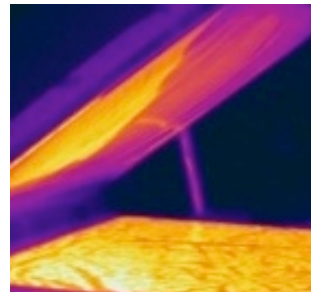


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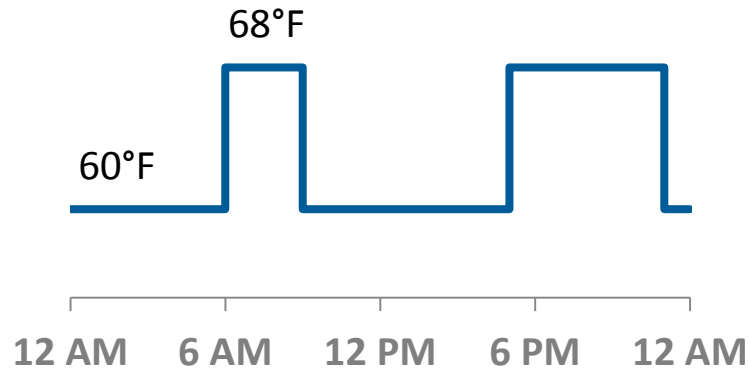
# Buildings, Energy and Behavior: Sapiens Happens



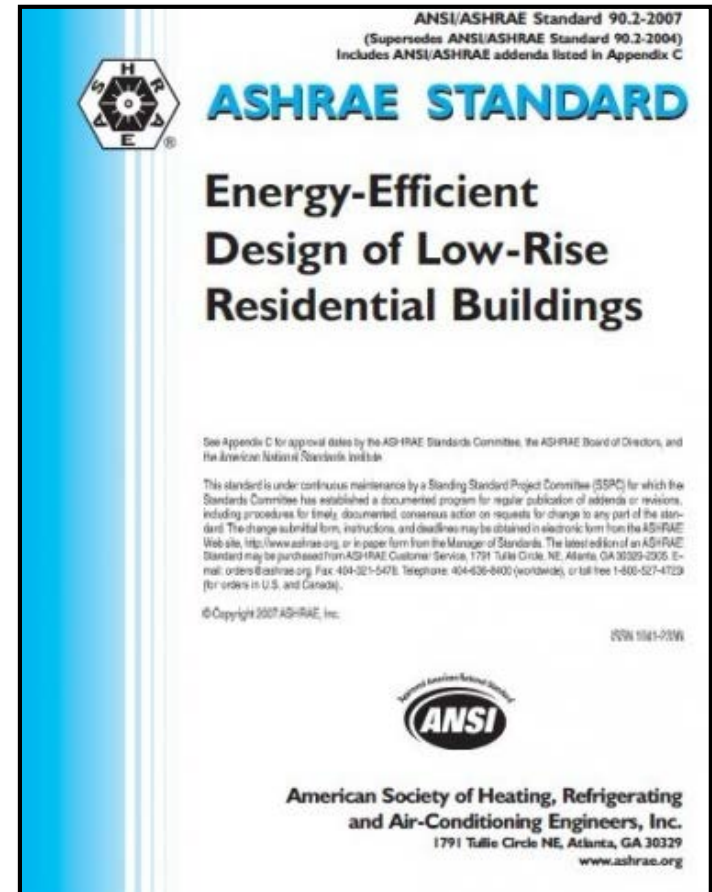
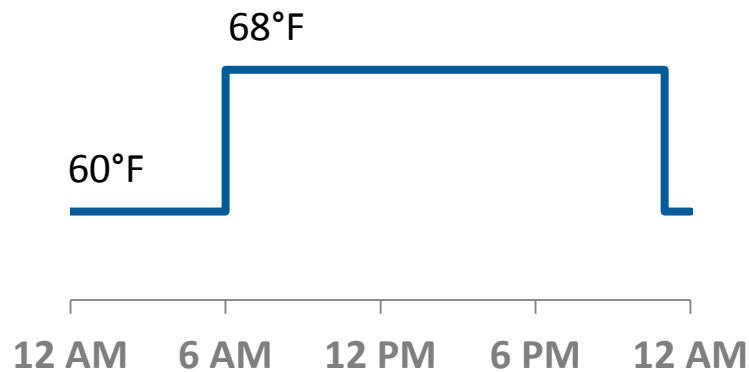
Kurt Roth, Ph.D.  
EIA Conference  
June 26, 2017

# IMPACT OF BEHAVIOR ON BUILDING ENERGY CONSUMPTION

## Sleeping Zone

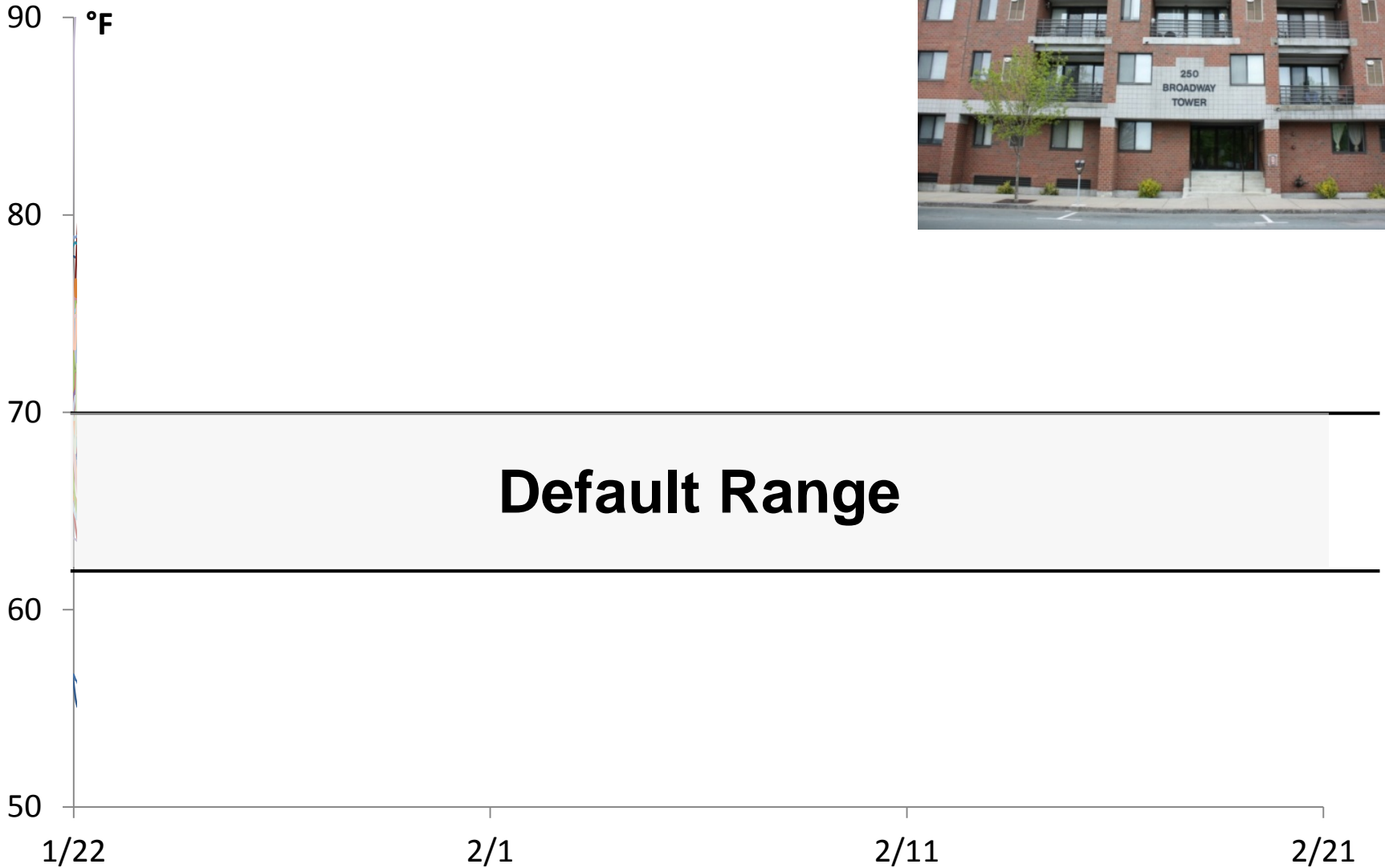


## Single Zone or Living Zone

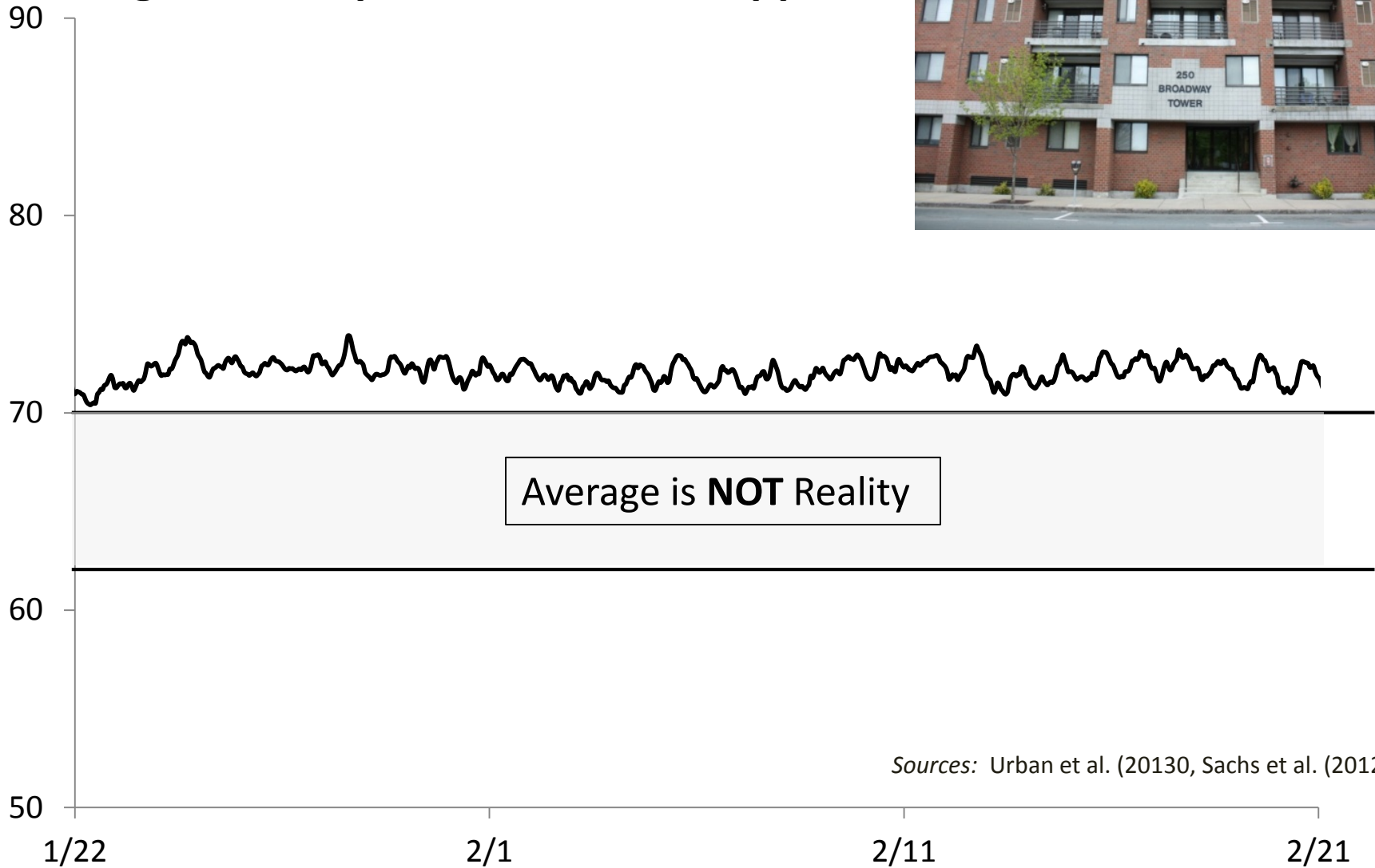


Source: ASHRAE (2007).

# Measured Air Temperature (n=67)

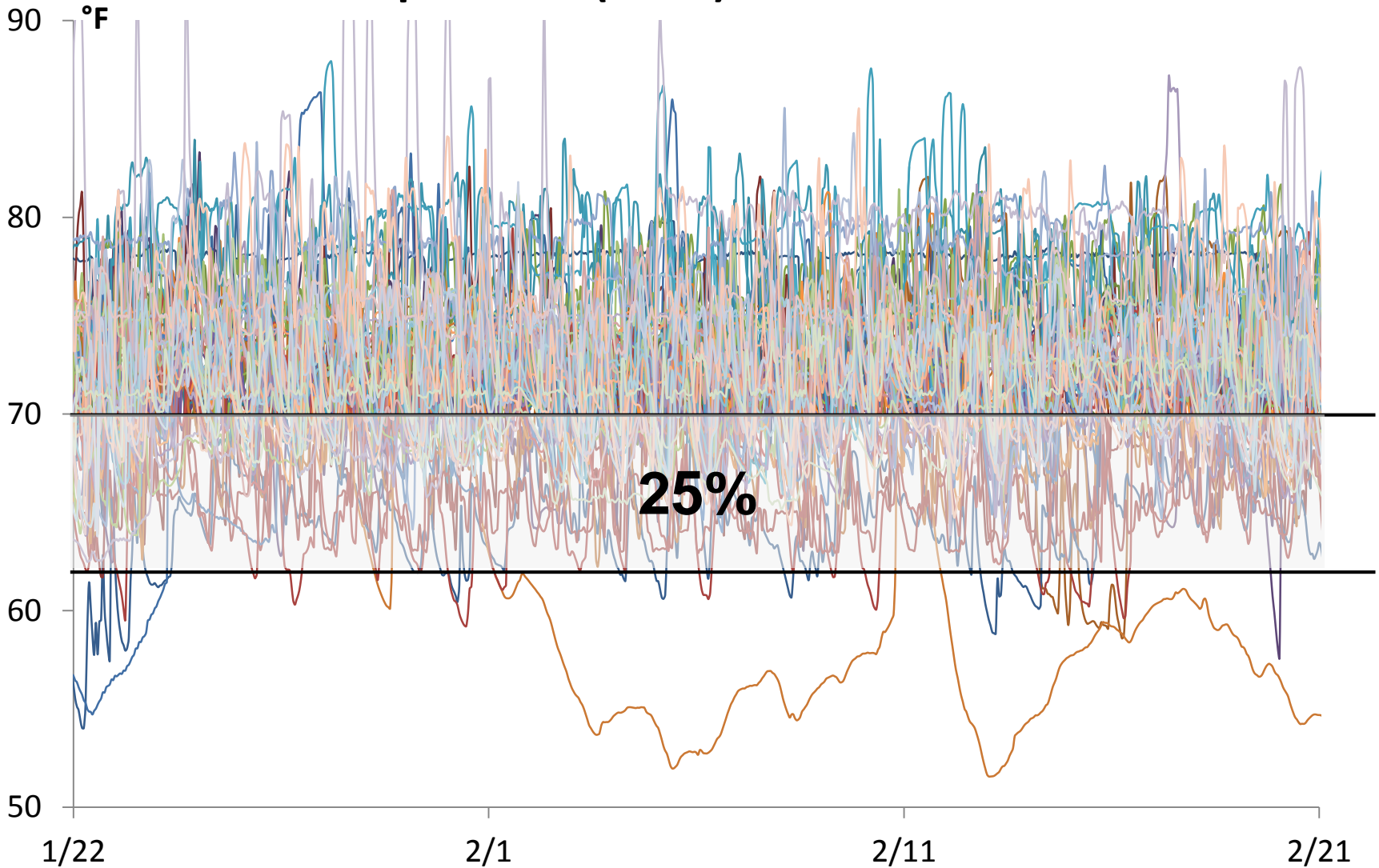


# Average Air Temperature over 67 Appts.



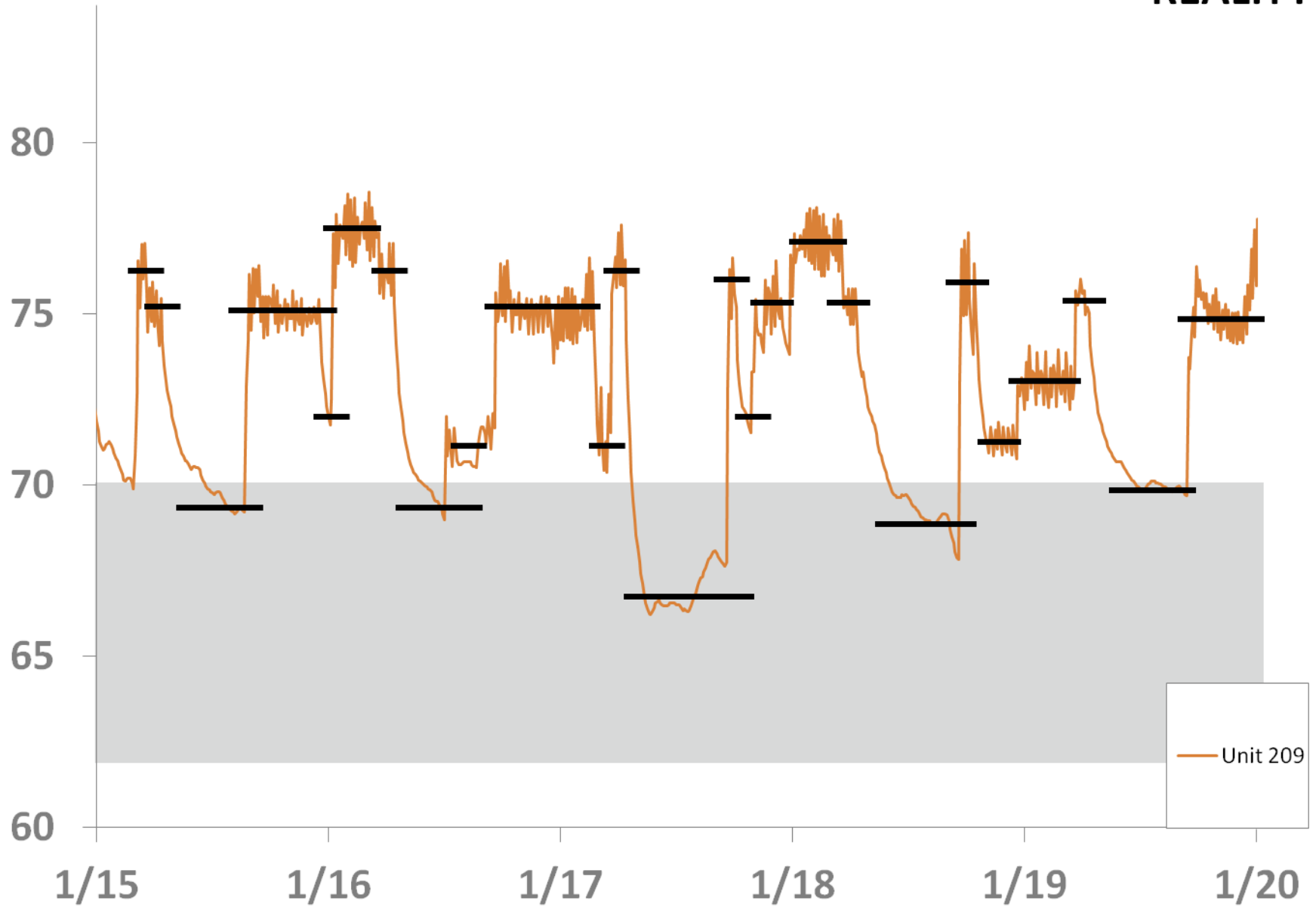
Sources: Urban et al. (2013), Sachs et al. (2012).

# Measured Air Temperature (n=67)



# Air Temperature °F

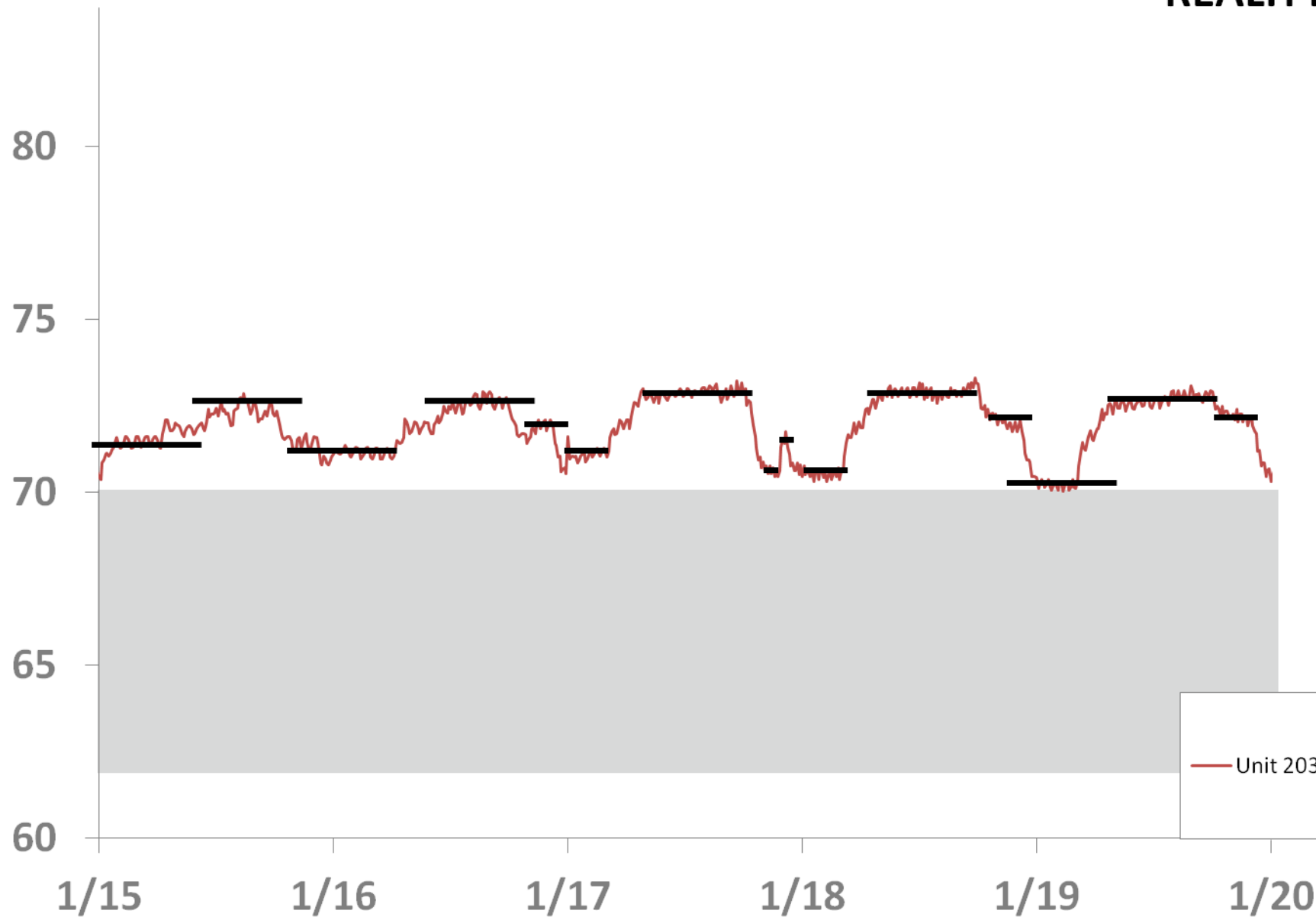
**REALITY**



Sources: Urban et al. (2013), Sachs et al. (2012).

# Air Temperature °F

**REALITY**

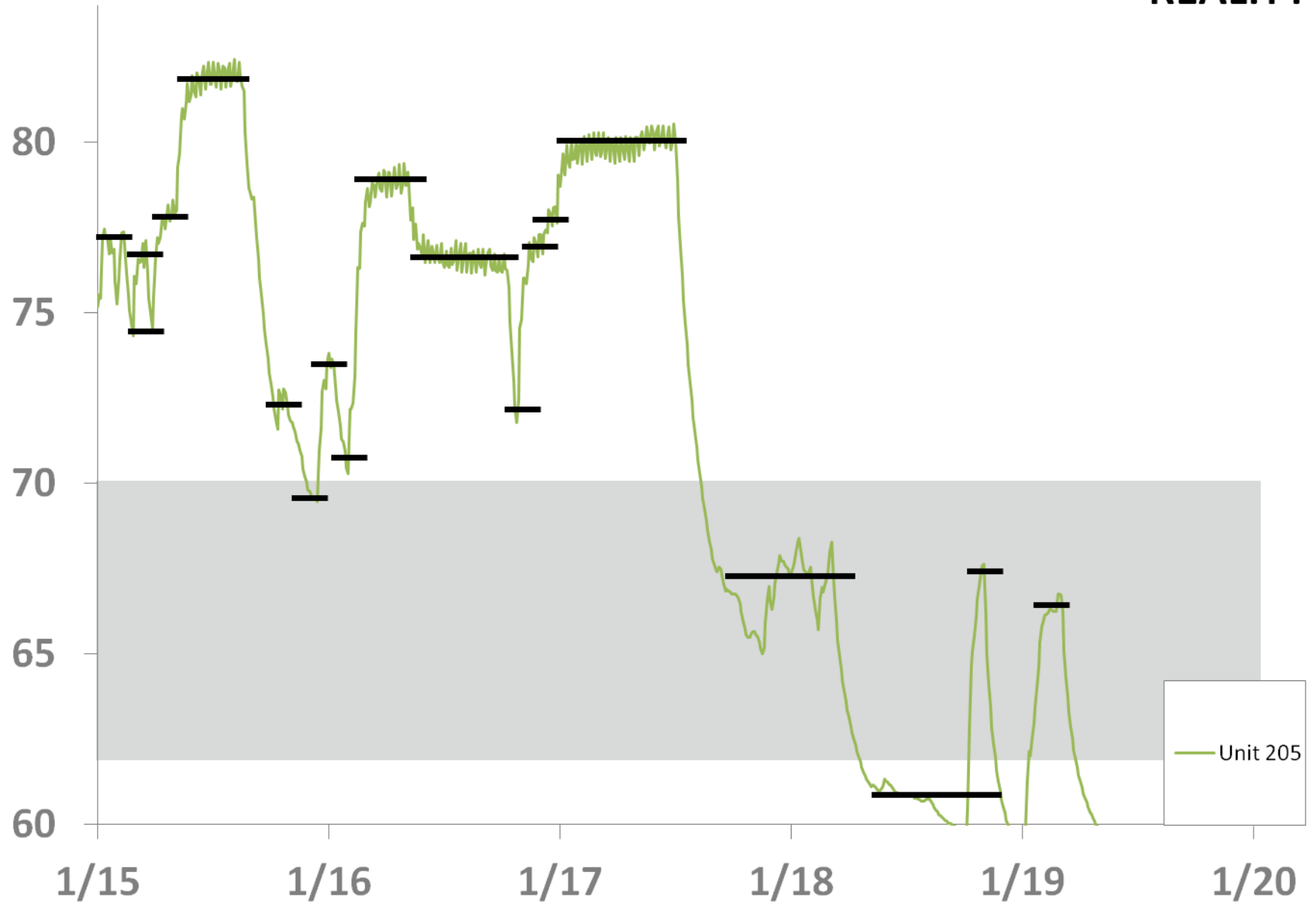


Sources: Urban et al. (2013), Sachs et al. (2012).



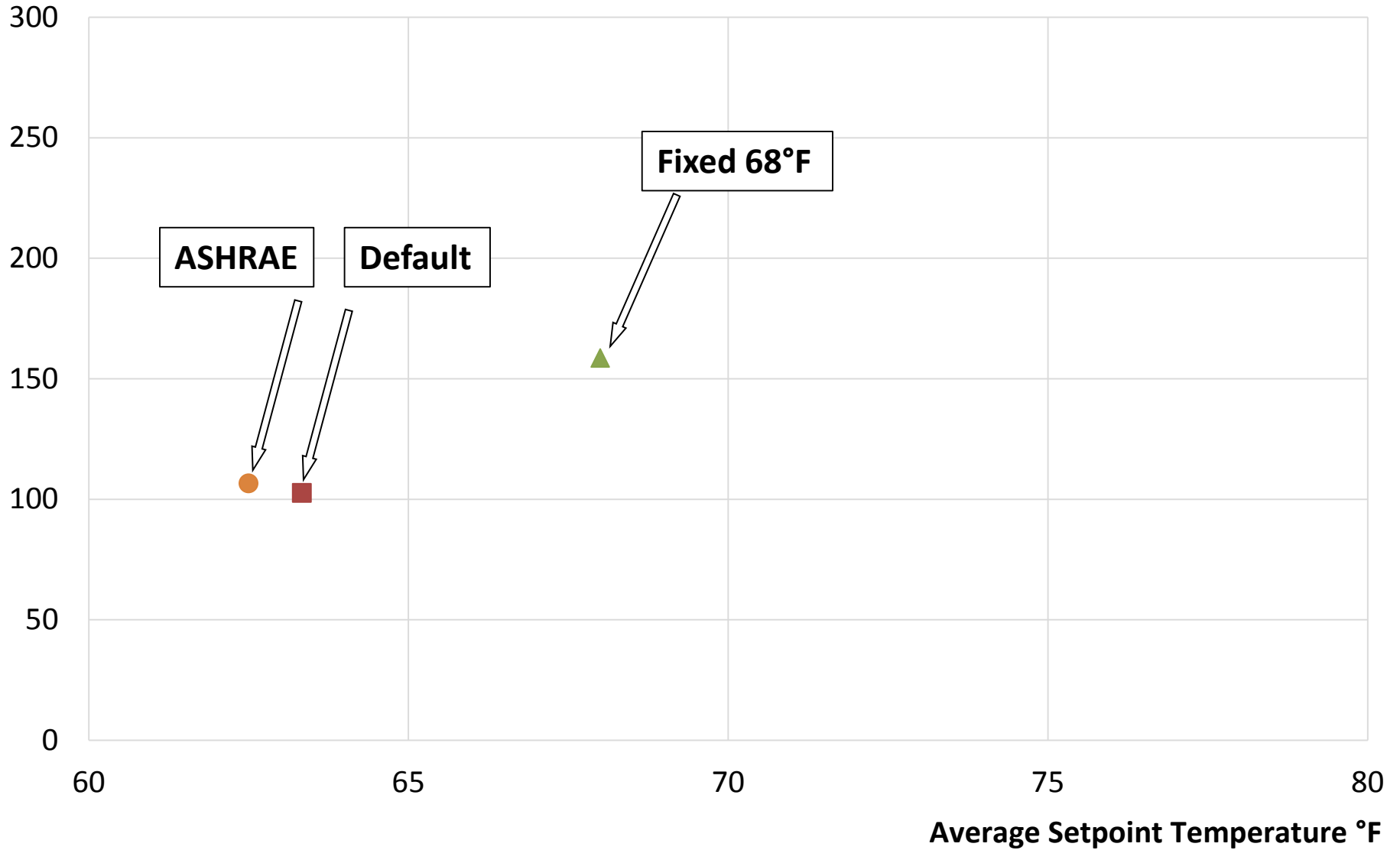
# Air Temperature °F

**REALITY**



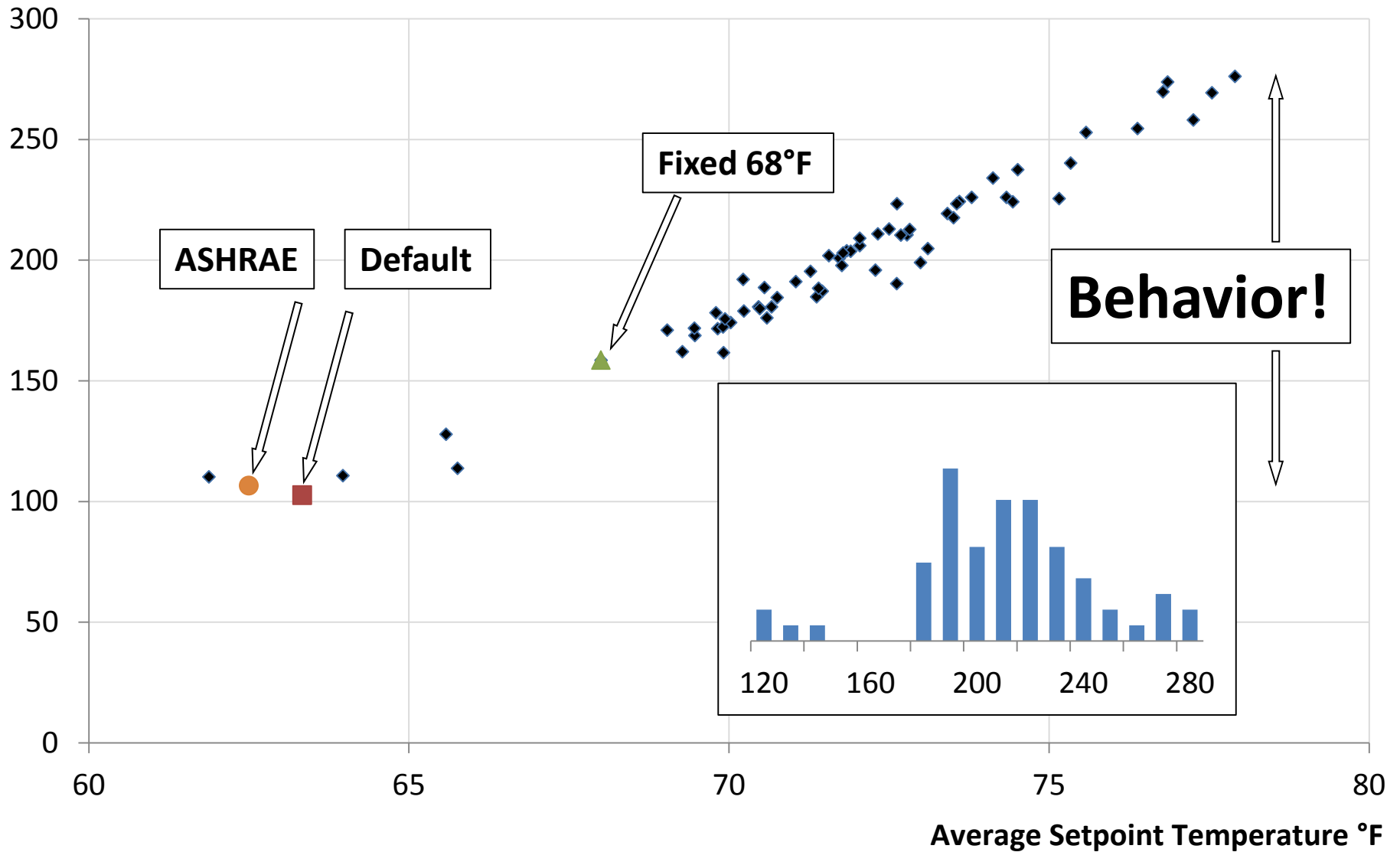
Sources: Urban et al. (2013), Sachs et al. (2012).

# Simulated Heating Energy



Source: Urban et al. (2013)

# Simulated Heating Energy



Source: Urban et al. (2013)

# Behaviors happens in the context of technology!

# Example: Programmable thermostats & Energy Saving

Energy savings due to programmable thermostats:

- Programmable thermostats **save** energy
  - 6% and 3.6% savings in a billing analysis of 7,000 and 25,000 households, respectively
  - 9% savings in a survey of 2,300 respondents
- Programmable thermostats **do not** save energy
  - No significant savings in billing and survey analysis of 299 households
  - No savings and/or some increases



Sources: RLW Analytics (2007), Michaud et al. (2009), Tachibana (2009), Nevius & Pigg (1999), Cross & Judd (1996), Conner (2001), Parker 2000)

# Fraunhofer DOE-Building America Project: Field Evaluation of Programmable Thermostats



- Conventional Wisdom: Thermostat usability likely responsibility for inconsistent PT savings
- Our reaction: Sounds good – what happens in homes??

## Project approach:

- Recruited multifamily building with 90 households
- Randomly installed high usability and basic thermostats
- Installed non-intrusive sensors to monitor temperatures and HVAC activity throughout winter
- Analyzed data to evaluate thermostat use



Image Source: Honeywell



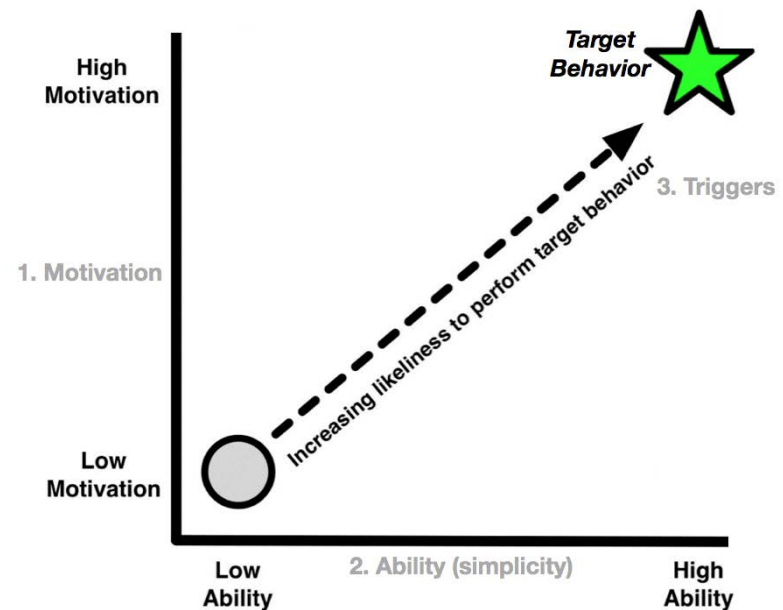
# Findings:

- **Negligible** use of nighttime setback in both groups
- **Comfort trumps energy:** average 72°F at night
- Suggests high usability alone is not sufficient for savings



## Why???

- Factors underlying behavior Change:
  - Ability
  - Trigger
  - Motivation



Sources: Sachs et al. (2012), Fogg (2009).

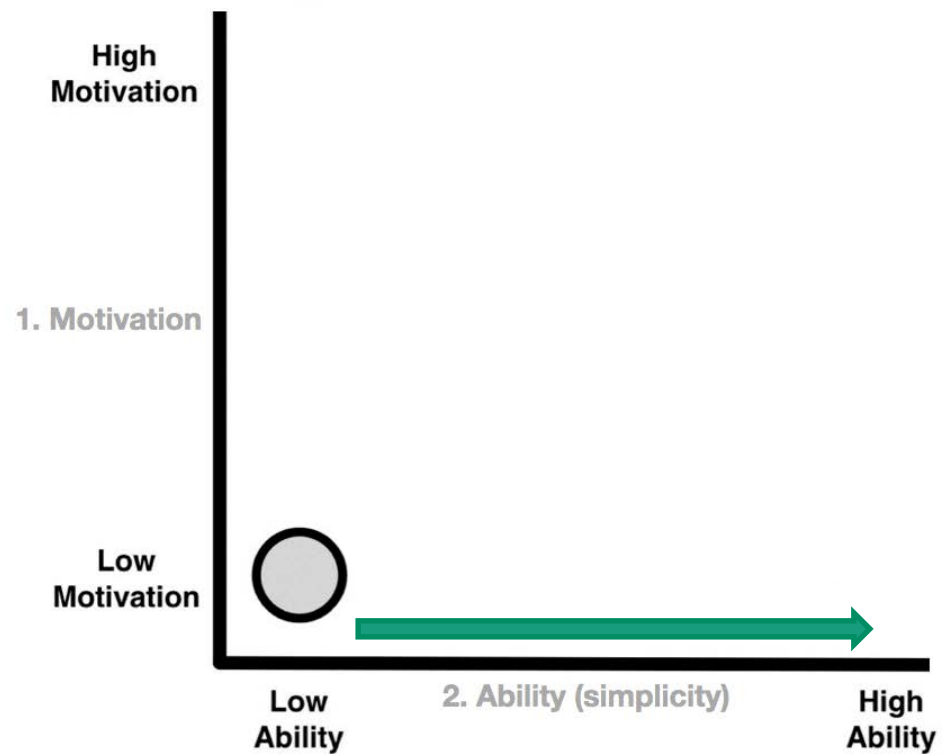
Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. To copy otherwise, to republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee.  
*Persuasive'09, April 26-29, Claremont, California, USA.*

# Thermostat behavior change: ability is NOT enough!



## ■ Three main factors:

- Ability
- ~~Trigger~~
- ~~Motivation~~



Sources: Sachs et al. (2012), Fogg (2009).



**NEW DATA SOURCES =  
NEW OPPORTUNITIES**

# New data sources can be used to reduce building energy consumption by shaping different types of behavior:

1. Operational behaviors



2. Purchasing behaviors



3. Installer behaviors



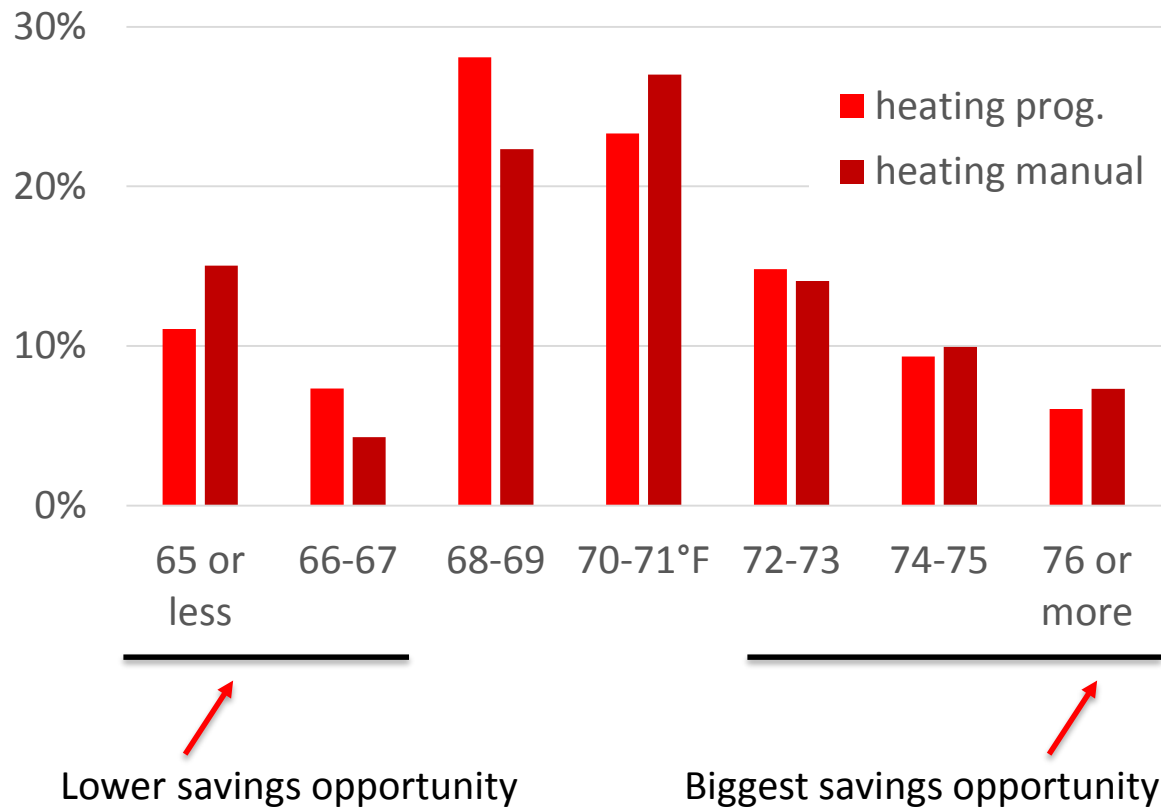
# ***Operational Behaviors* and communicating thermostats: Temperature set-point optimization and occupant feedback**

- People-centric control – give them comfort when they want it, and optimize HVAC operation around that
- Nudge people toward more efficient set point schedules



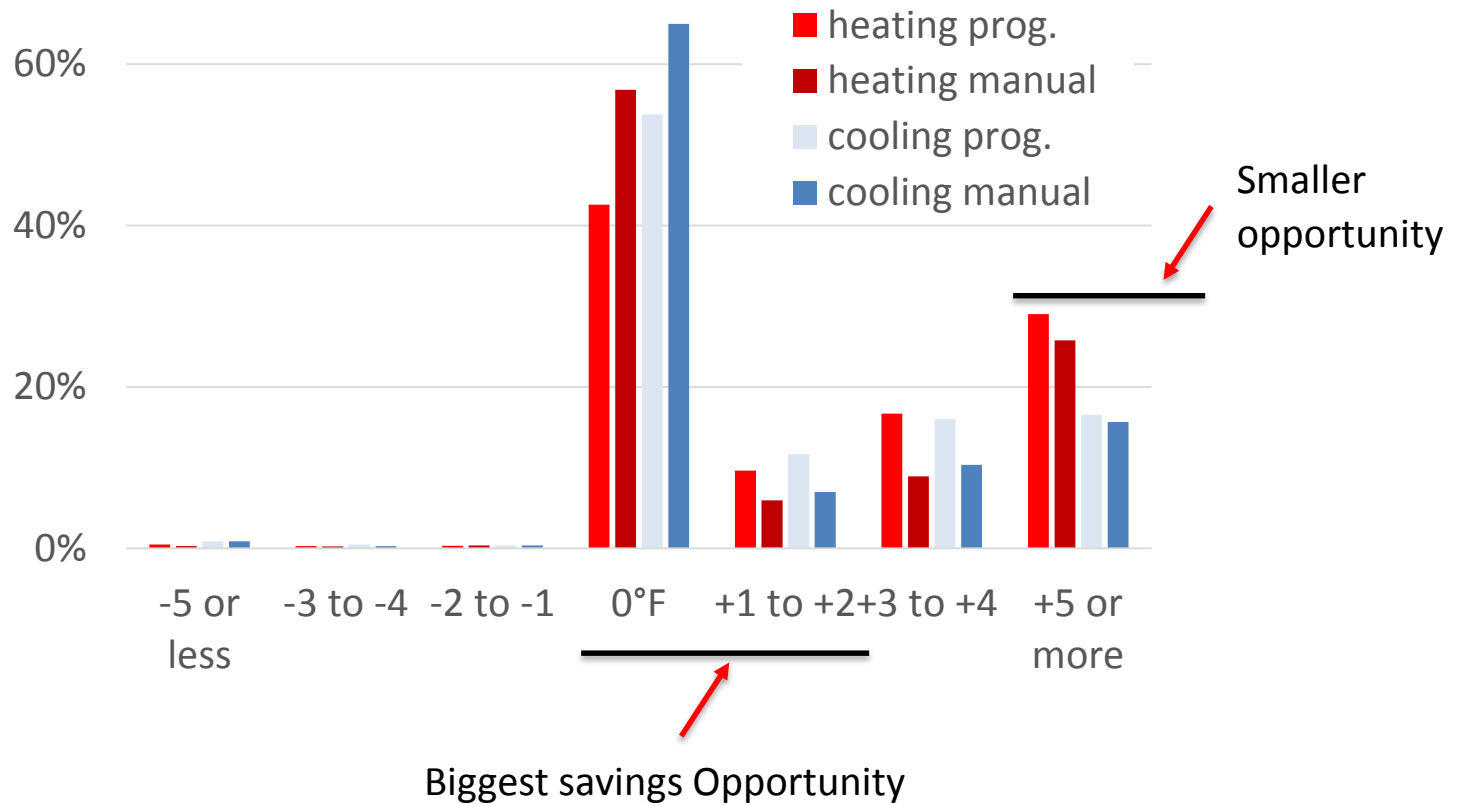
Image Source: Nest.

# Customize based on heating setpoint preferences



Source: DOE/EIA RECS 2009

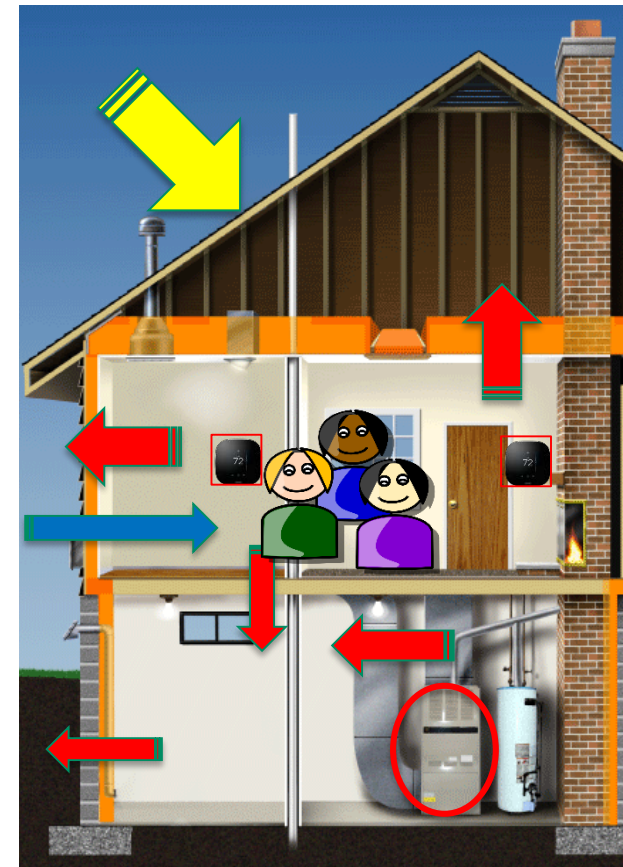
# Customize based on setback depth when away



Source: DOE/EIA RECS 2009

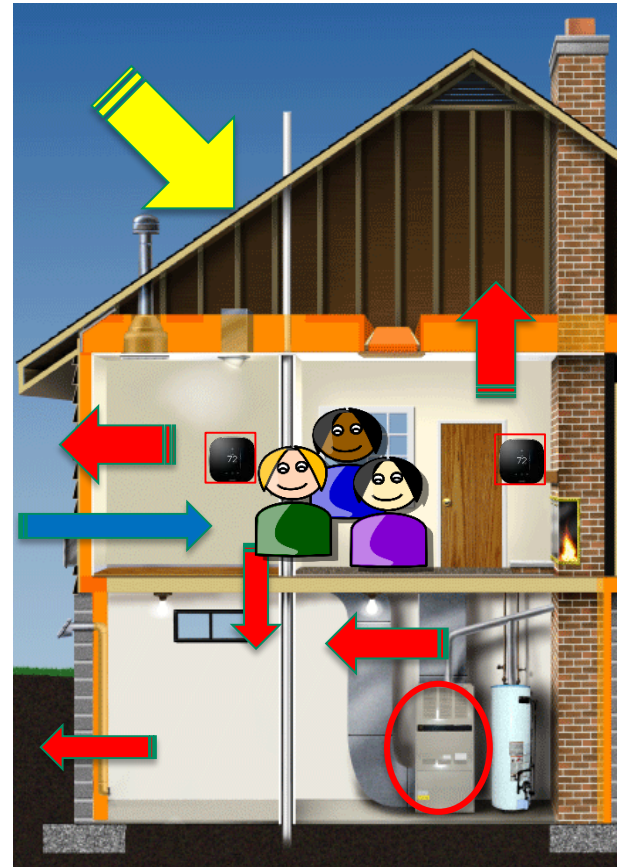
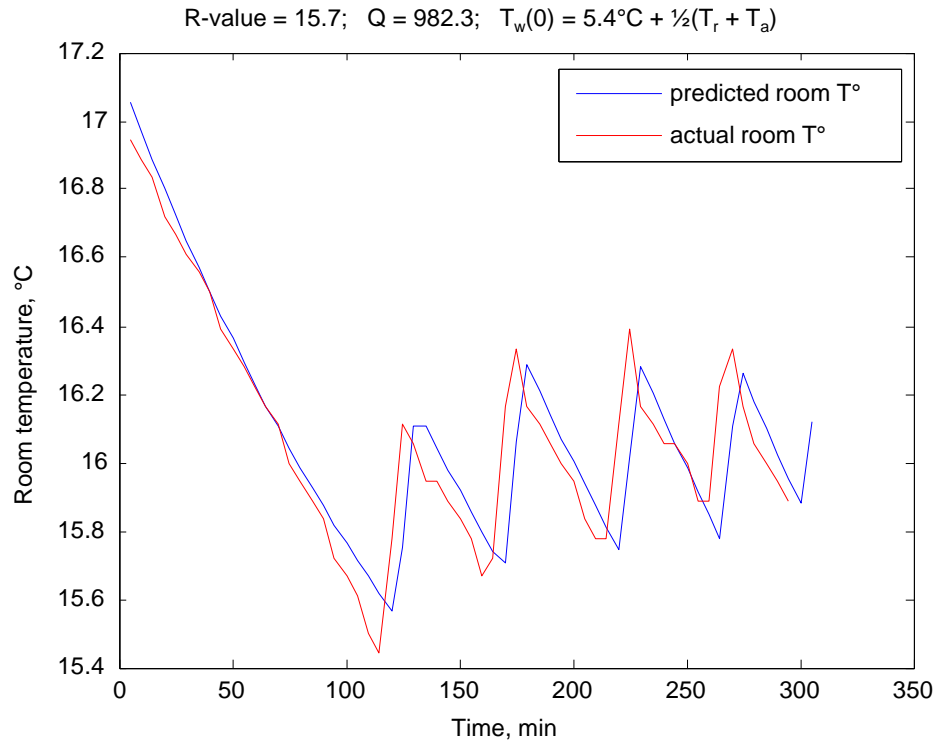
# Purchasing Behaviors and communicating thermostats: Remote home energy assessments

Date	Time	System Setting	System Mode	Calendar Event	Program Mode	Cool Set Temp (F)	Heat Set Temp (F)	Current Temp (F)	Current Humidity (%RH)	Outdoor Temp (F)	Wind Speed (km/h)	Cool Stage 1 (sec)	Heat Stage 1 (sec)	Fan (sec)
3/29/2016	0:00:00	auto	heatOff		Sleep	82	63	70	39	43.8	16	0	0	0
3/29/2016	0:05:00	auto	heatOff		Sleep	82	63	69.9	39	43.8	16	0	0	0
3/29/2016	0:10:00	auto	heatOff		Sleep	82	63	69.8	40	43.8	16	0	0	0
3/29/2016	0:15:00	auto	heatOff		Sleep	82	63	69.8	40	43.8	16	0	0	0
3/29/2016	0:20:00	auto	heatOff		Sleep	82	63	69.8	40	43.8	16	0	0	0
3/29/2016	0:25:00	auto	heatOff		Sleep	82	63	69.7	40	43.8	16	0	0	0
3/29/2016	0:30:00	auto	heatOff		Sleep	82	63	69.6	40	42.7	22	0	0	0
3/29/2016	0:35:00	auto	heatOff		Sleep	82	63	69.4	40	42.7	22	0	0	0
3/29/2016	0:40:00	auto	heatOff		Sleep	82	63	69.3	40	42.7	22	0	0	0
3/29/2016	0:45:00	auto	heatOff		Sleep	82	63	69.1	40	42.7	22	0	0	0
3/29/2016	0:50:00	auto	heatOff		Sleep	82	63	69	40	42.7	22	0	0	0
3/29/2016	0:55:00	auto	heatOff		Sleep	82	63	68.9	40	42.7	22	0	0	0
3/29/2016	1:00:00	auto	heatOff		Sleep	82	63	68.9	40	42.7	22	0	0	0
3/29/2016	1:05:00	auto	heatOff		Sleep	82	63	68.8	40	42.7	22	0	0	0
3/29/2016	1:10:00	auto	heatOff		Sleep	82	63	68.7	40	42.7	22	0	0	0
3/29/2016	1:15:00	auto	heatOff		Sleep	82	63	68.6	40	42.7	22	0	0	0
3/29/2016	1:20:00	auto	heatOff		Sleep	82	63	68.6	40	42.7	22	0	0	0
3/29/2016	1:25:00	auto	heatOff		Sleep	82	63	68.5	40	42.7	22	0	0	0
3/29/2016	1:30:00	auto	heatOff		Sleep	82	63	68.5	40	42.6	19	0	0	0
3/29/2016	1:35:00	auto	heatOff		Sleep	82	63	68.4	40	42.6	19	0	0	0
3/29/2016	1:40:00	auto	heatOff		Sleep	82	63	68.4	40	42.6	19	0	0	0
3/29/2016	1:45:00	auto	heatOff		Sleep	82	63	68.3	40	42.6	19	0	0	0
3/29/2016	1:50:00	auto	heatOff		Sleep	82	63	68.2	40	42.6	19	0	0	0
3/29/2016	1:55:00	auto	heatOff		Sleep	82	63	68.2	41	42.6	19	0	0	0
3/29/2016	2:00:00	auto	heatOff		Sleep	82	63	68.1	41	42.6	19	0	0	0



Source: Roth and Zeifman (2017).

# Fraunhofer DOE-Building America project developing algorithms using CT data to model home thermal response ...



Source: Roth and Zeifman (2017).

## Ultimately enabling:

- Identify household-specific retrofit opportunities
- Calculate household-specific energy savings potentials
- Provide targeted energy efficiency offerings to households
- Increase uptake of EE retrofits



*By insulating your home, you can reduce your heating bill by **\$183** per year ...*

*Image Source: S. Edwards-Musa.*



# ***Installation Behaviors* and communicating thermostats: Remote performance monitoring**

- For homeowners:
  - Are expected retrofit savings being achieved?
  - If not, why??
    - Poor retrofit implementation?
    - Operational fault?
    - Increased comfort?
- For utility EE programs:
  - Deliver for customers
  - Enable early identification of systematic problems, e.g.,  
condensing boiler supply water temperature reset schedules
  - Potential for customer engagement

## Use home electric interval (e.g., hourly) data to:

- Identify and target homes that are good candidates for EE and DR programs
- Identify and target homes for energy efficiency or demand response programs
- Perform remote EM&V
- Diagnose or predict HVAC faults



*Image Source: Itron.*



## Example: Analysis of West Coast utility residential behavioral EE and DR pilot

### *Fraunhofer hypothesis:*

- Likelihood to participate in EE and DR programs reflects energy-related attitudes and beliefs
- Energy-related attitudes affect energy-related behaviors
- Energy-related behaviors impact electricity consumption pattern

*Thus: Households likely to participate have similar electricity consumption patterns*

Sources: Zeifman (2014, 2015)

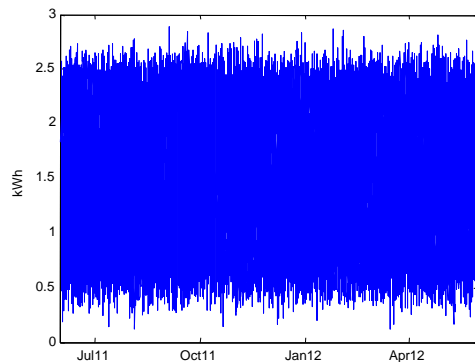
# Field Data Description

- Pool 1: Smart meter data on ~5,600 households that enrolled in the Program (out of 470,000 eligible households, or 1.2%)
- Pool 2: Smart meter data on ~32,000 households resided just outside the eligible area (still same city and microclimate zone)
  - Hourly electricity consumption for ~18 months (1 year before the Program) of each household
  - Zip code of each household
- Pool 1 seems to be similar to Pool 2
  - Socio-economic data do not differ significantly (US Census by zip code)
  - Average hourly electricity consumptions do not differ significantly

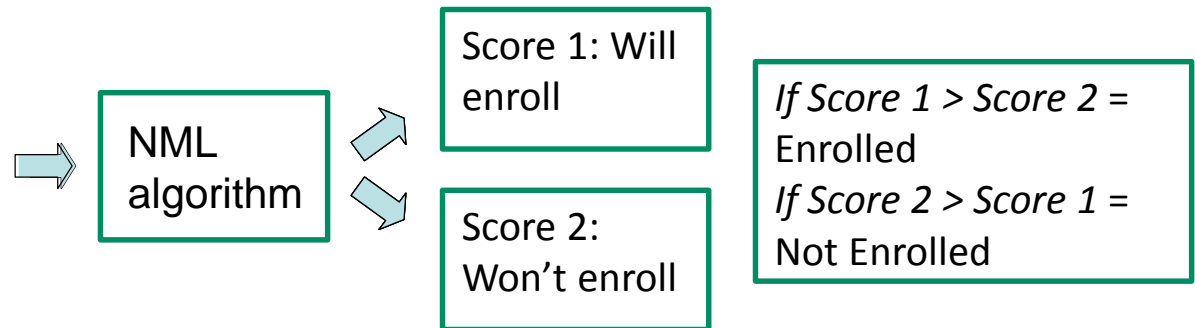
*Sources: Zeifman (2014, 2015)*

# Approach: Applied nonlinear machine learning (NML) algorithms

- Black box system: inputs → NML algorithm → output
  - *Input*: Year's worth of hourly electricity consumption data
  - *Output*: Binary (likely to enroll / unlikely to enroll)
- Algorithm cannot tell what visible signal/household features correlate with enrollment propensity, just whether a household is more or less likely to enroll.



Household hourly kWh data



Sources: Zeifman (2014, 2015)

# Algorithm Testing

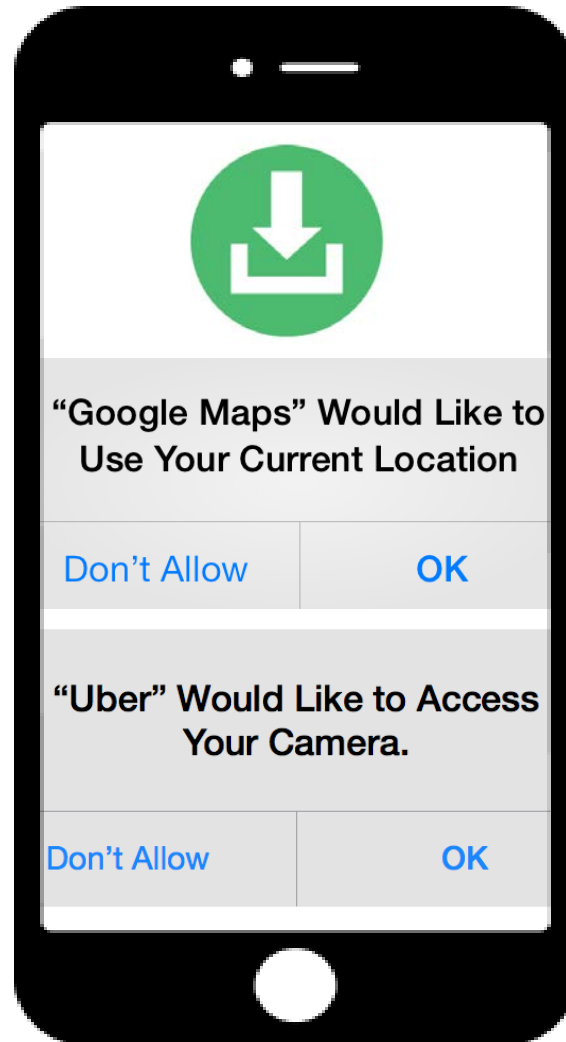
- Classify a random sample of 2,000 enrolled households and 2,000 not enrolled households not used for training
- Repeat the process of training and testing using random samples (multiple cross-validation)
- Random chance = 50% prediction accuracy.

Samples used	Enrolled households	Not enrolled households
Training samples	92.4±1.1 %	91.7±1.3 %
Testing samples	91.2±1.1 %	90.5±1.4 %

**Algorithm predicted what households would enroll with an accuracy ~five times greater than chance**

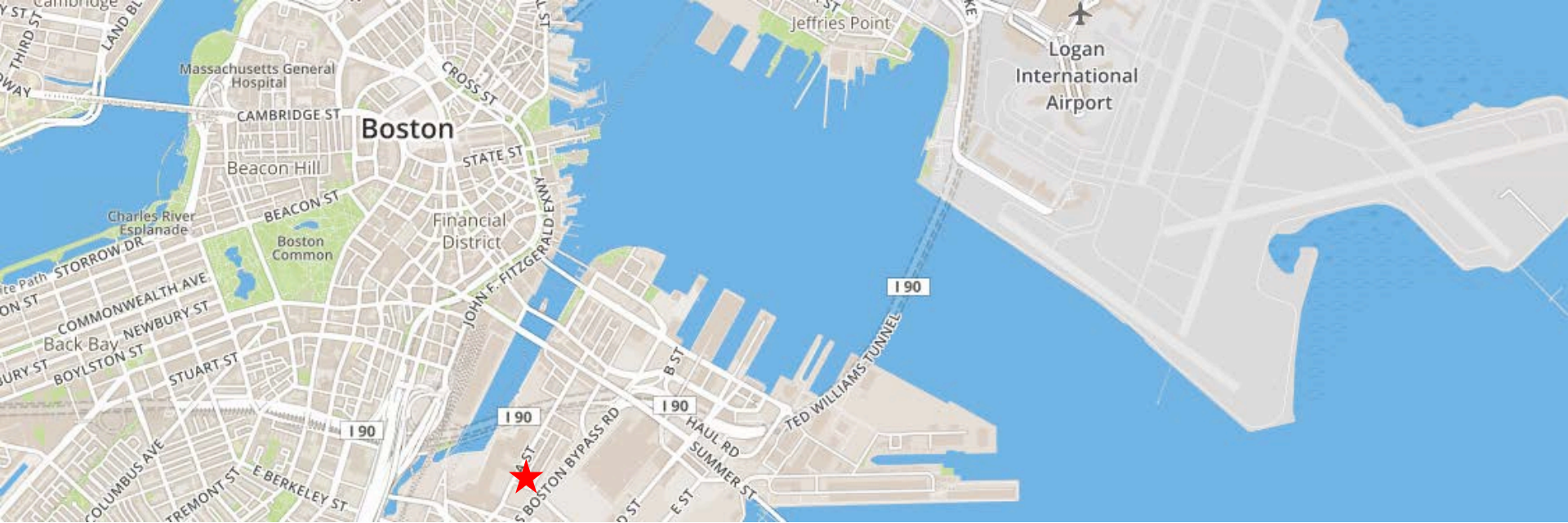
*Sources: Zeifman (2014, 2015)*

# NEED: Common Data Sharing Frameworks



# In short, Sapiens happens!





## Contact

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