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ABSTRACT

Consumer behaviors such as energy conservation. adoption of more efficient technologies, and fuel switching represent significant potential for greenhouse gas mitigation. Current efforts to model future energy outcomes have tended to use simplified economic assumptions to represent complex behavioral choices, based on a lack of available data. Simulation of various mitigation scenarios could be improved by better capturing the behavioral and attitudinal influences on energyrelated economic activity. Further, a better sense of how mitigation outcomes vary with con-sumer behavior will afford policymakers a clearer understanding of how to target use reduction initiatives strategically. To address these issues, we estimate a set of discrete choice models designed to capture variation in the degree to which consumers hesitate to adopt new energy-saving appliances and vehicles. Our models predict consumer purchasing behavior for HVAC systems and fuel-efficient vehicles, making use of ten years worth of detailed data collected by the U.S. Bureau of Labor Statistics Consumer Expenditure Survey from 2003-2012.

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We approximate variation in adoption probabilities based on consumer responses to changes in capital and operating costs, calculating specific levels of willingness to pay for savings through energy efficiency. These empirical results allow us to generate implicit discount, or "hurdle" rates, across a range of appliances and consumer groups. We exploit the large sample size and richness of this data set to stratify hurdle rate ranges by consumer and household characteristics such as income, education, region, and ownership status. We find that hurdle rates within narrowly defined choice sets for fuel efficient vehicles are low and exhibit minimal variation across different types of consumers. Widening the choice set to estimate the probability of adopting new technologies with more dramatic efficiency gains changes this finding. We find that hurdle rate estimates for high efficiency HVAC systems can range up to 55% from as low as 17.5% for single member households. Results are sensitive to a number of assumptions about consumer characteristics and appliance operating costs. The results from this work will feed into EPAUS9r, a regional database representation of U.S. energy system designed for us with the MARKet ALlocation (MARKAL) optimization model for further use in

developing future energy scenarios in the U.S.

Quantifying and Disaggregating Consumer Purchasing Behavior for Energy **Systems Modeling**

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INTRODUCTION

One reason for the seemingly modest pace of adoption for energy-saving technologies is that consumers vary in their evaluation of the trade-off between up-front costs and long-term savings. Understanding this behavioral variation is a priority for energy system optimization modeling and related policy initiatives. EPA's MARKAL model energy system database employs "hurdle rates" for various technology types in order to approximate "non-economic" barriers to cost-minimizing investments. Currently, the model applies a small range of hurdle rates uniformly across technologies to estimate the extent to which consumers deviate from the least cost decision framework implied by system-wide and technology specific discount rates (Lenox et al. 2013).

This analysis informs simulations of consumer purchasing behavior in MARKAL by shedding light on variation in hurdle rates across consumer strata. It provides data-driven empirical analyses of residential appliance choices, focusing on hurdle rates for different groups of residential HVAC purchasers. Discrete choice models reveal technology adoption propensities that can be considered in light of a consumer's economic utility function to generate estimates of willingness to trade off up-front expenditures for long-term savings on energy costs. These measures of willingness-to-pay (WTP) reveal implicit technology specific discount rates that approximate the minimum rate of return a consumer will accept on a new energy-efficient investment.

Our results show that the size and direction of hurdle rate estimates is not consistent across technology classes or consumer attributes. Models of consumer choice for energy efficient HVAC and window AC units reveal positive hurdle rates on the high end of ranges commonly reported in the literature. Higher levels of income and education, as well as location within regions with high electricity prices, all seem to lower the effective hurdle rate for HVAC adoption. Not all of these trends appear consistently for HVAC and window units, though higher incomes do seem to correspond to higher levels of WTP, and therefore, lower hurdle rates for all cooling technologies. Though not reported here, we also calculated hurdle rates for hybrid vehicles, modeling choice against a fuel-efficient non-hybrid alternative. These models showed that consumers in such situations appear willing to accept negative rates of return on a hybrid, leading to a hurdle rate that is, in theory, also negative.

DATA

This study makes use of detailed survey and interview data collected through the U.S. Bureau of Labor Statistics' Consumer Expenditure Survey (CES) from 2003-2012. Each year the CES collects detailed information on the complete range of household characteristics for a sample of over five thousand subjects and tracks their expenditures over five successive quarters. The survey was designed to study the expenditure patterns of specific groups of consumers and is well suited to the task of disaggregation of behavioral measures related to the consumption of energy.

| Study | Date | Hurdle Rate Estimate | Device | Citations Received |
|---------------------------------------|------|----------------------------|--|-----------------------|
| Hausman (1979) | 1979 | 0.25 | Space Cooling (A/C units) | 895 |
| Gately (1980) | 1980 | .45 - 3.00 | Refrigerators | 178 |
| Beggs, Cardell, and Hausman (1981) | 1981 | .2836 | Vehicles | 484 |
| Hasset and Metcalf (1994) | 1994 | 0.068 | "Energy-saving capital" | 195 |
| Sanstad et al. (1995) | 1995 | .06644 | "Energy-saving capital" | 88 |
| Revelt and Train (1998) | 1998 | 0.39 | Refrigerators | 1014 |
| Harrison et al. (2002) | 2002 | 0.28 | General subjective time preference | 509 |
| Ansar and Sparks (2008) | 2008 | 0.59 | PV Systems | 26 |
| Axsen et al. (2009) | 2009 | 0.213 | Vehicles | 68 |
| Gallagher and Muehlegger (2011) | 2011 | 0.146 | Hybrid Vehicles | 107 |
| EMP | PIRI | CAL | MODEL | |

SUMMARY OF PREVIOUS FINDINGS

The logit model procedures developed in Train and Croissant (2013), were used to compute cost coefficients to calculate how much of a price increase a consumer will tolerate to reduce annual operating expenses by one dollar. For instance, the base model in the table below finds the ratio of cost to price coefficients to be about 2.45, meaning that the consumer is willing to pay \$2.45 in installation costs in order to save one dollar in annual operating expenses. This value is obtained simply by computing the ratio of θ_c to θ_p in Equation (2), which represents the general form of the utility function in equation 1 after subtracting an error term for a consumer, *n*, facing technology choices, *i*, with prices, *p* and operating costs, c. If z is a vector of observed characteristics of the choice and choice maker, then the simple form of the probability model used to predict adoption of technology i over all other choices, *i*, may be represented in equation (3). This is the logit model of binary choice where the outcome, Y, is the decision to adopt the energy-efficient alternative, *i*. Equation (4) gives us a discount factor, ρ , that can be used to estimate the implicit discount, or hurdle rate using equation (5).

> 1) $U_{ni} = V_{ni} + e_{ni}$ 2) $V_{pi} = \theta_p p_i + \theta_c c_i + \beta z_{i-p}$ 3) $Pr[Y_n=i] = e^V_{ni} / [\Sigma_i e^V_{ni}]$ 4) $\theta_c / \theta_p = \rho[(1 - \rho^L) / (1 - \rho)]$ 5) $\rho = 1/(1+r)$

RESULTS

| HVAC Selection Mo Probability of adop | | nt HVAC syst | em (SEER 14-1 | 5) among alt | ernatives | |
|--|------------------------|------------------------|--------------------------------|------------------------|------------------------|------------------------|
| | Base Model | Family size < 4 | Single member households | No College | College | High income |
| LOGISTIC REGRES | SION RESULT | ŝ | | | | |
| capitalcost | -0.00104*** (-8.02) | -0.00108*** (-6.98) | -0.00160*** (-3.98) | -0.00091*** (-5.28) | -0.00105*** (-4.78) | -0.00087*** (-3.48) |
| operating cost (estimated) | -0.00255* | -0.00201 | -0.00782 | -0.00272 | -0.00307 | -0.00265 |
| | (-2.23) | (-1.46) | (-1.69) | (-1.65) | (-1.58) | (-1.13) |
| Constant | 2.506*** -6.01 | 2.486*** -5.17 | 4.375*** -3.58 | 2.213*** -4.13 | 2.384** -3.17 | 0.224 -0.22 |
| Observations | 514 | 377 | 92 | 262 | 196 | 111 |
| WTP Cost Ratio hurdle rate - r | 2.451 0.401 | 1.861 | 4.888 | 2.969 | 2.923 | 3.032 0.318 |

RESULTS

| officiency unit | nits – meaium 's | -to-nign | | | | |
|------------------------------|---------------------|-------------------|-------------|-------------------------|-----------------|------------|
| | | | | | | |
| | | | | | | |
| | -1 | -2 | -3 | -4 | -5 | -6 |
| | Base Model | Income> 30,000 | Large house | Fewer than six rooms | Under age 60 | Over 60 |
| ni efficiency | | _ | _ | _ | _ | |
| apital cost | -0.00374*** | -0.00300* | -0.00490* | -0.00243 | -0.00152 | -0.0147*** |
| | (-3.41) | (-2.23) | (-2.44) | (-1.56) | (-1.23) | (-4.57) |
| | | | | | | |
| operating cost estimated) | -0.00268* | -0.00349** | -0.00400* | -0.00282 | -0.00254* | -0.00396 |
| | (-2.57) | (-2.68) | (-2.03) | (-1.89) | (-2.03) | (-1.65) |
| | | | | | | |
| Constant | 1.223*** | 1.083** | 1.715*** | 0.997* | 0.777* | 3.265*** |
| | -4.44 | -2.86 | -3.37 | -2.5 | -2.18 | -4.18 |
| Observations | 756 | 549 | 221 | 383 | 605 | 148 |
| | | | | | | |
| | | | | | | |
| VTP Cost Ratio | 0.717 | 1.163 | 0.816 | 1.160 | 1.671 | 0.269 |
| nurdle rate - r | 1.398 | 0.859 | 1.226 | 0.862 | 0.596 | 3.717 |
| | | | | | | |
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CONCLUSIONS/DISCUSSION

- · wide range of hurdle rate findings across consumer types, as well as the three technology families
- many of the results of our models confirm some of the general trends in the empirical literature
- base model HVAC estimate of 40% is within the range of established estimates Hausman's (1979) stratification of income levels that revealed hurdle rates from 5.1 - 89%, and Wilkerson et al.'s (2012) 15-42%
- higher income and education groups demonstrate slightly lower hurdle rates near 30%, a significant drop from the base model
- interestingly, we see significant departures from the base estimate for single member households (17.5%) and small families (53.6%)
- regions facing high energy prices appear to have lower hurdle rates though this could be due to a number of additional factors that we are unable to observe.
- results for hybrid vehicles revealed negative hurdle rates and are not presented here
- several assumptions about our sample that hinder the level of certainty we can apply to these results.
- findings provide a basis for concrete adaptations to the behavioral components of modeling platforms such as MARKAL by informing disaggregation of hurdle rates on the basis of consumer characteristics

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