ASPECTS OF CONSUMERS' AND FIRMS' ENERGY DECISION-MAKING: A REVIEW AND RECOMMENDATIONS FOR THE NATIONAL ENERGY MODELING SYSTEM (NEMS)

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1. INTRODUCTION

NEMS projections of residential and commercial energy demand patterns, as well as predictions about these sectors' response to various energy policies, are a complex function of model structure, input data, functional form assumptions, and other factors and inputs. The specific assumptions regarding households' and firms' decision-making are one important component. This paper reviews research relevant to certain of these assumptions, including studies on demographic influences, the magnitudes and interpretations of hurdle rates for energy technology and efficiency investments, consumers' and firms' expectations regarding such variables as future energy prices, and energy price and income elasticities. We recommend possible applications of these findings to further development of the NEMS Residential and Commercial modules.

With the emergence of energy policy as a national priority and numerical energy modeling as a key policy tool in the 1970s, the characteristics of economic agents' energy-related decisions, and their appropriate representations in models, became very active areas of research, modeling application, and policy analysis. The NEMS Residential and Commercial modules are based in part upon results in that body of work, including both the underlying structures of the modules and their parameterizations. By the 1990s, however, with energy losing prominence as a public policy priority as well as an academic research area, the flow of this supporting work focused on U.S. energy markets was substantially curtailed. This results in limitations on the availability of more recent work that might be readily applied to NEMS. Nevertheless, we find that there are some results of this type, as well as work from the 1970s and 1980s that remains relevant to NEMS but has not yet been applied.

We also recommend that recent work by EIA on diagnostic techniques for computer models and model forecast evaluation be integrated with the evaluation of these findings for possible use in NEMS and with any actual applications to the model. Finally, we

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briefly discuss research frontiers in consumer decision-making that may be relevant for long-term model development.

2. RESIDENTIAL SECTOR

The NEMS residential module reflects the modeling philosophy that end-use energy consumption is predictable as a function of physical characteristics of housing stocks and energy-using equipment and the life-cycle costs of the equipment itself. This approach has its roots in detailed engineering analysis of energy systems, and among its other advantages it is naturally suited to policy analysis involving technology-focused regulations. It is therefore appropriate to highlight themes in the research literature on residential energy demand that bear on this approach.

As noted in the Introduction, the first decade of the era of contemporary technology-focused energy policies, roughly from the mid-1970s to the mid-1980s, saw a great deal of both academic and applied program-related research on consumers' energy-related investment decisions. Indeed, much of the knowledge currently available dates to that period as a result of interest motivated by the oil price shocks of 1973 and 1979. When oil prices declined, U.S. research in this area fell off sharply in the late 1980s and early 1990s. Since the late 1990s, research on energy markets, consumer behavior, and related topics in other countries has expanded significantly.

Broadly, three methodologies underlie the literature on consumer energy decision-making: Micro-economic, engineering, and non-economic social scientific, especially anthropological and social psychological.[1] Of the first, the application of discrete or qualitative-choice econometric methods is most important in generating micro-scale evidence, in contrast to, for example, large-scale representative-agent computable general equilibrium models. The engineering methodology frames both energy investments and consumer decisions as phenomena of life-cycle cost minimization.

The third category applies primarily qualitative methods to elicit ethnographic, cultural, and psychological aspects of energy use. Multi-disciplinary social science research on energy use emerged fairly rapidly in the 1970s and generated a body of evidence that remains relevant; Lutzenhiser (1993) is an authoritative review.

Overall, both the methods and the findings of these various strands of research reveal that there is no single generally accepted theory, model, or empirical literature describing how individual consumers or residential households make energy-related investment decisions. There is, however, evidence of various sorts on this question, which has revealed certain regularities even given considerable methodological pluralism.

For the present purpose, most important among these is that engineering-based models, such as life-cycle cost, incorporating information only on technologies and costs are subject to certain limitations both in empirically accounting for observed behavior and in

[1] These three approaches are compared in Sanstad (1993).

predicting consumer responses to policies. Several important examples are summarized in the following paragraphs.

First, it has long been recognized that technology models omit "hedonic" features of energy-using equipment that consumers value and that will therefore affect and possibly dominate their purchase decisions. The capacity to incorporate such features and their role in consumer decisions is one important feature of discrete or qualitative choice methods (Train 1986). However, the applications of these methods to household non-transportation energy demand have typically not included full details of non-engineering aspects of energy-using equipment, in our view primarily because of data requirements that have proven very difficult to fulfill.[2]

Second, occupant behavior can significantly influence household energy consumption after controlling for the effects of equipment, weather, and other factors. For example, in a study of natural gas demand, Sonderegger (1977/78) found that "...unpredictable behavior patterns of the occupants introduce a large source of uncertainty in the computation of residential space heating energy requirements." A very recent study, also of residential space heating, found that while thermal shell characteristics predicted demand well under stable conditions, energy-conservation efforts on the part of occupants made such prediction essentially impossible (Emery and Kippenhan 2006).

Third, socio-demographic characteristics have also been found to have significant effects on energy demand patterns. In a study using data of the 1993 Residential Energy Consumption Survey (RECS), Liao and Chang (2002) found significant differences in energy consumption patterns of older consumers. Tonn and Eisenberg (2007) argue that energy affordability among older U.S. consumers will be a major policy issue in the future as the number and proportion of these consumers in the population increases and upward pressure on energy prices continues. Poyer et al. (1993, 1997), also using the RECS from several years, found sizable differences in consumption patterns, as well as in price and income elasticities, by household ethnic group.

Finally, life-cycle cost models of energy use require specification of discount rates for computing present values of future operating costs, and in an empirical forecasting model such as NEMS this entails calibrating these rates to observed purchase behavior, i.e., consumers' own "hurdle rates" or "implicit discount rates." The magnitude and interpretation of these rates has long been one of the most contentious topics in energy policy and modeling, and remains unresolved.

By way of background, virtually from the inception of applied programs – such as utility demand-side management – in the 1970s, it was observed that in practice consumers and firms frequently chose not to invest in efficiency devices or measures that analysts

[2] Although conceptually distinct, the method of hedonic price analysis is related to this issue: Under certain assumptions regarding market structure, the contributions to product prices of hedonic features will reflect consumers' valuation of these features. Greening et al. (1997) conducted a hedonic analysis of refrigerator prices and the impact of energy efficiency standards thereupon that took account of a number of characteristics of refrigerators in addition to their energy consumption.

applying engineering-economic criteria estimated *ex ante* would be cost-effective. This stimulated the literature on “barriers” to energy-efficiency.[3] Also during this period, econometricians and other researchers conducted analyses of actual purchase decisions in markets for energy-using equipment, including appliances, heating and cooling systems, and automobiles. With observations of choices made when a range of energy-efficiencies for a given product were available, knowledge of or additional assumptions regarding fuel prices and other factors, and an economic model of the decision, researchers could *ex post* empirically estimate the rates at which consumers traded-off increased purchase prices for more efficiency equipment against future savings on operating costs from reduced energy use. These implicit discount rates for energy-efficiency were in many instances found to be well in excess of market rates for borrowing or saving. Table 1 summarizes estimates presented in Train (1985), a widely-cited review of this literature.[4]

Table 1 – Implicit Discount Rates in Consumer Energy-Efficiency Investments

Study	*End-use*	*Average rate*
Arthur D. Little (1984)	Thermal shell measures	32%
Cole and Fuller (national survey, 1980)	Thermal shell measures	26%
Goett (1978)	Space heating system and fuel type	36%
Berkovec, Hausman and Rust (1983)	Space heating system and fuel type	25%
Hausman (1979)	Room air conditioners	29%
Cole and Fuller (1980)	Refrigerators	61-108%
Gately (1980)	Refrigerators	45-300%
Meier and Whittier (1983)	Refrigerators	34-58%
Goett (1983)	Cooking and water heating fuel type	36%
Goett and McFadden (1982)	Water heating fuel type	67%

It is worth noting that in subsequent debate regarding consumer energy-related decision-making, continuing to the present day, the *ex ante* engineering “potential” and *ex post* economic results tend to be conflated, and both invoked as evidence of the so-called energy efficiency “gap,” the apparent systematic underinvestment in efficient equipment by consumers. These two sources of evidence are, however, quite different, insofar as evidence on implicit discount rates obtained by econometricians using discrete-choice methods does not rely on engineering judgments and other assumptions that underlie potential studies. In addition, by virtue of both methodology and the type of data involved, the econometric estimates are either not affected by, or take account of, such factors as the “rebound” effect, the offsetting increase in energy service demand resulting from a decline in the service cost as a result of incremental energy-efficiency.[5]

[3] The original work on this subject was Blumstein et al. (1980); this paper referred to “social and institutional barriers.” The now more-familiar term “market barriers” arose later.
[4] It is pertinent that the research reviewed by Train had been conducted by the early 1980s, and much of it appeared in the 1970s; that is, the “stylized facts” about implicit discount rates are now two-to-three decades old.
[5] One aim of the micro-econometric studies was to jointly analyze equipment purchase and fuel utilization decisions, for example Hausman (1978) and Dubin and McFadden (1984).

Efforts to explain anomalously high implicit discount rates for energy efficiency have generated a very large literature over several decades without resolving the issue. It is not generally recognized, however, that a close relationship between hurdle rates and household was detected in a number of the early studies. This is illustrated in Table 2, in which further results of three of the studies discussed by Train are presented. As the results indicate, there is a pronounced inverse relationship between household income and implicit discount rates, and moreover, the rates observed among the higher income brackets are within ranges that are consistent with commercially-available consumer discount rates for borrowing.

Table 2 – Implicit Discount Rates for Selected End-uses by Household Income

Study	*End-use*	*Household income*	*Implicit discount rate*
Arthur D. Little (1984)	Thermal shell investments	< $5,000	88%
		$5,000-6,999	79%
		$12,000-14,999	53%
		$25,000-29,999	27%
		$40,000-49,999	9%
		> $50,000	0.4%
Berkovec et al. (1983)	Space heating system and fuel type	$1,000	56%
		$5,000	46%
		$10,000	38%
		$25,000	25%
		$40,000	19%
		$60,000	14%
Hausman (1979)	Room air conditioners	$6,000	89%
		$10,000	39%
		$15,000	27%
		$25,000	17%
		$35,000	8.9%
		$50,000	5.1%

This relationship was robust among studies that included income in analyzing energy technology and efficiency purchase decisions. Several explanations have been suggested but neither confirmed nor falsified: Limited access to credit among lower income households is one hypothesis; a correlation between lower income and lower educational levels that impedes these households from fully assessing costs and benefits is another. The latter conjecture can be viewed as a variation on the hypothesis that underinvestment in energy efficiency is due to consumers lacking appropriate information, which was possibly the earliest hypothesis regarding this phenomenon. However, it was also found rather early on in research and programmatic experience that information on energy efficiency, per se, has relatively little effect on consumers' investment decisions.[6] More generally, the correct explanation of high implicit discount rates remains to be determined. We return to this issue in subsequent sections.

[6] Early work is summarized in Stern and Aronson (1984); Sanstad (2007) discusses the limited energy savings from utility information-only efficiency programs.

Consumer expectations

All models of energy demand that incorporate some dynamic or intertemporal representation, whether theoretical or empirical, must make an assumption regarding economic agents' expectations of future conditions, including energy prices. In theoretical models such as those based on optimal control principles and in some computable general equilibrium models, perfect foresight is assumed. In empirical (econometric) models as well as numerical simulation models, "myopic" expectations are commonly assumed: Consumers are assumed to expect that future values, for example of energy prices, will be the same as current values. A variation on the latter formulation is to assume that future prices change at a fixed rate.

Implicit discount rate estimates of the type discussed reported, for example, depend upon such assumptions. In the results reported by Train (*op cit*.), myopic expectations were assumed. It is worth noting that these estimates do not imply any particular expectations-formation processes on the part of consumers.

A panel of the National Academy (Stern 1984) described the use of the "adaptive expectations" model in early energy demand studies, which combines aspects of the perfect and myopic foresight assumptions: In this model, consumers predict one-period-ahead energy prices based on a weighted combination of the current and previous period prices. (In some variations, a longer "history" of prices is incorporated.) It noted that while the adaptive expectations model had performed well in empirical studies, the technical details of its application did not allow for the distinction among several theoretical models that implied the same coefficients in a standard econometric model.

Despite its presumed importance, we have identified very little more recent research focused directly on how households forecast or form expectations of future energy prices or other variables that affect demand, or that incorporate other assumptions than those just described. Cowing and McFadden (1984) note that both of the two numerical models of residential energy demand that they analyzed assume myopic expectations, which they characterize as both inconsistent within the framework of the models and "...likely to be a very inaccurate specification."

Kamerschen and Porter (2004) estimated several models of U.S. residential electricity demand incorporating a form of adaptive expectations for fuel prices: Consumers are assumed to form expectations according to a first-order moving average process. They did not, however, report the effects of this assumption compared to, for example, myopic expectations.

The fundamental challenge in analyzing consumer expectations related to energy in a quantitative form that could be incorporated into energy models is that expectations are not observable or measurable in the way that variables such as demands or market prices are. Kaufmann (1994) constructs a proxy for consumer price expectations using the difference between oil price changes and a real interest rate, where oil prices are also a proxy for the prices of other fuels. He finds that expectations defined in this way have, as would be expected, a significant effect on the impact of a hypothetical carbon tax. This result highlights the dilemma that consumer expectations are both important for energy modeling and very difficult to model empirically in a robust manner.

3. COMMERCIAL SECTOR

There has been much less applied research on commercial firms' energy decision-making than on residential consumers. In part, this reflects both the greater difficulty, from a research perspective, of gaining access to firms, and the fact that the methods of the social science disciplines that were applied to energy studies in the 1970s and 1980s did not lend themselves easily to analyzing commercial firms. There has been some work, however, on the specific question of investment and non-investment in energy efficiency analogous to the corresponding question for households – the energy efficiency "gap" - although in the case of commercial enterprises there is not an equally rich body of evidence on quantitatively measured (*ex post*) implicit discount rates.

DeCanio (1993, 1998) provided a theoretical rationale for the systematic under-investment in cost effective energy-efficiency in private firms, emphasizing principal-agent effects within firms affecting, for example, the allocation and evaluation of capital budget resources separate from decisions about operating budgets, as well as "bounded rationality" on the part of managers. Certain of these theoretical findings are supported by the observations of Ross (1986), which, although focused on industrial firms, may also be relevant to large commercial companies: In multi-layered management hierarchies, the application internal criteria for investment evaluation with the aim of capital rationing can appear as "high" hurdle rates for efficiency investments. On the other hand, as Anderson and Newell (2003) point out, such decision-making may affect all types of investments, and does not necessarily provide evidence of a particular bias against or systematic under-weighting of energy efficiency opportunities.

Payne (2006) illustrated the differences in how energy consumption information (from the utility bill) is handled in different commercial enterprises. He notes that businesses can encompass one or many buildings, and that the organizational structure varies depending upon the size of the business. A small business may have one decision-maker, while large businesses may assign different responsibilities to various employees, including accountants to pay the energy bills, and facility managers to make recommendations to management about purchasing energy-using equipment. Information is processed differently in different organizations, and often not communicated well among different parties.

High hurdle rates across firms in the NEMS Commercial module are interpreted as "risk premia" of varying magnitudes. It is therefore of interest to summarize several models of decision-making under uncertainty that have been posited to account for these hurdle rates. Sutherland (1991) argued that high hurdle rates could be "rationalized" by the theory of decision-making under uncertainty, specifically the Capital Asset Pricing Model (CAPM). However, as Metcalf (1994) pointed out, the relationship between returns to energy efficiency and returns to other investments implies, in the logic of portfolio theory, that "risk premia" for efficiency investments should be *negative*;

intuitively, investments in energy efficiency will tend to yield positive returns under conditions in which other investments do not. Thus, the correct application of the CAPM would serve only to heighten the anomaly. Responding to the need for an economic explanation of high efficiency hurdle rates, Metcalf (op cit), and Metcalf and Rosenthal (1995) instead applied the theory of option values, which predicts a "wedge" between investors' underlying discount rates and their hurdle rates for investments with uncertain returns and applies in principle to private firms as well as to individuals. As Sanstad et al. (1995) demonstrated, however, the actual predictions of this model when applied to energy-efficiency investments fall far short of accounting for hurdle rates of the magnitudes reported in the literature.[7] To date, standard microeconomic models of investment under uncertainty have failed to account for the implicit discount rate evidence of both individuals and commercial firms.

Other studies have examined companies' hurdle rates and forecast horizons more generally. Poterba and Summers (1995) presented evidence that U. S. firms set an average hurdle rate of 12.2% (in constant dollar terms) in capital budgeting calculations, which as they point out is higher than both equity holders' average rates of return and the return on debt during the past fifty years. They also note an absence of correlation between real hurdle rates and financial variables representing risk. While they hypothesized that some managers may set high hurdle rates as a "screening device" for overly optimistic individual project cash flow projections, their survey data did not allow for investigation of this or other possible behavioral explanations of the phenomenon.

4. CROSS-CUTTING ISSUES

The problem of high implicit discount rates for energy investments on the part of both households and firms has been one source of a literature on characteristics of markets for energy efficiency and the appropriateness of policies to promote efficient technology adoption. Among other topics, this literature has addressed whether high hurdle rates reflect market failures for energy efficiency or anomalies in consumers' actual decision processes.

Sutherland (*op cit*.) distinguished between market "barriers" to efficiency, as these were described in the engineering literature, and market "failures" as defined in microeconomics: Misallocations in competitive equilibrium due to non-rivalry and/or non-excludability ("public goods" and "externalities"). Sutherland argued that only "failures," not "barriers," provided a justification for policy interventions, that the former was a much smaller set of factors than the latter. This distinction between market "barriers" and "failures" related to energy efficiency was elaborated upon by Jaffe and Stavins (1994), who emphasized informational problems as key factors in the intersection

[7] This is also granting the *ceteris paribus* aspects of the option value model in this application: Many if not most purchases of appliances and other energy-using durables are for replacement of failed equipment, and thus involve minimizing consumers' time without the energy service in question and do not have the discretionary nature assumed by the option value model.

of the two categories.[8] Narrowly, since information on energy efficiency is a public good, its predicted under-provision by the market may be reflected in consumers' purchase decisions. More broadly, asymmetric information on energy efficiency – for example between owners and occupiers of rental housing or manufacturers and purchasers of efficient appliances – might similarly result in efficiency under-investment.

The public good character of information provides a rationale for such measures as appliance energy labeling and information-based utility programs. However, as noted above, a consistent and robust finding from both research and programmatic experience is that providing information, per se, has little effect on consumers' efficiency investments.[9] But consumers and firms are not the only actors in markets for energy efficiency; manufacturers, builders, property owners, contractors, retailers, energy companies and government agencies influence decisions regarding energy-using equipment. Table 3 illustrates the categories of decision-makers that help determine information flows, transaction costs, and, ultimately, purchase decisions.

The interactions among different actors and/or market segments not only complement, but are likely to partially determine, the decision rules that individual agents use in making energy choices. Asymmetric information between owners and occupiers of rental housing is an example. More generally, consumers' choice sets, or perceived range of available technology options, are over time determined in part by the interplay among consumer preferences, manufacturers' production capabilities and costs, government regulation, and other factors. Beldock (1988) determined that there were a range of factors that influenced manufacturers to offer more energy efficient products, and anecdotal evidence indicates that information may influence product offerings, as manufacturers prefer avoiding being identified with the least efficient product. Fischer (2005) analyzed the relationship between market structure and the effects of energy efficiency standards.

The dynamics of these interactions also influence the rate at which technical innovation related to energy becomes embodied in equipment; for example, how quickly basic engineering research is transmitted to the marketplace in the form of commercially-available products. Asymmetric information may be an important element of these interactions, but there has been almost no empirical research to gauge its magnitude. A notable exception is Brechling and Smith (1994), who found an "occupancy" effect on efficiency investments in an econometric study focused on housing in the United Kingdom.

[8] The general topic of market failures and energy efficiency is also discussed by Koomey (1990), Sanstad and Howarth (1994b), and Sanstad et al. (2006).
[9] Stern and Aronson (op cit.).

Table 3. Decision-makers and actions in markets for energy efficiency

Actor	*Actions*	*Examples*
Manufacturers	Determine products to offer and influence equipment prices and operating characteristics	Size/capacity, range of efficiencies, standby power
Builders	Select initial equipment in new building	Heating and cooling systems, water heating, lighting
Property owners	May pay operating expenses; specify replacement equipment	Most end uses
Contractors	As intermediaries, select replacement equipment	Residential HVAC, water heating
Retailers	Influence product offerings and equipment prices	Appliances
Occupants	Exhibit usage behavior; pay operating expenses	Thermostat settings, leaving lights on
Energy companies	Influence energy prices; may offer incentives toward purchase of efficient equipment	Utility energy efficiency programs
Government agencies	May provide information, incentives	Labels, building codes, energy performance standards, tax credits to manufacturers and to consumers

5. REMARKS ON “PERFECT FORESIGHT” IN ENERGY MODELING

We have briefly discussed the topic of consumer foresight related to energy, and mentioned perfect foresight in intertemporal optimization models, in which an objective function such as discounted utility or cost is maximized or minimized implicitly subject to complete knowledge of all relevant future conditions. There are several reasons that this formulation is used despite a lack of supporting empirical evidence. One reason is that some models structured this way are explicitly normative and designed to identify optimal intertemporal allocations rather than realistically represent actual behavior. Others, however, implicitly or explicitly treat perfect foresight as a behavioral assumption. This, in turn, has roots in part in the theory of “rational expectations.”

However, the theory of rational expectations does *not* assert that economic agents perfectly predict the future, as is assumed in deterministic perfect foresight models. On the contrary, it posits that their errors, or mis-forecasts, will not differ systematically from actual market outcomes. The stochastic foundations of this idea are fundamental, and passage to a deterministic simplification is not straightforward. The underlying empirical rationale for the hypothesis appeals to repetition of particular types of choices, and stability of the choice environment; colloquially, one can imagine economic agents in “repeated trials” of a given optimization problem involving some random variable, all other factors held constant. The idea of rational expectations is informally that agents will, with experience, not repeatedly err in one direction. To the extent that reducing such an environment to a non-stochastic reduced form is plausible at all, such simplification requires some “steady state” assumption. By contrast, for households and many if not most commercial firms, energy-related investments tend to be infrequent, underlying circumstances dynamic, and opportunities for learning limited.

In addition, the power of the rational expectations hypothesis comes in its application to market phenomena, and particularly in the further hypothesis that markets transmit all available, relevant information (i.e., relevant to whatever choices are the object of analysis). In modeling terms, whether numerical or theoretical, one can again question whether this is an accurate reflection of energy markets. At least two deviations suggest themselves: “Efficient markets” will generally be among other things perfectly competitive, and if not actually stable with respect to exogenous factors then at least quite dynamic in processing information on changing conditions. In our view, consumer markets for energy and energy technology satisfy neither condition.

We also note that incorporating perfect foresight in the form of rational expectations in energy models requires that key long-term variables be represented accurately, particularly with respect to their stochastic properties. So long as long-term energy prices are treated as smooth trends, decisions will fail to account for the actual variability and uncertainty observed in price fluctuations. Short-term price spikes may have a disproportionately high impact on decisions about energy efficiency and energy-using behaviors. Spikes in world oil prices in 1973-1974 and 1979 were a significant driver of long-term changes in technology choice still felt today, even though oil prices declined in 1986. The California “energy crisis” of 2001 resulted in some dramatic changes, including an increase in the share of compact fluorescent lamps sold from 1% to 8% in one year, and a more than 20% decrease in electricity consumption by more than 35% of households, such that residential electricity consumption declined about 8% in one year.

We see these considerations as having several implications for NEMS given its focus on forecasting and estimation of actual market responses to policies. Any consideration of including perfect foresight systematically should be conditional on re-designing the model to fully incorporate uncertainty, which in turn would entail substantial trade-offs in resolution, tractability, and accessibility. In addition, as in the previous quote of Cowing and McFadden (1984), perfect foresight on the part of consumers or firms would if correctly implemented need to be fully integrated with the equilibrium structure and solution methods of the model.

6. RECOMMENDATIONS

Model diagnostics and forecast evaluation

The findings we have surveyed suggest a number of potential enhancements to the NEMS Residential and Commercial modules. However, given the complexity of the model and the constraints upon resources available for its enhancement and development, it is important to consider how specific changes might be ranked according to their potential contributions to improving NEMS.

Such a ranking is not possible without a framework for both defining and measuring "improvement." Ultimately, the specification of decision making by consumers and firms in NEMS as well as any changes thereto should be driven by the purposes to which the Residential and Commercial modules are applied. As stated in the model documentation (USEIA 2007a, 2007b), these purposes are three-fold: Forecasts of energy demand, analysis of potential policies, and interaction with other components of NEMS. As we understand it, EIA's recent work on developing methods for NEMS forecast evaluation and for statistical model diagnostics is aimed at developing formal, quantitative criteria for assessing the performance of these and other modules with respect to these functions (Buck and Lady, 2005; Lady 2006, 2007). We believe that these tools will provide a means of creating criteria for gauging the costs and benefits of new efforts to change, enhance, or expand model structure, data inputs, algorithms, or other features, including those having to do with decision-making by households and firms. Specifically, they can be used among other purposes for comparing *ex ante* the possible effects on model outputs and performance of improving estimates of different model parameters or inputs, and allocating resources accordingly. Put simply, parameters whose variation has little effect on model results may not warrant resources for more careful measurement.

In contrast to, for example, macroeconomic forecasting, in which forecast horizons are typically several calendar year quarters, full model forecast evaluation for long-run models such as NEMS – i.e., those with multi-decadal time horizons – poses the simple problem of being strictly speaking impossible until history has run its course over these time periods. This highlights the importance of making the fullest possible use of long-run historical information in assessing the model's full-horizon projections. Here we recommend expanding upon, to the extent possible given data limitations, EIA's existing practice of reporting in graphical form in the *Annual Energy Outlook* series the relationships between historical trends and model projections. We recommend quantitative comparisons of *joint* historical trends in major variables with their counterparts in the projections and identifying the reasons both for key departures of the latter from the former and for continuity of trends that might otherwise be expected to shift in the future, depending on the variables in question. This differs from the current forecast evaluation work in that it does not compare model predictions with actual events; it might more accurately be called forecast "credibility" analysis. We emphasize the need to conduct this type of analysis for important variables jointly rather than, or in addition to, singly, because it is of course often the case in energy markets, even the norm, that a confluence of influences determine major outcomes, for example the interactions among fuel prices, technology characteristics, energy policies, and end-use demand patterns. An example is provided in a study of Stanford University's Energy Modeling Forum, in which a quantitative decomposition of factors determining energy intensity trends was performed on a suite of numerical models (EMF 1996). Because data limitations would preclude conducting this type of analysis at the full level of disaggregation embodied in NEMS, we suggest that it be carried out at the level of aggregation needed to take advantage of EIA and other time series data.

We also believe that EIA's current forecast evaluation and model diagnosis work could be extended to improve parameter setting and calibrations involved in assigning values to hurdle rates and market shares for energy technology investments in the residential sector as well as to price and other elasticities in both modules. In the case of hurdle rates, the current method for assigning their values in several end-uses in the model combines existing information data both on these specific variables and others, functional form assumptions, and modelers' judgment. This is motivated in part by both data availability issues and the fact that the complexity of the model tends to preclude the use of conventional estimation techniques in any case. A combination of the diagnostic and evaluation methods with new data sources could result in more transparent and possibly improved methods for assigning these parameters. In the case of elasticities, it is not clear to us from the documentation how exogenous estimates from the literature are mapped into NEMS, but here again new data sources (summarized below) in conjunction with these same methods and the endogenous elasticity estimation framework discussed by Wade (2003) could yield improvements.

Demographic disaggregation

As we have discussed, there is ample evidence of heterogeneity in household energy demand-related behavior with respect to variation in socio-demographic characteristics. We recommend that the implications of unrepresented socio-demographic heterogeneity for both forecast accuracy and policy response in the Residential module be investigated, and that, if warranted by the results, approaches to incorporating key socio-demographic variables be explored. At a minimum, we recommend that the relationship between household income and hurdle rates for energy technology and efficiency investments with respect to their effects on Residential module outputs be investigated, per the next topic.

Hurdle rates

We recommend that priority be given to updating the input data on hurdle rates in both the Residential and Commercial modules. We think it likely that more recent data could be identified that would reflect shifts in markets and behavior since the estimates in the various sources currently used for NEMS inputs. Moreover, we believe that new data sources could be better targeted to the particular functional forms and decision assumptions in the modules. For example, regarding the use of hurdle rates inferred from parameters in multinomial choice models that are one source for the Residential module, Johnson et al. (1994) note that "These discount [hurdle] rates are provided mainly as an intuitive interpretation of the logit parameters and should be used with caution if transferred to other consumer choice models, such as life-cycle cost minimization models."[10] We recommend that data updating be conducted in conjunction with further analysis of the calibration methods currently employed in the Residential module for setting discount or hurdle rates and related parameters and experimentation with possible alternatives that might allow for greater flexibility and accuracy in representing observed market outcomes and responses to policies. Among other considerations, as discussed in preceding sections, there is a documented, first-order effect of household income on hurdle rates that should be accounted for. It is possible that in the case of space conditioning this effect is partially accounted for in the disaggregation and calibration by

[10] Johnson et al, *op cit*., p. 33.

U.S. Census housing data (Cymbalsky 2008), but this is a question that should be addressed empirically.

With regard to discount rates in the Commercial module, in addition to the desirability of more recent data, we noted previously that observed hurdle or discount rates of commercial firms in excess of risk-free borrowing rates – for energy technology investments and more generally – cannot necessarily be interpreted as risk premia. The implications of this distinction for Commercial module outputs may be important, and should be the object of further analysis.

Elasticities

The sources of various elasticities in the Residential module are not clear to us from the documentation (USEIA 2007b). In the case of the Commercial module, as we noted in the Introduction, the vintage of elasticity assumption reflects in part the significant slowdown in energy demand research of the past two decades. We have identified several studies that we recommend be evaluated by EIA for possible use; these provide more recent estimates than those surveyed by Dahl (1993).[11]

Poyer and Williams (1993) estimated short and long run price and income elasticities of electricity and total energy consumption by household group: Black, Hispanic, or "Majority." Espey and Espey (2004) conducted a meta-analysis of price and income elasticities regarding U.S. residential electricity demand, drawing on 36 studies published between 1971 and 2000 covering observations during the period 1947 to 1997. Kamerschen and Porter (*op cit*.) estimated both flow-adjustment and simultaneous equation models for residential electricity demand (as well as models for industrial and total demand), and reported price and income elasticities. Reiss and White (2005) estimate price elasticities of electricity demand for a sample of California households; their findings include substantial heterogeneity in household responses to price changes.

Mansur et al. (2008) estimated a national multinomial discrete-continuous econometric model of U.S. households' and firms' energy demand representing fuel choice and conditional fuel use. Their results include price elasticities including the potential effects of climate change. Denton et al. (2000) estimated a model of energy demand in the U.S. commercial sector, incorporating among other factors declining rate schedules as well as building characteristics, and yielding price elasticity estimates for electricity and natural gas.

Several other studies are of interest although they do not estimate elasticities. Long (1993) analyzed U.S. residential expenditures on energy conservation investments and renewable energy, and found household income as well as energy prices and climate conditions to be important factors. Scott et al. (2007) presented results of a detailed model of potential energy impacts of climate change on energy use by U.S. residential and commercial buildings, and the potential mitigating effects of energy efficiency programs.

[11] In addition to the studies we cite here, Madlener (1996) is an interesting methodological survey that also reviews work in other countries.

Future directions

Our discussion and recommendations have been directed toward potential improvements to the NEMS Residential and Commercial modules in essentially their current forms. In the long run, however, we anticipate that fundamental changes to the model's structure – including choice assumptions and algorithms – will be considered by EIA. In this event, research on decision-making that is currently at the frontiers of economics may have advanced to the point of applicability to numerical models. We conclude this paper with a discussion of key points.

We have noted that anomalously-high hurdle rates for energy-efficiency investments remain essentially unexplained. As argued in Sanstad (2005) and Sanstad et al. (op cit, 2006), it is clear that this is in the first instance a methodological issue. The puzzle arises from the "as if" character of both discrete-choice utility maximization models and engineering economic life-cycle cost models: Both provide an interpretation for describing outcomes, but not the processes, of consumers' investment decisions. If consumers are employing neither discounted cash-flow calculations nor decision rules based on marginal trade-offs between first costs and future returns, then there are in fact no "discount rates" to be interpreted, and the empirical pattern is an artifact.[12]

Emerging models and evidence within what is often referred to as "behavioral economics" theoretically describe and empirically document deviations from the assumptions and predictions of neoclassical theories of individual behavior.[13] In certain cases, there is qualitative consistency between such findings and evidence on consumer energy-related investments. One example is that of "non-compensatory" decision-making. The hallmark of standard microeconomics is that of trade-offs and indifference at the margin; this is the assumption underlying substitution elasticities. Alternative models have been proposed in which decision-makers instead apply some form of sequential procedure in complex choice situations. Such behavior can be described in the simplest form by lexicographic preferences; Tversky's "Elimination-By-Aspects" model is a probabilistic generalization (Tversky 1972).[14] This class of model would appear to capture underlying features of consumer energy choice that are widely if informally recognized but that have to-date not been modeled quantitatively. For example, given a choice among different models of an appliance – say, refrigerator - that has a range of features including price and energy efficiency, a consumer might first narrow her choice set to all those within a certain volume or size range, or door configuration. Within that set, all models above (or below) a certain price might be excluded, and thence such features as color, ice-making features, and energy efficiency. Such behavioral models

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[12] An important example is the use of the payback heuristic. Under appropriate assumptions, the decision criterion of "short" payback times can be shown to be observationally equivalent to the life-cycle cost model with a suitably "high" discount rate – that is, on the basis of observed behavior alone, ceteris paribus, these two behavioral rules cannot be distinguished. Their implications for understanding consumer choice and policies intended to affect it, however, are quite different.

[13] Sanstad and Howarth (1994a) discuss the hypothesis that "bounded rationality" may be a factor underlying high implicit discount rates.

[14] Tversky proposed his model as a means of addressing the so-called "independence of irrelevant alternatives" problem in models of utility.

might substantially enhance both predictive accuracy and the representation of market responses to policies.

Another class of examples pertains to intertemporal decision-making. This is one of the most active areas of behavioral economics, having amassed robust evidence regarding deviations from discounted utility theory, as well as theoretical models – drawing on cognitive psychology, among other sources – to account for observed behavior (Frederick et al. 2002). One example is an intertemporal model incorporating the concept of "loss aversion," the asymmetric weighting of gains and losses from an initial reference point, which was introduced by Kahneman and Tversky in their so-called "prospect theory" (Kahneman and Tversky 1979). Loewenstein and Prelec (1992) suggest that the energy-efficiency investment problem and the finding of high hurdle rates are consistent with the predictions of a loss aversion model, with initial investments being given asymmetrically greater weight than future savings.

Research of this kind has accelerated very rapidly in recent years, across a variety of specific market and choice applications, and there is every reason to expect that this will continue. The current state-of-the-art does not provide the types of results – including econometric or statistical – that can be robustly applied to quantitative energy modeling, and such results are not likely to be forthcoming without an investment of resources aimed specifically at energy applications. We recommend that such an investment be considered as national energy modeling evolves towards a new generation of models and methods.

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