

**Ca1BEM**  
**2025**

November 19-20

📍 Sacramento, CA


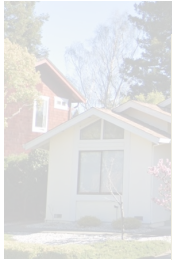
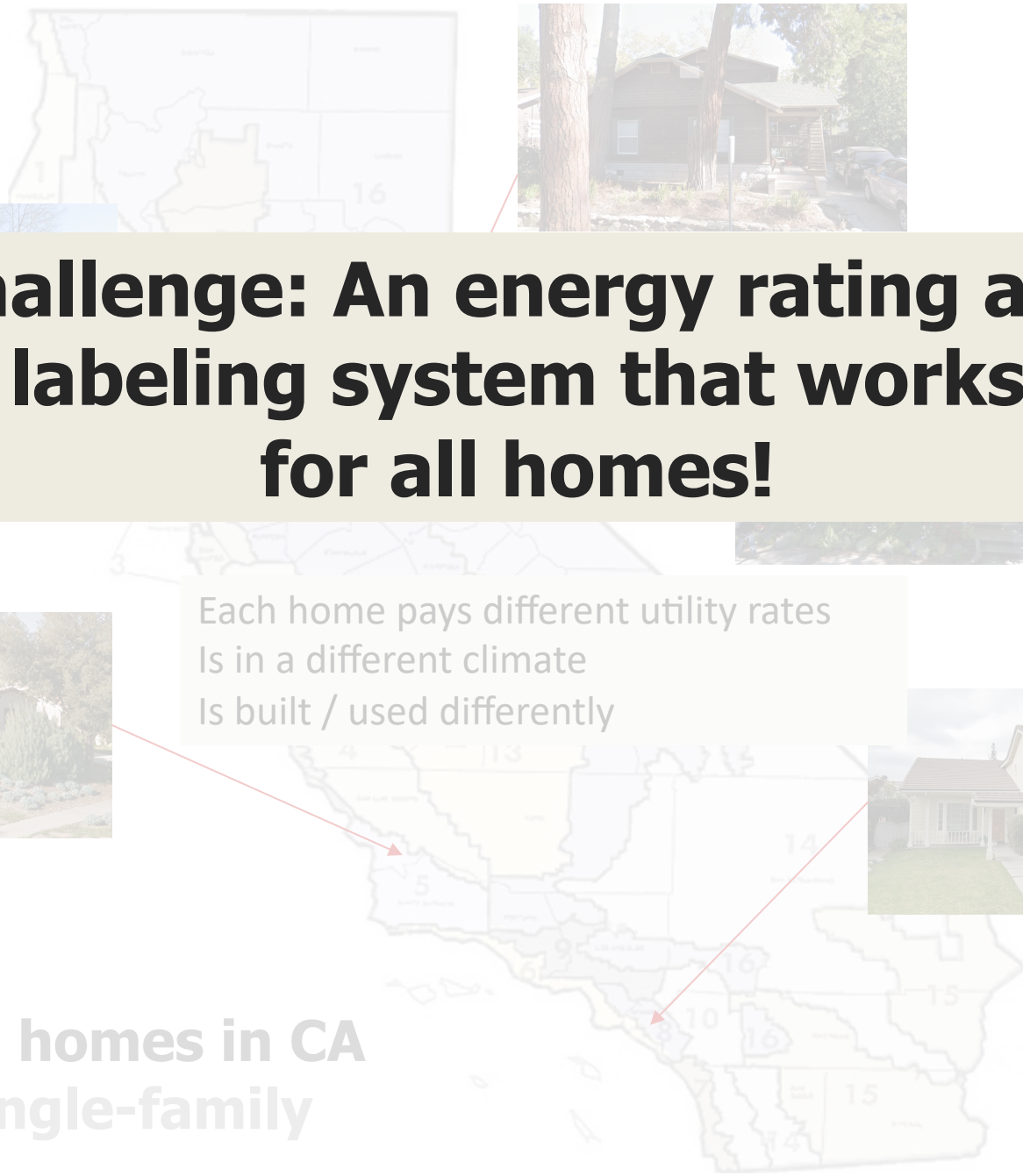
# **From Data to Action: Equitable Home Energy Labeling at Scale**

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# Acknowledgement


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# Challenge: An energy rating and labeling system that works for all homes!



Each home pays different utility rates  
Is in a different climate  
Is built / used differently



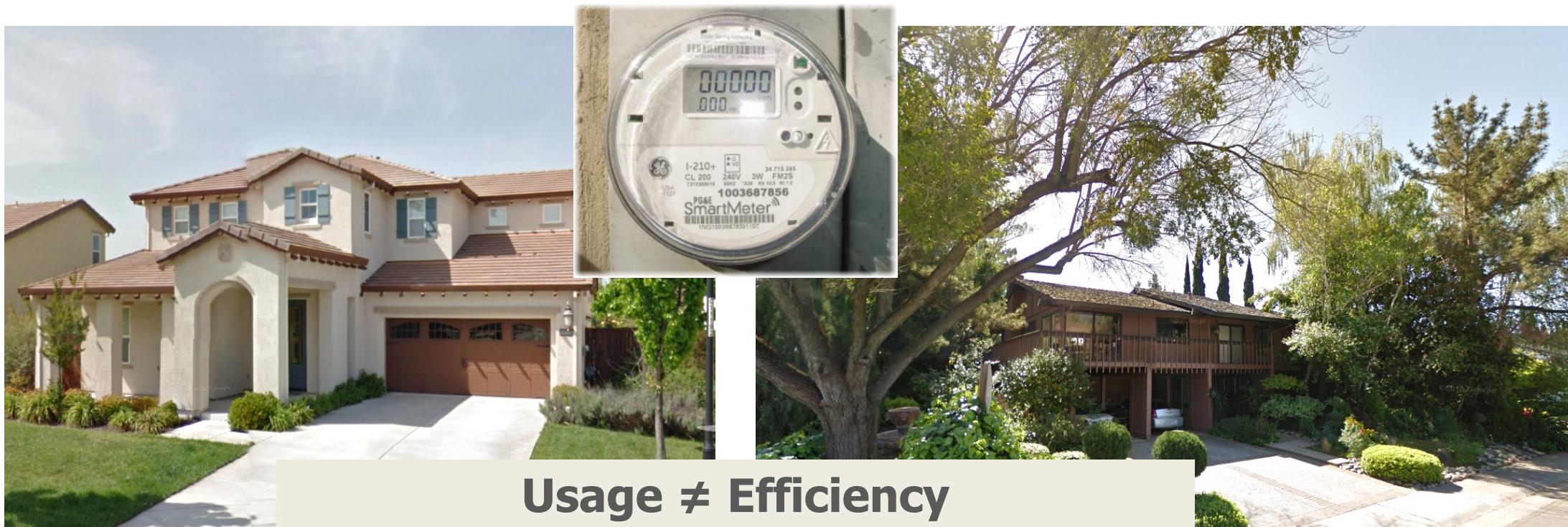
14.2 Mil homes in CA  
9 Mil. single-family

# If Only Some Homes Get Labeled ... We Risk Leaving Others Behind





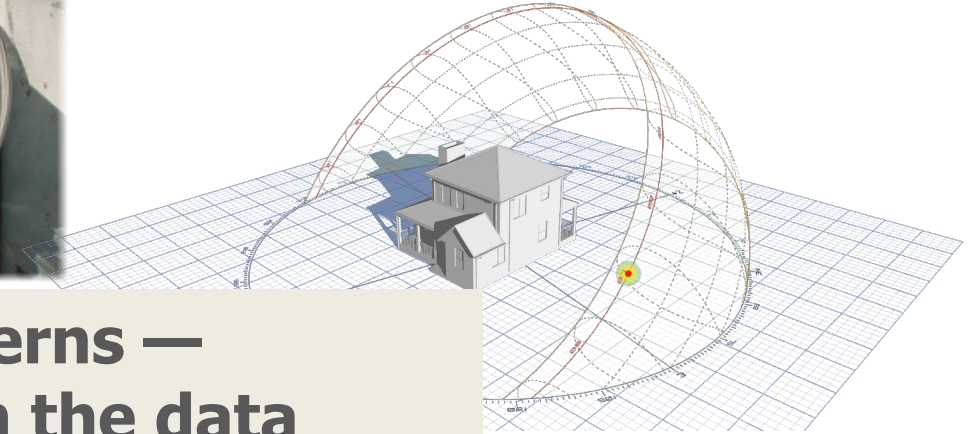
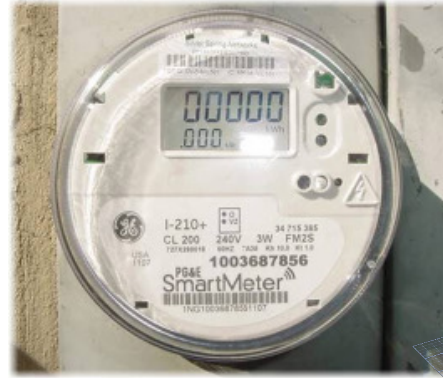
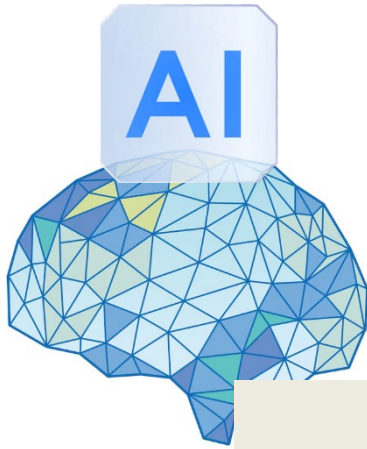
# Can Energy Usage Data Alone Be Used To Develop a Home Rating?



- 🏠 **Size Effect:** Small inefficient homes, same usage as large efficient homes.
- ⚡ **Behavior Bias:** Changes with occupants / occupant lifestyle.
- 🌤️ **Weather Variability:** Year-to-year weather shifts distort results.

# What About Machine Learning?

## LLMs, Neural Networks, AI






**AI can find patterns —  
Physics can explain the data**

### ML Model:

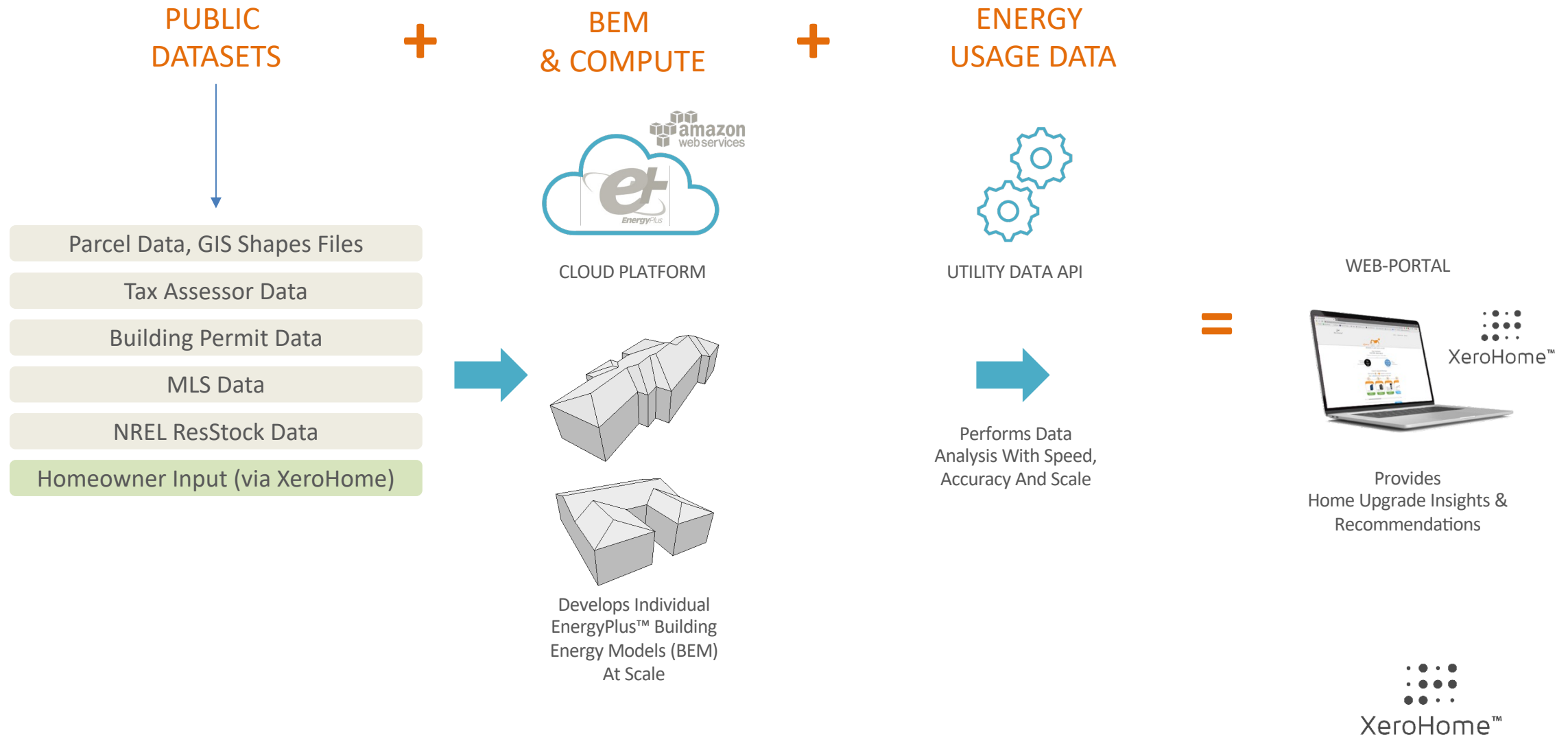
Usage Data In → Rating Out  
(No explanation)

### Physics-Based Model:

Understands how the  
home works

-  **Black Box:** Hard to explain why two homes get different ratings.
-  **Data Burden:** Reliable ML needs tagged, standardized data at scale for millions of homes.
-  **Missing Physics:** Without a building model, AI can't predict upgrade impacts

# A Scalable, Equitable Path: 'Building Energy Modeling (BEM) + Energy Usage Data'



# Piloting 'BEM + Energy Usage Data' Approach

## XeroHome™ Deployments 2018 - 2025




**Deployments funded by:** Southern California Edison (SCE), Sacramento Municipal Utility District (SMUD), Pacific Gas & Electric (PG&E), Silicon Valley Clean Energy (SVCE), Association of Monterey Bay Govts. (AMBAG), City of Sacramento, New York State Energy & Research Development Auth. (NYSERDA), Ameren Missouri, National Grid New York, Alabama Power, Georgia Power, Electric Power Research Institute (EPRI)



# Analysis of Data from XeroHome™ Deployments

Analysis of XeroHome™ deployment data was done to demonstrate the feasibility of a 'no cost to participant' statewide home energy rating that is:

- ☒ **Feasible** to implement
- ☐ **Accurate** in its results  **Today's presentation**
- ☒ **Scalable** across millions of homes

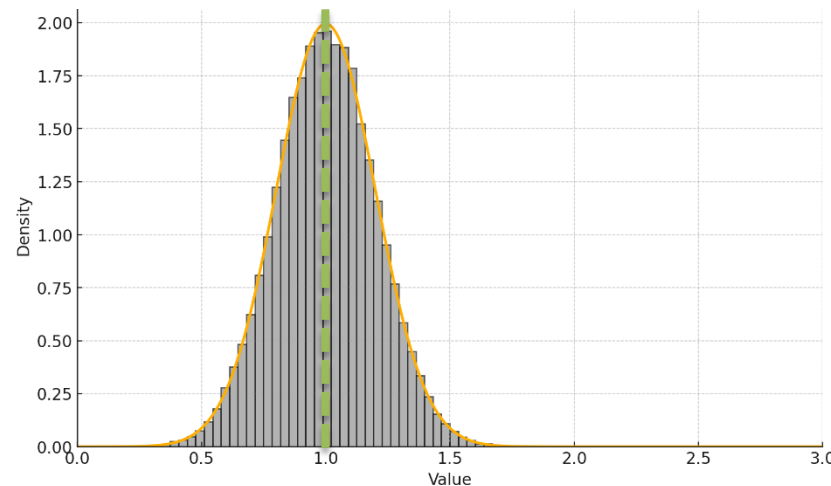
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# Visualizing Model Accuracy

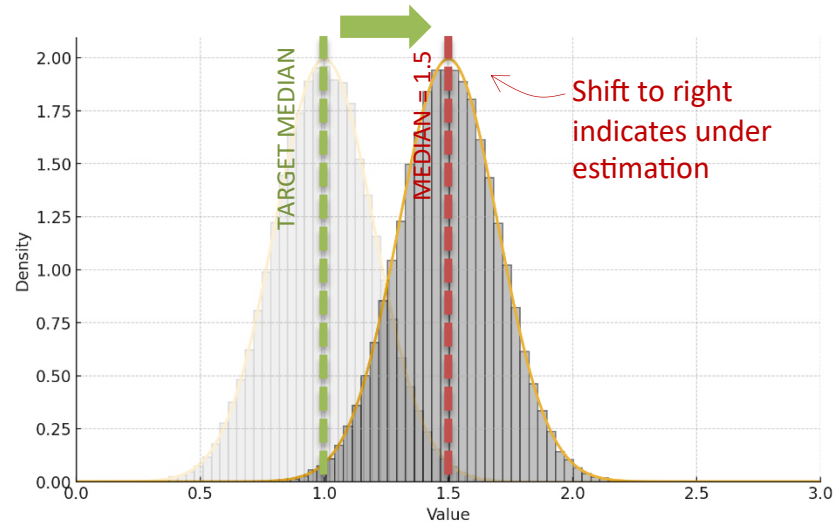
- Modeled electric energy use **compared to** metered electric energy use for each home

$$\text{Calibration Coefficient} = \frac{\text{Energy Use}_{\text{Actual}}}{\text{Energy Use}_{\text{Modeled}}}$$

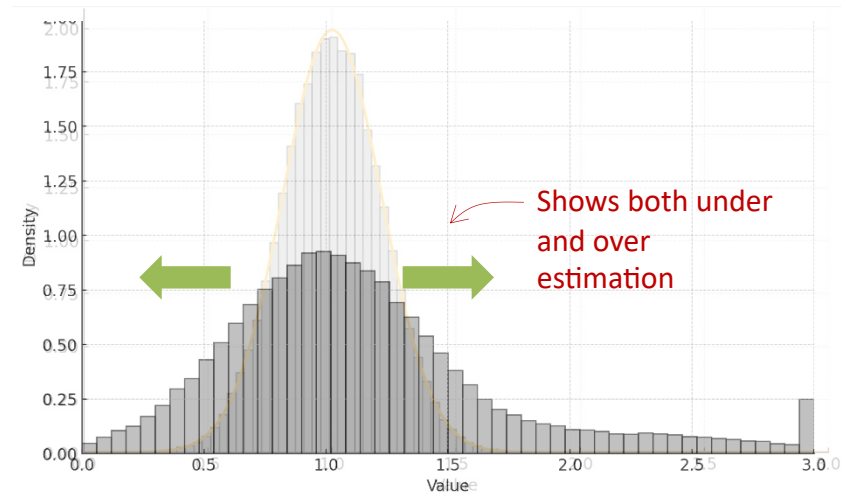
- <1 Calib. Coef. means actual energy use was **less** than modeled
- 1 Calib. Coef. means an **exact match**
- >1 Calib. Coef. means actual energy use was **more** than modeled



# Bias and Uncertainty



- When most predictions cluster to one side of the true value, the models have a consistent **bias** - systematically under or over estimation.



- When predictions spread widely around the true value, the models have high **uncertainty** - sometimes under, sometimes over estimation, but no consistent pattern.

# Hypothesis #1 – Adding Energy Use Data Improves Accuracy of the Home Energy Models

- Quantify the improvement in **Bias** and reduction in **Uncertainty** when energy use data is used to calibrate the home energy models.
- Is there a difference between mild (coastal) vs extreme (inland) climates?

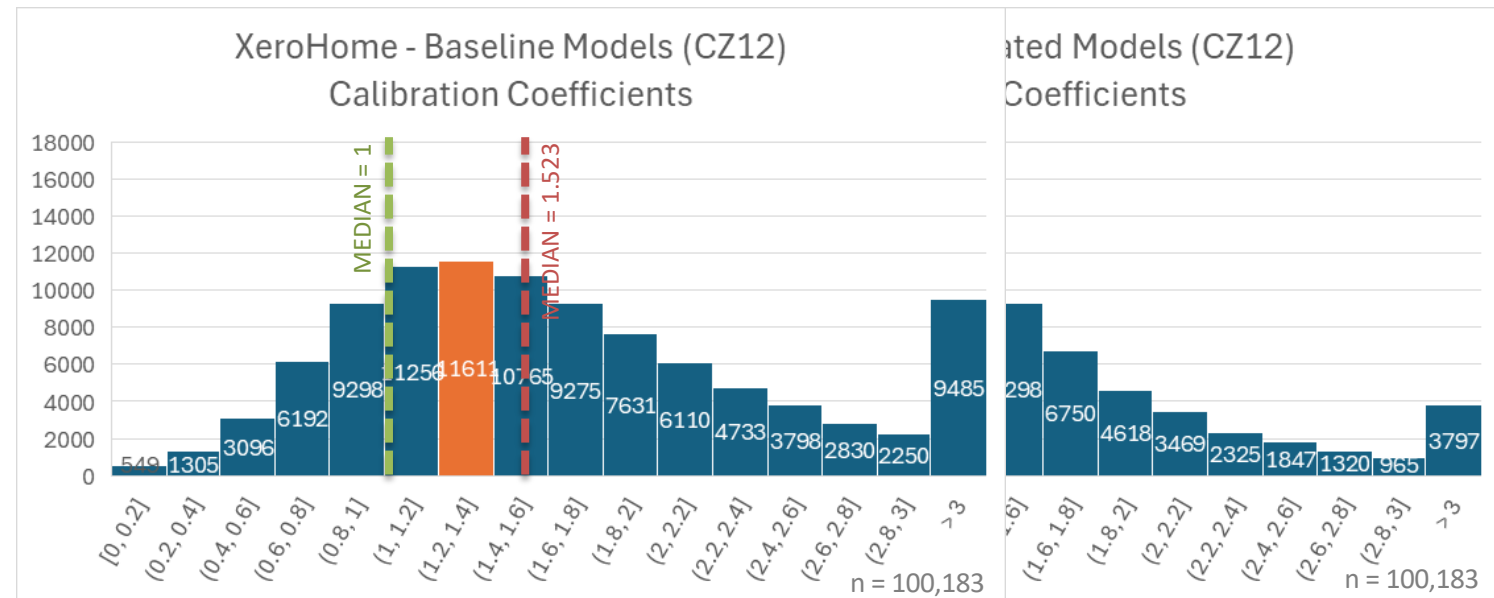


# Model Accuracy: Without / With Energy Data

## Calibration Coefficients Histogram

Example 1 – CZ12 XeroHome™ home energy models

### Without Energy Data    With Energy Data



1st Quartile	Median	3rd Quartile	1st Quartile	Median	3rd Quartile	IQR	Std Dev.
1.086	1.523	2.129	1.043	1.049	1.567	0.778	0.793

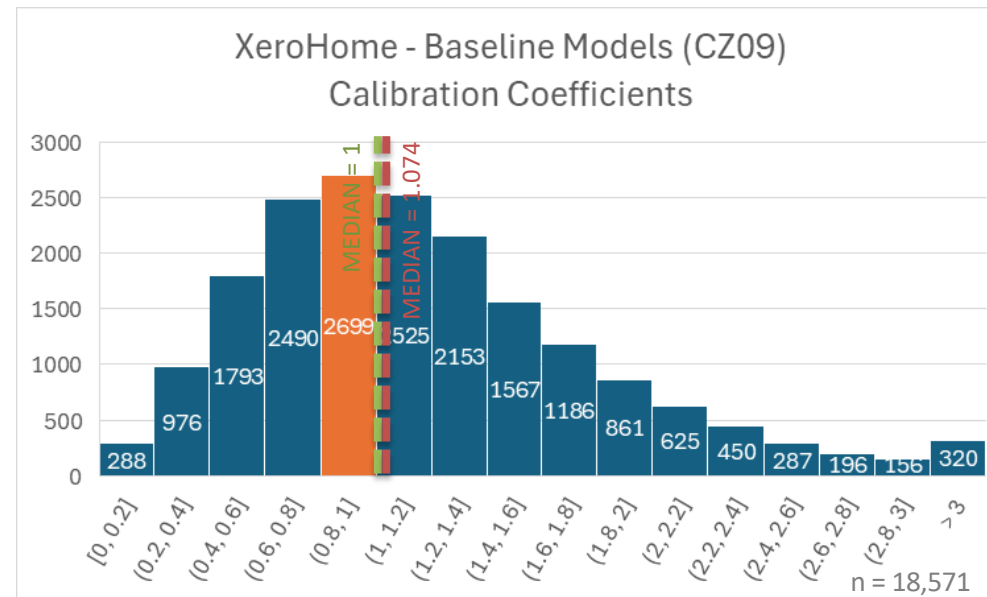
- **Bias: 78% reduction in systematic bias.** Median moved closer to 1: from 1.523 → 1.117
- **Uncertainty: 24% reduction in uncertainty.** Std Dev moved closer to 0: from 1.049 → 0.793

# Model Accuracy: Without / With Energy Data

## Calibration Coefficients Histogram

Example 2 – CZ9 XeroHome™ home energy models

### Without Energy Data



1st Quartile	Median	3rd Quartile	IQR	Std Dev.
0.734	1.074	1.521	0.787	0.734

- **Climate Zone 9** is a coastal (mild) climate and the home energy models showed high accuracy even without adding energy data.

## **Hypothesis #2 – Adding Inputs Collected by a Homeowner Improves Accuracy of the Home Energy Models**

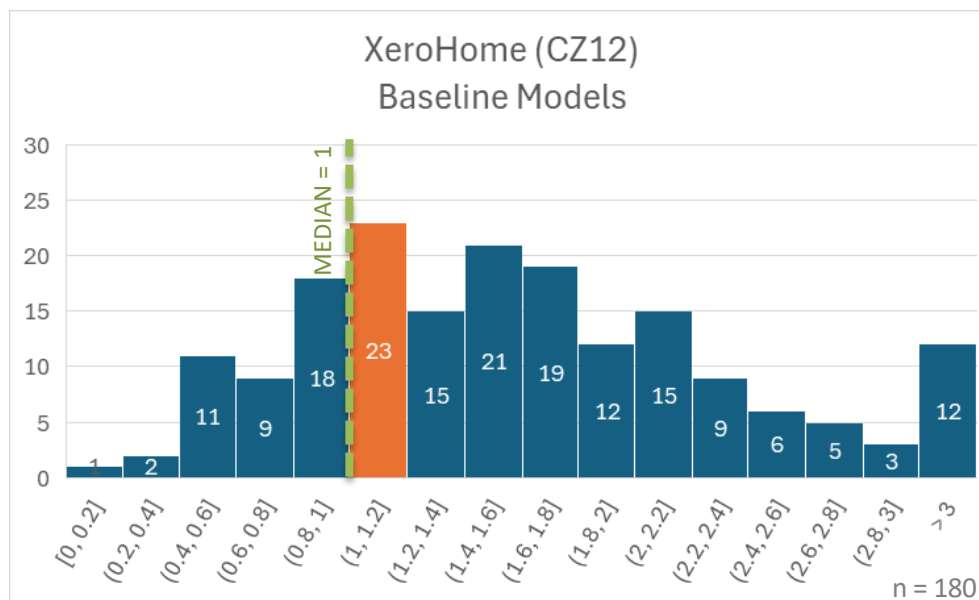
- Quantify the improvement in Bias and reduction in Uncertainty when data collected by a homeowner is used to improve the assumptions in the home energy models.

# Model Accuracy: Without / With Homeowner Inputs

## Calibration Coefficients Histogram

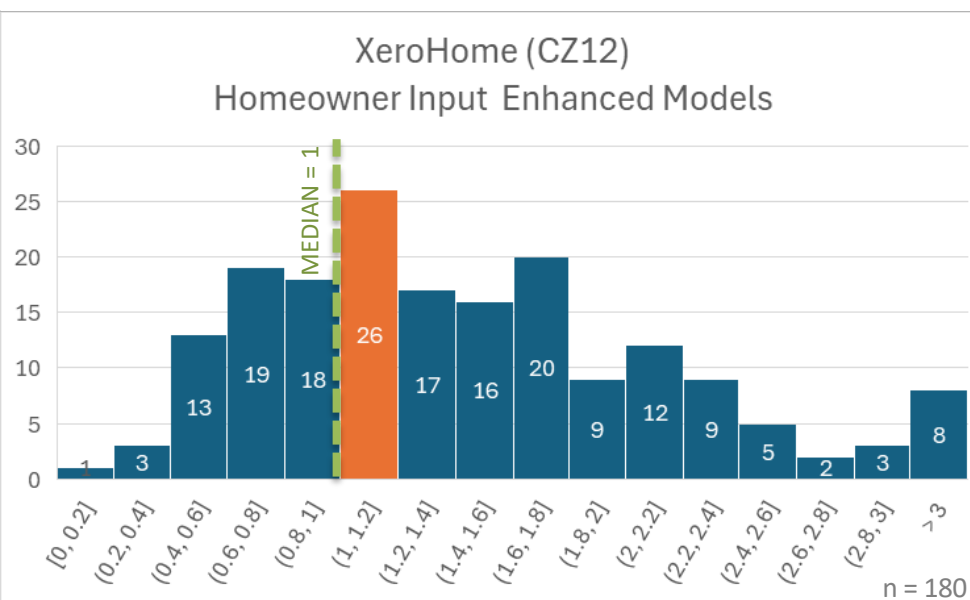
Example 1 – CZ12 XeroHome™ Models built without and with access to homeowner data

### Without Homeowner Input



1st Quartile	Median	3rd Quartile	IQR	Std Dev.
1.048	1.510	2.066	1.018	0.983

### With Homeowner Input



1st Quartile	Median	3rd Quartile	IQR	Std Dev.
0.906	1.310	1.849	0.943	0.951

- **Bias: 39% reduction in systematic bias.** Median moved closer to 1: from 1.510 → 1.310
- **Uncertainty: 3% reduction in uncertainty.** Std Dev moved closer to 0: from 0.983 → 0.951

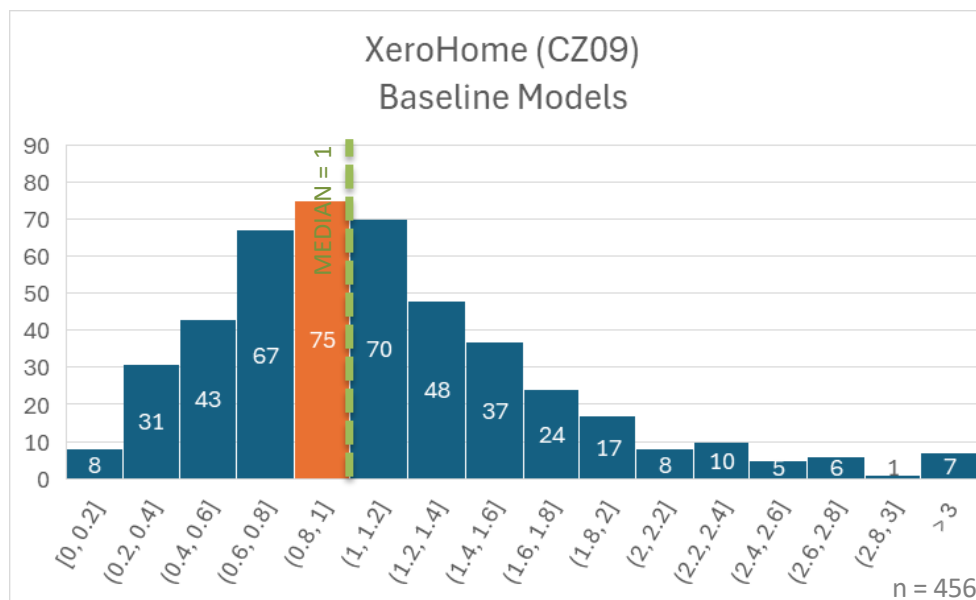


# Model Accuracy: Without / With Homeowner Inputs

## Calibration Coefficients Histogram

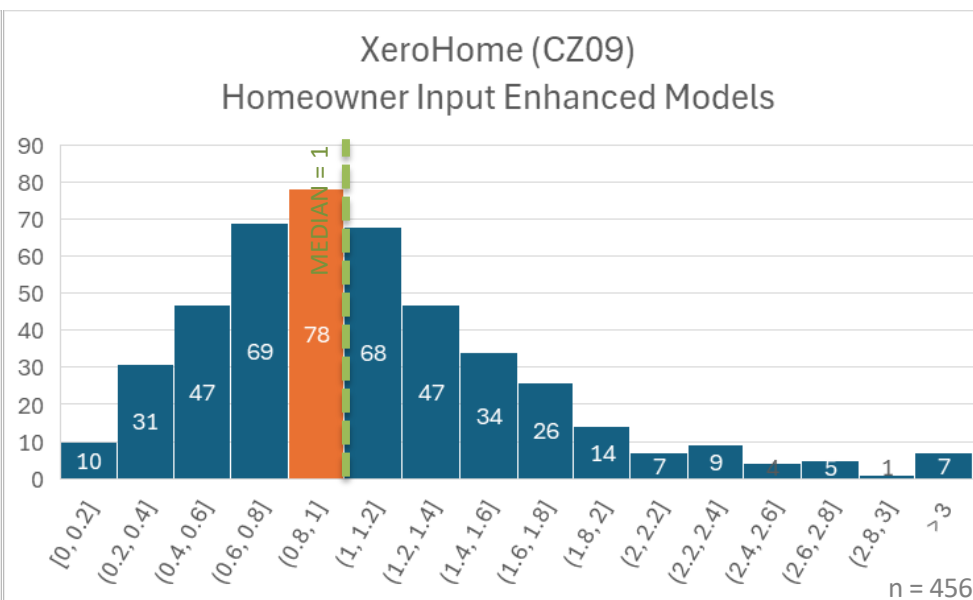
Example 2 – CZ9 XeroHome™ Models built without and with access to homeowner data

### Without Homeowner Input



1st Quartile	Median	3rd Quartile	IQR	Std Dev.
0.706	0.982	1.350	0.643	0.650

### With Homeowner Input



1st Quartile	Median	3rd Quartile	IQR	Std Dev.
0.718	1.009	1.407	0.690	0.643

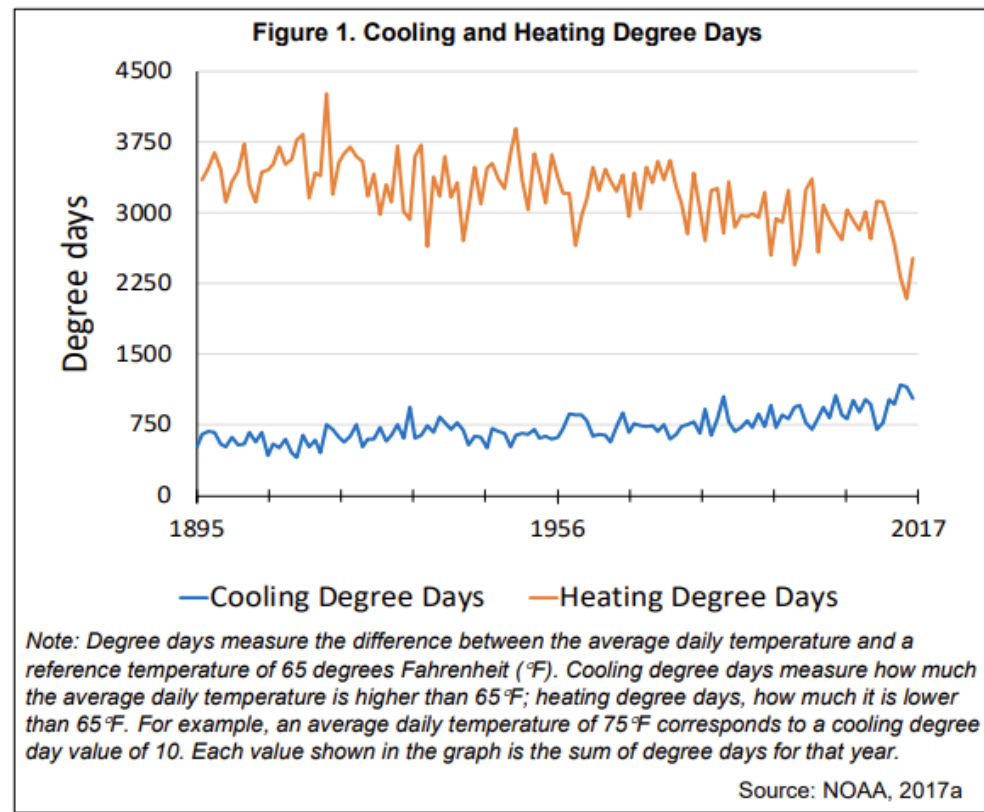
- **Bias: 47% reduction in systematic bias.** Median moved closer to 1: from 0.982 → 1.009
- **Uncertainty: 1% reduction in uncertainty.** Std Dev moved closer to 0: from 0.650 → 0.643

# Key Takeaways

- **Hypothesis #1 – Energy Usage Data:** With energy data, modeling predictions can become both more accurate (less biased) and more consistent (less uncertainty), creating a stronger foundation for statewide ratings.
- **Hypothesis #2 – Homeowner Input:** Using homeowner inputs to replace key initial assumptions about the home can improve accuracy mainly making the models less biased.

# Discussion on Variance

- **Weather Impacts:** Energy use can vary year over year due to weather changes – Hotter years drive more cooling, less heating and vice versa

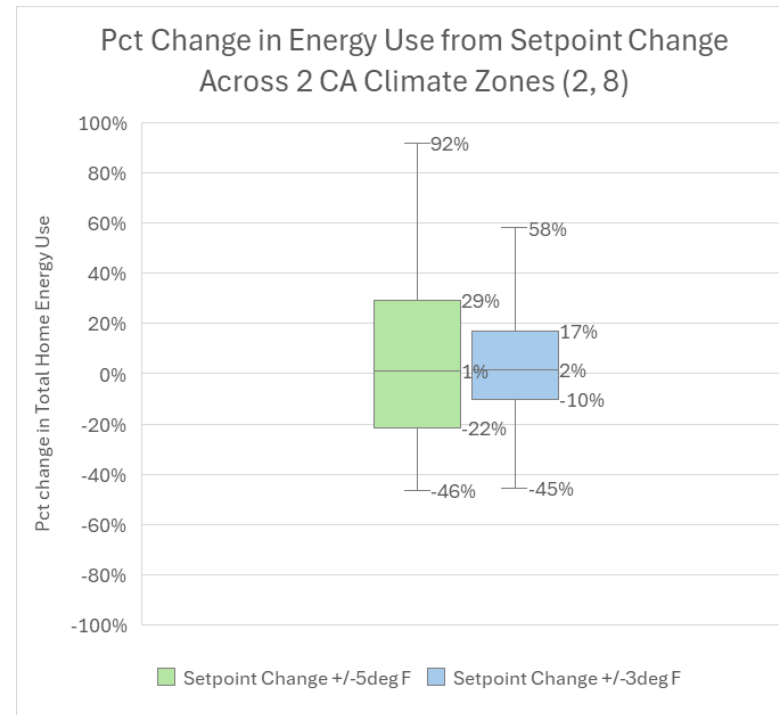


# Discussion on Variance

- **Behavioral Impacts:** Energy use can vary with operational changes – Thermostat settings, time spent at home (e.g., working from home), window operation, and number of occupants, etc.

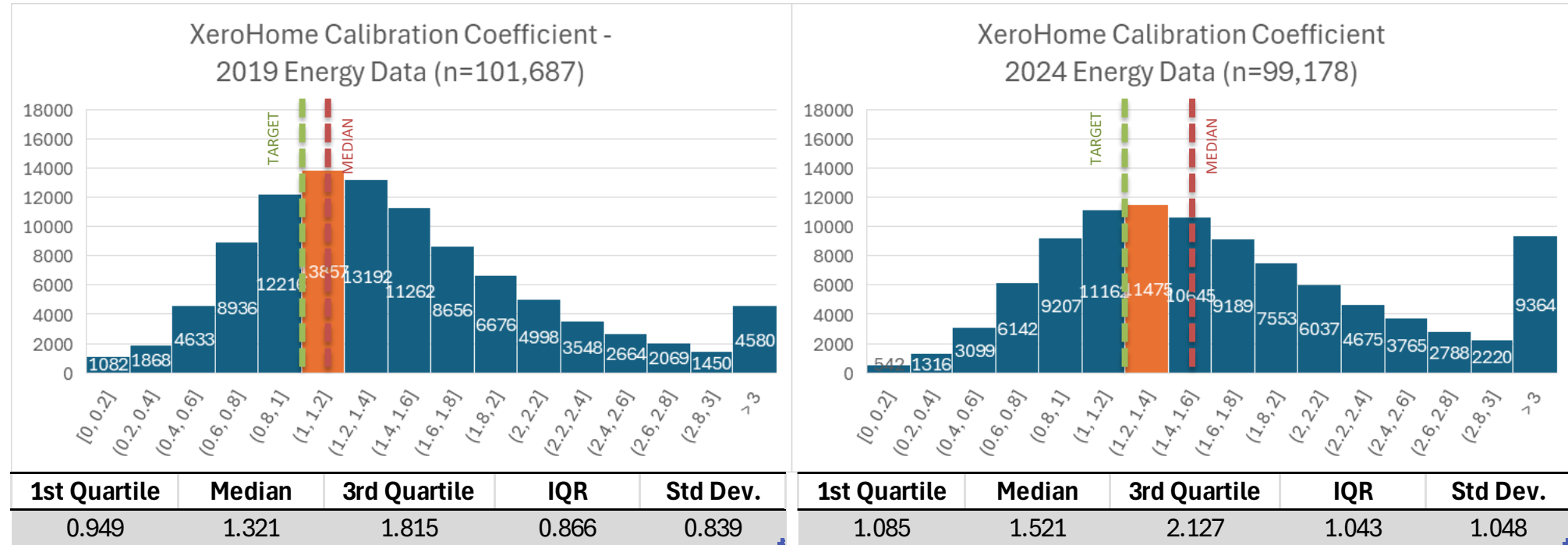


Setpoint changes:





# Natural Energy Usage Variance Due to Weather + Behavior



Comparing the same home energy models against 2019 and 2024 energy data shows:

- **±7% variance in systematic bias** due to factors like weather, occupant behavior etc.  
Median varies: 1.321 – 1.521
- **±11% variance in uncertainty** due to factors like weather, occupant behavior etc.  
Std Dev varies: 0.839 – 1.048

These differences highlight the role of external factors – rather than model error – in year-to-year energy use variance.

# Conclusions

- **‘BEM + Energy Usage Data’** offers a scalable, no-cost path to statewide home energy labeling that is **credible**, **equitable** and **cost-effective**.
- Publicly available data can form the foundation of an energy model, integrating **actual energy-use data** and **homeowner-provided details** enhances **accuracy**.
- Even a well-calibrated home energy model may not perfectly align with measured energy use, due to **inherent variability** in a home’s consumption patterns.

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