Dollars and Sense – How Utility Rebates Influence Implementation Beyond Economics

Peter Worley, Charles Schreier & John Seryak, Go Sustainable Energy

ABSTRACT

Indiana and Ohio have recently lifted or relaxed requirements for utilities to run energy-efficiency programs as legislators and other stakeholders skepticism grew of program effectiveness. These changes have stirred up fundamental reflections among policy makers and industrial energy managers on the usefulness of utility energy efficiency programs. The question of what factors influence industry's investment in efficiency, in particular rebates, is at the heart of these policy debates.

Traditionally, proponents argue that utility incentives serve to increase implementation of energy efficiency projects by reducing initial cost and payback. We utilized the Industrial Assessment Center (IAC) Database and employed a logistic regression statistical analysis on the data to assess the significance of availability of incentives, initial cost, payback length, and other factors on the implementation rate of identified energy conservation measures (ECM). Importantly, the IAC database provides implementation rates of ECMs in states with and without incentive programs, for those eligible manufacturers that have self-selected to receive a free energy audit.

Our study shows that availability of rebates, length of simple payback, and implementation cost have a statistically significant impact on the implementation rate of specific ECMs. The odds of implementation for capital-upgrade ECMs increases by 67% purely from the availability of a rebate. Three specific ECMs had implementation rates that ranged from 5 to 16 percentage points higher than projects with no incentives, but with equivalent upfront costs and simple paybacks. These results indicate that incentives promote implementation in ways beyond economic metrics of decision making, potentially within investor psychology.

Introduction

Utility companies navigate the ever changing landscape of resource availability, technological development, and geopolitical climate. Over time energy-efficiency rebate programs have been developed by utilities, and ratepayer-funded 3rd-parties, both to meet legislated targets as well as to cost effectively manage generation and distribution infrastructure. As ever increasing greenhouse gas (GHG) emissions continue to influence climate and weather patterns, these programs have also been argued to provide a crucial incentive for reducing energy consumption and the associated GHG emissions.

The industrial sector accounts for 31% of US energy consumption, compared to 21% and 19% for the residential and commercial sectors, respectively (EIA 2017). Yet engaging the industrial sector in implementing cost effective, energy efficient improvements within their facilities can be difficult. Often times, capital resources are directed towards increased production rather than energy efficiency projects. Specific rebate programs for the industrial sector continue to evolve to address obstacles to efficiency upgrades.

As debates continue between opponents and supporters of these programs there is a lack of quantitative analysis on the influence of these offerings on efficiency-project investment decisions that is introduced into these policy debates, at least in certain states. Discussion between those who argue the effectiveness of these programs and those who view it as unnecessary government influence on market forces rarely include hard evidence. This is understandable given there are few resources which provide the information to conduct such analysis. Much of the knowledge on the effectiveness of rebates to influence investment decisions is either anecdotal or from evaluation surveys. However, large electricity-consuming businesses frequently and publicly oppose efficiency programs, and will testify that their participation in efficiency programs, if it exists, is free-ridership. These testimonies are effective at undermining the findings of evaluation surveys, and thus open the door to claims that rebates do not in fact produce an effect, and simply subsidize investment decisions that were already being made.

Clarity on the impact of rebates upon implementation of energy efficiency solutions is critical to informing grid management and its associated legislation. In 2015, utilities in the U.S. spent approximately $2.7 billion on commercial and industrial electric energy efficiency programs (CEE 2017). Optimizing this investment could have the potential to reduce efficiency program costs and inform messaging and research around different opportunity areas. This paper is an investigation to understand and quantify the impact and effectiveness of utility rebate programs for industrial customers, and yields insights that could be used to optimize efficiency program investments.

Even though utility costs for industrial operations are substantial there is surprisingly little information available with which to conduct analysis. Many manufacturers are understandably hesitant to disclose information about their process facilities. However, most of the energy efficiency opportunities pursued apply to fairly standard equipment and processes.

The Industrial Assessment Centers database was the only resource we could identify that tracked whether ECMs were implemented or not (IAC 2017). The Industrial Assessment Centers is a Department of Energy (DOE) sponsored program at 28 universities that provides small to medium manufacturers with free energy audits conducted by faculty and engineering students. The IAC audit teams quantify energy savings opportunities through site visits, data measurements, and calculations. The IAC Database archives information generated from these assessments at the plant level such as utility costs and products manufactured. It also archives at the recommendation level such as savings, initial cost, payback, and rebate existence. One practice critical to our analysis is that the IAC students call manufacturers back six to nine months after the report was issued to document what recommendations were implemented. Over the past 30 years the database has collected data on over 100,000 energy savings recommendations. Recommendations are categorized by Assessment Recommendation Code (ARC) codes. For example, ARC 2.4133 is for using a more efficient type of electric motor.

The data represents a subset of manufacturers, defined by the eligibility criteria established by the IACs (DOE 2017). Manufacturers must: be within Standard Industrial Codes 20-39, be located less than 150 miles of a participating university, have gross annual sales below $100 million, have fewer than 500 employees at the site, have annual energy bills more than $100,000 buts less than $2.5 million, and have no professional staff to perform the assessment.

Further, the data only represents those small-medium manufacturers that agreed to host an energy audit, adding a further bias. Results from this analysis cannot be extrapolated to all manufacturers. Rather, the implications and insights developed from analyzing this data set should promote data collection efforts industry-wide.

Within this study, data quality is susceptible to variation since 54 independent universities have contributed to this information over time. Some universities no longer participate in the IAC program and new universities join. The grade-level and experience of students participating varies between member universities. Additionally, student accuracy and consistency of entering ARC data likely has variation from student to student, and university to university. Though, the IAC program does publish standard guidelines on how to perform calculations and enter information into the database.

From our perspective, the IAC database captures a wide range of information, and its continued maintenance is critical for further understanding to be obtained. At the same time, the lack of additional information with which to inform our analysis on the effectiveness of rebates for energy efficiency improvements is disappointing. Particularly since this is during a period when our legislative debates and decisions are being made based upon definitive arguments which cannot be substantiated with data.

Methodology

Logistic Regression – Statistical Requirements

Our analysis seeks to determine what factors influence implementation of energy saving recommendations to industrial users and to what magnitude. The outcome, or dependent variable, implementation, is a binary occurrence: the recommendation was either implemented or not. In this case, we want to determine the percentage likelihood for this binary occurrence taking place based on various conditions. Logistic regression is a statistical model that serves this scenario. It can translate the effect of numerical and categorical independent variables into the likelihood of a binary outcome (dependent variable) occurring.

In order for a logistic regression analysis to be valid, the following requirements must be satisfied according to a heuristic rule provided by Pennsylvania State University (PSU 2017):

1. Observations (data points) are independent.
2. Linear relationship between the logit of the independent variables and the dependent variable.
3. Independent variables are not linear functions of each other.

4. The data sample is “large.” One popular rule is that less than 20% of categorical combinations have less than five occurrences.

Unlike other regressions, logistic regression does not require the dependent variables to be normally distributed. Our analysis meets the above four conditions. The information in the IAC database is comprised of independent observations. Independent variables were tested in their linear forms (e.g. x) as opposed to non-linear forms (e.g. sin(x)). Subsequently, the logit of them have a linear relationship with the dependent variable. Collinearity tests were run and were negative, proving the independent variables are not linear functions of each other. Lastly, we only ran logistic regressions on ARC recommendations that had sufficiently large samples according to the fourth feature of the heuristic rule provided by Pennsylvania State University. (There is no consensus on what constitutes a data sample to be “large.”) In our case we have only four categorical combinations of rebate existence and implementation status (1. Rebate=Yes & Implementation=Yes 2. Rebate=Yes & Implementation=No, etc.) Therefore, we need at least five occurrences for each combination for our test to be valid. We only ran logistic regressions on recommendations that met this criteria.

Filtering Data

The IAC database provides over 100,000 recommendations each with 30 fields of information. Before running logistic regressions the data was parsed to include only pertinent and quality data points. First, three fields from 30 were established as likely the most impactful factors, or independent variables, on the dependent variable implementation status: rebate existence, simple payback, and implementation cost. Rebate existence was included because it is the factor this paper attempts to investigate. Simple payback and implementation cost were included because they are standard economic considerations when investing capital. It is important to note that is standard practice at IACs to include rebate savings in the implementation cost and thus the simple payback (Muller 2017).

With the data filtered down to four fields – implementation status, rebate existence, simple payback, and implementation cost – recommendations with incomplete or questionable data in one of these fields were removed from the analysis. A recommendation was removed if a field was blank or “NA”, if the payback was less than 0 or greater than or equal to 10, if payback was equal to 0 and cost was greater than 0, if implementation cost was greater than or equal to \$1,000,000, or if implementation cost was less than 0. Recommendations with paybacks greater than or equal to 10 were removed because previous research on the IAC database found them to be dubious (Anderson and Newell 2003.) Recommendations with cost of one million dollars or more were eliminated given that limit is well above the conventional ECMs we wish to assess.

Next, only recommendations recorded after 1991 were kept because it was possible rebate existence was not accurately recorded prior to 1991. The database contained no instances of rebates existing prior to 1991, which left uncertainty as to when the IAC started recording the existence of rebates. Then, to ensure only recommendations with appropriately large sample sizes were analyzed, recommendations that had less than five instances in one of the four combinations were excluded.

From the group that remained we selected 11 to analyze that were capital upgrades and were common to prescriptive electricity rebate programs. A focus was created to see the impact of rebates on manufacturers upgrading equipment as opposed to adjusting operations or effecting new equipment purchases. Further, it was deemed important to separately analyze rebates that are prescriptive versus custom since prescriptive are conspicuous acknowledgements that the recommendation is popular, which could have distinct effects versus the latent custom rebates.

Logistic Regression – Models Performed

Before running the logistic regressions, two last steps were taken, the dollars values of implementation cost were adjusted for inflation. Dollar values were converted to 2015 dollars, the most recent year in the database, using the producer price index (finished goods, series WPUFD49207) from the U.S. Bureau of Labor Statistics (US BLS 2016). After the conversion, the dollar amounts were put in terms of thousands of dollars.

Logistic regression analyses were performed in R Studio for three individual recommendation types. An additional logistic regression analysis was performed which included those three ARC numbers as well as eight other ARC numbers selected as common recommendations. A forward selection approach was used for each analysis. First a model was performed with only rebate existence as the independent variable. If rebate existence was statistically significant, defined as a P-value below 0.05, then, implementation cost was incorporated into the model. If it was not, then a new model with implementation cost as the sole independent variable was tested. Then, payback was incorporated into the model in the same method. The model with the most independent variables that were statistically significant was then selected as the final model for the analysis.

Logistic regression models identify which of the independent variables have a statistically significant impact on the implementation rate. The models also quantify the magnitude of the impact through the parameter estimates that are calculated for each independent variable. The magnitude of impact can be described by the change in odds of implementation or the difference in probability of implementation. The odds ratio estimate describes how much one unit change in an independent variable affects the odds of a recommendation being implemented. It is calculated by using the parameter estimate, shown below, where β is a parameter estimate.

Equation 1: Odds Ratio Estimate

$$Odds\ Ratio\ Estimate = e^{(\beta)}$$

For example, if the parameter estimate in a model for rebate existence is 0.5, then the odds ratio estimate equals 1.65, which means if a rebate exists the odds of implementation is 65% greater than if it does not exist. This is true for any combination of simple payback and implementation cost scenarios. Further, if the parameter estimate is -0.5, then the odds ratio estimate equals 0.61, which means for every $1,000 increase in implementation cost the odds of implementation decrease by 39%.

The parameter estimates can also be utilized to create a mathematical formula to calculate the probability of implementation across different payback and implementation cost ranges and when a rebate exists or not. Below is that formula.

Equation 2: Logistic Regression Mathematical Model for the Probability of Implementation

$$Probability(Implementation) = \frac{1}{1 - e^{-(\beta_0 + \beta_{RB} * RB + \beta_{PY} * PY + \beta_{IC} * IC)}}$$

Where,

β_0 = Intercept parameter estimate
β_{RB} = Rebate parameter estimate — RB = Existence of rebate (= 1 yes, = 0 if no)
β_{PY} = Payback parameter estimate — PY = Payback
β_{IC} = Implementation cost parameter estimate — IC = Implementation cost

Parameter estimates equal zero if the associated independent variable was determined to be statistically insignificant. The above formula is used to generate the graphs in this paper.

Results

Data Filtering

The data filtering process distinguished eleven ARC types, encompassing 28,106 individual recommendations, which were pertinent and had sufficient data for this study. They are listed in groups 1-9 in the table below. Group 6 is a collection of three ARCs. Group 10 is the collection of ARC types that were not applicable or did not have sufficient data for this study.

Table 1: Categorization of Suitable ARC Types

Group	Description	Count
1 - Improve Belt Efficiency	Improve Belt Efficiency	2173
2 - Compressed Air Controls	Compressed Air Controls	544
3 - Improved Lighting Efficiency	Improved Lighting Efficiency	3020
4 - Improved Motor Efficiency	Improved Motor Efficiency	4055
5 - Improved Lamp/Ballast Efficiency	Improved Lamp/Ballast Efficiency	9528
6 - Lighting Controls	Lighting Timers	5095
	Photocell Control	
	Occupancy Sensors	
7 - Multi-Speed Motor	Multi-Speed Motor	1934
8 - Reduced Illumination Levels	Reduced Illumination Levels	1293
9 - Improved HVAC Efficiency	Improved HVAC Efficiency	464
10 - Other	Other	66362

General Model

We began our investigation by combining the eleven suitable ARC types into one collection representing prescriptive rebates. We generated a logistic regression model for this collection. Using R, we began the forward selection method by first assessing a logistic regression model which only included rebates as an influence on implementation and then considered implementation cost and payback. Ultimately all three variables were significant to predicting the likelihood of implementation. In the table below, the third to last row shows all three had P-vales less than $2x10^{-16}$, much less than the 0.05 requirement to be significant. The parameter and odds ratio estimates for the variables are also included in the table below.

Table 2: Model Parameter Results for the Combination of All Suitable Recommendations.

	P-Values		
Implementation Likelihood Model	Rebate (Available)	Implementation Cost	Simple Payback
As a function of Rebate, Implementation Cost, and Simple Payback	<2e-16 ***	<2e-16 ***	<2e-16 ***
Parameter Estimate	0.5098	-0.0007577	-0.1753
Odds Ratio Estimate	1.665	0.99924	0.839

The parameter estimates are used to calculate the odds ratio estimate using Equation 1 and the probability of implementation using Equation 2. The 0.839 odds ratio estimate for simple payback indicates that for every year the payback length extends, the odds of implementation decreases by 16.1% (1- 0.839). This is true if it extends from three to four years or from eight to nine years. This is also true no matter the implementation cost or state of rebate existence.

This initial glimpse is not surprising and yet promising. It indicates that the availability of rebates has a large impact on the likelihood of implementation. At the same time, the implementation cost has very low influence. One future avenue of investigation would be to see at what magnitude of implementation cost starts to have a more sizable impact on implementation as this could provide insights on the thresholds of capital costs as a driver.

ARC Type Inspection sans Rebate

Next we ran a model which removed rebates and looked at the difference in odds ratio estimates for various ARC project types. The odds ratio estimate for each ARC project type indicates which ARC types are more likely to be implemented versus the others. A few of the ARC types with higher odds ratio estimates were individually assessed to determine the impact of rebates on them specifically. We believe this method of identification allows us to separate out the example ARC types for projects which are more likely considered and pursued by industrial facilities and see how impactful rebates are in those areas of improvement. We also included Multi-Speed Motors as an example of a project type which is least likely to be implemented.

When we ran our test, the analysis indicated that for the improved HVAC group, the parameter estimate was not significant. Consequently it was removed from further analysis. Additionally, improved belt efficiency ARC was removed from analysis because it did not pass through the data filtering process. We then generated a model for the remaining ARC types producing the parameter and odds ratio estimates in the table below.

Table 3: Model Parameter Estimates for ARC Categories

Group	Odds Ratio Estimate	Group	Odds Ratio Estimate
Implementation Cost	0.999	5 - Improved Lamp/Ballast Efficiency	1.523
Simple Payback	0.799	6 - Lighting Controls	0.627
2 - Compressed Air Controls	0.766	7 - Multi-Speed Motor	0.491
3 - Improved Lighting Efficiency	1.357	8 - Reduced Illumination Levels	0.815
4 - Improved Motor Efficiency	2.282	10 - Other	0.818

From this information we chose to further investigate the following ARC types: improved motor efficiency, improved lamp/ballast efficiency, and multi speed motors (variable frequency drives). The first two were chosen due to their high odds ratio estimates and high number of cases. We included the multi-speed motors ARC with its low odd ratio estimate in order to investigate an upgrade that is less naturally pursued and that is more complicated. For each ARC type we generated a logistic regression model, continuing to use the forward selection method.

Model for Improved Motor Efficiency ARC

The table below illustrates the forward selection process and provides the results of the logistic regression model for the improved motor efficiency ARC.

Table 4: Improved Motor Efficiency Model Results

Improved Motor Efficiency			
	P-Values		
Implementation Likelihood Model	Rebate (Available)	Implementation Cost	Simple Payback
As a function of Rebate and Simple Payback	.000129 ***	NA	0.018008 *
Parameter Estimate	0.35032	NA	-0.04486
Odds Ratio Estimate	1.420	NA	0.956

For purchasing a more efficient motor, implementation cost was not a significant parameter. Alternately, simple payback was significant. This means that economics are a factor but the magnitude of the cost is not a deterrent. Motor improvements are often considered at end of life. The implementation cost from the database is either the incremental cost between motor rewind and buying a premium motor or in some cases the cost of entire motor replacement. The statistical insignificance of implementation cost could be due to differences in investment practices when required to make replacement at equipment end of life, or due to the wide range of costs that exist under this ARC type.

The odds ratio estimate of 0.956 demonstrates that for every year the payback period is lengthened the odds of implementation a more efficient motor reduces by 5%. Inserting the parameter estimates into Equation 2, we were able to generate a graph showing how the probability of an efficient motor recommendation being implemented changes based on simple payback and whether a rebate exists. See the graph below.

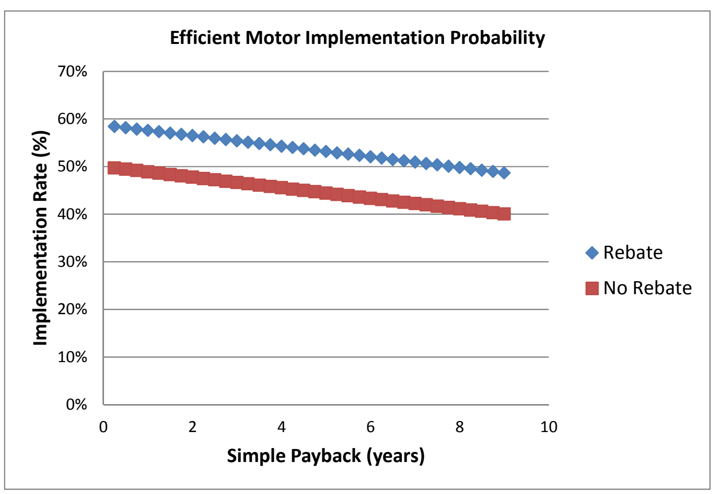

Figure 1: Efficient Motor Implementation Probability

From the graph it can be seen that implantation probability decreases almost linearly as payback length increases for both when rebates exist and when they do not. The difference in probability between rebate and no rebate, despite having the same payback, is most intriguing. For example, efficient motor recommendations with four year paybacks when no rebate is available have a 46% probability of being implemented. Comparatively, when that recommendation has a rebate it has a 54% probability, a marked difference. The simple paybacks include the rebate when rebates exist so the recommendations are economically equivalent.

Model for Improved Lamp/Ballast Efficiency

The table below presents the results of the logistic regression model for the improved lamp/ballast efficiency ARC.

Table 5: Improved Lamp/Ballast Efficiency Model Results

Improve Lamp/Ballast Efficiency			
P-Values			
Implementation Likelihood Model	**Rebate (Available)**	**Implementation Cost**	**Simple Payback**
As a function of Rebate and Simple Payback	9.21e-06 ***	NA	<2e-16 ***
Parameter Estimate	0.25081	NA	-0.12042
Odds Ratio Estimate	1.285	NA	0.887

For improved lamp and ballast efficiency we arrive at the same independent variables in the efficient motor model, albeit implementation cost was identified as insignificant after simple payback had been added to the model. The payback odds ratio estimate of 0.887 is lower than the efficient motor's 0.956, which means payback length has a greater effect discouraging implementation for lamp and ballast upgrades versus efficient motors. Viewing the probability graph below, the greater impact of payback can be seen by the more intense slopes.

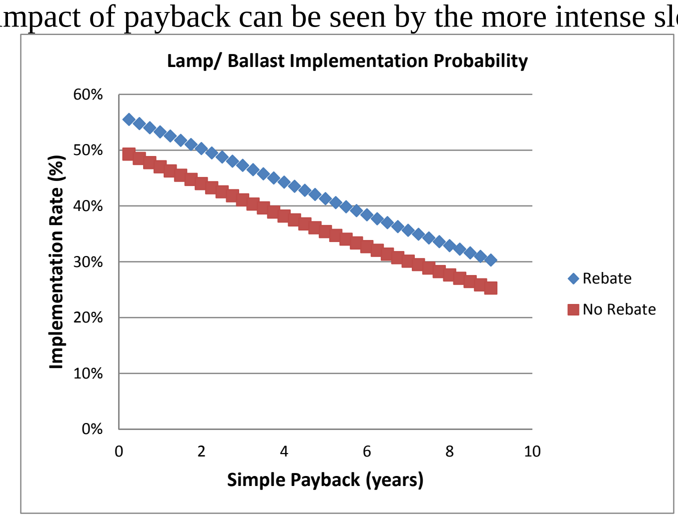

Figure 2: Lamp/Ballast Implementation Probability

The implementation probability of lamp and ballast upgrades is generally less than efficient motors. Within a project simple payback range of 7-9 years, the implementation probability decreases to near 30% for both rebate cases, while efficient motors did not drop below 40%. For lamp and ballasts the difference in probability between rebates cases were not as great as efficient motors. While lower, the odds ratio estimate of 1.29 indicates a rebate does increase the odds of implementation by 29%. They had on average an approximately 6% points difference across the range of paybacks. Efficient motors had a 9% point average difference

Model for Multi-Speed Motor

The table below presents the results of the logistic regression model for the multi-speed motor ARC (also known as variable frequency drive).

Table 6: Multi-Speed Motor Model Results

Multi-Speed Motor			
	P-Values		
Implementation Likelihood Model	Rebate (Available)	Implementation Cost	Simple Payback
As a function of Rebate, Implementation Cost, and Simple Payback	6.23e-05 ***	NA	0.00239 ***
Parameter Estimate	0.63296	NA	-0.13607
Odds Ratio Estimate	1.883	NA	0.873

For multi-speed motor, we again arrive at the same final model. It is interesting to note that while the odds ratio estimate for multi-speed motor was the lowest of the three within the combined model (see Table 3) the impact of rebates when looking solely at this option is the largest. The odds of implementation when rebates exist increase by 88%. Further investigation into individual cases will provide the necessary information to build a hypothesis based upon this initial insight. The probability of implementation can be seen in Figure 3 below.

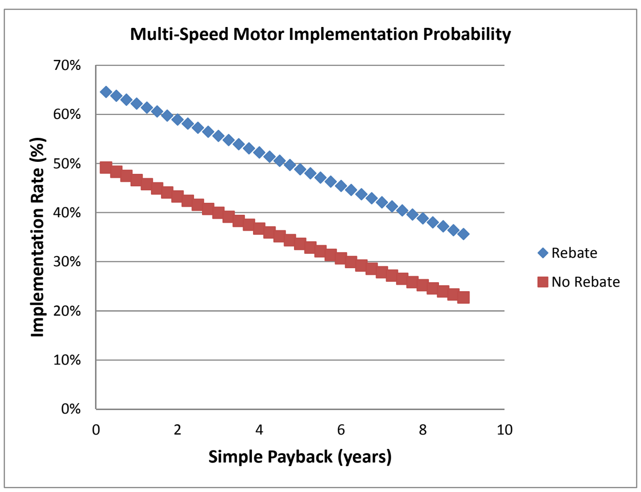

Figure 3: Multi-Speed Motor Implementation Probability

The range of implementation probability is much larger for the multi-speed motor ARC versus the other two ARCs, a result of having greater parameter estimate values. It had on average an approximately 15% points difference across the range of paybacks. This shows that manufacturers are much more sensitive to payback length and rebates for multi-speed motors.

Conclusion

The results of the general model proved that rebates, implementation cost, and payback are significant factors when manufactures consider energy efficiency implementations. Odds of implementation increase by 67% when rebates exist and the other two variables are held constant. Unsurprisingly, as payback and implementation cost increase, the odds of implementation decrease as indicated by the odds ratio estimates for those parameters being less than one. Lower paybacks are inherently more economic and lower implementation costs hold less risk and require less bureaucratic approvals. However, the effect of the existence of rebates is surprising. One would expect rebates to increase implementation rate because it lowers cost and payback. They do have this effect as shown by the parameter estimates of implementation cost and payback. The logistic regression model shows it has an additional effect, though. Purely the existence of a rebate increases implementation rate even though the economics are the same.

However, due to the use of observational data, our test cannot be used as proof that rebates make implementation more likely. Confounding variables, such as geography, or the influence of an energy audit, cannot be excluded from the potential cause of the phenomenon observed and quantified. We can note that the data is consistent with proposed hypotheses.

It is unclear why rebates have an effect beyond economics. Investor psychology might explain that implementation rate increases because rebates reduce the manufacture's risk perception and creates a bargain scenario. Consultation from experts from the field of psychology could analyze this to build upon insights from this study. It is possible rebate existence is an indicator of the region's energy and environmentalist culture. Perhaps, utility areas with rebates are areas where people are more receptive to efficiency and greenhouse gas mitigation. An investigation of the data inspecting the correlation between geography, demographics, and rebate existence could clarify this hypothesis.

Individual models were created for the efficient motor, lamp/ballast upgrade, and multi-speed motor ARCs. They revealed that implementation cost was not a significant factor for these three. For efficient motor and lamp/ballast upgrade, ARC types with higher point estimates and thus naturally more likely to be implemented, perhaps they are perceived as less risky and thus the initial cost is not as discouraging.

The multi-speed motors odds ratio for rebates was 30% greater than the other two and the efficient motor odds ratio for payback was 7% less impactful then the other two. The granular difference between specific ARCs highlight the utilities have promising opportunities to direct rebates towards recommendations that are most sensitive to rebate existence and simple payback.

The implications from our study provide strong support for a number of positions. First, the value of the data set created through the IAC program is unique and critical for an analysis and understanding of rebate program and business investment decision behavior insights. Consequently, this is another reason to consider future support of the IAC together with the many other benefits of the program. Secondly, we have shown that for this data set, rebates proved substantially effective in increasing the likelihood of implementation for efficiency projects. This supports the hypothesis that incentives can positively influence industrial ratepayers which receive an energy audit to improve the efficiency of their facility. Furthermore, the impact is even greater for specific opportunities. Finally, this initial investigation has led to identification for further questions whose answers could provide incredible leverage towards utility program efficiency. Identification of ARC types where rebates have the most impact could help support more focused marketing and funding for those areas where utility incentives can be positively leveraged. Alternately, identifying which rebates provide low increases in the likelihood of implementation could justify elimination of funds going towards improvements which would happen anyway. Finally, identifying which project types and at what cost and payback levels rebates are no longer influential would allow identification and elimination of ineffective program components. This would reduce the cost passed along to ratepayers.

As with any data analysis process, improving data quality is always beneficial. It is our hope that continued excellence is pursued within the IAC programs and continuous improvement of their data collection and reporting process continues to evolve.

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