

Hurdle rates, coupled with behavior rules and decision types, are the primary drivers of end-use technology choice in the commercial sector. Modifications to the model for this study will be limited to adjusting these rates.

3.4 Residential Sector Module

The Residential Sector Demand Module is similar to the Commercial Module in general structure. In effect, it is also a building and appliance stock model. Its purpose is to predict energy consumption projections in the residential sector by housing type, fuel, region, and end-use energy service. It does this by tracking the housing and appliance stocks, including new additions and the decay and attrition of older units. From the housing stock, the model estimates demand for energy services, which are in turn satisfied by particular technologies.

Unlike the commercial sector module, which chooses technologies on a segmented least-cost basis, the residential sector uses a logit function to weight the relative importance of capital and operating costs in a consumer's decision making process.

Technology characteristics considered in the module include building shell integrity and improvement factors based on 2005 Residential Energy Consumption Survey (RECS), market share trends, capital costs and efficiencies, appliance penetration and saturation factors, and appliance lifetime and retirement rates. End-use technologies are drawn from the same Navigant Consulting forecast that is used to parameterize the commercial sector module.

Fig. 5 shows the key steps in computing energy consumption in the residential module. As with the commercial sector module, there are many computations required to forecast energy consumption in this sector, such as distributed generation; however, we will only identify these as they pertain to how consumer preferences influence the forecasts. The Residential Module documentation gives a thorough treatment of how each part of this sector is modeled (EIA, 2010c).

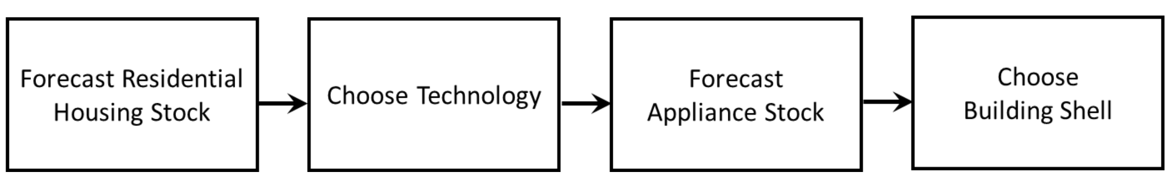

Fig. 5. Key steps to determining energy consumption in NEMS Residential Demand Module

3.4.1 Housing Stock and Energy Intensity

The first part of generating demand in this sector is to create a housing projection for the current model year in each region using historical data and exogenous housing growth and attrition rates. The attrition and new construction rates for all residential building types are assumed to be constant over time, based on historical data, and a small fraction are assumed to be renovated each year. There are only three building types: single-family, multifamily, and mobile homes. Unlike the normalized square-foot energy service demand used in the Commercial Sector, the residential sector module considers only average home size or average square footage.

To represent historical trends, new houses are modeled with larger volumes than homes in previous years, impacting heating and cooling loads. Data are derived from the 2005 RECS, so there are two vintage classes of buildings in this sector: new homes (post-2005) and existing homes (pre-2006). Energy service demand is derived as Unit Energy Consumption (UEC) relative to the base year (2005) and projections of improvements of shell efficiency combined with heating and cooling equipment efficiency over time. UEC, which is a measure of energy intensity, is derived from the 2005 RECS.

3.4.2 Consumer Preferences

Once the module generates an estimate of housing stock for the new model year, it applies technology choices rules to determine the new appliance mix and building shell efficiencies. These choices must meet 21 major and minor end use energy services. Major services include space heating, space cooling, and cooking; minor services include specific appliance services such as refrigeration, coffee makers, and personal computers. Most services include multiple technology classes to choose from to meet demand. For example, there are eleven classes of space heating technologies, such as electric furnace, natural gas radiators, geothermal heat pumps. Furthermore, each class is populated with equipment types that represent the installed products.

A logit function determines the mix of equipment used to meet the energy service demand, based on input parameters that specify a consumer's focus on capital costs versus operating costs. This process is applied to both new equipment purchases, as well as to decisions to replace or retrofit existing equipment. Each competing technology for a particular service is given a weight, and these weights are used to determine a market share of the technology. In general, these parameters are the same across an equipment class, although they often vary for different equipment types. Eq. (2) shows a simplified version of the equation used within NEMS to determine the weight of each competing technology and the resulting market share. For the full set of equations duplicated for new and replacement equipment, see equations B-20 through B-25 in the documentation for the Residential Demand Module.

$$\text{Market Share}_i = \frac{\text{Weight}_i}{\sum \text{Weights}} \qquad (2)$$

$$\text{Weight}_i = e^{(\beta_1 \times \text{Capital Cost} + \beta_2 \times \text{Operating Cost})}$$

The weightings are dependent on two parameters that are calibrated to observed behavior. The two logit variables, or fit parameters, indicate the preferences in the consumers' decision making process. Capital costs are scaled by β_1 and operating costs are scaled by β_2. Changing these values will change the modeled preferences relative to capital and operating costs. The logit value of some pair of parameters is weighted against that of all the other pairs used, so that the share is expressed in relative, rather than absolute, terms. Using the new market shares, the module integrates the changes to the appliance stock resulting from the applied consumer preferences. This logit function collapses the complexity of actual behavior into two parameters.

As with the commercial sector, the residential sector allows for price-induced technology change based on fuel prices. When the hurdle rate is above 7 percent, the model reduces the portion above this rate in proportion to the ratio of the three year trailing average of current prices to the base year's prices, raised to the – 0.5 power. This allows faster diffusion of future technologies if fuel prices increase rapidly and remain high over the multi-year period. While this is not defined explicitly in the module documentation, details of the equation can be found in the Price Induced Technology Change (PITC) subroutine of the FORTRAN source code.

The technology and logit parameters are contained in the technology input file ***rtekty.txt***, which includes data for over 1900 specific technologies. Each energy service contains multiple equipment classes, which in turn contain multiple equipment types; each type has an associated set of logit parameters, β_1 and β_2.

Table 1 illustrates a few energy services and the implied discount rates used in the reference case. As an example, there are five equipment classes for residential space cooling: electric room air conditioner, central air conditioner, electric air-source heat pump, electric ground-source heat pump, and natural gas heat pump. The first class, electric room air conditioners, has three equipment types in the base model representing different levels of technology. The NEMS user can modify the logit parameters to change the implied discount rates for each type, or add new types within the class structure. As discussed above, logit function parameters are relative weights, rather than absolute measurements; therefore, the implied discount rate can only be calculated relative to other options in the decision set.

Table 1) Sample of Energy services, equipment classes and types, and their implied discount rates.

Energy Service	Equipment class	Equipment type	Implied discount rate
Space Heating	1, 3 - 11	1, 6 - 31	15%
	2	2 - 5	25%
Space Cooling	1	1 - 3	42%
	2	4 - 7	25%
	3 - 5	8 - 14	15%
Clothes Washers	1	1 - 3	30%
Dishwashers	1	1 - 3	15%

To modify the parameters, we used a simple residential technology spreadsheet provided by Steve Wade from EIA. This tool incudes all equipment classes and types and calculates their implied discount rates. Logit parameters cannot be set in isolation since their values only have meaning in relation to all the other members in the choice set.

Using the spreadsheet, we can choose logit values from technologies with the desired discount rate and apply those exponential parameters so all future technologies have the same discount rate.

Once these choice preferences are determined, the model assesses changes in building shell efficiency over time and projects the fraction of energy demand met by distributed generation. Shell improvements to the existing housing stock are driven primarily on the cost of fuel for space heating and cooling. New housing uses both capital costs and operating costs of building technology options to determine the building envelope integrity of new construction. The resulting building shell efficiency includes an updated factor for existing houses and a new efficiency factor for new construction. Distributed generation rate of implementation, which includes photovoltaics, fuel cells and wind turbine energy systems, is based on a cash flow analysis.

To summarize, the model projects building stocks, building shell efficiency, energy service demands, distributed generation, and market shares for each end-use technology. These factors produce the final energy demanded in the residential sector.

3.5 Scenarios

In the Commercial Demand module, NEMS chooses end-use technologies using a least-cost net present value calculation within a set of rules governing the options available to different consumer segments. Capital costs are amortized using hurdle rates, which are parameterized in input files. These hurdle, or discount, rates explicitly represent consumers' value of money spent in the present on capital costs versus in the future on operating costs.

In the Residential Demand module, NEMS chooses end-use technologies using a logit function. This econometric form collapses the complexity of past consumer behavior into two parameters that approximate an individual consumer's preferences relating to capital costs versus operating costs.

The hurdle rate framework of the commercial sector makes the NEMS representation of consumer behavior transparent and enables policy analysts to easily modify consumers' modeled time value of money for assessment of impacts. In contrast, the residential sector's logit structure makes it difficult to analyze policy impacts or consider changes to consumer choices.

To evaluate the impact of consumer preferences on energy consumption, and to enable a comparison between the Commercial and Residential Sectors of NEMS, we created a set of scenarios. We set scenario parameters by picking representative discount rates. In the commercial sector, we selected time preference premiums to match the discount rate in each case. Thus, the commercial sector hurdle rate is the time preference premium plus the forecasted federal funds rate. In the residential sector, we selected logistic weights that correspond to the implied discount rate, using the spreadsheet provided by EIA staff as described in Section 3.4.2 above.

- Reference Case. The reference, or base, case uses the time preference premiums and logit parameter values as defined in the AEO2010 release of NEMS.

- Minimum Efficiency (1000 Percent Discount Rate). All agents in the commercial module were given a time preference premium of one thousand percent, starting after the year 2010. This is a bounding case for the effect of time preference premiums as there would be virtually no incentive to purchase more expensive (but also more efficient) equipment.
- Moderate efficiency (20 Percent Discount Rate). All agents in the commercial module were given a time preference premium of twenty percent (above the federal funds rate), starting after the year 2010. Residential consumers were given a balanced set of parameters allowing tradeoffs between capital and operating costs. The purpose of this case is to simulate a situation where consumers pay attention to full costs, have all relevant information available to them, and can finance equipment at a rate comparable to consumer credit cards.
- Maximum Efficiency (0 Percent Discount Rate). All agents in the commercial module were given a time preference premium of zero percent (i.e., the hurdle rate equals the federal funds rate), starting after the year 2010. Residential consumers were given parameters that approximated an exclusive focus on operating costs, not capital costs. This scenario simulates the case where all consumers pay attention to full costs, have the relevant information available to them, and have access to extremely cheap financing. It represents the opposite extreme from the 1000 Percent Discount Rate scenario.

To help put results from this study in perspective, we also compare our scenarios with several of the 31 published NEMS side cases. Of these, five cases are most important to consider: two economic growth sensitivities, and a set of three technology side cases. There are additional assumptions for these EIA scenarios (EIA, 2010e), but the key assumptions are summarized here for convenience.

- High Economic Growth scenario: the average GDP growth rate is raised from the reference rate of 2.4 to 3.0 percent per year.
- Low Economic Growth scenario: the average GDP growth rate is lowered from 2.4 to 3.0 percent per year.
- 2009 Technology scenario: fixes future equipment purchases based on equipment available in 2009 and fixes existing building shell efficiencies at 2009 levels.
- High Technology scenario: allows for earlier availability, lower costs, and higher efficiencies for more advanced equipment. This scenario evaluates the effects of a successful end-use R&D policy. All energy efficiency investments are evaluated at 7 percent. Commercial building shell efficiencies increase 25 percent faster than the reference case, and residential new construction meets Energy Star specifications.
- Best Available Technology scenario: bases future equipment purchases on the most efficient technologies available by fuel. This scenario evaluates the effect of the highest-efficiency equipment on energy consumption. All energy efficiency investments are evaluated at 7 percent. Commercial building shell efficiencies increase 50 percent faster than the reference case, and residential new construction assumes the most efficient available.

4 Results

The first order of business was to run a local copy of the 2010 version NEMS and verify it produced the published AEO2010 results. When a NEMS run is initiated, it computes each year in sequence through the entire time horizon, year 2035, which takes nearly four hours on a moderately new laptop. At the end of this cycle, NEMS evaluates the convergence criteria and determines if the run is sufficiently converged. If it hasn't, the model uses the current solutions as inputs to the next cycle and starts over.

Several convergence criteria are combined into a single number with a range of 0-4.0, which the NEMS documentation compares to a grade-point average (GPA) grading scale. The can set the desired convergence threshold GPA and a few other parameters such as minimum and maximum number of cycles. If the minimum number of cycles has passed and the criteria have been met, the run will terminate. Significant detail and justification of the inputs to the convergence criteria can be found in the NEMS Integrating Module documentation (EIA, 2010a). The default GPA defined with our copy of NEMS 2010 was 3.78; however, we adjusted this to a more stringent 3.9 to ensure our modifications did not affect the quality of the results.

The number of cycles required for convergence depends on the significance of the change from the base case input parameters. Subtle changes may not increase the number of cycles, while substantial changes may lead to several more cycles. Reproducing the published AEO2010 base case scenario results required two cycles, while all other scenarios in this study converged in four cycles.

4.1 Commercial Sector

For the Commercial Sector cases, we modified the time preference premiums of all agents so that they all have the same discount rate. This allows us to see the magnitude of the impact of consumer preferences on energy consumption as modeled within this sector (Fig. 6). All changes to the module take effect at the end of model year 2010 so all cases produce the same result in 2010 and diverge from there. The projected Base Case final energy demand forecast for the sector grows from 8.60 quads in 2010 to 11.03 quads in 2035.

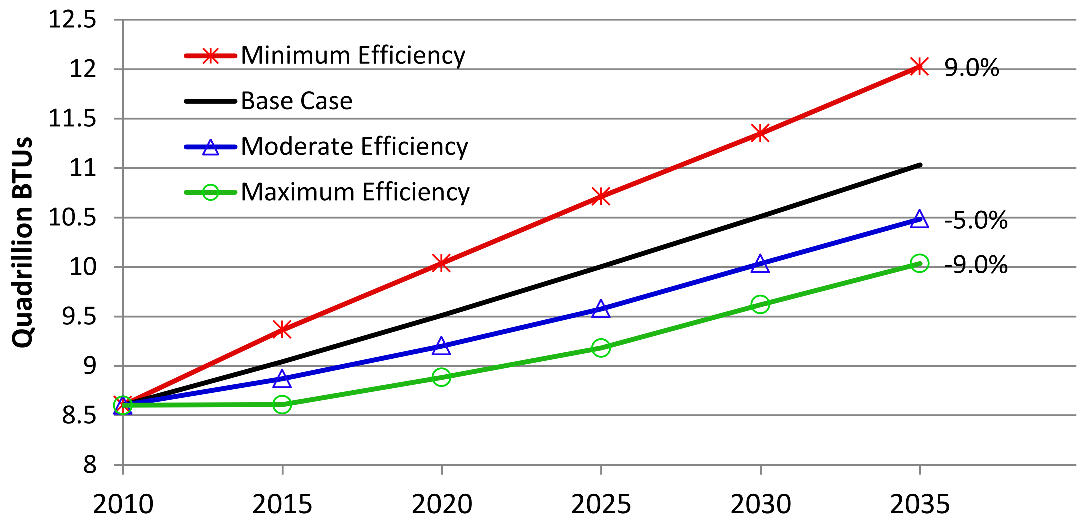

Fig. 6. Final energy demand, commercial sector

When we adjust all discount rates to 1000 percent, all commercial floorspace becomes controlled by agents who only care about up-front capital cost. They have a strong aversion to energy efficiency if it costs a penny more than an equivalent, less efficient technology, which reduces the efficiency of installed technologies relative to the base case. If the entire commercial sector behaved this way, final energy demand in 2035 would be 1.0 quad greater (+ 9.0%) than the base case consumption.

Setting all discount rates to 20 percent allows some efficient technologies to be adopted. These consumers have credit-card-like financing rates and pay strict attention to all costs. Although credit card rates are considered relatively high interest rates, 20 percent is lower than the discount rate of almost 90 percent of the base case commercial floorspace agents. In general, these agents already have working equipment in place but are willing to replace it under this financing scenario, which affects energy consumption through the model horizon. If the entire sector behaved this way, final energy demand in 2035 is reduced by 0.55 quads (– 5.0%) from the base case.

The most efficient scenario occurs when we set all floorspace agent premiums so that the effective discount rate matches the federal funds rate. These consumers have excellent financing options, pay strict attention to all costs, and are quite willing to replace working equipment. Compared to the base case projection, this scenario leads to a reduction of 0.99 quads (– 9.0%) of final energy demand by 2035.

It is initially surprising that reducing risk premiums to zero (federal funds rate) has only a nine percent improvement in final energy demand, since the reference case risk premiums are all substantially higher; however, there are several factors that limit the energy savings in this scenario. Technology choice only affects the major end-use services (first seven listed in Table 2), The share of consumption for these services decreases from 60.5 in percent 2010 to 52.4 in 2035, reducing the impact of efficiency improvements in later years. Also, many types of equipment in this sector have relatively long life spans, which increases the time needed to realize efficiency improvements. Another factor is with high forecasted energy prices and a finite set of technology options, the model is already exploiting available efficient end-use technologies. This would imply a weakness of the bottom-up approach to long-term forecasting, which ultimately requires detailed assumptions about the availability of future technology.

The published economic growth scenarios report changes from the reference case in 2035 by + 5.3 percent for the High Growth scenario and – 4.4 percent for the Low Growth scenario (EIA, 2010d). During periods of low economic growth, consumers shift preferences toward equipment with lower operating costs. However, the primary driver of energy service demand in NEMS is floorspace, which is directly affected by exogenous economic growth forecasts. In contrast, our scenarios directly modify consumer preferences under the reference case floorspace forecasts, which illustrates the significance of only changing consumer behavior about efficient technologies.

We can also compare our results to the published technology side cases. The results of those cases are +4.71, –12.50, and –17.57 percent changes in final energy demand in 2035 from the reference case for the 2009-fixed, high, and best available technology scenarios, respectively. The EIA high technology case shows the benefit of both improving consumer preferences toward efficiency and reducing the technology costs through R&D investments. This, in effect, makes better technology available and encourages consumers to buy it. In contrast, our best scenario gives consumers access to risk-free capital and but doesn’t affect the technology choice set. The best available technology case assumes that consumers will always pick the best technology and is an extreme bound; while consumers in our scenarios will only pick the best if the combination of up-front capital and operating costs meets the least-cost criteria as defined within the NEMS framework.

When each case is disaggregated by energy service demand we can see what services are most impacted by consumer preferences in NEMS. Space heating and lighting are responsible for about 35 percent of the energy consumed in commercial buildings in 2010. Average heating and lighting technologies are assumed to improve over time, so these two categories are projected to account for only a combined 27.5 percent by 2035. Comparing the different scenarios (Table 2), we see that changing consumer discount rates does not significantly alter the demand further.

Table 2) Final energy by service demand, commercial sector

Commercial Sector / Final Energy by Service		Year 2010 Base Case	2035 Base Case	2035 Minimum Efficiency	2035 Moderate Efficiency	2035 Maximum Efficiency
Annual Final Energy	Space Heating	1.98	1.84	1.97	1.73	1.58
(Quad Btu)	Space Cooling	0.53	0.70	0.76	0.66	0.64
	Water Heating	0.57	0.72	0.76	0.70	0.65
	Ventilation	0.51	0.68	1.06	0.40	0.37
	Cooking	0.20	0.26	0.30	0.24	0.24
	Lighting	1.02	1.20	1.51	1.14	0.95
	Refrigeration	0.39	0.39	0.41	0.37	0.36
	Office Equipment (PC)	0.25	0.26	0.26	0.26	0.26
	Office Equipment (non-PC)	0.26	0.46	0.46	0.46	0.46
	Other Uses	2.88	4.52	4.53	4.52	4.51
	Total	**8.60**	**11.03**	**12.03**	**10.48**	**10.04**
Percent of Total	*Space Heating*	*23.0%*	*16.6%*	*16.4%*	*16.5%*	*15.8%*
(Scenario = 100%)	*Space Cooling*	*6.2%*	*6.4%*	*6.3%*	*6.3%*	*6.4%*
	Water Heating	*6.6%*	*6.5%*	*6.4%*	*6.7%*	*6.5%*
	Ventilation	*5.9%*	*6.2%*	*8.8%*	*3.8%*	*3.7%*
	Cooking	*2.4%*	*2.3%*	*2.5%*	*2.3%*	*2.4%*
	Lighting	*11.9%*	*10.9%*	*12.6%*	*10.9%*	*9.5%*
	Refrigeration	*4.5%*	*3.5%*	*3.4%*	*3.5%*	*3.5%*
	Office Equipment (PC)	*2.9%*	*2.4%*	*2.2%*	*2.5%*	*2.6%*
	Office Equipment (non-PC)	*3.1%*	*4.2%*	*3.9%*	*4.4%*	*4.6%*
	Other Uses	*33.5%*	*41.0%*	*37.7%*	*43.1%*	*45.0%*
	Total	*100.0%*	*100.0%*	*100.0%*	*100.0%*	*100.0%*
Percent Change from Base Scenario	Space Heating		0%	7.3%	-5.8%	-13.9%
(index = Base Case 2035 results)	Space Cooling		0%	8.0%	-5.6%	-9.1%
	Water Heating		0%	6.0%	-3.3%	-9.3%
	Ventilation		0%	55.1%	-41.6%	-45.6%
	Cooking		0%	17.1%	-5.7%	-5.7%
	Lighting		0%	25.9%	-4.9%	-20.5%
	Refrigeration		0%	5.1%	-5.5%	-8.0%
	Office Equipment (PC)		0%	0.2%	-0.1%	-0.1%
	Office Equipment (non-PC)		0%	0.1%	-0.1%	0.0%
	Other Uses		0%	0.2%	0.0%	-0.2%
	Total change *		**0%**	**9.0%**	**-5.0%**	**-9.0%**

Note: * This is a weighted net change. Column does not directly sum to the total.

For most other major energy services, adjusting the discount rate has only a minor impact on energy demand. The exception to this is ventilation, which has the most significant change in energy consumption of any service. The extreme efficiency cases affect energy demand for ventilation by a factor of three. Ventilation in particular is affected by compounding gains, as operation and maintenance (O&M) and fuel costs vary depending on the intensity of the other equipment installed. However, while the change in energy required for ventilation is significant, it accounts for less than nine percent of total energy consumption in the least efficient case.

Minor services, which include both Office Equipment categories and Other Uses, are not significantly affected by consumer choices. This is not surprising, because demand for Office Equipment and Other Uses are not modeled at the technology level. As a result, demand for these services is not affected by technology choice parameters. Consequently, relative portion of energy demand for these services becomes larger as more energy efficient technologies are chosen elsewhere.

We also look at how a change in consumer preferences affects type of end-use fuel demanded from this sector. Although the Commercial Module tracks thirteen different fuels, these are aggregated into five types of energy resources consumed directly on the premises. NEMS holds two of these, coal and non-electric renewables, constant through the entire model run. Combined, coal and non-electric renewables represent less than two percent of the 2010 Base Case demand for commercial buildings, a fraction that decreases as energy use grows.

The remaining types are liquid fuels, natural gas, and electricity which all change according to the scenario (Table 3). The liquid fuels category is disaggregated into distillate and 'other' since only distillate is considered a major energy resource and is, therefore, the only liquid fuel affected by major end use changes.

In general, as demand is reduced, the demand for all three types decreases. Most electricity- and liquid fuels-related efficiency gains take place between the minimum and moderate efficiency cases, with only nominal improvement from the most efficient scenario. The relative shares of these two increases between the moderate and maximum efficiency cases, implying that the efficiency of some natural gas technologies can only be adopted when agents have access to cheap capital and pay strict attention to all costs.

Table 3) Final energy delivered by fuel type, commercial sector

Commercial Sector		**Year**				
		2010	2035			
Final Energy by Fuel		Base Case	Base Case	Minimum Efficiency	Moderate Efficiency	Maximum Efficiency
Annual Final Energy	Distillate Fuel Oil	0.320	0.263	0.280	0.255	0.253
(Quad Btu)	Other Liquid Fuels	0.200	0.256	0.256	0.255	0.255
	Natural Gas	3.291	3.789	3.980	3.660	3.446
	Coal	0.064	0.067	0.067	0.067	0.067
	Renewable Energy	0.103	0.103	0.103	0.103	0.103
	Electricity	4.622	6.554	7.339	6.143	5.910
	Total	**8.601**	**11.032**	**12.026**	**10.485**	**10.035**
Percent of Total	*Distillate Fuel Oil*	*3.7%*	*2.4%*	*2.3%*	*2.4%*	*2.5%*
(Scenario = 100%)	*Other Liquid Fuels*	*2.3%*	*2.3%*	*2.1%*	*2.4%*	*2.5%*
	Natural Gas	*38.3%*	*34.3%*	*33.1%*	*34.9%*	*34.3%*
	Coal	*0.7%*	*0.6%*	*0.6%*	*0.6%*	*0.7%*
	Renewable Energy	*1.2%*	*0.9%*	*0.9%*	*1.0%*	*1.0%*
	Electricity	*53.7%*	*59.4%*	*61.0%*	*58.6%*	*58.9%*
	Total	***100.0%***	***100.0%***	***100.0%***	***100.0%***	***100.0%***
Percent Change from Base Scenario	Distillate Fuel Oil		0.0%	6.6%	-3.1%	-3.7%
(index = Base Case 2035 results)	Other Liquid Fuels		0.0%	0.0%	-0.1%	-0.1%
	Natural Gas		0.0%	5.1%	-3.4%	-9.1%
	Coal		0.0%	0.0%	0.0%	0.0%
	Renewable Energy		0.0%	0.0%	0.0%	0.0%
	Electricity		0.0%	12.0%	-6.3%	-9.8%
	Total change *		**0.0%**	**9.0%**	**-5.0%**	**-9.0%**

Note: * This is a weighted net change. Column does not directly sum to the total.

4.2 Residential Sector

For the Residential Sector cases, we modified the beta values of the logit function so that all agents are facing the same implicit discount rates. This allows us to see the magnitude of the impact of consumer preferences on energy consumption as modeled within this sector (Fig. 7). The structure of the input file means that these logit changes take place immediately, and are not delayed until after 2010. The projected Base Case final energy demand for the sector grows from 11.22 quads in 2010 to 12.12 in 2035. The shape of the base case demand curve represents EIA's expectation of a slow recovery from the current economic downturn in the residential sector.

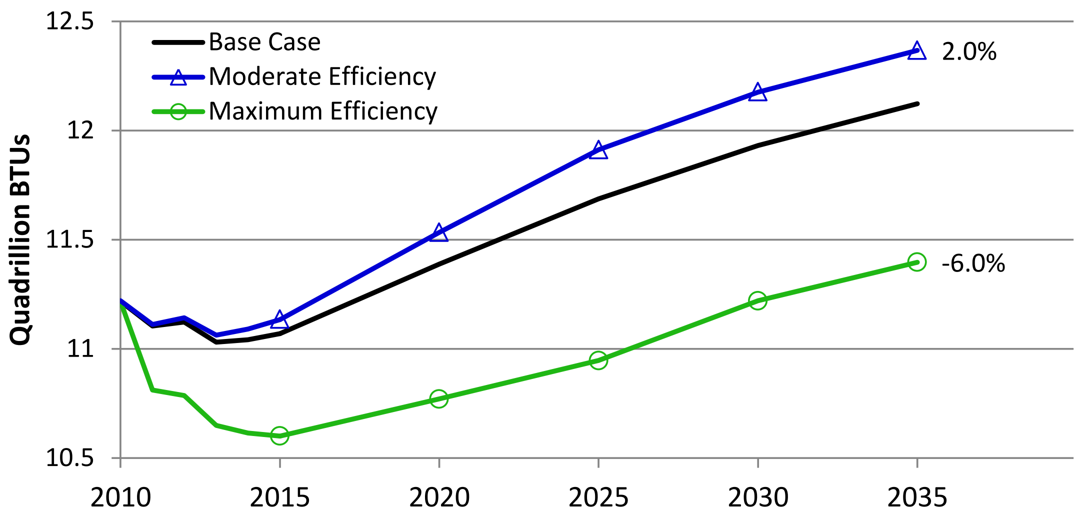

Fig. 7. Final energy demand, residential sector

When we set the logit parameters for all technologies in the model to represent an implied discount rate of 20 percent over the Federal funds rate (β_1 = –0.024, β_2 = –0.1), we increased the sector energy demand over the model horizon by 0.24 quads (+ 2.0%) above the base case in 2035. When residential consumers are faced with credit card-like financing, they are less inclined toward energy efficiency. This suggests that NEMS already considers that consumers historically make relatively economically efficient energy choices for equipment that is included as part of a mortgage or home equity loan.

The most efficient scenario occurs when we adjust the logit parameters to represent an implied zero percent discount rate to match the federal funds rate (β_1 = –0.004, β_2 = –0.1). These consumers have better financing options than consumers in the base case, which leads to a decrease in energy demand of 0.73 quads (– 6.0%) from the 2035 base case result.

Adjusting logit parameters affects the weighted market share of each technology class and type. Parameters need to be similar to the other numbers used in the input files, whose ratio approximately gives us the discount rate similar to those values used in the commercial sector (for comparison), and are within the numerical constraints of the logit framework. We were unable to meet all of these criteria when attempting to replicate the minimum efficiency scenario, despite trying a range of parameters. The largest discount rate in the base formulation is 90 percent, which suggests that including higher numbers may lead to runtime errors or other phenomenon not already explored by model developers or model documentation. Since we cannot replicate the minimum efficiency case, but the moderate and maximum efficiency scenarios bound the residential base case, we did not run an additional arbitrary residential scenario.

We can compare these residential results to the published high and low economic growth sensitivity scenarios. The impact to 2035 delivered residential energy in those cases is + 7.3 percent and – 6.7 percent, respectively. As in the commercial sector, changes in economic growth projections affect the number of housing starts which leads to changes in total energy service demand. In contrast, our scenarios match the reference new construction rate, so our smarter consumers reduce the same order of sector energy consumption but at the same economic disposition.

The published residential technology side case results are + 7.3, – 16.4, and – 27.1 percent from the 2035 reference case final energy demand for the fixed, high, and best available technology cases, respectively. Our moderate efficiency case is not much better than the fixed technology case, implying either that existing technologies already exhibit higher efficiency, or more efficient future technologies are not well represented. EIA's high technology case illustrates the importance of R&D in reducing the cost of technology and improving the availability. Our most efficient case uses a lower interest rate while keeping technology parameters the same as with the reference case, resulting in smaller savings than the EIA high technology case. This suggests that simply changing consumer preferences relating to technology operating costs is not enough to significantly reduce energy demand in this sector, and that technological improvements may also be required.

When we disaggregate the residential sector, we can see that space heating, space cooling, and water heating account for about 67 percent of 2010 residential energy demand (Table 4). Along with water heating and space cooling, clothes washers and dishwashers are the most sensitive to changes in discount rate. Even modest changes in the discount rate can increase or decrease the space cooling demand by more than 10 percent. Despite the remarkable increase in energy demand for space cooling, the moderate efficiency case displays both increases and decreases throughout the remaining service demands. For example, there is a 4.6 percent increase in space heating, yet a 4.1 percent decrease in water heating. Similarly, there is an increase in refrigeration, cooking, and dishwashers, while clothes washers experience a decrease in energy demand.

Table 4) Final energy by service demand, residential sector

Residential Sector / Final Energy by Service		Year 2010 Base Case	2035 Base Case	2035 Moderate Efficiency	2035 Maximum Efficiency
Annual Final Energy	Space Heating	4.82	4.56	4.77	4.53
(Quad Btu)	Space Cooling	0.76	0.99	1.11	0.89
	Water Heating	1.97	1.97	1.89	1.38
	Refrigeration	0.37	0.43	0.44	0.43
	Cooking	0.36	0.41	0.42	0.41
	Clothes Dryers	0.34	0.41	0.41	0.41
	Freezers	0.08	0.09	0.09	0.09
	Lighting	0.72	0.52	0.52	0.53
	Clothes Washers	0.03	0.03	0.03	0.03
	Dishwashers	0.09	0.12	0.12	0.11
	Color Televisions and Set-Top Boxes	0.37	0.50	0.50	0.50
	Personal Computers	0.19	0.21	0.21	0.21
	Furnace Fans	0.14	0.19	0.19	0.19
	Other Uses	1.04	1.68	1.68	1.69
	Total	**11.27**	**12.12**	**12.37**	**11.40**
Percent of Total	*Space Heating*	*42.7%*	*37.6%*	*38.6%*	*39.8%*
(Scenario = 100%)	*Space Cooling*	*6.7%*	*8.2%*	*9.0%*	*7.8%*
	Water Heating	*17.5%*	*16.2%*	*15.2%*	*12.1%*
	Refrigeration	*3.2%*	*3.6%*	*3.5%*	*3.8%*
	Cooking	*3.2%*	*3.4%*	*3.4%*	*3.6%*
	Clothes Dryers	*3.0%*	*3.3%*	*3.3%*	*3.6%*
	Freezers	*0.7%*	*0.8%*	*0.8%*	*0.8%*
	Lighting	*6.4%*	*4.3%*	*4.2%*	*4.6%*
	Clothes Washers	*0.3%*	*0.2%*	*0.2%*	*0.2%*
	Dishwashers	*0.8%*	*1.0%*	*1.0%*	*0.9%*
	Color Televisions and Set-Top Boxes	*3.3%*	*4.1%*	*4.0%*	*4.4%*
	Personal Computers	*1.7%*	*1.8%*	*1.7%*	*1.9%*
	Furnace Fans	*1.3%*	*1.6%*	*1.5%*	*1.7%*
	Other Uses	*9.2%*	*13.8%*	*13.6%*	*14.9%*
	Total	*100.0%*	*100.0%*	*100.0%*	*100.0%*
Percent Change from Base Scenario	Space Heating		0%	4.6%	-0.7%
(index = Base Case 2035 results)	Space Cooling		0%	11.4%	-10.3%
	Water Heating		0%	-4.1%	-30.0%
	Refrigeration		0%	0.8%	-0.6%
	Cooking		0%	0.2%	-1.1%
	Clothes Dryers		0%	-0.1%	0.6%
	Freezers		0%	-0.5%	-4.2%
	Lighting		0%	-0.1%	0.7%
	Clothes Washers		0%	-1.3%	-10.9%
	Dishwashers		0%	0.6%	-10.2%
	Color Televisions and Set-Top Boxes		0%	-0.1%	0.7%
	Personal Computers		0%	0.0%	0.0%
	Furnace Fans		0%	0.1%	-0.1%
	Other Uses		0%	-0.1%	0.9%
	Total change *		**0%**	**2.0%**	**-6.0%**

Note: * This is a weighted net change. Column does not directly sum to the total.

The residential module tracks nine different fuels that are aggregated here into the same five categories used in the commercial sector. Residential energy consumption is dominated by natural gas and electricity, which account for more than 85 percent of demand in all cases. Naturally, any efficiency improvements in the sector will be evident here. Also, both the moderate and maximum efficiency cases result in more consumption in liquid fuels relative to the base case. A significant share of the use of liquid fuels in the residential sector is for heating; that equipment would likely be included in mortgage or home equity financing.

Table 5) Final energy delivered by fuel type, Residential sector

Residential Sector	Final Energy by Service	Year 2010	2035		
		Base Case	Base Case	Moderate Efficiency	Maximum Efficiency
Annual Final Energy	Distillate Fuel Oil	0.68	0.41	0.44	0.43
(Quad Btu)	Other Liquid Fuels	0.48	0.43	0.44	0.44
	Natural Gas	4.95	5.01	5.18	4.69
	Coal	0.01	0.01	0.01	0.01
	Renewable Energy	0.41	0.43	0.43	0.43
	Electricity	4.73	5.83	5.87	5.41
	Total	**11.27**	**12.12**	**12.37**	**11.41**
Percent of Total	*Distillate Fuel Oil*	*6.1%*	*3.4%*	*3.6%*	*3.8%*
(Scenario = 100%)	*Other Liquid Fuels*	*4.3%*	*3.5%*	*3.6%*	*3.9%*
	Natural Gas	*43.9%*	*41.3%*	*41.9%*	*41.1%*
		0.1%	*0.1%*	*0.1%*	*0.1%*
	Renewable Energy	*3.7%*	*3.5%*	*3.5%*	*3.8%*
	Electricity	*42.0%*	*48.1%*	*47.5%*	*47.4%*
	Total	*100.0%*	*100.0%*	*100.0%*	*100.0%*
Percent Change from Base Scenario	Distillate Fuel Oil		0%	7.3%	4.9%
(index = Base Case 2035 results)	Other Liquid Fuels		0%	2.3%	2.3%
	Natural Gas		0%	3.4%	-6.4%
	Coal		0%	0.0%	0.0%
	Renewable Energy		0%	0.0%	0.0%
	Electricity		0%	0.7%	-7.2%
	Total change *		**0%**	**2.1%**	**-5.9%**

Note: * This is a weighted net change. Column does not directly sum to the total.

5 Discussion

This study examines the levers that NEMS users have to represent consumer preferences in the commercial and residential building sectors. Using these levers, we examined the changes in final energy consumption that would result from different consumer decision-making behaviors with respect to end-use technology choices.

In the commercial sector, the NEMS structure closely parallels that of traditional economic optimization models. Consumers make choices about technologies on the basis of costs, using a hurdle rate to levelize operating and capital costs. With its default parameters, NEMS assumes the commercial sector features significant market failures, behavioral complications, and/or transaction costs, as represented by the time preferences adopted by consumers that are significantly above "normal" discount rates used in economic policy analysis or in commercial financing. This suggests the potential for policy to intervene and increase the overall efficiency of the economy, as Sanstad et al. (2001) have previously argued with respect to NEMS.

In practice, if consumer awareness suddenly improved and levelized costs were readily available, the problem of technology choice becomes a problem of finance. (As a reminder, neither the AEO2010 version of NEMS nor this study deals with consumer risks from novel or unproven technologies.) An innovative government or private sector approach to deliver low-cost financing for end-use appliances should result in interest rates somewhere between the Treasury Bill and credit card rates; hence, our 20 percent Case and 0 percent Case effectively bound the technical potential for energy savings from improved end-use decision-making in the commercial sector. Any behavioral complications or market failures would further limit this potential.

In the residential sector, NEMS uses a logit function to translate empirically observed market shares of technologies into an econometric representation of the driving forces that guide consumer choice. Two parameters are used to weight consumer responses: one each for capital costs and operating costs.

While the logit method may be able to replicate historical patterns of end-use technology choice, we found it an unwieldy formulation for investigating behavioral change. There is no direct economic or psychological analogy as to what a specific β_1 value of – 0.0014 means, for example; the parameters do not have any meaning outside of the context of those estimated for other technologies in the logit framework. Nevertheless, we were able to modify the parameters to investigate how consumer decision-making might change. While we cannot bound with confidence how much impact “better” consumer choice in the residential sector could have, our residential cases demonstrate that additional savings are possible.

This study also addresses the limitations of using NEMS to evaluate current research topics in energy efficiency economics. Although NEMS considers an incredibly rich set of technologies, each with a detailed description of costs and operating characteristics, the model’s economic analysis of end-use technology choice is somewhat simplistic. In the commercial sector, the model segments different consumer groups which minimize costs, using discount rates used to levelize costs. In the residential sector, technology market shares are assigned on the basis of a logit model, which is parameterized by two estimates of the relative importance of capital and operating costs in consumers’ preferences. Thus, in both sectors, the complexity of consumer choice is reduced to a set of input parameters that approximate the time value of money. This design choice makes it difficult to use the model to estimate (or account for) the variety of energy efficiency market failures and behavioral complexities identified in the academic literature (e.g., Gillingham et al., 2009, 2012; Shogren and Taylor, 2008). Addressing these topics would require a new set of input parameters that translate the barriers studied into the hurdle rate and logit framework used in NEMS.

5.1 Implications for Energy Forecasting

NEMS relies on input parameters to guide economic decision-making for end-use energy technologies in the residential and commercial sectors. As a result, model users need to be sure that the chosen parameters match current consumer behaviors, as well as any expected changes in model scenarios. In order to evaluate the user’s choices, it is instructive to consider where the current parameters come from.

EIA originally derived the commercial sector parameters from a Ph.D. thesis that investigated energy efficiency choices in commercial office buildings (Koomey, 1990). These parameters have been updated by three studies from Johnson Controls and

Building Design + Construction (a trade publication), published between 2008 and 2009 (EIA, 2010b). EIA used the three consulting studies to update its original static parameters, but has no stated plans for future updating.

The residential sector parameters are not explicitly sourced in the EIA documentation. EIA suggests that data for the residential module in NEMS is drawn from RECS; the AEO2010 version of NEMS used the 2005 RECS (EIA, 2010c, Appendix E). While RECS is among the most detailed data sources available on U.S. residential energy choices, it is infrequently updated, due to budgetary constraints. Additional documentation describing how the parameters are calculated from RECS may assist future studies of whether and how to change the NEMS parameters.

NEMS users should consider whether these parameters are an appropriate basis for forecasting future energy consumption. Changes in consumer behavior, macroeconomic conditions, end-use technology, or marketing strategies could conceivably undermine the current parameter set. Consumer preference parameters are drawn from older academic work updated by a suite of recent consulting reports, while end-use technology options analyzed by consumers in NEMS are taken from a forecast from Navigant Consulting. Because the technologies and their associated consumer preference parameters are draft from separate external reports, this presents the possibility that parameter forecasts do not match the scenario conditions specified by model users.

Finally, we note that the changes in our scenarios largely arise within the first ten or fifteen years of the model run, with the remaining model years following the slope of the base case forecasts in parallel. We interpret these results as indicating that the available efficiency options—moving to either more or less energy efficient equipment—are quickly exhausted over a relatively short time horizon, due to relatively rapid equipment turnover. In a bottom-up energy model, the quality of the forecast depends on the richness and robustness of the technology options forecast; we do not examine these issues here, but note that our results confirm the importance of further work in this area.

5.2 Implications for Policy Analysis

As this study demonstrates, changes to consumer time preference premiums can either increase or decrease end-use energy consumption. If these changes follow from an exogenous change—for example, an increase in consumer awareness or financing options—they should also affect the macroeconomic costs and benefits as modeled by NEMS. Because NEMS assumes general equilibrium principles no matter the time preferences expressed by agents in the residential and commercial sector modules, a change in these preferences should translate into macroeconomic gains (for a conceptual overview, see Sanstad et al., 2001). Since we lacked the Macroeconomic Activity Module license, we do not estimate these effects. Nevertheless, there may be important macroeconomic consequences to the parameter changes we explore.

Although NEMS includes dynamic, price-based feedbacks to its discount rates, the magnitude of these dynamics is much smaller than the range of cases presented here. In both sectors, end-use technology choice parameters can be revised downward if prices rise, roughly by a factor of the ratio of prices raised to the – 0.5 power. As a result, it would take a price increase of a factor of four to produce a reduction in the hurdle rates of a factor of two, which would result in hurdle rates significantly above the cases considered in this paper. Thus, if a NEMS user analyzes a scenario that involves market interventions designed to change consumer decision-making behavior beyond the dynamics currently captured in the model, the model's internal logic will conflict with the scenario drivers. Model users should be aware of these potential inconsistencies when using NEMS to explore policies that could give rise to this phenomenon; modification to the model code may be required.

6 Conclusion

A sensitivity analysis shows that reasonable modifications to the parameters governing end-use technology choice in buildings modestly impact final energy demand. In the residential sector, the impacts of end-use technology choice decision parameters on energy demand range from a reduction of 0.73 quads (– 6.0%) to an increase of 0.24 quads (+ 2.0%). In the commercial sector, the impacts range from a reduction of 1.0 quads (– 9.0%) to an increase of 0.99 quads (+ 9.0%). We note that our sensitivity analysis shows that end-use technology choice plays only a modest role in the overall trajectory of national energy demand. Other factors, especially those determining the overall level of energy services demanded in each sector, are more important in shaping NEMS forecasts. Our results indicate the future work exploring the model structure and data determining energy service demand could produce useful insights and guidance for improving subsequent energy model design.

In addition to making these calculations, this paper identifies four conceptual problems with the way NEMS projects how end-use energy demand is satisfied.

First, the model uses hurdle rates to guide the choice of end-use technologies. As expressed in a least-cost optimization framework (the commercial module), or implied by the key parameters in a logit framework (the residential module), hurdle rates resemble discount rates. As defined in NEMS, however, hurdle rates include a variety of other concepts, beyond those associated with discount rates. Specific market barriers, such as information costs, transaction costs, and bounded rationality, are known to affect consumer decisions in the energy sector (Bataille et al., 2006; EMF, 2011; Huntington, 2011). However, NEMS does not model any of these barriers directly, and instead implicitly assigns their causal role with hurdle rates. In both sectors, NEMS defines a single hurdle rate that applies to both decisions to retrofit existing equipment and decisions to purchase new equipment, although the financial barriers, market failures, and behavioral aspects may differ across the two decision types. Thus, analysts must be careful to distinguish how hurdle rates are defined in NEMS from external analyses of specific market failures or consumer behaviors, all of which are amalgamated into the hurdle rate in NEMS.

Second, NEMS implements similar end-use technology choice issues in significantly different ways across the commercial and residential sectors. The commercial sector is structured as a segmented, least-cost optimization model. The combination of market segmentation and discount rates creates heterogeneous outcomes, whereas if a simple-least cost optimization were performed on the sector as a whole, presumably only one technology would be selected for each energy service. In contrast, the residential sector uses a logit model with parametric weighting that assigns market shares to each available technology. Because of the nonlinear functional form, heterogeneity is unavoidable; even with extremely unattractive parameters, any technology will claim at least a tiny market share. As a result, it is difficult to compare conceptually similar issues across the two sectors.

Third, the model's behavioral parameters are not linked to regularly updated data, which leads to what Ascher (1978) called "assumption drag." Model assumptions drive the results, and therefore outdated methods or infrequent updates to parameters produce forecasts that favor older trends. While EIA updated the commercial sector hurdle rates between the AEO2008 and AEO2010 versions of NEMS, these data are not specifically tied to any particular source or method. The model documentation gives no indication of how often this fit is re-evaluated with recent choice data. Technology options in both sectors are drawn from consulting reports from Navigant Consulting, the most recent version of which was published in 2008. In addition, both sectors rely on two of EIA's end-use energy consumption surveys, RECS and CBECS, to determine changes to important parameters driving energy consumption in the model, but these surveys are now conducted only once every four years—and less often when budgets are cut. Making funding of existing data collection authorities a budgeting priority at the Department of Energy would address many of these concerns.

Fourth, the hurdle rate price dynamics incorporated in the model are relatively modest, and may not capture the full range of possible feedbacks applicable to model users' policy and forecasting scenarios. This situation presents the risk of making a "big mistake" in technological forecasting, as described by Koomey (2002). The problem arises when model scenarios include policy interventions or simulated price changes that have the potential to change consumer behaviors from their pre-established parameters (or the constrained range of dynamic feedbacks). Examples include policies designed to increase consumer awareness of energy efficiency, consumer financing, or persistent high (or low) end-use prices in the model scenario. In these situations, the model's internal logic may become inconsistent because end-use technology choice is parameterized by hurdle rates that approximate a different set of conditions than is actually forecast under the particular model scenario. While NEMS does include price-based adjustments to the time preference premiums, the model only permits downward revisions in the hurdle rates. Moreover, the price changes need to be large to have significant affects: to reduce the hurdle rates in half (which is still larger than two of the cases we model in this paper) requires prices to rise by a factor of four. With precious few empirical data available on energy consumer behavior, and even fewer models linking these data directly into model calculations (Bataille et al., 2006), no obvious alternatives are available; yet the problem remains one to which model users should pay more attention.

Finally, we wish to highlight the financial challenges facing EIA in the current political climate. In FY2011, EIA experienced an unexpected 14% budget cut—at a time when demand for EIA data and analysis was rising in response to new dynamics in U.S. energy markets and federal policy. In order to address this shortfall, EIA had to make significant cuts in major programs, including suspension of further upgrades to NEMS, not to mention cutbacks in its primary data collection programs.[3] Despite these challenges, EIA staff members have been responsive to outside researchers and offered us invaluable help with this project. We hope this paper will contribute to further refinements and encourage our academic colleagues to seek new ways to collaborate with EIA, including the development of new data and methods to improve NEMS.

6.1 Acknowledgements

The authors thank Erin Boedecker, Steve Wade, and Paul Kondis at EIA and Peter Chan at LBNL for their assistance running and interpreting NEMS. We also thank John Weyant, Jon Koomey, Kenneth Gillingham, Hill Huntington and participants at the 2011 International Energy Workshop at Stanford University for their comments on a draft of this paper. Any remaining errors—and all opinions expressed—are the responsibility of the authors.

Funding for this project came from three sources at Stanford University: the Emmett Interdisciplinary Program on Environment and Resources (E-IPER), a School of Earth Sciences Levorsen Grant, and the Energy Modeling Forum. In addition, D.C. was supported by a David and Lucile Packard Foundation Stanford Graduate Fellowship.

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[3] EIA Press Release (April 28, 2011), available at: http://www.eia.gov/pressroom/releases/press362.cfm

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