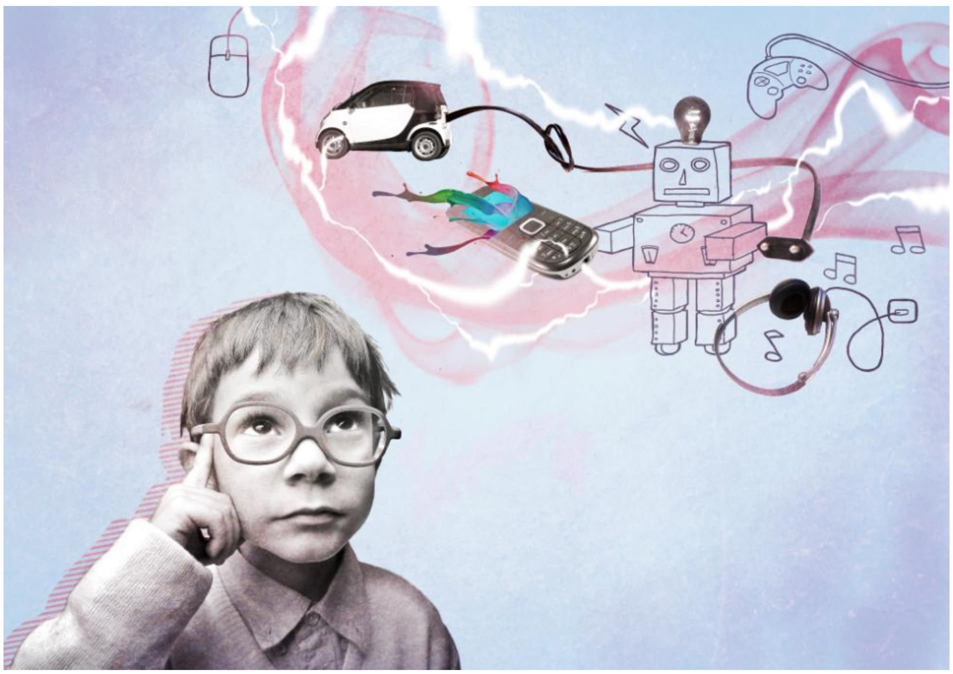
The Effect of Prepayment on Energy Use



By: Michael Ozog, Ph.D.
Integral Analytics, Inc.

A research project commissioned by the
DEFG Prepay Energy Working Group
March 2013

Introduction

In the U.S. and abroad, data has shown a linkage between prepayment of energy bills and a conservation effect, with significant usage reductions of 5 to 15% found when customers switched from post-payment to prepayment. While there is an apparent link between prepayment and energy reduction, this link is not well understood or documented.

DEFG—a specialized consulting firm focused on energy consumers—launched the Prepay Energy Working Group in 2010 to explore the many critical issues presented by prepay service. The issues—an amalgam of challenges and opportunities—basically fall into four buckets: regulatory, consumer, operational, and the potential for an energy conservation impact. Arguably, the most compelling area of study is the effect of prepayment on usage.

The Prepay Energy Working Group sponsored efforts to identify the proper methodology for measuring the potential impact on usage. This study is an extension of that work—a data analysis undertaken to determine the relationship between participation in prepayment and impacts on energy consumption.

Data Collection

The data for this research was obtained from Oklahoma Electric Cooperative (OEC), which launched prepay service in 2006 and utilizes Exceleron Software's patented Prepaid Account Management System (PAMS). PAMS is integrated with OEC's existing advanced metering infrastructure (AMI), meter data management (MDM) and customer information system (CIS) platforms.[1] Every OEC customer, including the prepaid customers, has a smart meter installed.

The fundamental data used in this analysis was monthly billing data customers in PAMS, covering both their usage under post-pay and under prepay service. Specifically, this analysis used monthly consumption data for 1,217 households, with an average of 32 months under post-pay and 22 months under prepay, with the latest date being March 2012. In addition to the monthly usage, this analysis had information on the number of disconnects in each month for every customer under both post-pay and prepay, and included monthly temperature data (based on zip code).

The billing histories were cleaned to capture missing or erroneous information and then merged with the monthly disconnects data and the appropriate temperature data to form the evaluation database. This database served as the foundation of the regression analysis presented in the next section.

Key Findings

In order to determine the effects of prepayment on energy usage, a fixed-effects panel model was used. The details of this methodology can be found in DEFG's Series of Regulatory Choices, No. 7,[2] and is summarized in the addendum to this report.

The fixed effects model can be viewed as a type of differencing model in which all characteristics of the home, which (1) are independent of time and (2) determine the level of energy consumption, are captured within the customer-specific constant terms. In other words, differences in customer characteristics that cause variation in the level of energy consumption, such as building size and structure, are captured by constant terms representing each unique household.

[1] Details of OEC's PAMS program can be found in Buck, Jonna. "Prepaid Service Benefits A Co-op and its Customers." Utility Automation, May 2008.

[2] DEFG's Series of Regulatory Choices, No. 7, "A Method for Estimating the Conservation Effects of Energy Prepayment," November 2011, available at http://defgllc.com.

Algebraically, the fixed-effect panel data model is described as follows:

$$\ln(kWh_{it}) = \lambda_t + \alpha_i + \beta(\lambda_t \cdot Temp_t) + \delta PP_{it} + \gamma PP_{it} Disc_{it} + \psi Disc_{it} + \varepsilon_{it}$$

where:

kWh_{it}	=	energy consumption for home *i* during month *t*
λ_t	=	a binary (1/0) variable denoting each month in the analysis
α_I	=	constant term for home *i*
$Temp_t$	=	temperature during month *t*
PP_{it}	=	a binary variable denoting if home *i* was under prepay during month *t*
$Disc_{it}$	=	the number of disconnects for home *i* during month *t*
ß	=	vector of estimated coefficients denoting the effect of temperature on energy consumption during each month
δ	=	the estimated change in energy usage associated with prepay
Ψ	=	the estimated change in energy usage associated with a disconnection
γ	=	the estimated change in energy usage associated with a disconnection under prepay
ε_{it}	=	error term for home *i* during month *t.*

With this specification, the only information necessary for estimation is those factors that vary month to month for each customer, and that will affect energy use, which effectively are weather conditions and program participation. Other non-measurable factors can be captured through the use of monthly indicator variables (e.g., to capture the effect of potentially seasonal energy loads).

Note that a log specification was used (i.e., $\ln(kWh_{it})$), so the estimated coefficient represents the percentage change in energy use associated with participation in prepayment. Table 1 below presents the key estimated coefficients, with the complete set of estimated coefficients presented in the Addendum.

Variable	Coefficient	t-value
Enrolled in Prepay	-11.0%	-17.79
Disconnects under Prepay	2.4%	2.06
Disconnects at any time	3.3%	3
Sample Size	65.628 obs (1,217 houses)	

Table 1: Estimated impact from prepay and disconnects

The estimated coefficient for the enrollment in prepay variable (i.e., -11.0) indicates that enrollment in prepay results in a reduction in energy usage of 11% (about 1,690 kWh/year for the OEC customer). The t-value associated with this estimated coefficient shows that the estimated impact is very precise, with a 95% confidence interval going from a savings of 10.2% to a savings of 13.0%. The on average 11% decrease, moreover, is attributable to usage reductions while service is connected and not a consequence of service disconnection.[3] Since the average monthly bill for OEC's customers is \$146, this 11% savings implies a \$192 per year reduction in a customer's energy bill.

[3] Savings estimated without accounting for disconnect periods is only slightly lower (10.4%).

This 11% energy use reduction is quite large relative to other common energy efficiency measures (see Table 2). The large savings associated with prepaid service is particularly noteworthy considering that this service is generally free for the customer to implement, whereas the other energy efficiency measures involve a significant investment by the customer in equipment.

Measure	Annual Savings	
	kWh	Percent
Duct Sealing	32	0.2%
CFL	62	0.3%
Water Heater Wrap	79	0.4%
Insulation retrofit	96	0.5%
HVAC tune-up	118	0.6%
Low-Flow Showerhead	130	0.6%
Pipe Insulation	133	0.6%
Energy Star Refrig	142	0.7%
Energy Star Cloths washer	200	1.0%
Normative report	300	1.5%
Heat Pump Water Heater	500	2.4%
CAC early replacement	700	3.4%
Refrig. Early replacement	1,376	6.7%
Prepay	1,690	**11.0%**
Ground Source Heat Pump	2,744	13.4%

Table 2: Savings associated with common EE measures[4]

Referring back to Table 1, the estimated coefficients of the disconnects under prepay and the disconnects prior to prepay are both positive, which indicates that the higher the number of disconnections each month, the higher the usage is for the customer, with increases of 2.4% and 3.3% respectively. One possible interpretation for this result is that disconnects are driven by usage, so that they are more likely to occur when usage is high. This is confirmed by observing the relationship between usage and disconnects over time, as presented below in Figure 1.

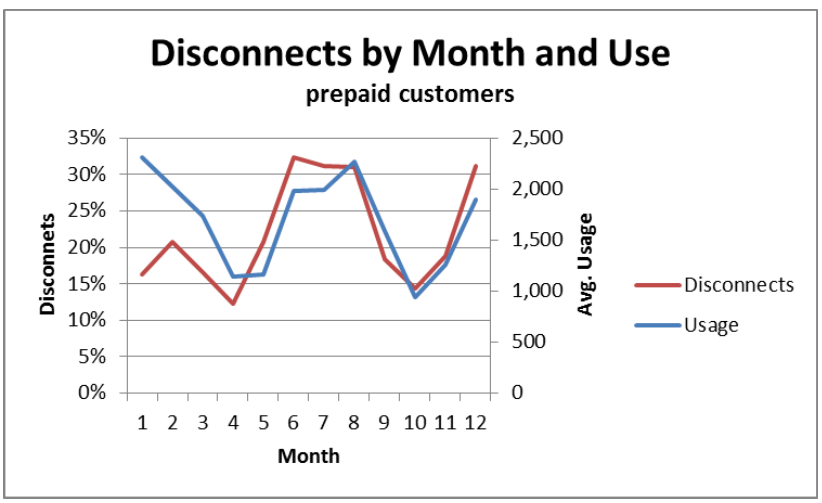


Figure 1: Relationship between usage and disconnects

[4] Based on the State of Ohio Energy Efficiency Technical Reference Manual, August 2010. These results are specific to the weather in Ohio and thus may not be representative of the savings that would occur in OEC's service territory.

The figure shows—the higher the level of usage, then the higher the number of disconnects (which explains the positive coefficient for these variables in Table 1). This is counter to the suggestion that an impending disconnection will result in the customer reducing energy usage and potentially entering a state of deprivation that may be harmful. There are valid customer safety concerns tied to the notion of prepay service and AMI-enabled remote—and potentially immediate[5]—shut off upon hitting a zero balance. The new "flip of a switch" capability that is unsettling likewise means that service can also more quickly be restored. "Smart" metering has conceivably made the duration of disconnection a more critical data point than the frequency of disconnection. The fact is, with AMI, reconnection times can be substantially quicker.

Figure 2 below presents the rate of reconnection for OEC prepay customers in 2011. The data shows that 91% of prepay customers that were disconnected in 2011 were reconnected the same day. Of the remaining 9%, the data provides that 5% were reconnected the next day, 3% were reconnected within 3 to 7 days, and the last 1% was reconnected 8 to 14 days later. Therefore, 96% of disconnected prepay customers were reconnected the same day or the next day.

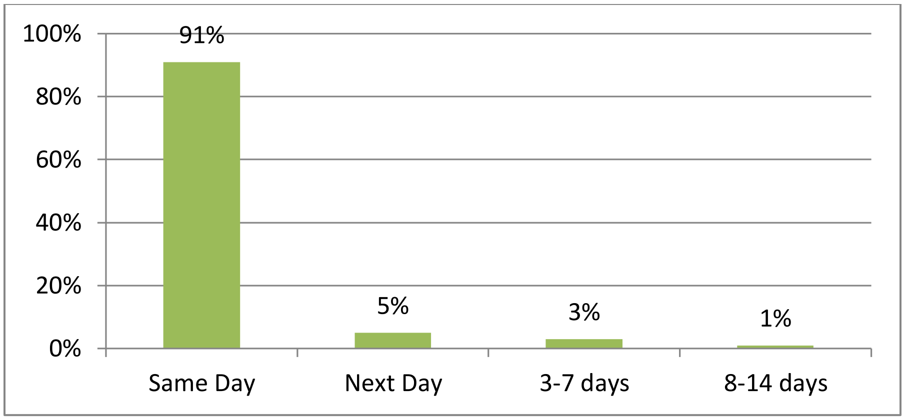


Figure 2: Rate of reconnection by day

Figure 3 presents the rate of reconnection by hour for those customers reconnected the same day. Of the 91% reconnected the same day, 32% were reconnected within 1 hour, 19% within 2 hours, and so on. Arguably, service disconnects on prepay are less stressful than service disconnects endured under traditional post-pay service. With post-pay, a significant debt has typically accumulated and late payment penalties and additional deposits are often required to restore service. These hurdles may result in a longer disconnection period and an increased burden for the customer.

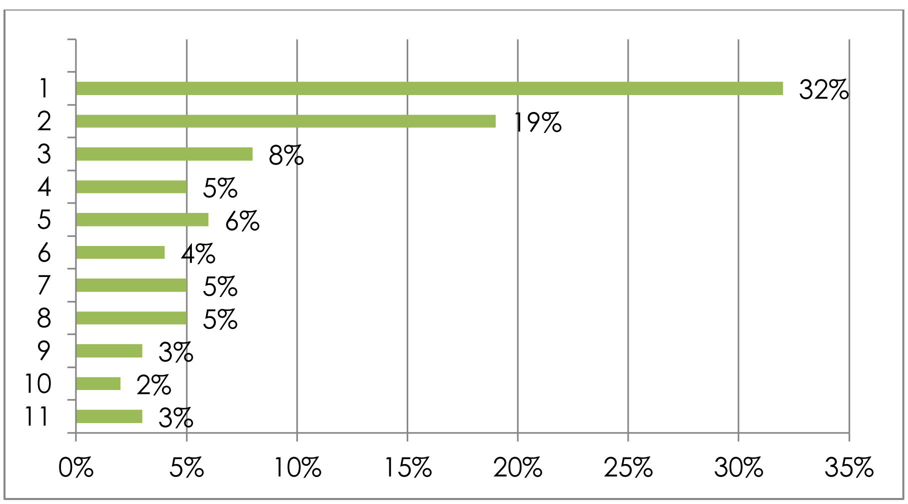


Figure 3: Same Day Reconnects (rate of reconnection by the hour)

[5] Disconnection may not actually be immediate—time lags are often necessary to allow for meter validation and for alerts to be sent to the customer to provide ample notice. Counting a time lag and/or friendly-credit period (e.g., no disconnects during nights, weekends or holidays), disconnection may in fact take place anywhere from 2 to 48 hours after reaching a zero balance.

Conclusion

This study quantified the relationship between prepaying for energy usage using techniques that are accepted and widely used in the evaluation of utility-sponsored energy efficiency programs.

Using Oklahoma Electric Cooperative's consumer data from the Prepaid Account Management System (PAMS) within a regression model, this research determined that enrollment in prepay results in a significant reduction in energy usage of on average 11%. This 11% energy use reduction is quite large relative to other common energy efficiency measures and requires no upfront financial outlay on the part of the customer. Furthermore, the 11% decrease is attributable to reductions in usage while service is connected and is not a consequence of service disconnection.

This analysis also indicates that the level of disconnects is driven by usage and not by deprivation. However, further research needs to be conducted on the relationship between usage and disconnection. There are important questions to explore. (E.g., What actions do customers take to save energy / dollars? What is the "cost" to the household to achieve such savings?) Further insights can help customers to more quickly, practicably and safely reach energy efficiency goals.

Finally, the potential of time-based pricing should be explored. This study confirms that regular communications providing actionable information (usage tied to dollars and cents) result in a material customer response and shift in usage behavior. How might time-based pricing complement the prepay model to result in additional savings?

About DEFG and the Prepay Energy Working Group

Distributed Energy Financial Group LLC (DEFG), a specialized consulting firm focused on energy consumers, manages the Prepay Energy Working Group. Currently in its fourth year, the Prepay Energy Working Group sponsors in-depth research exploring the challenges and opportunities presented by prepaid energy offerings in the North America. To ensure a broad spectrum of perspectives and experiences, working group members include utilities, energy retailers, regulators, consumer advocates, and metering and software solution vendors.

Cindy Boland O'Dwyer, a Vice President with DEFG and a lawyer, leads the Prepay Energy Working Group and DEFG's activities in legal and regulatory matters. Cindy can be reached at: codwyer@defgllc.com.

To receive DEFG's regular notifications, please join our mailing list: http://defgllc.com/publications/.

To cite this publication, please use: "The Effect of Prepayment on Energy Use," a report of the Prepay Energy Working Group, DEFG LLC, Washington DC, March 2013.

ADDENDUM

Methodology Used

Based upon the characteristics of a prepay program and the regulatory requirements for receiving credit for energy conservation behavior or efficiency measures that may arise from the program, we recommend that the analysis uses the following regression model:

$$kWh_{it} = \lambda_t + \alpha_i + \beta(\lambda_t \cdot Weath_t) + \delta PP_{it} + \gamma PP_{it} SD_{it} + \psi SD_{it} + \varepsilon_{it} \qquad (1)$$

Where $Weath_t$ is the weather conditions (temperature or HDD/CDD), PP_{it} indicates whether the individual was a prepay participant during time *t*, and SD_{it} denotes the total amount of time the customer was disconnected during time *t*. The energy effects associated with prepayment is therefore estimated by δ and γ. By differentiating between energy savings due to prepay in general from those that are due to self-disconnection, it becomes possible to differentiate between more efficient use of energy from budgetary imposed restrictions on energy use.

Further, it is proposed that equation (5) is estimated over the prepayment customers only, as discussed below, there is no need to include a control group because, in a sense, the treatment group serves as its own comparison group. Eliminating the control group significantly reduces the effort and cost associated with conducting an analysis and eliminates the challenge of matching participants to comparable non-participating customers.

This approach has been used extensively in the evaluation of utility-sponsored energy efficiency programs, and has been used and accepted for measurement and verification of impacts across North America.

The natural (and important) questions that arise are, since this is based on the assumption of random assignment, how can it address the issues of self-selection bias and gross/net savings discussed previously? Each of these issues will be addressed below.

Accounting for Self-Selection Bias

One aspect of the issue of self-selection bias that was not included in the prior discussion, indeed one that is rarely addressed at all, is whether or not it is truly necessary to account for self-selection bias. Following Heckman's (1979) discussion of selection bias, self-selection arises because of the endogenous decisions by individuals to participate in the program or not. This implies that any comparison between a self-selection participant group and a non-participant group will result in biased estimates of the program effect that would result from a random treatment of the population.[6]

This has two significant implications. First, for the purposes of evaluating a prepay program, the goal is to determine how much electricity savings the program actually produces for participants, ex post. This is a fundamentally different question than trying to estimate how much electricity savings the prepay program would produce if participation is *randomly assigned*. In addition, since it is likely that the decision to participate in a prepay program will always be up to the customer, there will never be random treatments across the population. Therefore, the issue of self-selection bias, within the context of programs that will always be voluntary, is usually irrelevant from the perspective of a retrospective determination between prepay and reduced energy usage.

In addition, it can be shown that a fixed-effect estimator in equation (3) is indeed free of self-selection bias if one assumes (as is usually the case) that the selection bias relates to the level of energy use and as such is a function of time-

[6] See James Heckman, "Sample Selection Bias as a Specification Error." Econometrica, Vol. 47, No. 1 (Jan., 1979), p. 154.

invariant individual-specific effects.[7] The intuition behind this result is relatively straightforward. Suppose each customer has an inherent motivation to participate in the prepay program, and this inherent motivation to participate is constant during the period covered by the analysis, then a fixed-effect panel model will automatically include this customer-specific motivation (as well as other unobservable characteristics) directly into the customer-specific fixed-effect term. In this manner, self-selection bias is directly accounted for within the model specification.

Of course, if the selection bias is not constant, but varies over time, then the fixed-effect term will not capture this motivation. This is also true for the two-step Heckman approach that is widely addressed in program evaluation literature.

Non-Program Effects

Perhaps the most surprising aspect of the proposed approach is that it does not include a control group. The two most widespread beliefs are that 1) a control group is necessary to ensure that the estimated kWh savings are net of non-program effects (i.e., general economy wide influences), and 2) including a control group will somehow automatically correct for "natural conservation," i.e., free ridership. However, both of these assumptions are misleading. Perhaps the easiest way to understand this is through an actual example.

Assume that there is a relatively simple relationship between monthly energy use, temperature, whether or not there is an economic recession, and program participation. Assume that this relationship can be expressed as:

$$\mathrm{kWh}_{i,t} = 3 + 5.6\bullet\mathrm{temp}_t - 25.0\bullet\mathrm{recession}_t - 0.5\bullet\mathrm{part}_{i,t} \qquad (2)$$

Where "temp" is the monthly average temperature, "recession" is an indicator variable which equals to the number of months in a recession (i.e., 1 for the first month, 2 for the second, etc.), and "part" is an indicator variable which equals one if that household was randomly assigned (to eliminate any confusion about self-selection bias) to participate in the EE program. This simple data generation process tells us that everyone has a "base load" of 3 kWh (the constant term), for every degree increase in the average temperature there is a 5.6 kWh increase in usage, and during a recession, all customers consume 25 kWh less than otherwise for each month in the recession. Finally, if a customer is involved in the utility EE program, they will save 0.5 kWh for each month.[8]

We can simulate the data generation process by adding a normally distributed random error term (with average of 0 and large standard deviation of 4 to introduce significant variation in the data) to equation (1) and generate, for example, 12 months of simulated data spanning the last 6 months of last year and the first 6 months of the current year. We create this dataset for 10,000 control group customers (part is always equal to 0) and 10,000 participating customers. For participants, we further assume that there are two equal groups, one group that participated in November of the first year, and another in March (this is done to introduce a simple form of variability in the participation variable, and is typical of the type of monthly participation tracking found in most EE programs).

In addition, assume that there was a recession that starts in December of the first year, and lasts for four months. Thus, there is an overlap between the participation period and the recession. Finally, the temperature is the same for all customers, and starts at 75° and decreases 5° each month for six months, and then increases 5° during the next six months to return to 75° by the end of the ten months.

---

[7] See Marno Verbeek and Theo Nijman, "Testing for Selectivity Bias in Panel Data Models." International Economic Review, Vol. 33, No. 3 (August 1992), or Francis Vella, "Estimating Models with Sample Selection Bias: A Survey." The Journal of Human Resources, Vol. 33, No. 1 (Winter, 1998). The appendix presents a detailed discussion of how the fixed-effect model corrects for static self-selection bias.

[8] These coefficients are purely arbitrary.

Let's start by estimating a regression model of the "true" data generation process with both the participant and control groups. The coefficients and t-values are shown in Table A1. Of course, in this case, the estimated coefficients match the true coefficients.[9]

Table A1: Estimated true specification, participants and non-participants

Independent Variable	Coefficient	t-value
Constant	3.05	41.74
Temperature	5.60	5,025.32
Recession	-25.01	-3,496.08
Participation	-0.48	-25.36
R-Squared	99.7%	

Table A2 shows the results from a regression model where *only* the participants are included (there are no non-participants in the estimation) using the true specification. Note that *the estimated coefficients match their true values*, even though there is no control group and program participation is occurring during the recession. The immediate implication, *empirically,* is that a control group of non-participants is not required to control for general market effects. But, let's investigate further.

Table A2: Correct specification, participants only

Independent Variable	Coefficient	t-value
Constant	3.04	29.37
Temperature	5.60	3,520.58
Recession	-25.00	-2,396.64
Participation	-0.48	-19.86
R-Squared	99.7%	

In the third estimated model (Table A3), both participants and non-participants are included in the model, but let's assume that the modeler was unaware of the recession, so it is not included in the estimated model (thus there is an omitted variable bias). Now *none* of the estimated coefficients match their true value, and indeed the estimated savings from the program is significantly larger at -4.31 kWh than the true value given the masked recession bias. Note as well that the t-values and R-squared give no indication that anything is amiss, and one may even inappropriately prefer this model relative to the correct model just on the basis of the high t-value on the participation variable.

The reason that the estimated coefficients are incorrect is that the variables in the model are "picking up" the effect of the omitted recession variable on kWh. *The fundamental implication here is that naively including a control group in the model does not automatically account for market-wide effects;* there must be variables within the model to capture this effect. So, the blind application of a control group does not guarantee accurate, unbiased estimates of energy savings.

Table A3: Incorrect specification, participants and non-participants

Independent Variable	Coefficient	t-value
Constant	-140.08	-321.37
Temperature	7.60	1,103.28
Participation	-11.60	-85.40
R-Squared	84.6%	

[9] The random error introduced into the model limits a perfect match.

For the fourth model (Table A4), the control group is eliminated from the model, the modeler still does not know about the recession, but he/she includes monthly indicator variables (omitting one to avoid collinearity with the constant term) to insure that any general (unknown) market trends are controlled for in the model (this is the general approach that will be used in these evaluations).

Table A4: Include monthly variables, participants only

Independent Variable	Coefficient	t-value
Constant	2.88	3.50
Temperature	5.60	494.52
Month 9, Year 1	0.06	0.58
Month 10, Year 1	0.06	0.37
Month 11, Year 1	0.00	0.00
Month 12, Year 1	-24.96	-95.90
Month 1, Year 2	-49.97	-191.96
Month 2, Year 2	-74.94	-365.26
Month 3, Year 2	-100.04	-645.05
Month 4, Year 2	-0.01	-0.11
Month 5, Year 2	-0.08	-1.12
Month 6, Year 2	0.02	0.28
Participation	-0.44	-11.09
R-Squared	99.7%	

Note that *the estimated savings from participation now, once again, is close to the correct value.* And while it may seem that the coefficient on the constant term appears incorrect, one has to remember that the constant term is now modified to contain both the original constant as well as the omitted month. Two conclusions can be derived from this result:

- The analyst does not need to know *a priori* the specific nature of the general market-wide trends to develop a correct specification; all that is needed are time-effect variables that vary period by period, the collection of which capture the intended effects and lead to accurate model specification.
- As before, a model estimated only over participants will indeed account for general market trends, even when there is a strong correlation between the participation period and these general market trends.

So, generally speaking, there is no guarantee that the blind application of a control group will yield accurate, unbiased estimates of energy savings. Sometimes control groups are useful. Sometimes they are misleading, as we have seen here. From the above examples, it is apparent that simply including a control group does not automatically account for changing trends in electricity usage.

Self-Selection Bias and Fixed-Effect Panel Models

The key assumption is that there is a latent variable, denoted as s_i, that describes the likelihood that an individual will decide to participate in the program or not (the selection process), and this latent variable is time-invariant and specific to each individual. In other words, one can view s_i as the probability of participation, and this probability differs across people, but does not change over time.

Suppose that the i[th] customer's energy usage at time t (kWh_{it}) is a function of exogenous variables that vary over time and across customers, denoted x_{it} and this latent variable[10]

$$kWh_{it} = x_{it}{}'\beta + \theta s_i + \varepsilon_{it} \tag{3}$$

Clearly, estimating (1) without the latent variable can potentially lead to bias results. We can express the fixed-effects model as a least squares regression of the deviations from the group means[11]

$$kWh_{it} - \overline{kWh_{it}} = (x_{it} - \overline{x_{it}})'\beta + (s_i - \overline{s_i})'\theta + (\varepsilon_{it} - \overline{\varepsilon_{it}}) \tag{4}$$

Since the selection process is assumed to be time-invariant, s_i equals $\overline{s_i}$, so the term $(s_i - \overline{s_i})'\theta$ drops out of (2), and the equation becomes

$$kWh_{it} - \overline{kWh_{it}} = (x_{it} - \overline{x_{it}})'\beta + (\varepsilon_{it} - \overline{\varepsilon_{it}}) \tag{5}$$

Thus, the fixed-effect model "nets out" the effect of the selection process, so estimation of (3) (with no latent variable) yields unbiased and consistent estimates of β.

[10] For simplicity, the model is assumed not to contain an intercept term.
[11] See Greene, Econometric Analysis, fifth edition, 2003, pp. 297-289.

Estimated Model

```
Fixed-effects (within) regression               Number of obs      =     47499
Group variable: account                         Number of groups   =      1217

R-sq:  within  = 0.2541                         Obs per group: min =        15
       between = 0.0065                                        avg =      39.0
       overall = 0.0787                                        max =        80

                                                F(80,46202)        =    196.73
corr(u_i, Xb)  = 0.0045                         Prob > F           =    0.0000
```

ln_kwhd	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
part	-.1157519	.0070443	-16.43	0.000	-.1295588	-.1019451
pp_disc	.009919	.0183428	0.54	0.589	-.0260332	.0458711
cnt1	.0492606	.0179234	2.75	0.006	.0141304	.0843908
tym#c.temp						
200901	.0136406	.0030189	4.52	0.000	.0077235	.0195577
200902	.0242386	.0040345	6.01	0.000	.0163309	.0321463
200903	.0295166	.0062162	4.75	0.000	.0173327	.0417004
200904	.0218042	.0051336	4.25	0.000	.0117422	.0318662
200905	.0037913	.0044379	0.85	0.393	-.0049071	.0124898
200906	-.0198333	.0105405	-1.88	0.060	-.0404928	.0008263
200907	-.0276393	.0078764	-3.51	0.000	-.0430773	-.0122014
200908	-.0171125	.0052151	-3.28	0.001	-.0273342	-.0068907
200909	-.024077	.0063201	-3.81	0.000	-.0364645	-.0116894
200910	-.1062604	.0300845	-3.53	0.000	-.1652266	-.0472943
200911	.0605412	.0398971	1.52	0.129	-.0176576	.1387401
200912	.1048442	.0280519	3.74	0.000	.0498621	.1598263
201001	.070803	.0208185	3.40	0.001	.0299985	.1116075
201002	.1597655	.0339548	4.71	0.000	.0932136	.2263174
201003	.0002282	.0240973	0.01	0.992	-.0470029	.0474594
201004	-.0212127	.013977	-1.52	0.129	-.0486079	.0061825
201005	.010337	.0126145	0.82	0.413	-.0143876	.0350616
201006	.040306	.0162289	2.48	0.013	.008497	.0721149
201007	.0122771	.0132306	0.93	0.353	-.013655	.0382092
201008	.0342642	.0121521	2.82	0.005	.0104459	.0580826
201009	-.0083645	.0132781	-0.63	0.529	-.0343897	.0176607
201010	-.0018192	.0103289	-0.18	0.860	-.022064	.0184257
201011	.0088715	.0117253	0.76	0.449	-.0141101	.0318532
201012	-.006339	.0118863	-0.53	0.594	-.0296363	.0169584
201101	-.0120594	.0093326	-1.29	0.196	-.0303514	.0062327
201102	-.0139872	.0173499	-0.81	0.420	-.0479933	.020019
201103	.0104832	.011936	0.88	0.380	-.0129115	.0338778
201104	-.0318057	.1688645	-0.19	0.851	-.3627828	.2991713
201105	.0209485	.0151454	1.38	0.167	-.0087367	.0506337
201106	.0125932	.011865	1.06	0.289	-.0106624	.0358487
201107	.0040597	.0231068	0.18	0.861	-.0412299	.0493493
201108	.0134982	.0252711	0.53	0.593	-.0360335	.0630298
201109	.0490842	.0176353	2.78	0.005	.0145187	.0836496
201110	.0401106	.0130088	3.08	0.002	.0146131	.0656081
201111	.0222779	.011474	1.94	0.052	-.0002112	.0447671
201112	-.0116357	.0108509	-1.07	0.284	-.0329036	.0096322
201201	.0103317	.0112439	0.92	0.358	-.0117065	.0323699
201202	.0273957	.0159894	1.71	0.087	-.0039438	.0587351
201203	.029338	.0169862	1.73	0.084	-.0039551	.0626311
tym						
200902	-.7281899	.2306246	-3.16	0.002	-1.180218	-.2761621
200903	-1.370513	.3594479	-3.81	0.000	-2.075037	-.6659899
200904	-1.160671	.3285658	-3.53	0.000	-1.804665	-.5166773
200905	-.2247134	.3193401	-0.70	0.482	-.850625	.4011981
200906	1.842935	.8545841	2.16	0.031	.1679373	3.517933
200907	2.905189	.6598607	4.40	0.000	1.611852	4.198526
200908	1.931622	.4319993	4.47	0.000	1.084897	2.778347
200909	2.096092	.4673429	4.49	0.000	1.180092	3.012091
200910	6.203331	1.747892	3.55	0.000	2.777435	9.629226
200911	-3.230717	2.154931	-1.50	0.134	-7.454414	.9929806
200912	-3.278846	.9924419	-3.30	0.001	-5.224048	-1.333645
201001	-1.870515	.7554918	-2.48	0.013	-3.35129	-.3897394
201002	-5.161601	1.2308	-4.19	0.000	-7.573989	-2.749213
201003	.435514	1.197815	0.36	0.716	-1.912222	2.78325
201004	1.421323	.8865232	1.60	0.109	-.3162762	3.158922
201005	-.7352097	.8877974	-0.83	0.408	-2.475306	1.004887
201006	-2.851582	1.338097	-2.13	0.033	-5.474273	-.2288914
201007	-.4185099	1.101094	-0.38	0.704	-2.576671	1.739651
201008	-2.233271	1.048305	-2.13	0.033	-4.287965	-.1785764
201009	1.068185	1.012615	1.05	0.291	-.9165564	3.052927
201010	.1382827	.6659178	0.21	0.835	-1.166926	1.443492
201011	-.3404674	.617593	-0.55	0.581	-1.550959	.8700243
201012	.7153729	.4979487	1.44	0.151	-.2606141	1.69136
201101	.9926074	.3584975	2.77	0.006	.2899469	1.695268
201102	1.138198	.7259215	1.57	0.117	-.2846193	2.561015
201103	-.4217302	.6521703	-0.65	0.518	-1.699994	.8565335
201104	2.262314	11.10644	0.20	0.839	-19.50648	24.03111
201105	-1.39756	1.052299	-1.33	0.184	-3.460083	.6649625
201106	-.9451764	1.02366	-0.92	0.356	-2.951565	1.061212
201107	.2677809	2.091002	0.13	0.898	-3.830616	4.366178
201108	-.3769922	2.242562	-0.17	0.866	-4.772449	4.018464
201109	-2.764573	1.279087	-2.16	0.031	-5.271603	-.2575426
201110	-2.261914	.8256673	-2.74	0.006	-3.880234	-.643593
201111	-1.133409	.5936204	-1.91	0.056	-2.296914	.0300966
201112	.7967668	.4616627	1.73	0.084	-.1080993	1.701633
201201	-.0513939	.5069587	-0.10	0.919	-1.045041	.9422529
201202	-.8727546	.7362738	-1.19	0.236	-2.315863	.5703533
201203	-1.748508	1.029492	-1.70	0.089	-3.766328	.2693124
_cons	3.463454	.1197378	28.93	0.000	3.228766	3.698141