ENERGY

Behavior and Energy Policy

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Investment in scalable, non–price-based behavioral interventions and research may prove valuable in improving energy efficiency.

Many countries devote substantial public resources to research and development (R&D) for energy-efficient technologies. Energy efficiency, however, depends on both these technologies and the choices of the user. Policies to affect these choices focus on price changes (e.g., subsidies for energy-efficient goods) and information disclosure (e.g., mandated energy-use labels on appliances and autos). We argue that a broader approach is merited, one that draws on insights from the behavioral sciences. Just as we use R&D to develop "hard science" into useful technological solutions, a similar process can be used to develop basic behavioral science into large-scale business and policy innovations. Cost-effectiveness can be rigorously measured using scientific field-testing. Recent examples of scaling behaviorally informed R&D into large energy conservation programs suggest that this could have very high returns.

Behavioral Research in Energy Efficiency

The focus on price and information derives from traditional economic models of rational choice. Behavioral research, however, suggests a more complex, less idealized, view. People procrastinate; attention wanders. Peripheral factors subconsciously influence perceptions and decisions. These behavioral tendencies influence real-world outcomes and can inform interventions. For example, we often resist actions with clear long-term benefits if they are unpleasant in the short run. Programs that allow people to commit in advance to such actions—e.g., saving money or exercising—have proven quite popular, even when that commitment is costly (*1*, *2*). Default ("no-action") options strongly influence choices [e.g., when choosing between 401(k) plans], even when an alternative option is markedly better and switching appears easy (*3*, *4*). Small changes in context ("nudges") can affect behavior as much as large price changes (*5*). Such findings are striking in a cost-benefit framework; psychological cues typically cost very little compared with price changes.

In terms of energy efficiency, many studies suggest that people fail to adopt existing technologies that would save them money by using less energy, such as better insulation, fuel-efficient vehicles, and efficient appliances and lighting (*6*). For example, a recent consulting report concluded that many households and businesses in the United States have yet to take such relatively straightforward measures, even though doing so could reduce energy consumption by 23% from baseline and, thus, earn $1.2 trillion at an up-front cost of $520 billion (*7*). Although there are multiple explanations for this finding (*8*) and more evidence is needed, some barriers may be behavioral.

This suggests a potential role for non–price-based, behavioral interventions. Many such ideas have been studied in a large body of ongoing research on social approval, consumption feedback, goal setting, commitment, and other mechanisms (*9*, *10*). Although many of these were small-scale, short-term pilot studies on nonrepresentative populations, they do show proof of concept (*11*).

Recent work by a company called OPOWER, informed by academic work showing the power of social comparisons in environmental conservation (*12*), suggests that behavioral programs can be cost-effectively scaled to millions of households. OPOWER sends home energy-use reports to electricity and gas consumers that display the household's energy consumption, compare it with that of similar households, and provide energy conservation tips. Using randomized, controlled trials with hundreds of thousands of utility customers across the United States, these reports have been shown to reduce electricity consumption in the average household by over 2% (*13*).

As shown in the table, right, an OPOWER-like program costs an electric utility 2.5¢ per kilowatt-hour (¢/kWh) saved (*14*). This compares favorably with estimates of the average cost of other energy-efficiency programs, which in two recent studies range from 1.6¢ to 3.3¢ (*15*) and 5.5¢ to 6.4¢/kWh (*16*). If scaled nationwide, a program like this could reduce U.S. carbon dioxide (CO_2) emissions from electric power by 0.5%, while actually saving $165 per metric ton of reductions. This compares very favorably with other, more traditional strategies to reduce carbon emissions; wind power, carbon capture, and storage added to new coal power plants, and plug-in hybrid vehicles are estimated to cost $20, $44, and $15 per metric ton of CO_2 abated (*17*). The table shows that a comparable intervention scaled across the United States would net $2.2 billion per year over the program's life.

Systematically Structuring Interventions

Although laboratory studies and small-scale pilots demonstrate academic insights and proofs-of-concept, scalable behavioral interventions require in situ testing. OPOWER illustrates this: It would be difficult to predict the effects without randomized, controlled field trials in a representative population. Fortunately, randomized field experiments have become increasingly feasible. Large-scale social science field experiments began 40 years ago and are now used by businesses (*18*), governments, development agencies, electric utilities (*19*), and other organizations

COSTS AND BENEFITS OF BEHAVIORAL INTERVENTIONS IN THE UNITED STATES*

Cost-effectiveness of behavioral program	
Reduction in electricity consumption (%)	2.7
Average household electricity consumption (kWh/year)	11,232
Savings (kWh/household-year)	305
Program cost to the utility ($/household-year)	$7.48
Cost effectiveness (¢/kWh)	2.5
Comparison: other efficiency programs (¢/kWh)	1.6–6.4
Cost per ton of carbon abatement	
Long-run marginal cost of electricity (¢/kWh)	8.0
Net savings from behavioral program (¢/kWh)	5.5
Marginal carbon intensity (metric tons/MWh)	0.34
Carbon abatement cost ($/metric ton CO_2)	–$165
Comparison: Wind, carbon capture, hybrids	$20, $44, $15
Value of a comparable intervention, scaled across entire U.S.A.	
Annual carbon abatement (MMT CO_2/year)	12.7
Assumed value of CO_2 reduction ($/metric ton)	$10
Total value of CO_2 reduction (millions of $/year)	$127
Value of electricity saved (millions of $/year)	$3,020
Total cost to the utility (millions of $/year)	$927
Net value of intervention (millions of $/year)	$2,220

* See supporting online material for data sources and analysis details.

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in the United States and around the world (*20*). In our own work testing behaviorally informed interventions, we have seen how the long-understood insight of randomization can be made practical. Useful techniques include randomizing letter content across groups, encouragement designs that simultaneously evaluate program marketing and the program itself, and phased implementation (*21*). In some settings, outcomes can be measured with little additional cost; utilities, for example, already record their customers' energy consumption. In the OPOWER example, it is straightforward to send letters to a study group and not to a group of controls, and effects are measured simply by comparing the two groups' electricity bills.

Careful design must ensure external validity: that estimated treatment effects apply beyond the experimental sample. Dynamic electricity-pricing experiments in France and the United States illustrate this. Randomization over representative samples (*22*), rather than those who express interest in a program, (*23*, *24*) is essential, because the interested are likely more motivated and engaged and, therefore, have different treatment effects. Similar electricity-pricing experiments have been carried out in different geographic areas, informing whether results from one program can generalize to others.

As in other R&D processes, behavioral experiments benefit from iterative design, testing, and refinement, which suggests long-term partnerships between researchers and implementing businesses (*25*). Of course, randomized field trials are only one tool; other approaches, such as laboratory experiments and qualitative interviews, are invaluable in the iterative design of behavioral interventions.

Policy Implications

Our argument has three key policy implications. First, governments can provide funding for potentially high-impact behavioral programs as part of their broader support for energy innovation. A bill under consideration in the U.S. House of Representatives, HR 3247, would establish a program at the Department of Energy to understand behavioral factors that influence energy conservation and speed the adoption of promising initiatives.

Criteria for funding such behavioral research should be similar to those used for allocating resources to engineering and "hard-science" research. In those domains, promising technologies are theory-driven; similarly, successful behavioral interventions have typically drawn on existing theoretical and empirical work. Behavioral interventions should also have clearly measurable outcomes; projects should include careful testing protocols, including randomized field trials when possible. Perhaps most important, promising interventions must be scalable; although basic behavioral science questions and theoretical nuances are also important, here we are advocating for ideas that have large effects on energy consumption and can cost-effectively be scaled to millions of consumers. As such, R&D that brings together scientific knowledge and industry testing and scaling capacity can be particularly powerful.

Second, through market incentives, policy-makers can encourage—or fail to encourage—private-sector firms to generate and utilize behavioral innovations that "nudge" consumers to make better choices. Historically, economists and policy-makers have focused on how regulation affects relative prices—for example, how emissions caps or taxes on pollution-intensive goods affect the prices firms set. In practice, however, firms interact with consumers in many ways in addition to pricing. Utilities, for example, can give consumers clear or opaque information about energy-efficient goods, can make it easy or difficult to find out about energy-efficiency promotions, and can otherwise nudge consumers in ways that cause them either to increase or decrease consumption. Regulatory changes such as "decoupling," which separate electricity retailers' profits from quantities sold, are one mechanism that could encourage firms to nudge consumers toward reducing energy use (*26*).

Third, government agencies often provide independent information disclosure, such as vehicle and appliance energy-efficiency ratings. This helps catalyze private-sector innovation by allowing firms to credibly convey the financial value of energy efficiency to consumers. The effect of information on choices, however, depends critically on how the information is conveyed, and government agencies should carefully consider behavioral factors in the disclosures they control. For example, rating fuel economy in miles per gallon (MPG) can mislead consumers; most people approach MPG as a linear indicator of the cost of fueling a vehicle, whereas, in reality, annual fuel costs will scale nonlinearly in MPG (*27*).

Nuanced research into human behavior and energy-use decisions is not new, nor is the idea that energy efficiency may be generally cost-effective. What has been missing is a concerted effort by researchers, policy-makers, and businesses to do the "engineering" work of translating behavioral science insights into scaled interventions, moving continuously from the laboratory to the field to practice. It appears that such an effort would have high economic returns.

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