Behavioral Effects of a Smart Phone Mobile App

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ABSTRACT

Utilities continue to look for new ways to engage their customers while generating cost effective energy savings from behavior change. DTE Energy (DTE) developed an innovative mobile app, DTE Insight, to achieve behavior-based electric and gas savings by providing customers with access to information and tools designed to motivate customers to take energy saving actions. All customers with a smart meter who download the app can see their hourly energy usage the next day; participants also have the option to install an "Energy Bridge" in their home that allows them to see their electricity usage every three seconds and stores it on a minute-by-minute basis.

This paper discusses the unique features of the program's design and evaluation approach, and the app's energy savings. Results indicate that gas savings are higher than electric savings (2.27% versus 1.63%) and that the bridge saves almost three times as much as the app alone (4.84%). We also present savings for different customer segments; environmentalists and do-it-yourselfers tend to download the app and have high savings. Finally, customers who continue to engage with the app through time have higher savings than those who stop.

Introduction and Background

Utilities continue to look for new ways to engage their customers while generating cost effective energy savings from behavior change. In 2014, DTE Energy (DTE) developed an innovative mobile app called "DTE Insight" (hereafter referred to as "the app") to achieve behavior-based electric and gas savings. Customers access information and tools designed to motivate them to take energy saving actions. These include gas and electric historic hourly interval data, budget target settings, weekly challenges, and tips for completing various home projects that can save the user energy and money on their bill. Participants also have the option to install hardware in their home (an "Energy Bridge") that allows them to see their electric energy use every three seconds in real-time and stores electricity usage on a minute-by-minute basis.

The app became available for download showing only electric data on Apple devices in July 2014, and on Android devices in August 2014. In December of 2014, the app began showing gas usage data to DTE combo (i.e., gas and electric service) customers. Figure 1 shows some screen shots of the app: (1) the electricity usage screen without the Energy Bridge, (2) the electricity usage screen with the Energy Bridge, and (3) the budget target screen.[1]

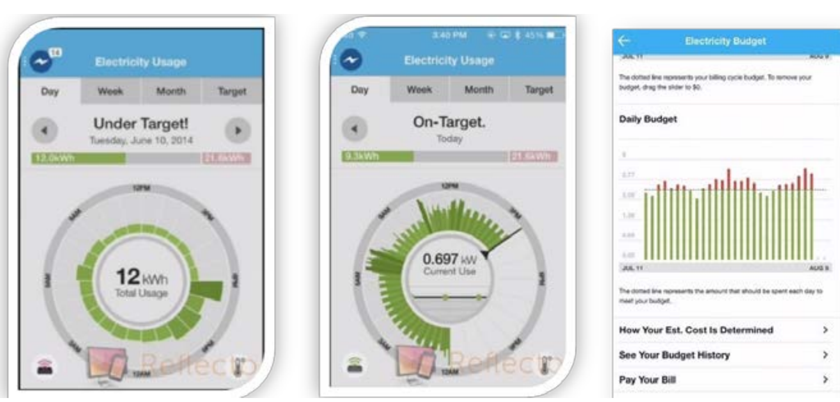

Figure 1. Screen shots from the app. From the left the pictures show: (1) the electricity usage screen without the Energy Bridge, (2) the electricity usage screen with the Energy Bridge, and (3) the budget target screen. *Source:* DTE.

[1] More information about the app can be found at: https://www.newlook.dteenergy.com/wps/wcm/connect/dte-web/insight/insight-app.

Anyone can download the app, but usage of the app requires a DTE Energy login and customers will only see usage data if they have a smart meter.[2] Customers with an electric AMI meter see hourly interval data (it is typically available in the app at mid-morning the next day), unless they also have the Energy Bridge in which case they can see their usage every three seconds in real-time and that usage is stored minute-by-minute. Customers with a gas AMR meter see daily gas usage data (typically at mid-morning the next day). Our analyses only include customers with a smart meter for the relevant fuel type such that they see interval usage data in the app.

The savings values for the app and Energy Bridge estimated in this paper have since been adopted into the 2017 Michigan Energy Measures Database (MEMD White Papers 2016a, b, and c). Electric savings from the app are based on all customers who had the app for one year at the end of 2015, whereas gas savings from the app and electric savings from the Energy Bridge include all customers who downloaded the app by the end of 2015.

This paper also shows savings by customer lifestyle segmentation codes and by length of engagement with the app. The lifestyle segmentation codes were developed by DTE in partnership with Market Strategies International to classify customers for targeted marketing efforts.[3] Engagement was based on the length of time a customer had been using the app. The lifestyle and engagement segmentation analyses do not require customers to have had the app for a full year to be included in the analysis. Disaggregating savings by these segments allows DTE to know what type of customer is using the app most successfully and can be used to help with marketing for both acquisition and continual engagement with the app.

Methodology

The app is run as an opt-in program, meaning customers choose whether to join the program, rather than being randomly assigned to receive the treatment. Specifically, customers can join the program at any time by downloading the app to their smartphone and linking the app to their utility account. Electric and gas savings are measured ex-post using quasi-experimental design in which a matched control group is constructed to serve as the baseline against which the participant group is compared.[4]

The Energy Bridge is also opt-in, in that customers chose to request an Energy Bridge; however, the evaluation is designed as a modified random encouragement design (RED) in which only some of the customers who request the Energy Bridge actually receive it.[5] The Energy Bridge portion of the program was originally designed as a recruit-and-deny design, but because not everyone who is sent the Energy Bridge actually installed it, the evaluation wound up being more similar to a RED. Had we evaluated the program as a recruit-and-deny design, our estimate of savings from the Energy Bridge would have included the customers who received but did not install the Energy Bridge; by utilizing an RED we were able to obtain an estimate of savings for those participants who actually installed the Energy Bridge and were able to see real-time data in the app. Those customers who are randomly selected not to receive the Energy Bridge after requesting it form an experimental control group.[6]

Navigant also segmented the app and Energy Bridge savings estimates by lifestyle segment and by length of engagement with the app. The following subsections discuss each evaluation methodology including the lifestyle segment and engagement level descriptions.

[2] All DTE customers who have not chosen to opt-out have a smart meter. Customers without a smart meter who link the app to their DTE account can access app features that do not rely on usage, such as the tips.

[3] The segmentation codes were developed for internal use by DTE and no public reference exists.

[4] An evaluation protocol report (SEE Action 2012) cites matching as a reasonable method for establishing baseline conditions when an experimental design is not an option. Further, the matched control group method is common in academic literature (see, for example, Cameron and Trivedi 2005).

[5] During the period this paper covers, one in every four customers who requested the bridge was randomly chosen not to receive one.

[6] An RED is an experimental design and thus the results are proven to be unbiased (SEE Action 2012).

App Alone

The estimation of savings for the app (without the Energy Bridge) relies on a quasi-experimental Matched Control Group (MCG) method to develop baseline usage in the absence of the program. After the MCG is chosen, regression analysis is run to estimate electric or gas energy savings. The savings from the regression analysis are then adjusted for double counting, which occurs when participants achieve savings by joining another utility-run energy efficiency (EE) program.

Participants in the Analysis and Data Cleaning. Navigant used 11,178 participants who downloaded the app in 2014 in the estimation of electric savings from the app and 8,891 participants who downloaded the app by the end of 2015 in the estimation of gas savings.[7] These participants represent a mix of single and multi-family residences, and a mix of customers who remained in their home versus relocating in the year after they downloaded the app.[8]

These counts represent the number of customers used in our analysis after cleaning the original dataset. The vast majority of removals were for: (1) customers who did not have smart meters and thus could not see interval usage data in their app, and (2) on the electric side, customers who had not had the app for a full year by the end of 2015.[9] In estimating electric savings from the app, we also removed any observations that occurred after a customer installed the Energy Bridge to get a pure estimate of the electric savings from the app alone.

Development of the Matched Control Group. Navigant selected the control group matches by identifying one non-participant that had the closest energy use profile (electric or gas) to each participant, based on minimizing the sum of squared difference in usage during the 12-months before a participant downloaded the app.[10]

The main assumption of this method is that if two customers (match and participant) had very similar electric or gas use profiles in the 12-months before the participant downloaded the app, then their profiles would have continued to be similar if the participant had not downloaded the app. If this is the case, then the match provides a good approximation of what the participant's electric or gas use would have been in the absence of the program.

Figure 2 shows usage by participants and their matched controls in the 12-months leading up to when the participant downloaded the app. Participants and their matched controls had very similar usage profiles. The average percent difference in average daily usage (participants minus matched controls) between the two groups across the 12-months was -0.4% for electric and -0.7% for gas.

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[7] The electric savings estimation includes only 2014 downloaders as they had the app for a full year by the end of 2015. For gas, all 2014 and 2015 downloaders were included as there were not enough who had gas data in the app for a year to segment in that way.

[8] The data did not allow the authors to distinguish between single and multi-family households. More information on relocation can be found in the MEMD White Papers (2016 a and b).

[9] Detailed descriptions of the data cleaning and the number of customers removed in each step can be found in the MEMD White Papers (2016 a and b).

[10] The non-participant pool included 100,000 randomly drawn DTE customers who had smart meters, had annual usage in the range of app participants, and had complete billing data (i.e., no missing bills) from July 2013 to December 2015. Electric and gas matches were drawn separately, with replacement, such that a participant could have a different match for each fuel type. A match was only selected for participants who had bills in at least 8 of the 12 months prior to when the participant downloaded the app.

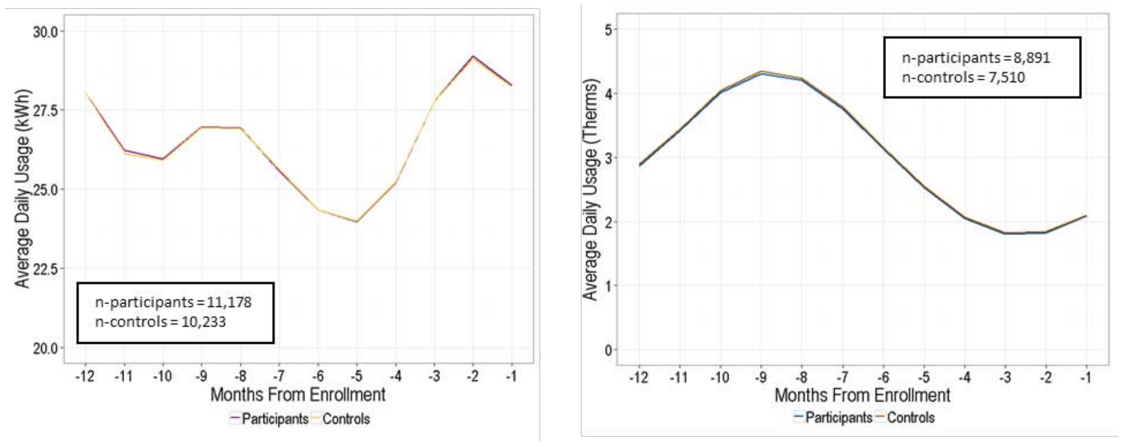

Figure 2. Usage by Participants and Matched Controls. Electric usage is shown in the left-hand panel and gas usage in the right-hand panel. *Source:* Navigant.

Regression Analysis. After selecting matched controls, Navigant estimated per-participant daily energy savings with two regression models, as described in Table 1. Although the two models are structurally very different, assuming the treatment and matched control group are well balanced with respect to the drivers of electric or gas use, for a single set of customers they should generate very similar estimates of savings. We estimate both as a robustness check on the savings.

Table 1. Regression approaches used in savings analysis

Approach 1 - Regression with Pre-Program Matching (RPPM)	Approach 2 - Matching with Bias Correction (MBC)
The first approach follows Ho et al. (2007), who argue that matching a comparison group to the treatment group is a useful "pre-processing" step to assure that the distributions of the covariates (i.e., the explanatory variables on which the output variable depends) for the treatment group are the same as those for the comparison group. This minimizes the possibility of model specification bias. The regression model is applied only to the post-treatment period, and the matching focuses on those variables expected to have the greatest impact on the output variable.	Matching with bias correction (MBC) was introduced by Abadie and Imbens (2011). In this model, the effect of the program in month *t* is the difference between the energy use of participant *k* and their estimated counterfactual (baseline) consumption. The estimated counterfactual consumption is the average consumption of the matched household amended to reflect differences between participants and their matches in pre-period electric or gas consumption and spatial location (i.e., zip code). The amendment of consumption and spatial location is based on a post-enrollment regression equation involving matched comparison customers only.

These two approaches use the same set of matched comparison customers. *Source:* Navigant

The model specification for the RPPM approach is shown in Equation 1.

Equation 1. Approach 1 - RPPM

$$ADU_{kt} = \alpha_1 Treatment_k + \sum_J \alpha_{2j} YrMo_{jt} + \sum_J \alpha_{3j} PREuse_{kt} \cdot YrMo_{jt} + \sum_L \alpha_{4l} Zip_{kl} + \varepsilon_{kt}$$

Where,

ADU_{kt} = Average daily electric or gas usage by household *k* in month *t*

$Treatment_k$ = A 0/1 indicator variable, taking a value of 1 if household *k* is a participant and 0 otherwise

$YrMo_{jt}$ = A set of binary variables taking a value of 1 when *j* = *t* and 0 otherwise[11]

$PREuse_{kt}$ = Average daily usage by household *k* during the most recent month before *k* (or its match) downloaded the app that is the same month as calendar month *t*

Zip_{kl} = A set of binary variables taking a value of 1 when household *k* is in zip code *l* and 0 otherwise

[11] If there are T post-program months, there are T monthly dummy variables in the model, with the dummy variable $Month_{tt}$ the only one to take a value of 1 at time *t*. These are, in other words, monthly fixed effects.

ε_{kt} = cluster-robust model error term

The model specification for the MBC approach is shown in Equation 2.

Equation 2. Approach 2 - MBC

$$Savings_{kt} = ADU_{kt} - ADU_{kt}^{C}$$
$$ADU_{kt}^{C} = ADU_{kt}^{M} + \hat{\beta}_2\left(PREuse_{kt} - PREuse_{kt}^{M}\right) + \hat{\beta}_{3l}(Zip_{kl} - Zip_{kl}^{M})$$
$$ADU_{kt}^{M} = \sum_{J}\beta_{1j}YrMo_{jt} + \sum_{J}\beta_{2j}PREuse_{kt}^{M}\cdot YrMo_{jt} + \sum_{L}\beta_{3l}Zip_{kl}^{M} + \varepsilon_{kt}$$

Where all common variables are as defined in Equation 1 and,

$Savings_{kt}$ = savings by household *k* in month *t*

ADU_{kt}^{C} = estimated counterfactual average daily usage by household *k* in month *t*

ADU_{kt}^{M} = average daily usage by household *k*'s match in month *t*

$\widehat{\beta_2}$ = the factors used to adjust household *k*'s usage to reflect differences between *k* and its match in $PREuse$; these are estimated by the regression in the third line of Equation 2

$PREuse_{kt}^{M}$ = average daily usage by household *k*'s match during the most recent month before *k* downloaded the app that is the same month as calendar month *t*

$\widehat{\beta_{3l}}$ = the factors used to adjust household *k*'s usage to reflect differences in the coefficient on the zip code of *k* and its match; these are estimated by the regression in the third line of Equation 2

Zip_{kl}^{M} = A set of binary variables taking a value of 1 when household *k*'s match is in zip code *l* and 0 otherwise

ε_{kt} = cluster-robust model error term

Double Counting Analysis. Participation in the app may encourage participants to enroll in other utility-run EE programs, a process commonly called uplift. If participants and controls participate in other EE programs at similar rates, the savings estimates from the regression analyses are already "net" of savings from the other programs. However, if the app affects participation rates in other EE programs, then savings across all programs are lower than indicated by the summation of savings for the app and the other EE programs. For instance, if the app increases participation in other EE programs, these savings may be allocated to either the app or the other program, but cannot be allocated to both.[12] On the other hand, if the app reduces participation in other EE programs, then there is no double counting of savings.[13]

We estimated uplift using a difference-in-difference (DID) statistic which is in line with the Uniform Methods Protocol for behavioral programs (NREL 2015).[14,15] To calculate the DID statistic, Navigant subtracted the change in the participation rate in another EE program between the 12-months after a participant downloaded the app (the post period) and the 12-months before (the pre period) for the matched control group from the same change for the treatment group.[16] This calculation is shown in Equation 3.

[12] It is difficult to avoid double counting from programs without tracking data, such as upstream CFL programs, and no effort was made to do so for this analysis.

[13] This might happen, for instance, if the app encourages behaviors that reduce the value to customers of participating in other EE programs. The negative savings associated with this negative double counting are included as app savings because they represent a downward bias in the statistical estimate of the app program savings. In other words, because the statistical analysis does not account for the lower rate of energy efficiency participation by app participants, estimated savings are lower than actual savings by an amount equal to the negative savings.

[14] The DID statistic generates an unbiased estimate of uplift when the baseline average rate of participation is the same for the treatment and control groups, or when they are different due only to time-invariant factors, such as the square footage of the residence.

[15] We considered uplift in the Audit and Weatherization, Energy Efficiency Assistance, Home Energy Consultation, Home Energy Survey, HVAC, and Multi-Family Residential programs. Double counting with DTE's Home Energy Report (HER) program was not included as that takes place in the HER program evaluation.

[16] For each matched control, these periods are defined by the download date of their participant match.

Equation 3. DID Statistic Calculation

$$(post\ period\ treatment\ group\ participation - pre\ period\ treatment\ group\ participation) - (post\ period\ control\ group\ participation - pre\ period\ control\ group\ participation) = DID\ statistic$$

Multiplying the DID statistic by the number of participants gives the change in the number of people participating in each of DTE's other EE programs because of the app. Multiplying this number of people by the median savings from the other program gives the double counted savings. The double counted savings is calculated for each other program considered and is then summed across all the programs to get total annual double counted savings. Dividing this total annual number by the number of participants in the double counting analysis gives the annual double counted savings per participant. The per participant double counted savings can then be subtracted from the savings estimates from the regression analysis described in the previous section to get savings adjusted for double counting.

Energy Bridge

The estimation of savings from the Energy Bridge relies on an experimental design called a RED to create a control group. Experimental designs eliminate self-selection bias, wherein customers who choose to join a program are different from those who choose not to join, and thus produce unbiased estimates of savings. The remainder of this section covers customers in the analysis and data cleaning, and the RED regression analysis.[17]

Customers in the Analysis and Data Cleaning. Navigant used 17,382 customers in the analysis of electric savings from the Energy Bridge;[18] of these, 12,743 received the Energy Bridge and 4,639 were placed into the control group. After receiving the Energy Bridge, customers must still link it to their AMI meter to view real time usage data and not all customers did so;[19] the RED methodology ensures an unbiased estimate of savings for the customers who actually see real time data in the app.[20]

Random Encouragement Design Regression Analysis. Navigant used an instrumental variable (IV) regression to estimate daily per participant savings from the Energy Bridge; the IV regression produces an unbiased estimate of savings in an RED.[21] App users who request the Energy Bridge are randomly assigned, based on a 4:1 ratio, to a participant group (who receives the Energy Bridge) and a control group (who does not receive the Energy Bridge). Upon receiving the Energy Bridge, participants must link it to their AMI meter to see real time data in the app. Thus, in this RED design, encouragement is receiving the Energy Bridge and treatment is installing the Energy Bridge such that real time data can be viewed in the app. Because both the encouraged and the control groups have the app, the savings estimated for the Energy Bridge are incremental to savings estimated for the app alone. Figure 3 illustrates the RED design.

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[17] There is no double counting adjustment for the bridge as all electric double counted savings (both before and after the installation of the bridge) are accounted for in the app only double counting adjustment.

[18] The bridge estimation includes all 2014 and 2015 downloaders.

[19] Linking the bridge to an AMI meter can be done by the customer themselves following the step-by-step instructions provided with the bridge (without the presence of an electrician or other professional). Customers can request support directly from the app and may also contact DTE Insight Customer Support via phone or email. In-home service technicians are also available to customers who require additional assistance with installation and/or troubleshooting connection concerns.

[20] Detailed descriptions of the data cleaning and the number of customers removed in each step can be found in the MEMD White Paper (2016 c).

[21] For a recent academic paper applying this approach to an energy program evaluation see Fowlie, Greenstone, and Wolfram 2015.

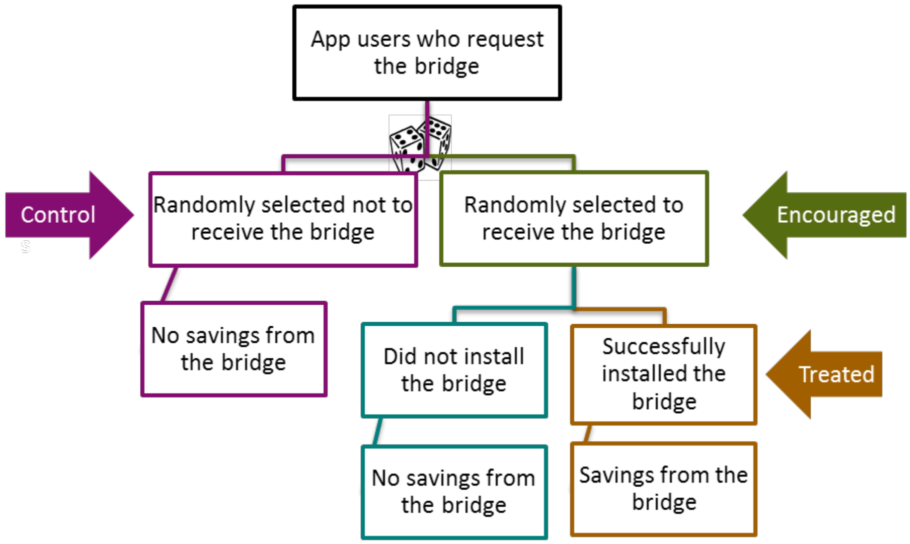

Figure 3. Illustration of RED Design. *Source:* Navigant.

The resulting savings estimate is for customers who successfully installed the Energy Bridge ("treated" in Figure 3). However, there is a delay between when DTE ships the Energy Bridge and when the customer installs it, and not everyone who receives an Energy Bridge successfully installs it. The decision of whether to install the Energy Bridge, and when to install it, are non-random choices. This means an estimate comparing treated customers to the control group directly would produce a biased estimate of savings. To produce an unbiased estimate of savings, the evaluation team utilized an IV design in which a billing observation in a month after the Energy Bridge was installed, which is non-random, is predicted (or "instrumented" for) by the observation being post encouragement (or in a month after the customer is shipped the Energy Bridge), which is random. Savings are then calculated using a regression model comparing the encouraged, treated, and control customers.[22]

Lifestyle Segments

To estimate savings for different lifestyle segmentation codes, Navigant interacted the lifestyle segment indicator with the treatment indicator in the regressions described in the previous sections.[23] Table 2 shows descriptions of each lifestyle segment. The Affluent Greens, Do-It-Yourself (DIY) Conservers, Greens, and Energy Indifferent segments are the most common users of the app; the prevalence of these segments among app users is frequently higher than the prevalence of these segments in DTE's population.

Table 2. DTE lifestyle segmentation code descriptions

Segment	Prevalence in DTE population	Prevalence among app users	Key attributes	
Affluent Greens	14%	27%	• Highest income • Early adopters	• Confident, curious • High EE propensity
DIY Conservers	12%	21%	• Moderate income • Budget shoppers	• Late adopters • High EE propensity
Greens	17%	17%	• Moderate income • Youngest segment, self-identify as "green"	• Early adopters • High EE propensity
Energy Indifferent	13%	8%	• 2nd highest income • Not early adopters	• Like consistency in life • Average EE propensity, interest in SmartMeters
Traditionals	16%	2%	• Lower income	• Late adopters

[22] The IV design, including the actual regression model, is explained in more detail in MEMD White Paper 2016c.
[23] The lifestyle segmentation analysis includes all 2014 and 2015 downloaders.

			• Older, retired, comfort oriented • Low EE propensity
Cash Flow	12%	1%	• Low income • High unemployment • Comfort oriented • Low to average EE propensity
Budget DIY	15%	<1%	• Low income • High unemployment, budget driven • Late adopters • Low EE propensity

Twenty-four percent of the app participants were missing the lifestyle segment indicator and were excluded from our results. Adopter classifications in the key attributes column are general across DTE's EE portfolio and are not specific to the app. The lifestyle segments were assigned at the beginning of the analysis and were not updated based on demographic changes over time. *Source:* Navigant.

Engagement Levels

Electric savings for both the app and the Energy Bridge were also segmented by length of engagement with the app.[24] Engagement was defined using the number of days between the date when a customer downloaded the app (Created Date) and the date of their most recent login (Modified Date).[25] Participants were assigned into one of three engagement buckets split at 60 and 280 days between the Created and Modified dates. Customers with 0 to 59 days between the two dates were defined as "Short Engagement", customers with 60 to 279 days were defined as "Moderate Engagement", and customers with more than 280 days were defined as "Long Engagement". Figure 4 shows the breakdown of app and Energy Bridge participants into the three engagement buckets.

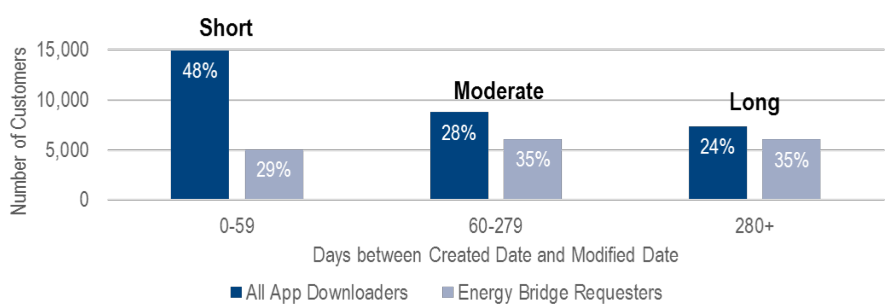

Figure 4. Engagement Bucket Breakdowns. *Source:* Navigant.

Results

App Alone

Table 3 shows the estimates of per participant daily savings from the app alone for the RPPM and MBC approaches prior to adjusting for double counting. The two approaches estimate similar savings indicating that the savings are robust to different model specifications. Navigant prefers the RPPM approach as this model aligns with models typically used to evaluate other behavioral programs. The daily savings divided by the daily baseline is equal to the percentage savings. The standard errors are shown in italics below each savings estimate.

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[24] The engagement analysis includes all 2014 and 2015 downloaders. Information on the number of logins was not available at the time of this analysis but will be used to explore engagement in future analyses.
[25] Truncated at December 31, 2015.

Table 3. Per participant app savings for RPPM and MBC approaches

Statistic	Electric savings (kWh)		Gas savings (therms)	
	RPPM approach	MBC approach	RPPM approach	MBC approach
Average daily savings per participant	0.45	0.48	0.060	0.064
Standard error	*0.09*	*0.05*	*0.007*	*0.007*
Baseline daily usage*	26.23	26.25	2.64	2.65
Percentage savings (%)	1.69%	1.80%	2.27%	2.43%
Standard error	*0.34%*	*0.17%*	*0.26%*	*0.26%*

*Baseline daily usage is average daily usage by participants during the post program period plus the estimate of average daily savings. *Source:* Navigant

Annual savings per participant were calculated by multiplying the average daily savings values in Table 3 by 365. The double counted savings per customer per year were subtracted from the annual savings estimate from the regression analysis to get a savings estimate that was adjusted for double counting. Removing double counting reduced the electric savings by 5.98 kWh per year and the gas savings by 0.07 therms per year. Figure 5 shows savings estimates from the RPPM model after adjusting for double counting (with 90% confidence bounds). In percentage terms, electric savings were lower than gas savings by about two-thirds of a percentage point.

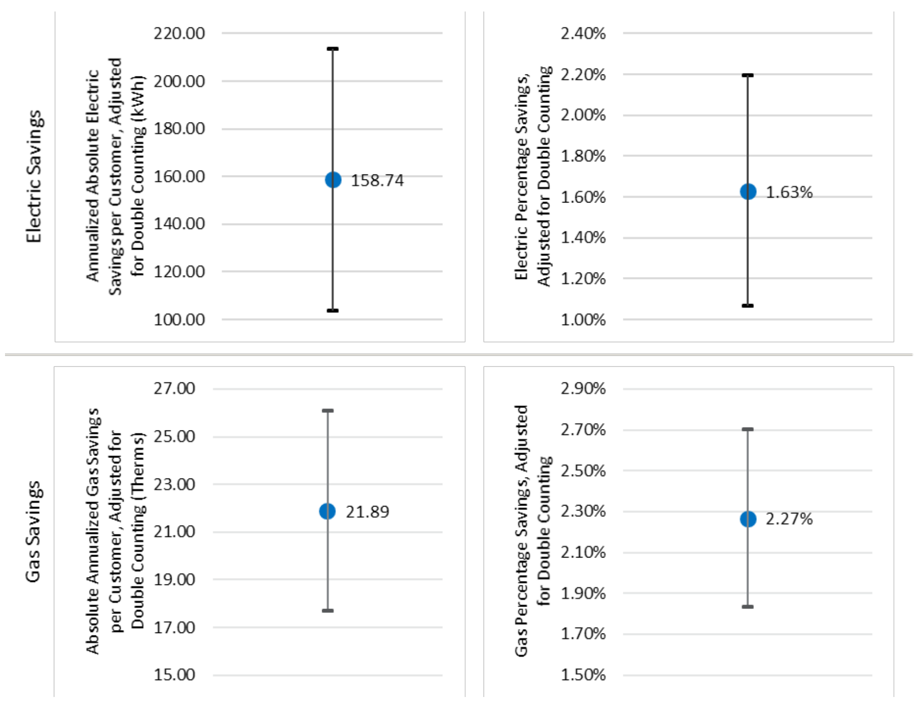

Figure 5. Absolute Annual and Percentage App Savings per Customer with 90% Confidence Bounds, Adjusted for Double Counting. The top panel shows electric savings and the bottom panel shows gas savings. *Source:* Navigant.

Energy Bridge

The incremental electric savings from installing the Energy Bridge are shown in Figure 6 with 90% confidence bounds.[26] The electric percentage savings from the Energy Bridge were almost triple the savings from the app alone. Because the Energy Bridge was evaluated using an RED, we know that these savings are due to the

[26] Gas savings were not estimated for the bridge as the bridge does not make any changes in the gas usage information provided to customers in the app.

Energy Bridge itself rather than other differences, such as motivation to save, between customers who received an Energy Bridge and those who did not.

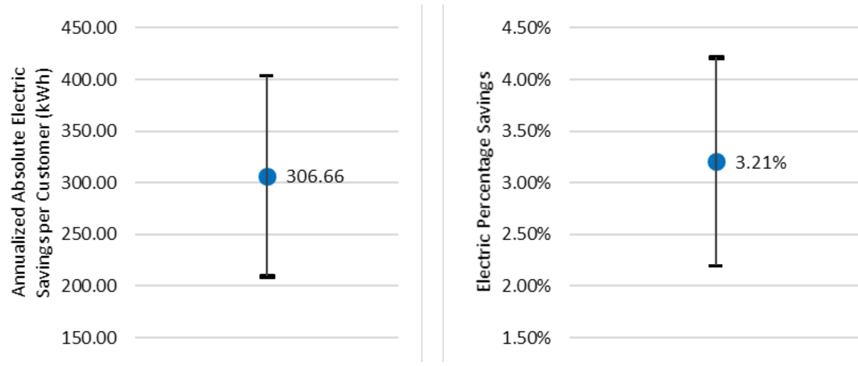

Figure 6. Absolute Annual and Percentage Electric Energy Bridge Savings per Customer with 90% Confidence Bounds. *Source:* Navigant.

Since both the encouraged and the control groups have the app, these Energy Bridge savings are incremental to the app savings, i.e., the total electric savings for customers with both the app and the Energy Bridge are the app savings plus the Energy Bridge savings. Therefore, customers who have the Energy Bridge achieve average total electric savings of 4.84%, equivalent to 465 kwh per year.[27]

Lifestyle Segments

Examining download dates of the app and installation dates for the bridge, Navigant found that Affluent Greens and Greens were frequent early adopters of the app. This was not surprising as these customers tend to be environmentalists who might be actively seeking out ways to save energy. More surprisingly, DIY Conservers also tended to be early adopters of the app. These customers may appreciate the projects and tips that the app offers that often show ways to conserve energy that would appeal to DIYers. Table 4 shows the savings estimates for each lifestyle segment.

Table 4. Annual savings by lifestyle segment

	App				Energy Bridge	
Segment	Number of electric participants	Electric annual savings (kWh)	Number of gas participants	Gas annual savings (therms)	Number of Energy Bridge installers	Electric annual savings (kWh)
Affluent Greens	9,893	236*	2,418	12.02	2,342	225*
Budget DIY	254	-38	110	46.55*	34	-492
Cash Flow	497	129	253	40.13	77	1,133*
DIY Conservers	7,734	24	1,473	36.38*	1,517	365*
Energy Indifferent	2,935	365*	803	23.69*	666	231
Greens	5,575	178*	2,017	20.07*	1,129	414*
Traditionals	634	-47	213	43.58*	121	879*
All customers**	33,159	77*	8,891	22*	7,379	307*

An asterisk (*) indicates that the estimate is statistically significant compared to the comparison group at the 90% confidence level.
**The all customers row includes the customers for whom we did not have lifestyle segment data.
Source: Navigant

[27] We did not calculate a confidence bound on the sum of app and bridge savings.

Savings trends by lifestyle segment across the three components (electric and gas savings from the app and electric savings from the Energy Bridge) are difficult to tease out because a segment that has higher than average savings for one component is often lower than average for another. Also, some of the segments are quite small and thus have very large confidence bounds which further obscures the trends. Furthermore, the lifestyle segments were assigned at the beginning of the analysis and were not updated based on demographic changes over time. Overall, Affluent Greens, Greens, and DIY Conservers have strong savings across the three components. Additionally, the Energy Indifferent group is a large segment of app downloaders who has decent savings across all three components and could be further targeted with future marketing.

Engagement Levels

Figure 7 shows the annual electric savings for the app and the Energy Bridge by engagement segment. Unsurprisingly, savings for the Energy Bridge are higher than savings for the app at each engagement level.[28] Additionally, the point estimates of savings for both the app and the Energy Bridge grow with the level of engagement.[29] These results suggest that DTE could achieve higher savings by keeping customers engaged with the app. DTE has invested in things like push notifications to keep customers coming back.

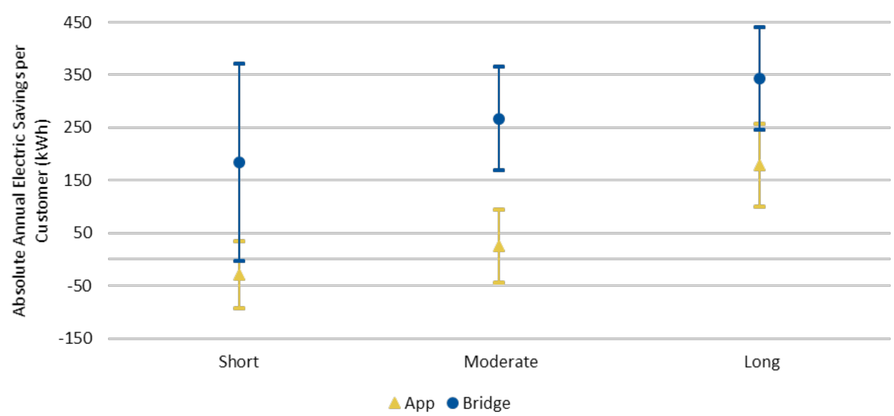

Figure 7. Absolute Annual Electric App and Energy Bridge Savings per Customer by Engagement level with 90% Confidence Bounds. *Source:* Navigant.

Conclusions

DTE launched the app in 2014 to push market transformation in the behavioral program space and move behavioral savings beyond traditional home energy report programs. Since then several other app-based programs have emerged and this seems to be a fast growing space for utility energy efficiency programs.[30] DTE Insight provides customers with access to information and tools designed to motivate energy saving actions, including interval data, target setting, weekly challenges, and tips for completing various home projects that can save the user energy and money on their bill. Participants also have the option to install an Energy Bridge that allows them to see their electric energy use every three seconds and stores it on a minute-by-minute basis. Overall, our analysis of DTE Insight leads to several conclusions relevant to app-based behavioral EE programs.

First, we found that an app that shows hourly electric and daily gas interval usage with a one-day delay drives both electric and gas savings. For DTE Insight, electric savings are 1.63% and gas savings are 2.27%. The

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[28] The point estimates for the bridge at each engagement level are statistically higher than those for the app at a 90% confidence level using a Wald test (despite the overlapping confidence intervals).
[29] Although the differences across levels are not statistically significant at a 90% confidence level.
[30] Other app programs include Bidgely and Meter Genius.

higher savings for gas are surprising[31]; one reason for this could be that HVAC drives much of the savings for this program and DTE customers mostly have gas heat and thus are achieving high winter savings. This runs contrary to popular belief that behavioral programs achieve the highest savings in the summer from AC, rather than in the winter from heating.

Second, the addition of real-time electric data to the app considerably increased the electric savings. For DTE Insight, the electric percentage savings for customers with the app and the Energy Bridge are 4.84%, almost triple the electric savings from the app alone. These finding are in-line with other studies that suggest real-time usage information can drive higher savings than interval usage (Ehrhardt-Martinez 2012).

Third, Affluent Greens and Greens are likely to be among the early adopters of energy apps, but these programs may also be popular among DIYers. Affluent Greens were the most frequent downloaders of DTE Insight (especially early on), but DIY Conservers were second, with Greens coming in third. The project and tips section of the app may appeal to DIYers as the tips show how much effort the project will take, how much it will cost, and offer step-by-step instructions to get the project done. Additionally, DTE Insight allows customers to set goals both in terms of usage and in terms of money which helps broaden the appeal of conserving energy and gives customers the ability to mitigate high bill risk. The money saving and high bill risk mitigation opportunities may be why DTE has also attracted a lot of customers in the Energy Indifferent lifestyle segment to use the app.

Finally, getting customers to engage with an app on an ongoing basis may help drive savings. Unsurprisingly, we found that DTE Insight customers who continue to engage with the app have higher annual savings than those who stop using it shortly after downloading. This suggests that engaging with the app for a short amount of time may not create lasting behavioral change and that drawing users back to the app will help drive savings. For example, the app contains push notifications to remind people to check their usage or alert them when their usage spikes. DTE is working on other methods to increase continual engagement with the app.

Acknowledgements

The authors of this paper would like to acknowledge the following staff at Navigant and DTE for their contributions to the DTE Insight evaluation: Latisha Younger-Canon, Craig McDonald, Debbie Brannan, Cherish Smith, Knox Cameron, Manish Rukadikar, Jason Kupser, Dennis Mullan, Sophia Francois, Luis Salas, Rosana Laurain, Kate Ten Brink, Joel Miller, and Thelma Dobson.

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[31] Most behavioral programs achieve higher percentage electric savings than gas savings.

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