**Question 1**

For this analysis, I used Python with several data science libraries:

* **Pandas** for data manipulation and cleaning
* **Matplotlib** and **Seaborn** for creating visualizations.
* **Scikit-learn** for polynomial regression analysis.
* **NumPy** for numerical computations

These tools were selected for their robustness in data analysis, flexibility in visualization customization, and reproducibility of results.

**Visualization 1:**

A graph of different colored lines

Description automatically generated

Figure 1: This visualization compares hourly energy consumption patterns between winter (December-February) and non-winter months, with separate lines for weekdays and weekends:

**Key Insights:**

* Winter shows significantly higher energy consumption overall, particularly during morning hours (6-9 AM)
* The morning peak is more pronounced on weekdays during winter months, suggesting heating needs increase when households wake up during colder months
* Weekend patterns show later peaks and more gradual consumption changes in both seasons
* Non-winter months show flatter consumption patterns with minimal difference between weekdays and weekends

This visualization helps identify the winter morning peak that Tacoma Power is concerned about, showing clear opportunities for targeted interventions.

**Visualization 2**

A graph of a graph showing the temperature of a person

Description automatically generated with medium confidence

Figure 2: This time series plot shows the relationship between daily energy consumption and temperature over the entire dataset period:

**Key Insights:**

* A clear inverse relationship exists between temperature and energy consumption - consumption increases as temperatures drop.
* Seasonal patterns are evident with higher consumption during winter months (Nov-Mar) and lower consumption during warmer months.
* The interquartile range (shaded area) shows significant variation between households, suggesting different responsiveness to temperature changes.
* Notable temperature extremes correspond with consumption spikes, particularly during cold snaps.

This visualization demonstrates how external temperature drives energy consumption patterns throughout the year.

**Visualization 3**

A graph of a graph showing the average temperature and the average temperature

Description automatically generated with medium confidence

Figure 3: This polynomial regression analysis quantifies the relationship between temperature and energy consumption:

**Key Insights:**

* The U-shaped curve (R² = 0.881) confirms that energy consumption increases at both temperature extremes
* **Optimal temperature**: 61.9°F, where energy consumption is minimized at approximately 31.9 kWh per household
* Consumption increases more steeply at lower temperatures than at higher temperatures, suggesting heating demands are greater than cooling demands in this climate
* The strong fit (high R² value) indicates temperature is a primary driver of energy consumption for homes with heat pumps

This analysis provides a quantitative foundation for understanding how temperature changes affect energy consumption and can help predict the impact of weather variations on system load.

**Question 2**

To rigorously assess a winter morning peak reduction intervention for heat pump-heated homes, I would design a **controlled experimental study** or a robust quasi-experiment. The goal is to isolate the intervention’s effect on peak-hour energy use amid normal variations in weather and behavior.

**Sample Selection and Experimental Design:** Using data like the provided 30-home dataset (hourly usage and temperature), I would first identify *eligible participants* – homes with electric heat pumps that exhibit high winter morning usage peaks. Ideally, we would recruit a **larger representative sample** of such homes. We could then randomly assign half to a **treatment group** (receiving the new peak-reduction intervention) and the other half to a **control group** (no changes), ensuring both groups have similar baseline usage and characteristics. Random assignment maximizes statistical validity by avoiding selection bias. If randomization is not feasible, an alternative is to use *matched pairs* or **propensity score matching** – pairing each participant home with a similar non-participant home (in terms of heat pump usage patterns, house size, etc.) – and then proceed with a **difference-in-differences** framework. In either design, we would track energy consumption for both groups over a period *before and after* the intervention implementation.

**Effectiveness Measurement Technique:** The primary metric would be the change in electricity use during winter peak hours (e.g. 6–9 AM) for the treatment group relative to the control. A **difference-in-differences (DiD)** statistical analysis is well-suited here: it compares the pre- vs. post-intervention change in peak period consumption for participants against the same change for non-participants. This controls for common influences like weather or seasonal trends. For example, if both groups’ usage rises on colder days, DiD will net out that shared effect, isolating the intervention’s impact. A regression model can augment this, with an interaction term for (Treatment × Post) to estimate the average treatment effect on peak usage, while controlling for daily temperature (from NOAA data), day of week, and household fixed effects. This approach improves precision and accounts for variability in winter weather. Given Tacoma Power’s IRP expectations that demand response might only shave ~1–2% of peak load, ensuring a sufficiently large sample is important for statistical power (detecting such a small effect). We might conduct a **power analysis** up front, using the variability in the provided data, to determine how many homes are needed to confidently observe a reduction in morning peak demand.

**Data Requirements and Enhancements:** In addition to the interval consumption and temperature data, several extra data elements would strengthen the analysis. **Weather normalization** is crucial, so integrating more granular temperature data (hourly if available) or using heating degree-hours would help attribute changes in usage to the intervention rather than cold spikes. Customer attributes like home size, insulation level, or occupancy could be collected to ensure the treatment and control groups are comparable and to control for usage drivers. If possible, data on **heat pump operation** (e.g. smart thermostat data or whether auxiliary heat strips activate on very cold mornings) would help verify how the intervention achieves savings. We would also log **intervention event details** (which days/hours customers were asked or signaled to reduce usage) to analyze impacts specifically during called peak events versus non-event days. This comprehensive data collection aligns with Tacoma Power’s focus on demand-side solutions in its 2024 IRP. In fact, the IRP’s action plan calls for piloting demand response programs and scaling those that prove cost-effective. By carefully designing the study with control groups and rigorous statistical techniques, we can confidently determine whether the intervention delivers measurable winter peak reduction and supports Tacoma Power’s peak management goals.

**Question 3**

A Difference-in-Differences (DID) analysis finding that program participants used more energy relative to non-participants after an intervention designed to reduce usage is a counterintuitive but not uncommon result. This outcome suggests that the fundamental assumption of the DID model—the "parallel trends" assumption—has likely been violated, or that other behavioral factors are at play.

My interpretation would focus on three primary explanations:

**1. Selection Bias (Violation of Parallel Trends):** This is the most probable cause. The treatment and control groups were not equivalent before the program began. The participants who self-selected into the program were likely already on a higher consumption trend. For example, these may be customers who:

* Are more energy-intensive in general (e.g., larger homes, older heat pumps, poorer insulation).
* Were already experiencing increasing energy use due to factors like a growing family or working from home.
* Joined the program because they had high bills and were seeking help.

The DID model cannot fully adjust for this pre-existing difference in trends. The intervention may have successfully reduced their energy use from what it would have been, but not enough to bring it below the level of the less energy-intensive control group.

**2. Behavioral Rebound Effect (The "Snapback" Effect):** The intervention may have caused an unintended behavioral change. If the program involved temporary load curtailment (e.g., cycling heat pumps off for short periods on winter mornings), customers may have responded by:

* **Pre-heating:** Cranking up the heat before the anticipated curtailment period.
* **Rebound:** Overcompensating by setting the thermostat higher immediately after the curtailment period ends to restore comfort.  
  This "rebound" effect could lead to a net increase in overall consumption, negating the savings from the curtailment period itself.

**3. Measurement and Program Design Issues:**

* **Free-Ridership:** The control group may have independently adopted energy-saving behaviors (e.g., purchasing efficient appliances, adding insulation) because of general efficiency trends or publicity around the program, making their consumption fall faster than expected.
* **Improper Counterfactual:** The control group may not be a valid comparison. For instance, if the control group consists of customers who are inherently more energy-conscious and less likely to join such programs, their lower consumption is not a fair benchmark.

**Conclusion and Next Steps:** This result should not be interpreted as the intervention causing an increase in consumption. Instead, it is a strong indicator of a flawed study design, primarily severe selection bias. Before abandoning the intervention, I would recommend:

1. Re-evaluating the data to test the parallel trends assumption visually and statistically.
2. Using a more robust method like **Randomized Controlled Trial (RCT)** or **Matched Cohort Analysis** (pairing participants with nearly identical non-participants based on pre-program consumption and home characteristics) to isolate the true treatment effect.
3. Conducting customer surveys to understand participant behavior and potential rebound effects.