The Multiplier Effect: How the Priming Effect Increases the Effectiveness of Behavioral Efficiency Programs

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ABSTRACT

Conventional wisdom suggests that spending on energy efficiency follows the law of diminishing returns, where the lowest-hanging fruit would deliver the greatest and cheapest savings while the marginal effectiveness of each subsequent dollar spent would decrease. Following this principle, one would expect behavioral programs to be less effective in states that spend more on energy efficiency programs. However, there is an opposing view that layering behavior programs on top of existing measures could result in more effective savings. The hypothesis is that priming the market through spending on institutionalized energy efficiency can improve results from behavioral energy efficiency programs.

This paper explores the relationship between historic energy efficiency spending and results from behavioral energy efficiency programs. By comparing the results of 152 behavioral energy efficiency programs with varied levels of energy efficiency spending and ACEEE state scorecard rankings, this paper applies a regression analysis to demonstrate that the priming effect has on the efficacy of behavioral energy efficiency programs. Our results indicate that if energy efficiency spend increased one standard deviation from today's average, the efficacy of behavioral efficiency programs would rise by approximately 10%. In addition to presenting this finding, we discuss several theories as to what mechanisms may be pushing this relationship.

The results explained herein could have a significant impact on both the size and composition of energy efficiency portfolios going forward. Since priming demonstrates a multiplier effect on the impact of behavioral programs, portfolios managers should consider this increased potential when designing plans to reach their efficiency goals.

Background

Conventional wisdom suggests that spending on energy efficiency follows the law of diminishing returns, where the lowest-hanging fruit would deliver the greatest and cheapest savings while the marginal effectiveness of each subsequent dollar spent would decrease. This theory is supported by data from the Edison Foundation's Institute for Electric Efficiency (IEE 2011; IEE 2012), which has noted that the average cost of ratepayer-funded electric efficiency programs has risen from 4.0 cents per kilowatt-hour (kWh) in 2008 to 4.3 cents per kWh in 2010, presumably as portfolios have needed to include less cost-effective programs in order to meet their efficiency targets. Lisa Wood, IEE's executive director, commented on this trend by noting that the cost of energy efficiency is "not going to get better over time – it's going to get harder" (St. John, 2012).

However, there is an opposing perspective that presumes that increased funding may have a priming effect that would ultimately result in more effective uptake of energy efficiency measures. Just as Meyer and Schvaneveldt's psychology study in 1971 (Meyer and Schvaneveldt 1971) found that people were able to more quickly identify strings of letters as words when pairs of commonly associated words were used together, utility consumers may be more likely to take energy-efficient actions after they are sufficiently exposed to the increase in energy efficiency programs, marketing, and general awareness associated with increased expenditures.

In order to assume that EE spend per capita can be used as a proxy for priming, we must first establish that we believe that whatever relationship exists between this variable and behavioral energy savings is causal and not simply a manifestation of correlation of both spend and savings with some third variable. The most likely counter-explanation would be that the attitude of people within a state drives both state spend on energy efficiency and savings rates within that state. We do not perform a detailed analysis of the former, but documentation of spend on energy efficiency cites many factors that affect the level of spend outside of “attitude,” including total utility revenues within that state, makeup of energy end use in that state, and the structure of the state’s utility system (Barbose, et al. 2013; Arimura, et al. 2012; MPSC 2011). This combats the possibility that attitudes are primary drivers of state energy efficiency spend and thus allows us to assume that spend is an exogenous variable.

We set out to investigate how the countervailing forces of diminishing returns and market priming impacted behavioral energy efficiency measures. If forces of diminishing returns were stronger, we would expect to find the overall performance of behavioral programs to be inversely correlated with the level of funding in that state since there would be less “low-hanging fruit” for these programs to capture. Conversely, if forces of market priming were stronger, we would expect to find a direct correlation between the performance of behavioral programs and the level of funding in a state due to the population being better conditioned to act upon the insights provided in the efficiency programs.

An investigation into the role of efficiency spending as a market priming mechanism is an important first step into a body of research that could ultimately help efficiency portfolio managers maximize the performance of their programs through a better understanding of the maturity of the efficiency landscape within their service territory. Maximizing the benefit of this dynamic could have a significant impact on both the size and composition of energy efficiency portfolios going forward.

Method

To better understand the relationship between relative energy efficiency spending and the marginal effectiveness of behavioral energy efficiency programs, we investigated the relative effectiveness of Opower Home Energy Report programs within and across various states. We specified an ordinary least squares model that regresses percent savings estimates on a set of predictive factors, and we will focus on the impact attributed to per capita state energy efficiency spend by state (Eldridge, et al. 2009; Molina, et al. 2010; Sciortino, et al. 2011; Foster, et al. 2012; Downs, et al. 2013), which we consider representative of priming the market for energy efficiency. The savings estimates are monthly measurements collected over 5 ½ years (2008 - 2014) from 152 behavioral energy efficiency experiments in the form of Opower Home Energy Reports. These experiments were run at 71 utilities in 25 different states. Opower experiments are randomized controlled trials that yield measured savings estimates rather than deemed savings numbers. A plot of per capita energy efficiency spend by state vs. average annual percent savings can be found in Figure 1 below.

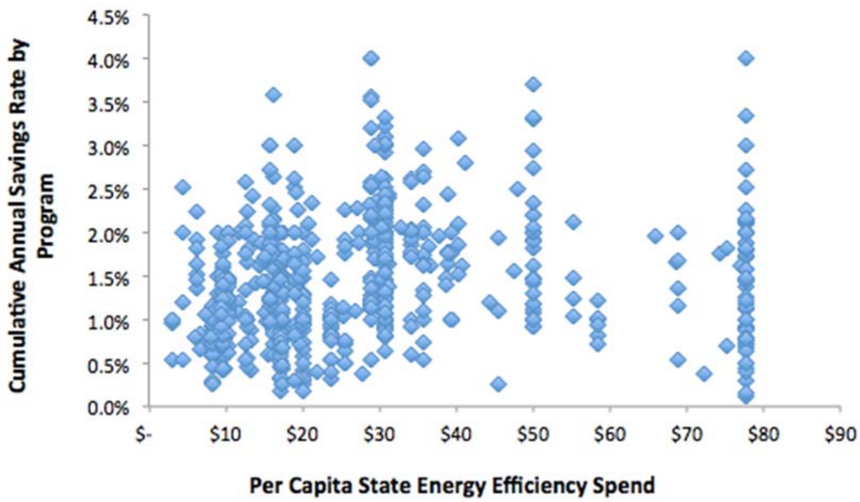

Figure 1. Relationship of annual per capita state energy efficiency spend and average annual Opower Home Energy Report program electricity savings rates.

The correlation between state per capita energy efficiency spend and average annual savings in our dataset exhibits a coefficient of approximately 0.23. However, many other factors impact the savings rate of a given behavioral energy program, creating a large amount of variability within states, as well. The most important of these factors is the specific set of treatments applied to a program, primary among them the number of home energy reports sent per household.

If there is in fact a priming effect, we would expect that holding just the variations in program treatment[1] constant and then analyzing the relationship of state energy efficiency spend and savings rates would yield a positive coefficient. A simple model wherein just the program treatment and state energy efficiency budget are considered allows us to determine this core relationship. That model is specified as follows:

Regression 1. "Simple specification"

$$percent\_impact = \beta_0 + \beta_1 state\_ee\_spend\_per\_capita + \beta_2 log(reports\_per\_capita) + e$$

Though our simple model will provide directional evidence of a relationship between state energy efficiency spend and savings rates due to behavioral energy efficiency programs in that state, we want to be able to quantify this "priming" effect. A number of other factors are responsible for a large amount of variation within savings rates in a given state, and in order to accurately quantify the priming effect, we will account for these other changes that may have driven differences in savings rates both between and within states. A better specified model would incorporate other factors at the state level, utility level, program level, and household level. The resulting model is specified as follows:

$$percent\_impact = \beta_0 + \beta_1 ln(state\_ee\_spend\_per\_capita) + \beta_{2:n}(all\ treatment\ variables) + \beta_{i:j}(state,\ utility,\ program,\ and\ household\text{-}level\ factors)_{i:j} + e$$

[1] Variations in program treatment can include number of reports sent, digital communications, and program life.

To ensure robustness of our results from each of these models, we first employed a variation of 2-fold cross-validation. By “training” the model on a subset of data and then testing it on a second subset of the dataset we were able to determine that we had not over-specified the model. We then performed a second round of robustness checks designed specifically to determine whether or not the data surrounding a single state for which we had many observations or for which the value of state EE spend per capita is on the tail of that variable’s distribution was skewing the model in any way. For instance, if we drop all observations from California (a state with among the highest per capita spend on annual efficiency) from our dataset, will our model continue to find the same relationship across the rest of our data? If the answer is yes, then we can assert that the conclusions we draw from this model are not biased toward results from just one state. Finally, this state-by-state validation allows us to control for variations in attitude between states, thus ensuring that the relationship we find is truly the impact of priming on behavioral energy savings.

Results

Though today’s literature largely focuses on the low-hanging fruit of behavioral energy efficiency as already being plucked, our analysis suggests that it may in fact be possible to generate greater savings per capita from this resource than today’s programs already create. Our initial analysis of the simple model yielded results that indicate that state spend on energy efficiency increases savings rates in behavioral energy efficiency programs, shown below in Table 1.

Table 1. Results of Regression 1, “Simple specification”

	Estimate	**Standard Error**	**Significance**
Intercept	0.004954	0.0003495	***
I(log(reports_per_capita + 1, base = exp(1)))	0.003901	0.0001238	***
state_ee_spend_per_capita	0.00009862	0.000006182	***

Note: Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

It is first important to note that the magnitude of the impact of the number of reports per capita sent to the participant group of the Home Energy Report program is larger than that of the impact of state energy efficiency budget on electricity savings. This indicates that the primary treatment (paper home energy reports) do in fact drive energy efficiency savings. We chose to specify this variable as a logarithmic relationship because other experiments have shown that the marginal impact of home energy reports decreases over time (Allcott and Rogers 2012; The Brattle Group 2012; KEMA 2012).

Of interest to this paper, however, our “priming” variable “aceee_state_ee_per_capita” has a coefficient of 0.00009862, significant at the 95% confidence level, which indicates that for each marginal dollar per capita spent on energy efficiency one can expect an additional 0.0099% on top of the base program savings rate. This indicates that a basic relationship does exist and that this theory of priming merits further digging. Our more carefully specified model, then, worked to capture the other factors that we have found significant in explaining the variation of energy savings between states over time. This model also used dummy variables for each state in order to control for other un-quantified differences between states (such as attitudes) that may have confounded the relationship between our variables of interest, thus validating our assumption that attitudinal differences (or some other un-quantified differences) between states are not driving the differences in energy savings rates. Our results from this model are shown in Table 2 below.

Table 2. Results of Regression 2, “specification”

	Estimate	**Standard Error**	**Significance**
Intercept	0.005355	0.001153	***
I(log(reports_per_capita + 1, base = exp(1)))	0.004529	0.000166	***
state_ee_spend_per_capita	0.00009539	0.00002145	***
State, utility, program, and household-level factors	*various*		

Note: Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Results from this more rigorously specified model indicate that for every incremental dollar per capita a state spends on energy efficiency, a behavioral home energy report program can expect an additional 0.0095% savings rate on top of what is being achieved with energy efficiency spend remaining at status quo (coefficient of 0.000095, significant at 95% confidence level).

To give this context, the standard deviation of state energy efficiency spend for 2013 is $16.745 per capita. To jump one standard deviation of spend forward from the average would yield approximately a 10% increase over the average savings rate in our sample – far from insignificant. All else equal, the difference between the minimum and maximum savings resulting from a state’s energy efficiency spending is more than 0.8%. Figure 2 below shows the expected marginal savings rates by state due to their respective 2013 energy efficiency budgets.

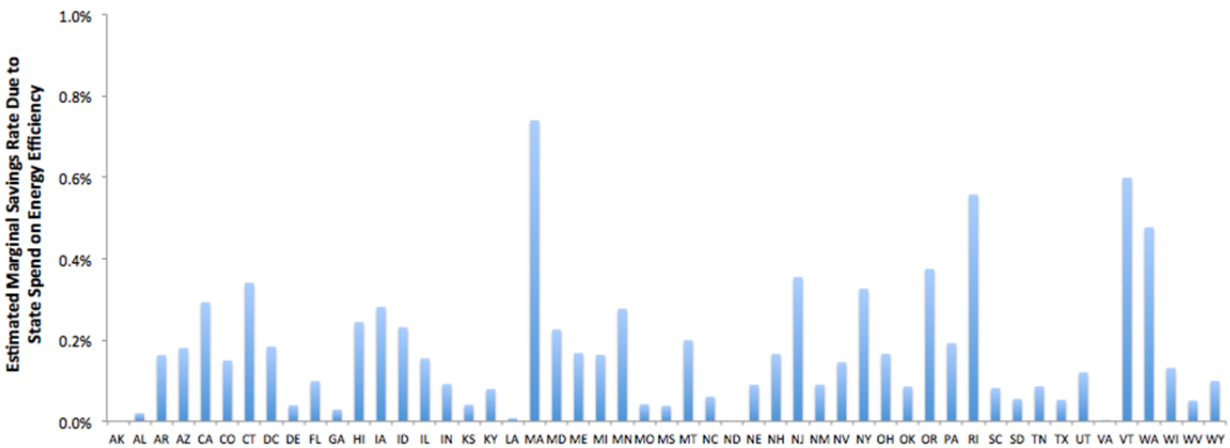

Figure 2. Marginal percent savings potential for behavioral programs due to state spend on energy efficiency.

As is visible above, the range of energy efficiency spend is wide, so as described previously, we validated our model specification by regressing it on a series of datasets that omitted one or more states whose spend falls in one of the tails of the energy efficiency spend distribution in order to determine whether the "priming" variable's coefficient remains relatively constant. In all cases, the model found a consistent relationship between state energy efficiency spend and energy savings, significant at the 95% confidence level.

As described in the previous section, we employed a 2-fold cross-validation test in order to obtain these results, so we can be confident that our impact estimates are not only significant, but robust. In addition, dropping observations from states with particularly high or low per capita spend levels yielded results within the margin of error of our larger model, indicating that the estimates are not skewed by any one state.

Discussion

The positive relationship of a state's energy efficiency budget and behavioral energy savings could be explained by several mechanisms. One mechanism argues that high energy efficiency spend indicates that sentiment toward energy efficiency in that state is already positive and that this positive sentiment drives higher uptake of energy efficiency. A second mechanism explains the relationship as causal: it has been demonstrated that those who are enrolled in behavioral energy efficiency programs are more likely to participate in other energy efficiency programs (ODC 2011; Navigant Consulting 2012; BGE 2011). The argument is, therefore, that energy efficiency spend is increasing awareness efforts and availability of energy efficiency programs and thus those people who are being treated in behavioral energy efficiency programs then are more aware of opportunities for taking action.

Because our analysis explores this relationship both among states and within each state over a period of time, we have been able to effectively hold sentiment constant, thereby controlling for attitudinal differences that would impact both spend and behavioral savings activity and thus ruling out the first proposed mechanism. Consequently, we believe that there exists a causal relationship where greater state spend is in fact driving greater energy efficiency.

Next Steps

With the low cost of energy today – projected to stay relatively flat over the next several decades (EIA 2013) – utilities are challenged to run cost-effective energy efficiency programs. Increasing the efficacy of behavioral programs would broaden the potential for energy efficiency as a low-cost resource. Though there likely exists a decreasing marginal benefit to energy efficiency spend per person, the significance exhibited by the linear specification of the variable in our model indicates that the range of spend we see today is still below the point where the slope of the relationship truly starts to diminish.

Further research will be necessary in order to fully understand the relationship of energy efficiency spend and potential. Key questions that deserve further exploration include:

- How does the type of spend influence this dynamic? It is likely that spend on certain programs yields higher returns than on others. This analysis would allow DSM portfolio managers to allocate their budgets in the most efficient manner.
- What is the "tipping point," i.e. what is the most cost-effective level of energy efficiency spend to drive people to save energy?

- Does this relationship hold with results from other programs (ideally other measured programs, such as other behavioral energy efficiency savings, or participation in rebate programs)?
- Does this relationship hold for behavioral efficiency programs for natural gas?

Conclusion

The findings presented in this paper point to the fact that efficiency portfolio managers can avoid the pitfalls of decreasing marginal returns in areas where existing efficiency expenditures are already robust. Additional research is needed to better understand the more granular drivers of this relationship and the best way to leverage this relationship in the interest of driving the highest possible savings per dollar spent going forward. Specifically, it is important to determine where investment is the most effective at driving awareness and priming residents to be more receptive to other energy efficiency programs. A better understanding of this relationship can ultimately be applied by portfolio managers to optimize their efficiency portfolios to maximize savings given their available levels of spending.

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