Opinion Dynamics

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Memorandum

To: Fernando Morales, Ameren Illinois; Jennifer Morris, Illinois Commerce Commission

From: Opinion Dynamics Evaluation Team

Date: October 21, 2019

Re: 2018 Behavioral Modification Initiative Persistence Study - Year One

Study Background

In 2018, a substantial portion of Behavioral Modification treatment group customers who were added to the Initiative between PY3 and the Transition Period stopped receiving home energy reports (HERs).[1] This cessation of treatment created a natural experiment that allowed the evaluation team to estimate persisting savings for previously treated customers. Persisting savings is defined as the savings that occur after a treated customer stops receiving reports due to changes in energy efficiency equipment or habituated behaviors. In particular, this study evaluated the persisting savings of the treatment customers one year after they stopped receiving reports (January - December 2018). After estimating the persisting savings, the evaluation team calculated a persistence factor (i.e., the percentage of savings that persist after cessation of treatment).[2]

The evaluation team designed this study to answer the following research questions:

- What are the persisting savings achieved in 2018?
- What is the difference in initiative savings between customers who received reports for a longer duration and those customers who received reports for a shorter duration (i.e., are there differences across cohorts)?
- What is the persistence factor?

In addition, this memo provides a proposal to enhance the methods used to estimate the persistence factor going forward. We believe this alternative approach has the potential to provide more power and confidence to the persistence factor results given the way in which AIC suspended treatment.

Persistence Study Results

2018 Behavioral Modification Persisting Savings

The evaluation team used a consumption analysis approach to determine savings from the last year customers received treatment (2017) and the first year after customers stopped treatment (2018). Given that the

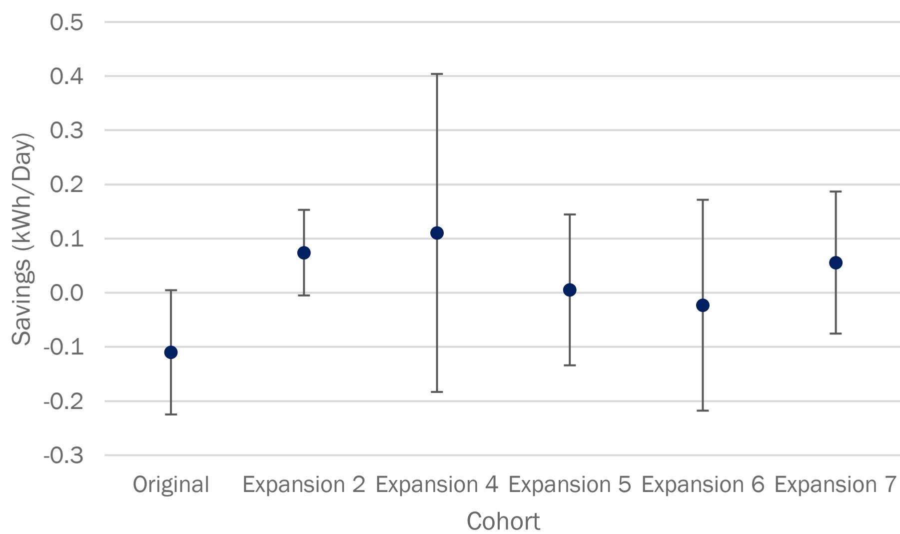
[1] All previously treated cohorts, with the exception of Expansion Cohort 1, no longer received home energy reports in 2018.

[2] A persistence factor is the percentage of savings that persist after cessation of treatment. To calculate a persistence factor, the evaluation team compared the savings from the year after the customers stopped receiving reports to the final year in which treated customers received reports (i.e., 2018 savings divided by 2017 savings).

Initiative uses an experimental design, the evaluation team utilized the treatment and control group customers' monthly billing data for the consumption analysis. This approach is consistent with the methodology used to evaluate this Initiative's annual program impacts.

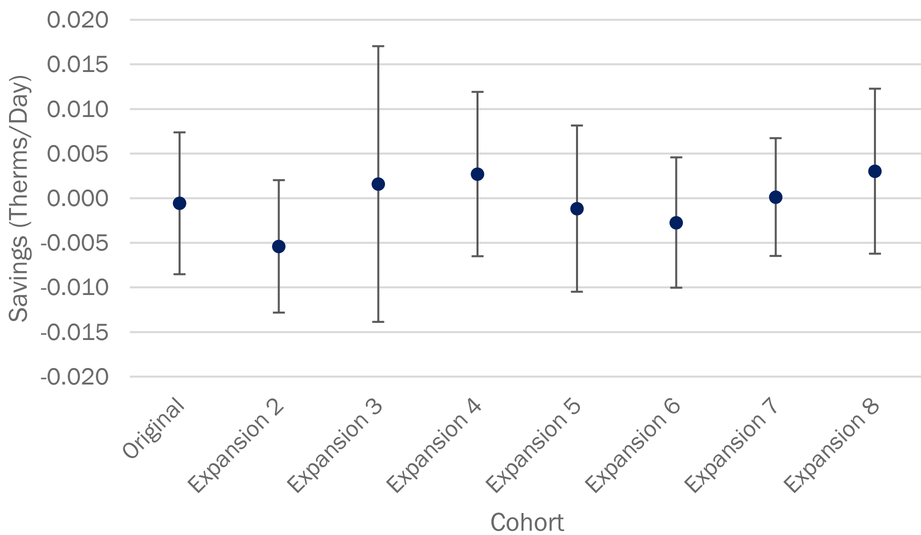
Overall, the evaluation team found no evidence of savings decay for any of the cohorts or fuel types. In particular, when comparing the 2018 estimated savings to the savings generated from the last year treated customers received reports (i.e., 2017 savings), the evaluation team did not find statistically significant differences in savings at the 90% confidence level. Figure 1 and Figure 2 show the differences in the 2018 and 2017 average daily savings per cohort and fuel type (represented by the blue dots) along with the combined standard error (represented by the error bars). These figures demonstrate a lack of statistical difference in savings values between the last year of receiving reports and the first year of not receiving reports.

Figure 1. Difference in Average 2017 and 2018 kWh/Day Savings per Cohort



Note: A positive savings difference (represented by the blue dots above the 0.0 kWh/day axis) indicates the 2018 average daily savings were larger than the 2017 average daily savings for a given cohort.

Figure 2. Difference in Average 2017 and 2018 Therms/Day Savings per Cohort



Note: A positive savings difference (represented by the blue dots above the 0.000 therms/day axis) indicates the 2018 average daily savings were larger than the 2017 average daily savings for a given cohort.

These results are consistent with research conducted for Commonwealth Edison (ComEd) that estimated a persistence factor the first year and third year after customers were removed from the program. As part of this study, the evaluation team at Navigant (2016)[3] found that the savings for the participants still receiving reports (Continued Report group) were not statistically different than the savings from participants that stopped receiving reports (Terminated Report group) after the first year of cessation of treatment[4]. However, subsequently, Navigant (2017)[5] analyzed persisting savings for the same participants after the third year of cessation of treatment and found that savings for the Continued Report (CR) group were statistically different than the Terminated Report (TR) group. Therefore, while the statistically insignificant savings results found for AIC are similar to other studies estimating persistence after the first year of cessation of treatment, the later Navigant (2017) study shows that it is possible to see statistically different savings results after the third year of not receiving reports. As such, it is possible that a statistically significant difference in savings from the last year of treatment and the first year after cessation of treatment was not detected for AIC's program due to the relatively short duration of time that has passed since treatment customers last received reports.

Difference in Savings across Cohorts

Because the evaluation team did not find statistically significant persistence factors for the cohorts, we cannot draw any conclusions about persistence factors as a function of how long customers participated in the

[3] Navigant (2016). "Home Energy Reports Opower Program Decay Rate and Persistence Study: Final." Chicago, Illinois: Navigant Consulting, Inc.

[4] The Opinion Dynamics evaluation team calculated statistical significance of the savings for the first and third year studies completed by Navigant, as they were not included in their findings. Statistical significance for the second year was not calculated because standard errors were not included in the study findings.

[5] Navigant (2017). "Home Energy Report Opower Program Decay Rate and Persistence Study – Year Three: Final." Chicago, Illinois: Navigant Consulting, Inc.

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Behavioral Modification Initiative prior to stoppage of treatment. However, the evaluation team reviewed the existing literature to identify potential trends in terms of duration of exposure and persisting savings that could be useful in thinking about future persistence studies and their results. Based on this review of the literature, no general trend exists related to how average annual persistence factor changes based on the amount of time a treated customer receives home energy reports. The evaluation team provides findings from a series of recent studies in Table 1 and Table 2 below to illustrate these mixed results.

Table 1 shows the results from the Navigant (2017) persistence factor study completed for ComEd. The first two years suggest that a longer period of receiving reports before a stoppage of treatment is correlated with a higher persistence factor; Wave 1 was in the treatment period before termination for the longest period and had the smallest change in persistence factors between the first two years, while Wave 5 was in the treatment period for the shortest time and has the largest change in yearly persistence factors. This makes intuitive sense; as a treated customer receives more reports, it could provide them with more opportunity to adopt energy efficient habits that could then take longer to "wear off" relative to treated customers who stopped receiving reports after a shorter treatment period. As noted above, this study did not find statistically significant persistence factors until the third year after cessation of treatment.

Table 1. Navigant (2017) Persistence Factors by Wave and Year

Authors	Wave	# of Months in Program	# of Months of Post-Treatment	Stoppage of Treatment Customers	Incremental Savings	Annual Persistence Factor (Year 1)	Annual Persistence Factor (Year 2)	Annual Persistence Factor (Year 3)	Average Annual Persistence Factor
Navigant (2017)	1	52	36	5,420	1.70%	96%	85%	61%*	81%
	3	30		6,583	2.07%	98%	83%	82%*	88%
	5	16		4,193	0.89%	78%	40%	53%*	57%

*CR and TR participant groups have statistically different savings results at the 90% confidence level.
Navigant (2017). "Home Energy Report Opower Program Decay Rate and Persistence Study – Year Three: Final." Chicago, Illinois: Navigant Consulting, Inc.

In contrast, a study by Thomas, Huber and Smith (2016)[6] shows the opposite pattern (see Table 2). In this study, treated customers that were in the program for a longer period of time have lower average annual persistence factors. Thomas, Huber and Smith (2016) estimated persistence for two waves within the Pennsylvania Power & Light (PPL) territory and found that the persistence factor for the wave that had treated customers in the program for 36 months was lower than that for the wave that was in the program for 24 months.

Table 2. Literature Review Findings - Average Annual Persistence Factors

Authors	Utility	# of Months in Program	# of Months of Treatment Stoppage	Stoppage of Treatment Customers	Incremental Savings (Per Customer)	Average Annual Persistence Factor
	Upper Midwest	24-25	26	12,368	NA	79%
	Northwest	24	29	11,543	NA	82%

[6] Thomas, J., Huber, J., and Smith, J. "Residential Behavioral Program Persistence Effects in Pennsylvania." ACEEE Summer Study on Energy Efficiency in Buildings, August 2016.

Authors	Utility	# of Months in Program	# of Months of Treatment Stoppage	Stoppage of Treatment Customers	Incremental Savings (Per Customer)	Average Annual Persistence Factor
Allcott and Rogers (2014)[7]	Southwest	25-28	34	12,117	NA	85%
Thomas, Huber and Smith (2016)	PPL	38	16	48,700	2.0%	70%
		24	16	52,900	1.7%	78%
	Duquesne Light Company	10	21	52,200	1.0%	99%
Integral Analytics (2012)[8]	Sacramento Municipal Utility District (SMUD)	27	12	9,965	1.6%	68%
DNV-KEMA (2012)[9]	Puget Sound Energy	24	12	9,674	NA	79%
DNV-GL (2014)[10]	Puget Sound Energy	24	36	7,796	1.1%	89%

Future Research

The approach used to estimate an AIC persistence factor in this study reflects a coordinated and consistent approach across the Illinois utilities. This approach serves to inform the "counterfactual," (i.e., what the treated customers' usage would have been if they continued receiving reports). To estimate this counterfactual properly, the approach needs to include three groups of customers for each cohort: 1) customers that continue to receive reports, 2) customers that stopped receiving reports, and 3) customers that never received reports. However, given that AIC discontinued treatment for customers in all cohorts except for Expansion Cohort 1 as opposed to randomly selecting customers to stop receiving treatment, the evaluation team could only use the latter two customer groups in the analysis.

Given this design limitation, Opinion Dynamics suggests using an alternative methodological approach for next year's analysis. The proposed approach uses a "combined" regression model that incorporates all cohorts within the Behavioral Modification Initiative. The combined model includes both treatment and control group information to control for exogenous factors that may affect energy savings or consumption within a household over time. In addition, this modeling approach incorporates all three groups outlined above by including the cohort that is currently receiving reports, making it feasible to more accurately and precisely estimate the counterfactual. Through this approach, the evaluation team believes it is more likely to be able to estimate

[7] Hunt Allcott, Todd Rogers (2014). The Short-Run and Long-Run Effects of Behavioral Interventions: Experimental Evidence from Energy Conservation. American Economic Review, 104(10), 3003-3037. doi: 10.1257/aer.104.10.3003.
[8] Integral Analytics (2012). "Impact & Persistence Evaluation Report: Sacramento Municipal Utility District Home Energy Report Program." Cincinnati, Ohio: Integral Analytics, Inc.
[9] DNV-KEMA (2012). "Puget Sound Energy's Home Energy Reports Program – Three Year Impact, Behavioral, and Process Evaluation." Madison, Wisconsin: DNV-KEMA
[10] DNV-GL (2014). "Residential Energy Efficiency Special Projects: 2014 Impact Evaluation of Home Energy Reports Program." Madison, Wisconsin: DNV-GL.

statistically significant persistence factors for each cohort, as well as an overall weighted persistence factor for all cohorts that stopped receiving reports.

Appendix – Detailed Methodology and Results

Methodology

Stoppage of Treatment Program Design

There are a variety of methods for estimating persistence, generally dictated by program design and implementation changes made to who receives HERs. One of the most common methods is to randomly sample a group of treated customers to stop receiving reports (terminated group), while the rest of the treated customers continue to receive reports (continued group) within a particular treated customer group. This allows for both the terminated group and the continued group to include similar treated customers. For this type of design, persistence is calculated by estimating the relationship in savings between the terminated and continued groups for similar treated customers within the year when reports were discontinued. This approach was used to estimate persistence factors for Commonwealth Edison 2013 through 2017.

Another common method is to terminate treatment for all treated customers within a particular treated customer group, which is the approach employed for this analysis. This is because the Behavioral Modification Initiative terminated treatment for eight of the nine cohorts in the Initiative in 2018. As a result, all treated customers were in the 'terminated' group for each of the eight cohorts that stopped receiving reports. Since this method cannot compare savings between a terminated group and a continued group for similar treated customers (as described above), it relies on comparing savings after treated customers stopped receiving reports to savings for the last year the treated customers were in the program to estimate savings persistence.

Table 3 shows the difference in calculating the persistence factor across the two most common methods. The terminated/continued group method compares savings within the same year across two treatment groups (i.e., terminated group and continued group), whereas the method used for the Behavioral Modification Initiative compares savings for a given year to the savings from the prior year (i.e., 2018 vs 2017 savings) for each cohort.

Table 3. Comparison of Persistence Factor Equations Across Sampling Methods

	Terminated/Continued Group Method	Behavioral Modification Method
Persistence Factor Equation	$\frac{Year_t\ Savings_{Terminated\ Group}}{Year_t\ Savings_{Continued\ Group}}$	$\frac{Year_t\ Savings}{Year_{t-1}\ Savings}$

Model Specifications

The evaluation team used a consumption analysis approach to determine the last year of savings while receiving treatment (2017) and the first year of savings after stoppage of treatment (2018). Given that these programs use an experimental design, the evaluation team utilized the treatment and control group customers' monthly billing data for the consumption analysis. This approach is consistent with the methodology used in evaluating this Initiative's annual program impacts.

For each cohort and savings type (i.e., 2018 savings vs 2017 savings), the pre-period reflects the cohort's pre-enrollment period (i.e., the year before the cohort enrolled in the Initiative). Using the same pre-period across each model per cohort allowed for a proper assessment of savings when estimating persistence. Table 4 shows the pre-enrollment periods per cohort as well as the post-periods for each year. Notably, because this program began as early as 2010 for some cohorts, the pre-period covers a substantial portion of time.

Table 4. Persistence Study Analysis Periods

Cohort	Pre-Enrollment Period	Treatment Period (2017 Savings)	Stoppage of Treatment Period (2018 Savings)
Original	Aug 2009 – Jul 2010	Jan 2017 – Dec 2017	Jan 2018 – Dec 2018
Expansion 2	Nov 2010 – Oct 2011		
Expansion 3	Nov 2010 – Oct 2011		
Expansion 4	Jun 2012 – May 2013		
Expansion 5	Sep 2013 – Aug 2014		
Expansion 6	Apr 2014 – Mar 2015		
Expansion 7	Sep 2015 – Aug 2016		
Expansion 8	Sep 2016 – Aug 2017		

The evaluation team used a consumption analysis approach for this analysis that is similar to the method used for the PY2018 Behavioral Modification Initiative evaluation. Specifically, the evaluation team used an intent to treat (ITT) approach and estimated savings using a difference-in-differences (DID) approach. The DID refers to the model's implicit comparison of consumption before and after treatment of both treatment and control group customers. The model includes customer-specific intercepts (i.e., fixed effects) to capture unobserved differences between customers that do not change over time and which affect customers' energy use.

As part of the impact analysis, the evaluation team used three different models to estimate 2017 and 2018 savings:

1. An overall model (Equation 1), that incorporates the post-treatment period only. This is the lagged dependent variable (LDV) model.
2. An overall model with the addition of weather adjustments (Equation 2)
3. A simple overall model (Equation 3).

The evaluation included impact estimates from the LDV, or the first model, in the persistence factor equation (presented below in Equation 4). LDV models use seasonal usage from the pre-treatment period, but do not explicitly adjust for weather differences between the pre- and post-treatment periods. The other two models were used as robustness checks. The sections below provide results using the second model to allow for comparisons of savings year over year, and the third model to provide results using the most basic model specification. The model specifications are as follows:

Model 1: Post-Treatment Only Model

For reporting purposes, the evaluation team estimated an LDV model. This is also the model used to claim savings for the PY2018 Behavioral Modification Initiative. An LDV model differs from the linear fixed effects regression (LFER) model in that only usage from the post-treatment period is used in estimating the model. Information from the pre-treatment period is used only to calculate pre-usage variables that are incorporated into the LDV model, but pre-period usage is not directly modeled. The LDV model used three levels of pre-treatment period usage for each customer: overall pre-treatment period average daily consumption (ADC), summer pre-treatment period ADC, and winter pre-treatment period ADC. The LDV model uses the control group in the same way as the LFER model, in that the treatment effect is corrected for control group ADC so that the coefficient of the treatment variable is the average ITT effect. The evaluation team employed the following estimating equation:

Equation 1. Post-Treatment Period Only Model Estimating Equation

$$ADC_{it} = \alpha_i + \beta_1 Treatment_i + \beta_2 PreUsage_i + \beta_3 PreWinter_i + \beta_4 PreSummer_i + \beta_5 MonthYear_t + \beta_6 PreUsage_i \cdot MonthYear_t + \beta_7 PreWinter_i \cdot MonthYear_t + \beta_8 PreSummer_i \cdot MonthYear_t + \varepsilon_{it}$$

Where:

ADC_{it} = Average daily consumption (therms or kWh) for household *i* at time *t*
α_i = Household-specific intercept
β_1 = Coefficient for the change in consumption for the treatment group
β_2 = Coefficient for the average daily usage across household *i* available pretreatment meter reads
β_3 = Coefficient for the average daily usage over the months of December through March across household *i* available pretreatment meter reads
β_4 = Coefficient for the average daily usage over the months of June through September across household *i* available pretreatment meter reads
β_5 = Vector of coefficients for month-year dummies
β_6 = Vector of coefficients for month-year dummies by average daily pretreatment usage
β_7 = Vector of coefficients for month-year dummies by average daily winter pretreatment usage
β_8 = Vector of coefficients for month-year dummies by average daily summer pretreatment usage
$Treatment_i$ = Variable to represent treatment and control groups (0 = control group, 1 = treatment group)
$PreUsage_i$ = Average daily usage for household *i* over the entire pre-treatment period
$PreWinter_i$ = Average daily usage for household *i* over the pre-treatment months of December through March
$PreSummer_i$ = Average daily usage for household *i* over the pre-treatment months of June through September
$MonthYear_t$ = Vector of month-year dummies
ε_{it} = Error

Model 2: Weather-Adjusted Model

In addition, the evaluation team incorporated weather terms for one of the models. The evaluation team controlled for weather by accounting for HDD and CDD, using a base of 65°F for HDD and 75°F for CDD. This model also helps account for differences between treatment and control group usages that correlate with weather.

Equation 2. Weather-Adjusted Model Estimating Equation

$$ADC_{it} = \alpha_i + \beta_1 Post_t + \beta_2 Treatment_i \cdot Post_t + \beta_3 HDD_{it} + \beta_4 CDD_{it} + \varepsilon_{it}$$

Where:

$ADC_{it}, \alpha_i, Treatment_i$ and ε_{it} are defined as above in Model 1
β_1 = Coefficient for the change in consumption between pre- and post-treatment periods
β_2 = Coefficient for the change in consumption for the treatment group in the post-treatment period compared to the pre-treatment period and to the control group; this is the basis for the net savings estimate
β_3 = Coefficient for HDD
β_4 = Coefficient for CDD
$Post_t$ = Variable to represent the pre- and post-treatment periods (0 = pre-treatment period, 1 = post treatment period)
HDD_{it} = Sum of HDD (base 65°F)
CDD_{it} = Sum of CDD (base 75°F)

Model 3: Original Model

Equation 3. Original Model Estimating Equation

$$ADC_{it} = \alpha_i + \beta_1 Post_t + \beta_2 Treatment_i \cdot Post_t + \varepsilon_{it}$$

Where:

$ADC_{it}, \alpha_i, Treatment_i$ and ε_{it} are defined as above in Model 1
β_1, β_2 and $Post_t$ are defined as above in Model 2

Detailed Savings Results

Table 5 shows the savings results across each cohort, fuel type, and year for the LDV model. The differences in savings between the 2017 and 2018 savings for a given cohort and fuel type is generally small. These small differences help to demonstrate a lack of statistical difference in savings values between the last year of receiving reports and the first year of not receiving reports.

Table 5. 2017 and 2018 Savings Results by Cohort and Fuel Type

Cohort	Electric (kWh/Day)		Gas (Therms/Day)	
	2017 Savings (Last Enrollment Year)	2018 Savings (Stoppage of Treatment)	2017 Savings (Last Enrollment Year)	2018 Savings (Stoppage of Treatment)
Original	0.46	0.57	0.021	0.022
Expansion 2	0.27	0.19	0.016	0.021
Expansion 3	NA	NA	0.049	0.047
Expansion 4	0.53	0.42	0.014	0.012
Expansion 5	0.33	0.32	0.022	0.023
Expansion 6	0.20	0.22	0.004	0.007
Expansion 7	0.25	0.19	0.015	0.015
Expansion 8	NA	NA	0.014	0.011

Estimating Persistence Factors

As stated above, the persistence factor equation is the relationship between the savings from the year after the treated customers stopped receiving reports and the savings from the last year treated customers received reports (i.e., 2018 savings vs 2017 savings). Equation 4 shows this calculation, where δ_i is the persistence factor for cohort *i* for the first year after they stopped receiving reports.

Equation 4. Persistence Factor Equation

$$\delta_i = \frac{2018\ Average\ Daily\ Savings_i}{2017\ Average\ Daily\ Savings_i}$$

Where:

δ_i = persistence factor for cohort *i*
$2018\ \mathrm{Average\ Daily\ Savings_i}$= average daily savings for the year after stoppage of treatment for cohort *i*
$2017\ \mathrm{Average\ Daily\ Savings_i}$ = average daily savings for the last year treated customers were in the Initiative for cohort *i*

Table 6 shows a wide range of persistence factors by cohort and fuel type. Some cohorts show a persistence factor less than 100% (i.e., treated customers saved less after they stopped receiving reports, while others show a persistence factor greater than 100% (i.e., treated customers saved more after they stopped receiving reports). Seeing persistence factors higher than 100% and lower than 100% highlights the limited reliability of these estimates. In addition, each persistence factor is statistically insignificant, meaning the evaluation team cannot confirm that the savings after a year of not receiving reports is different than the last year of receiving reports.

Table 6. Electric and Gas Persistence Factors

Cohort	Persistence Factor	
	Electric	Gas
Original	124%	103%
Expansion 2	72%	134%
Expansion 3	NA	97%
Expansion 4	79%	81%
Expansion 5	98%	105%
Expansion 6	112%	169%
Expansion 7	78%	99%
Expansion 8	NA	78%