1 EXECUTIVE SUMMARY

Minnesota Power's Energy Engagement Behavioral Program (EEBP) leverages online engagement and two-way communication with residential customers to generate behavioral energy savings. The foundation of EEBP is an online energy tracking and account management tool branded "MyAccount". The MyAccount system allows customers to use a computer, tablet, or smartphone to manage their energy usage, make changes to their account, and pay their monthly bill. Through the interactive online portal, customers can set up notifications and alerts, track events, view available upgrades, and set goals that affect their electricity use. Additionally, customers can access their billing history and make online payments.

As a result, the MyAccount online portal is primarily:

- A data-driven and visually informative tool that promotes energy awareness and helps customers modify their energy use behavior
- An online option that allows customers to view and pay their bill online

Minnesota Power (MP) retained Demand Side Analytics (DSA) to perform a third party independent impact evaluation of EEBP. The key research question for the evaluation was "*what were the energy savings achieved by EEBP participants during calendar year 2021*?" Specifically, what were the:

1. Daily electric energy savings (kWh per day)?
2. Annual electric energy savings (kWh per year)?
3. Percentage savings relative to baseline consumption (%)?
4. Average annual savings using the Average Savings Method (ASM)[1] in kWh per year?

DSA completed a quasi-experimental analysis of EEBP using daily usage data from 2017 to 2021. To conduct the analysis, DSA utilized a difference in differences empirical framework. The modeling includes additional modern econometric techniques, including pseudo controls and household-level fixed effects.

Table 1 shows the results. We estimate an average daily savings of **0.445 kWh** per service location, or a **1.68% decrease** in consumption. This estimated effect is statistically significant with a 95% confidence interval ranging from 0.42 kWh per day to 0.47 kWh per day. These results translated to annual savings

[1] The Average Savings Method requires utilities to claim one-third of the observed savings in each year of a triennial planning period.
https://www.edockets.state.mn.us/EFiling/edockets/searchDocuments.do?method=showPoup&documentId=%7b1733C21D-B866-4A7F-821C-7DFCC6C64D83%7d&documentTitle=20122-70948-03

of **162.5 kWh** per service location, or a **54.2 kWh** of annual reduction per service location using the ASM method.

Table 1: 2021 Average Savings per Service Location

Result	Daily Savings (kWh/day)	Annual Savings (kWh/year)	Percentage Savings	Annual Savings (ASM kWh/year)
Point Estimate	0.445	162.5	1.68%	54.2
95% CI	(0.421, 0.469)	(153.6, 171.4)	(1.58%, 1.77%)	(51.2, 57.2)

Participation in EEBP is constantly changing with new customers enrolling in the service daily and other customers moving and closing their account with Minnesota Power. There were an average of 51,468 active service locations with MyAccount credentials in 2021. This report focuses on the 45,614 residential service locations. Table 2 presents aggregate results for all active residential service locations. We estimate that EEBP saved an average of **20.3 MWh** per day or **7,411 MWh** annually**.** Dividing the annual MWh savings by three returns aggregate savings of **2,470 MWh** using the ASM method.

Table 2: 2021 Total Savings (MWh) for all Active Service Locations

Daily Savings	Annual Savings	Annual Savings (ASM)
20.3	7,411	2,470

Table 3 compares the evaluated results to the 2021 projections in Minnesota Power's Triennial Plan. The participation totals were higher than projected and the aggregate energy savings exceeded planed totals. While percent savings were lower than projected, the average baseline consumption was higher. These two factors offset and lead to an annual kWh savings per home estimate that is approximately 5% lower than planned.

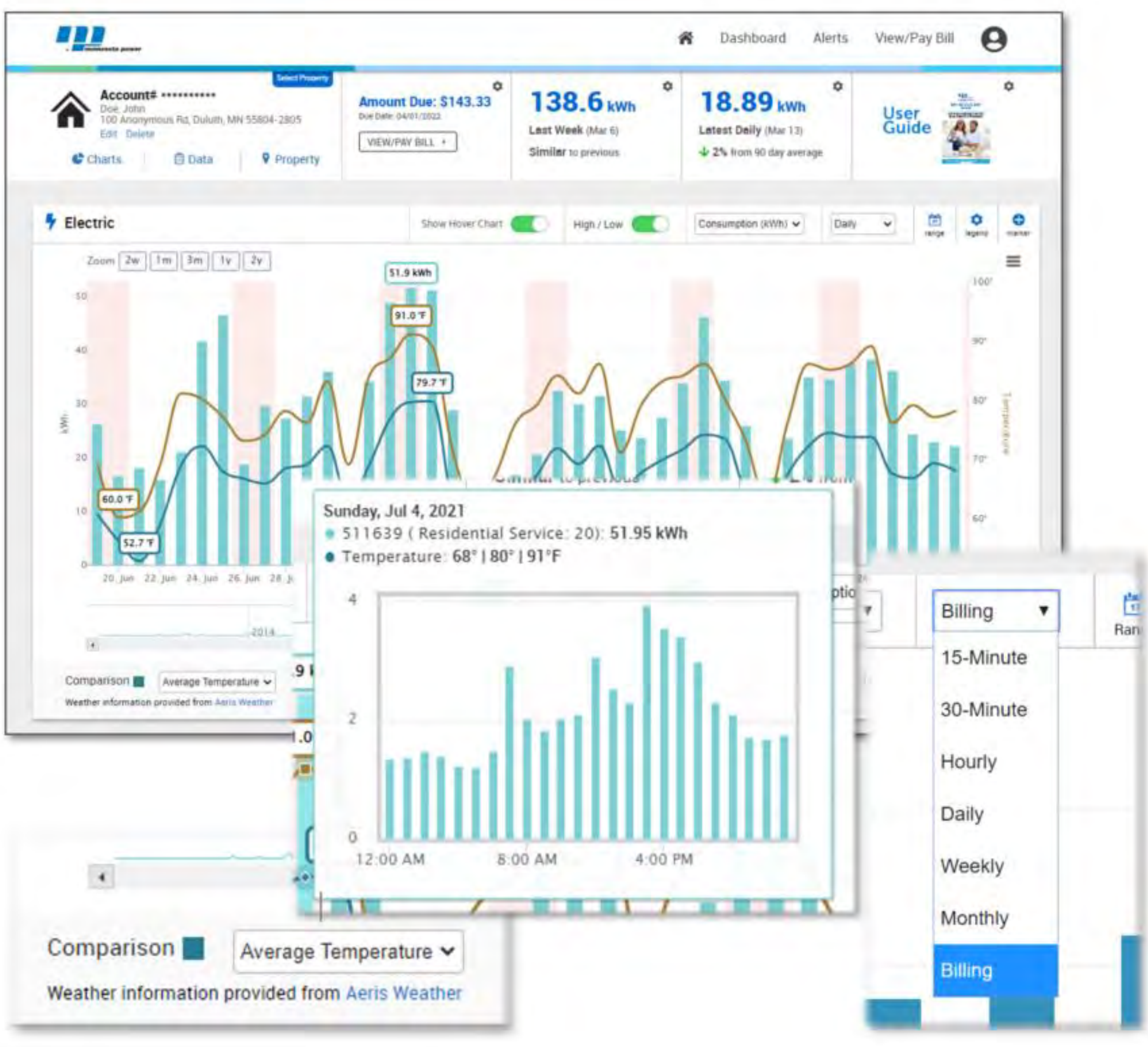
Table 3: Comparison of Evaluation Results with Triennial Plan Projections

Program Year	2021 Planned	Evaluation Results
Assumed Participants (Registered Accounts)	35,000	Higher (45,614 service locations)
Average annual consumption - kWh	8,500	Higher (9,693)
Total participant estimated kWh	297,500,000	Higher (442,136,502)
Expected average annual savings - %	2%	Lower (1.68%)
Expected average savings per participant - kWh	170	Lower (162.5)
Expected total program savings - kWh	5,950,000	Higher (7,410,780)
Total savings after ASM applied - kWh	1,983,333	Higher (2,470,260)

2 PROGRAM OVERVIEW

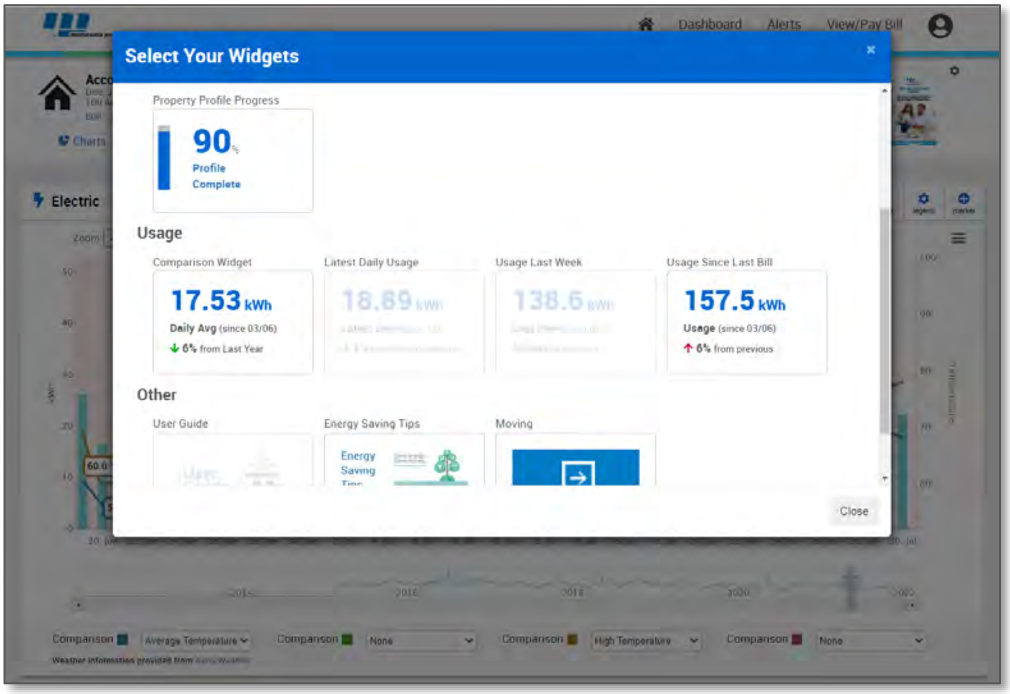
The MyAccount platform that powers EEBP is a customer self-service portal managed by Accelerated Innovations on behalf of Minnesota Power. Figure 1 shows sample screens where users can view and download their historic consumption data at an hourly, daily, or monthly level, add information about their property or set energy conservation goals. MyAccount users are able to interact with usage visualization with controls to zoom and drill-down to examine trends, and view changes in usage in comparison to weather variables such as average or high temperature:

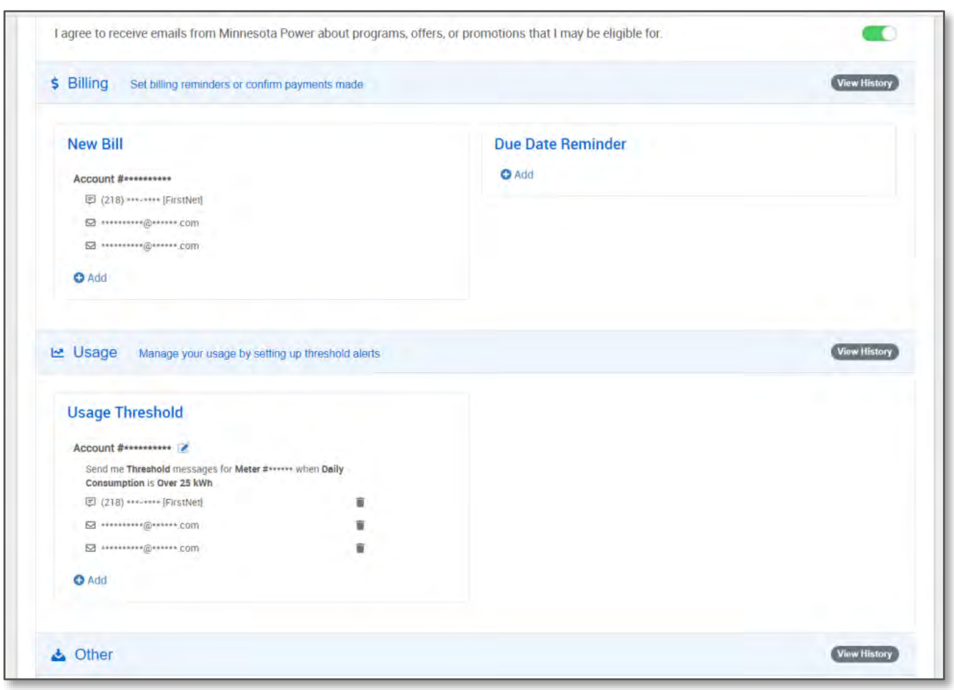
Figure 1: Sample MyAccount Screens



EEBP participants can customize their usage dashboard to view at-a-glance metrics on usage or link to resources like an Energy Saving Tips library. Users can set notifications and alerts to be notified about billing events and when their usage (e.g., daily, weekly) exceeds a set threshold.

Figure 2: Additional MyAccount Screens



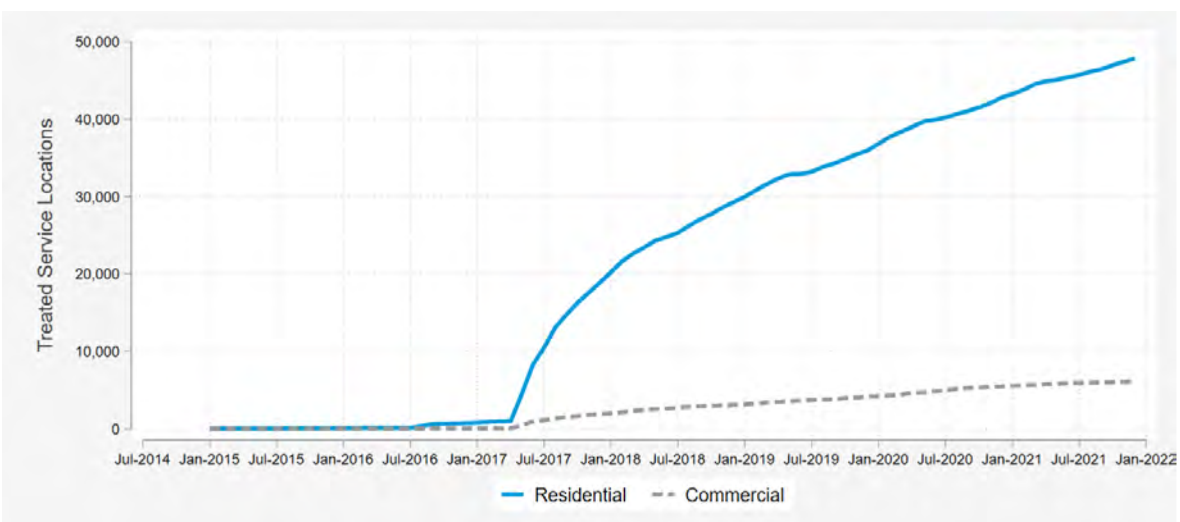


Features of the MyAccount platform include:

1. Utility customer self-service portal (online and mobile app) for:
    a. Online bill payment and presentment
        i. Make payment
        ii. Auto pay
        iii. Paperless billing
        iv. Manage digital wallet
    b. Start/stop/transfer service requests
    c. Utility program promotion and enrollment
2. Energy usage engagement
    a. Access to monthly billed usage and weekly/daily/hour/15-minute AMI/interval usage data
    b. Real-time energy use feedback and alerts (e.g.., high usage, "Notify me when…") via email/text/push notifications
    c. Dynamic charting interface with zoom/drill-down capabilities and comparisons to weather data and usage history
    d. At-a-glance feedback and analytics from configurable widget content

MyAccount was available to a small test group of customers as early as 2014 and has been widely available since 2016. Figure 3 shows the number of active service locations by sector over time.

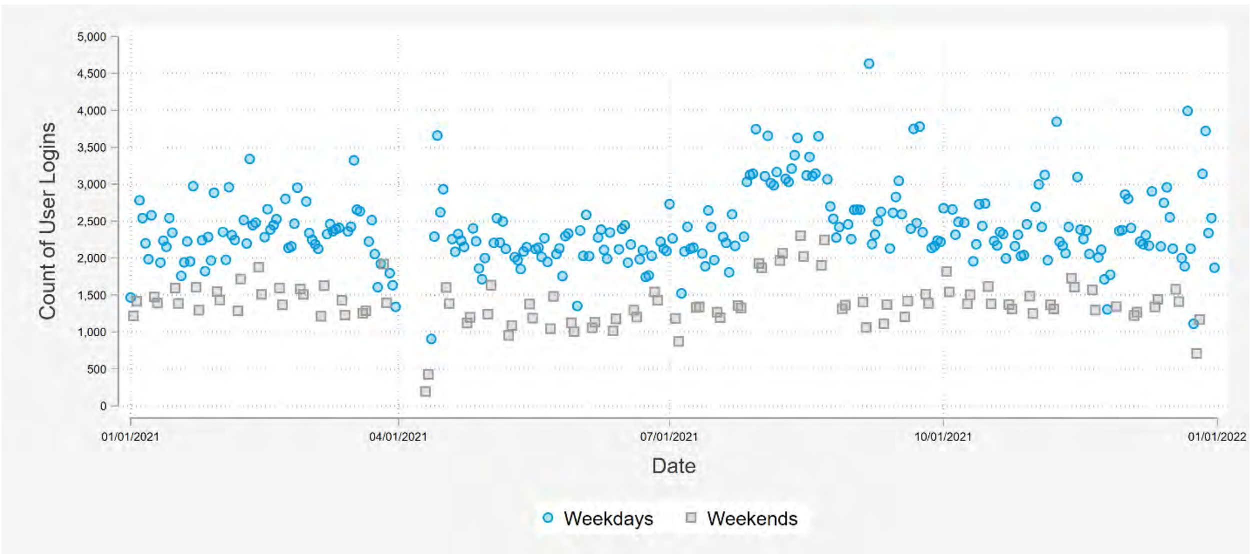
Figure 3: Time Series EEBP Participation Trend by Sector



EEBP differs from the ubiquitous utility behavioral Home Energy Report programs in that it is available to all Minnesota Power customers on an opt-in basis. This means that all participants took some action to enroll in the program rather than being assigned to it. It also means that there is no randomly assigned control group to act as the counterfactual for modeling purposes.

While the number of enrolled customers grew gradually over 2021, the level of activity on the portal was relatively steady. Figure 4 shows the number of distinct users who logged into the portal each day during 2021. Activity tends to be higher on weekdays than on weekends.

Figure 4: Count of Distinct Users to Access MyAccount by Date



While users' total engagement is evenly distributed over time, the distribution of engagement across participants is not. Figure 5 shows a histogram of 2021 logins among active users and Table 4 shows the mean, 10th percentile, 25th percentile, median, 75th percentile, 90th percentile. Some participants access the portal frequently while others only logged in a handful of times or not at all.

Figure 5: Distribution of 2021 Logins across Active MyAccount Users

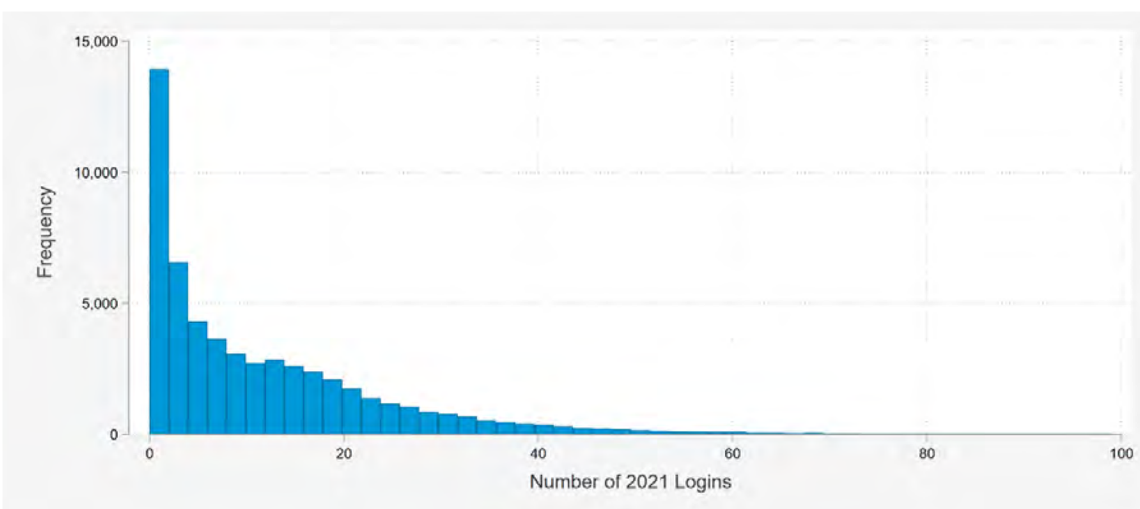


Table 4: 2021 Login Summary Statistics

Mean	P10	P25	Median	P75	P90
11.82	0	2	7	17	30

User interaction with the MyAccount portal is likely a proxy for the distribution of energy savings amongst EEBP participants. While this evaluation estimates the average savings per participant, that average is likely composed of a mixture of homes that save much more than the average and households that save little or no energy because they rarely engage with the platform features.

3 METHODS

3.1 DATA MANAGEMENT

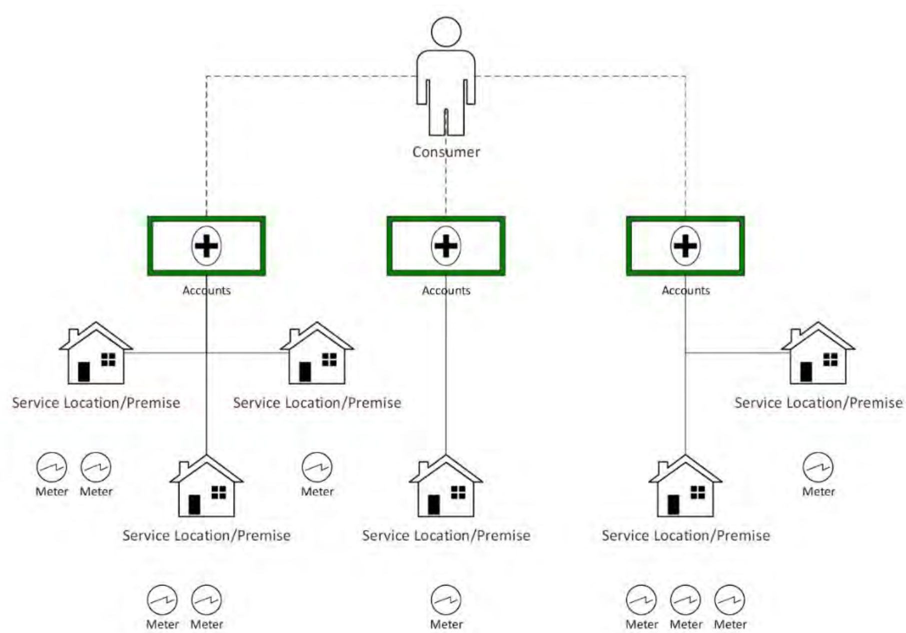
Panel data for the EEBP evaluation came from Minnesota Power and Accelerated Innovations and includes customer characteristics, daily electricity usage, and monthly billing data from 2017 to 2021. DSA completed a series of data management steps to clean and prepare the data for regression analysis. For the purposes of this report, these data management stages are condensed. This section briefly describes the five fundamental data management steps:

1. Linking EEBP Participants to their Energy Usage
2. Refining the Analysis to be for Residential Participants Only
3. Preparing Daily Usage Data for Analysis
4. Reconciling Daily Usage Data with Monthly Billing Data
5. Incorporating Weather Data

3.1.1 LINKING EEBP PARTICIPANTS TO THEIR ENERGY USAGE

Figure 6 illustrates the relationship between a Minnesota Power customer (shown in Figure 5 as Consumer) and their energy consumption at the meter level. To estimate the effect of EEBP on energy consumption, we first had to link EEBP participants to their corresponding energy usage. As previously mentioned, not all MP customers are EEBP participants. For this analysis, only data for EEBP participants are used.

Figure 6: Consumer to Consumption Associations



We initially defined EEBP participation at the customer level. We consider a customer enrolled in EEBP if they have a MyAccount User ID. EEBP participation begins on the date that the customer created their User ID. In the case where a customer created multiple User IDs, the minimum User ID creation date is defined as the day of enrollment. Multiple User IDs can exist when customers who forget their original User ID can create new ones when attempting to log in. The existence of multiple User IDs was not problematic for the analysis.

We then linked customers to their Minnesota Power account (service agreement number). If a customer is enrolled in MyAccount, then all of their accounts were considered to be treated. If multiple customers are associated with an account (e.g. a husband and wife), then there only needed to be one enrolled customer for that account to be considered treated. Once treatment status and enrollment dates were established for an account, we were able to link accounts to their respective service locations. If at least one treated account was associated with a service location, then we considered that service location to be treated.

Treatment continued to the present unless the MP account closed or the customer moved to a different service location. In other words, once treatment begins, we consider it "on" as long at the account remained active at the same service location. Through this process, we were able to identity treatment status for a service location for each day. Ultimately, we used a "service location—day" as the unit of analysis for the impact evaluation.

Lastly, we aggregated consumption from all meters to the service location level. When multiple meters are present at a single service location, we take the sum of those meters' daily usage levels to compute that service location's daily energy use. Figure 7 summarizes the process whereby we linked EEBP participants to their daily electricity use.

Figure 7: Linkages from MyAccount User to the Meter

3.1.2 Refining the Analysis to Residential Participants Only

We chose to restrict this analysis to residential customers since Minnesota Power filed EEBP as a residential program and approximately 90% of participants are residential. Engagement with the MyAccount platform likely has different impact on daily kWh levels for residential customers compared to commercial customers as consumption levels and the mechanisms through which EEBP can influence energy savings are inherently different in these sectors. We may evaluate savings for commercial customers in a separate framework for future iterations of this impact report. Table 5 provides a frequency table of the residential rate codes found in the final analysis data set. It is worth noting that rate code is a property of a meter, not a service location so a service location can have two meters billed on different rate codes. Rate codes can also change over time for a given meter. We received the most current rate code for each meter. The 'MP' rate codes represent participants who closed their account before transitioning to the current 'ME' array of tariffs.

Table 5: Rate Codes Used in Analysis Data Set

Rate Code	Description	Number Meters in Analysis (2017-2021)
ME20	ME Residential Service	43,476
ME20TOD	ME Residential Time-of-Day	85
ME21	ME Residential Dual Fuel	2,996
ME22	ME Residential All Electric	3,053
ME22TOD	ME Residential All Electric Time-of-Day	2
ME23	ME Residential Seasonal	1,004
MP-20	MP Residential Service	98
MP-21	MP Residential Dual Fuel	12
MP-22	MP Residential All Electric	13
MP-23	MP Residential Seasonal	4
Total		**50,743**

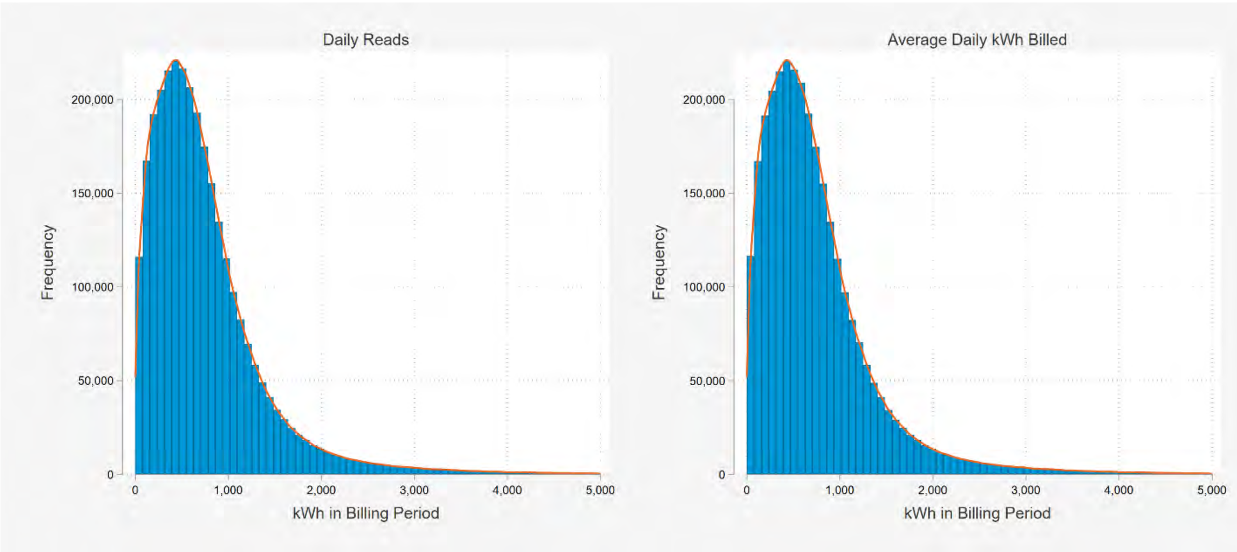
3.1.3 Preparing Daily Usage Data for Analysis

Minnesota Power's metering infrastructure has evolved since EEBP enrollment began to ramp up in 2017. Today most customers have advanced meters that record consumption on an hourly or sub-hourly basis as well as daily totals. However, in 2017 most residential customers still had meters that recorded a single daily register read. We chose to use daily data for this analysis based on the quality and completeness of observations over the period of interest. The most important step in this process was converting daily register reads to uniform 24-hour intervals, since "daily" interval data was sometimes recorded for inconsistent durations due to the nature of the legacy metering and communications technology. The most common alternative time interval was 27 hours. We also excluded outlier observations from the analysis, since these could artificially skew the results. Notably, we restricted daily kWh values at the meter to be between 0 kWh and 5,000 kWh. By doing so, we excluded negative generation values and removed extreme negative values caused by meters cycling over from their maximum storage value back to zero.

3.1.4 Reconciling Daily Usage Data with Monthly Billing Data

As a data quality step, we verified that the daily usage data was consistent with the monthly billing data. This is an important consideration because customers are most aware of their monthly electricity bills. To make an accurate comparison, we aggregated the daily usage data from each billing cycle. The sum of the daily kWh was between 99% and 101% of the billed kWh for almost all cases. We excluded a limited number of meters from the analysis where the daily kWh totals did not align with the billed energy. Figure 8 compares the distribution of replicated billing totals from daily reads with the actual billed kWh.

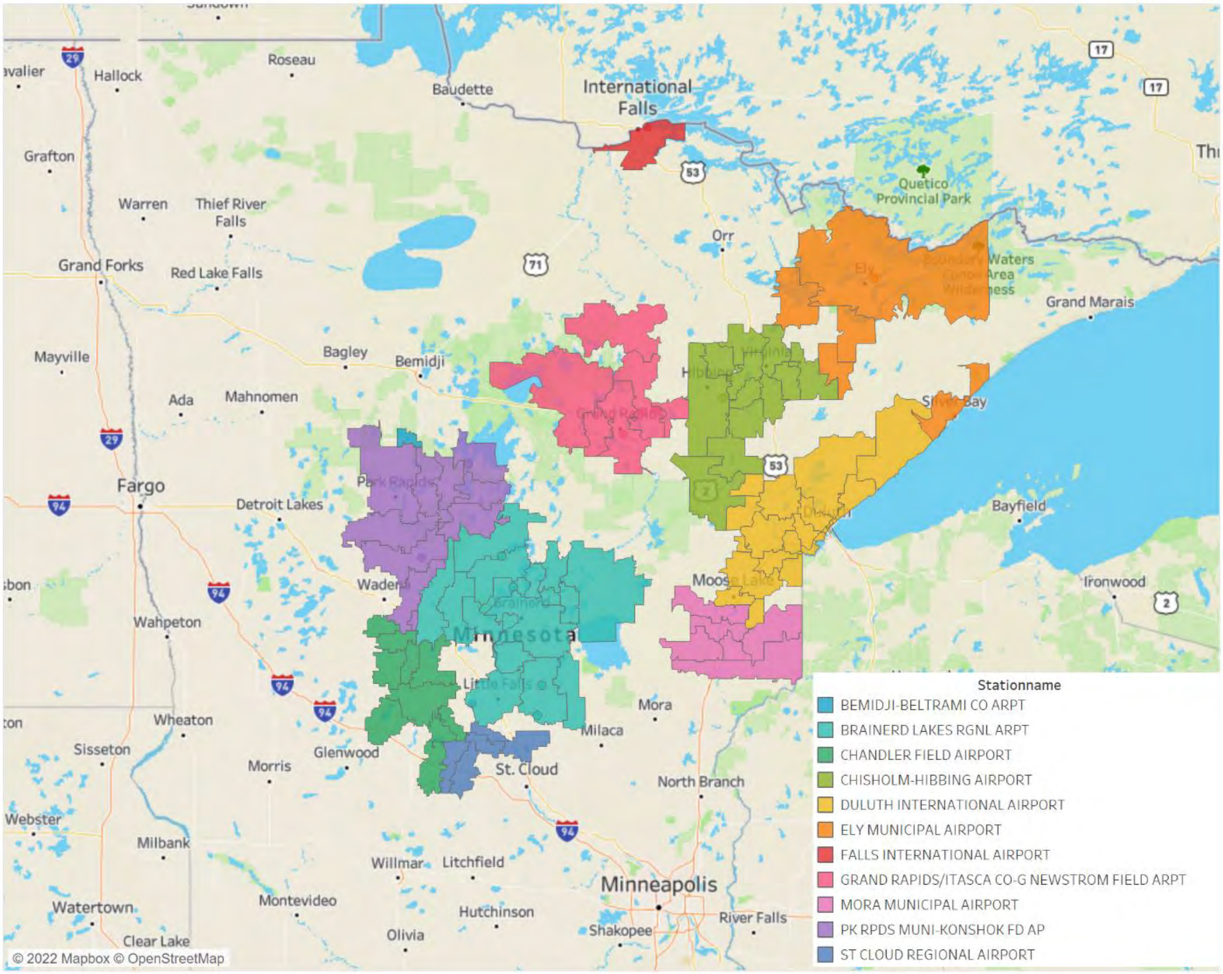
Figure 8: Comparison of Billed kWh with Daily kWh Totals



3.1.5 INCORPORATING WEATHER DATA

Each Minnesota Power service location has a service zip code and weather is a strong predictor of electric consumption. Figure 9 illustrates how we matched service locations with historic daily weather data. Service location zip codes were linked to the closest weather station with dependable weather data.

Figure 9: Zip Code to Weather Station Mapping



We used eleven different Minnesota weather stations for the analysis, allowing for a decent amount of weather variation even within a condensed geographic area. Table 6 lists the eleven stations and the average CDD and HDD base 60 degrees (F) observed over the five years of data analyzed.

Table 6: Average Annual CDD and HDD by Weather Station 2017-2021

Weather Station	USAF	CDD60	HDD60
BEMIDJI-BELTRAMI CO ARPT	727550	741	8,115
BRAINERD LAKES RGNL ARPT	726555	1,064	7,144
CHANDLER FIELD AIRPORT	726557	1,231	7,003
CHISHOLM-HIBBING AIRPORT	727455	458	8,436
DULUTH INTERNATIONAL AIRPORT	727450	710	7,504
ELY MUNICIPAL AIRPORT	727459	574	8,229
FALLS INTERNATIONAL AIRPORT	727470	635	8,252
GRAND RAPIDS NEWSTROM FIELD ARPT	727458	703	7,799
MORA MUNICIPAL AIRPORT	727475	729	7,212
PK RPDS MUNI-KONSHOK FD AP	727453	922	7,768
ST CLOUD REGIONAL AIRPORT	726550	1,067	6,956

3.2 CAUSAL IDENTIFICATION STRATEGY

Since Minnesota Power did not roll out EEBP as a randomized control trial, there is an innate challenge in identifying the causal effects of the EEBP participation. The opt-in component created the greatest threat to validity for the analysis because individuals who opt-in to EEBP are inherently different from those who do not; this is called the "selection effect". As a result, a natural control group does not exist. Some sort of comparison group is necessary to control for exogenous factors like the COVID-19 pandemic and because of the small expected effect size. The absence of a control group can create a variety of problems in causal analysis. The "selection effect" may bias results since the "effect of EEBP" would not only capture a change in energy usage from EEBP participation but also include the naturally occurring, time-varying energy usage differences between those who opted-in to EEBP and those who did not. A variety of unobservable factors related to EEBP enrollment and independently associated with energy usage could bias results.

For example, customers may have opted-in to EEBP because they use more energy, were more financially conscious, or were more likely to reduce their energy usage over time in response to climate change. If these unobservable factors are correlated with the outcome variable, an analysis comparing participants to non-participants could be biased. Because of these concerns and the absence of a pure control group, we utilized a quasi-experiential technique to estimate EEBP savings.

Figure 10 comes from the Uniform Methods Project Protocol[2] for this type of analysis with our selected approach highlighted. For this analysis, we use prior participants as the comparison group.

[2] https://www.nrel.gov/docs/fy17osti/68564.pdf. Page 13

Figure 10: Uniform Methods Project Protocol Overview of Comparison Group Approaches

Table 1. Program Characteristics, Comparison Group Specifications, and Consumption Data Analysis Structure and Interpretation

Randomized Controlled Trial?	Stable Population?	Comparison group	2-Stage and Pooled with Comparison Group	Gross or Net Savings	Unknown Biases
Yes	N/A	Randomly selected control group	Yes	Net	Spillover from T to C, if it exists
No	Yes	Prior and/or future participants	Yes	Gross	Time-varying Characteristics
No	No	Matched comparison group	Yes	Likely between gross and net	Time-varying Characteristics, Self-selection unaccounted for by matching and same-period NP spillover
No	No	General eligible nonparticipants	Yes, With additional characteristics in the 2nd stage or pooled regression	Likely between gross and net	Time-varying Characteristics, Self-selection unaccounted for by regression and same-period NP spillover

Specifically, we used early EEBP adopters (Wave 1) as a comparison group for more recent EEBP adopters (Wave 2). Using prior participants mitigates concerns about selection effects because the comparison group also chose to enroll in EEBP. Wave 1 was comprised of participants who enrolled in EEBP from 2017-2018, while Wave 2 was comprised of participants who enrolled in EEBP from 2019-2020. Since Wave 1 participants do not have a change in treatment status from 2019-2020, they can be effectively used as a control group for the Wave 2 participants who do experience a change in treatment status from 2019-2020. The underlying assumption of this strategy is that there are not any time-varying differences between Wave 1 and Wave 2 participants that affect their energy usage.

Figure 11 visualizes the quasi-experimental identification strategy. Real data for Wave 2 from 2017-2021 is used for the analysis. To effectively use Wave 1 as a control group, the true treatment status for Wave 1 participants could not change. So, while they actually enrolled in EEBP at some date from 2017-2018, only their post-enrollment data was kept. Wave 1's true enrollment dates were then shifted forward in time by two years (730 days). As a result, Wave 1 energy usage data could be used as control data for Wave 2's energy usage data. By shifting Wave 1's enrollment data forward 2 years, we preserve the true enrollment month, which helped mitigate the effect of enrolling in EEBP during a specific month.

Figure 11: Quasi-Experimental Identification Strategy

Real Wave 1 and Wave 2 Data

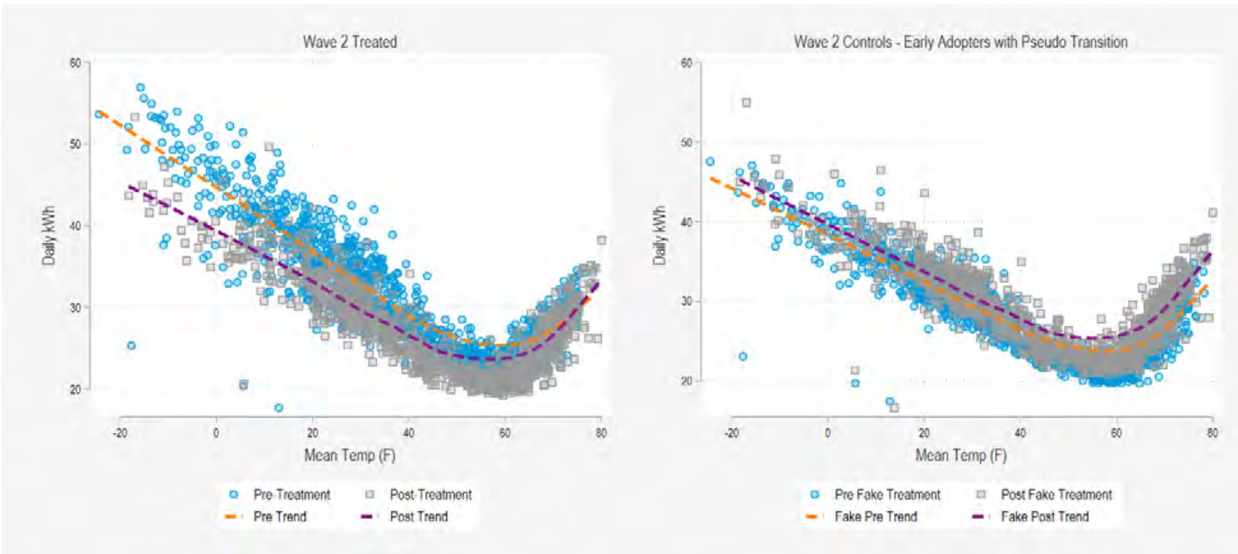
	2017	2018	2019	2020	2021
Wave 1	Change from Pre to Post		Pure Post Data		
Wave 2	Pure Pre		Change from Pre to Post		Pure Post Data

Real Wave 2 Data Using Wave 1 as Synthetic Controls

	2017	2018	2019	2020	2021
Wave 1	Synthetic Pre Data (After Real Enrollment Date)		*Synthetic Change* from Pre to Post		Pure Post Data
Wave 2	Pure Pre		Change from Pre to Post		Pure Post Data

Figure 12 illustrates how we use this identification strategy to estimate the average effect of EEBP. After controlling for the effects of weather, we see a reduction in daily electric consumption amongst the Wave 2 households following enrollment in EEBP. The slight change in average daily consumption amongst the Wave 1 households over the same period is subtracted from the change in the Wave 2 homes. Of course, the Wave 1 households did not experience a change in treatment status during this period so the differences in energy consumption are attributed to exogenous factors.

Figure 12: Differences in Differences Visual Using the Selected Identification Strategy



We complete the actual analysis via regression analysis as described in the following chapter.

4 REGRESSION ANALYSIS

4.1 PREFERRED MODEL

The preferred model specification leverages pseudo control participants in order to use a difference in differences design with appropriate fixed effects and controls. This difference in differences design utilizes panel data from 2017 to 2021 to estimate the average effect of EEBP on daily kWh for a service location. A difference in differences approach compares changes in outcomes over time for a treated group versus a comparison group. In this case, we compared the change in energy usage that resulted from EEBP status for Wave 2 versus Wave 1. Simply put, this difference in differences regression calculated the average treatment effect of EEBP for a service location in Wave 2. Since Wave 2 is active in EEBP from 2019-2021, (β_2) represents the average treatment effect from 2019-2021.

Equation 1: Regression Model Specification

$$kWh_{s,d} = \beta_0 + \beta_1 * Post_{s,d} + \beta_2 * Post_{s,d} * Treat_s + \beta_3 * CDD_{d,s} + \beta_4 * HDD_{d,s} + \varepsilon_{s,d} + \delta_{ym}$$

Where:

- **β_0** is the average of the service-location fixed effects. This term acts as the model intercept
- **$Post_{s,d}$** is an indicator variable equal to 1 for each date (d) after the service location (s) enrolls in EEBP and zero otherwise. For Wave 1, the post transition date is set to two years after the actual enrollment date.
- **$Treat_s$** is an indicator variable equal to 1 for service locations in Wave 2 and zero for service locations in Wave 1.
- **$CDD_{d,s}$** is the equal to the average daily temperature (F) at service location s minus 60 degrees or zero, whichever is greater.
- **$HDD_{d,s}$** is the equal to 60 degrees (F) minus the average daily temperature or zero, whichever is greater.
- **$\varepsilon_{s,d}$** is the error term
- **$\delta_{y,m}$** is an array of year-month fixed effects

4.2 UNDERSTANDING THE MODEL

Equation 2 shows the basic average treatment effect formula, which is naturally embedded in Equation 1 given the model specification.

Equation 2: Difference in Differences Fundamental Equation

$$\Delta kWh = (kWh_{Wave\ 2\ Post} - kWh_{Wave\ 2\ Pre}) - (kWh_{Wave\ 1\ PseudoPost} - kWh_{Wave\ 1\ PseudoPre})$$

The "pre" period includes days before EEBP enrollment, and "post" includes days after EEBP enrollment. It is easy to see here how the approach removes static, pre-treatment differences between Wave 2 and Wave 1 in terms of energy consumption in addition to removing the natural energy consumption time trend that would have occurred without EEBP. Table 7 shows the results using this simplified approach for homes with at least one year of billing history in their pre and post periods.

Table 7: Simplified Analysis - Comparison of Means

Group	Average Daily kWh Post	Average Daily kWh Pre	Inner Difference
Wave 2	31.195	31.676	-0.481
Wave 1	28.964	29.039	-0.075
Difference in Differences via Simple Means (kWh per day)			**0.406**

Equation 1 also includes fixed effects and temperature control variables to estimate the treatment effect more precisely. The month-year fixed effects control for any observable or unobservable factors within a certain month that are common amongst all service locations. Thus, the month-year fixed effects absorb seasonal shocks that could affect energy consumption at the month-year level. In addition, the service location fixed affects control for any time-invariant service location characteristics related to energy consumption, e.g. home size, age of home, geographic location. It is clear that something like "home size" is an important factor to account for as larger homes use more energy, which gives them more energy use available for conservation. If participants were more likely to own larger homes than non-participants, results could be biased upwards, leading to an overestimate of energy savings. Furthermore, the CDD and HDD variables absorb variation in energy consumption related to weather. Given that Minnesota experiences significant variation in temperature, especially during the winter months, these variables are important to include.

As a result of the difference in difference strategy and additional controls, it is difficult to imagine a scenario in which the effect of EEBP on energy consumption is biased due to the model specification. There would have to be some omitted factor that varied within a month and was differentially trending in terms of its effect on energy savings for Wave 2 participants compared to Wave 1 participants. Thus, the greatest threat to internal validity is not the model specification but, as previously mentioned, the absence of a natural control group.

4.3 REGRESSION RESULTS

We chose to limit the analysis dataset to service locations with at least one year of data in the pre and post-periods. This filter omits approximately 30% of participants from the regression model and caused the average usage amongst analyzed participants to exceed the average consumption across the program population. Table 10 at the conclusion of the section shows how DSA calibrated the regression outputs to the program population.

Wave 2 households enrolled in EEBP, and Wave 1 households had pseudo transition dates, at various points in time over 2019 and 2020. While we required at least one year of post-period data for inclusion in the model, we did not filter the post-period to exclusively calendar 2021 or the first year after enrollment. For example, if a service location enrolled in EEBP on July 12, 2019 their post-period consumption data and estimated treatment effect includes all days from July 13, 2019 to December 31, 2021. DSA feels that inclusion of up to three years of data in the modeling is consistent with the Average Savings Method accounting procedures in Minnesota and provides a more robust estimate of the average effect of EEBP participation.

Table 8 shows the regression output. The coefficient of the 'treatpost' term (β_2 from Equation 1) represents the average change in daily kWh consumption following enrollment in EEBP.

Table 8: Regression Output

```
HDFE Linear regression                              Number of obs   = 36,549,850
Absorbing 2 HDFE groups                             F(   4,36526075)=  161272.75
                                                    Prob > F        =     0.0000
                                                    R-squared       =     0.5687
                                                    Adj R-squared   =     0.5684
                                                    Within R-sq.    =     0.0174
                                                    Root MSE        =    20.7706
```

daily_kwh	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
post	-.01341	.0154769	-0.87	0.386	-.0437441	.0169242
treatpost	-.5317877	.0148488	-35.81	0.000	-.5608908	-.5026846
cdd	.6062201	.0012271	494.02	0.000	.603815	.6086252
hdd	.2778444	.0004137	671.57	0.000	.2770335	.2786553
_cons	23.25723	.01193	1949.48	0.000	23.23384	23.28061

Absorbed degrees of freedom:

Absorbed FE	Categories	- Redundant	= Num. Coefs
servicelocationnumber	23712	0	23712
ym	60	1	59

Table 9 shows the derivation of the key outputs from the estimation sample. Amongst residential Wave 2 households with at least one year of continuous billing history before and after EEBP enrollment, we estimate an average daily reduction in consumption of 0.532 kWh. Multiplying this result by 365 returns an average annual savings of 194.1 kWh per service location.

Table 9: Results Summary – Estimation Sample

Performance Metric	Result
Effect of EEBP on Daily kWh	-0.532 kWh per service location per day
Annual Savings	194.1 kWh
Standard Error	0.015 (significant at the 99% confidence level)
95% Confidence Interval	(-0.56, -0.50)

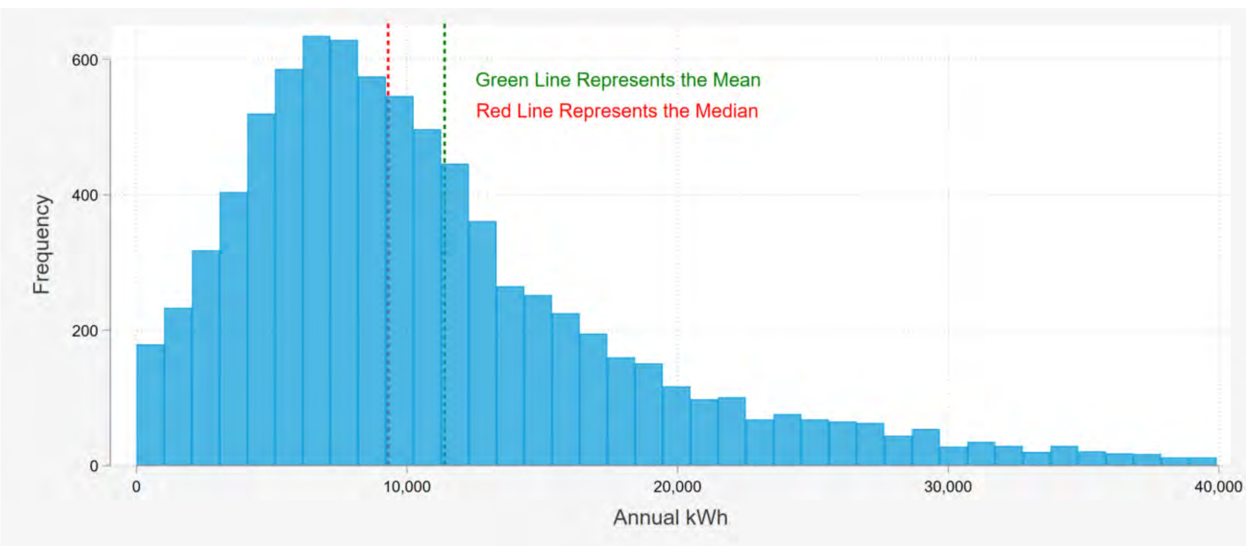
To estimate the average percent savings, we "add back" the estimated treatment effect to the average daily consumption of the Wave 2 homes in the post-period as shown in Equation 3.

Equation 3: Percent Savings Calculation

$$Percent\ Savings = \frac{0.5318}{(31.195 + 0.5318)} = 1.676\%$$

The implied baseline consumption in Equation 3 is 31.7 kWh per day, or approximately 11,580 kWh per year. As shown in Figure 13, the long right tail of the distribution skews the mean upward. The median annual consumption amongst Wave 2 households included in the regression is 9,300 kWh per year.

Figure 13: Distribution of Annual Consumption amongst Wave 2 Homes



As noted above, our decision to limit the analysis dataset to service locations with at least one year of billing history before and after EEBP enrollment caused the average EEBP participant analyzed to have higher average annual electric consumption than the full population of EEBP participants. Since we are ultimately interested in an estimate of the average effect for the population, DSA applied the average percent savings from the analyzed homes to the entire EEBP population. Table 10 shows the calculation of the final study results.

Table 10: Expansion of Regression Results to EEBP Population

Parameter	Value
Average Percent Savings per Service Location	1.676%
Average Annual Consumption Amongst All EEBP Participants	9,693
Average Annual kWh Savings per Service Location	162.5
Average Daily kWh Savings per Service Location	0.445
Average Annual kWh Savings per Service Location – ASM	54.16

EEBP participants are slightly above average in terms of annual consumption for Minnesota Power customers. In its 2020 U.S. Energy Information Administration (EIA) Form 861 filing[3], Minnesota Power showed sales of 1,047 GWh to 123,617 residential customers, or approximately 8,470 kWh service agreement number. This difference is due, in part, to our decision to use service location as the analysis unit rather than service agreement number. It also makes sense that homes with larger monthly energy expenditures are more likely to opt into a service that helps manage their energy consumption. As Minnesota Power looks to grow the EEBP offering and projects savings from additional enrollments, we anticipate the average household size will decline.

[3] https://www.eia.gov/electricity/data/eia861/

5 CONCLUSION

Our estimated treatment effect of 1.68% is consistent with impact evaluation results for residential behavioral efficiency programs, which typically show energy savings between 1% and 2%. The Energy Engagement Behavior Program is different from typical Home Energy Report in two important ways.

- **Customers choose to enroll in the offering**. The fact that EEBP participants opt into the service rather than being defaulted suggests a greater degree of interest or motivation than traditional Home Energy Report programs. This characteristic suggests that EEBP might produce larger savings than Home Energy Reports.
- **EEBP does not include normative comparisons**. One of the key components of traditional Home Energy Reports is a comparison with 'neighboring' households. These comparisons are widely believed to act as a "call to action" for recipients and make them more receptive to energy savings recommendations. The fact that EEBP does not include this feature suggests that savings might be lower than traditional Home Energy Report and other behavioral program models that use this "social norming" tactic.

It is interesting that the directional effects of these two features appear to offset and return average savings similar in magnitude to Home Energy Report programs. It is important to note that utilities typically deliver Home Energy Report programs as a randomized control trial with no variation in treatment timing so the measurement of impacts is far more straightforward than approach used for this study. Our quasi-experimental design makes certain assumptions about Minnesota Power customers. These assumptions can largely be broken down into two categories:

- **Participants vs. Non-Participants** - Since EEBP participants are inherently different than non-participants, comparing trends across the two populations could introduce bias in the results. We considered matching methods to leverage non-participants but felt that selection effects was the largest threat to validity for the study and thus called for a study design focused on mitigating selection effects. The key decision is therefore our use early adopters of EEBP as the control group and comparing participants to participants. By doing so, static, pre-treatment differences between participants and non-participants became irrelevant. However, this approach still cannot control for time-varying characteristics between the populations and only allows us to analyze the effect of Wave 2 homes during the period of interest (2019-2021). For robustness, we performed the opposite quasi-experimental design of using Wave 2 households with their treatment timing shifted back two years as a comparison group for Wave 1 households. This analysis returned a similar average treatment effect from 2017-2019, which supports our decision to apply the percent impacts from the 2019-2021 modeling results to all EEBP participants.

- **Wave 1 Participants vs. Wave 2 Participants** - While using Wave 1 participants as the control groups mitigates the selection effect, there are still some underlying assumptions we make by using Wave 1 as the control population. In short, we assume that Wave 1 participants are similar to Wave 2 participants. Additionally, we assume that EEBP does not have any cumulative effects over time. In other words, we assume that the effect does not grow or fade away over time.