Does <u>How</u> You Pay Your Energy Bill Affect <u>How Much</u> You Pay for Your Energy Bill?

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ABSTRACT

A recent study by Sexton (2015) investigates the causal effects of enrolling in automatic bill payment (ABP) and budget billing (BB) on household level electricity consumption.[1] Sexton finds that enrollment in an ABP program increases average monthly electricity consumption by about 4% overall and up to 6% for more recent enrollments. Sexton also reports an increase in consumption of 7% due to enrollment in a BB program designed to smooth seasonal bill extremes. These effects have not previously been demonstrated in the state of California. This paper presents findings from an evaluation of the effect of ABP and BB among California's IOU residential customers based on the prepared analysis datasets used in the impact evaluation of two of Pacific Gas & Electric's (PG&E) multiyear Home Energy Report (HER) programs. This approach we take allows for a basic replication of Sexton's work and offers an extension of the work to compare effects of ABP and BB on customers with and without Home Energy Reports. This combined analysis is made possible because Sexton's approach and the econometric model used in the study are similar to the "pooled" fixed effects approach used to evaluate behavioral programs such as Opower's HER program. While we believe the potential concerns regarding self-selection need further consideration, this paper contributes empirical evidence to an important new area of investigation that explores the unintended impacts of automation and customer convenience on energy consumption. Findings from this research are relevant to utilities, regulators, and consumer advocates among others.

Introduction

A recent paper by Steven Sexton in the Review of Economics and Statistics entitled "Automatic Bill Payment and Salience Effects: Evidence from Electricity Consumption" provides valuable theory and evidence to support the hypothesis that programs such as ABP and BB cause an increase in customers' energy consumption. ABP is a means of automating payment for a recurring bill that offers customers' convenience and minimizes or eliminates late payments. BB is a payment plan that allows customers to spread their bills over the course of a year through a flat monthly rate determined based on their past usage and bills. Budget billing programs are also referred to as flat billing, balanced billing, or level payment programs. ABP alters the importance of cost or price salience because there is no requirement for people to look at their bills before funds are withdrawn for payment. Sexton hypothesizes that the reduction in price salience due to inattention to the cost of energy results in consumption increases. This "loss of price salience" argument is also essential to motivating the econometric analysis performed to produce the estimates of program effect. It can be difficult to estimate effects of a decision where participants opt into a program. If the decision to participate is correlated with the person's outcome, then estimates of the treatment effect may suffer from selection bias. In this case, because the effect is hypothesized to be due not to the choice itself but to the resulting loss of price salience, the correlation may be less likely. As Sexton states, "the treatment effect is essentially unintended, and the self-selection constraint is likely satisfied."[2] Further, "intuitively, it is unlikely that an individual selects into ABP or BB

[1] Automatic Bill Payment and Salience Effects: Evidence from Electricity Consumption, Steven Sexton, The Review of Economics and Statistics, May 2015, 97(2): 229-241

[2] Ibid. p. 233.

because he expects to consume more electricity than he otherwise would."[3] Sexton makes additional, more technical arguments to support his claim that the estimates of these treatment effects are valid. Ultimately, the purpose of the analysis is not to assess the validity of Sexton's argument but to see if the results are consistent when the analysis is applied to California data. For this analysis, we accept Sexton's findings on ABP as a given.

Similar to ABP, Sexton hypothesizes that budget billing diminishes price salience by disconnecting the cost of consumption in a given month from the actual energy consumed. Sexton appears to believe that BB can be understood on the same terms as ABP and that his arguments regarding loss of price salience apply for BB as well. From our perspective, the motivation to participate in BB, however, has an important distinction relative to ABP that Sexton overlooks. To the extent that price is experienced through total monthly bills, BB effectively changes the price of energy. BB causes an effective drop in price during the summer months, as perceived through the bill, and an increase in price during months where consumption was previous lower than the mean bill across the year. From an economic perspective, an effective price decrease would be consistent with an increase in consumption during those summer months. While this disconnect does not rule out price insalience as a consequence of BB, it opens the possibility of motivations to participate in BB that could be more closely tied to consumption increases.

It seems reasonable, for instance, that BB could be motivated by customers who find it challenging to pay high summer cooling bills. BB would support an effort to maintain desired comfort during the summer by spreading the cost over the full year. This is quite different from an argument based on "loss of price salience" though it could have the same effect of increasing consumption overall.

This recognition means that BB participants may need to be considered independently from ABP. With regards to the analysis challenge of estimating a treatment effect in the presence of self-selection, we can no longer necessarily understand consumption increase as an unintended consequence. This increases the likelihood of self-selection bias in estimated treatment effects. Also, per Sexton, in this case there is reason to believe the bias would be upward as consumption is directly associated with comfort. Despite this, Sexton believes the results are still valid for the subset of the population opting into these programs – "Although strict exogeneity is necessary to interpret (treatment effects) as estimates of PATEs (population averaged treatment effects), their interpretation as population averaged treatment effects on the treated (PATTs) does not depend on independence of treatment status and potential outcomes."

We examine the effect of ABP and BB among California's IOU residential customers based on the prepared analysis datasets used in the impact evaluation of each of Pacific Gas & Electric's (PG&E) multiyear Home Energy Report (HER)[4] programs. In particular, we focus on assessing the impact of ABP and BB on the residential electricity consumption trends of PG&E's HER participants in two different waves. This approach we take allows for a basic replication of Sexton's study while offering an extension of the work to compare effects of ABP and BB on customers with and without Home Energy Reports. The combined results are facilitated by the fact that Sexton's approach and the econometric model used in the study are similar to the "pooled" fixed effects approach [2] used to evaluate behavioral programs such as Opower's Home Energy Reports (HER) program.

[3] Ibid. p. 233.

[4] Home Energy Reports are electronic or paper reports on energy consumption sent to customers at regular intervals (often monthly, like an energy bill) educating them on their consumption, how their consumption compares to other similar homes or to their own consumption historically, and provides then with energy saving tips and information. Experimental waves of the Home Energy Reports program are not representative of PG&E's customer base. With the exception of the Gamma Wave, each experiment excludes one or more of the customers in the lowest quartiles of energy use. Phase I of this evaluation will represent a proof-of-concept and widening the scope of customers studied can be considered for Phase II of this evaluation.

Model Specification

We identify ABP and BB enrollment for all members of PG&E's HER treatment and control groups and combine monthly consumption data of all participants in a wave into a single regression analysis[5]. This is also referred to as a "time-series cross-sectional analysis" because observations vary both across time and across individual dwellings. We then use a pooled fixed effects regression model to measure the joint effect of HER and ABP and BB enrollment on electricity consumption and the effect of ABP and BB conditional on Opower participation. Using a pooled fixed-effects approach allows for the measurement of ABP and BB-related impacts on the HER program while also controlling for other possible confounding factors.

The pooled fixed effects model we estimate is given by:

$$Cjt = \mu_j + \lambda t + \gamma_A ABPjt + \gamma_B BBjt + \gamma_H HERjt + \gamma_{AH} ABPjt * HERjt + \gamma_{BH} BBjt * HERjt + \varepsilon_{jt}$$

- Cjt = the log of average daily consumption during interval t for household j
- μ_j = unique intercept for each household j
- λt = 0/1 indicator for each time interval t (month-year) that tracks systematic change over time
- $HERjt$ = 0/1 dummy variable equal to 1 if household j is in the HER treatment group in period t, 0 if household j is in the comparison group in period t
- $ABPjt$ = 0/1 dummy variable equal to 1 if household j is an ABP enrollee in period t, 0 otherwise
- $BBjt$ = 0/1 dummy variable equal to 1 if household j is an BB enrollee in period t, 0 otherwise
- ε_{jt} = error term or random noise of the model

Table 1 provides a definition of each parameter of interest from our model. The names of the parameters are also used in tables where we present results based on model estimates in Section 3.1.

Table 1. Definition of model parameters of interest

Model Coefficient	Name of Parameter
γ_H	Post HER treatment
γ_A	On ABP
γ_B	On BB
γ_{AH}	Post HER treatment on ABP
γ_{BH}	Post HER treatment on BB

Interest in this model centers around the estimates associated with the ABP and BB flags, or indicator variables, that show the consumption effect of enrollment in these two programs. The coefficient estimates of γ_A and γ_B will reveal if the hypothesized increase in consumption due to loss of price salience occurs, and if it does, the extent of the increase for PG&E's residential electric ABP and BB enrollees.

Unlike the dataset that Sexton used in his study, which features a long time series for each household with sufficient pre- and post-ABP and BB enrollment data, our dataset includes a lot of households who have been on these payment plans longer than the span of the dataset. The long term effect of ABP and BB for such households is absorbed in the individual-specific intercept term, μ_j. Therefore, the estimated

[5] ABP and BB enrollment data was merged to HER program data and billing data for this analysis.

coefficients for the ABP and BB indicator variables will reflect the effect of ABP and BB on customers that are more recent enrollees. In particular, the coeffcients will reflect the effect these plans have on customers who enrolled in either or both since the start of the analysis period for each HER cohort.

Additionally, our model provides an estimate of HER treatment effect on consumption (captured by an estimate of the parameter γ_H) for customers that are not enrolled in either ABP or BB. This provides an estimate of baseline HER treatment effect across all report recipients. The model also provides the marginal (additional) effect of HER treatment on those enrolled in ABP and BB. The interaction between the post HER treatment indicator, and the ABP and BB enrollment flags measure this effect. In particular, the estimates of the parameters of these interactions (γ_{HA} and γ_{HB}) indicate the direction and degree of these marginal effects. The total HER treatment effect on ABP and BB enrolles, though, is the sum of the estimated baseline HER treatment effect and the incremental (marginal) HER treatment effect on these customers. It is given by sums of the following parameters for ABP and BB, respectively:

$$\gamma_H + \gamma_{AH}$$

$$\gamma_H + \gamma_{BH}$$

Both the estimates of the sum and marginal effects permit us to discern if HER treatment has an effect that is greater, less than or about the same on ABP and BB enrollees than on those in the HER treatment group not enrolled in either. They indicate if HER treatment effect has the same or greater effects on customers who use these forms of payment methods. Following Sexton, we log the left hand side variable of the model so that the estimated coefficients can be interpreted as percent changes.

Billing and Program Data Used

We used PG&E's HER program dataset to leverage the experimental design and the prepared analysis dataset used in the impact evaluation. We focus our study on PG&E's HER wave 3 and wave 4 rollouts (Table 2)[6]. We estimate the pooled fixed effects model for each wave separately to identify the effect of enrollment in the two payment plans on consumption as well as the additional effect of HER treatment for households enrolled in these programs. HER wave 3 began in July 2013 and involved 225,000 and 75,000 randomly assigned treatment and control households. PG&E’s 4th HER wave started in March 2014 and involved 200,000 and 75,000 randomly assigned treatment and control households.

Table 2. Features of HER dataset used in the study

Wave Three	Dual or single – standard frequency	13-Jul	highest 3 usage quartiles
Wave Four	Dual fuel – standard frequency	14-Mar	highest 3 usage quartiles

Impact evaluation of HER treatment for each cohort requires at least 12 months of pre- and post-treatment data. Thus, the wave 3 HER dataset we use has monthly consumption data for each treatment and control households from July 2012 until December 2015 except for households that terminate service sometime before the end of the study period. Similarly, wave 4 data has monthly consumption for the period March 2013 until December 2015. Consumption data is sourced from utility billing records and is supplemented with customer information data from the utility. A thorough discussion of data preparation and disposition can be found in DNV GL's "Review and Validation of 2015 Pacific Gas and Electric Home

[6] We focus on more than one HER wave to ascertain that our findings are stable across waves and not a function of a specific dataset. These specific HER waves were chosen from a set of possible 6 waves as they represent the widest possible coverage (territory and consumption level) and included a higher number of customers on both ABP and BB relative to other HER waves.

Energy Reports Program Impacts."[7] We identified which of the HER participants, both treatment and control, enrolled in ABP and BB plans using the participant roster for both services.

Data Summary

We present a summary of the data for each wave in Table 3. First, we note that 9-10% of households in each wave are enrolled in ABP while 6-8% of households are enrolled in BB. The mean date of ABP enrollment is January 2008 for wave 3 and June 2009 for wave 4. These start times precede the start of the analysis period in each dataset. In fact, a full 85-89% of those on ABP and about 80% of those on BB are enrolled before the start of the analysis period in the dataset for each wave. There are households that have been on either of these payment methods as early as 2001. As we indicated in Section 1.2, the estimated ABP and BB effects reflect the consumption impact of these payment plans on households that have enrolled in these plans since the start of our study period.

Table 3. Summary Statistics of dataset used in the study

	Wave Three	Wave Four
Number of households	229,522	223,859
Number of ABP households	21,287	21,488
Number of BB households	18,480	13,664
Percent of households in ABP	9%	10%
Percent of households in BB	8%	6%
Number of HER treatment households	173,653	162,836
Number of HER control households	57,709	61,023
Number of ABP households in HER treatment	15,939	15,636
Number of BB households in HER treatment	13,841	9,927
Mean date of ABP enrollment	Jan-08	Jun-09
Minimum date of ABP enrollment	Jan-02	May-02
Mean date of BB enrollment	Jun-08	Jan-10
Minimum date of BB enrollment	Mar-01	Sep-01
Percent ABP enrollment before data start	85%	89%
Percent BB enrollment before data start	80%	79%
Mean daily kWh	18.02	16.02
Minimum daily kWh	0.00	0.00
Maximum daily kWh	509.31	631.55

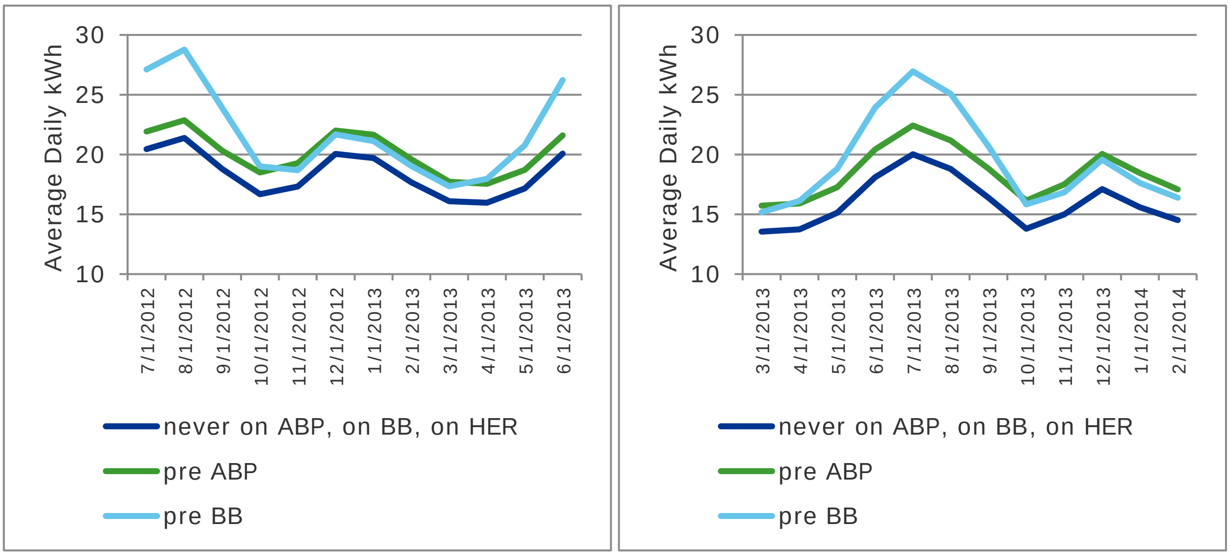
The table also provides the average, minimum and maximum daily consumption for each cohort. Such summary figures are useful, but it would also be informative to examine the pattern of consumption over a 12-month period to see seasonal variations and differences in consumption among households that eventually enroll in these payment plans versus those who never do.

We compare the level of consumption among ABP and BB households before their enrollment in these plans to the consumption of those that never do. For this purpose, we use monthly consumption data from March 2013-February 2014 from the HER wave 4 cohort for those that enroll in ABP and BB after March 2014 and for those who do not. This is the pre-HER treatment period as well and reflects electricity usage

[7] http://calmac.org/publications/DNVGL_PGE_HERs_2015_final_to_calmac.pdf

that is unaffected by any of the programs under consideration in this study. Figure 1 provides plots of monthly consumption for all three types in the HER wave 3 and wave 4 datasets.

Figure 1. Average daily consumption (kWh) before ABP and BB enrollment and HER treatment wave 3 and wave 4



Both figures indicate that consumption among eventual ABP and BB enrollees is higher than it is for those that never enrolled in these plans. It is also higher for eventual BB enrollees than for ABP enrollees. For eventual BB enrollees, the summer month consumption is clearly well above the rest, while their consumption coincides with that of future ABP enrollees during the rest of the months. These figures suggest that there is something different about the people who end up enrolling on these payment plans. The modeling approach controls for mean differences in consumption and, by extension, other non-time-varying effects across customers. The model also only measures program effect for customers who joined the payment plans during the analysis period, and have pre- and post-participation consumption data. However, it is the kinds of differences in consumption across groups noted in the figure above that support the concern that potential self-selection could affect estimated results.

Results

We provide model estimates from the pooled fixed effects model for both waves in Table 4. The model standard errors are clustered at the household level because monthly consumption values for a given household are not independent. This approach allows us to avoid standard errors that over-estimate the precision of estimated coefficients.

Table 4. Pooled fixed effects model estimates for HER wave 3 and wave 4

	Wave 3 Model Estimates			Wave 4 Model Estimates		
Parameter	Coefficient Estimate	Standard Error	P value	Coefficient Estimate	Standard Error	P value
Post HER treatment	-0.010	0.001	0.000	-0.007	0.001	0.000
On ABP	0.016	0.004	0.000	0.011	0.004	0.006
On BB	0.047	0.004	0.000	0.038	0.004	0.000
Post HER treatment on ABP	-0.008	0.002	0.000	-0.012	0.002	0.000
Post HER treatment on BB	0.001	0.002	0.650	-0.006	0.002	0.008

The model we specify included time-month effects (λt) for each of the 42 months in wave 3 and 34 months in wave 4. These effects control for exogenous trend common to all households and do not affect the parameter estimates of interest that the model is designed to address. Therefore, we do not present the parameter estimates of the time-specific effects in the table to conserve space.

We use the logged value of the dependent variable (average daily kWh) in these models. Parameter estimates from a model with a logged dependent variable can be interpreted as percent changes. For instance, the parameter estimate for HER treatment (post HER treat) has a value of -0.010 in the model for wave 3, which can be interpreted as a 1.0% reduction in average daily use as a result of HER treatment.

Effects of ABP and BB

The parameter estimates on ABP and BB indicate that enrollment in both forms of payment plans are associated with statistically significant increases in consumption. Within the first two years after ABP enrollment, we estimate a 1.6% increase in consumption in HER wave 3 and a 1.1% increase in HER wave 4. The corresponding increase in consumption for BB enrollment is estimated at 4.7% for the wave 3 cohort and at 3.8% for the wave 4 cohort.

In this study, we have attempted to replicate Sexton's work on the effect of ABP and BB enrollments using electric data from one California IOU. Similar to Sexton's results, we find that both ABP and BB participation are associated with increases in consumption. It appears that the loss of price salience may be at work for ABP. For BB, some combination of loss of price salience and effective summer price reduction may be at work.

Unlike those reported in Sexton, where consumption increases average about 4% for ABP residential customers and 6% for BB residential customers, the increases we see in this setting are more modest at about 1% to 1.6% for ABP and at about 4% to 5% percent for BB. The lower estimates may reflect differences in payment plan recruitment, the structure of the plans, differing behavioral responses to such offerings, and possible differences in weather correlation between ABP and BB in the two jurisdictions.

More importantly, the lower estimates may also reflect differences in the datasets we use to study the effects of ABP and BB. Unlike Sexton, who had the advantage of a long time-series with sufficient pre-ABP and BB enrollment information, we have people who are on these plans for much longer than we have data for in our study. Given the data available, there is no model that can distinguish between program effects and general program population characteristics of these long-term participants. The model specification we use effectively removes the effects of ABP and BB for those who enrolled in these plans prior to the start of our dataset. The individual- or household-specific terms (μ_j) absorbs these effects for such households. The coefficient estimates on the ABP and BB flags then pick up the effect of ABP and BB for those who go on these plans during the time period covered by the data. For HER wave 3, the coefficients estimate the effect of ABP and BB for those who enroll in the plans after July 2012 while they pick up their effects for those who enroll after March 2013 for the HER wave 4 cohort. The effects we estimate are, therefore, short-term ones, which may explain why our estimated effects, especially for ABP, are lower those reported in Sexton's study.

Effects of HER Treatment on ABP and BB Enrollees

Our study also features the additional interactive effects of these programs and HER treatment on consumption. The parameter estimates from the models indicate that HER treatment induces about a 1% reduction in consumption in wave 3 and 0.7% reduction in wave 4. These estimates are statistically significant at least at the 95% confidence level.

The models also indicate that the additional (marginal) HER treatment effect for those enrolled in ABP and BB are statistically significant except for those on BB in wave 3. The results indicate that effects of HER treatment for such enrollees are different than baseline HER treatment effect. We obtain the total effect of HER treatment for those enrolled in these payment plans by adding the baseline HER effect to the marginal effect. For instance, for the wave 3 cohort, the total HER treatment effect on those enrolled in ABP is -0.018, which reflects a reduction in consumption of 1.8% for this group. We provide the total HER estimate effects along with their statistical significance for ABP and BB enrollees in both cohorts in Table 5.

Table 5. Estimate of total HER effect for ABP and BB enrollees in HER wave 3 and wave 4

	Wave 3 Model Estimates			Wave 4 Model Estimates		
Parameter	Coefficient Estimate	Standard Error	P value	Coefficient Estimate	Standard Error	P value
Total HER effect on ABP	-0.018	0.002	-0.015	-0.019	0.002	0.000
Total HER effect on BB	-0.010	0.002	-0.006	-0.013	0.002	0.000

Another way to look at these effects is provided in Table 6. The outcomes for each group are provided relative to the control group customers who were enrolled in neither program.

Table 6. Marginal effects of ABP and BB

	HER Wave 3		HER Wave 4	
	Control	Treatment	Control	Treatment
No ABP/BB	100.0%	99.0%	100%	99.3%
ABP	101.6%	99.8%	101.1%	99.2%
BB	104.7%	103.8%	103.8%	102.5%

It is evident that HER treatment has a greater effect on ABP and BB enrollees than those not enrolled in either program, except for the BB enrollees in wave 3. For BB enrollees in wave 3, the HER treatment effect is no different than the baseline effect. HER treatment appears to shave off the entire increase in consumption for those enrolled in ABP in both waves. For example, in wave 3 while ABP enrollees see an average consumption increase of 1.6%, HER treatment decreases their consumption by 1.8%. HER treatment counteracts about 20% to 30% of the increase in consumption for BB enrollees.

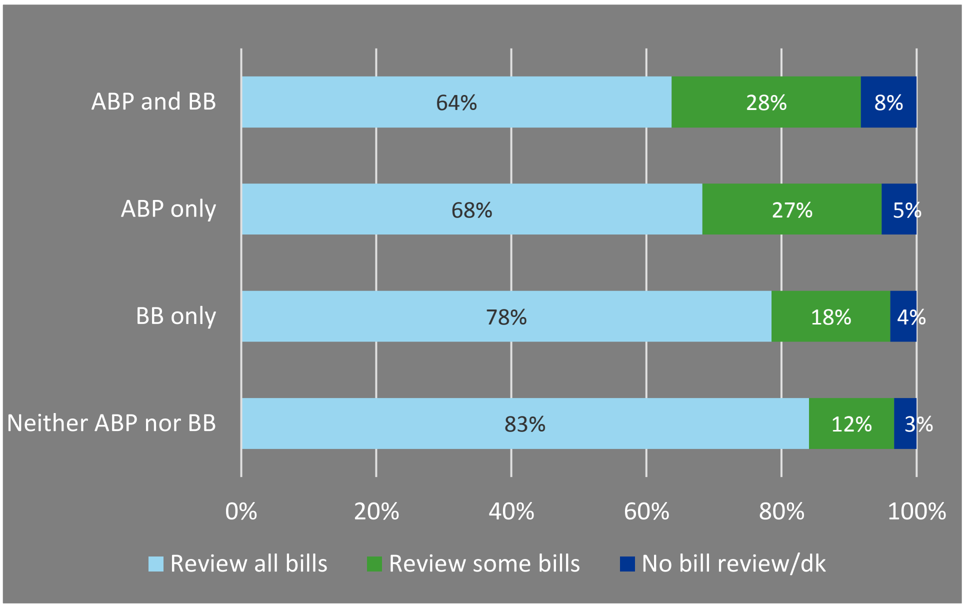
ABP and BB Customer Characterization

While the impact evaluation quantifies differences in consumption among ABP and BB enrollees, a survey among ABP and BB users and non-users helps to unpack the motivation to participate and the variability in customer demographics and behaviors that could potentially lead to these differences in consumption. The ABP and BB survey was a web survey (n=7,279) fielded in May 2017 and the sample frame mirrors the base used in the impact evaluation for this study – waves 3 and 4 of PG&E's HER experimental design.

Bill Review Behavior by ABP and BB use

Respondents were asked to indicate if they reviewed their monthly utility bill for the amount they owed. Regular bill review without fail each month is most common (83%) among respondents using neither ABP nor BPP, and least common (64%) among respondents using both ABP and BB (Figure 2). In particular, ABP seems to be associated with lower frequency of bill review. The direction of causality is unclear: People who are uninterested in reviewing their bills may be more likely to enroll in ABP, but it is also possible that enrolling in ABP may cause people to review their bills less frequently.

Figure 2. Bill review behavior by ABP and BB use



Customer Profile

We examined the survey sample on key demographic characteristics and compared against statewide statistics for California and within the sample by users and non-users of ABP and BB. The overall population targeted for the HER program waves were customers in the top 3 load quartiles, so we expect that demographic comparison from the overall California population accordingly. Survey respondents had a higher proportion of those with annual household incomes greater than $75,000 and a college degree education or higher (Table7).[8] A comparison of ABP and BB users versus non-users within the survey shows some significant demographic differences with ABP only customers being more affluent and educated relative to their BB only counterparts. ABP only customers report significantly higher income with around three-fourth (78%) reporting incomes over $75,000 versus between 52% and 65% for all other user and non-user groups. ABP users are also more likely to have a graduate degree or higher relative to BB only users at 81% versus 61% respectively.

Table 7. Customer profile

	CA	Total Survey (n=7,279)	ABP and BB non-user (n=3973)	BB only user (n=386)	ABP only user (n=2,520)	ABP and BB user (n=400)
Income over $75,000	42%	65%*	58%	52%	78%*	65%
Education – Bachelor's degree or higher	31%	69%*	63%	61%	81%*	63%

Note: * Indicates statistically significant difference at the 95% confidence level between CA and the survey sample and ABP only users and all other groups.

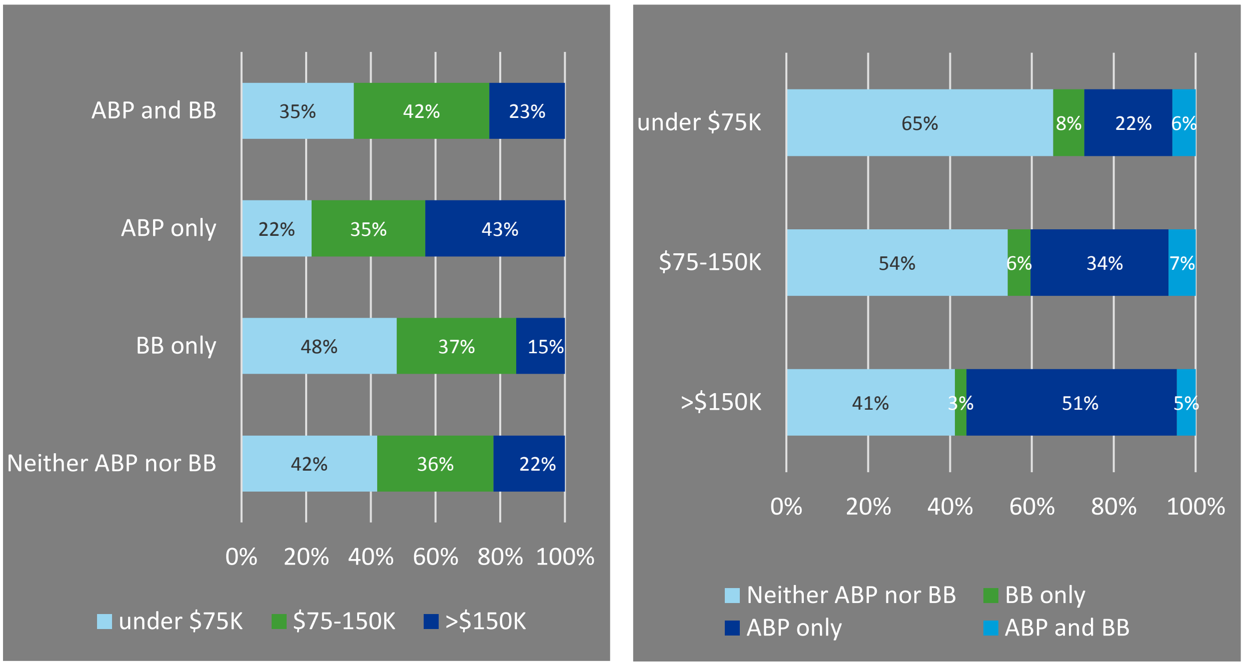
A Closer Look at Income and ABP and BB Use

An examination of the income distribution within each of these groups reveals that ABP only users are the most affluent with 43% reporting a household income over $150,000 (Figure 3). BB only users have the lowest prevalence of high income customers, at around one-third that of ABP only customers, at 15%. In fact, an analysis of ABP and BB use by income reveals that ABP use steadily increases with income, which may reflect access to technology, having a steady and sufficient income to easily make bill payments, or

[8] Low income or in-language/non-English speaking customers who face the barrier of the digital divide in higher proportions are not as likely to participate in a web survey in English.

both. In comparison, BB use among those with annual household incomes under $75,000 is nearly three times as likely than those with incomes above $150,000 at 8% to 3% respectively.

Figure 3. Income by payment method and payment method by income



We find that ABP use is associated with higher levels of education and income in contrast with BB use which has a higher prevalence of customers with relatively lower incomes. BB users see a higher spike in consumption relative to ABP. Budget billing is currently marketed as a way for customers to have more manageable monthly payments. Our findings suggest a closer look at the inadvertent increase in consumption that accompanies BB use, especially given that a higher proportion of BB users have relatively lower incomes and can likely ill-afford the increased bills.

Conclusions and Recommendations

This research provides evidence that ABP and BB programs are associated with increases in energy consumption by customers. The research also provides information on characteristics of program participants through the process evaluation. The ultimate intent of this research is to support insight on how ABP and BB may be modified to promote energy conservation. Below we propose opportunities to combine ABP and BB with other energy management technology options such as Home Energy Reports that counteract the loss of price salience that accompanies ABP and BB services.

1) The results presented here provide further evidence to support Sexton's claim that there are consumption increases associated with participation in ABP and BB programs. Due to data constraints, our results only capture relatively short term effects, but despite this limitation we find consistent, statistically significant increases in electric consumption across two independent groups of PG&E customers. As might be expected given the shorter duration, the magnitudes of the effects that we identify are smaller than those reported by Sexton. While we replicate the spirit of Sexton's paper, we also find that the self-selection implications of the endeavour need further consideration, particularly for BB customers.

2) In an extension to Sexton's work, we also provide evidence that HERs at least partially claw back these increases in consumption associated with ABP or BB participation. These findings are consistent with the underlying theory put forward by Sexton that the increases in consumption are due to a loss of price salience. While ABP and BB are hypothesized to decrease customers'

awareness of their spending in any given month, HERs increase customers' awareness of consumption itself perhaps counteracting the loss of price salience. HERs counteracted 100% of the increased consumption associated with ABP, while reducing the much greater increases by BB customers by up to 30%.

These results have different implications for customers choosing to go onto the two different programs. The choice to go on ABP is based on convenience. The customer prefers to forego that monthly hassle of paying the bill so automates the process. The effects that Sexton identifies and that we also find can be seen as a hidden cost of this service, whether tied to a loss of price salience or otherwise. Further, from a regulatory perspective, increased consumption due to loss of salience is an unintended and possibly unnecessary side effect of the increased convenience of ABP. It would be appropriate to take action that attempts to limit the unnecessary effects of the ABP service. These actions could include something like a HER report that would help to maintain a focus on consumption level combatting loss of price salience. This analysis indicates that, at least in the short term, HER reports can fully counteract the consumption increases associated with participation in ABP.

BB, on the other hand, is a service that customers choose to even out utility payments over the year. The service directly separates consumption from its immediate price effect in terms of the utility bill that is received after a month of consumption. In this respect, during summer months, BB potentially offers a short term negative price effect. The effective cost of cooling has been substantially reduced in terms of the payment on summer bills. This could cause additional upward pressure on consumption in addition to the effect of loss of salience. That an increase of this magnitude occurs in such a short span of time supports the possibility that more than loss of price salience is occurring. Another way to understand the increase in consumption is that BB, by effectively lowering the immediate cost of cooling by spreading them over the full year, makes it easier for BB participants to meet their full comfort needs despite tight budgets. Both explanations flow from the same economic mechanism but put a different emphasis on the outcomes. As a result, the regulatory perspective on the BB effect may need to be more nuanced than for ABP. In addition to receiving HER-type reports, which do address a portion of the consumption increase, perhaps HVAC program options offered to BB customers could be enhanced with additional incentives. This could facilitate BB customers meeting their comfort needs while still lowering their overall cooling consumption. It could also help target customers with substantial AC load and high potential AC savings with either a tune up or an EE unit replacement.

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