The Impact of Bill Protection on Demand Response and Program Retention Under a Residential CPP Rate

Dr. Stephen S. George, Freeman, Sullivan & Co., San Francisco, CA
Mr. Josh Bode, Freeman, Sullivan & Co.
Elizabeth Hartmann, Freeman, Sullivan & Co.

ABSTRACT

Pacific Gas & Electric Company's SmartRate is a voluntary dynamic tariff that charges significantly higher prices during the peak period on selected event days, which are offset by rate discounts on summer non-event days. It has been in place for three years and with current enrollment of roughly 25,000 customers, it is one of the longest running and largest dynamic rate programs for residential customers in the country. In order to encourage program enrollment, PG&E offers customers first year bill protection. Under this program feature, participants are guaranteed that they will not pay more on the new rate than they would have paid under PG&E's standard tariff. Roughly 25% of customers currently enrolled in the program have had bill protection expire. This affords the opportunity to assess the impact of bill protection on demand response and customer retention.

The analysis summarized below shows that bill protection reduces average demand response by about 25%. However, we also found that bill protection reduces program attrition during the initial period on a dynamic tariff. What is not yet known is the extent to which bill protection increases enrollment on dynamic rates, which is its primary purpose. Even with lower average load reductions for participants under bill protection, aggregate impacts could be higher with bill protection than without it if bill protection increases program enrollment. Several studies will be conducted over the next few years that will reveal whether bill protection significantly increases participation in dynamic rate programs.

Introduction

Dynamic pricing has the potential to produce significant load reduction during peak periods, thus helping to reduce market clearing prices and limit the need for additional generation capacity. There are decades of research, and many recent pricing pilots, which show that consumers can and will respond to time varying price signals. On the other hand, there is also ample evidence concerning the challenge of getting consumers to sign up for dynamic rate options. A significant barrier to customer enrollment is risk aversion. Prospective participants in dynamic rate programs often focus more on the downside risk of higher bills than on the upside potential for significant bill savings afforded by dynamic rates. The lack of experience with such rates in the context of electricity use, combined with limited knowledge about the relationship between usage behavior and cost, make it difficult for consumers to make intelligent decisions about the rate that serves them best. On the other hand, there is ample evidence that once consumers try time-varying rates, many prefer them over traditional flat pricing. A key marketing challenge is getting large numbers of consumers to try dynamic rates.

One option for addressing risk aversion is first year bill protection. With bill protection, consumers are guaranteed that they will not pay more under the new tariff than they would under the otherwise applicable tariff (OAT). At some point in time, typically at the end of a year or the end of a tariff season, a customer's bill is calculated based on the OAT and the dynamic tariff. If a customer would have paid less under the OAT, the utility credits their account or issues a check payable in the amount of the difference in the two bills. First year bill protection allows consumers to try a dynamic tariff risk free for up to a year after enrollment.

Some have argued that demand response will be lower under bill protection than without it because customers are rewarded for using less electricity but not penalized for using more during critical peak hours. Others have argued that demand response will be the same because the potential for reimbursement at the end of the summer is outweighed by the immediacy of paying each monthly bill, which could drive customers to respond to price signals regardless of bill protection.

This paper presents the first empirical evidence of which we are aware that concerns whether bill protection reduces demand response. We also examine the relationship between bill protection and program attrition. Specifically, we consider whether bill protection mitigates attrition during the first year on a rate, and also whether attrition increases or stays the same immediately after the bill protection period ends. The findings presented here should be considered when designing marketing and retention strategies for dynamic rate programs.

The impact of bill protection is examined in this paper through analysis of Pacific Gas and Electric Company's (PG&E) SmartRate tariff. The SmartRate tariff has been offered to residential customers with SmartMeters since 2008. Program enrollment equals roughly 25,000 customers, making it the largest residential dynamic rate program in the country. The tariff was marketed with first year bill protection and is the only residential tariff of which we are aware that allows for an empirical assessment of the effect of bill protection. Roughly 6,300 of the 25,000 participants that were enrolled on the tariff in 2010 experienced their third year of participation in the program. For almost all of those customers, bill protection expired at the end of the 2009 summer.

The remainder of this paper is organized as follows. The next section provides a brief summary of PG&E's SmartRate tariff. This is followed by an assessment of the difference between peak period load impacts for customers with and without bill protection. The third section examines the relationship between bill protection and program attrition. Section 4 provides a brief overview of additional empirical findings that were obtained from a detailed analysis of the SmartRate program. The final section summarizes the primary conclusions from the analysis.

Overview of PG&E's SmartRate Tariff

PG&E began offering SmartRate to residential customers in the Bakersfield and greater Kern County area in May 2008. This region was the first in PG&E's service territory to receive SmartMeters, which record hourly electricity consumption. By the end of the 2008 program year, enrollment in the Kern County area exceeded 10,000 customers. SmartRate marketing was suspended from the fall of 2008 through early spring 2009. Starting in May 2009, enrollment expanded both in terms of the number of customers and the geographic regions covered. At the beginning of the 2009 program season, roughly 8,500[1] residential customers were enrolled in the program and at the start of the 2010 summer season enrollment had grown to around 25,500 customers.

[1] The drop in enrollment from 10,000 to 8,500 was primarily due to normal customer churn (e.g., move outs, account closures, etc.) combined with the absence of marketing between the end of summer 2008 and the start of a marketing effort in spring 2009.

Under SmartRate, there can be up to 15 event days during the summer season, which runs from May 1st through October 31st. Prices only vary by time of day on SmartDays, unless a customer's underlying rate is a time-of-use (TOU) rate.[2] The peak period on SmartDays is from 2 PM to 7 PM and participants are notified that the next day will be a SmartDay by 3 PM on the preceding day. Participants have several options for receiving event notification (e.g., email, phone, etc.), including not being notified at all. Roughly 20% of customers either chose not to be notified or provided notification information that was initially incorrect or became outdated.

Customers that enroll in SmartRate receive first-year bill protection. This ensures that, initially at least, customer's bills will not increase under the new rate option relative to what the bill would have been over the same period under the OAT.

SmartRate pricing consists of an incremental charge that applies during the peak period on SmartDays and a per kilowatt-hour credit that applies for all other hours from June through September. For residential customers, the additional peak-period charge on SmartDays is 60¢/kWh. The SmartRate credit has two components, both of which apply only during the months of June through September.[3] The first SmartRate credit applies to all usage other than peak-period usage on SmartDays. For residential customers, the credit equals roughly 3¢/kWh. An additional credit of 1¢/kWh applies to tier 3 and higher usage for residential customers regardless of time period.

PG&E's standard residential tariff, E-1, is a five-tier, increasing block rate, with the price per kWh increasing more than threefold between Tier 1 and Tier 5.[4] The usage level where prices change is tied to a baseline usage amount that varies by climate zone. Table 1 shows the prices for each tier for the E-1 tariff for both CARE and non-CARE customers who are not all-electric homes. CARE stands for California Alternate Rates for Energy and is a program through which enrolled, low income consumers receive lower rates than non-CARE customers.[5] As shown in Table 1, the CARE discount is quite significant, especially for low income households that have usage in Tier 3 and above. For example, the ratio of marginal prices between E-1 and CARE customers is more than 4 to 1 in Tier 5. Almost half of all customers on SmartRate are on CARE.

There have been 37 critical event days since SmartRate was first offered, 9 in 2008, 15 in 2009 and 13 in 2010. The average load reduction during peak periods on event days in 2010 was 14.1%. In spite of a change in customer mix over the three-year period, the average demand reduction in prior years was quite similar. The average hourly estimated percentage load reduction across the 9 event days in 2008 equaled 16.6%.[6] In 2009, the average percentage load reduction was 15%.

[2] Currently, there are roughly 10 SmartRate customers with underlying TOU rates (PG&E's E-6 and E-7 tariffs).
[3] Credits were applied only during the four-month period from June through September rather than for the whole summer in an attempt to smooth out the bill impacts across the summer months. Since most event days are likely to fall in the months of June through September, having the discount apply only in these months would do a better job of partially offsetting the negative bill impacts associated with the higher prices on event days.
[4] PG&E is in the process of trying to flatten the price increases across tiers and was recently successful in making the Tier 4 and 5 prices the same.
[5] Qualification for CARE is based on self-reported, household income and varies with the number of persons per household. The maximum qualifying income for a household with 1 or 2 people is $30,500. For a four-person household, the maximum qualifying income is $43,200.
[6] 2008 event days were significantly hotter than 2010 event days.

Table 1. E-1 CARE and Non-CARE Prices for PG&E[7]

Usage Tier	% of Baseline Usage	E-1 Price for Tier (¢/kWh)	Average E-1 Price Based on Mid-Tier Usage (¢/kWh)	CARE Price for Tier (¢/kWh)	Average CARE Price Based on Mid-Tier Usage (¢/kWh)
1	100%	11.9	11.9	8.3	8.3
2	130%	13.5	12.1	9.6	8.5
3	200%	29.1	15.8	9.6	8.8
4	300%	40	22.5	9.6	9.1
5	>300%	40	27.5	9.6	9.2

Impact of Bill Protection on Demand Response

In order to examine the impact of first year bill protection on demand response, it is necessary to select a control group of customers who are similar to SmartRate customers but who are not on the tariff. Estimating the change in average load reduction for a group of customers before and after bill protection is removed ignores exogenous factors that might also influence energy use over the same time period, such as the impact of the economic slow down on energy use. With an external control group, the potential impact of exogenous factors can be controlled.

A suitable control group was selected using a method called propensity score matching.[8] Both the SmartRate and control groups were drawn from Kern County for two reasons. First, approximately 5,500 out of the 6,500 accounts that had bill protection expire in 2010 are located in the Kern area. Second, focusing solely in this region allowed us to better account for the effects of weather and the timing of when customers enrolled. Over 90% of participants were enrolled for all event days in 2009 and 2010. Accounts that were dually-enrolled in PG&E's SmartAC program, an emergency direct load control program that can also be used to cycle air conditioning on event days for dually-enrolled customers, were excluded from the control and participant samples in order to isolate price response solely due to customer behavior during event days.

Table 2 compares the observable characteristics for participant and control customers selected using propensity score matching. As seen, the two groups are quite similar on key factors such as the likelihood of AC ownership, weather sensitivity, CARE enrollment and other factors. There is less than a 2% difference in annual usage between the two groups, and less than a 1% difference in summer usage and the correlation

---

[7] For E-1 customers, the fixed monthly charge is approximately $4.50. For CARE customers, it equals roughly $3.60.

[8] Propensity score matching is a technique designed to ensure that control group members are as similar as possible to those who enrolled based on observable variables. It corrects for selection effects that can be observed. The approach works best when there is a rich set of explanatory variables and many potential control customers to choose from (i.e., there are many potential "look alikes"). The primary criticism of matching is that it cannot control for unobservable characteristics. If there are systematic differences in unobservable characteristics *and* those are strongly correlated with SmartRate effects, estimates may be biased.

between monthly usage and heat intensity. None of the differences on any observable variables are statistically significant.[9],[10]

Table 2. Comparison of SmartRate Participants to Matched Control Group

Characteristic	SMR Sample	Control	t Value
Percent CARE customers	0.48	0.49	-0.16
Percent all electric customers	0.03	0.05	-1.25
Annual Usage	8184	8380	-0.57
Summer usage	4599	4635	-0.19
Correlation between monthly usage and heat intensity	0.75	0.74	0.45
Median household income in CBG	52348	50116	1.20
Average house age in CBG	27.27	28.19	-0.73
Average family size in CBG	3.71	3.73	-0.40
Median age of homeowner in CBG	45.99	45.42	1.47
Percent English speakers in CBG	0.61	0.62	-0.64
Population density in CBG	50.13	52.32	-1.20
Ratio of Mar-Apr usage to Jun-July Usage	2.38	2.28	1.21

In total, 213 treatment and 213 control customers[11] were included in the estimating sample. A very simple regression specification was used, as shown in the following equation:

$$lnkW_i = \alpha + \beta \cdot Event_i + \gamma_i \cdot Event_i \times billprotect_i + \sum_{i=1}^{28} \delta_i \cdot date_i + \varepsilon$$

The dependent variable is the log of kW for each hour during the event period from 2 to 7 PM for event days only. Thus, the coefficients represent the percent difference in load associated with each variable. The constant reflects the average event-period load for the control group. In addition, binary variables for each day were included to control for any day-specific characteristics such as day of week, weather and other factors that affect the SmartRate and control group loads equally. In other words, time effects were controlled for. The only other two variables in the model were an event variable equal to 1 for SmartRate participants and 0 otherwise, and an interaction of the event variable with a variable indicating whether the customer was under bill protection. The event variable captures the average percent load reduction attributable to SmartRate. The interaction term captures the incremental effect of bill protection on the

---

[9] Statistical significance at the 95% level of confidence would have a t-value exceeding 1.96. The 90% confidence interval is associated with a t-value of 1.64.

[10] As indicated in a prior footnote, there may still be selection effects associated with unobservable variables.

[11] The sample sizes used in this analysis were small primarily because the analysis was one of many factors being examined within a much broader study. Samples of 400 SmartRate and 400 control customers were pulled for the broader study and the sample used here was a subset of those samples. Customers that were dually enrolled in PG&E's SmartRate and SmartAC programs were eliminated so the estimates could be attributed to behavior change only, not enabling technology. Other observations were lost during the matching process.

percentage load reduction, where for SmartRate participants, the bill protection variable was equal to 1 if they were under bill protection, 0 otherwise.

The coefficient on the event variable was -0.181, and was highly significant, with a t-statistic equal to -12.2. This implies that the average percentage load impact was 18.1%[12] for SmartRate customers across all event days, with a 95% confidence band that ranged from a load reduction of 15.1% up to 20.9%, absent bill protection.

The coefficient on the interacted bill protection variable equals 0.053. This indicates that demand response is roughly 30%[13] less on average for customers under bill protection than when bill protection is no longer in effect. That is, the average load impact for customers under bill protection would be around 12.7% (i.e., 18.0% minus 5.3%), compared with 18.0% for customers not under bill protection. The 95% confidence band for the incremental effect of bill protection ranges from a decrease in price responsiveness of 1.7 percentage points to a decrease of 8.9 percentage points.

In summary, first year bill protection reduces average demand response by roughly 25%. Importantly, this does not necessarily mean that offering first year bill protection is not a sensible or effective policy option. The primary intent of bill protection is to encourage customers to try dynamic rates. If bill protection increases enrollment over what it otherwise would be, offering it could still produce much larger aggregate impacts compared with a program that does not offer bill protection even if average demand response is lower. As seen in the next section, there is also a relationship between bill protection and customer retention that must be factored into the policy equation. Unfortunately, currently there is no empirical evidence on the impact of bill protection on customer enrollment. This will change over the next several years as several consumer behavior studies that are getting under way through Smart Grid Investment Grant funding by the Department of Energy will examine the impact of bill protection on customer acceptance. A study by PECO Energy Company that will get underway in 2012 will also examine the impact of bill protection and other marketing features on customer enrollment in dynamic and time-of-use rate programs.[14]

Impact of Bill Protection on Retention

Retention rates and patterns are important components of program performance. They affect the overall load reduction level, costs and the cost-effectiveness of DR programs. An important policy question is whether first year bill protection influences customer retention. To answer this question, it was necessary to develop a model of customer retention/attrition.

Overall, there are two main types of attrition from SmartRate. The first is normal turnover due to accounts opening and closing as a result of customer relocation. This is mainly a function of customer characteristics and is unrelated to participation in SmartRate. For example, a program with a high share of renters typically has higher participant turnover simply because renters relocate more frequently than homeowners.

---

[12] This average impact is higher than the overall program average of 14.1% because of differences in the characteristics of the subset of customers that was used for this analysis.
[13] 30% = 100% - (18% - 5.3%)/18%
[14] See *PECO Energy Company's Initial Dynamic Pricing and Customer Acceptance Plan.* October 28, 2010.

The second type of attrition concerns active customer de-enrollments. These are instances when a participant requests a rate change even though they remain at the same location. This type of attrition is the focus of the analysis summarized below.

Assessing retention and attrition rates is complicated by the fact that customers start and leave a program at different times. The participant population is constantly in flux. For any period of time, some customers will enroll and others will close their account for reasons unrelated to SmartRate. In estimating retention, it is critical to define the "decision" of interest and to track the time customers spend on the rate. Simply dividing the number of de-enrollments by the number of accounts ever enrolled in SmartRate produces misleading estimates of retention rates.

The vast majority of customers who sign up for SmartRate have stayed on the program. After controlling for normal turnover, the attrition rate is quite low. The attrition rate is highest during the first two months a customer is on SmartRate. Roughly 1.1% of SmartRate customers left the program within one month of being on the rate and another 0.67% dropped out during the second month. Over a 28-month period, the average dropout rate was 0.23% per month.

To better understand what factors drive attrition from SmartRate, we used a Cox proportional hazards model[15] to quantify how various factors affect customer opt-outs. A Cox model tracks both the amount of time a customer has remained on the rate and customer opt-out decisions, when observed.[16]

At a basic level, the model quantifies the risk of opt-outs as a function of time. With most products, initial opt-out or failure rates are higher in the first few months after they have been purchased. In other words, if the SmartRate is a bad fit for a customer, they discover this quickly. In addition to time, explanatory variables can be introduced that explain the extent to which the variable leads to higher or lower opt-out rates than that of the average customer. The explanatory factors can be time invariant or they can vary for each observed time period. Geographic location is an example of a time-invariant factor and monthly bill is an example of an explanatory factor that varies for each period observed.

The Cox proportional model is a non-linear regression technique and is interpreted differently than a linear regression. The results are best understood in terms of hazard ratios, which reflect relative risk. At the simplest level, a hazard ratio indicates the extent to which each explanatory variable changes the relative risk of customer opt-outs. A variable that does not have any effect on opt-out rates has a value of 1.00 – it does not increase or decrease the risk that a customer leaves the SmartRate tariff. If a factor such as loss of bill protection increases the risk that a customer leaves the tariff, the hazard ratio exceeds 1.0. For example, a value of 1.11 would indicate that loss of bill protection in the prior month increases the risk of opt-out by 11%, holding all other factors constant. If the base opt-out rate for a given month is, say, 1.00%, loss of bill protection increases the risk of leaving the program from 1.00% to 1.11% for that month. Likewise, factors that decrease the risk that customers leave have values below 1.0.

Table 3 summarizes the model variables and Table 4 shows the regression results. As seen in Table 4, nearly all variables in the regression are statistically significant. Two variables associated with bill

---

[15] Cox, D.R. 1072. *Regression Models and Life-tables.* Journal of the Royal Statistical Society. See also Box-Steffensmeier, J. and B. Jones. 2004. *Event History Modeling: A Guide for Social Scientists.*

[16] We cannot observe what the opt-out decision would have been for an account that closes. This phenomenon is technically referred to as a censored observation.

protection are included in the model. The first variable, with a coefficient equal to 0.95, indicates whether or not a customer was bill protected in the prior month. The second variable, with a coefficient of 1.11, indicates whether a customer lost bill protection in the prior month. The variable indicating the presence or absence of bill protection is marginally significant and shows that customers are 5% less likely to drop out while under bill protection. The variable representing the loss of bill protection in the prior month indicates that the likelihood of de-enrollment is about 11% greater the month following the loss of bill protection.

The variables labeled Greater Bay Area through Stockton represent the location of each customer with respect to Local Capacity Areas (LCAs). An LCA is a load pocket designated by the California Independent System Operator (CAISO). Climate and customer characteristics vary across LCAs. The coefficients on these variables indicate that all LCAs have higher attrition rates than the Greater Bay Area. The largest difference is for Kern, where the coefficient of 2.84 indicates that customers are roughly 1.84 times more likely to drop out of the SmarRate program compared with Bay Area customers. In Fresno and Stockton, customers are roughly 50% more likely to drop out than in the Bay Area.

The coefficients on the monthly binary variables indicate that customers are less likely to drop out of the program in January than in any other month, and most likely to drop out in July. The likelihood of dropping out is much higher during all summer months than during the winter period. Higher opt-out rates during the summer are logical given that this is when customers are most aware they are on SmartRate and of the effort required to stay attuned to events and reduce loads. During summer months, customers are also reminded about SmartRate through bill line items and event notifications. The very high July value may result in part from the fact that in 2008, 2009 and 2010, the first SmartRate event occurred in late June and customers were reminded they were on the tariff through event notifications.

The CARE variable is not statistically significant. However, to fully understand CARE opt-out rates, it is necessary to include the interaction between CARE and the log of the monthly bill. On its own, the coefficient on the log of last month's bill indicates that higher bills increase the likelihood of dropping out of the program for non-CARE customers. The coefficient on the interaction between CARE status and the log of last month's bill indicates that changes in CARE customer bills do not influence their likelihood of dropping out of the program.[17] This may largely reflect the fact that bill fluctuations for CARE customers are much less than for non-CARE customers because of the relatively flat tier structure under the CARE rate compared with the standard E-1 tariff. Under the CARE rate, bills increase proportionally with usage whereas for non-CARE customers, bills can increase dramatically as both usage and prices increase simultaneously. In addition, as CARE customers increase their usage into tiers 3, 4 and 5 they begin to receive a 1¢ additional credit for usage in higher tiers. Relative to the price for usage in tiers 3, 4 and 5, the additional discount is much larger for CARE customers than it is for non-CARE customers. To put this in perspective, usage in tiers 3, 4 and 5 is priced at 11¢/kWh for CARE customers and ranges between 25¢ and 40¢/kWh for Non-CARE customers.

[17] The coefficient of 0.98 indicates that CARE customers are 2% less likely than non-CARE customers to drop out when bills increase across the summer months due to fluctuations in weather, for example, and the coefficient of 1.02 for the log of the monthly bill indicates that non-CARE customers are 2% more likely to drop out when bills increase due to normal fluctuations. These two values offset each other, indicating that bill fluctuations do not influence drop-out rates for CARE customers.

The last variable in the model represents the number of events experienced in the prior month. Although statistically significant, the coefficient of 0.99 indicates that a greater number of events in any particular month has little influence on opt-out rates.

Table 3. Cox Proportional Hazards Model Regression Variable Definitions and Purpose

Variable	Description
Greater Bay Area - Stockton	Dummy variable for each local capacity area used to pick up variation in attrition due to geographic locations
January - December	Dummy variable for each month designed to pick up time-of-year effects in attrition
Non-CARE/CARE	Dummy variable for CARE status to pick up the effect of being on the low income tariff on attrition
Percent loss/win last month	Equals customer's percent loss or win compared to their OAT for the previous month. The previous month is used because the customer does not yet know their bill for the current month
Log (last month's bill)	Equals the log of the customer's bill last month
CARE x log (last month's bill)	Equals the log of the customer's bill last month if the customer is on CARE or zero if the customer is not. Picks up the incremental effects that CARE status has on attrition as a customer's bill changes
Bill Protected/Not Bill Protected	Dummy variable that indicates whether a customer was bill protected in the prior month
Bill protection not lost in last month/Bill protection lost in last month	Dummy variable that indicates whether a customer lost bill protection in the previous month
# of events in previous month	Equal the number of events the customer experienced in the prior month

Table 4. SmartRate Survival Regression

Variable	Hazard Ratio	Std. Err.	z	P>z	*	[95% Conf. Interval	
Greater Bay Area	base omitted						
Greater Fresno	1.48	0.20	2.83	0.01	*	1.13	1.93
Kern	2.84	0.32	9.37	0.00	*	2.28	3.54
Other	1.70	0.22	4.07	0.00	*	1.32	2.19
Sierra	1.88	0.29	4.02	0.00	*	1.38	2.55
Stockton	1.48	0.22	2.58	0.01	*	1.10	1.99
January	base omitted						
February	1.51	0.89	0.71	0.48		0.48	4.78
March	3.85	1.99	2.61	0.01	*	1.40	10.61
April	3.28	1.73	2.26	0.02	*	1.17	9.22
May	8.14	4.05	4.22	0.00	*	3.07	21.56
June	8.79	4.32	4.42	0.00	*	3.35	23.01
July	20.92	10.04	6.33	0.00	*	8.16	53.60
August	15.18	7.27	5.68	0.00	*	5.94	38.80
September	16.04	7.67	5.81	0.00	*	6.29	40.93
October	6.92	3.32	4.03	0.00	*	2.70	17.71
November	2.37	1.21	1.68	0.09		0.87	6.46
December	3.02	1.50	2.22	0.03	*	1.14	7.98
Non-CARE	base omitted						
CARE	1.01	0.02	0.36	0.72		0.98	1.04
Percent loss/ win last month	1.00	0.00	-3.99	0.00	*	1.00	1.00
Log(last month's bill)	1.02	0.00	6.54	0.00	*	1.02	1.03
CARE x log(last month's bill)	0.98	0.00	-4.66	0.00	*	0.97	0.99
Bill protected	base omitted						
Not bill protected	0.95	0.03	-1.64	0.10		0.90	1.01
Bill protection not lost in last month	base omitted						
Bill protection lost in last month	1.11	0.04	2.90	0.00	*	1.03	1.19
# of events in previous month	0.99	0.00	-2.60	0.01	*	0.99	1.00

* = statistically significant at the 5% level

Other Important Findings

In conjunction with the work summarized above, FSC investigated a number of other issues of potential interest to program planners and policymakers. Limitations on the length of this paper prevent a detailed discussion of this additional analysis. Below, we provide a high-level summary of some of the most interesting findings. The detailed analysis and additional discussion can be found in the following report, which PG&E filed with the California Public Utilities Commission on April 1st: Stephen S. George, Josh

Bode and Elizabeth Hartmann, *2010 Load Impact Evaluation of Pacific Gas and Electric Company's Time-Based Pricing Tariffs.* Final Report. April 1, 2011.

The findings summarized below are primarily derived from an analysis of load impact estimates for individual program participants. Given the "on-off" nature of peak-period pricing for SmartRate customers (that is, high peak-period prices are in effect on some days and not on others), customer specific load impacts can be estimated based on time-series regressions for each individual customer. These individual customer impact estimates were then used as dependent variables in a second-stage regression relating the percent load reduction to customer characteristics and other variables of interest. The aforementioned report provides a detailed discussion of the methodology and summarizes the results of a variety of validation tests that were conducted, which illustrate that the average impacts across all customers have little bias. Key findings from this analysis include, but are not limited to, the following:

- An important policy question is whether load reductions decline with the number of events experienced, which is a measure of impact persistence. PG&E's SmartRate program is one of the longest running dynamic rate programs in the country for residential customers, with many customers having experienced up to 37 event days spanning three summers. A variable equaling the number of events experienced by each participant was not statistically significant in the regression of percent impacts. Put another way, average load impacts appear to persist over time for customers that have been on the program for multiple years.
- Another important policy issue is whether balanced payment plans offered by utilities to better manage bill volatility mute price signals for customers on dynamic rates. The regression analysis showed that load impacts for customers on a balanced payment plan were not statistically significantly different from those of customers who were not on such a plan. This is an important finding, because some policymakers and analysts have proposed alternative methods for managing perceived risk from bill volatility under dynamic rates, such as hedging options, offering consumers the option of only participating in every other event, and others. In reality, bill volatility under dynamic rates is not dramatically different from normal bill fluctuations caused by variation in usage across seasons, which is what traditional balanced payment plans are designed to address. The fact that such plans do not negatively impact demand response means that this tried and true option can be offered along with dynamic rates to help manage bill fluctuations.
- Structural winners are participants whose bills fall when they sign up for SmartRate even if they do not change their usage pattern. An important issue is whether structural winners respond the same or differently from participants whose bills would be higher if they did nothing to reduce energy use during peak periods. The analysis shows that structural winners do respond less than non-structural winners. A customer whose bill falls by 5% simply by signing up for the rate, would have an average load reduction that is about 5% less than the average customer. Similarly, a customer whose bill was 5% higher on the rate compared with the otherwise applicable tariff, would be expected to have about a 5% greater average impact than a customer who breaks even.
- Another important issue is whether low income customers respond differently to dynamic tariffs compared with non-low income customers. For SmartRate, the average load reduction for CARE customers is roughly one third as large as for non-CARE customers. Across the 13 event days in 2010, CARE customers reduced their peak period load on average by 0.13

kW, or 6.6%. Non-CARE customers, on the other hand, reduced load on average by 0.39 kW, or 21.4%. However, this does not necessarily mean that CARE customers are inherently less responsive to price signals. Indeed, the regression analysis shows that, after controlling for variation in underlying characteristics, such as air conditioning ownership, event notification and other factors, percent reductions for CARE customers are not significantly different from those for non-CARE customers.

- Event notification is highly correlated with load impacts. For the average SmartRate event, about one quarter of customers were not successfully notified, mostly due to missing or incorrect contact information. When these customers were dropped from the participant population, the average load reduction across all 13 events increased by more than 2 percentage points. Comparative statistics show that both the average and percent load reduction roughly triple between customers who are successfully notified through one option and those that receive four successful notifications. However, the regression analysis showed a more muted but still strong correlation between the number of successful notifications and demand response, with almost a 25% increase in average load reduction for customers that were successfully notified four ways compared with those notified through a single channel.
- Air conditioning ownership is a strong driver of demand response. For non-CARE customers, the percent and absolute load reductions increase substantially with the likelihood of owning central air conditioning. Indeed, percent load impacts were 65% greater for households with greater than a 75% likelihood of owning central air conditioning than for households with less than a 25% probability of owning air conditioning. Absolute impacts were six times higher for high likelihood, non-CARE households than for low likelihood households.
- Customers that were enrolled in both SmartRate and SmartAC (PG&E’s air conditioning load control program) produced significantly greater demand response than those who were only on SmartRate. Dual enrolled customers have the option of having their air conditioner cycled during the event period on Smart Days. The average demand reduction for dual enrolled customers was roughly 23% higher than for SmartRate customers with central air conditioning who did not have any enabling technology.

Conclusions

This paper summarizes the first empirical findings associated with the impact of first year bill protection on demand response for a dynamic pricing tariff. The analysis shows that bill protection reduces average demand response by about 25%. However, we also found that bill protection reduces program attrition during the initial period on a dynamic tariff. What is not yet known is the extent to which bill protection increases enrollment on dynamic rates, which is its primary purpose. Even with lower average load reductions for participants under bill protection, aggregate impacts could be higher with bill protection than without it if bill protection increases program enrollment. Several studies will be conducted over the next few years that will reveal whether bill protection significantly increases participation in dynamic rate programs.