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# End-Use Load Research Home Energy Metering Study – Final Report

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# Glossary of Terms

**AMICS (Advanced Metering Infrastructure Customer Segmentation):** An approach to weather normalization that produces a portfolio of daily energy use load shapes, representing how each customer uses energy across a wide range of different weather conditions.

**CDD (Cooling Degree Day):** A measurement of how much warmer the average daily temperature is above a baseline temperature (typically 65°F), used to estimate cooling energy demand and correlate air conditioning usage with weather conditions.

**Demand Response:** Programs that incentivize customers to reduce or shift their electricity usage during peak demand periods through financial incentives, automated controls, or time-of-use pricing signals.

**Distributed Generation:** Small-scale electricity generation systems located at or near the point of consumption, such as rooftop solar panels or residential battery storage, that can reduce demand from the central grid.

**End Use:** A specific function or appliance that consumes energy in a home, such as space heating, water heating, lighting, or refrigeration.

**HDD (Heating Degree Day):** A measurement of how much cooler the average daily temperature is below a baseline temperature (typically 65°F), used to estimate heating energy demand and correlate space heating usage with weather conditions.

**Interval Data:** Energy consumption measurements recorded at regular, frequent time intervals (every 1 minute for HEMS power measurements), providing detailed temporal resolution for analyzing usage patterns and peak demand periods.

**Load Forecasting:** The process of predicting future electricity demand based on historical consumption patterns, weather data, economic factors, and other variables to support grid planning and operations.

**Load Shape:** The pattern of electricity or energy demand over time, typically shown as a graph displaying how energy consumption varies throughout a day, week, or season for a specific end use or entire building.

**Renewable Energy:** Energy generated from naturally replenishing sources such as solar, wind, hydroelectric, or geothermal power that produce little to no greenhouse gas emissions during operation.

**Residential Building Stock Assessment (RBSA):** NEEA's comprehensive study that collects detailed energy consumption data, building characteristics, and occupant behavior information from a representative sample of homes across the Northwest to understand regional residential energy use patterns and inform energy efficiency program development.

**Shoulder Season:** The transitional periods in spring and fall when heating and cooling demands are typically at their lowest, resulting in reduced overall energy consumption compared to peak summer and winter months.

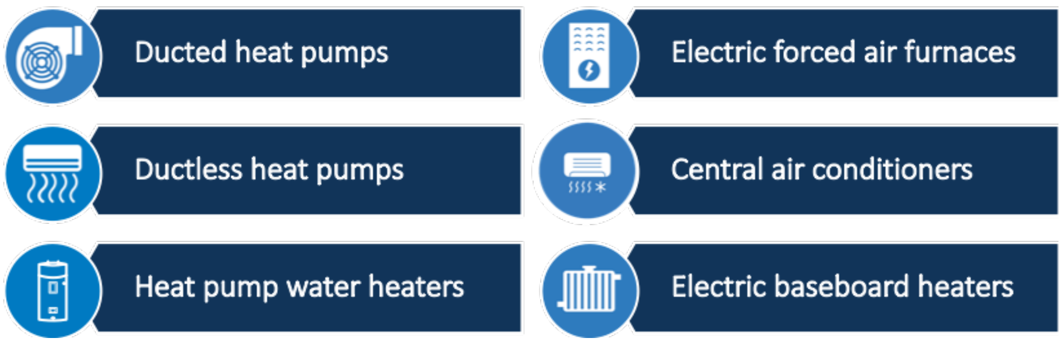
**TMYx (Typical Meteorological Year):** TMYx weather data represent the weather conditions that are typically experienced at a selection of weather stations across the country. The data are publicly available (https://climate.onebuilding.org/).

**Working Group:** The Working Group consists of utilities and regional organizations including Clark Public Utilities, Energy Trust of Oregon, Tacoma Power, Seattle City Light, Avista Utilities, Eugene Water and Electric Board, Snohomish Public Utilities District, Northwest Power and Conservation Council, Portland General Electric, Bonneville Power Administration, National Renewable Energy Laboratory, PacifiCorp, and Puget Sound Energy.

# Executive Summary

This is the final report for the residential End Use Load Research (EULR) Home Energy Metering Study (HEMS) conducted by Evergreen Economics.

The EULR HEMS includes collecting one-minute interval data by circuit and for the whole house from more than 400 homes across the Northwest that have one or more of the following targeted equipment types:




The analysis for this report was directed by NEEA to include updated load shapes from the full study period and an analysis of the potential for lasting impacts from the COVID-19 pandemic. All weather normalization for the analysis presented in this report uses Typical Meteorological Year (TMYx)[1] data as the reference temperature dataset. The load shapes were weighted to represent the populations of end uses across the Northwest using 2022 Residential Building Stock Assessment (RBSA) statistics.

This final report also provides descriptive statistics about the usage data for each targeted end use in Appendix D.

Figure 1 compares the annual load shapes of three central systems: central air conditioners (ACs), ducted heat pumps, and standalone electric forced air furnaces. These equipment types provide heating and cooling via ducts throughout homes in the Northwest. The average annual load shape for ducted heat pumps (Figure 1, in light blue) mimics the load shapes of standalone electric forced air furnaces and central ACs in terms of the times of the peaks and periods of lower usage. The shaded areas around the load shape lines represent a 95 percent confidence interval.

[1] Source: https://climate.onebuilding.org

**Figure 1: Comparison of Central System Annual Load Shapes**

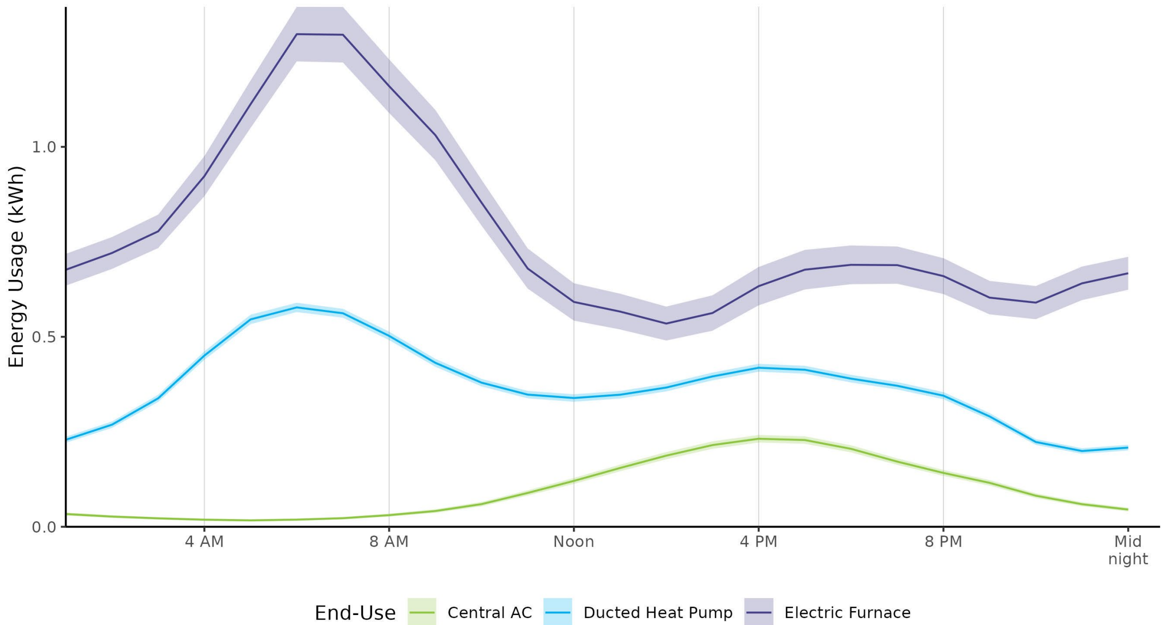
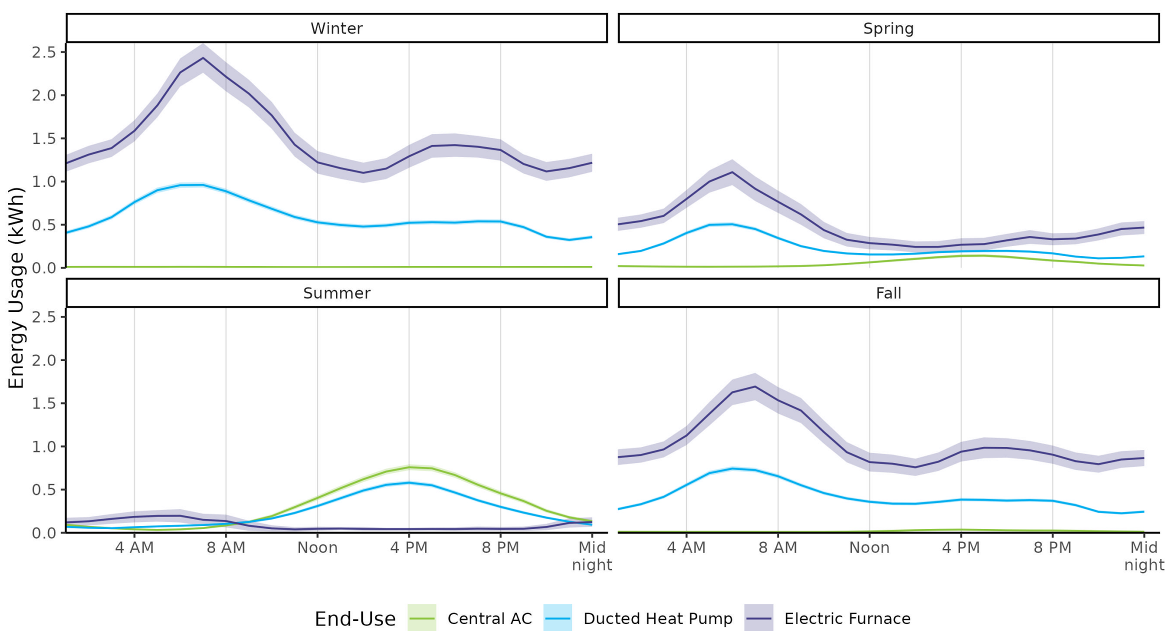



Figure 2 presents a comparison of central system load shapes by season. Here, the similarities in load shape are correlated, as expected, with seasonality; ducted heat pump load shapes are more similar to central AC load shapes during the summer cooling season and are more similar to electric furnace load shapes during the cooler parts of the year, including the shoulder seasons.

**Figure 2: Comparison of Central System Seasonal Load Shapes**



Ducted heat pump energy usage is much more time-of-day dependent than energy use of ductless heat pumps (on an annual basis). Figure 3 shows morning and afternoon peaks for ducted central heat pumps and a very flat load shape for ductless heat pumps.

**Figure 3: Comparison of Ductless and Ducted Heat Pump Annual Load Shapes**

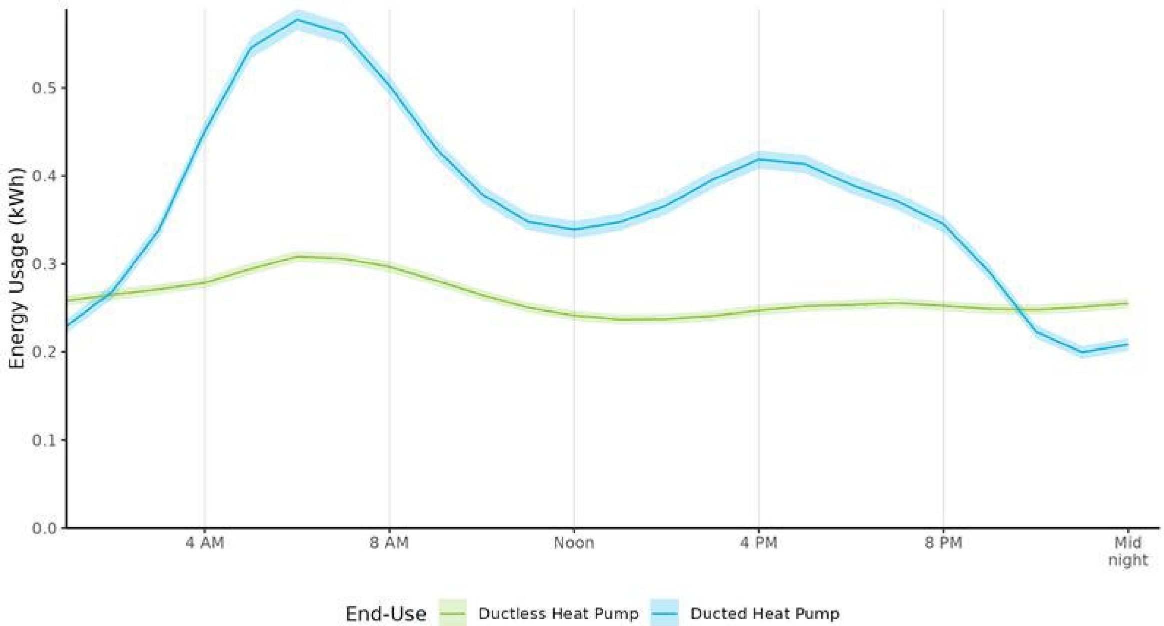



Figure 4 compares the annual load shapes of heat pump water heaters and electric resistance storage water heaters. Both exhibit a morning peak and an evening peak. The heat pump water heater load shape shows a more pronounced evening peak (7 p.m. – 8 p.m.) and a smaller morning peak, while electric resistance water heaters display a higher morning peak (8 a.m. – 9 a.m.) and more consistent energy use across the day. Electric resistance storage water heaters have higher load across all hours of the data.

**Figure 4: Comparison of Water Heating Annual Load Shapes**

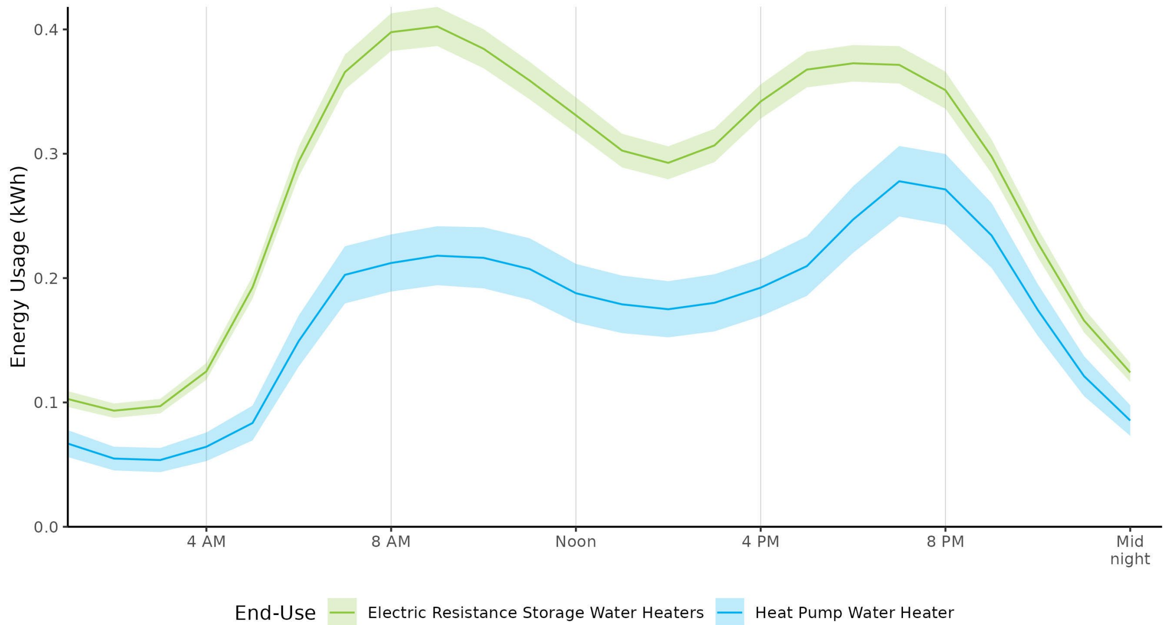



Figure 5 presents seasonal load shapes for heat pump and electric resistance storage water heaters. Both end uses show greater energy use in winter and lower usage in summer. The shape of demand remains similar across seasons, with morning and evening peaks, but summer load shapes are lower and flatter. The load shapes align most closely from the evening peak through the overnight hours, though heat pump water heater load is consistently lower.

**Figure 5: Comparison of Water Heating Seasonal Load Shapes**

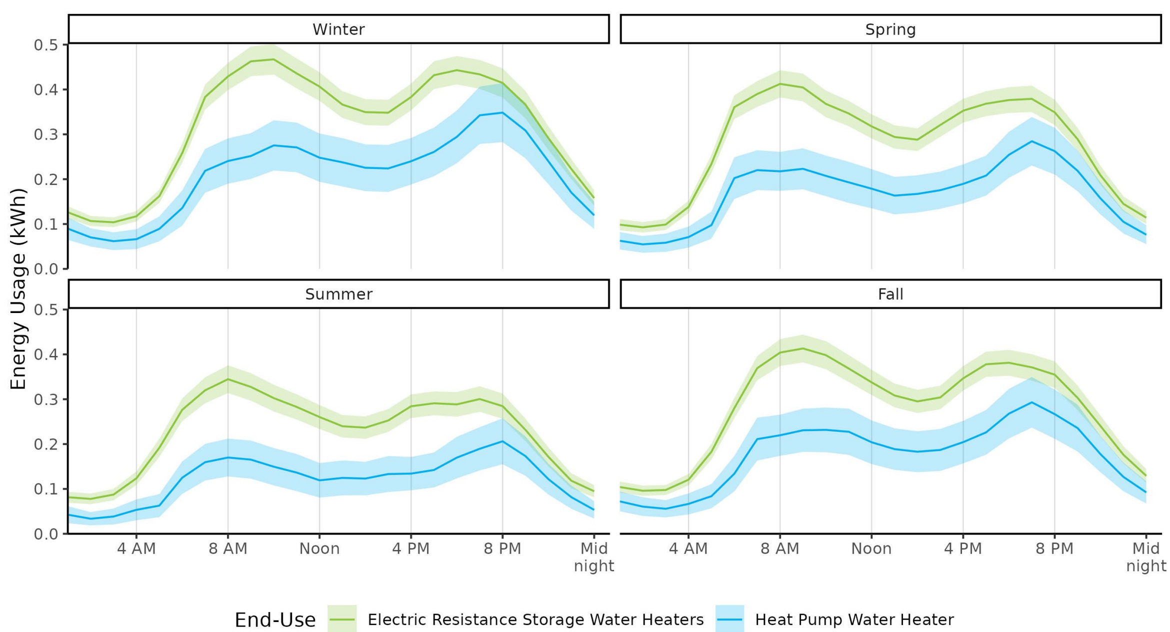
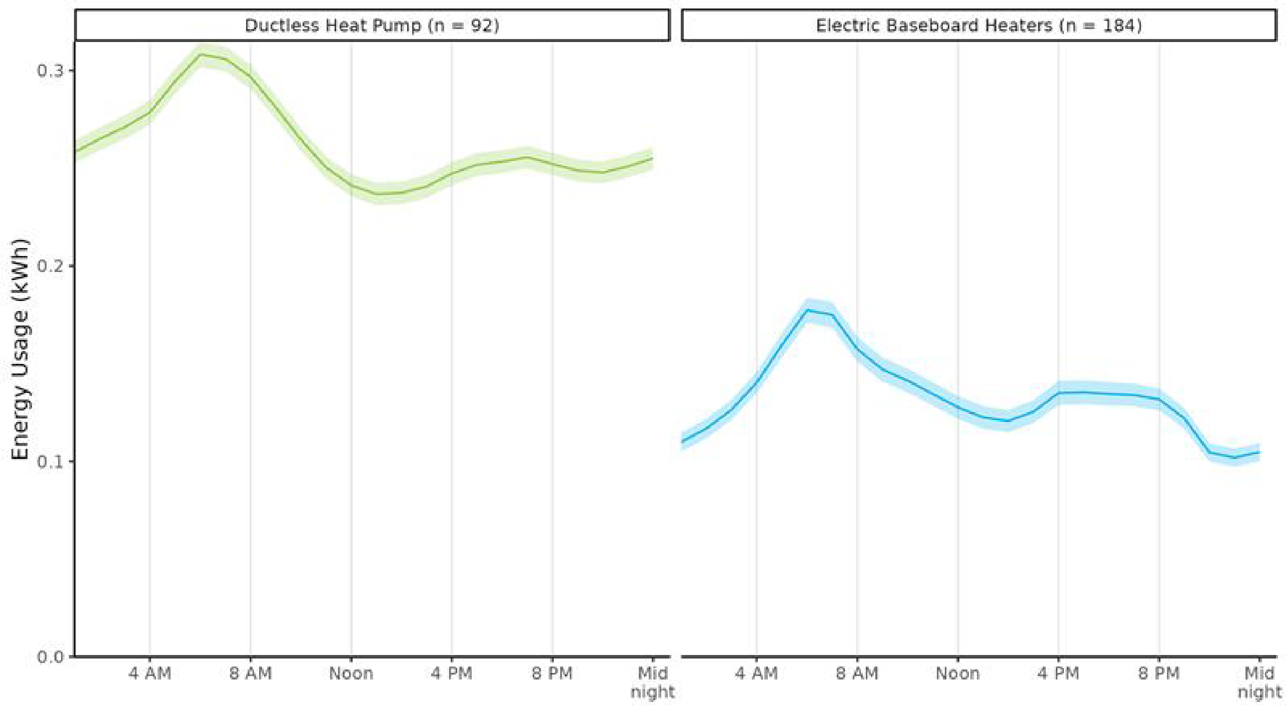


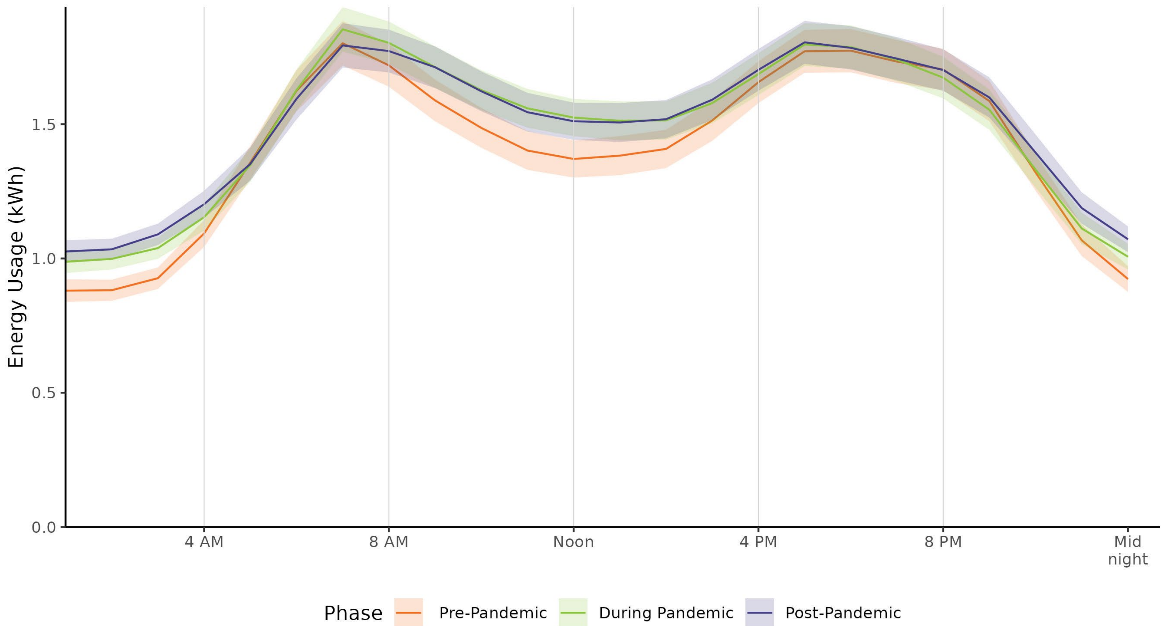
Figure 6 provides the annual load shapes of two zonal systems: ductless heat pumps and electric baseboard heaters. Ductless heat pumps provide both heating and cooling while baseboards only provide heating. The average annual load shape for ductless heat pump systems is like that of electric baseboard heaters (morning usage peak between 6 a.m. and 7 a.m.), but at a higher magnitude throughout the day. This is indicative of greater use and the ability to use a ductless heat pump for cooling on warm days.

**Figure 6: Zonal System Load Shapes (Ductless Heat Pumps and Baseboard Heaters)**




Analysis of HEMS data indicates that COVID-19 may have induced lasting change in how much energy is used by homes in the Northwest. Figure 7 shows that the whole home load shape has changed somewhat since the start of the COVID-19 pandemic (especially overnight), and that the changes persist. This may be from more people working remotely and spending more time at home. This analysis is based on a subset of the HEMS study participants.

**Figure 7: COVID-19 Impacts on Whole Home Load Shapes**



# Introduction

This is the final report for the EULR HEMS conducted by Evergreen Economics.

The EULR HEMS is a key component of a regional strategy to update end use and whole building load shape estimations. The study design was informed by a collaborative planning effort conducted by NEEA's partners, known as the EULR Working Group.[2]

The EULR HEMS research continues a tradition in the Northwest of sponsoring residential end use energy monitoring studies, including the End-Use Load and Consumer Assessment Program (ELCAP),[3] the Residential Building Stock Assessment Metering study (RBSAM),[4] and other, targeted studies. These studies have provided a wealth of information to entities in the Northwest and beyond, but key gaps (identified in the graphic below) highlight why NEEA and the Working Group rightly identified the need for the EULR HEMS:

| | |
|---|---|
| ELCAP | From 1986 to 1989, the Bonneville Power Administration monitored hourly end use electricity demand at 499 homes across the Northwest as part of ELCAP. ELCAP continued in the early 1990s as the Residential End-use Metering Project (REMP), ending in 1992.<br>**GAP:** Both buildings and end uses have evolved considerably since 1992. |
| RBSAM | In 2012, NEEA conducted the Residential Building Stock Assessment Metering study (RBSAM) that included end use monitoring at 100 homes across the Northwest.<br>**GAP:** Smaller sample sizes means it is difficult to draw statistically significant conclusions for subregions of the Northwest, and some end uses have very few observations. |
| Targeted Studies | NEEA and other agencies in the Northwest have conducted many targeted metering studies focused on specific end uses, as well.<br>**GAP:** The targeted studies are typically smaller in scope and scale and not intended to represent the population of the Northwest. |

[2] The Working Group consists of utilities and regional organizations including Clark Public Utilities, Energy Trust of Oregon, Tacoma Power, Seattle City Light, Avista Utilities, Eugene Water and Electric Board, Snohomish Public Utilities District, Northwest Power and Conservation Council, Portland General Electric, Bonneville Power Administration, National Renewable Energy Laboratory, PacifiCorp, and Puget Sound Energy.
[3] https://elcap.nwcouncil.org/
[4] Ecotope Inc. 2014. *Residential Building Stock Assessment: Metering Study*. https://neea.org/resources/2011-rbsa-metering-study

## Objectives

The main objective of the EULR HEMS study was to develop a **current**, **representative**, and **robust** characterization of continuous energy consumption of key heating and cooling measures to support achieving clean energy goals and utility information needs, providing:

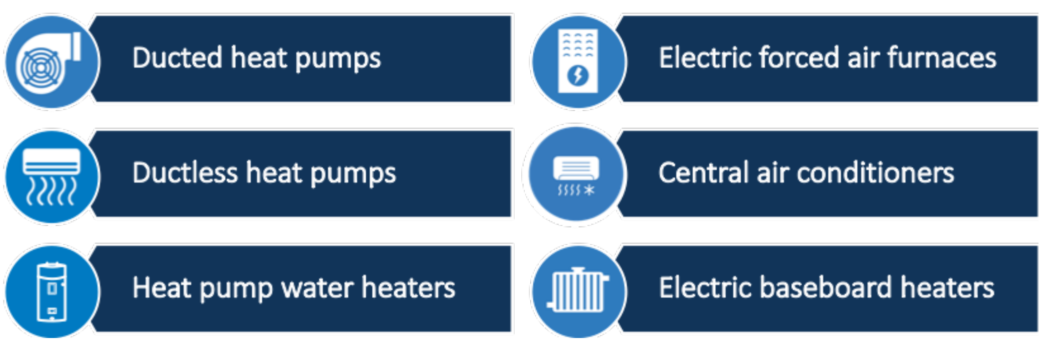
- A much more accurate assessment of the contributions of energy efficiency technologies towards reducing peak demand.
- A better understanding of how to integrate renewable energy into the grid, to increase reliability as the deployment of distributed generation and new end use technologies increases over time.
- Prioritized data by end use for use in a range of utility functions including demand response, load forecasting, and resource planning.

## Study Design

In 2018, Evergreen facilitated three formal Working Group meetings focused on EULR HEMS. Working Group members provided valuable input on the study implementation and sampling plans; they reviewed and provided feedback on numerous study documents, including recruitment scripts and lessons learned memorandums.

## Data Collection

The study included collecting one-minute interval data by circuit and for the whole house from more than 400 homes across the region that have one or more of the following targeted equipment types:




Data collection consisted of a three-step process. The steps included:

1. Recruitment and scheduling
2. Energy monitoring equipment installation
3. Data acquisition and processing

The **recruitment and scheduling** component started with identifying appropriate sample frames since HEMS had to identify and recruit only households with the targeted end uses. At the start of the study in 2018, the 2016 Residential Building Stock Assessment (RBSA) served as the sample frame. HEMS supplemented the sample starting in 2019 with regional rebate program databases for ductless heat pumps, air source heat pumps, and heat pump water heaters. In 2022 and later, coinciding with the 2022 RBSA fieldwork, HEMS recruited sites on a rolling basis from the group of 2022 RBSA participants.

The recruitment process itself involved distributing utility notifications prior to contacting prospective HEMS participants, advance notification postcards, and telephone calls.

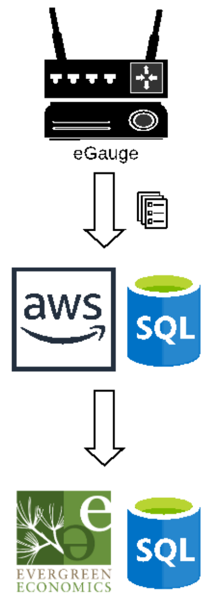
Once sites were recruited and scheduled, the **energy monitoring equipment installation** visits consisted of several steps:

1. First, trained study engineers conducted a pre-installation walkaround and discussion with the homeowner about equipment placement.
2. Second, the engineers conducted circuit mapping focused on targeted end uses and validating dedicated circuits (i.e., circuits serving a single end use).
3. Meanwhile, a local licensed electrician mounted the metering equipment box and then worked with the engineers to run wires into the panel and connect to each circuit.
4. Next, the electricians and engineers worked together to map the installed equipment to data points in a custom form tool to track the data points to the specific end uses metered.
5. Before leaving, the engineers validated that the equipment was functioning as intended and provided an incentive to the participant.

At the conclusion of the study, HEMS coordinated with electricians and home occupants to remove the installed monitoring equipment.

The **data acquisition and processing** involved three distinct steps, shown in Figure 8. The installed metering boxes each contained eGauge energy monitoring systems, which recorded readings every minute and transmitted data to an Amazon Web Services (AWS) server every 10 minutes using a cellular connection. The data were then stored in a relational SQL database and compressed file directory on AWS. Lastly, the data were extracted from AWS daily and written to internal Evergreen servers.

**Figure 8: EULR HEMS Data Intake Process**




HEMS provided monthly database extracts to NEEA during the study and provided a complete and thoroughly vetted final database in November 2025.

For additional information about data quality assurance and quality control, please see Appendix A.

## Data Analysis

Since 2018, Evergreen and NEEA have facilitated numerous additional Working Group meetings to help guide the analysis towards what would be most useful to Working Group members. This report focuses on the primary objective of the study: to develop **overall and seasonal weather-normalized load shapes** for whole homes and targeted end uses (as well as electric resistance storage water heaters) using Evergreen's Advanced Metering Infrastructure Customer Segmentation (AMICS) approach for weather normalization. The report also provides weekday and weekend weather-normalized load shapes, and documents changes in load shapes related to the COVID-19 pandemic.

A detailed description of the analysis methodology for this report is included in the next section.

# Analysis Methodology

The core objective of EULR HEMS was to estimate load shapes for priority end uses,[5] which are intended to be used for both energy efficiency program purposes and for load forecasting. In this report, weather normalized overall and seasonal load shapes were generated through Evergreen's AMICS modeling approach.

For additional details regarding sampling and weighting, see Appendix B. For additional information about the AMICS approach, see Appendix C.

## Overall, Seasonal, and Weekday vs Weekend Load Shape Analysis

For this report, weather-normalized seasonal, weekday, weekend, and overall load shapes were generated using AMICS. While AMICS is typically used to understand the impact on energy usage of some intervention, in this case, AMICS was only used to estimate load shapes while maximizing the amount of data included in the analysis.

Through extensive testing, it was found that estimating models for each site and end use individually was the most effective way of accurately predicting energy usage for specific end uses. Segmenting customers individually leveraged their unique behaviors and patterns to accurately estimate end use load shapes for each customer under a variety of circumstances. This process was done for all customers and end uses, allowing the formation of individual estimates of each end use for each customer using AMICS. The analysis included all monitored equipment with at least one completed season since being installed. This maximized the amount of data that could be used in this analysis but also meant that certain seasons may have included more sites than others within the same end use. Weighting was used to account for these differences and to ensure that load shapes were always representative of the population.

The load shape results were also weighted to represent the Typical Meteorological Year (TMYx).[6] TMYx weather data represent the weather conditions that are typically experienced at a selection of weather stations across the country. Weighting AMICS outputs that reflected these weather conditions ensured that the load shapes generated in this analysis reflected general trends in weather and were not being skewed by especially abnormal weather that may have occurred at study sites.

[5] Electric resistance storage water heaters were not a priority end use but were included in the analysis.
[6] Source: https://climate.onebuilding.org

## COVID-19 Comparison Load Shape Analysis

This analysis sought to identify the impacts of the COVID-19 pandemic on residential load shapes by comparing load shapes from before the pandemic (i.e., pre-COVID) to the COVID-19 pandemic period and to the period since the World Health Organization declared that COVID-19 no longer constituted a public health emergency of international concern on May 5, 2023.

To estimate the impacts of the COVID-19 pandemic on load shapes, the analysis was restricted to monitored homes and end uses with sufficient observations during the period prior to the pandemic, during the pandemic, and since the public health emergency was declared over. The load shapes were developed using the methods described in this section and are weighted to represent the population of households with each end use based on the 2022 RBSA. As with the overall load shape analysis, models were estimated for individual customers to maximize model accuracy. As with the other load shape analysis presented in this report, results for the impact of the COVID-19 pandemic on load shapes are normalized to TMYx.

To estimate the impact of the COVID-19 pandemic on the load shapes of priority end uses and the whole home, the AMICS modeling approach was used to predict weather-normalized load shapes while COVID-19 stay-at-home orders were in effect across the Northwest during the pandemic. These predicted load shapes were compared to the load shapes during the COVID-19 pandemic, and to the load shapes after the pandemic ended (since May 5, 2023) to understand the impact of the pandemic on behavior and energy use in homes in the Northwest.

## General Updates from Previous Analyses

The analysis in this report is intended to update load shapes based on an additional year of data collecion, with slight modifications to the prior analysis. These modification include using TMYx data instead of TMY3 data for normalizing weather, using 2022 RBSA to weight load shapes to represent the population, and separately analyzing standalone electric furnaces and furnaces that are used as backups to ducted heat pumps.

### Using TMYx for Weather Normalization

In the first four reports, load shapes were weighted to represent a previous Typical Meteorological Year dataset, TMY3. Since the prior report, the study has relied on TMYx weather data for weather normalization.

### Weighting Results based on 2022 RBSA

Since the completion of the previous HEMS reports, NEEA's 2022 RBSA dataset has been released to the public, and updated counts of each priority end use by climate zone are now available. This report utilizes the 2022 RBSA data to ensure that the analysis represents the most updated distributions of each end use across the climate zones of the Northwest.

## Separating Standalone Electric Furnaces from Backup Electric Furnaces

Previous analysis combined standalone electric furnaces with electric furnaces that provide backup heat for ducted heat pumps into a single load shape. For the analysis in this report, a detailed review of each furnace was conducted and determined whether it is being used to provide backup heat to a ducted heat pump or being used as a standalone system.

The backup furnaces supply the fan load associated with the heating and cooling for ducted heat pumps, and 11 of 50 standalone furnaces supply the fan load for central AC present at the sites.

# Normalized Load Shapes

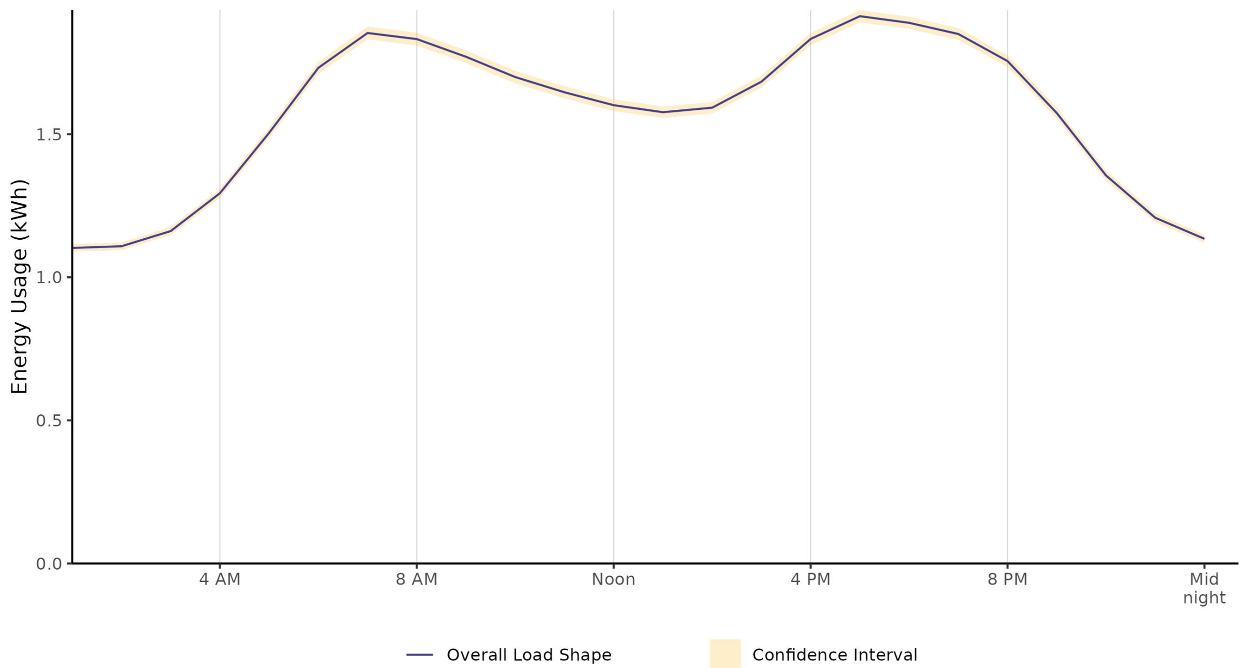
This chapter provides a series of AMICS normalized load shape estimates for whole home energy use and for each of the targeted end uses that are on dedicated circuits with at least one full calendar season of energy usage data. The AMICS approach processes a load shape for each customer across a variety of day types. The analysis in this report represents the average of these load shapes after weighting to the most up-to-date Typical Meteorological Year data (TMYx) and to the population of each end use.

The figures in this chapter provide a composite annualized and seasonal load shape for each targeted end use as a dark blue line, with the average kWh energy usage for each hour of the day. The yellow shaded area around this line is a 95 percent confidence interval, providing the estimate for the error bounds of the load shape. Other figures compare load shapes on weekdays and weekends, with weekdays shown in orange and weekends shown in green. The shaded areas in the weekday and weekend figures are the 90 percent confidence intervals.

## Whole Home

Analysis of whole home load shapes is based on data from 331 participant homes. The whole home load shape shown in Figure 9 is a typical annual residential load shape with peaks in the morning and early evening and a reduction in energy use during the middle of the day.

**Figure 9: Whole Home Load Shape – Overall (n=331)**




Whole home load shapes by season are provided in Figure 10. The heating season (winter) is characterized by relatively high overall usage among participants and exhibits a high morning peak and a similar overall shape as the annual load shape. Both spring and fall load shapes are similar but of lower magnitude, while the summer load shape is characterized by lower overall usage and only an afternoon peak from 4 p.m. to 5 p.m. (and no morning peak).

**Figure 10: Whole Home Load Shape – By Season**

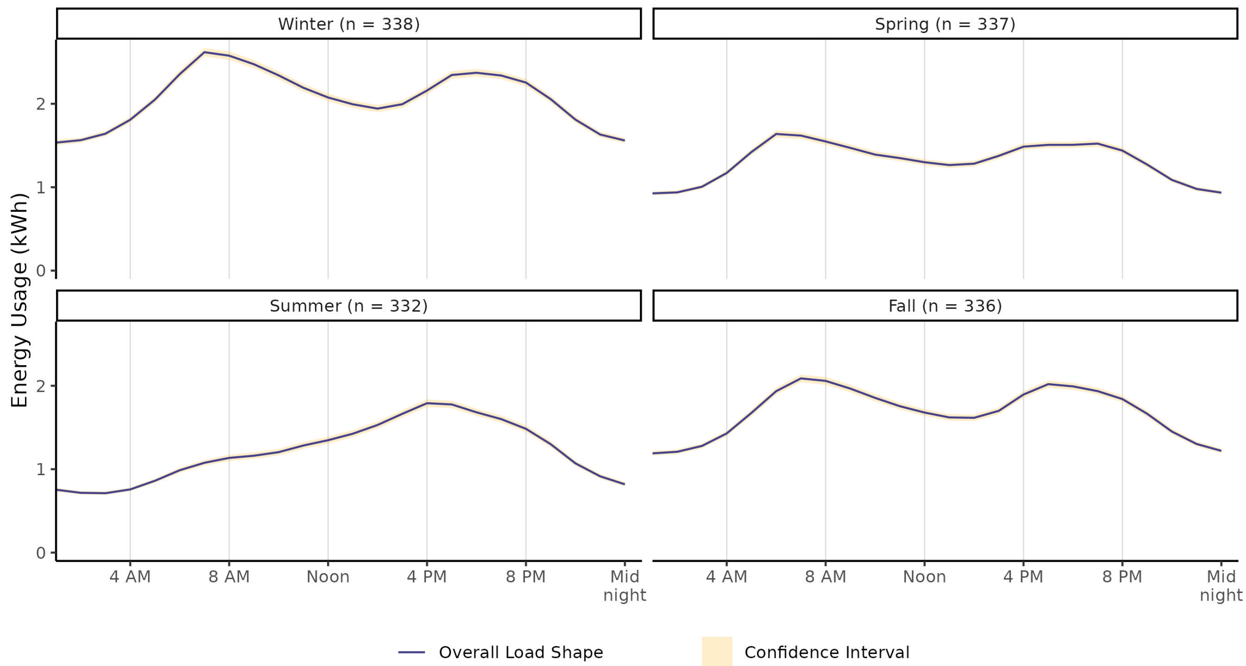



Figure 11 compares weekday and weekend whole home load shapes. Weekdays exhibit an earlier morning peak and a more pronounced reduction in energy use during the middle of the day, with similar evening load shapes.

**Figure 11: Whole Home Load Shape – Weekdays vs Weekends**

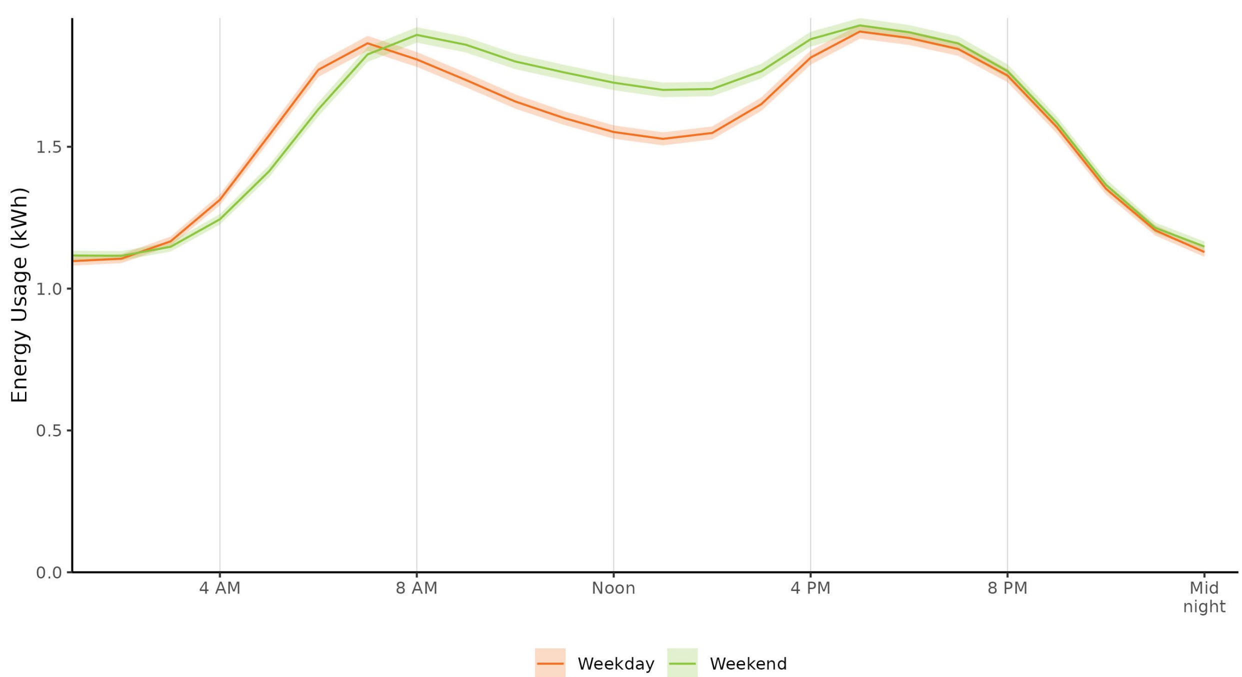
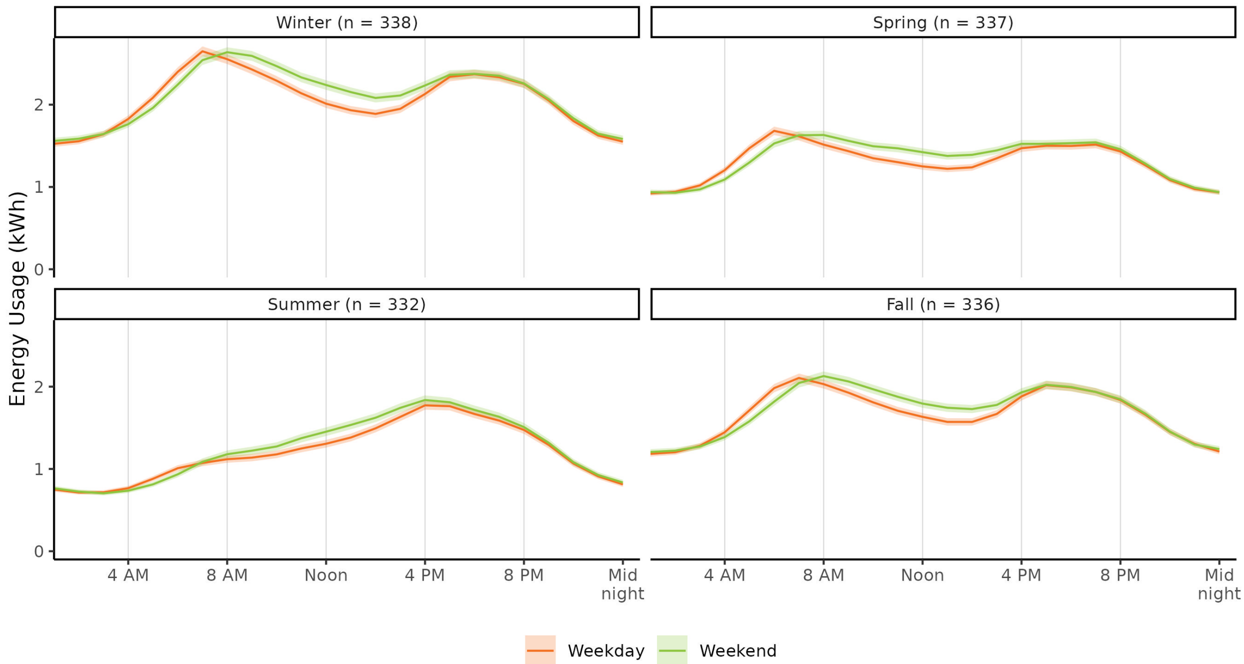


Figure 12 compares weekday and weekend load shapes for each season. In all cases, the weekday morning load increases slightly earlier and tapers off more in the middle of the day than on weekends. The load shapes are similar in the evening hours.

**Figure 12: Whole Home Load Shape – Weekdays vs Weekends, by Season**



## Ducted Heat Pumps

Figure 13 shows the estimated load shape of ducted heat pumps in the Northwest based on data collected on 126 heat pumps. In general, ducted heat pumps tend to be most used in the morning (between 5 a.m. and 8 a.m.) and in the early evening (4 p.m. to 5 p.m.), with lower usage periods in the middle of the day and overnight.

**Figure 13: Ducted Heat Pump Load Shape – Overall (n=126)**

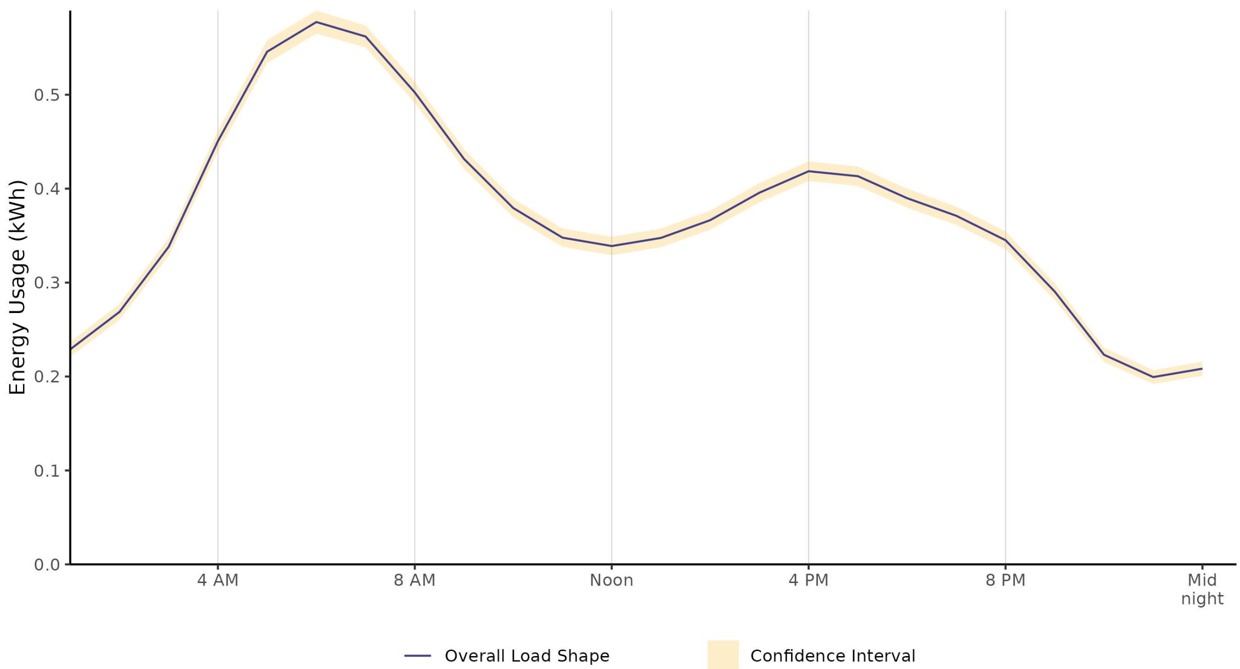



Figure 14 shows that ducted heat pumps are used in all four seasons, with morning peaks in the winter, spring, and fall associated with heating and an afternoon peak in the summer associated with cooling.

**Figure 14: Ducted Heat Pump Load Shape – By Season**

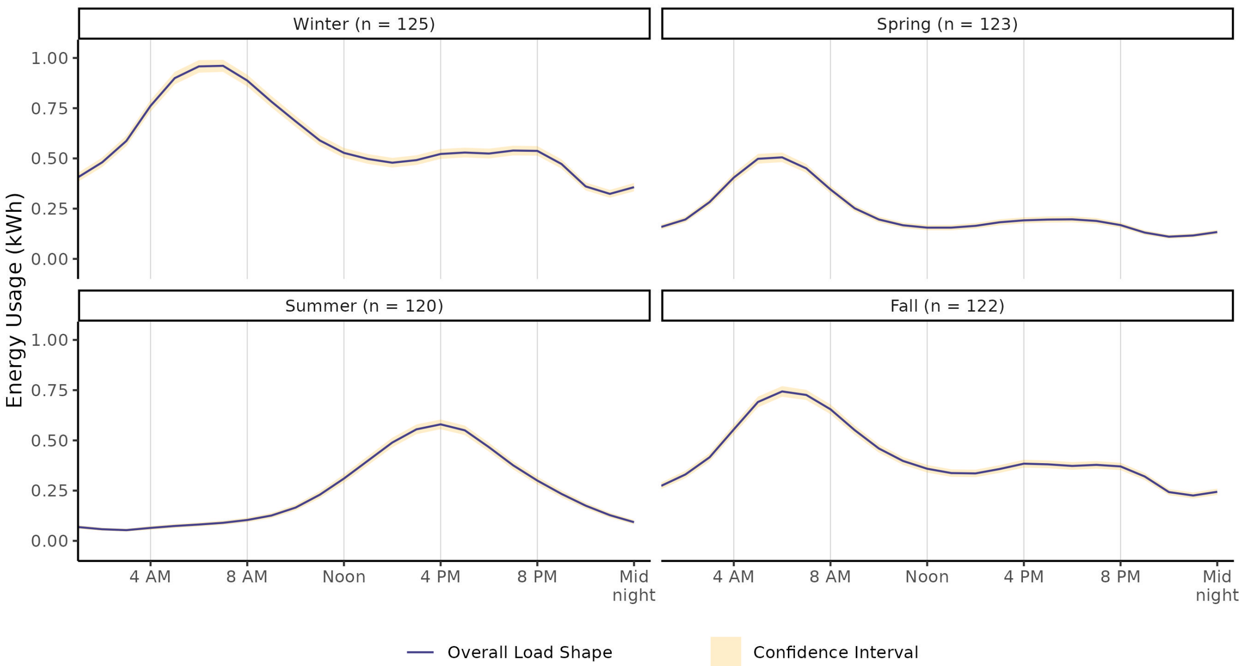



Figure 15 compares the load shapes of ducted heat pumps on weekdays and weekends. The load shapes are very similar, with a slightly earlier ramp-up on weekdays.

**Figure 15: Ducted Heat Pump Load Shape – Weekdays vs Weekends**

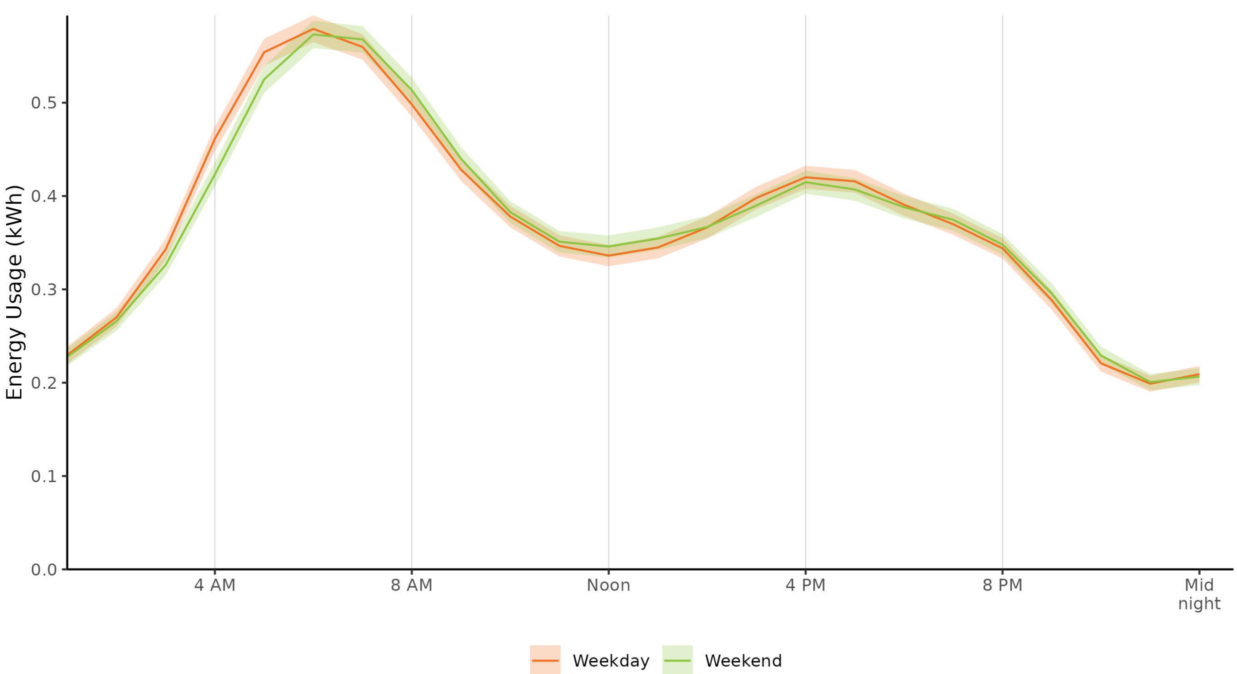
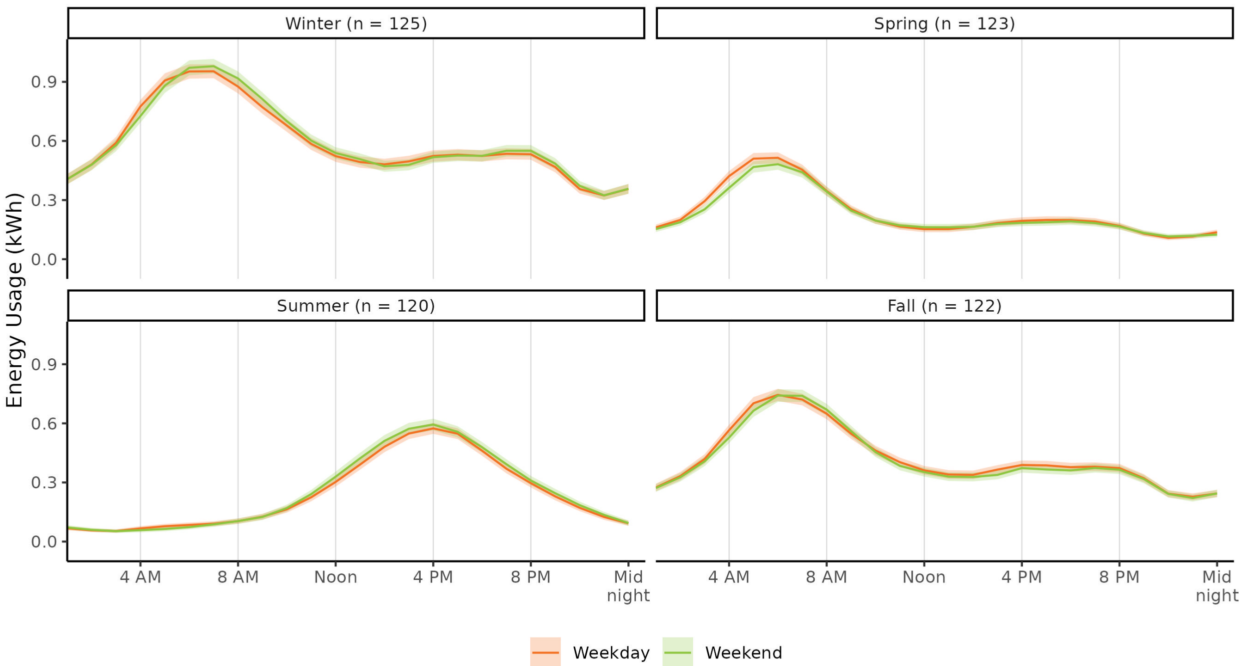
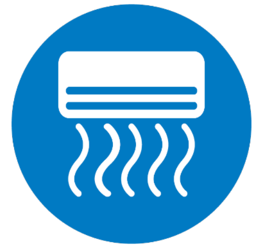


Figure 16 shows that ducted heat pump load shapes are similar on weekdays and weekends for each season, with a slightly earlier morning ramp up on weekdays during heating seasons (winter and shoulder seasons). This difference is not statistically significant except for at 4 a.m. in the spring.

**Figure 16: Ducted Heat Pump Load Shape – Weekdays vs Weekends, by Season**

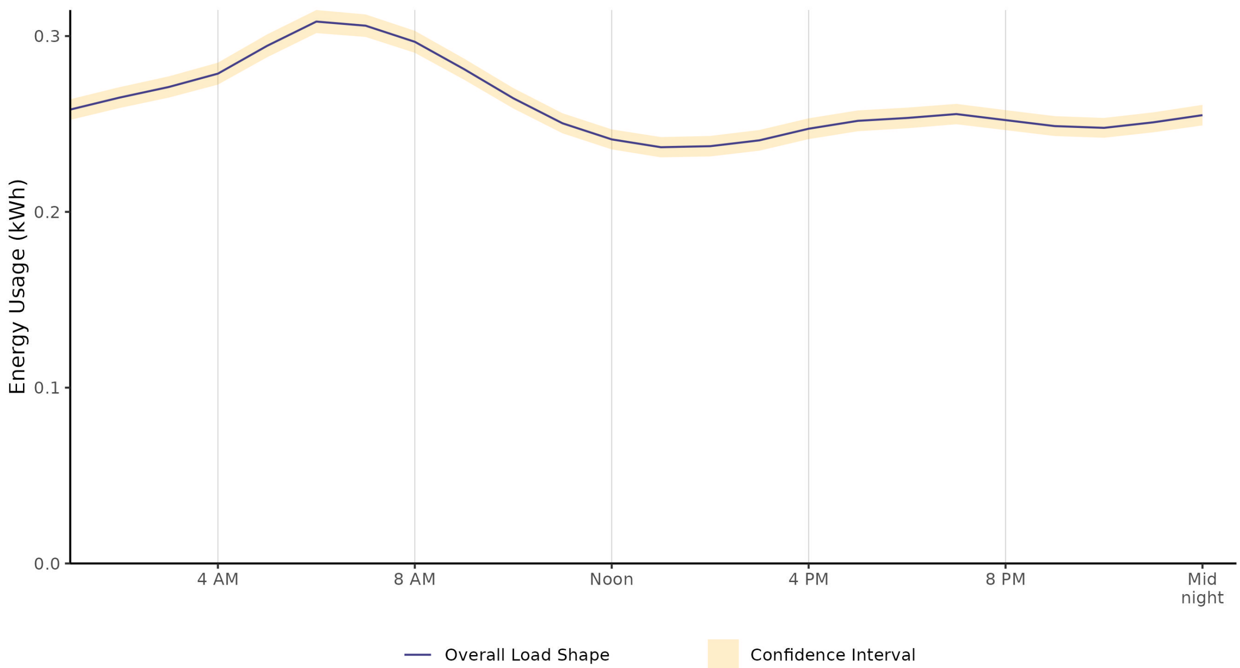




## Ductless Heat Pumps

Figure 17 shows the overall load shape for ductless heat pumps based on the 92 ductless heat pumps included in the analysis. The overall load shape for ductless heat pumps is relatively flat, with a slight morning peak and a slight lull in the middle of the day.

**Figure 17: Ductless Heat Pump Load Shape – Overall (n=92)**




Ductless heat pump load shapes split out by season are presented in Figure 18. In the winter, spring, and fall, the ductless heat pumps are mostly in use during the mornings and overnight (primarily heating). In contrast, in summer the peak is in the afternoon (around 4 p.m.) and indicates that they are used primarily for cooling.

**Figure 18: Ductless Heat Pump Load Shapes – By Season**

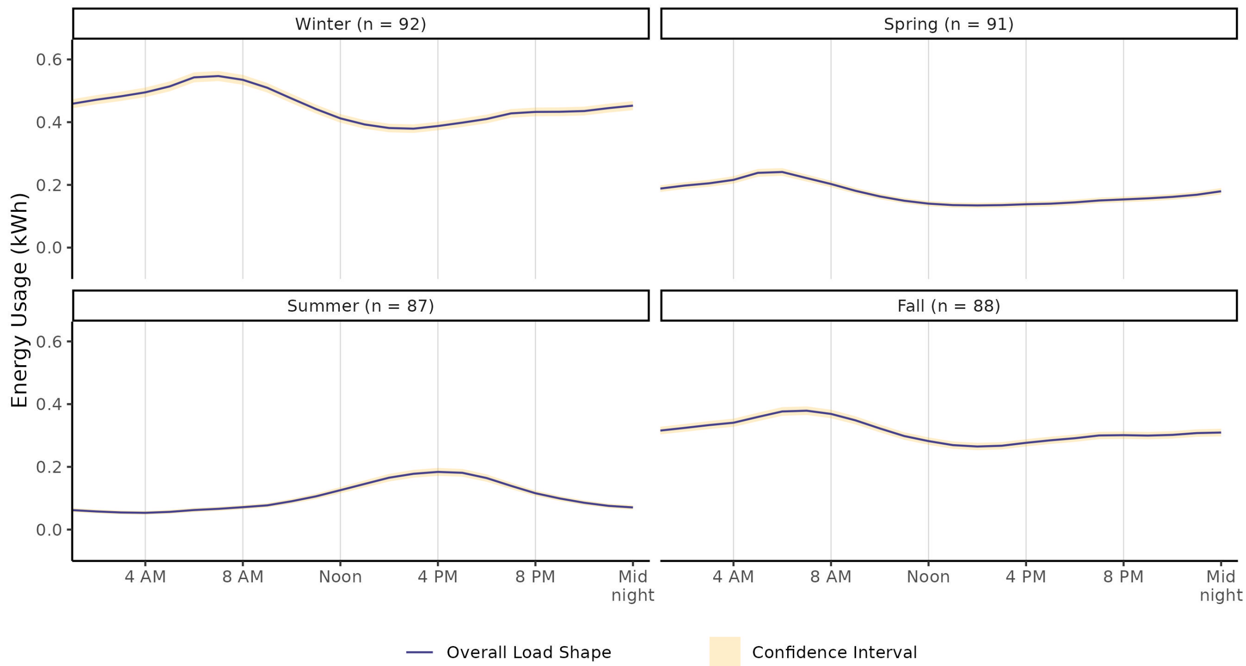



Figure 19 shows that ductless heat pump load shapes are similar on weekdays and weekends, except for a more pronounced and slightly earlier morning peak (although the difference is not statistically significant).

**Figure 19: Ductless Heat Pump Load Shapes – Weekdays vs Weekends**

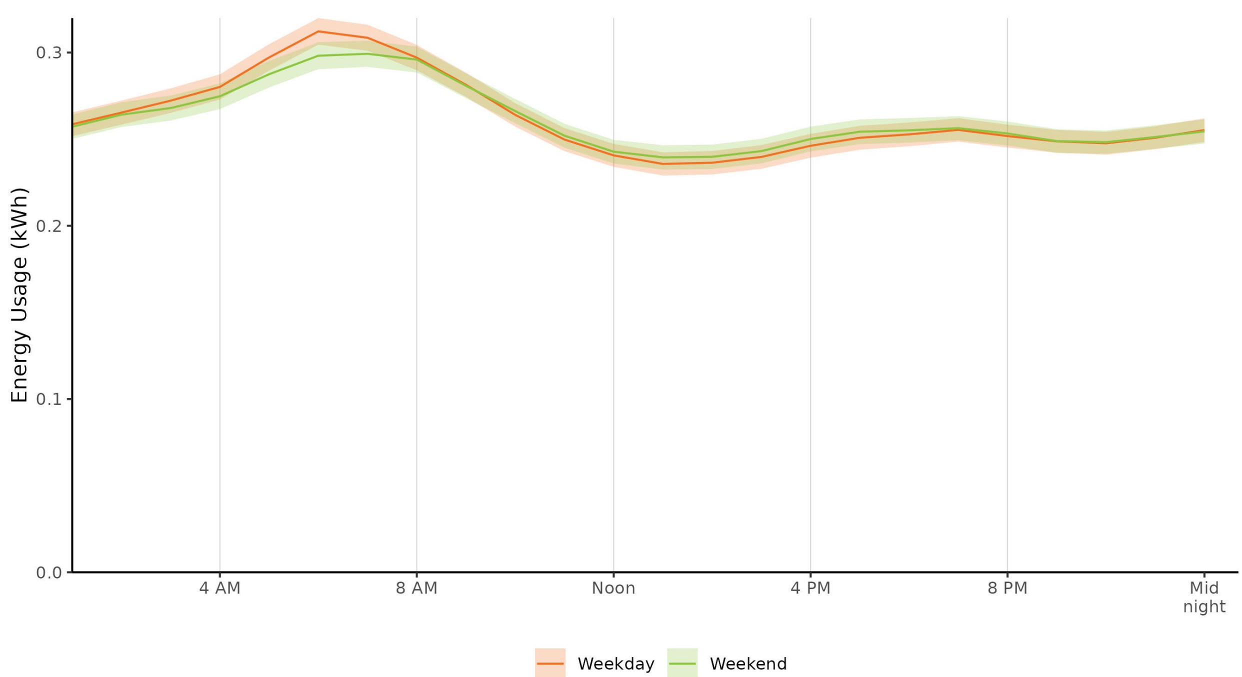
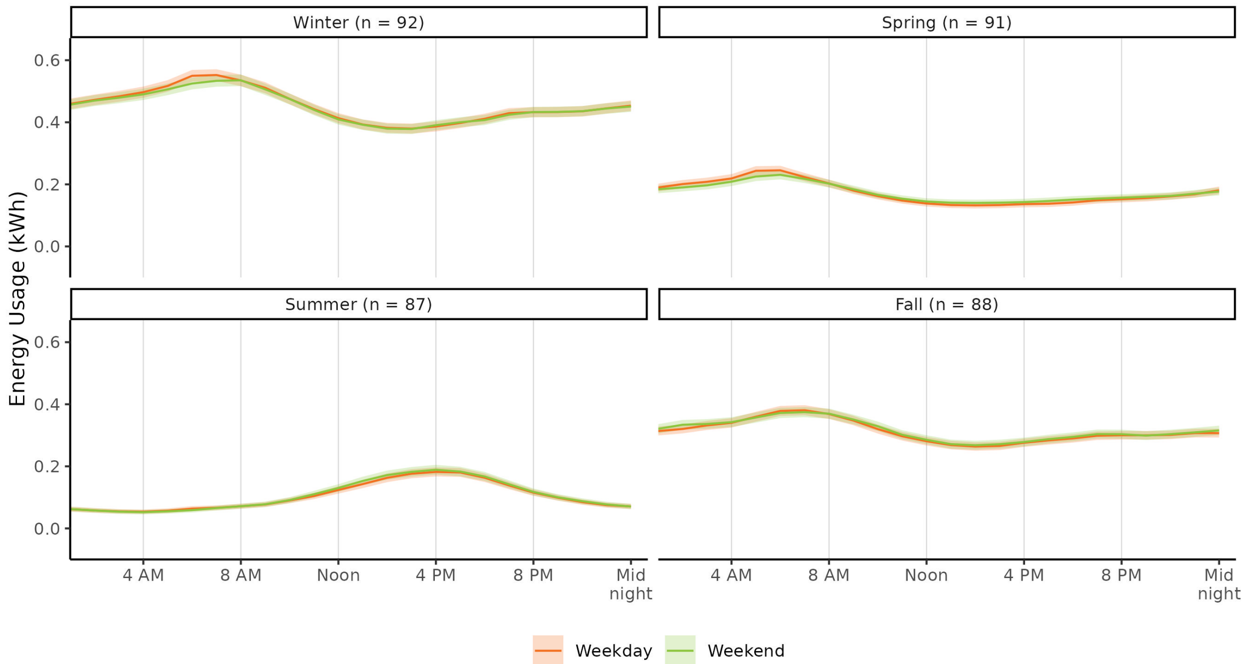


Figure 20 shows that the earlier and slightly larger morning peak on weekdays is due to increased morning usage during winter and spring on weekdays (compared to weekends). Weekday and weekend load shapes in the summer and fall are nearly identical.

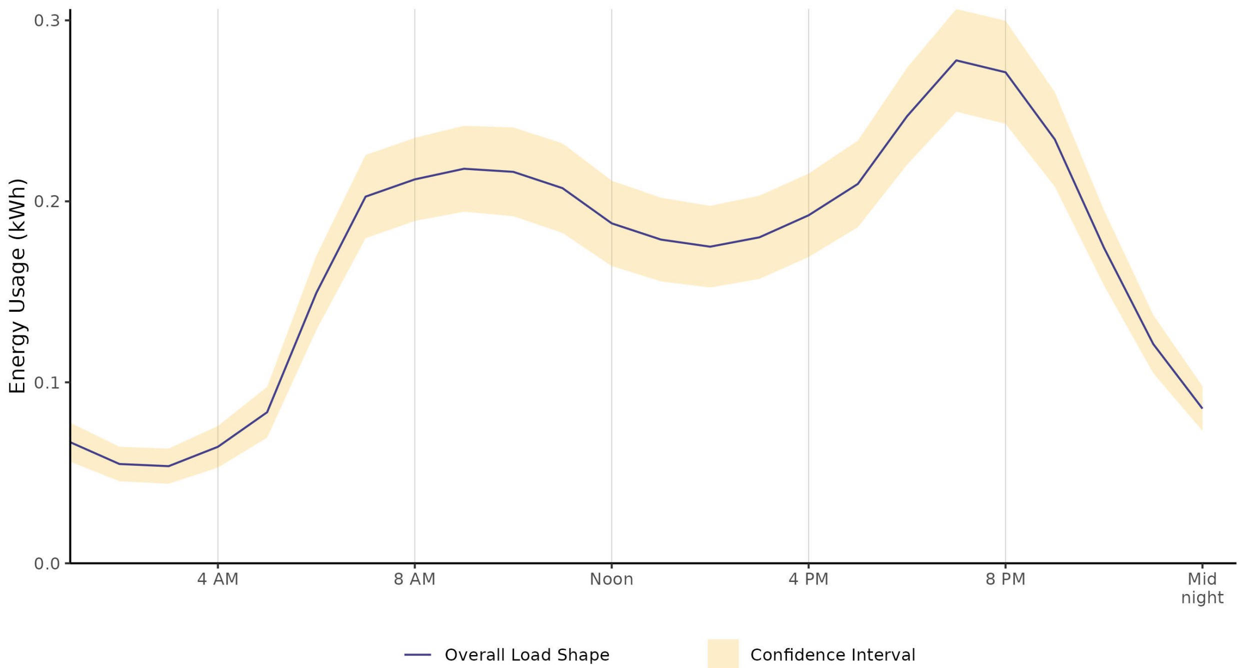
**Figure 20: Ductless Heat Pump Load Shapes – Weekdays vs Weekends, by Season**



## Heat Pump Water Heaters

The heat pump water heater load shape in Figure 21, which is based on observations from 54 water heaters, shows that there are two peaks in usage with the largest peak in the evening (7 p.m. to 8 p.m.).

**Figure 21: Heat Pump Water Heater Load Shape – Overall (n=54)**




Heat pump water heater load shapes are similar across seasons, but lower in magnitude in the summer as shown in Figure 22. Morning hot water usage, and therefore the heat pump water heater load, starts earliest in the spring.

**Figure 22: Heat Pump Water Heater Load Shapes – By Season**

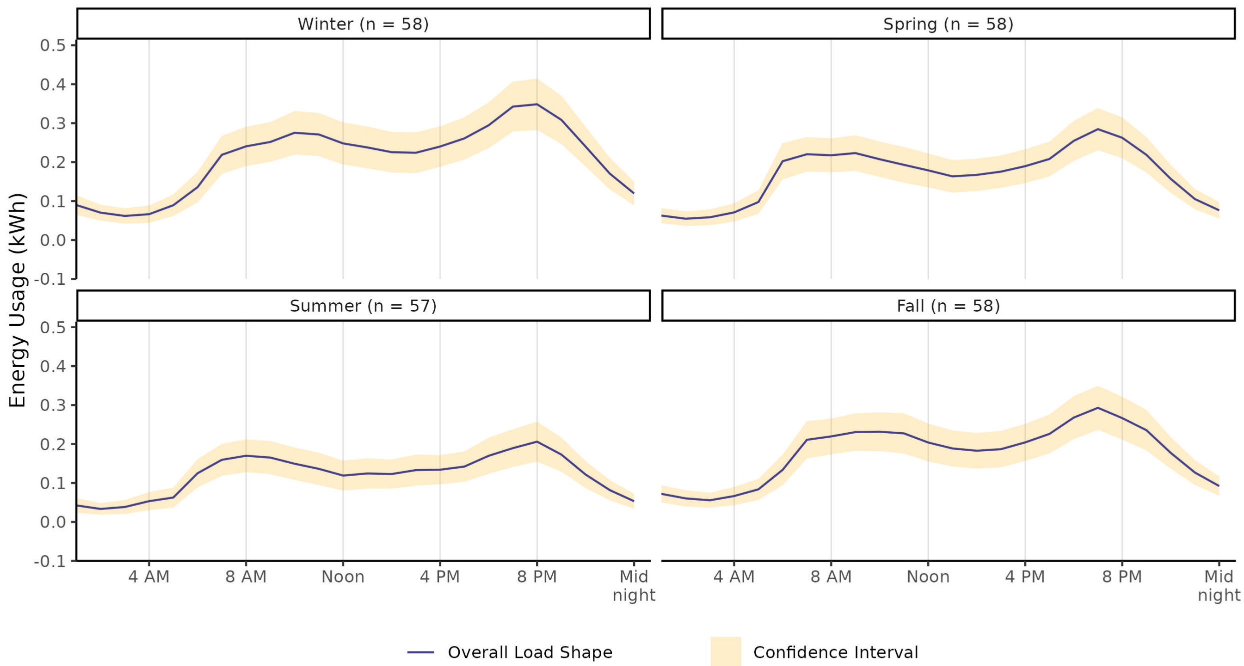



Figure 23 compares heat pump water heater load shapes during weekdays and weekends. During weekdays, hot water draws (and heat pump water heater loads) ramp up earlier than on weekends, and heat pump water heaters have higher midday usage on weekend days. Since hot water usage is generally associated with occupants being present in the home, additional hot water usage and heat pump water heater energy use on weekends makes sense. The evening load shapes are consistent on weekdays and weekends.

**Figure 23: Heat Pump Water Heater Load Shapes – Weekdays vs Weekends**

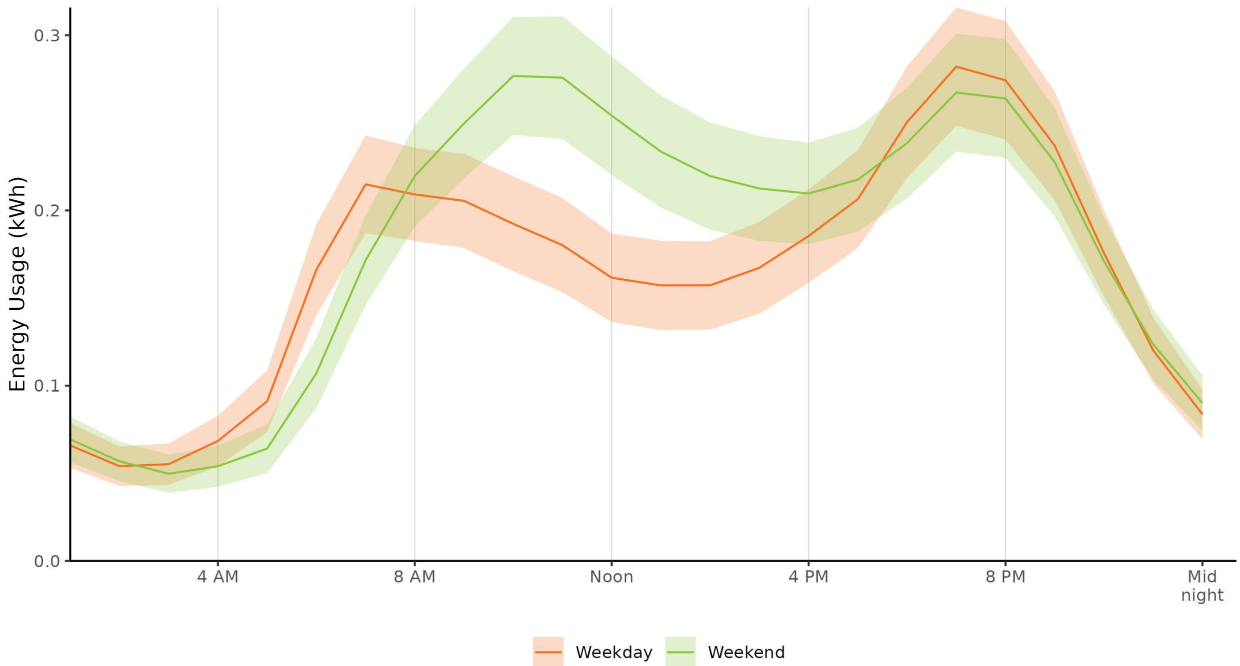
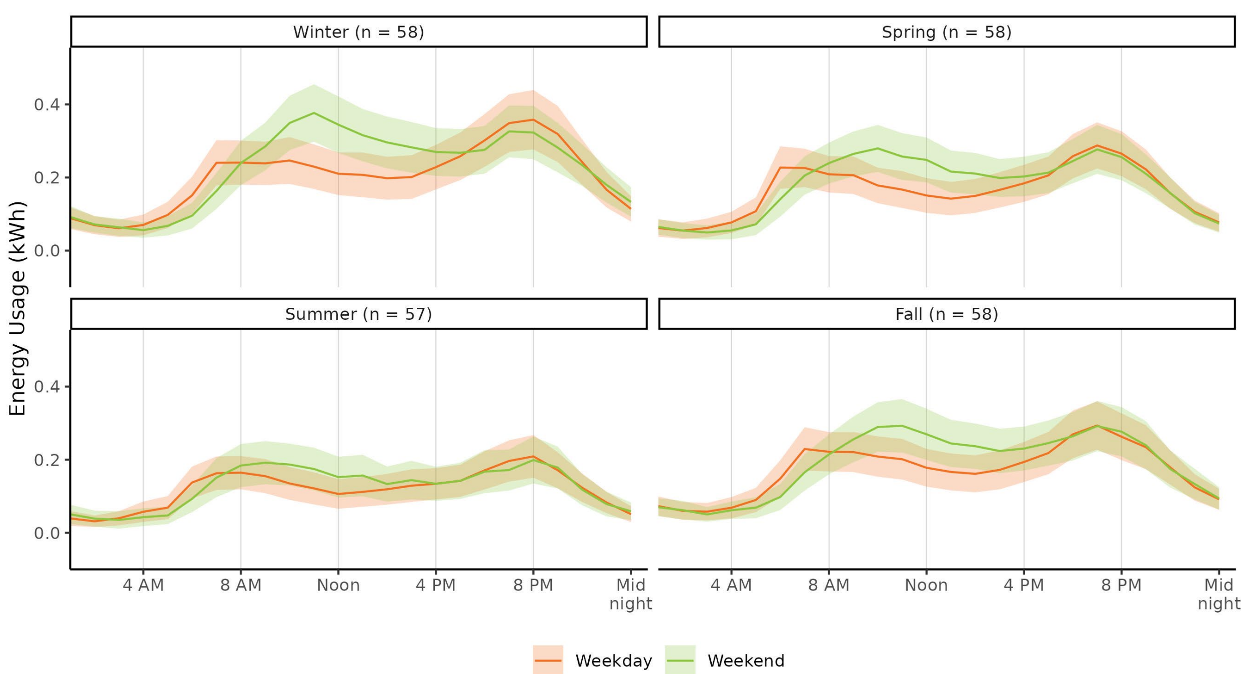



Figure 24 shows that the trend for earlier load on weekdays and more midday load on weekends is consistent across seasons.

**Figure 24: Heat Pump Water Heater Load Shapes – Weekdays vs Weekends, by Season**



## Standalone Electric Forced Air Furnaces

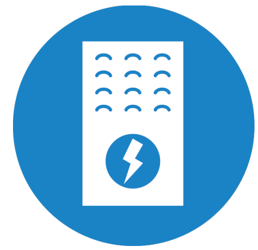


Figure 25 presents the load shape of standalone electric forced air furnaces in the Northwest, based on data from 45 furnaces. Electric forced air furnaces are used most in the morning (between 5 a.m. and 9 a.m.) and then taper off through the rest of the day, with a slight increase in usage in the evenings and overnight (compared to the middle of the day).

**Figure 25: Standalone Electric Forced Air Furnace Load Shapes – Overall (n=45)**

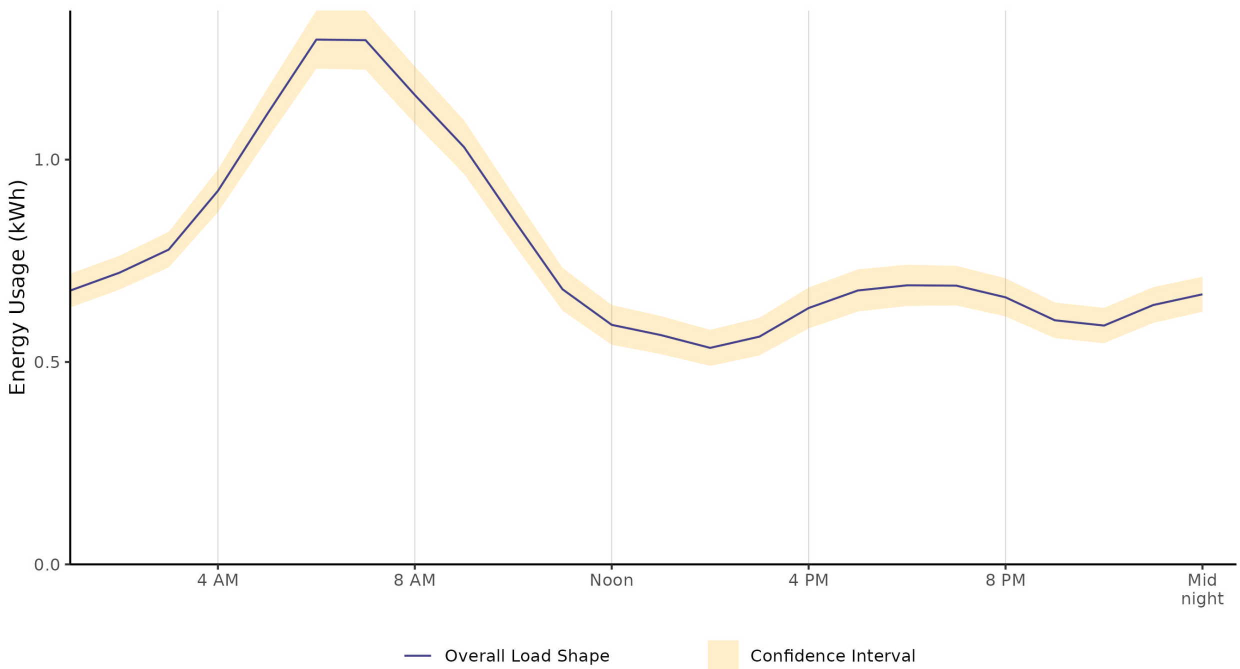



Figure 26 presents seasonal standalone electric forced air furnace load shapes. As expected, the greatest magnitude of use is in winter, when heating is required across the Northwest. There is shoulder season load, especially in the morning (with a peak in spring that is about one hour earlier than in winter and fall). Furnace usage in summer months is very low.

**Figure 26: Standalone Electric Forced Air Furnace Load Shapes – By Season**

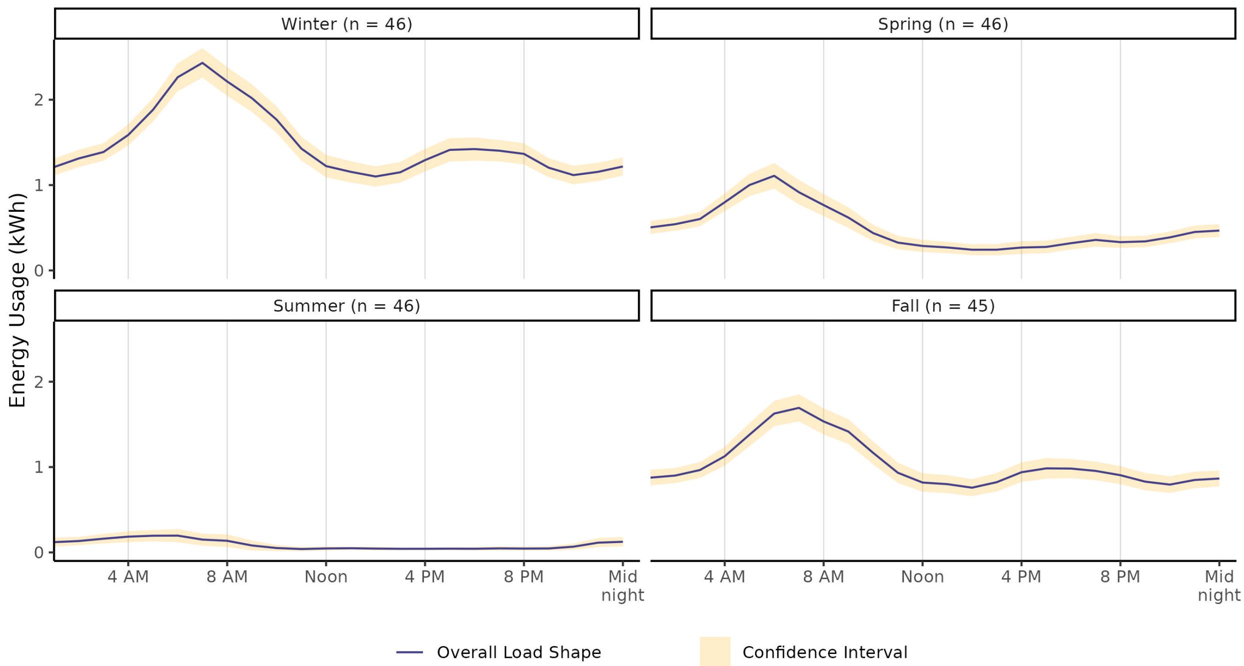
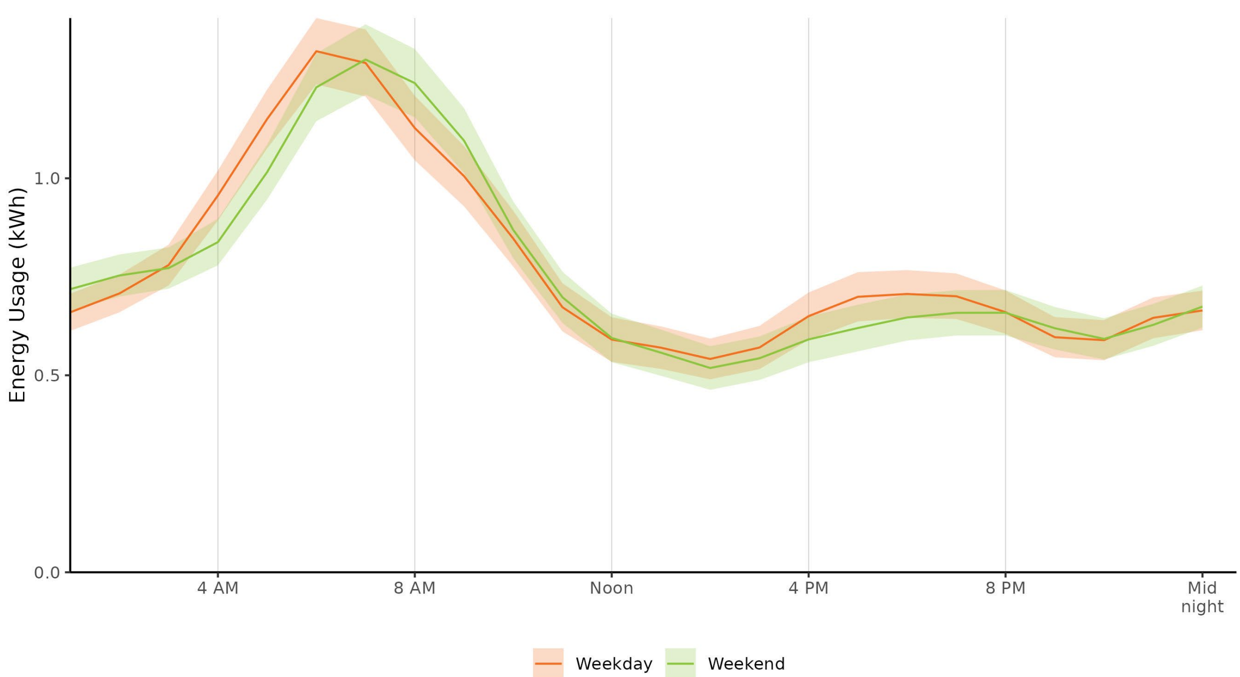


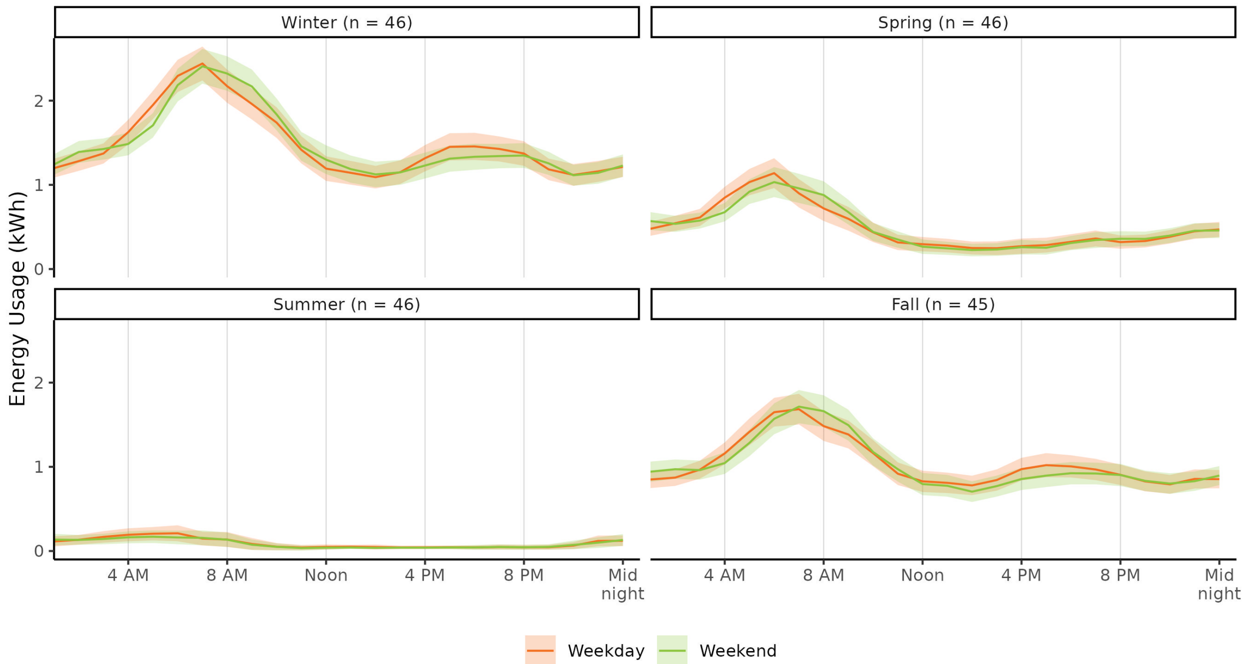

Figure 27 shows that standalone electric furnace load shapes are similar on weekdays and weekends, with some indication that there may be a slightly earlier peak on weekdays (though the difference is not statistically significant).

**Figure 27: Standalone Electric Forced Air Furnace Load Shapes – Weekdays vs Weekends**



Weekday and weekend load shapes for standalone furnaces are consistent across seasons, as shown in Figure 28.

**Figure 28: Standalone Electric Forced Air Furnace Load Shapes – Weekdays vs Weekends, by Season**



## Backup Electric Forced Air Furnaces

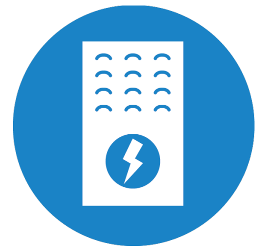


Figure 29 shows the load shape of electric forced air furnaces that serve as backup systems to ducted heat pumps. The load shape is based on data from 89 furnaces. In general, backup electric forced air furnaces have a similar morning peak to standalone electric furnaces, but at a lower magnitude.

**Figure 29: Backup Electric Forced Air Furnace Load Shapes – Overall (n=89)**

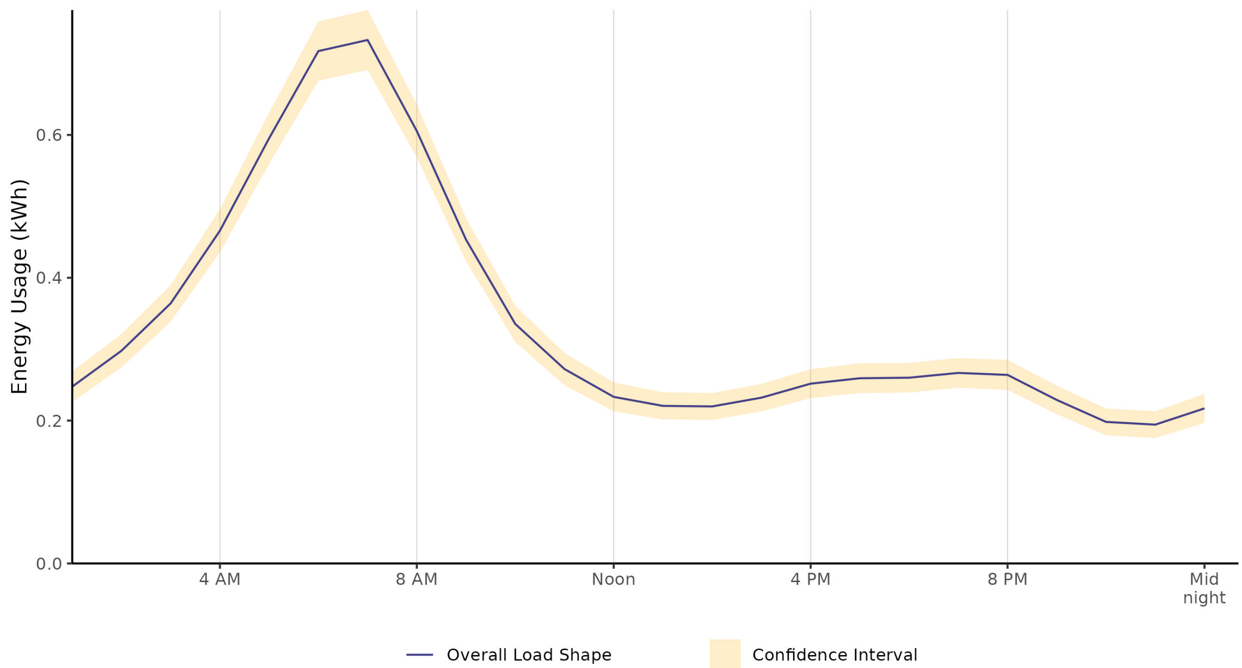



Figure 30 shows that backup electric forced air furnace load shapes for each season are likewise similar to standalone electric furnaces. The greatest usage is in the winter, with less usage in the shoulder seasons (spring and fall) and nearly no usage in the summer.

**Figure 30: Backup Electric Forced Air Furnace Load Shapes – By Season**

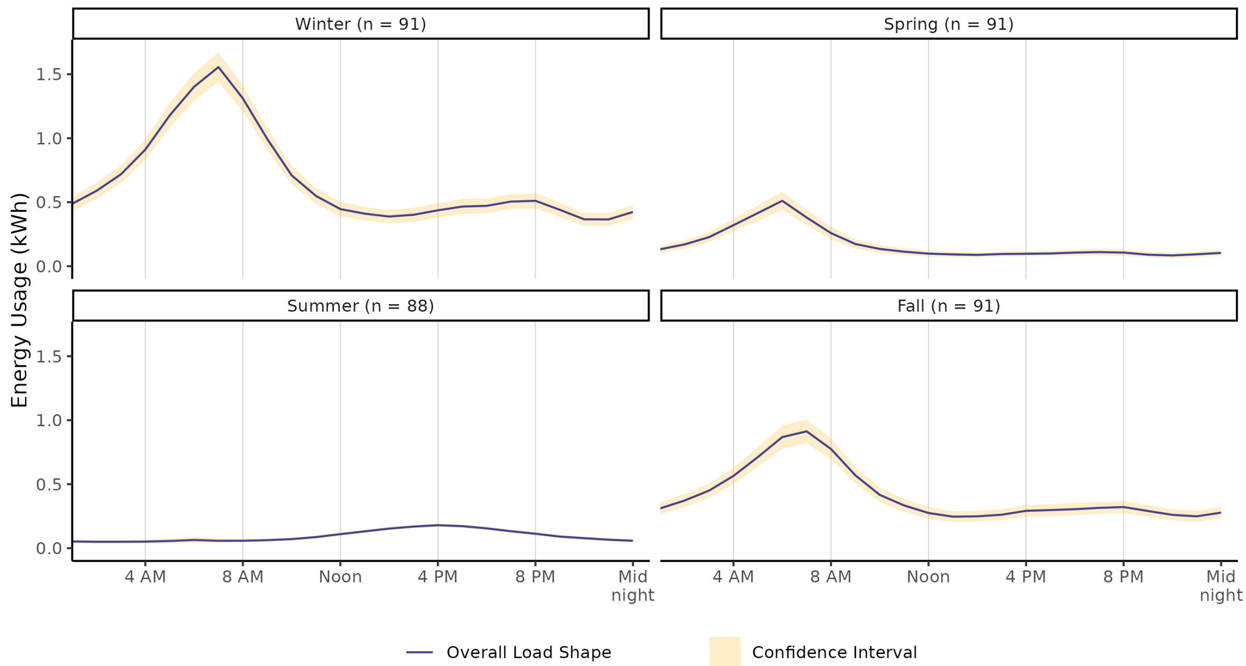



Figure 31 demonstrates that the overall load shape of backup electric furnaces on weekdays is consistent with the load shapes on weekends.

**Figure 31: Backup Electric Forced Air Furnace Load Shapes – Weekdays vs Weekends**

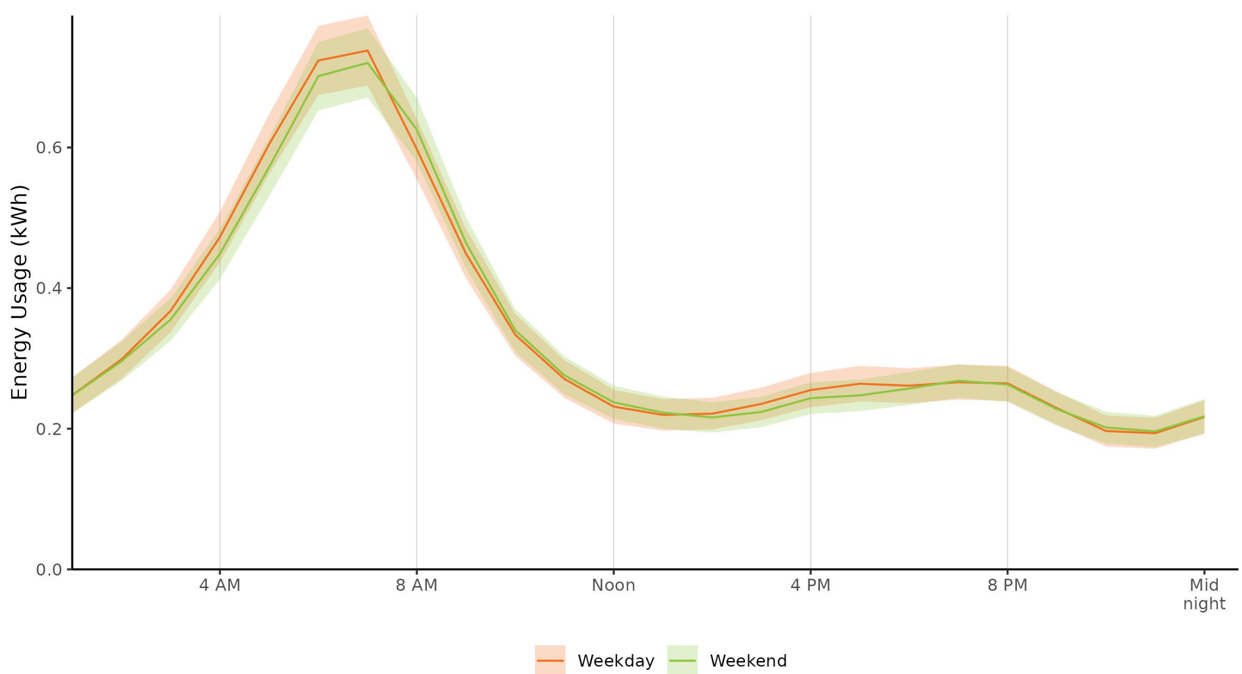
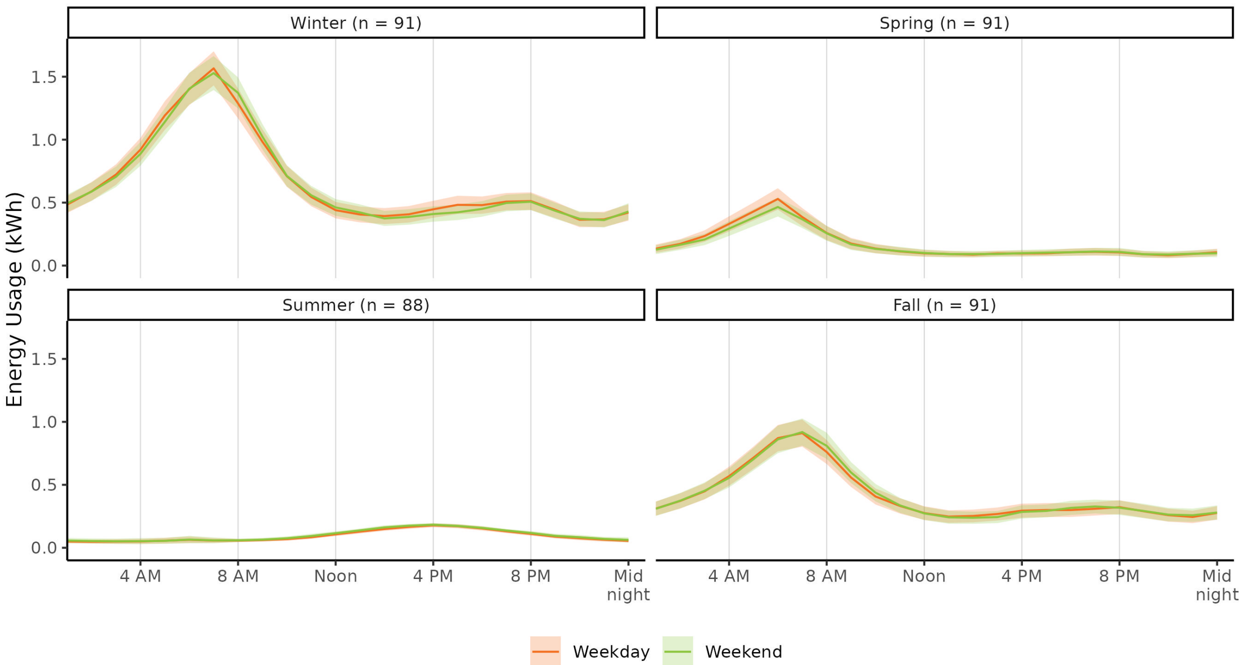


Figure 32 shows that for each season, the weekday and weekend load shapes are similar for backup electric furnaces.

**Figure 32: Backup Electric Forced Air Furnace Load Shapes – Weekdays vs Weekends, by Season**



## Central Air Conditioners

Figure 33 shows the overall load shape for central air conditioners (ACs), which is based on analysis from 132 ACs across the Northwest. As shown, cooling loads ramp up throughout the afternoon with peak usage occurring between 4 p.m. and 5 p.m.

**Figure 33: Central Air Conditioner Load Shape – Overall (n=132)**

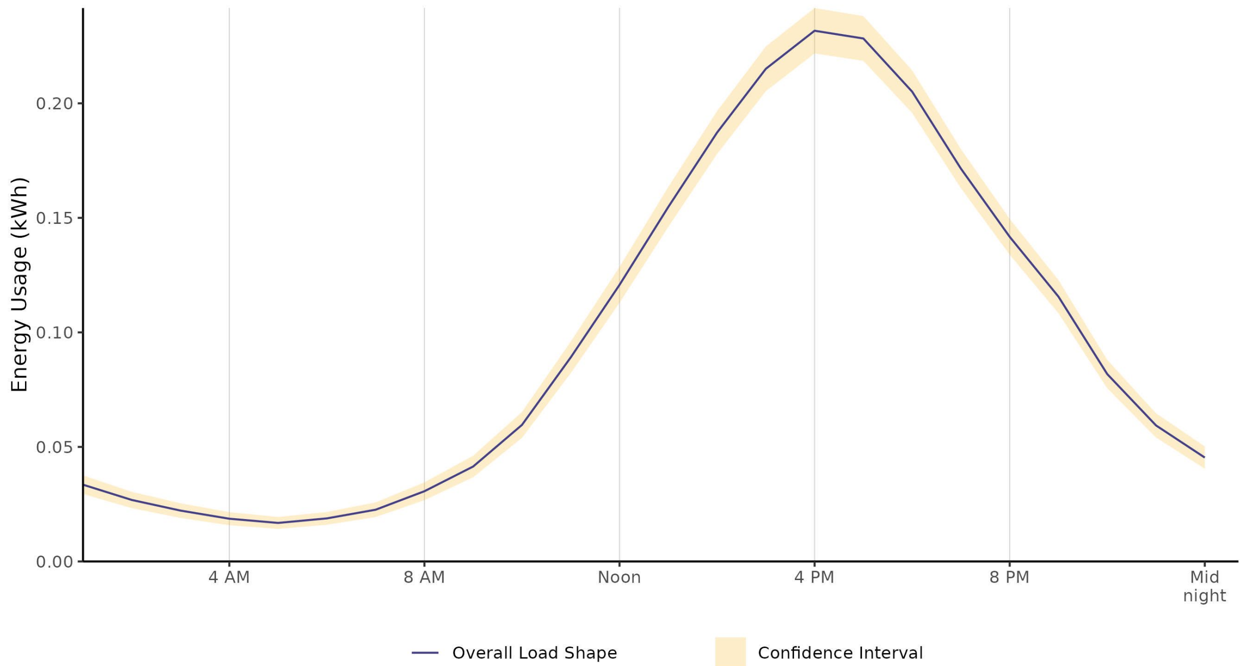
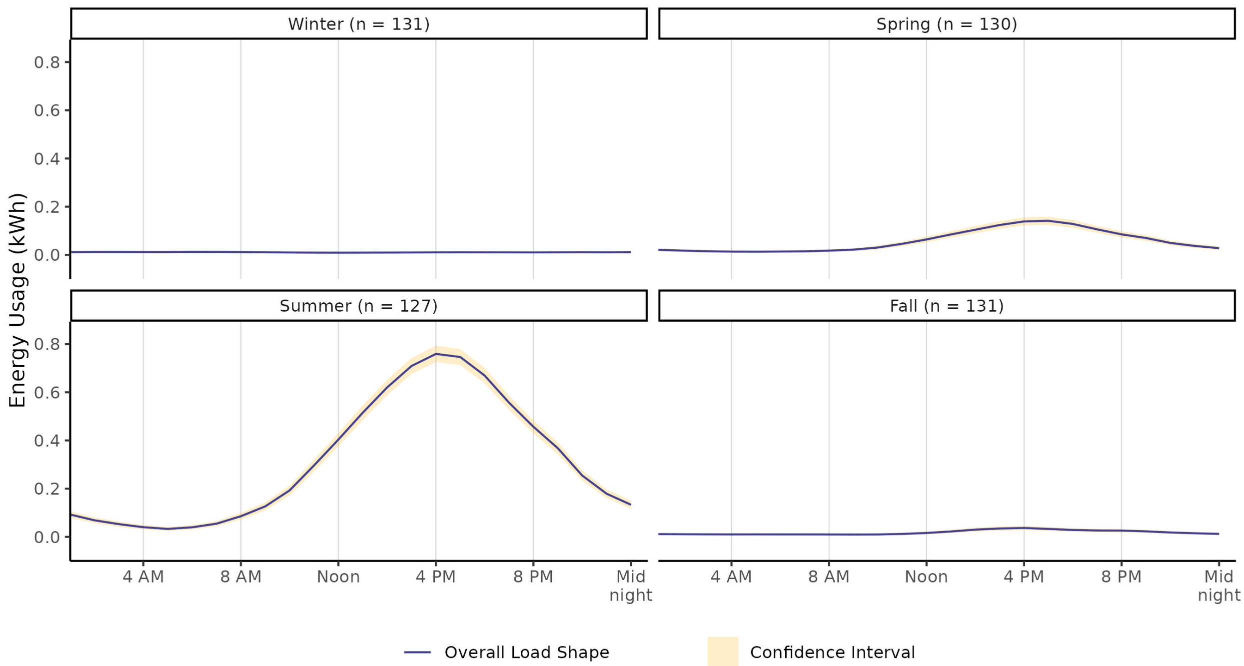



Figure 34 shows that ACs are primarily used in the summer, with some usage in the spring. This is expected as they only provide cooling and are therefore rarely used in winter and fall.

**Figure 34: Central Air Conditioner Load Shapes – By Season**




Central AC load shapes are consistent across weekdays and weekends, with some indication in Figure 35 that the 4 p.m. peak on weekends is slightly greater than the 4 p.m. peak on weekdays (though the difference is not statistically significant).

**Figure 35: Central Air Conditioner Load Shapes – Weekdays vs Weekends**

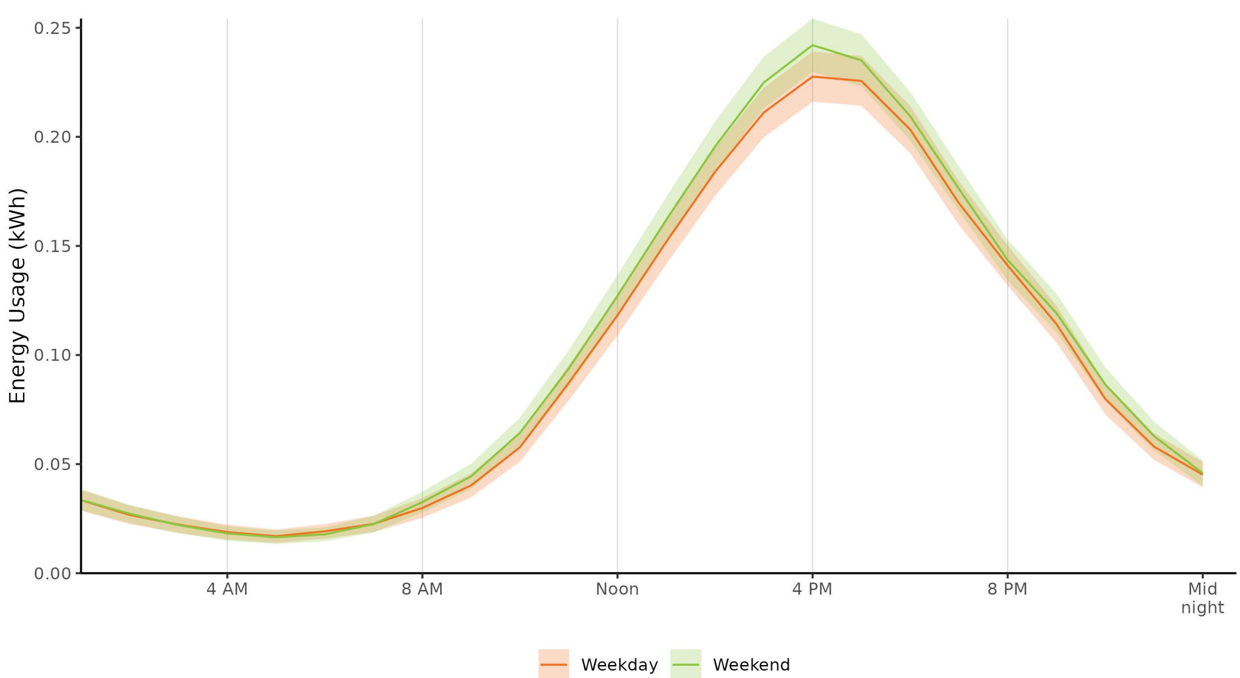
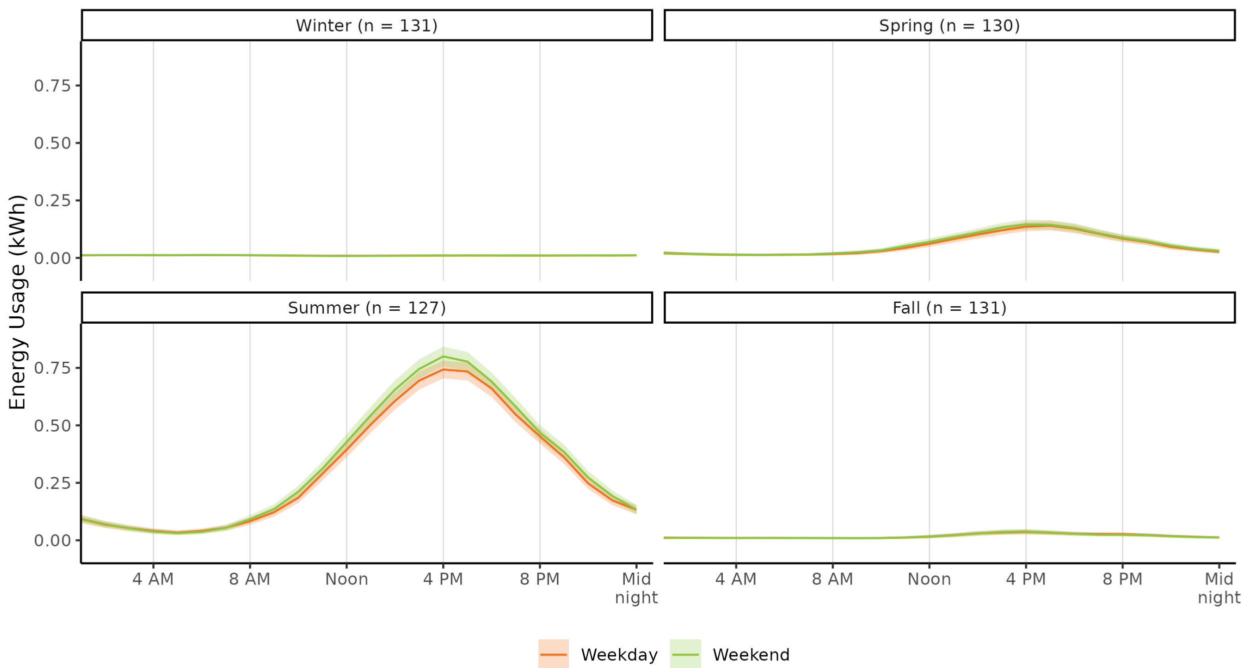


Figure 36 shows that seasonal central AC load shapes do not vary between weekdays and weekends, although in the summer the afternoon peak on weekends may be slightly greater than on weekdays (the difference is not statistically significant).

**Figure 36: Central Air Conditioner Load Shapes – Weekdays vs Weekends, by Season**



## Electric Baseboard Heaters

Figure 37 shows the load shape estimate from analysis of 184 electric baseboard heaters in 76 homes in the Northwest (this is an average of 2.4 baseboards per home). Electric baseboard heaters are used infrequently and only serve specific rooms or areas, and their load shapes are small in magnitude. This is likely due to the homes using other sources of heat for their primary heating. As with furnaces and other heating equipment, the peak is in the morning.

**Figure 37: Electric Baseboard Heater Load Shape – Overall (n=184)**

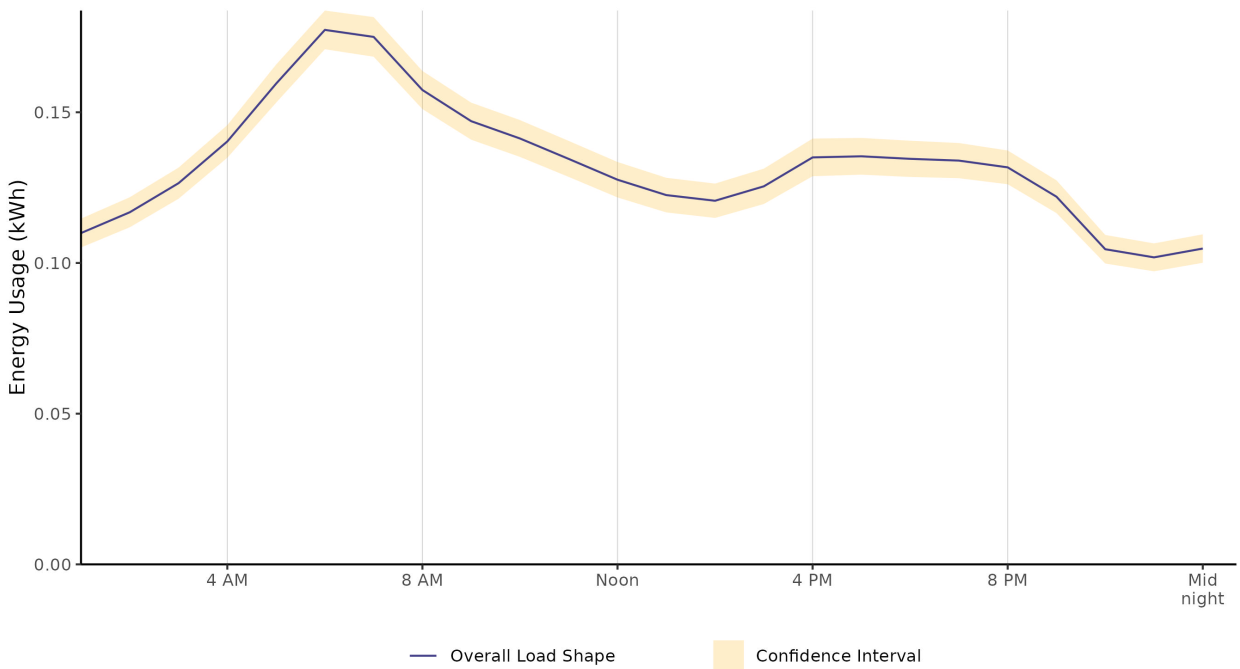



Figure 38 presents generalized load shapes by season. As expected, the greatest usage comes in the winter months, and there is moderate heating load during the shoulder seasons.

**Figure 38: Electric Baseboard Heater Load Shapes – By Season**

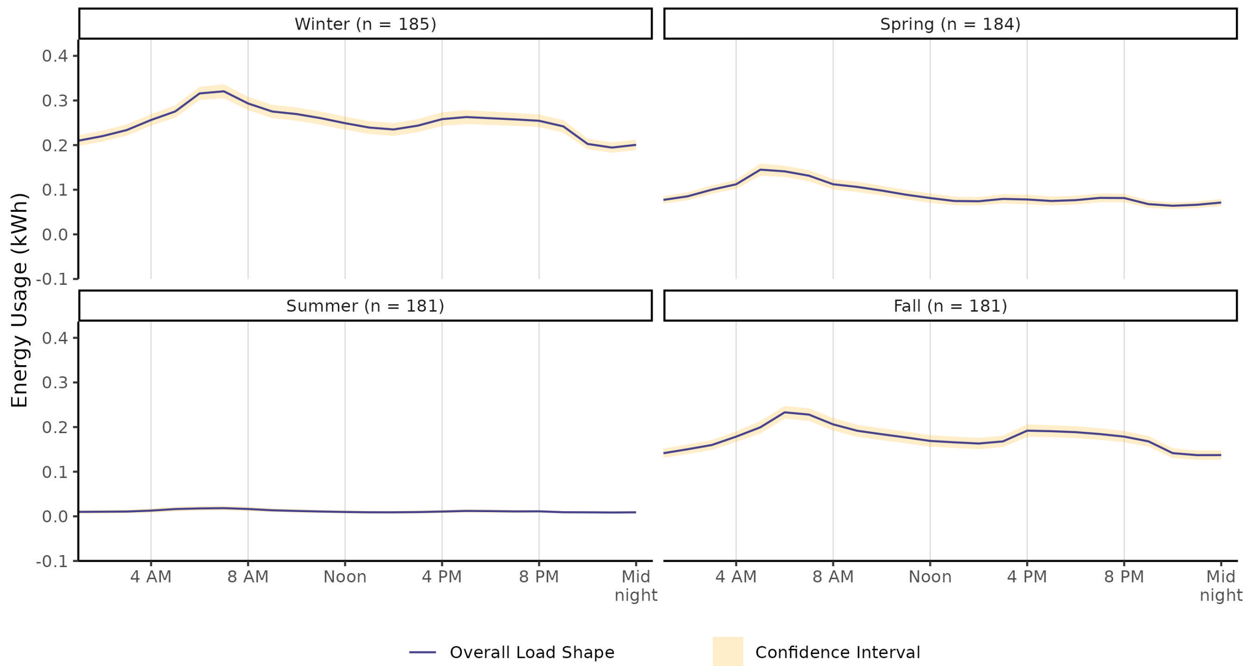
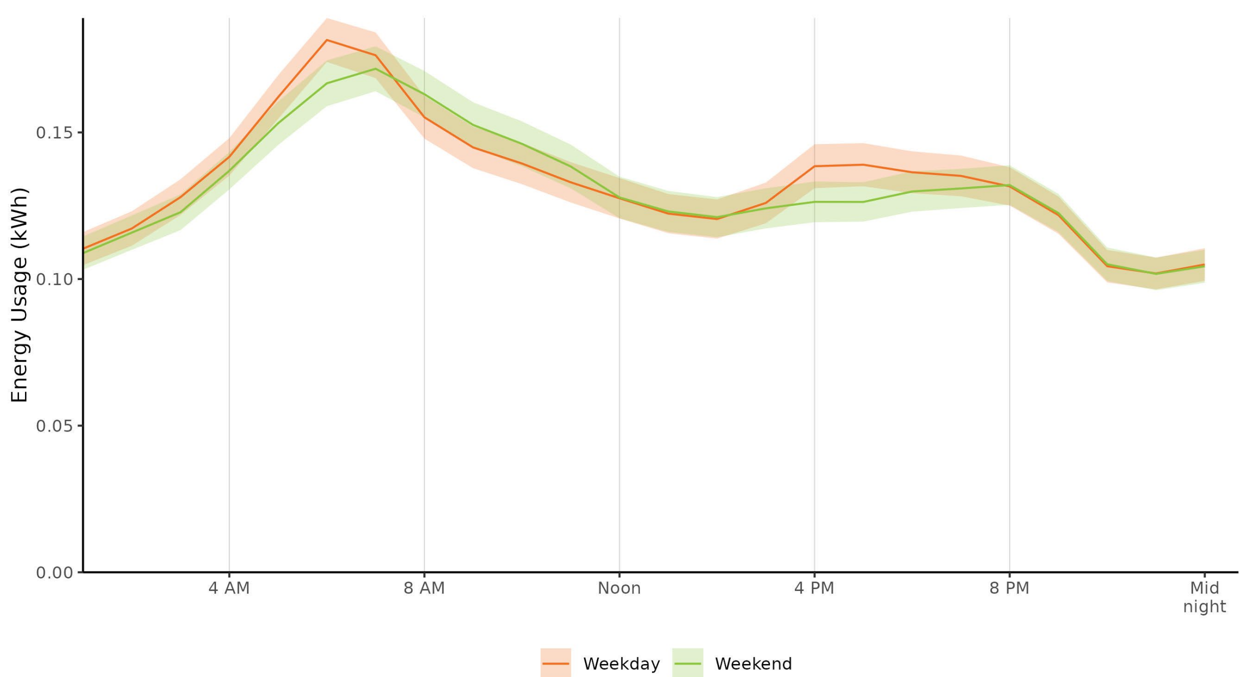


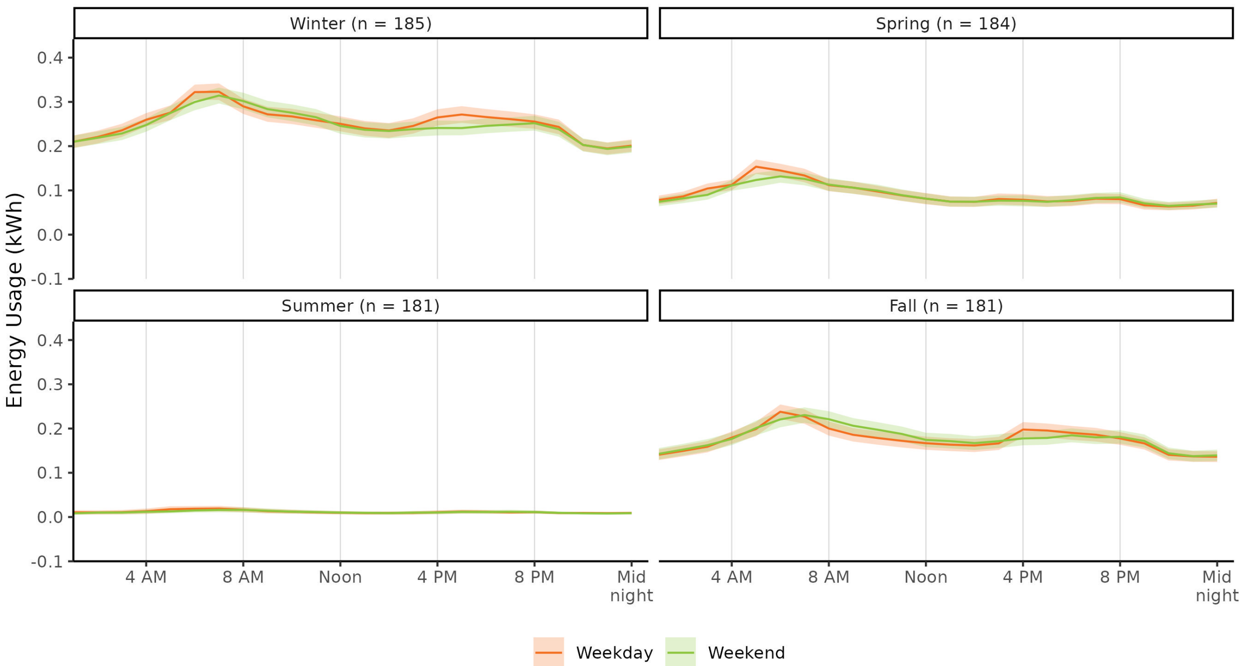

Figure 39 shows that the weekday morning peak (6 a.m. to 7 a.m.) and the weekday evening peak (4 p.m. to 7 p.m.) might be slightly higher than on weekends, but the differences are not statistically significant.

**Figure 39: Electric Baseboard Heater Load Shapes – Weekdays vs Weekends**



The seasonal comparison of weekday and weekend baseboard heater load shapes in Figure 40 shows that the weekday morning peak may be slightly earlier and larger in winter, spring, and fall, and the weekday afternoon peak may be greater in winter and fall (though all differences are not statistically significant).

**Figure 40: Electric Baseboard Heater Load Shapes – Weekdays vs Weekends, by Season**



## Electric Resistance Storage Water Heaters

As shown in Figure 41, the electric resistance storage water heater load shape (based on 202 water heaters) has two daily peaks—one in the early morning (6 a.m. to 8 a.m.) and another in the evening (6 p.m. to 9 p.m.). Energy use remains low overnight and drops somewhat in the middle of the day.

**Figure 41: Electric Resistance Storage Water Heater Load Shape – Overall (n=202)**

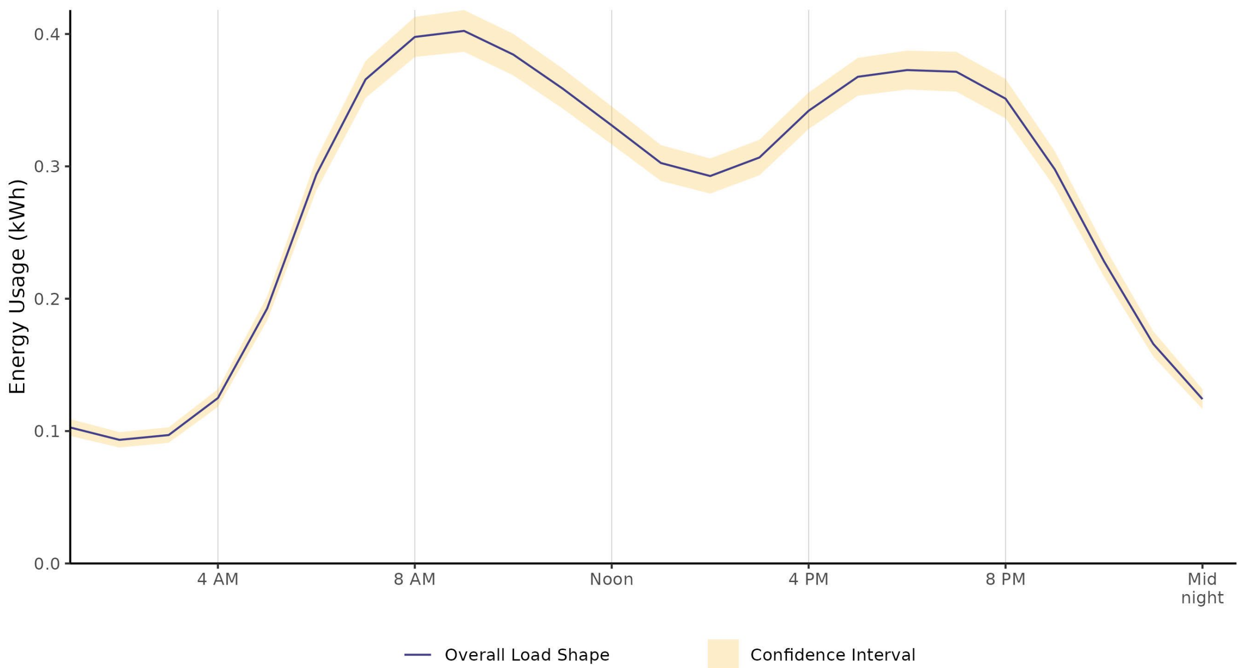



Figure 42 illustrates the seasonal variation in electric resistance storage water heater load shapes. While winter usage is highest, spring and fall are characterized by similar load shapes at slightly reduced magnitudes. Summer usage declines overall, with smaller peaks. Despite seasonal differences in load magnitude, the two-peak daily profile persists across all seasons.

**Figure 42: Electric Resistance Storage Water Heater Load Shapes – By Season**

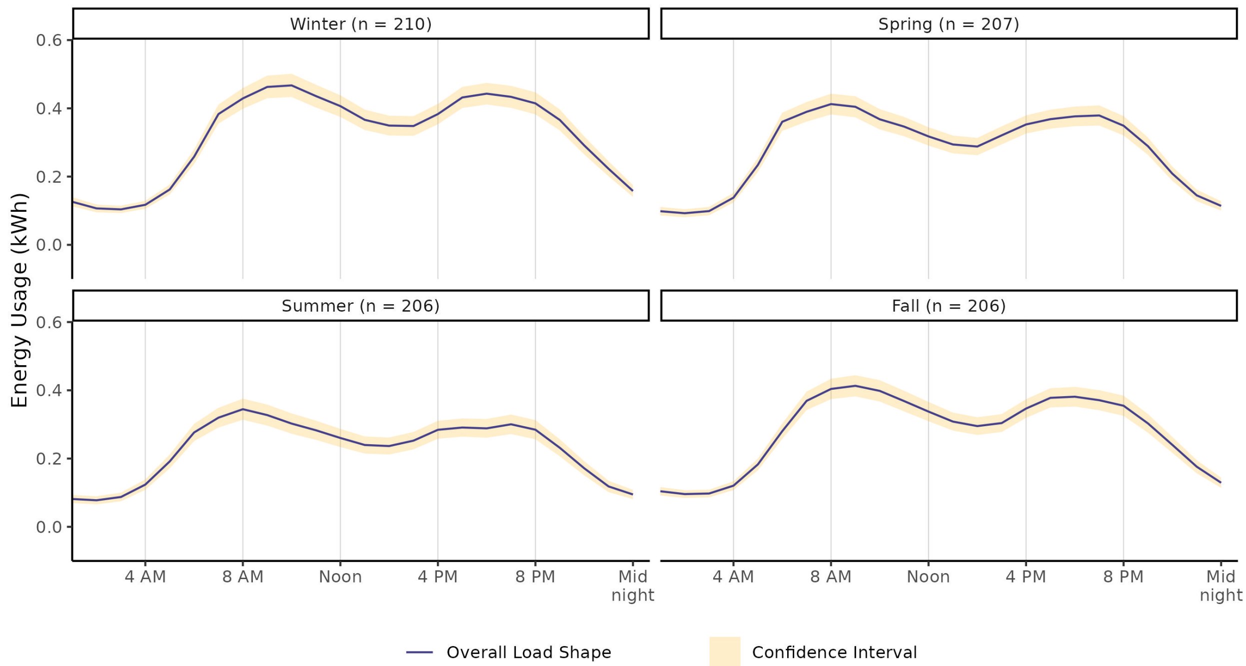



Figure 43 compares weekday and weekend load shapes for electric resistance storage water heaters. Weekday load shapes show slightly earlier morning peaks (around 8 a.m.) and lower mid-day energy use, while weekend load shapes have a later morning peak (around 9 a.m.). Evening peaks are consistent between weekdays and weekends.

**Figure 43: Electric Resistance Storage Water Heater Load Shapes – Weekdays vs Weekends**

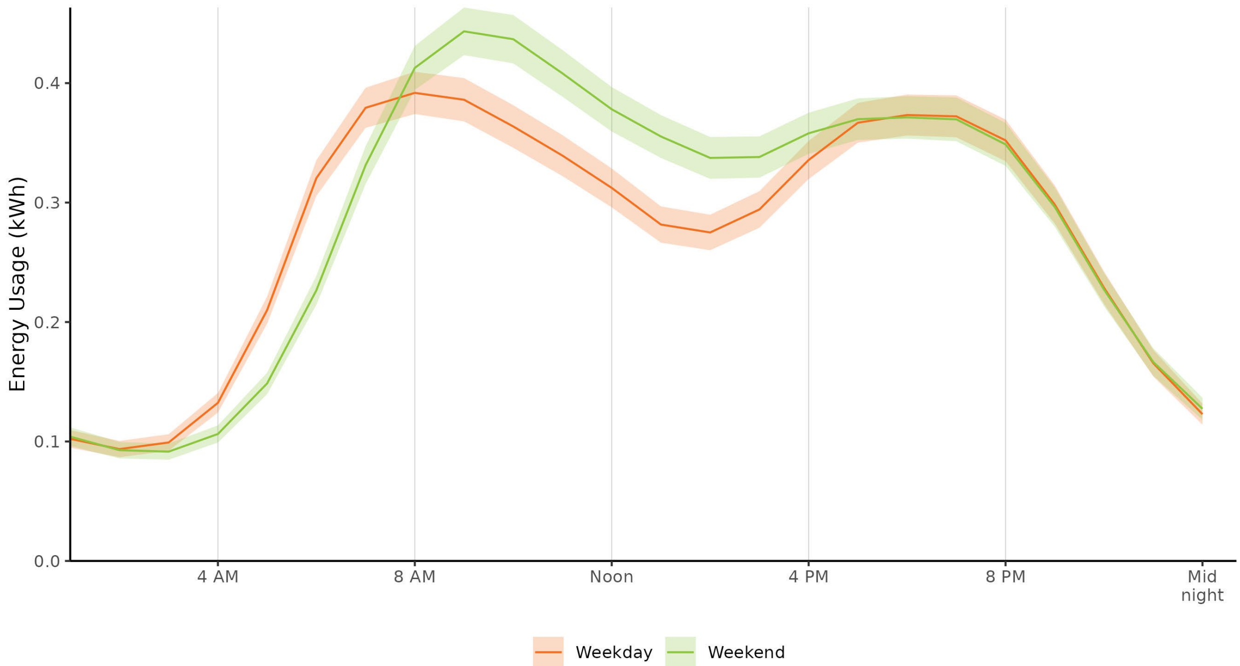
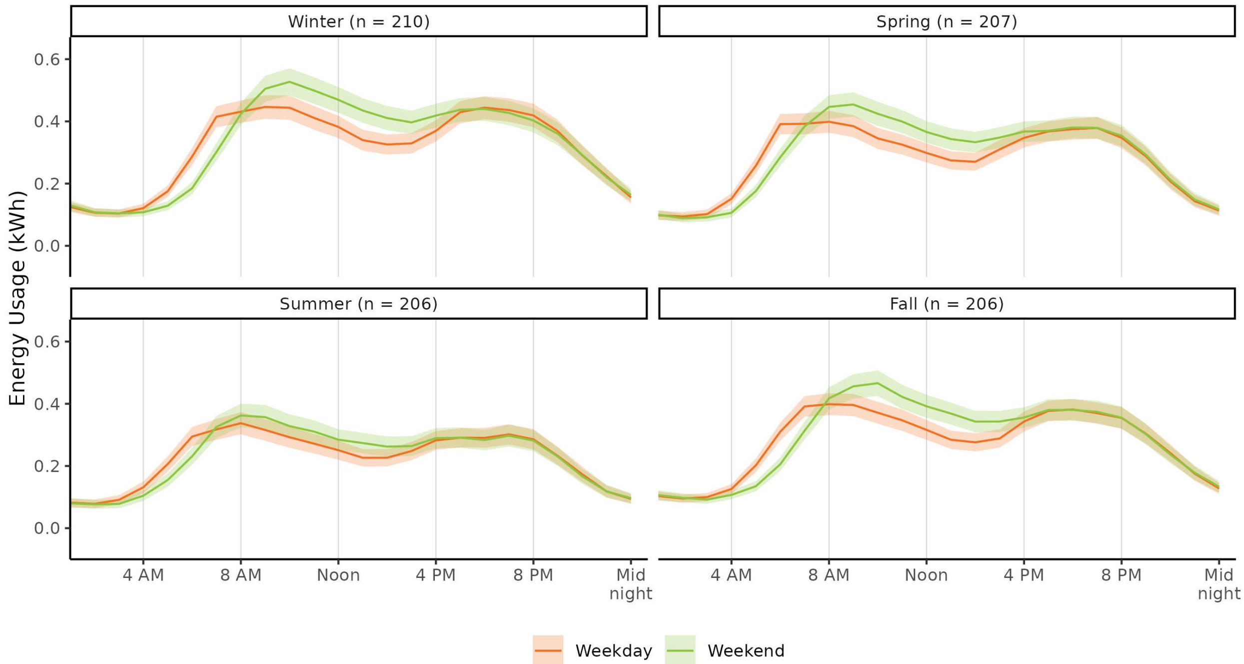



Figure 44 shows weekday versus weekend load shapes split by season. Across all seasons, the weekday morning peak occurs earlier than on weekends, though less so in summer. Seasonal differences remain similar to the overall pattern with higher loads in winter and lower in summer and a consistent two-peak profile across all combinations of season and day type.

**Figure 44: Electric Resistance Storage Water Heater Load Shapes – Weekdays vs Weekends, by Season**



# COVID-19 Comparison Load Shape Analysis

This chapter provides whole home and priority end use load shape estimates comparing the pre-COVID-19 pandemic, pandemic, and post-pandemic time periods.

This includes estimating **load shapes based on pre-COVID data as well as load shapes from during and after the COVID-19 pandemic**. Pre-COVID energy usage models were built using pre-pandemic energy usage data and represent the expected load shapes for these customers if the COVID-19 pandemic had not occurred. All load shapes have been normalized based to TMYx in this analysis. This analysis includes 95 percent confidence intervals around predictions.

When the confidence interval of a period was outside the confidence interval of another, it was determined that usage was significantly different between those two time periods. Pre-COVID load shapes are represented in orange, load shapes from during the pandemic are represented in green, and load shapes from after the pandemic ended are purple. Results have been weighted to represent the population of each targeted end use based on the 2022 RBSA.

Findings regarding changes in energy consumption are only *correlated* with the pandemic; other factors may have also influenced the observed changes in energy consumption. Lastly, heat pump water heaters were excluded from this analysis because the sample of heat pump water heaters with sufficient pre-, during, and post-pandemic data was too small to be meaningful (n=3).

## COVID-19 Comparison Load Shapes

The figures in this section show load shapes for the pre-pandemic period (orange), the period during the pandemic (green), and the period since COVID-19 was declared to be no longer a public health emergency, or post-pandemic (purple).

Figure 45 shows that the pandemic may have induced lasting change in how much energy is used by homes in the Northwest. For the homes included in this analysis, there is greater usage in the middle of the day (around noon) and overnight since the start of the pandemic that has persisted in the post-pandemic period. Slight differences in the load shapes at other hours are not statistically different. Lastly, the post-pandemic load shape does not capture more recent trends in employers calling more employees back to work (i.e., in offices).

**Figure 45: COVID-19 Impacts on Whole Home Load Shapes (n=40)**

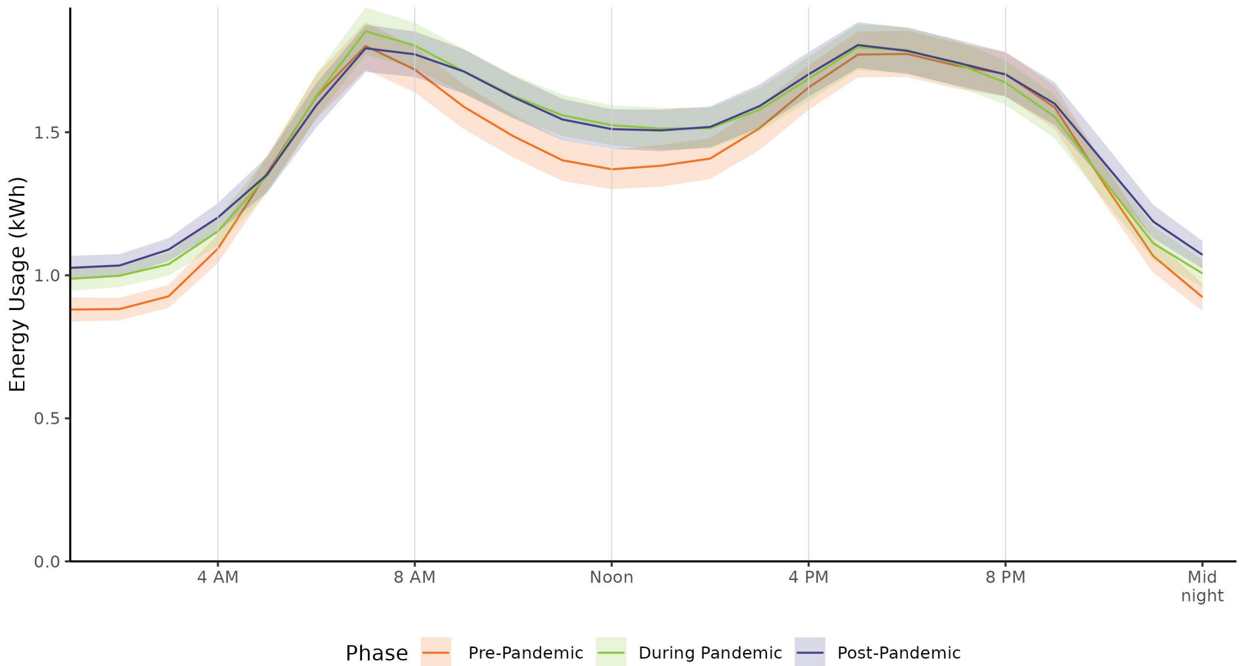



Figure 46 compares the load shapes of ducted heat pumps, and indicates that morning, afternoon, and late evening (9 p.m. to midnight) usage is different now than prior to the pandemic. Interestingly, the load shapes from before the pandemic and during the pandemic are very similar except in the morning hours (6 a.m. to 9 a.m.). It is unclear why the load shape changed more during the post-pandemic period than during the pandemic.

**Figure 46: COVID-19 Impacts on Ducted Heat Pump Load Shapes (n=31)**

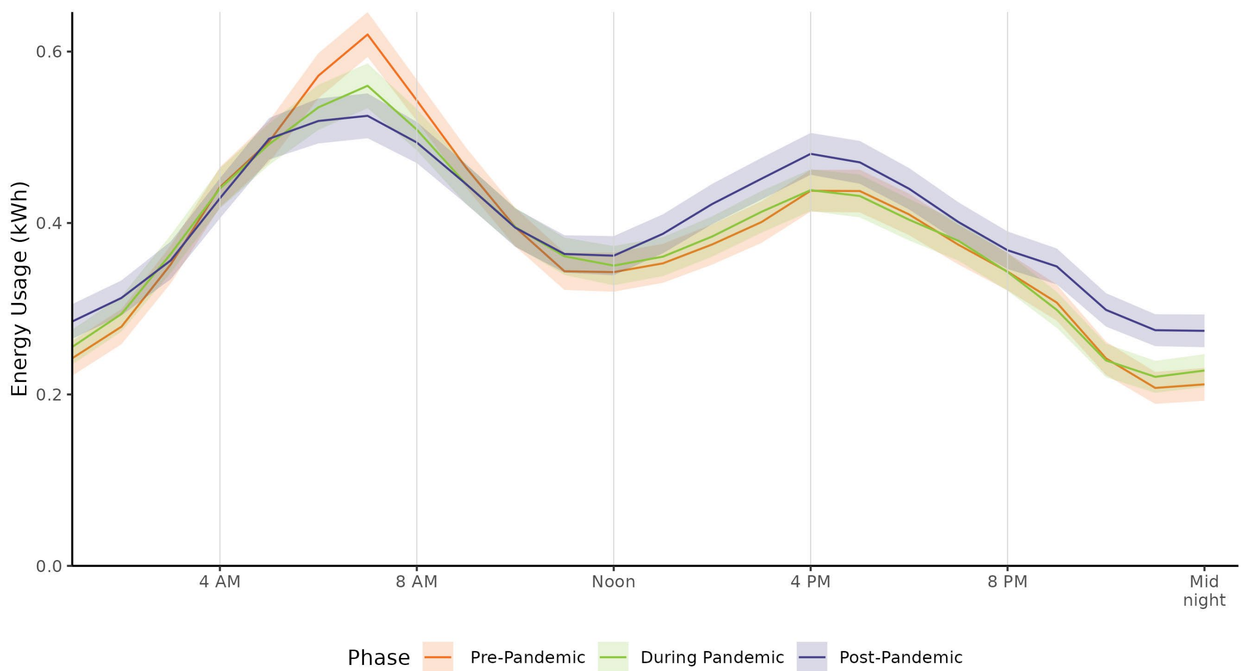



Figure 47 indicates that ductless heat pumps may be used less often since the start of the pandemic. This may be the result of relying more heavily on central heating and cooling systems in these homes. However, this analysis is based on a small sample of ductless heat pumps (n=13).

**Figure 47: COVID-19 Impacts on Ductless Heat Pump Load Shapes (n=13)**

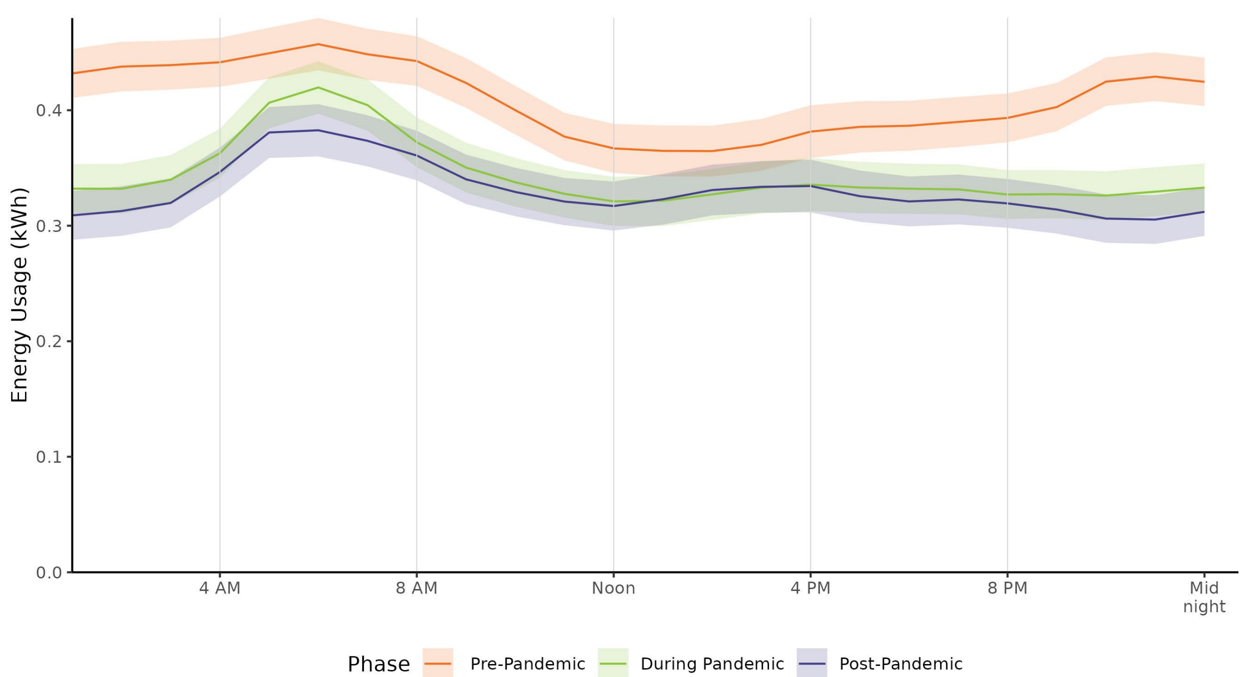
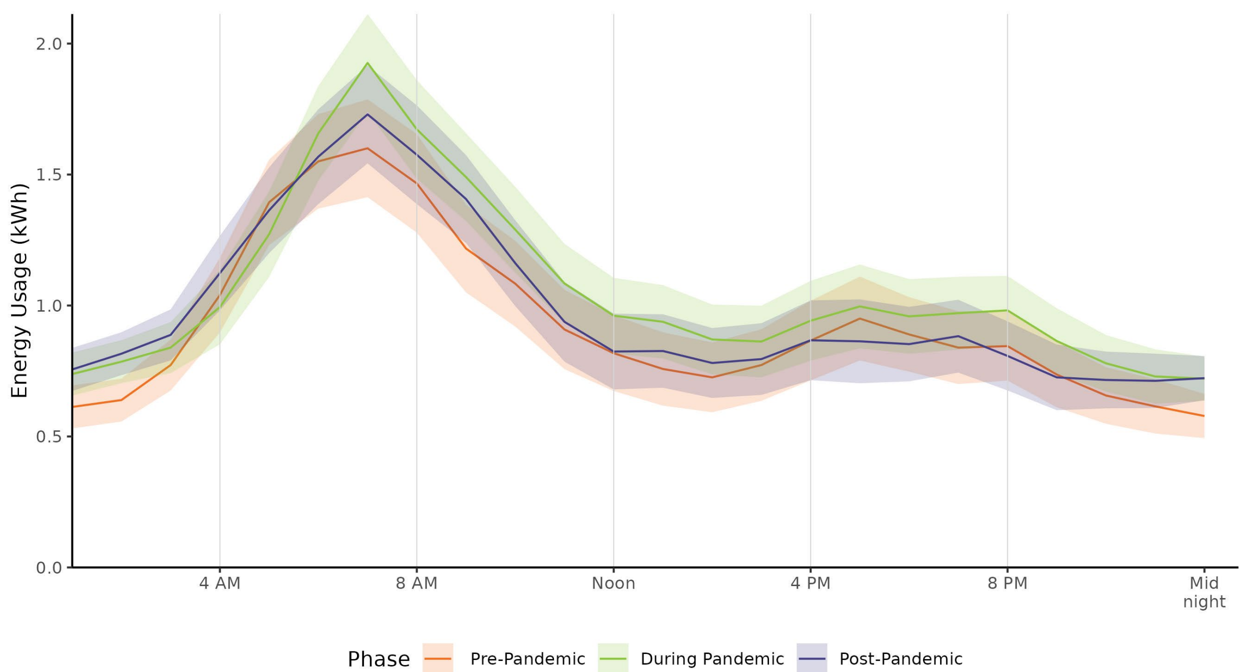


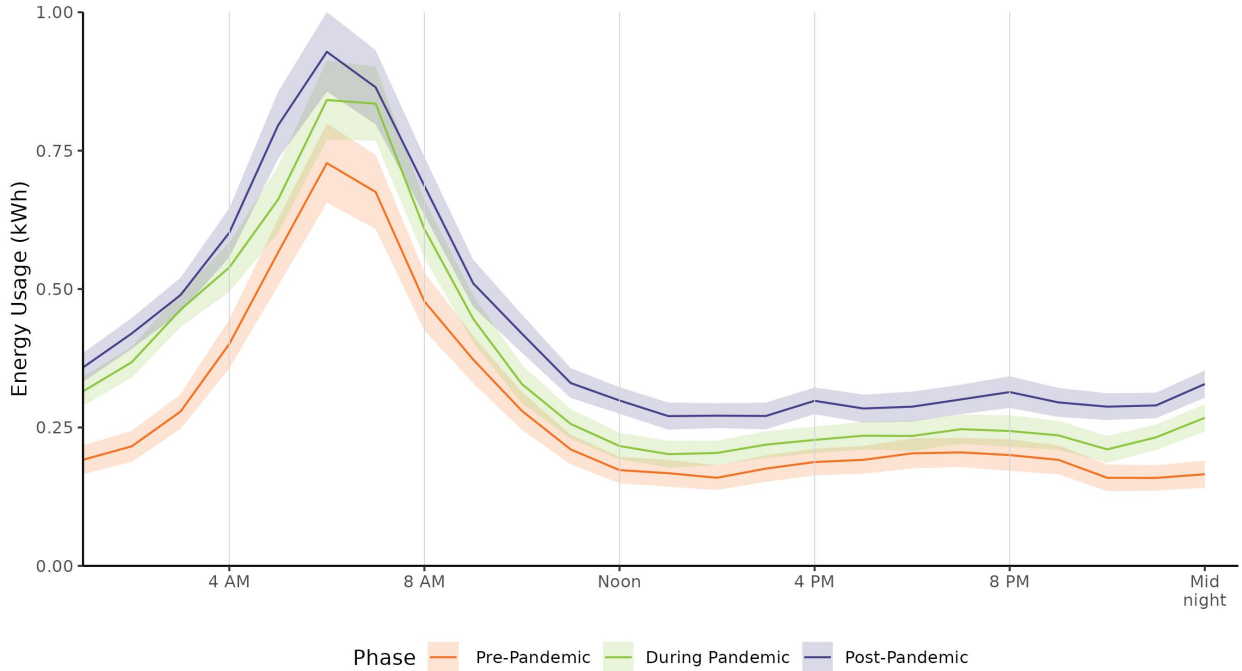
Figure 48 shows that the load shape for standalone forced air furnaces at the homes included in this analysis exhibited a higher morning peak during the pandemic than before, but that the peak is now more similar to pre-pandemic usage.

**Figure 48: COVID-19 Impacts on Standalone Forced Air Furnace Load Shapes (n=26)**



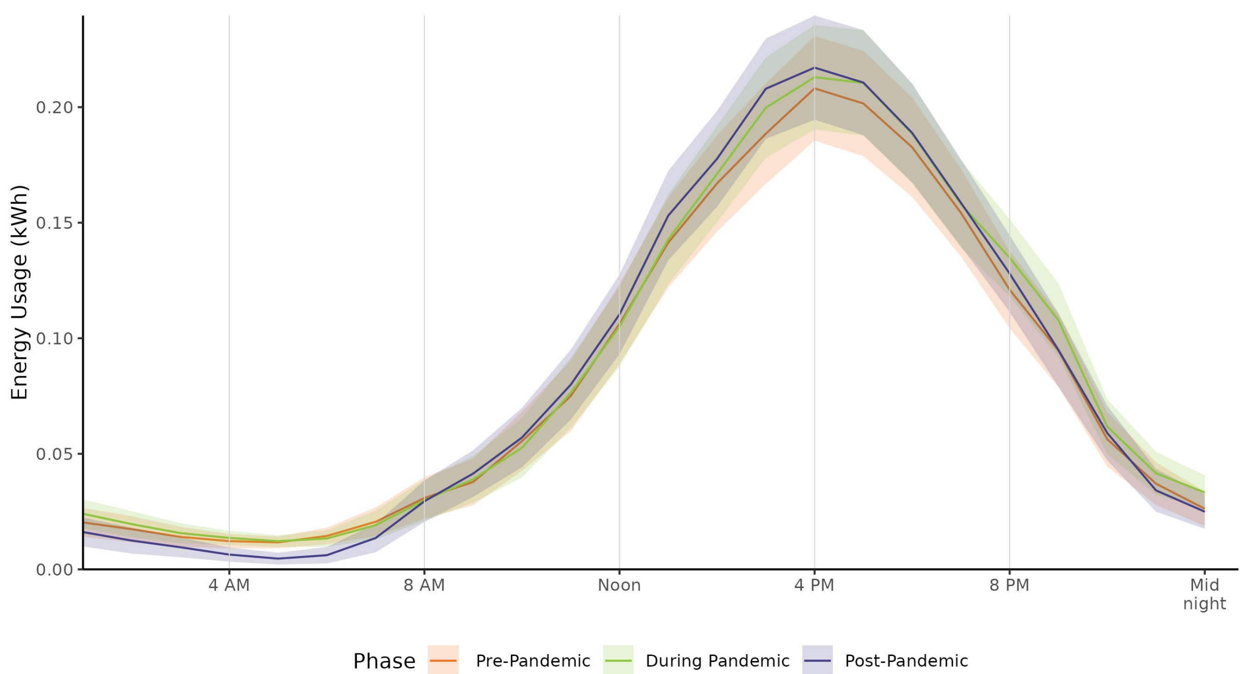

The backup furnace load shapes are shown in Figure 49, and indicate increased usage since the start of the pandemic, even increasing in the post-pandemic period.

**Figure 49: COVID-19 Impacts on Backup Forced Air Furnace Load Shapes (n=33)**



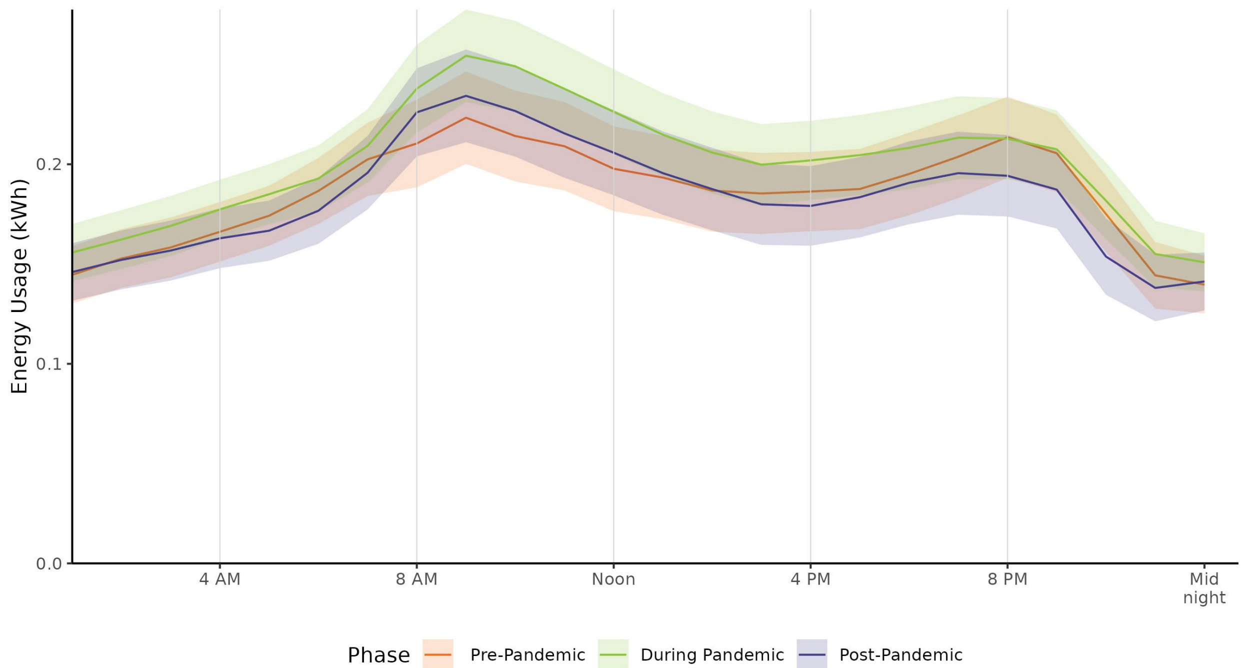

Central AC load shapes were mostly unimpacted by COVID-19, as shown in Figure 50. The afternoon peak remains essentially the same over time.

**Figure 50: COVID-19 Impacts on Central Air Conditioner Load Shapes (n=21)**



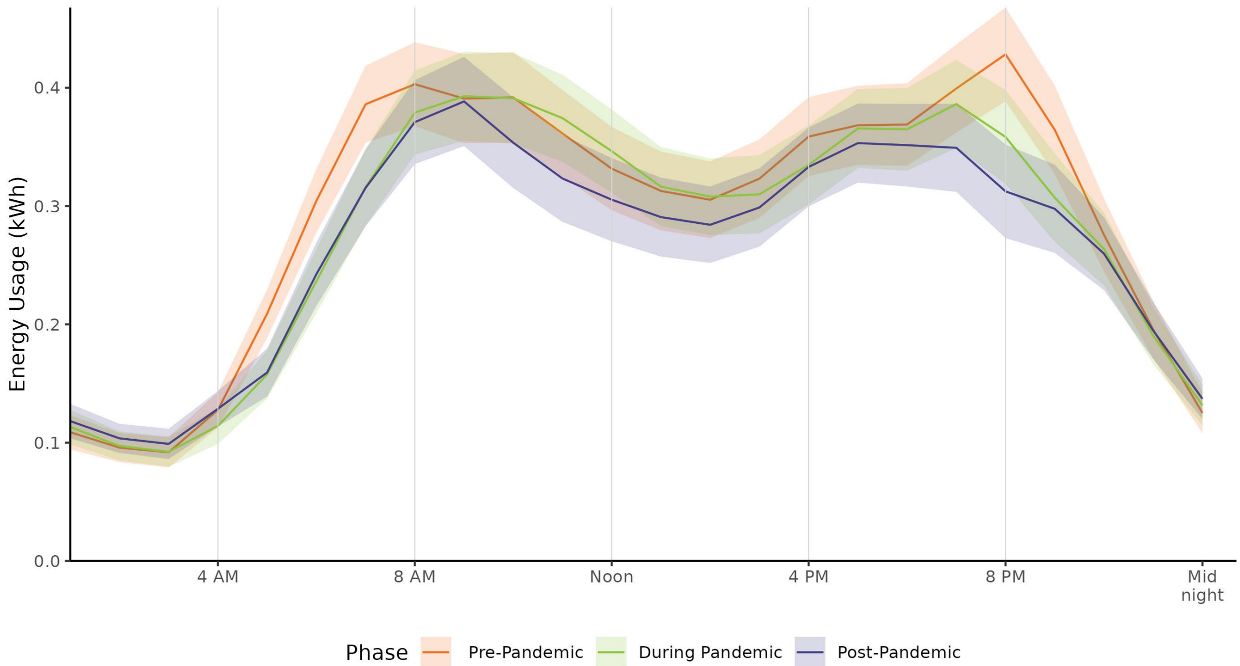
While the margin of error means there is nothing conclusive to say about changes in the electric baseboard heater load shape (Figure 51) due to the COVID-19 pandemic, there is some indication that they were used more in the morning and through midday during the pandemic than prior. That trend has reverted in the post-pandemic period to be more similar to the pre-pandemic period.

**Figure 51: COVID-19 Impacts on Electric Baseboard Heater Load Shapes (n=24)**




As shown in Figure 52 the morning ramp up in electric resistance storage water heater energy usage shifted slightly later during the COVID-19 pandemic, and this change has persisted in the post-pandemic period. This analysis also indicates that evening peak usage has decreased in the post-pandemic period relative to pre-pandemic usage levels (though not statistically significantly different). Overnight usage remains unchanged.

**Figure 52: COVID-19 Impacts on Electric Resistance Storage Water Heater Load Shapes (n=51)**



# Future Analyses

The data collected for the EULR HEMS are intended to support analysis beyond the scope of what is included in this report. The data are publicly available on NEEA's website (neea.org).

While not an exhaustive list, additional types of analyses that would be supported by the EULR HEMS data include:

- Load shape analysis of additional end uses beyond those included in this report.
- Weather normalized analysis using forecasted weather data based on climate change scenarios. This can be done at a "micro" level using publicly available data from Worldclim.[7]
- Measure-level energy savings analysis through comparing seasonal and/or annual energy use of baseline technologies versus efficient technologies (e.g., electric resistance storage water heater usage compared to heat pump water heater usage).
- For heat pump technologies, assessing the portion of heating or water heating load provided by the heat pump compressor versus electric resistance backup heating.
- Forecasting grid-level impacts of efficient technology adoption based on alternative forecasts of adoption rates of efficient technologies. Such an analysis could be paired with projections of local temperature data (as granular as 1 $km^2$) under various assumptions of climate change to understand how alternative adoption rates might mitigate the impacts of climate change on local temperatures across the Northwest.
- Assessing the potential impacts of load shifting in grid-constrained communities and sub-regions. This too could be paired with projections of potential local temperature to understand which areas in the Northwest may benefit the most from programs that promote load shifting through demand response or other programs.

These types of analyses are typically high cost due to the need to collect large volumes of granular end-use energy data. The EULR HEMS provides the data for free to support these—and other—analytical objectives.

[7] https://worldclim.org

# Appendix A: Data Quality Assurance and Quality Control

To ensure that incoming metering data would support rigorous analysis including the analysis presented here, Evergreen Economics employed a multi-stage quality assurance (QA) and quality control (QC) process on all metering data. While the primary goal of QA/QC is to ensure an accurate metering dataset, this was only possible through regular and thorough inspection of all incoming metering data. This approach consisted of four broad stages, each adding context to the data and providing new insights:

Stage 1: Data are checked to confirm that metering data are being received from all installed equipment. This simple check is critical, as there is no way to make use of data that were never collected in the first place.

Stage 2: Context is added by checking each individual observation against a set of predetermined expectations. A primary part of this process is to compare end uses to their industry standards for power and consumption.

Stage 3: The use of each piece of equipment is compared to how that piece of equipment has been used in the past. This enables us to confirm that changes in usage patterns are not being caused by metering equipment failure.

Stage 4: Individual data streams are contextualized with data from other sources to check the validity of each source. For example, this includes ensuring that indoor air temperature increases correspondingly and as expected with furnace usage.

Combined, these steps produce a robust metering dataset by showing that the real-world data meet expectations in multiple dimensions.

# Appendix B: EULR HEMS Sampling Overview

## Sample Sizes

The sample sizes for the overall load shapes for each of the four seasons are provided in Table 1 through Table 4, for the overall region and by climate zone.

**Table 1: Winter Analysis Sample Sizes by End Use, Total Region & by Climate Zone***

| | Homes with End Use | | |
|---|---|---|---|
| End Use | Total Region | Climate Zone 1 | Climate Zones 2 & 3 |
| Backup Electric Furnace | 89 | 67 | 22 |
| Central AC | 125 | 44 | 81 |
| Ducted Heat Pump | 124 | 97 | 27 |
| Ductless Heat Pump | 79 | 63 | 16 |
| Electric Baseboard Heater | 76 | 50 | 26 |
| Standalone Electric Furnace | 46 | 34 | 12 |
| Electric Resistance Storage Water Heater | 201 | 143 | 58 |
| Heat Pump Water Heater | 58 | 32 | 26 |

* Climate zone for Central AC is cooling zone; heating zone is used for all other end uses and the total.

**Table 2: Spring Analysis Sample Sizes by End Use, Total Region & by Climate Zone***

| End Use | Homes with End Use | | |
|---|---|---|---|
| | Total Region | Climate Zone 1 | Climate Zones 2 & 3 |
| Backup Electric Furnace | 89 | 67 | 22 |
| Central AC | 124 | 43 | 81 |
| Ducted Heat Pump | 122 | 97 | 25 |
| Ductless Heat Pump | 78 | 62 | 16 |
| Electric Baseboard Heater | 75 | 49 | 26 |
| Electric Furnace | 46 | 34 | 12 |
| Electric Resistance Storage Water Heater | 198 | 141 | 57 |
| Heat Pump Water Heater | 58 | 32 | 26 |

* Climate zone for Central AC is cooling zone; heating zone is used for all other end uses and the total.

**Table 3: Summer Analysis Sample Sizes by End Use, Total Region & by Climate Zone***

| End Use | Homes with End Use | | |
|---|---|---|---|
| | Total Region | Climate Zone 1 | Climate Zones 2 & 3 |
| Backup Electric Furnace | 86 | 66 | 20 |
| Central AC | 121 | 43 | 78 |
| Ducted Heat Pump | 119 | 95 | 24 |
| Ductless Heat Pump | 76 | 61 | 15 |
| Electric Baseboard Heater | 75 | 49 | 26 |
| Electric Furnace | 46 | 34 | 12 |
| Electric Resistance Storage Water Heater | 197 | 141 | 56 |
| Heat Pump Water Heater | 57 | 32 | 25 |

* Climate zone for Central AC is cooling zone; heating zone is used for all other end uses and the total.

**Table 4: Fall Analysis Sample Sizes by End Use, Total Region & by Climate Zone***

| End Use | Homes with End Use | | |
|---|---|---|---|
| | Total Region | Climate Zone 1 | Climate Zones 2 & 3 |
| Backup Electric Furnace | 88 | 67 | 21 |
| Central AC | 125 | 44 | 81 |
| Ducted Heat Pump | 121 | 95 | 26 |
| Ductless Heat Pump | 77 | 62 | 15 |
| Electric Baseboard Heater | 75 | 49 | 26 |
| Electric Furnace | 45 | 33 | 12 |
| Electric Resistance Storage Water Heater | 197 | 141 | 56 |
| Heat Pump Water Heater | 58 | 32 | 26 |

* Climate zone for Central AC is cooling zone; heating zone is used for all other end uses and the total.

# Population Statistics and Sampling Weights

The load shapes that were developed for each of the targeted end uses are intended to represent the population of households with that end use. Weights were developed that were applied to each end use and site prior to analysis.

Evergreen set recruitment targets for the EULR study by end use, and did not oversample by climate zone, region, or any other factor.

When the 2016-17 RBSA did not have sufficient contacts to fulfill the target sample allocation for a given end use, additional recruitment sources were identified on which to draw. These included heat pump water heater and ductless heat pump rebate incentive tracking databases from NEEA's partners. Evergreen also leveraged the 2022 RBSA to identify additional contacts for recruitment.

Table 5 provides an estimated count of homes and end uses by climate zone, based on the 2022 RBSA. This is the best estimate of the population of Northwest homes with targeted end uses.

**Table 5: Estimated Count of Homes with Targeted End Use, Total Region and by Climate Zone***

| | Homes with End Use | | |
|---|---|---|---|
| End Use | Total Region | Climate Zone 1 | Climate Zones 2 & 3 |
| Backup Electric Furnace | 336,249 | 259,970 | 76,279 |
| Central AC | 1,263,512 | 482,179 | 781,333 |
| Ducted Heat Pump | 758,846 | 604,789 | 154,057 |
| Ductless Heat Pump | 590,468 | 479,621 | 110,847 |
| Electric Baseboard Heater | 1,200,217 | 944,191 | 256,026 |
| Electric Furnace | 242,916 | 141,589 | 101,327 |
| Electric Resistance Storage Water Heater | 2,787,499 | 2,136,160 | 651,339 |
| Heat Pump Water Heater | 151,160 | 114,670 | 36,490 |

Source: Evergreen analysis of 2022 RBSA Combined Database, with case weights developed by Evergreen Economics.
* Climate zone for Central AC is cooling zone; heating zone is used for all other end uses and the total.

The weights are based on the number of homes with each end use represented in the sample versus the 2022 RBSA estimate of the population by climate zone. Table 6 through Table 9 show the weights for each of the end uses by climate zone for each of the four seasons for the overall load shape analysis.

**Table 6: Winter Analysis End Use Weights by Climate Zone***

| End Use | Climate Zone 1 | Climate Zone 2 | Climate Zone 3 |
|---|---|---|---|
| Backup Electric Furnace | 1.027 | 0.918 | 0.918 |
| Central AC | 1.084 | 0.954 | 0.954 |
| Ducted Heat Pump | 1.019 | 0.932 | 0.932 |
| Ductless Heat Pump | 1.019 | 0.927 | 0.927 |
| Electric Baseboard Heaters | 1.000 | 1.000 | 1.000 |
| Electric Furnace | 0.789 | 1.599 | 1.599 |
| Electric Resistance Storage Water Heater | 1.077 | 0.810 | 0.810 |
| Heat Pump Water Heater | 1.375 | 0.539 | 0.539 |

* Climate zone for Central AC is cooling zone; heating zone is used for all other end uses.

**Table 7: Spring Analysis End Use Weights by Climate Zone***

| End Use | Climate Zone 1 | Climate Zone 2 | Climate Zone 3 |
|---|---|---|---|
| Backup Electric Furnace | 1.027 | 0.918 | 0.918 |
| Central AC | 1.100 | 0.947 | 0.947 |
| Ducted Heat Pump | 1.002 | 0.991 | 0.991 |
| Ductless Heat Pump | 1.022 | 0.915 | 0.915 |
| Electric Baseboard Heaters | 1.000 | 1.000 | 1.000 |
| Electric Furnace | 0.789 | 1.599 | 1.599 |
| Electric Resistance Storage Water Heater | 1.076 | 0.812 | 0.812 |
| Heat Pump Water Heater | 1.375 | 0.539 | 0.539 |

* Climate zone for Central AC is cooling zone; heating zone is used for all other end uses.

**Table 8: Summer Analysis End Use Weights by Climate Zone***

| End Use | Climate Zone 1 | Climate Zone 2 | Climate Zone 3 |
|---|---|---|---|
| Backup Electric Furnace | 1.007 | 0.975 | 0.975 |
| Central AC | 1.074 | 0.959 | 0.959 |
| Ducted Heat Pump | 0.998 | 1.007 | 1.007 |
| Ductless Heat Pump | 1.012 | 0.951 | 0.951 |
| Electric Baseboard Heaters | 1.000 | 1.000 | 1.000 |
| Electric Furnace | 0.789 | 1.599 | 1.599 |
| Electric Resistance Storage Water Heater | 1.071 | 0.822 | 0.822 |
| Heat Pump Water Heater | 1.351 | 0.550 | 0.550 |

* Climate zone for Central AC is cooling zone; heating zone is used for all other end uses.

**Table 9: Fall Analysis End Use Weights by Climate Zone***

| End Use | Climate Zone 1 | Climate Zone 2 | Climate Zone 3 |
|---|---|---|---|
| Backup Electric Furnace | 1.015 | 0.951 | 0.951 |
| Central AC | 1.084 | 0.954 | 0.954 |
| Ducted Heat Pump | 1.015 | 0.945 | 0.945 |
| Ductless Heat Pump | 1.009 | 0.964 | 0.964 |
| Electric Baseboard Heaters | 1.000 | 1.000 | 1.000 |
| Electric Furnace | 0.795 | 1.564 | 1.564 |
| Electric Resistance Storage Water Heater | 1.071 | 0.822 | 0.822 |
| Heat Pump Water Heater | 1.375 | 0.539 | 0.539 |

* Climate zone for Central AC is cooling zone; heating zone is used for all other end uses.

# Appendix C: Regression Model Method

## Advanced Metering Infrastructure Customer Segmentation

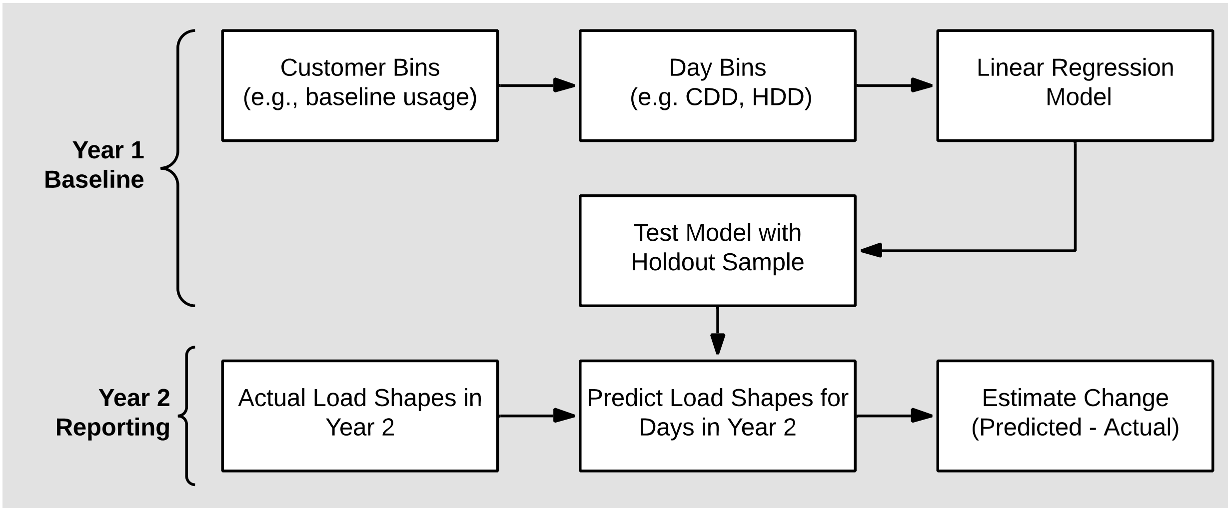
The AMICS modeling approach was utilized to perform weather normalization and conduct load shape analysis across sites, years, and regions. For the analysis of overall load shapes, emphasis was placed on maximizing the amount of data included in the model and using weights to ensure that the results represent the Typical Meteorological Year (TMY3).

The AMICS approach achieves this weather normalization by producing a portfolio of daily energy use load shapes, representing how each customer uses energy across a wide range of different weather conditions. A unique step in the AMICS modeling approach is segmenting the interval data into thousands of distinct segments (or "bins"), as shown in Figure 53. Each segment contains interval energy use data for customers with similar energy usage patterns in the baseline year on days with similar weather conditions (e.g., CDD, HDD, weekends vs. weekdays, and season). By segmenting the data before modeling, the amount of variation (across customers and days) that the model must account for is limited.[8]

[8] When applied to individual customers, AMICS uses the same model specification and day segmentation across all sites but creates separate load shape predictions for each site. While models by customer segment (and day segment) have the advantage of a higher number of observations, this does not guarantee an improvement in model fit. In fact, the benefits of customer segmentation are only realized when the segments are successfully identifying customers (and end use equipment) that are sufficiently similar to help explain patterns of energy usage in each other. If the customers have any systematic differences that are not controlled for in the regression model specification, the customer segmented model will have higher error (i.e., worse model fit) than an individual model.

Through extensive testing, segmenting customers individually was found to be the most effective way of accurately predicting usage. Customers exhibit high variation between each other and low baseline usage on end uses, a significant difference when compared to the whole-home data the AMICS approach is typically applied to. Segmenting customers that share similar characteristics did have a small improvement to model accuracy for whole-home data but not for individual end uses. To maintain consistency across circuits, individual models were estimated for whole home energy usage as well.

**Figure 53: AMICS Approach**




Load shapes are influenced by equipment specifications, controls/settings, and occupancy, among other factors. After normalizing to control for any changes in weather, load shapes of year 1 (baseline) to year 2 (reporting period) were compared, and then an assessment was made whether there were any statistically significant changes in load shape. For example, if a significant increase was detected in electric furnace load from year 1 to year 2 during the early morning hours after controlling for any differences in weather, this could be evidence of a change in their schedules or thermostat temperature set points. This analysis was repeated for each end use and reported on for any significant changes detected over the course of the study.

Once the data are segmented, the AMICS model approach involves estimating an ordinary least squares (OLS) regression model for each customer-day segment, shown in Equation 1, that contains a single dummy variable for each hour of the day.

**Equation 1: AMICS OLS Regression Model**

$$kWh_{i,t} = \beta_{0i}H00_{i,t} + \beta_{1i}H01_{i,t} + \beta_{2i}H02_{i,t} \ldots + \beta_{23i}H23_{i,t} + \varepsilon_{i,t}$$

*Where:*

$kWh_{i,t}$ =Energy consumption, for customer in segment *i* during hour *t*

$H00, H01 \ldots$ =Array of dummy variables (0, 1) representing the hour of the day

$\beta_{0i}$ =Coefficients estimated by the model for customers in segment *i*

$\varepsilon$ =Random error assumed to be normally distributed

This is not a proprietary "black box" method, but rather a series of simple linear regressions that are estimated with open-source statistical software (R and PostgreSQL). Unlike a traditional fixed effects regression approach, which produces a single set of coefficients and customer-specific constants, the AMICS regression model produces separate load shape estimates for each customer and day segment (weather and day type). Ultimately, the segmentation process reduces the prediction error for the load shape estimates, improving the predictive power of the baseline models. The AMICS approach was extensively tested on residential HVAC programs in Phase I of the AMI Billing Regression study.[9] The Phase II study expanded this research to include a variety of commercial HVAC programs and the gamma wave of Pacific Gas and Electric's residential Home Energy Reports program (treatment versus control).[10] AMICS was proven to be an effective method of estimating load shapes of individual sites (as opposed to customer segments) for Southern California Edison (SCE) in 2018 and 2019.[11]

## Computed Errors – Bootstrapping Method

In this analysis, the AMICS method was used to estimate an individual weather normalized load shape for each circuit (i.e., each site and metered end use), providing a load shape with kW energy usage for each hour by day type and weather conditions (in terms of its heating and cooling degree-days). For aggregated load shapes, such as the targeted end use load shapes by phase, bootstrapping was used to estimate the variance across circuits for each hour.

EULR HEMS metering data are complex, with extensive variability in electricity use on an hour-to-hour and home-to-home basis. In addition, electricity use is truncated at zero. The standard bootstrap approach of constructing pseudo samples by re-sampling from the empirical distribution of hourly data does not adequately approximate the data generating process associated with circuit level electricity use, which, while smooth over most of its range, often contains positive mass at zero (i.e., for some circuits there are hours in which there is no electricity use). Instead, confidence intervals were developed using the smoothed bootstrap approach,[12] which explicitly accounts for the positive mass at zero. The smoothed bootstrap draws a series of random samples with replacement from the kernel density estimate of the distribution, rather than the empirical distribution. Random noise is added to the drawn values from the kernel density. Specifically, the Gaussian smoothing kernel method, developed by Sheather & Jones,[13] was used.

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[9] Evergreen Economics. 2016. *AMI Billing Regression Study*. CALMAC SCE0383.01. http://calmac.org/publications/AMI_Report_Volume_1_FINAL.pdf

[10] Evergreen Economics. 2020. *Advanced Metering Infrastructure Billing Regression Study: Phase II*. CALMAC PGE0451.01. http://calmac.org/publications/Evergreen_Econ_AMI_Phase_2_FINAL.pdf

[11] Evergreen Economics. 2018. *AMI Analysis of Site Level Commercial HVAC Savings*. ET17SCE1130. Evergreen Economics. 2019. *NMEC Pre-Qualification Pilot Feasibility Study*. ET19SCE7010.

[12] Silverman, B.W. (1986). "Density Estimation for Statistics and Data Analysis." Monographs on Statistics and Applied Probability. https://ned.ipac.caltech.edu/level5/March02/Silverman/paper.pdf.

[13] Sheather, S. J. and Jones, M. C. 1991. "A reliable data-based bandwidth selection method for kernel density estimation." Journal of the Royal Statistical Society, series B, 53, 683–690. http://www.jstor.org/stable/2345597

In situations in which the empirical distribution of data is skewed and bounded (cannot fall below zero), smoothed bootstrap confidence intervals have been shown to be asymptotically more accurate than standard percentile-based methods, while retaining the desirable property of robustness. This approach adjusts for both bias and skewness in the distribution by estimating the density from the observed data, rather than assuming the data conform to a known parametric distribution. The confidence intervals that were developed using the smoothed bootstrap method are at least as good (if not superior) in performance to standard percentiles.

As with any confidence interval estimated from a small sample size, there is a potential for overstating confidence (i.e., estimating unrealistically tight error bounds) when the sample measurements are very similar by random chance. The sample size, in terms of the number of sites and metering duration, improves the accuracy of both the load shape estimates and error bounds—the confidence intervals do not necessarily get tighter, but they will provide a more realistic estimate of the true variability across sites.

# Appendix D: Descriptive Statistics for Targeted End Uses

Table 10 shows the minimum, mean, median, and maximum observed kWh values for each of the targeted end uses (and electric resistance water heaters) during the duration of the HEMS metering period.

**Table 10: Minimum, Mean, Median and Maximum kWh Values by Targeted End Use (All Observations)**

| End Use | Minimum Observed Value | Mean Value | Median Value | Maximum Observed Value | Coefficient of Variation |
|---|---|---|---|---|---|
| Ducted Heat Pump | 0.000 | 0.371 | 0.042 | 9.651 | 1.674 |
| Ductless Heat Pump | 0.000 | 0.274 | 0.082 | 4.971 | 1.417 |
| Central AC | 0.000 | 0.109 | 0.000 | 6.769 | 3.728 |
| Electric Furnace | 0.000 | 0.688 | 0.004 | 22.464 | 2.462 |
| Backup Electric Furnace | 0.000 | 0.349 | 0.032 | 33.125 | 3.021 |
| Electric Baseboard Heater | 0.000 | 0.141 | 0.000 | 9.865 | 3.039 |
| Heat Pump Water Heater | 0.000 | 0.161 | 0.003 | 5.468 | 2.813 |
| Electric Resistance Storage Water Heater | 0.000 | 0.285 | 0.001 | 5.911 | 2.113 |

Table 11 provides the same information (minimum, mean, median, and maximum observed kWh values) but when the reading is equal to or greater than 10 Watts. These statistics reflect usage when the end use is in operation ("when on").

**Table 11: Minimum, Mean, Median and Maximum kWh Values by Targeted End Use (Observations ≥ 10 Watts)**

| End Use | Minimum Observed Value | Mean Value | Median Value | Maximum Observed Value | Coefficient of Variation |
|---|---|---|---|---|---|
| Ducted Heat Pump | 0.010 | 0.599 | 0.339 | 9.651 | 1.166 |
| Ductless Heat Pump | 0.010 | 0.382 | 0.270 | 4.971 | 1.081 |
| Central AC | 0.010 | 0.702 | 0.383 | 6.769 | 1.147 |
| Electric Furnace | 0.010 | 2.083 | 1.496 | 22.464 | 1.156 |
| Backup Electric Furnace | 0.010 | 0.473 | 0.095 | 33.125 | 2.550 |
| Electric Baseboard Heater | 0.010 | 0.689 | 0.464 | 9.865 | 1.051 |
| Heat Pump Water Heater | 0.010 | 0.483 | 0.327 | 5.468 | 1.414 |
| Electric Resistance Storage Water Heater | 0.010 | 0.693 | 0.414 | 5.911 | 1.118 |