Phase III Statewide Evaluation Team

Addendum to Act 129 Home Energy Report Persistence Study

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November 2018

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1 INTRODUCTION

FirstEnergy operates residential Home Energy Report (HER) initiatives as part of the Act 129 EE&C plans for each of its Pennsylvania EDCs: Met-Ed, Penelec, Penn Power, and West Penn Power. Home Energy Reports are behavioral programs that use comparisons of energy use among similar residences in a community to evoke energy conservation and promote other EE&C offerings. FirstEnergy's HER programs in Pennsylvania are administered by Oracle (formerly Opower). The oldest waves have been receiving HERs since 2012; additional waves of participants were added in 2014. The Companies' Phase III EE&C plan called for a subset of treated customers to stop receiving HER service in June 2016. This created a natural experiment to assess the degree to which energy savings persist after reports stop being delivered. In this report, we refer to this natural experiment as a *persistence test*.

Previously, the effective useful life (EUL) of HER savings was assumed to be one year for Act 129 compliance and TRC calculations. An analysis[1] by the Phase II Statewide Evaluation (SWE) Team investigated this assumption using data from hiatuses in HER program delivery by PPL and Duquesne Light. The Phase II analysis found evidence that HER savings persisted for more than one year and discussed potential program design implications, but ultimately the one year EUL assumptions was used for the Phase III market potential study, goal-setting, and compliance accounting. This report summarizes the Phase III SWE team's analysis and findings for the FirstEnergy EDCs by reviewing the pretreatment equivalence of cohorts, their estimated savings, and the reduction in savings over time for groups that had their HER exposure discontinued at the beginning of Phase III.

The HER program was implemented as a randomized control trial for each of the EDCs. A randomized control trial is an evaluation technique that provides very precise and unbiased estimates of the effect of treatment – that is, the receipt of HER bill comparisons. Customers eligible to participate in this program are randomly assigned to either the treatment group (receive HERs) or a control group (do not receive HERs). The effect of treatment is then the difference between energy consumption in the treatment group *compared to* the control group in the periods after having received the treatment. Having been randomly assigned, the only explanation for differences in energy consumption between the two groups is the introduction of the home energy report. If properly implemented, randomized control trials (RCTs) are a very effective framework for estimating HER impacts for two key reasons, related to how HER programs are designed:

1. **Expected effect size:** Because the HER effect is generally small – on the order of 1-3% – the experimental design must be precise enough to detect the effect *and* must be able to account for any other factors that could bias energy consumption in the treatment group. By comparing consumption in the treatment group to the control group, external influences that are experienced by both the treatment and control groups are netted out of the treatment effect, reducing the amount of noise around the treatment's impact. Similarly, since characteristics that influence energy consumption (such as location, home size and age, and number of

[1] http://www.puc.state.pa.us/Electric/pdf/Act129/SWE_Res_Behavioral_Program-Persistence_Study.pdf

occupants) are equally distributed in both the treatment and control groups, there are no alternative explanations for differences in energy consumption between the two groups.

2. **Treatment duration:** HER programs can run for many years; some Pennsylvania households have been receiving them for over five consecutive years. Over such a long period, many things can change at an individual home that would affect energy consumption (e.g., occupancy changes, renovations, or weather pattern changes). These factors are not all directly observed or measured, so they cannot be modeled and therefore may be misattributed to the effect of treatment in a regression. However, because these changes will equally affect the control and the treatment group, they will be netted out of an RCT impact estimate.

The four FirstEnergy EDCs in question had control groups randomly assigned for each jurisdiction and cohort. In 2016, these cohorts were further divided to assess the decay rate of persistence. Treated customers were divided into *Continued Treatment* or *Persistence Test* cells, as shown in Table 1. Continued customers still receive reports each month in Phase III, while Persistent Test customers had their last reports delivered in May of 2016.

Table 1: Persistent and Reduced Cohort Assignments

EDC	Cohort	Continued Treatment	Persistence Test
Met-Ed	July 2012 Market Rate	√	√
	July 2012 Low-Income	√	
	Jan 2014 Market Rate	√	√
	Jan 2014 Low-Income	√	√
	Nov 2014 Remediation Market Rate	√	√
West Penn Power	June 2012 Market Rate	√	√
	June 2012 Low-Income	√	
	Jan 2014 Market Rate	√	√
	Jan 2014 Low-Income	√	√
	April 2014 – PA AMI		√
	Nov 2014 Remediation Market Rate	√	√
Penelec	July 2012 Market Rate	√	√
	July 2012 Low-Income	√	
	Jan 2014 Market Rate	√	√
	Jan 2014 Low-Income	√	√
	Nov 2014 Remediation Market Rate	√	√
	Nov 2014 Remediation Low-Income	√	
Penn Power	July 2012 Market Rate	√	√
	July 2012 Low-Income	√	
	Jan 2014 Market Rate	√	√
	Jan 2014 Low-Income	√	

2 METHODOLOGY

2.1 DATA PREPARATION & EQUIVALENCE TESTING

To estimate the impacts of HER exposure, the SWE team estimated a regression model that compares the average daily usage of the treatment and control group by month. To structure the data for analysis and place all homes on a common time series, the SWE team used a process called *calendarization*. The goal of calendarization is to prorate monthly billing data (with billing periods that do not always line up with the start and end date of a month) into a calendar month basis shared by all participants. This process is described through the example below. Table 2 contains three months of raw billing data in three bill cycles.

Table 2:Raw Billing Data

Billing Period	Nov 12th – Dec 11th	Dec 12th – Jan 11th	Jan 12th – Feb 11th
Usage (kWh)	1,058	1,301	940
Average Daily kWh	35.28	41.97	30.31

For each billing period, average daily usage can be estimated by dividing total usage by the number of days in the billing period. For example, there are thirty days in the November 12th – December 11th billing period, so the average daily usage is 1,058kWh / 61 = 35.28 kWh. This value can then be assigned to each day in the billing period. To retrieve prorated billing data, we simply sum up the estimated daily usage values within each calendar month. This is illustrated in Table 3 for December and January.

Table 3: Calendarization Calculation

Month	December 2017	January 2018
Estimated Usage (kWh)	(11 * 35.28) + (20 * 41.97) = 1,227.48	(11 * 41.97) + (20 * 30.31) = 1,067.87
Average Daily	1227.48/31 = 39.60	1067.87/31 = 34.45

Once the data had been prepared, the SWE team performed several detailed equivalence checks, paying particular attention to how the persistent customers performed versus the control group. This took the form of both visual inspection and statistical equivalence tests during the pretreatment period to ensure no differences appeared between the control and treatment groups. Confirming pretreatment equivalence between treatment and control groups is critical, as this assumption strengthens the causal impact of treatment – in this case, receiving HER reports.

Graphical inspection of control and treatment consumption was used to confirm that consumption patterns between the two groups matched during each month of the pretreatment period.

2.2 IMPACT ESTIMATION

The SWE team used a lagged seasonal (LS) regression model to estimate savings attributed to the HER program. The LS model works particularly well at providing precise savings estimates when there is good pretreatment equivalence between the treatment and control groups. The LS model is a post-only model because only observations from the post-treatment period are included in the regression. However, as its name suggests, the LS model does leverage some information from the pre-treatment period – the LS model contains three lagged variables as explanatory variables. These three lagged variables are (1) the average usage (across all months) in the pre-treatment period, (2) the average summer usage in the pre-treatment period, and (3) the average winter usage in the pre-treatment period. We defined *summer* as June, July, August, and September and *winter* as December, January, February, and March.

The formal model specification is shown below. Term definitions are provided in Table 4.

$$kWh_{imy} = \beta_0 + \sum_{m=1}^{12}\sum_{y=2012}^{2016} \mathrm{I}_{my} * \beta_{mys} * (AvgPre_i + AvePreSummer_i + AvePreWinter_i) + \sum_{m=1}^{12}\sum_{y=2012}^{2016} \mathrm{I}_{my} * \tau_{my} * \mathrm{treatment}_{imy} + \varepsilon_{imy}$$

Table 4:Impact Model Components

Variable	Definition
Daily kWh_{imy}	Customer i's average daily electricity consumption in bill month m in year y.
β_0	Intercept of the regression equation.
I_{my}	An indicator variable equal to one for each monthly bill month m, year y, and zero otherwise.
β_{mys}	The coefficient on the bill month m, year y indicator variable interacted with season s.
$AvgPre_i$	Average daily usage for customer i in the pre-treatment period.
$AvePreSummer_i$	Average daily usage for customer i in the pre-treatment period during June through September.
$AvePreWinter_i$	Average daily usage for customer i in the pre-treatment period during December through March.
$\mathrm{treatment}_{imy}$	The treatment indicator variable. Equal to one when the treatment is in effect for the treatment group. Zero otherwise. Always zero for the control group.
τ_{my}	The estimated treatment effect in kWh per day per customer; the main parameter of interest.
ε_{imy}	The error term.

In implementing the LS model, the parameter of interest (HER treatment) was interacted with a time-series (monthly indicator variables) to produce monthly estimates of the treatment effect (average daily kWh savings). To convert the results to aggregate program impacts (MWh), the average daily impact (per home per month) is multiplied by the number of days in the relevant month and the number of active homes in the treatment group for the relevant month. Then, the monthly totals are summed across the period of interest.

2.3 PERSISTENCE ESTIMATION

All cohorts that experienced a persistence test had their last HER report delivered before June of 2016. From then on, their electricity consumption was recorded and savings compared to the control group as before, with the goal of understanding how quickly the treatment effect dissipated. However, one particular complication arose from the implementation of this persistence test – the fact that assignment to the persistent group (the customers who stopped receiving reports) was not completely random. Customer assignment to this group was done on the basis of several criteria, including whether the customer was still actively receiving bills. This means that fewer customers remain in the dataset post June 2016, reducing the precision and increasing the variability of these estimates

To model the effect of persistence, a simple regression specification was used on the persistence test customers only to determine the decay of impacts as a function of the number of months since the cohort received their last report. The model specification is shown below. Each utility and cohort had their persistence effect modeled separately, and each months' percent savings was weighted by the reference load[2] in that month, to avoid over-weighting impacts in low-consumption months relative to high-consumption months. Additionally, because impacts can be seasonal and have uncertainty around them, a weighted average of the prior year's monthly impacts was used to create the intercept. That is, percent impacts from June 2015 to May 2016 were included in the regression at m = 0. An example of the persistence modeling exercise is shown in Figure 1.

$$pct\_impact_c = \beta_0 + \beta_c * m + \varepsilon_c$$

Table 5: Persistence Model Components

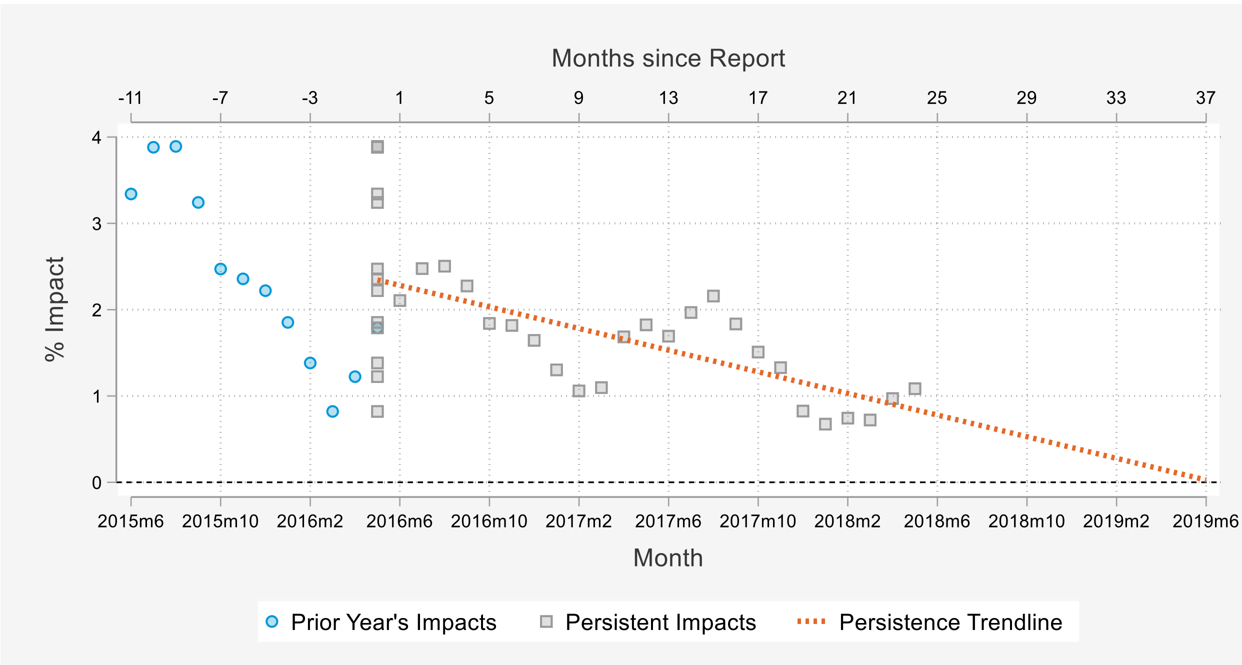
Variable	Definition
pct_impact_c	The treatment percent impact for cohort c.
β_0	**Intercept** of the regression equation. Equal to the reference load weighted average of the savings percent impact over the 12 months prior to the persistence test (i.e., June 2015 to May 2016).
β_c	The **slope** of the line indicating the monthly decay in HER savings for cohort c.
m	The number of months since the persistence test started.
ε_c	The error term for cohort c.

The key metric of interest to quantify the effect of persistence is how long it takes for impacts to reach zero. Once the regression is performed, the SWE team used the intercept and slope from the regression output to calculate the number of months it would take for the trend in impacts to go to zero. This is shown graphically below, where it takes approximately 37 months for the orange trend line to cross the

[2] The reference load is what the treated customers would have done had they not received treatment. The reference load is equal to the average treatment customer's observed average daily use plus the effect of treatment. That is, if the average daily use of the treatment customer in the post-treatment period was 30 kWh and the impact of treatment was 5 kWh, the percent impact would be 5/(30 +5) = 14.3%.

y-axis at zero. The intercept for the persistence regression line is set equal to the average savings in the prior 12-months (shown in blue circles and the grey squares at month = 0). The underlying assumption with this model is that the HER savings will continue to decay at the same rate observed in months 1-24 until reaching zero. The SWE team believes that, despite the seasonality of the impacts, a simple linear model is the safest methodological choice for extrapolating the decay of savings beyond 24 months.

Figure 1: Persistence Modeling Example



3 RESULTS

3.1 EQUIVALENCE TESTING

As discussed in the methodology section, establishing pretreatment equivalence is of particular importance in HER impact evaluations to ensure the causal relationship between receiving a home energy report and saving energy. At the same time, since HER treatment impacts are relatively small on a percent basis (usually no more than 3%), any small pretreatment difference between treatment and control groups could easily overwhelm the savings estimate. Shown below is a summary of pretreatment data, containing the following:

- The average number of treatment and control customers in the pretreatment period
- The number of months that comprise the pretreatment period (at least one full year is necessary to capture all seasonal effects
- The average daily kWh consumption for both the treatment and control group
- The p-value of a two-sided t-test comparing pretreatment consumption between the treatment and control group. Note that this is for the full pretreatment period, rather than on a month-by-month basis and will not capture seasonal difference between treatment and control. A value greater than 0.05 indicates no statistically significant differences between the groups at the 95% confidence level.

Table 6: Pretreatment Equivalence Summary for Persistence Test Cohorts

Utility	Cohort	Pretreatment Customer Count		Avg. # of Pretreatment Months		Average Daily kWh		
		Control	Treat	Control	Treat	Control	Treat	P-val
Penn Power	Jan 2014 Market Rate	9,751	3,616	12.4	11.8	51.6	51.6	0.7587
	July 2012 Market Rate	18,992	8,133	13.0	12.9	35.6	34.5	0.0000
Penelec	Nov 2014 Remediation	15,511	33,511	11.1	10.6	20.2	21.1	0.0000
	Jan 2014 Low-Income	6,519	4,339	11.3	11.0	42.2	42.3	0.3575
	Jan 2014 Market Rate	20,968	39,507	12.3	11.6	26.2	26.7	0.0000
	July 2012 Market Rate	27,383	37,769	12.9	12.9	36.9	36.8	0.0191
West Penn Power	Nov 2014 Remediation	12,590	12,655	11.3	10.1	40.4	43.0	0.0000
	April 2014 – PA AMI	8,399	8,399	13.0	13.0	45.0	45.0	0.6338
	Jan 2014 Low-Income	9,788	4,637	11.6	11.1	41.4	42.2	0.0000
	Jan 2014 Market Rate	14,724	8,542	11.6	10.4	55.0	55.6	0.0000
	June 2012 Market Rate	24,617	49,874	12.5	12.3	43.2	42.9	0.0000
Met-Ed	Nov 2014 Remediation	12,501	9,084	9.1	7.9	38.0	38.9	0.0000
	Jan 2014 Low-Income	6,496	3,440	11.3	10.6	49.1	49.2	0.5677
	Jan 2014 Market Rate	20,919	28,290	12.2	11.6	39.4	39.1	0.0000
	July 2012 Market Rate	38,781	47,938	12.9	12.8	39.6	39.2	0.0000

As summarized in Table 6, pretreatment equivalence between the persistence test customers and control groups was varied, with no more than one to two cohorts achieving it in each jurisdiction. This has important implications for this persistence study, as the regression model used to estimate impacts, and therefore the effect of persistence, performs poorly with groups that are not well randomized. Consequently, only a subset of cohorts was used to inform the persistence test results discussed in further detail below. That subset was chosen using both these results and the results of a visual inspection of monthly consumption patterns. The graphs showing these results by cohort are displayed in Appendix A.

3.2 IMPACTS FOR PERSISTENT COHORTS

The impacts for each persistence test cohort, estimated using the lagged seasonal regression detailed in the methodology section, are displayed on an annual basis in Table 7. To simplify reporting for the persistence period, the data is divided by years defined from June to May (the Act 129 program year definition). That is, the year 2016 in the table below is reporting impacts from June 2016 to May 2017 (Program Year 8). In this way, we can see the effects of persistence on their own, without the complicating effects of HER delivery between January and May 2016. More detailed monthly impacts by utility and cohort are summarized in Appendix B.

Table 7: Impacts for Persistence Test Cohorts by Year

Utility	Year*	July 2012 Market Rate		Jan 2014 Market Rate		Jan 2014 Low-Income		April 2014 – PA AMI		Nov 2014 Remediation Market Rate	
		%	Daily kWh	%	Daily kWh	%	Daily kWh	%	Daily kWh	%	Daily kWh
Met-Ed	2012	1.32%	0.52								
	2013	2.07%	0.84	0.94%	0.40	0.58%	0.32				
	2014	2.47%	0.98	1.12%	0.44	1.04%	0.52			-0.47%	(0.23)
	2015	2.37%	0.90	1.62%	0.60	2.02%	0.94			0.90%	0.35
	2016	1.28%	0.50	0.68%	0.26	3.12%	1.51			-0.61%	(0.25)
	2017	0.93%	0.36	0.31%	0.12	1.68%	0.84			-1.69%	(0.71)
West Penn Power	2012	0.90%	0.41								
	2013	1.61%	0.75								
	2014	1.25%	0.58	0.13%	0.07	0.28%	0.12	1.08%	0.48		
	2015	1.20%	0.52	1.58%	0.81	-1.24%	(0.51)	1.41%	0.58	0.52%	0.22
	2016	-0.20%	(0.09)	1.12%	0.58	-0.83%	(0.35)	1.21%	0.50	-0.42%	(0.18)
	2017	-1.14%	(0.51)	0.01%	0.01	-1.50%	(0.64)	0.54%	0.22	-0.37%	(0.16)
Penelec	2012	1.34%	0.51	0.00%							
	2013	2.00%	0.75	-0.30%							
	2014	2.31%	0.85	1.38%	0.37	1.55%	0.63				
	2015	2.31%	0.80	1.45%	0.37	0.95%	0.35			1.27%	0.26
	2016	1.81%	0.63	0.66%	0.17	1.56%	0.58			0.99%	0.21
	2017	1.25%	0.43	0.24%	0.06	1.17%	0.44			0.52%	0.11
Penn Power	2012	1.43%	0.50								
	2013	1.87%	0.66	0.33%							
	2014	1.48%	0.52	-0.62%	(0.34)						
	2015	-2.19%	(0.73)	-0.41%	(0.21)						
	2016	-8.08%	(2.78)	-3.08%	(1.67)						
	2017	-11.04%	(3.76)	-3.66%	(2.09)						

3.3 PERSISTENCE OF IMPACTS

As discussed above, not all of FirstEnergy's persistence cohorts showed robust pretreatment equivalence. Because of this, it is best to carefully consider which cohort's impacts should be included in an analysis of HER persistence. The criteria that the SWE team used to categorize cohort quality were threefold:

1. **Pretreatment equivalence must be established**: Without this condition, the lagged seasonal regression model cannot provide unbiased estimates of the savings associated with a HER program.
2. **The cohort must be large enough in the persistence period to provide a precise impact:** Cohorts with 10,000 or more unique – and active – customers after June 2016 provided enough information to ensure that impact estimates during the persistence period could be estimated precisely.
3. **Enough of the original cohort must remain active through the persistence period to feel confident in the internal validity of the impact:** It is possible that there were systematic reasons for customer account churn in the persistent cohorts, which could create a biased estimate of the cohort's savings. In other words, if customers who left the group responded to

the HERs differently than customers who remained active, the overall cohort's result would reflect only customers who remained active if enough other customers left. We focused our efforts on cohorts that had at least 50% of their original size still left by the persistence period.

These criteria are illustrated graphically in the next series of figures. The x-axis plots the average number of customers still active in the period between June 2016 and May 2018 for each cohort, while the y-axis shows the percentage of the original cohort size that is still active during this period. The markers for each cohort are also color-coded to highlight whether the cohort was used in the final analysis, or what the reason was for its exclusion. Finally, unless noted as 'Low Income' in the cohort's label, the results correspond to a market rate cohort.

Figure 2: Cohort Characterization for Penn Power

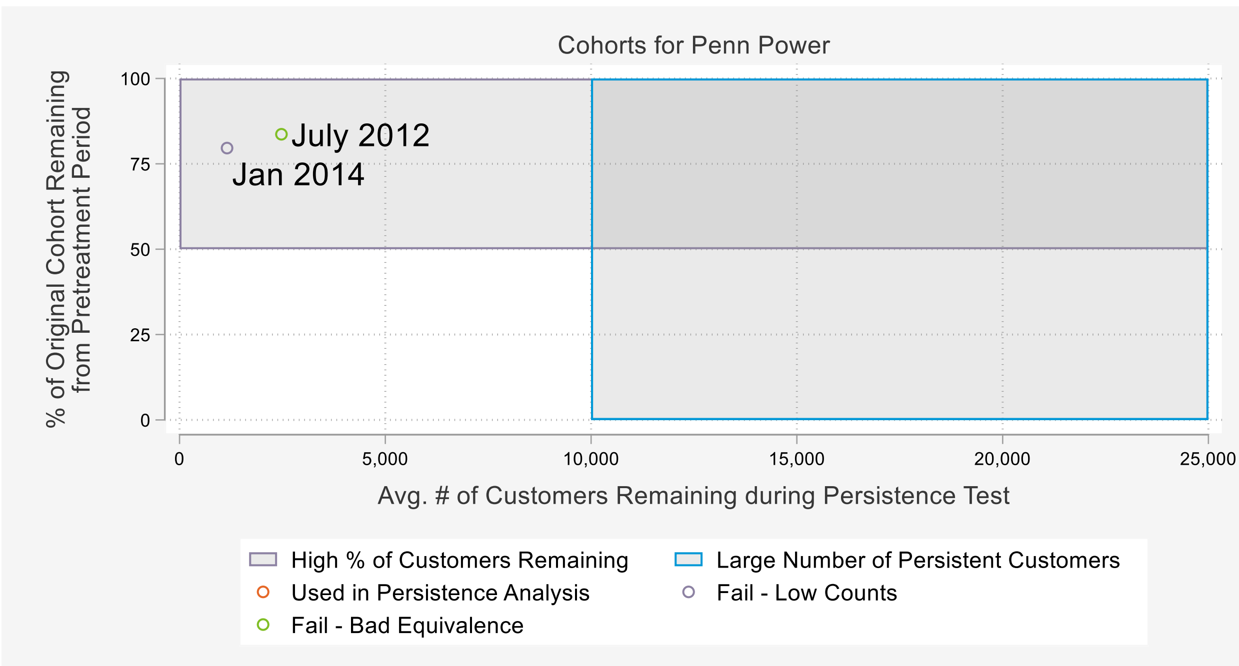


Figure 3: Cohort Characterization for Penelec

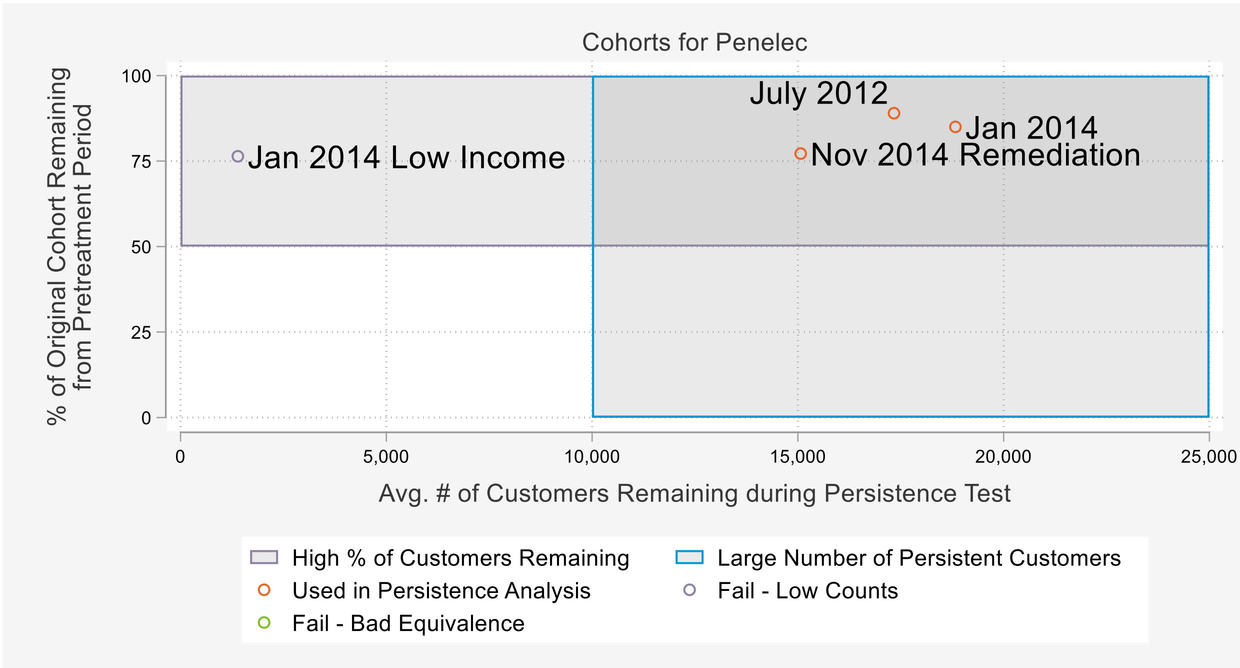


Figure 4: Cohort Characterization for West Penn Power

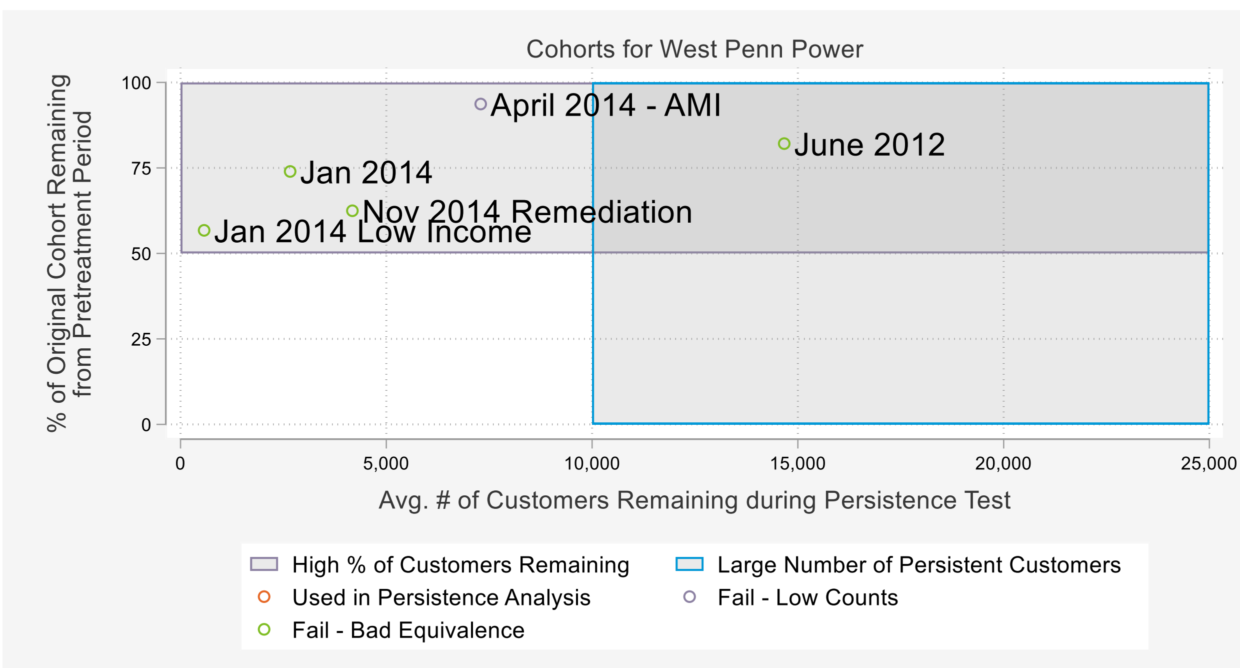
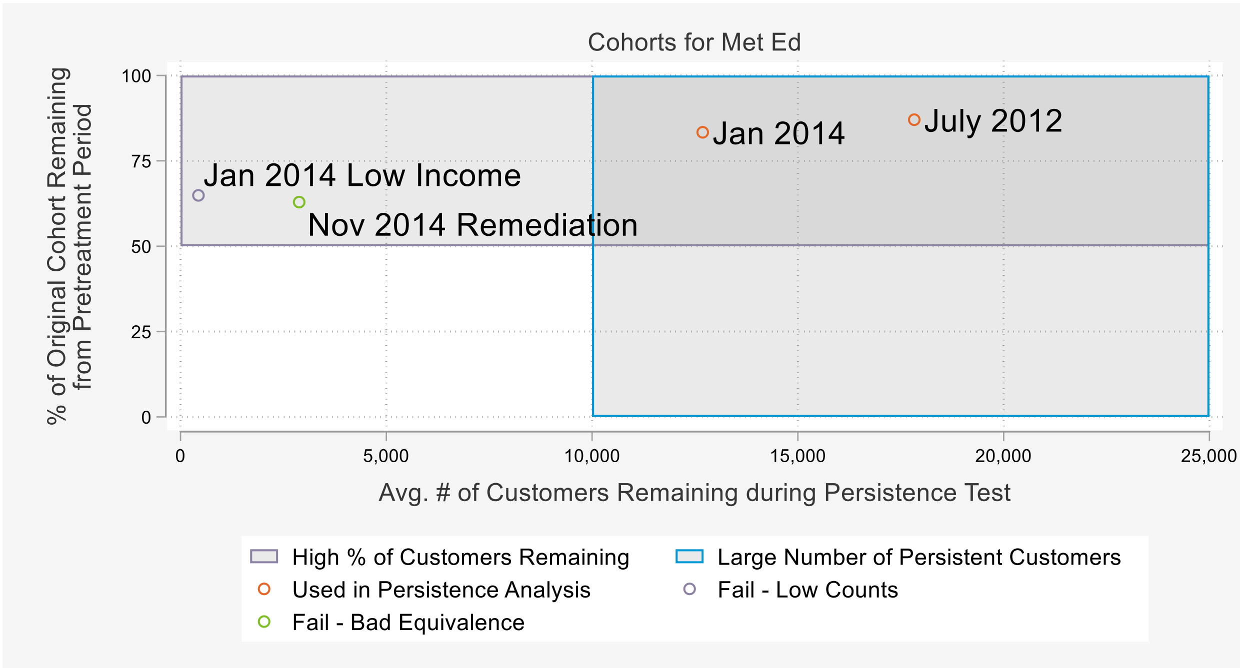


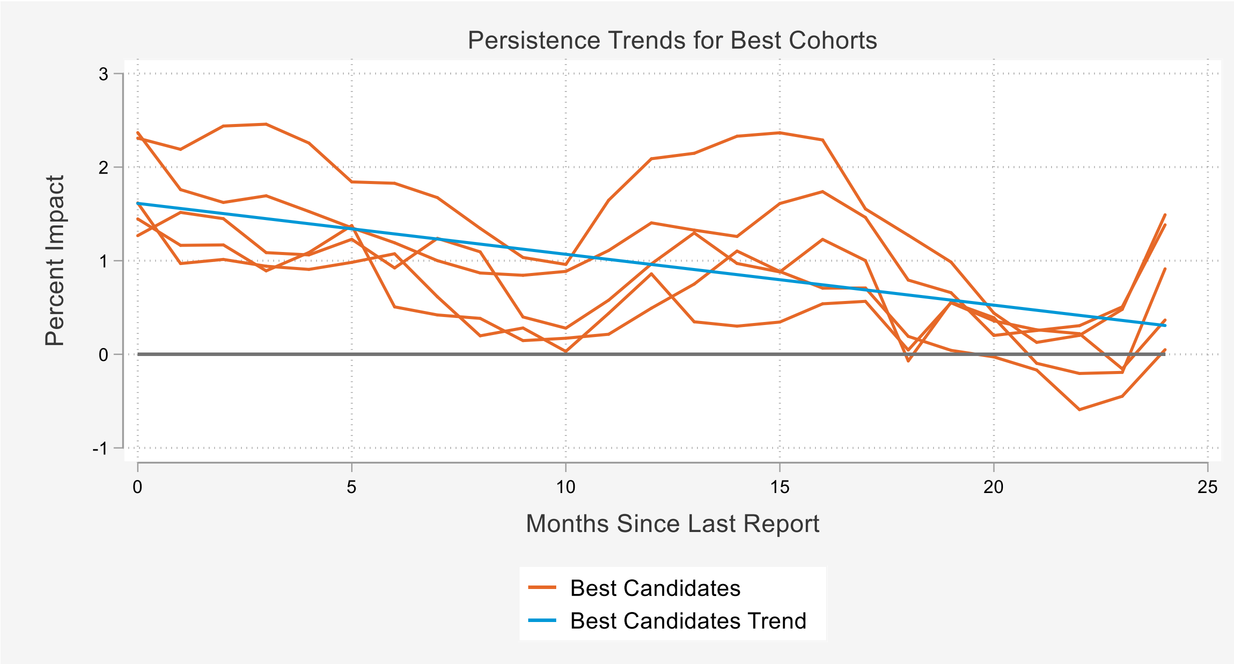
Figure 5: Cohort Characterization for Met-Ed



3.3.1 Combined Persistence Impact

The cohort characterization resulted in five cohorts analyzed in the persistence study: two from Met-Ed and three from Penelec. No cohorts qualified from either West Penn Power or Penn Power. The five cohorts that qualified were then fed in to a second-stage model that sought to determine the monthly decay rate of the savings estimates. Since there is noise in each savings estimate and seasonal variation in the savings estimates, the SWE team thought it most appropriate to set the intercept of each cohort's regression to equal the average savings percentage over the twelve months immediately prior to the persistence test. That is, the starting point of this regression was not simply what the customers saved in May of 2016 but a weighted average of the full year prior to the test. Figure 6 shows the raw data used to construct this analysis. The five cohorts that were identified as having good equivalence and the appropriate cohort size are shown in the figure below. The trend line of persistent savings is shown in blue. This figure displays the trend for First Energy cohorts only, and approaches zero nearly 30 months after the HER reports stop being sent to customers. This estimate is combined with other Pennsylvania studies, below, to provide an overall decay rate estimate.

Figure 6: FirstEnergy Persistence Trends – Good Cohorts Only



To estimate the HER effect duration more precisely, the SWE team fit a simple linear model that related the percent savings estimates – again weighted by the aggregate reference load – to the number of months it had been since the cohort received a HER. The weighting of the percent savings is necessary in this case because we are using percent savings as our variable of interest. Doing the weighting ensures that larger cohorts are have more impact than smaller ones, and that a 2% savings in a high-consumption month counts more than a 2% savings in a low-consumption month, while still creating a percentage metric that can be directly compared to other studies.

The regression resulted in a constant (intercept) value of 1.613% and a slope of -0.054%. That is, each month that the average customer does not receive an HER after having been in the program, their average percent savings declines by 0.054% and their savings will dissipate after 29.7 months (1.613% divided by 0.054%). Results for each of the included cohorts is shown in Table 8.These results were fairly consistent amongst the individual FirstEnergy cohorts, with an estimated savings lifetime ranging from 20.5 months to 34.7 months.

Table 8:Persistence Trends by Cohort

Utility	Cohort	Population	Intercept	Slope	Months to No Impact
Met-Ed	July 2012 Market Rate	17,828	1.753%	-0.051%	34.7
	Jan 2014 Market Rate	12,688	1.039%	-0.041%	25.1
Penelec	July 2012 Market Rate	17,335	2.387%	-0.069%	34.5
	Jan 2014 Market Rate	18,828	1.190%	-0.058%	20.5
	Nov 2014 Remediation	15,068	1.384%	-0.051%	27.4
FirstEnergy	**All**	**81,746**	**1.613%**	**-0.054%**	**29.7**

3.3.2 Comparison to other Persistence Findings

In 2015, the Phase II SWE team conducted a similar analysis of residential HER persistence for cohorts from PPL and Duquesne Energy that stopped receiving HERs. Three cohorts across these two EDCs experienced between 16 and 24 months of no report delivery, with resumption of HERs after that period had passed. Prior to having begun the persistence test, the two PPL cohorts had received reports since 2010 (Legacy), and since 2011 (Expansion). Duquesne's HER program began in PY4 (between June 2012 and May 2013), so at most customers received 11 months of HER treatment prior to report discontinuation.

Table 9:Persistence Trends for Other Pennsylvania HER Studies

Utility	Cohort	Pop.	Persistence Test Start	Persistence Test End	Months of Test	Intercept	Slope	Months to No Impact
PPL	Legacy	48,700	May-13	Oct-14	16	2.350%	-0.060%	39.2
	Expansion	52,900	May-13	Oct-14	16	2.040%	-0.040%	51.0
Duquesne	All	52,200	May-13	Mar-15	21	1.210%	-0.001%	1,210.0
First Energy	All	81,746	Jun-16	.	24	1.613%	-0.054%	29.7

In general, the FirstEnergy results are quite similar to those of the two PPL cohorts, with between 29.7 to 51 months of expected impact decay time. The PPL customers in the HER program had been receiving reports for a longer period than most FirstEnergy customers, but had generally similar savings rates prior to the start of the persistence test. This generally corresponds to the common understanding of HER reports; namely that they can deliver relatively consistent savings after a maturation period of one to two years when customers first start receiving reports. The decay rates, or slope of percent savings decay, in the PPL study is quite similar to that of FirstEnergy, with between a 0.04% and 0.06% drop in savings per month (roughly a 0.5% to 0.75% annual decay).

Duquesne's HER persistence test results are quite unusual and deserve additional consideration. First, the customers in this program had received less than a full year's worth of HERs prior to the commencement of the persistence test. This likely contributed to the low initial savings rate, or intercept, which was approximately half of the other Pennsylvania cohorts, despite the fact that the cohort is comprised of high-usage customers who typically deliver higher HER savings. The slope of the line, a decay rate of 0.001% per month, is between 40 to 60 times smaller than the other three Pennsylvania cohorts and could not statistically be distinguished from zero. This means that there is no statistical basis to say that the savings rate was decaying at all. Because of its unusual characteristics – specifically the short period of time that the HERs were in the field prior to the persistence test – the SWE team decided to remove this result from the joint Pennsylvania HER persistence summary, and instead keep only the PPL and FirstEnergy cohorts. The combined result is constructed as a weighted average, with each territory's estimated months until savings reach zero, weighted by cohort population. For the two PPL and overall FirstEnergy cohorts, the joint value is 38.3 months. This equates to a 31.3% annual rate of decay. That is, if it takes 38.3 months for savings to go to zero, savings must decline 31.3% each year (12/38.3 = 31.3%).

Other persistence tests have been done across the US, including at Eversource, ComEd, Puget Sound Energy, and SMUD. The results of these studies[3] suggest that HER persistence can have quite a strong effect in the year after a HER program is discontinued – between 42 and 99% of the prior year's impacts. There is less research available about the persistence of HER effects in Year 2 and especially beyond two years. A full summary of these results is shown in Table 10.

[3] Links to the studies referenced can be found by searching for the following:

- Impact & Persistence Evaluation Report (November 2012) for Sacramento Municipal Utility District, by Integral Analytics
- 2015 Home Energy Report Impact Evaluation (October 2016) for Puget Sound Energy, by DNV-GL
- Home Energy Report Opower Program Decay Rate and Persistence Study (2016 and 2017) for Commonwealth Edison by Navigant
- Evaluation of Persistence in Eversource Behavior PGM (2015) for Eversource by NMR Group.
- Residential Behavioral Program Persistence Study (2015) for the Pennsylvania Public Utility Commission, by GDS Associates, Nexant, Research Into Action, and Apex Analytics.

Table 10: Summary of Key Persistence Metrics Across Studies

Utility	Cohort	Sample Size	Treatment Dates	Persistence Dates	Metric	Year Prior to Persistence Savings	Y1 of Persistence	Y2 of Persistence
Eversource	Discontinued Monthly	1,670	Jan 2011 - Apr 2012	Apr 2012 - Nov 2014	Avg. Daily kWh Savings	1.75	1.49	0.71
					% Impact	3.6%	3.7%	1.7%
					% of Pre-Persist Savings	100.0%	85.1%	40.6%
	Discontinued Persistence	3,979	Jan 2011 - Aug 2011	Apr 2012 - Nov 2014	Avg. Daily kWh Savings	0.76	0.75	0.09
					% Impact	1.6%	1.9%	0.2%
					% of Pre-Persist Savings	100.0%	98.7%	11.8%
	Discontinued Quarterly	9,856	Jan 2011 - Apr 2012	Apr 2012 - Nov 2014	Avg. Daily kWh Savings	0.86	0.83	0.61
					% Impact	1.8%	2.1%	1.3%
					% of Pre-Persist Savings	100.0%	96.5%	70.9%
SMUD	-	9,965	April 2008 - Jul 2010	Jul 2010 - Sep 2011	Avg. Daily kWh Savings	0.71	0.49	
					% Impact	2.3%	1.6%	
					% of Pre-Persist Savings	100.0%	68.5%	
PSE	-	9,674	Nov 2008 - Dec 2010	Jan 2011 - 2015	Avg. Daily kWh Savings	254.90	246.40	196.00
					% Impact			
					% of Pre-Persist Savings	100.0%	96.7%	76.9%
ComEd	Wave 1	6,270	Jul 2009 - Oct2013	Oct 2013 - Oct 2016	Avg. Daily kWh Savings			
					% Impact			
					% of Pre-Persist Savings	100.0%	96.0%	85.0%
	Wave 3	7,603	May 2011 - Oct 2013	Oct 2013 - Oct 2016	Avg. Daily kWh Savings			
					% Impact			
					% of Pre-Persist Savings	100.0%	98.0%	83.0%
	Wave 5	5,605	Jul 2012 - Oct 2013	Oct 2013 - Oct 2016	Avg. Daily kWh Savings			
					% Impact			
					% of Pre-Persist Savings	100.0%	78.0%	40.0%
PPL	Legacy*	48,700	2010 - May 2013	May 2013 - Oct 2014	Avg. Daily kWh Savings			
					% Impact	2.4%	1.6%	
					% of Pre-Persist Savings	100.0%	71.1%	
	Expansion*	52,900	2011 - May 2013	May 2013 - Oct 2014	Avg. Daily kWh Savings			
					% Impact	2.0%	1.6%	
					% of Pre-Persist Savings	100.0%	78.0%	

Utility	Cohort	Sample Size	Treatment Dates	Persistence Dates	Metric	Year Prior to Persistence Savings	Y1 of Persistence	Y2 of Persistence
Duquesne	- *	52,200	Jun 2012 - May 2013	May 2013 - Mar 2015	Avg. Daily kWh Savings			
					% Impact	1.2%	1.2%	
					% of Pre-Persist Savings	100.0%	98.8%	
FirstEnergy	Met-Ed – July 2012 Market Rate	17,828	Jul 2012 - May 2016	Jun 2016 - Jun 2018	Avg. Daily kWh Savings	0.90	0.50	0.36
					% Impact	2.4%	1.3%	0.9%
					% of Pre-Persist Savings	100.0%	55.4%	39.7%
	Met-Ed – Jan 2014 Market Rate	12,688	Jan 2014 - May 2016	Jun 2016 - Jun 2018	Avg. Daily kWh Savings	0.60	0.26	0.12
					% Impact	1.6%	0.7%	0.3%
					% of Pre-Persist Savings	100.0%	43.2%	20.2%
	Penelec – July 2012 Market Rate	17,335	Jul 2012 - May 2016	Jun 2016 - Jun 2018	Avg. Daily kWh Savings	0.80	0.63	0.43
					% Impact	2.3%	1.8%	1.2%
					% of Pre-Persist Savings	100.0%	78.6%	53.9%
	Penelec – Jan 2014 Market Rate	18,828	Jan 2014 - May 2016	Jun 2016 - Jun 2018	Avg. Daily kWh Savings	0.37	0.17	0.06
					% Impact	1.4%	0.7%	0.2%
					% of Pre-Persist Savings	100.0%	46.7%	16.9%
	Penelec – Nov 2014 Remediation	15,068	Nov 2014 - May 2016	Jun 2016 - Jun 2018	Avg. Daily kWh Savings	0.26	0.21	0.11
					% Impact	0.01	0.01	0.01
					% of Pre-Persist Savings	100.0%	79.1%	41.6%

** Results shown for Y1 are shown over a period of 16 months, not 12*

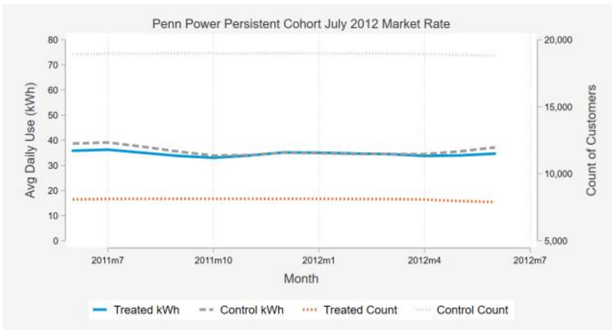
With the exception of Duquesne's HER persistence test, each study shows a similar downward trend in impacts associated with cohorts after they stop receiving HERs. These results are complicated by many factors, including cohort target population and size, amount of time that the customers had received HERs prior to report discontinuation, report frequency, and seasonal trends captured in the savings rates. They should not be directly compared to each other. Other studies assessed by Cadmus[4] find similar decay rates (between 11% and 83%), implying savings of between 17% and 89% in the year after treatment ends. Interestingly, the study Cadmus finds with the highest annual decay rate (83%) is also the one with the shortest amount of pre-persistence treatment time – only six months. This is in direct contrast to the findings for Duquesne Energy, where nearly 100% of savings persisted after only 11 months of HER delivery. Determining possible explanations for this finding is out of scope for this analysis; however, further study, either in the form of a more detailed literature review or new persistence tests, should be performed to explore this finding further.

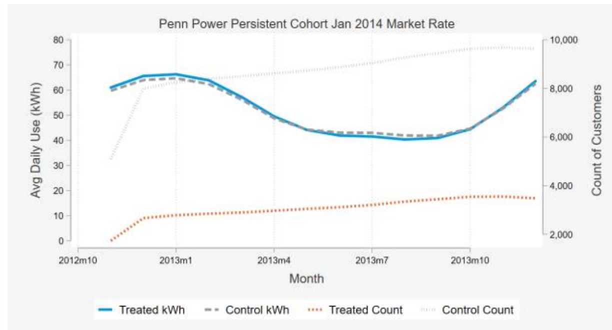
[4] Long-Run Savings and Cost-Effectiveness of Home Energy Report Programs, by M. Sami Khawaja and James Stewart (2017)

APPENDIX

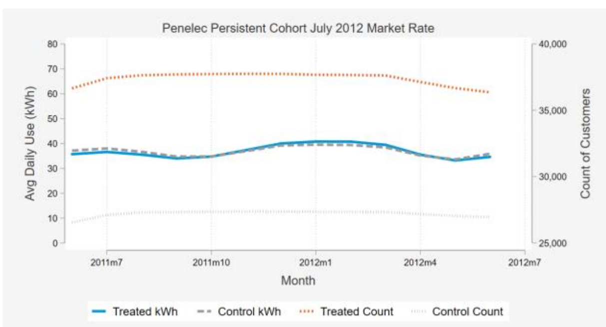
A. APPENDIX A – PRETREATMENT EQUIVALENCE GRAPHS BY COHORT

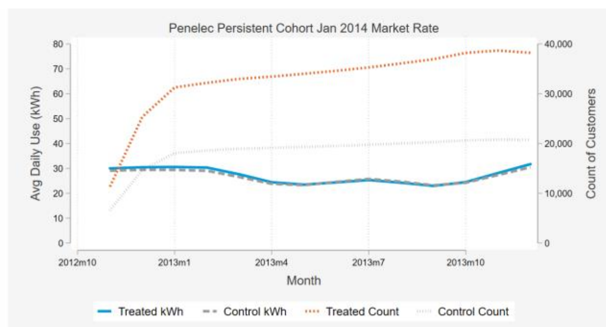
Penn Power – Pretreatment Equivalence for Persistence Test Cohorts

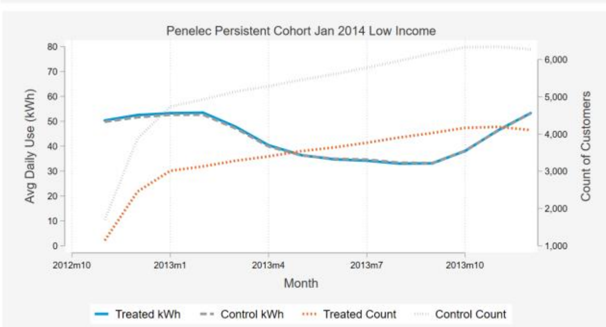


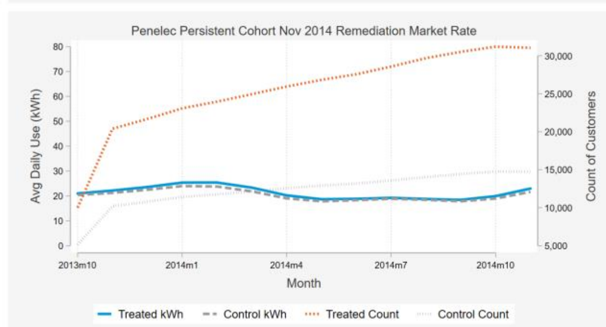


Penelec – Pretreatment Equivalence for Persistence Test Cohorts

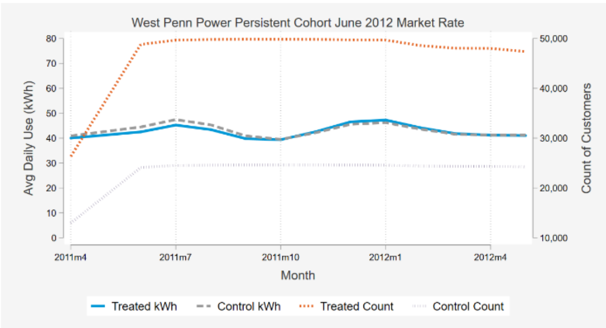


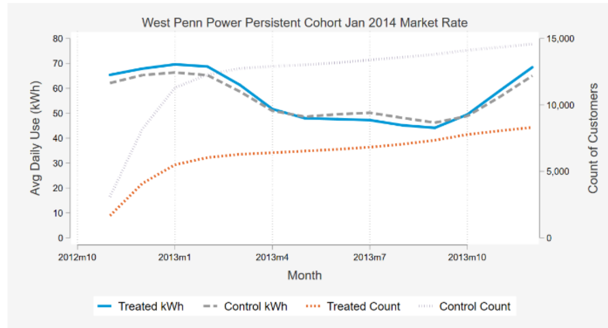


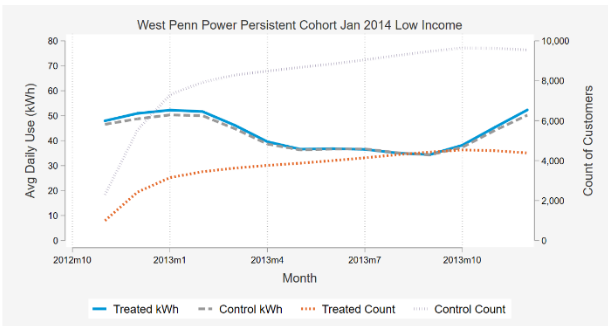


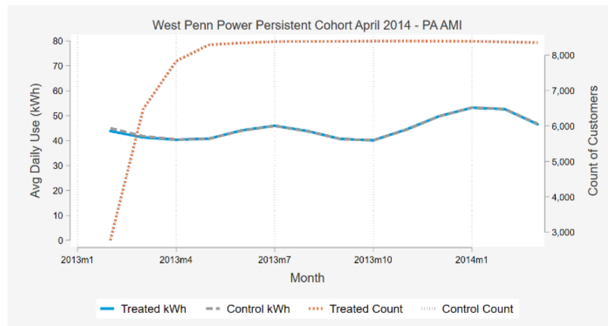


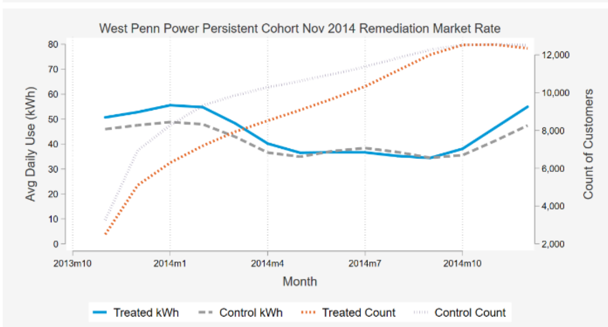
West Penn Power – Pretreatment Equivalence for Persistence Test Cohorts



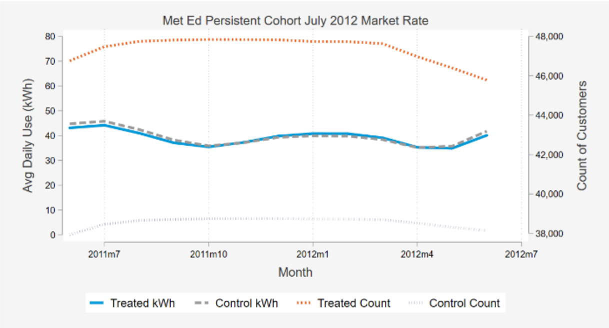


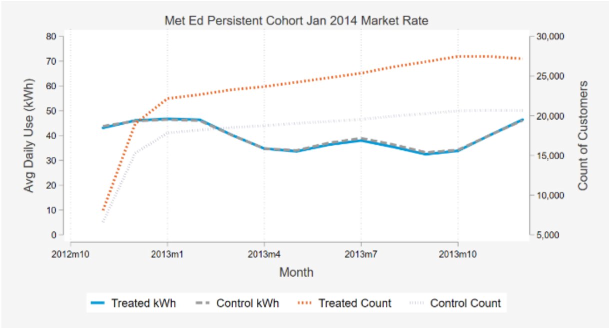


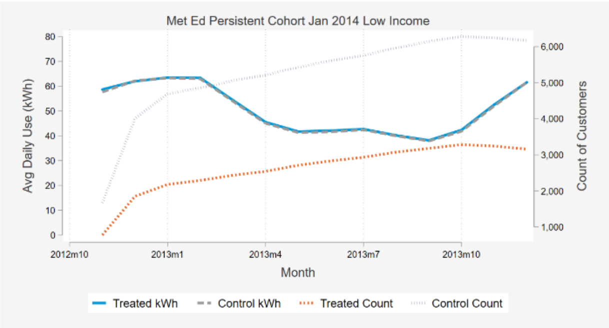


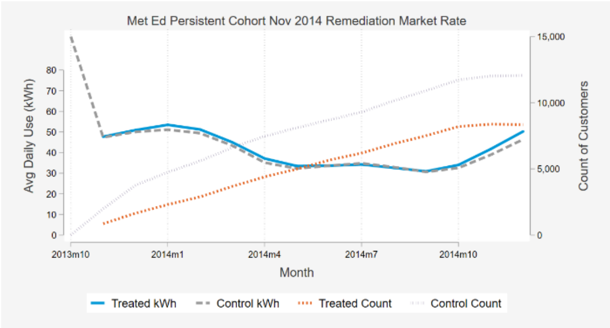


Met-Ed – Pretreatment Equivalence for Persistence Test Cohorts









B. APPENDIX B – MONTHLY IMPACTS FOR PERSISTENCE TEST COHORTS

Met-Ed – Monthly % Impacts for Persistence Test Cohorts

Year	Month	July 2012 Market Rate	Jan 2014 Market Rate	Jan 2014 Low Income	April 2014 - PA AMI	Nov 2014 Remediation Market Rate
2015	6	3.31%	1.37%	2.13%		2.69%
	7	3.26%	2.05%	3.68%		2.92%
	8	3.10%	2.26%	3.73%		2.56%
	9	2.87%	2.89%	3.79%		1.88%
	10	2.78%	1.95%	3.02%		0.66%
	11	2.84%	1.71%	2.83%		-0.72%
	12	2.45%	1.48%	1.16%		0.15%
2016	1	1.74%	0.97%	0.23%		0.00%
	2	1.19%	0.96%	0.68%		-0.64%
	3	1.33%	1.31%	0.50%		0.48%
	4	1.51%	1.40%	1.46%		0.81%
	5	1.81%	1.38%	3.05%		0.82%
	6	1.76%	0.97%	3.47%		1.01%
	7	1.62%	1.01%	3.16%		1.59%
	8	1.69%	0.94%	3.42%		1.22%
	9	1.53%	0.91%	4.05%		-0.13%
	10	1.35%	0.98%	3.28%		-0.57%
	11	1.19%	1.07%	2.08%		-1.43%
	12	1.00%	0.61%	2.42%		-0.84%
2017	1	0.87%	0.20%	2.98%		-1.08%
	2	0.84%	0.28%	3.27%		-1.98%
	3	0.89%	0.03%	3.66%		-2.12%
	4	1.11%	0.44%	3.40%		-2.24%
	5	1.40%	0.86%	2.48%		-0.66%
	6	1.33%	0.35%	1.98%		-1.70%
	7	1.26%	0.30%	1.84%		-1.71%
	8	1.61%	0.34%	1.65%		1.66%
	9	1.74%	0.54%	1.58%		1.18%
	10	1.46%	0.57%	1.74%		-0.99%
	11	0.79%	0.05%	3.42%		-2.06%
	12	0.66%	0.55%	3.22%		-1.52%
2018	1	0.20%	0.36%	1.65%		-2.39%
	2	0.25%	0.26%	0.41%		-2.83%
	3	0.31%	0.22%	0.46%		-2.98%
	4	0.51%	-0.15%	0.06%		-3.65%
	5	1.38%	0.37%	2.34%		-2.02%

Penn Power – Monthly % Impacts for Persistence Test Cohorts

Year	Month	July 2012 Market Rate	Jan 2014 Market Rate	Jan 2014 Low Income	April 2014 - PA AMI	Nov 2014 Remediation Market Rate
2015	6	5.06%	2.02%			
	7	6.01%	2.67%			
	8	5.51%	2.46%			
	9	4.43%	1.94%			
	10	1.22%	0.99%			
	11	0.52%	-0.84%			
	12	0.91%	-1.13%			
2016	1	-11.22%	-1.27%			
	2	-20.27%	-2.44%			
	3	-10.79%	-1.75%			
	4	-2.28%	-2.54%			
	5	-2.80%	-1.89%			
	6	-0.89%	-0.15%			
	7	-0.23%	-0.70%			
	8	-1.22%	-1.01%			
	9	-4.44%	-1.25%			
	10	-10.61%	-3.59%			
	11	-12.07%	-4.46%			
	12	-11.30%	-4.15%			
2017	1	-11.62%	-4.32%			
	2	-12.79%	-4.62%			
	3	-13.19%	-4.46%			
	4	-12.12%	-3.92%			
	5	-9.38%	-1.55%			
	6	-5.38%	-0.78%			
	7	-4.07%	-1.00%			
	8	-6.12%	-1.83%			
	9	-7.89%	-2.34%			
	10	-11.05%	-3.12%			
	11	-13.88%	-4.18%			
	12	-13.28%	-4.98%			
2018	1	-14.37%	-4.89%			
	2	-14.80%	-5.36%			
	3	-15.45%	-5.01%			
	4	-15.44%	-3.83%			
	5	-8.32%	-1.64%			

West Penn Power – Monthly % Impacts for Persistence Test Cohorts

Year	Month	July 2012 Market Rate	Jan 2014 Market Rate	Jan 2014 Low Income	April 2014 - PA AMI	Nov 2014 Remediation Market Rate
2015	6	4.19%	3.16%	3.22%	0.96%	3.10%
	7	4.15%	4.43%	3.47%	1.30%	4.38%
	8	4.03%	3.84%	3.12%	1.14%	3.75%
	9	3.74%	3.18%	1.84%	1.00%	2.47%
	10	2.81%	2.20%	0.49%	1.90%	0.80%
	11	1.30%	1.20%	-0.89%	1.51%	-0.28%
	12	0.01%	1.07%	-3.38%	1.48%	-0.58%
2016	1	-1.56%	0.41%	-4.92%	1.59%	-1.17%
	2	-2.39%	-0.57%	-5.26%	1.45%	-1.97%
	3	-1.31%	-0.87%	-5.13%	1.23%	-1.82%
	4	0.04%	0.53%	-2.39%	1.61%	-1.01%
	5	1.18%	2.28%	0.12%	1.86%	0.73%
	6	1.82%	2.79%	0.62%	1.13%	1.74%
	7	1.68%	3.04%	1.25%	1.26%	2.28%
	8	1.74%	3.12%	0.44%	1.10%	2.04%
	9	1.50%	2.57%	-0.24%	0.94%	1.01%
	10	0.32%	1.49%	0.52%	2.21%	-0.85%
	11	-1.22%	0.02%	-1.42%	1.32%	-2.33%
	12	-2.18%	0.03%	-3.46%	1.23%	-1.63%
2017	1	-2.28%	-0.35%	-3.61%	1.21%	-1.48%
	2	-2.17%	-0.80%	-2.59%	1.24%	-2.02%
	3	-1.59%	-0.19%	-1.95%	1.18%	-2.22%
	4	0.09%	0.59%	0.49%	0.69%	-1.30%
	5	0.90%	2.62%	3.08%	1.06%	0.82%
	6	1.57%	3.10%	1.95%	0.91%	1.87%
	7	1.48%	2.89%	1.18%	1.24%	2.16%
	8	1.59%	3.01%	1.34%	0.97%	1.70%
	9	1.27%	2.45%	1.14%	0.33%	0.70%
	10	-0.12%	1.37%	0.77%	1.28%	-0.23%
	11	-1.92%	-1.11%	-2.25%	0.02%	-1.36%
	12	-3.45%	-0.91%	-5.26%	0.22%	-0.99%
2018	1	-3.66%	-1.32%	-5.14%	0.62%	-1.41%
	2	-3.19%	-2.47%	-3.57%	0.38%	-1.86%
	3	-2.64%	-2.63%	-2.45%	0.37%	-1.63%
	4	-1.11%	-1.52%	-1.35%	-0.17%	-1.25%
	5	-0.51%	0.96%	1.57%	0.38%	0.06%

Penelec – Monthly % Impacts for Persistence Test Cohorts

Year	Month	July 2012 Market Rate	Jan 2014 Market Rate	Jan 2014 Low Income	April 2014 - PA AMI	Nov 2014 Remediation Market Rate
2015	6	3.34%	1.83%	1.17%		2.01%
	7	3.72%	2.39%	0.26%		2.27%
	8	3.40%	2.28%	-0.27%		1.82%
	9	2.71%	1.95%	0.28%		1.77%
	10	2.48%	2.11%	0.64%		1.29%
	11	2.35%	1.61%	-0.16%		0.94%
	12	2.30%	1.44%	1.69%		1.01%
2016	1	1.98%	0.88%	1.34%		0.90%
	2	1.41%	0.50%	0.70%		0.75%
	3	0.78%	0.59%	1.86%		0.56%
	4	1.39%	0.83%	1.80%		0.82%
	5	1.94%	1.15%	1.84%		1.26%
	6	2.19%	1.16%	1.82%		1.52%
	7	2.44%	1.17%	1.63%		1.45%
	8	2.46%	0.89%	1.65%		1.09%
	9	2.26%	1.09%	2.11%		1.06%
	10	1.84%	1.38%	2.36%		1.23%
	11	1.83%	0.51%	1.03%		0.92%
	12	1.67%	0.42%	1.36%		1.24%
2017	1	1.35%	0.38%	1.55%		1.09%
	2	1.03%	0.15%	1.34%		0.40%
	3	0.96%	0.17%	1.85%		0.28%
	4	1.65%	0.21%	1.16%		0.58%
	5	2.09%	0.49%	1.00%		0.97%
	6	2.15%	0.75%	0.06%		1.30%
	7	2.33%	1.10%	0.48%		0.97%
	8	2.37%	0.88%	0.98%		0.88%
	9	2.29%	0.71%	0.42%		1.23%
	10	1.55%	0.71%	2.01%		1.00%
	11	1.27%	0.19%	0.86%		-0.07%
	12	0.99%	0.04%	1.52%		0.56%
2018	1	0.44%	-0.03%	1.21%		0.39%
	2	0.13%	-0.17%	0.70%		-0.10%
	3	0.20%	-0.59%	1.61%		-0.20%
	4	0.48%	-0.45%	1.76%		-0.19%
	5	1.49%	0.05%	2.34%		0.91%