A Multi-Agent, Multi-Attribute Policy Model for Analyzing the Adoption of Energy Efficiency Technologies

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ABSTRACT

Understanding and modeling the complexities of technology adoption decisions by consumers and firms is vital for designing and implementing effective policies to promote the diffusion of energy efficiency, renewables, and other environmentally-friendly technologies. Such decisions are a function of a range of factors that may influence economic agents' evaluations of costs and benefits, including information regarding technology characteristics, evaluation of potential co-benefits, and the influence of government policies. Moreover, differences among agents' decision rules can have a significant impact on the market outcomes of technology adoption. Such factors, however, are typically omitted in simulation models based on the assumptions of representative agents, cost minimization under perfect information, and competitive market equilibrium.

This paper applies a heuristic model of technology adoption in which a heterogeneous population of agents makes decisions regarding electricity supply or energy efficiency technologies subject to distributions of characteristics and decision rules influencing individual cost-benefit calculations. We show that this approach can provide an enhanced understanding of the policy-relevant complexities of technology adoption.

Introduction

Understanding the factors influencing consumers' and firms' adoption decisions regarding energy efficient or greenhouse-gas reducing technology is essential for designing effective and efficient energy and climate policies. In one view, these decisions can be taken *prima facie* to be socially optimal – given a set of available technologies – provided that environmental externalities are reflected in prices for energy services. This assumption has several policy consequences: First, of course, the price mechanism becomes the primary or sole lever to influence adoption decisions. Second, current adoption decisions are assumed to be optimal, given current prices, so that technology policy should be focused on long-term, "revolutionary" breakthroughs to lower adoption costs some time in the future. Indeed, this view is commonly embodied in energy-economic and integrated assessment models for many of the energy and carbon policy studies now underway. These models characteristically incorporate the behavioral assumption of cost-minimization subject to perfect information, most often at a high level of aggregation. Moreover, competitive equilibrium is the almost universal assumption in such models, so that private and social costs and benefits are presumed to coincide, subject only to pricing of externalities. (Note: for a critique of the standard modeling paradigm, see DeCanio 2003 and Laitner et al. 2000).

In addition to masking potentially important heterogeneities among decision-makers, however, these assumptions capture imperfectly or not at all a number of empirically observed phenomena that are relevant to understanding technology adoption decisions and thus to policy development and evaluation. Examples include the failure of consumers and businesses to adopt profitable energy-saving innovations, the apparent ability of some businesses to transform environmental technology investments into a competitive advantage, and the seemingly unexpected success of wind energy technologies. Such phenomena illustrate the influence on technology adoption decisions of factors including information diffusion, co-benefits attending to technology investments, and policies to accelerate adoption in cases where a compelling social justification exists. Such phenomena, and their importance for policy, indicate the value of modeling approaches that can represent a richer array of both behavioral assumptions and factors affecting the wider impacts of individual decisions.

This paper provides an example of such an approach, specifically, illustrating how a multi-agent, multi-attribute modeling perspective can exhibit the kinds of multi-factor influences that characterize technology diffusion in the real world. This, in turn, may highlight the opportunities and non-pricing policies that encourage or accelerate the adoption of energy efficiency technologies. Although computationally simpler, our analysis is in the spirit of "agent-based computational modeling," which is aimed at analyzing and understanding how observed properties of the economy emerge from the micro-level interactions among agents, without resorting to "…externally imposed coordination devices such as fixed decision rules, common knowledge assumptions, representative agents, and market equilibrium constraints" (Tesfatsion 2003). Agent-based models are seeing increasing use within the energy policy arena (DeCanio & Laitner 2003; Lempert 2003; and Roop & Fathelrahman 2003). Compared to more traditional representative agent models, agent-based models can better represent the effects of imperfect information and bounded rationality as well as providing means for analyzing the behavior of heterogeneous populations with different information, preferences, and capabilities

In this study we explore how factors such as improved information and awareness can influence individual agents' adoption decisions, and thus the distribution of technology market shares. We extend a heuristic spreadsheet model of technology diffusion previously employed to analyze the effects of learning-by-doing (Laitner & Sanstad 2004) as a means to assess the influence of information and greater awareness of new technologies and their associated costs and benefits.

Our analysis serves to illustrate some of the complexities of real-world technology adoption that tend to be omitted in standard simulation models. In some ways, the finding of our heuristic exercise may be intuitively obvious – that is, opening up policy models to reflect a greater heterogeneity among both consumers and technologies is likely to produce a different result than models which rely largely on the price signal to drive technology market shares. Yet, there are times when the obvious needs to be more fully explored so that modeling biases can be corrected. It is in that spirit that we explore the impact of a multi-agent, multi-attribute modeling perspective in the discussion that follows.

A Spreadsheet Model of Electricity Technologies and Choices

Our analysis is based on the widely-used life-cycle cost model of technology adoption, in which agents' adoption decisions are a function of capital costs and the present value of operating costs. However, we depart in two ways from the conventional use of the life-cycle cost model. First, rather than employ a representative or average agent to represent the consumer or the firm, we explicitly model a population of agents with distributions of different characteristics that affect technology choices. Second, we treat the discount or hurdle rate in the life-cycle cost calculation as an index representing factors that increase or decrease individual agents' propensity for technology adoption. Specifically, in our model we represent 100 different consumers who choose among four technologies (described below), given a random distribution of characteristics that impact their decisions regarding the purchase of technologies for obtaining energy services from electricity, either through electricity supply technologies or through energy-efficiency investment. In effect, each consumer sees four technologies and their associated costs, and is influenced (or not) by four additional information variables (in addition to normal cost information) that impact their choice. Finally, we assume that each of our agents or consumers assign different weights to the total of the five influences that impact technology choice.

In order to explore the role of information or behavioral attributes in choosing from among the mix of electricity technologies, we follow Manne and Richels (2002) and suppose that there are four aggregate sets of technologies to meet both existing and new electricity demands. One important distinction is that in addition to the mix of electricity generation resources reflected in Manne and Richels, our model also incorporates energy efficiency technologies that compete with the supply side generation systems.

1. ***Defender Technology***. This technology is the same as the existing aggregate capital stock used to generate electricity. In short, it is an aggregate representation of existing coal-fired units, natural gas combined cycle combustion turbines, nuclear power, and conventional hydropower. Hence, the defender technology reflects average costs and environmental impacts of electric generating stations.

2. ***Challenger Technology***. The challenger technology, generally reflecting the entrance of advanced power supply technology, initially shows higher costs but is also assumed to benefit from lower heat rates as well as improved environmental performance and non-energy benefits. The latter include benefits that range from increased system reliability, positive impacts on fuel prices as a result of improved heat rates, and enhanced national security benefits as a result of a more decentralized deployment.

3. ***Renewables Challenger***. This is an aggregate of renewable energy technology including wind energy and photovoltaic systems. While they are subject to higher initial capital costs, they also benefit from improved environmental performance and non-energy benefits.

4. ***Demand-Side Efficiency Investments***. This aggregate of end-use technologies will impact reference case demand for electricity. Hence, they can greatly affect the market share for the three supply-side technologies. While the reference case demand-side technologies are assumed to cost less than the busbar cost of existing capital stock and Defender Technologies — penetrating as part of the normal reduction in electric intensity of the economy, these additional demand-side efficiency technologies are assumed to have initial costs similar to the Challenger Technologies. At the same time, they also have potentially higher environmental performance and non-energy benefits compared to the other technologies.

Simultaneously, we incorporate five implicit decision rules which influence an agent's perception of technology costs and, in turn, guide its decision regarding technology adoption.

These decision rules include the usual capital and operating costs of a given technology, but they also expand the range of cost information to reference other attributes that might affect a decision to adopt. These rules include:

1. The conventional life-cycle cost under imperfect information which translates into an amortized cost per kilowatt-hour (kWh).

2. Life-cycle cost with enhanced information or "awareness" of technology characteristics, costs, and performance. Such awareness is translated as reduced search and/or transaction costs per kWh.

3. Life-cycle cost incorporating information on non-energy benefits per kWh. This includes such items as greater system reliability, savings of operating and maintenance expenses, and increased safety.

4. Life-cycle cost influenced by knowledge of other agents' adoption of the technology. By seeing others actually adopt a technology, or by seeing more demonstration projects associated with a given technology, it might be seen as less risky. This, in turn, reduces the expected return to capital investment which further lowers the cost per kWh.

5. Finally, life-cycle cost incorporating benefits from policies to internalize externality costs. Such policies might reflect a tradable emissions regime within a large company, or the new technologies might reduce traditional pollution control costs in addition to saving on energy costs. A change in consumer preferences for technologies that benefit the environment might increase market share beyond normal market penetration which can lower unit production costs. Moreover, the new technologies might also return goodwill or institutional benefits in ways that also lower marketing and other costs.

Further details and cost characteristics of these technologies, reflected in an equivalent cost per kilowatt-hour (kWh) are provided in Table 1 below.

Table 1. Illustrative Values of Cost Parameters ($/kWh)

	1 **Cost**	2 **Awareness**	3 **Benefits**	4 **See Others**	5 **Externalities**
Defender	0.040	0	0	0	0
Challenger	0.060	0.002	0.004	0.002	0.004
Renewables	0.080	0.008	0.015	0.008	0.008
Efficiency	0.060	0.004	0.012	0.004	0.010
Lower Weight	80	60	40	40	20
Upper Weight	100	100	80	80	80

As shown in the above table, we assume that our agents choose among these technologies in order to minimize cost, but that the cost as assessed by the agents may be a function of the factors or attributes listed above. To maintain consistency in reporting, the impacts of all decision variables are reported as equivalent cost reductions. Thus, if all decisions were made using life-cycle cost with imperfect information, the significantly lower cost of the defender technology would make it the overwhelming choice as suggested in column one.

Moving to Column 2, greater information regarding, or awareness of, a technology can reduce the perceived cost necessary to encourage adoption by reducing the implicit discount rate. This might have the effect of reducing transaction or search costs as noted in the rules described above. Greater productivity and safety benefits might lower the cost at levels amounts consistent with the values in Column 3.

Greater awareness of technology adoption by one's peers may inspire greater confidence in the viability of an emergent technology. This is suggested in Column 4. For example, if a consumer currently evaluates a technology using a 30 percent discount rate, a greater awareness or familiarity with a new technology might increase confidence in the reliability of that technology. In effect, the greater familiarity might lower the perceived risk such that the consumer might now evaluate the technology using a 27.5 or a 25 percent discount rate. This would reduce the evaluated cost by about 0.4 or 0.8 cents, respectively. Finally, environmental externalities – incorporated through any number of mechanisms described in the decision rules referenced above – might contribute further cost reductions consistent with the values shown in Column 5.

Given different values associated with the decision criteria, each of the decision variables is randomly assigned a range of weights that impacts an agent's decision to adopt a given technology. For example, the conventional cost variable might be assigned a weight ranging from 80 to 100 while externalities might be assigned a much wider range from 20 to 80. The lower the weight, the lower the impact on net cost. Conversely, the higher the weight, the larger the variable impact.

Consistent with Laitner and Sanstad (2004), we assume new technologies are introduced using a Market Share algorithm[1] as a function of annualized net costs per kWh:

$$MS_k = \frac{NetCost_k^{-v}}{\sum_{k=1}^{J} NetCost_k^{-v}} \qquad \text{(Eq. 1)}$$

where:

MS_k = market share of technology k
$NetCost_k$ = amortized capital and operating costs of technology k less the impact of the other decision variables to the extent that they influence the initial cost.
v = variance parameter representing cost homogeneity
J = technologies competing to provide the same service as k.

The function MS_k is a logistic curve whose slope is determined by a variance parameter, v, a measure of product substitutability not captured by the other characteristics. Low values would indicate that the products are almost perfect substitutes. An extremely low value for v, such as 1, means that new equipment market shares are distributed almost evenly among all competing technologies, even if their annual costs differ significantly. An extremely high value (such as 100) means that technology with the lowest cost captures almost all of the new equipment stocks, as would occur with a linear programming model. A lower intermediate value, such as 10, means that the most cost-effective equipment gains a proportionately higher

[1]This algorithm is a standard logistic curve used in a variety of existing modeling systems including the CIMS, AMIGA, and MARKAL models.

market share. For example, a technology with a 25 percent cost advantage would grab 90 percent of market share. In this exercise, we adopt a value of 4. In this case, a technology with a 25 percent cost advantage would grab 71 percent of the market share.

Numerical Results

With the model in place, we can now explore the impact of a "cost-only" perspective and how it begins to evolve as different categories of information begin to cumulatively affect the multi-agent model. Table 2 summarizes key results from a typical set of runs. If we rely only on the cost comparison in column 1, the Defender technology generates a 68.6% market share of new capital stock. The Challenger technology picks up 13.6 percent market share while Renewables and Efficiency garner 4.3 and 13.6 percent, respectively. This pattern becomes the basis for comparing the evolution of market share as more and more influences are allowed to cumulatively impact technology choice.

If we retain the same cost data as shown in table 1, column 1, but now allow greater awareness as defined in table 1, column 2 to also impact the solution, the dominance of the Defender technology declines slightly – dropping to a 63.8 percent market share. As might be expected, the three other technologies gain in the overall market. Similarly, as non-energy benefits are allowed to enter the calculations (characterized in Table 1, column 3), the Defender technology shows a more pronounced reduction in market share (Table 2, column 3). Again, the other three technologies increase market penetration.

Next, we allow the agents to actively "see others" installing and using the emerging technologies (with values defined in Table 1, column 4), the market shares again move in favor of the new technologies (shown in Table 2, column). Interestingly, the Defender technology continues to see a decline in market share, but in this case, the Challenger technology also loses market share compared to the run summarized in Table 2, column 3. Finally, adding information about the value of externalities (Table 1, column 5) into the calculations produces another large shift in market. While the Challenger and Renewable Technologies maintain their approximate pattern in Column 4, the Defender technology loses another 10 percentage points in market share with efficiency picking up that same 10 percentage points.

Table 2. Representative Market Shares

	1	**2**	**3**	**5**	**5**
	Cost	**Awareness**	**Benefits**	**See Others**	**Externalities**
Defender	68.6%	63.8%	51.6%	46.4%	36.5%
Challenger	13.6%	14.2%	14.1%	13.9%	12.9%
Renewables	4.3%	5.8%	9.0%	11.5%	12.4%
Efficiency	13.6%	16.1%	25.3%	28.2%	38.2%

Note: With each column summing to 100 percent, this table illustrates the changing technology market share as a function of the cumulative influence of multiple attributes (moving from left to right) which impact an agent's decision to adopt a given technology.

We also examined the impact of different assumptions with respect to initial costs, the spread of weights, the values associated with the different agent attributes, and the variance parameter in the market share algorithm. Although the specific outcomes obviously differed in each of the sensitivity run, in each case the impact of new information and the greater awareness of efficiency and renewable energy technologies significantly affected the overall market share with each of the scenarios. Hence, the conclusion remains that any meaningful estimation of technology market share should include the influence of information and behavioral attributes. Perhaps more to the point, a modeling exercise that examines future energy policies should also provide a means to reflect the impact of information programs and demonstration projects as well as other voluntary initiatives within the overall results.

Discussion and Policy Implications

If every consumer or firm shared the same characteristics and confronted the same set of choices, simulation or policy models might easily evaluate the adoption of emerging technologies based either on costs or price signals. Although most policy analysts and modelers acknowledge the existence of heterogeneity among decision agents and the mix of technologies available within the market, most treat consumers, firms, and technologies "as if" they shared similar characteristics. As our modeling exercise suggests, however, this assumption introduces an important bias that limits the ability of policy makers to explore program innovations beyond the price signal.

Although we apply a useful but simple algorithm that relates both cost and information attributes directly to the evaluation of technology market shares, it is important to note that this is a reduced form for a much richer and more complicated set of phenomena. Including information attributes in the evaluation of technology penetration captures, at least in a simple way, some of this richness in behavior that might greatly impact technological change and diffusion. Our results point to the need for further theoretical and empirical model development as it relates to both behavior and technological change, and the absorption of these new results into the policy process.

Acknowledgements

Mr. Sanstad's participation in this modeling exercise was supported by the Office of Atmospheric Programs of the U. S. Environmental Protection Agency and prepared for the U. S. Department of Energy under Contract No. DE-AC03-76SF00098. The opinions expressed in this article do not necessarily reflect those of the U.S. Environmental Protection Agency or Department of Energy. All errors and misuse of statistics remain the sole responsibility of the authors.

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