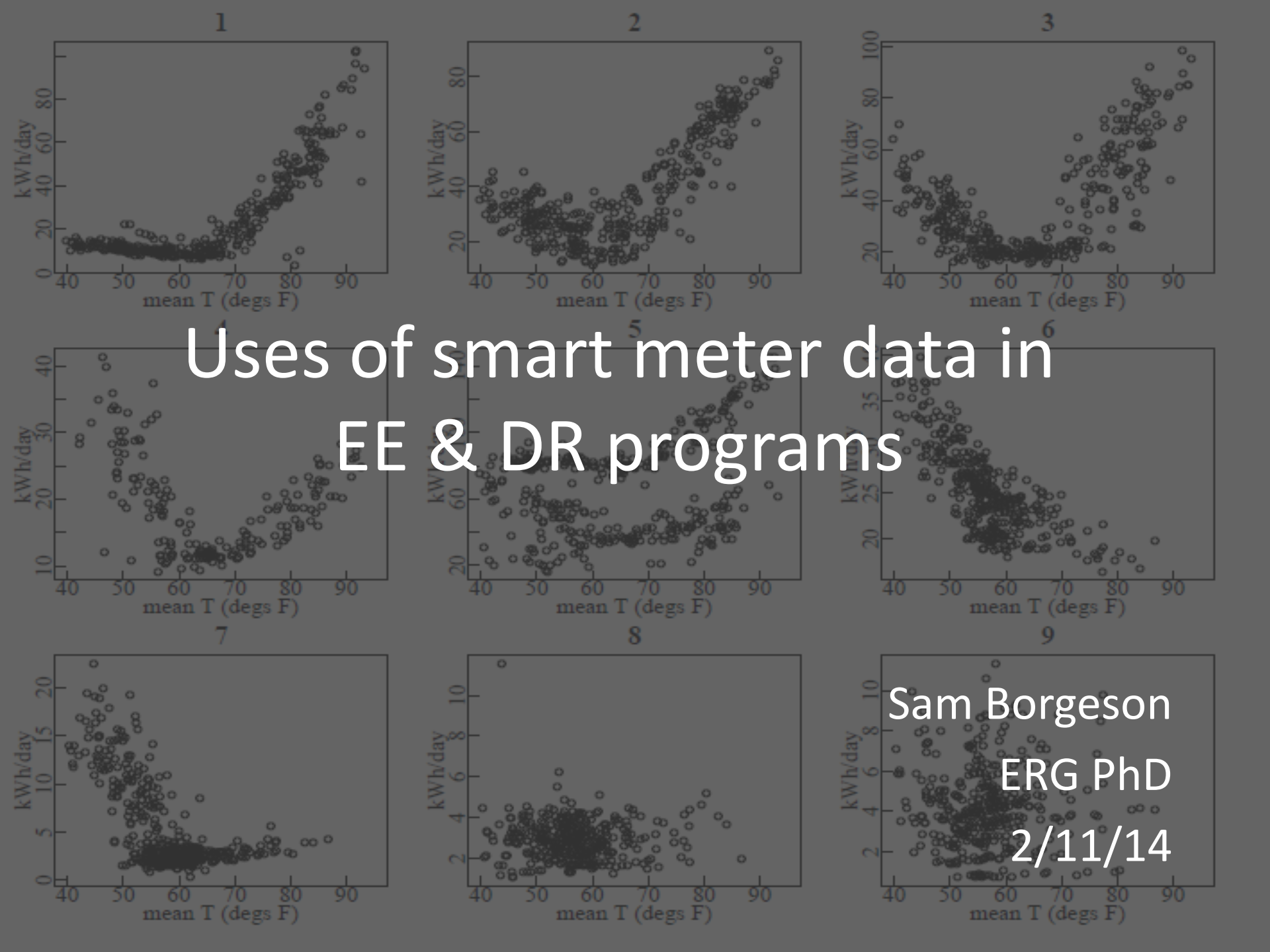
Uses of smart meter data in EE & DR programs



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2/11/14

Definitions for today

- **Smart meter data** – hourly averaged observations of electricity consumption, typically spanning a year or more
- **Energy efficiency (EE)** – reductions in energy demand (kWh) through engineered efficiency, service substitution, conservation, controls, or waste reduction
- **Demand response (DR)** – automated or manual control of power demand (kW) on command, achieved through energy storage, load curtailment, or other control changes

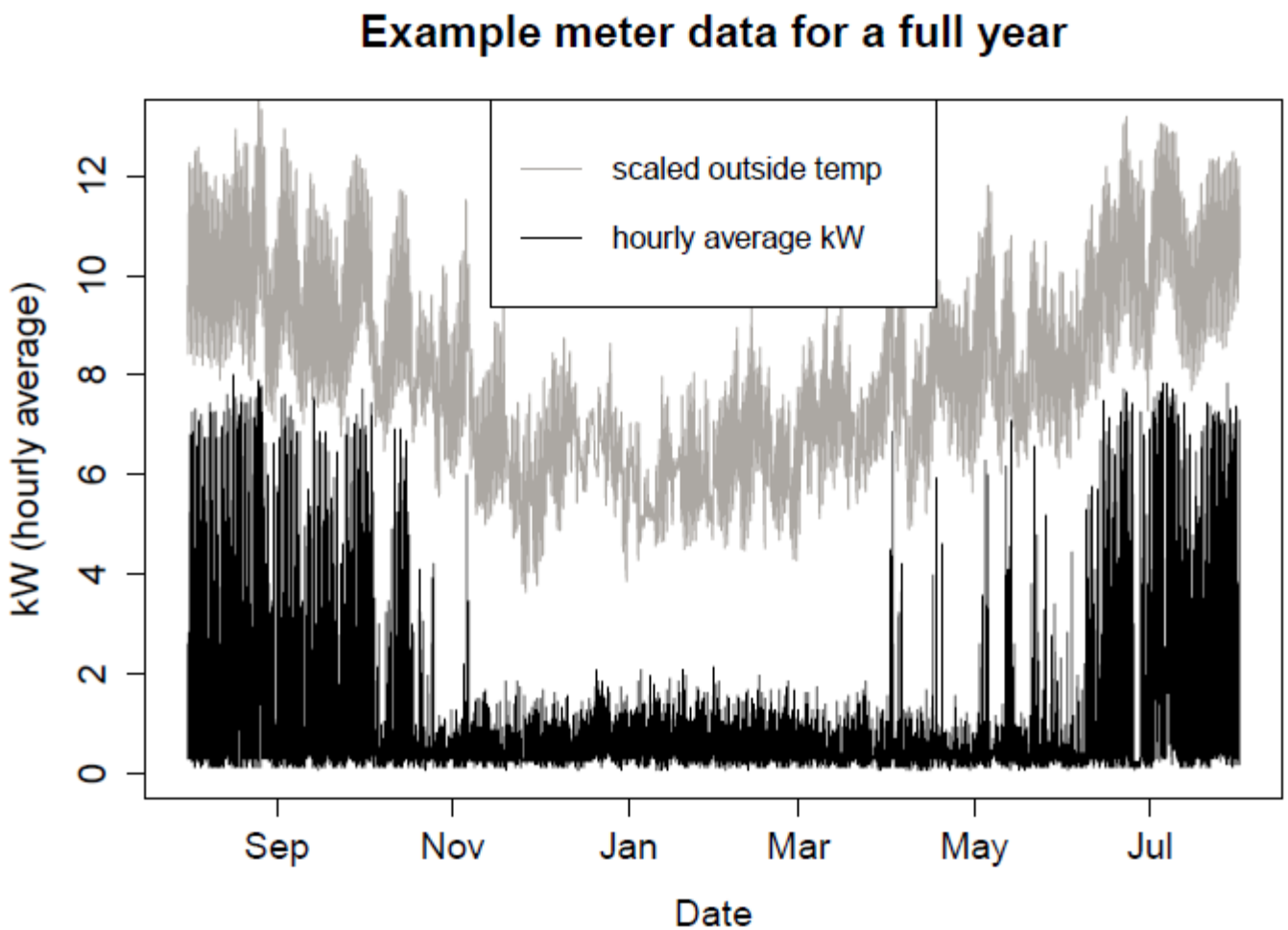
Talk outline

1. Mitigation efforts will require unprecedented delivery of energy efficiency (EE) and demand response (DR) resources.
2. Smart meter data can facilitate EE and DR by enabling well informed and targeted programs to reach all customers.
3. Meter data expresses the diversity of site conditions and occupant preferences and behaviors most responsible for variation across homes.
4. Meter data reveals information about occupant/behavior/habit driven energy choices
5. There is much more public interest analysis that can be done!

Building efficiency mitigation challenges

Challenge	Response
Future programs **must out-perform** current programs	Focus on methods and tools that can identify **deep savings** and **scale** to the whole population
Timely changes must come from **existing buildings**	Focus on technologies and processes that can be retrofit (e.g. **operations and controls**) ; pursue organizational and behavioral changes
Demographics **weakly predict** energy performance and characteristics	Use consumption data to plan and evaluate projects: look for **patterns of use** that indicate opportunity; **benchmark** using peer comparison
There is limited **building attribute data** available	**Extract metrics** (descriptive and predictive) from meter data, public records, digital maps, etc.
Energy consumption **characteristics vary widely** across buildings	Go beyond blanket prescriptions: identify candidates for **targeted savings** and **group similar customers** to repeat successful strategies

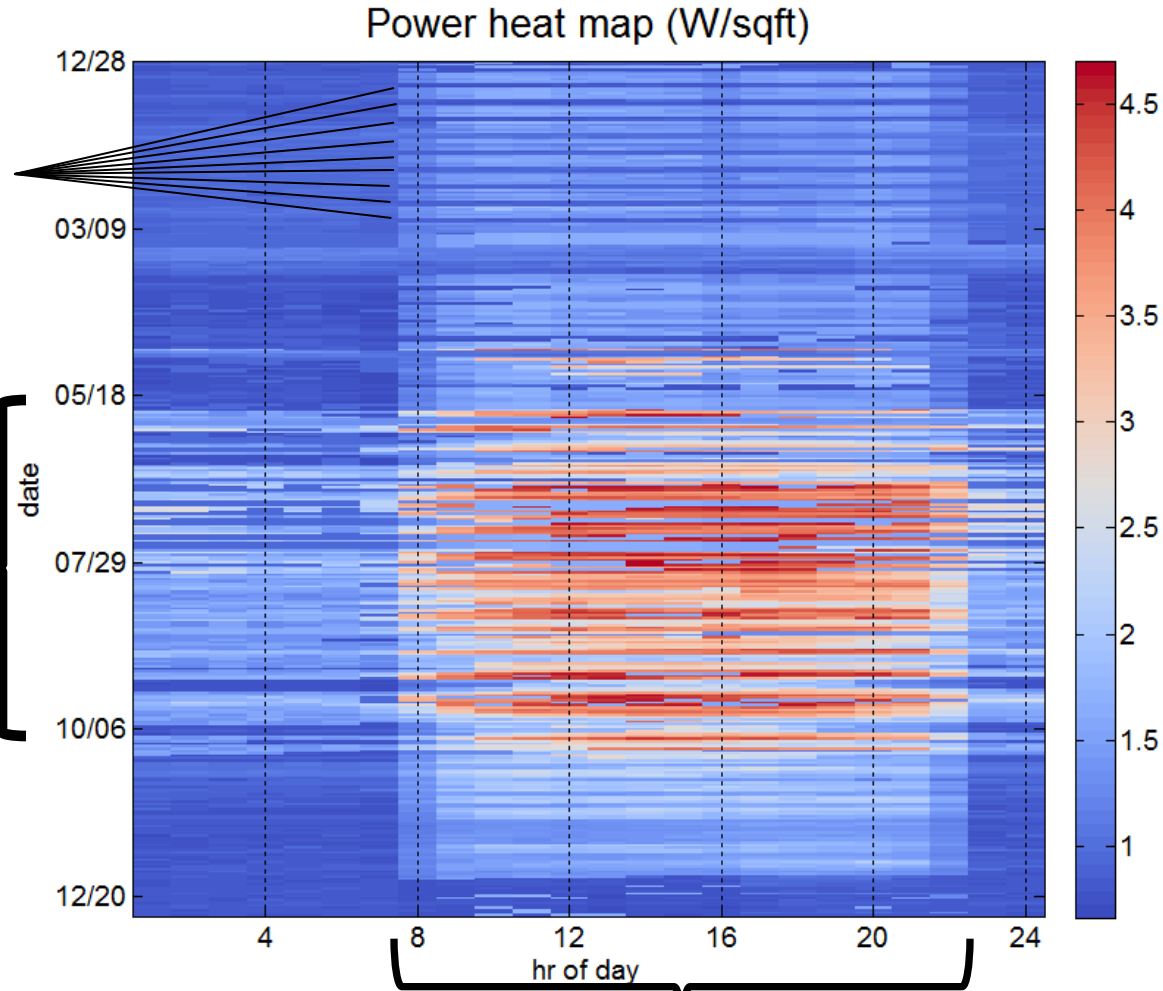
Example smart meter data



A year of data made legible

Banding from weekend schedules

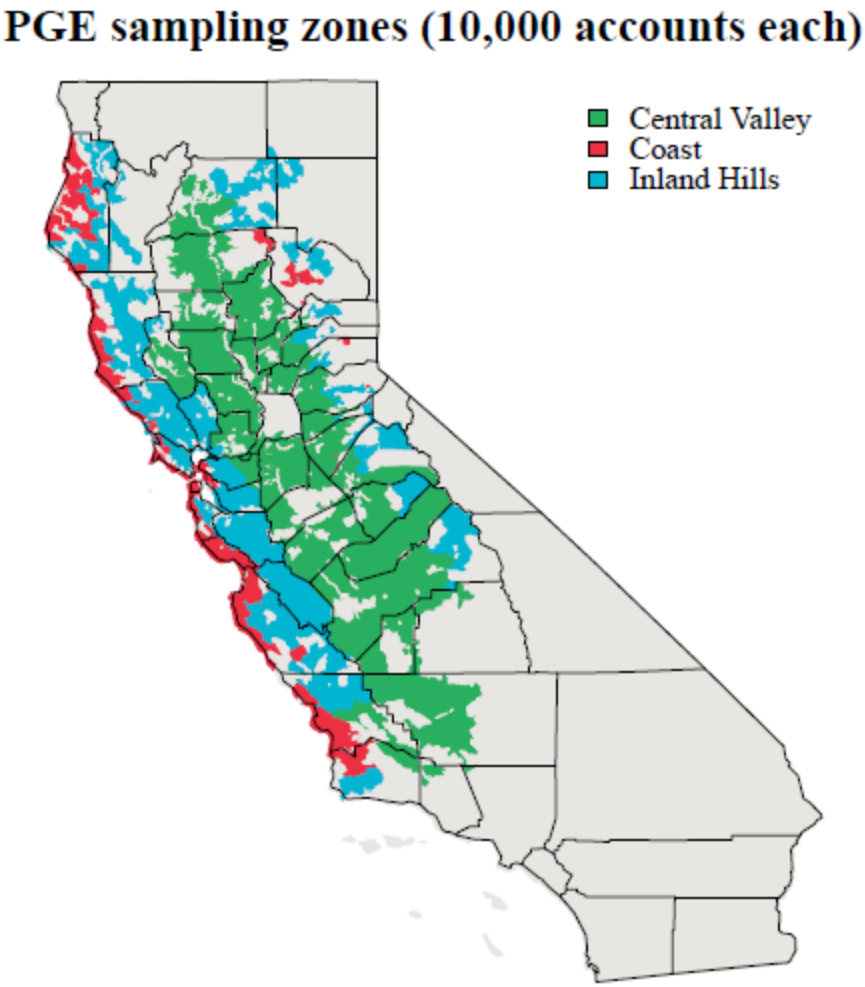
Summer cooling season (runs after hours)



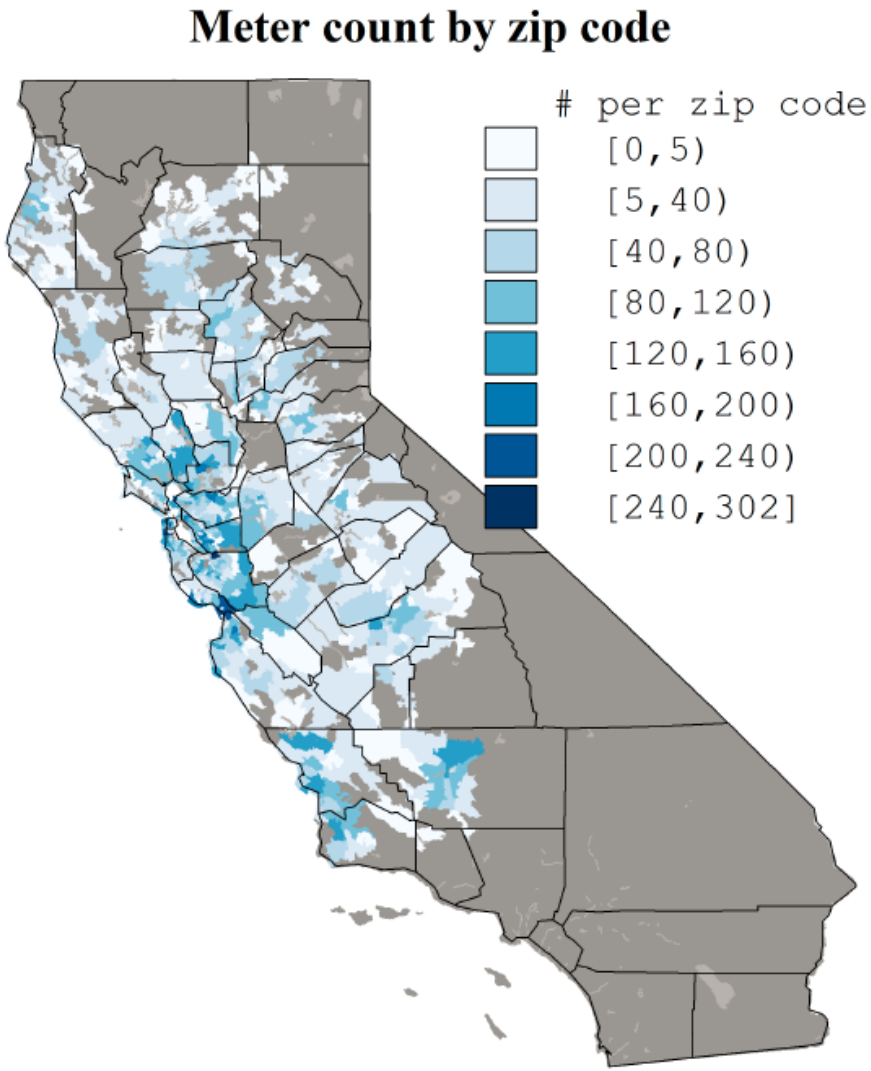
Daily schedule – 7am to 10pm!

Sampling zones for the Wharton data

- 30,000 accounts
- 10,000 randomly sampled from each of 3 zones
- Hourly electricity
- Daily natural gas



Wharton sample



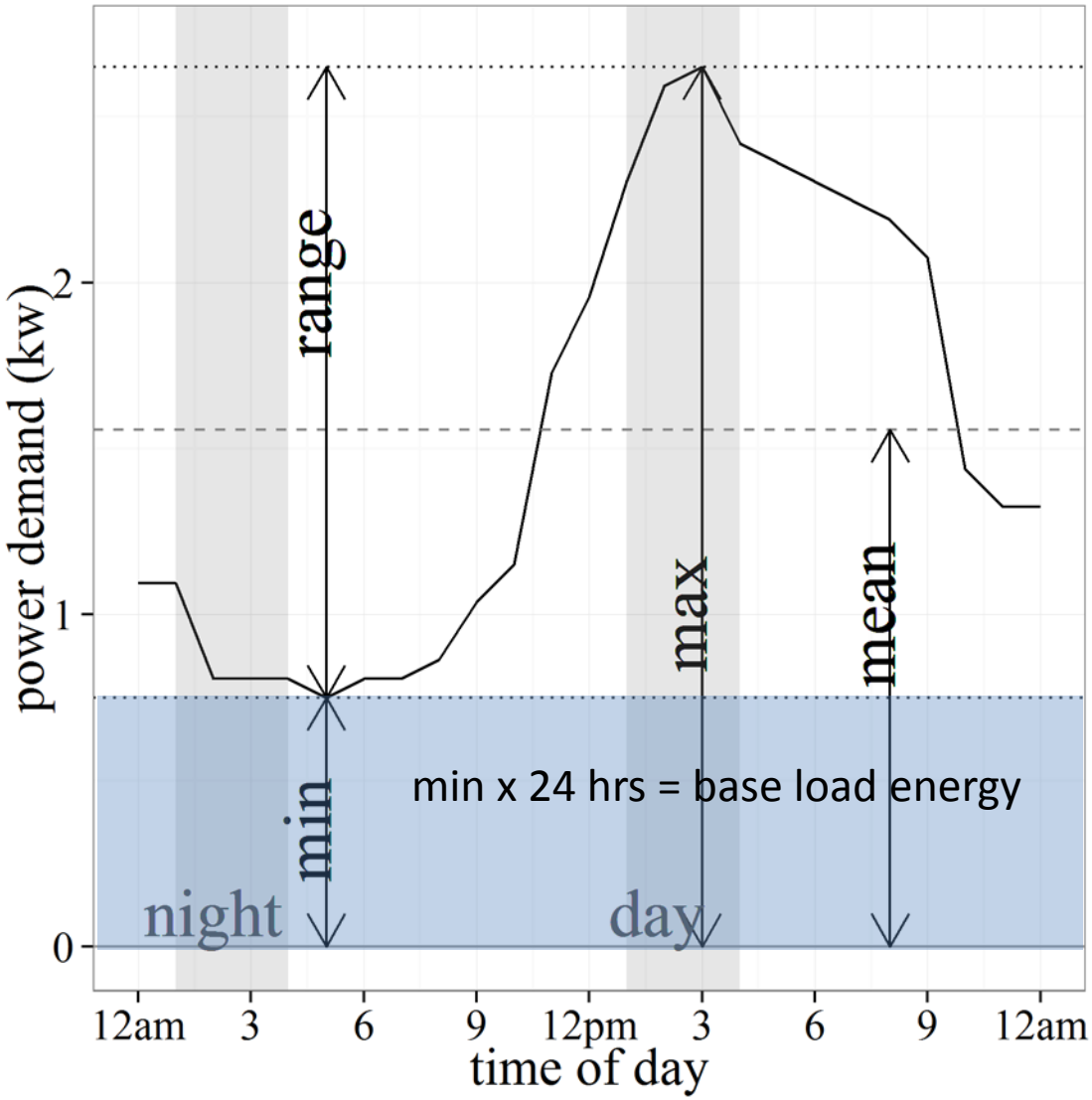
Examples of smart meter data analysis

- Smart meters **record actual consumption**, the sum of all relevant end uses, complete with occupant behaviors and schedules, automation, and imperfections
- Smart meter data documents patterns of consumption in **unprecedented spatial** (individual customers) and **temporal** (hourly) detail
- Automated analytical algorithms, using meter data as inputs, **can scale to large populations**
  - As of May 2012, electric US utilities had deployed ~36 million smart meters (1 in 3 households), with 65 million projected to be deployed by 2015
- Examples and analysis drawn from large samples of PG&E's 4.5M residential customers

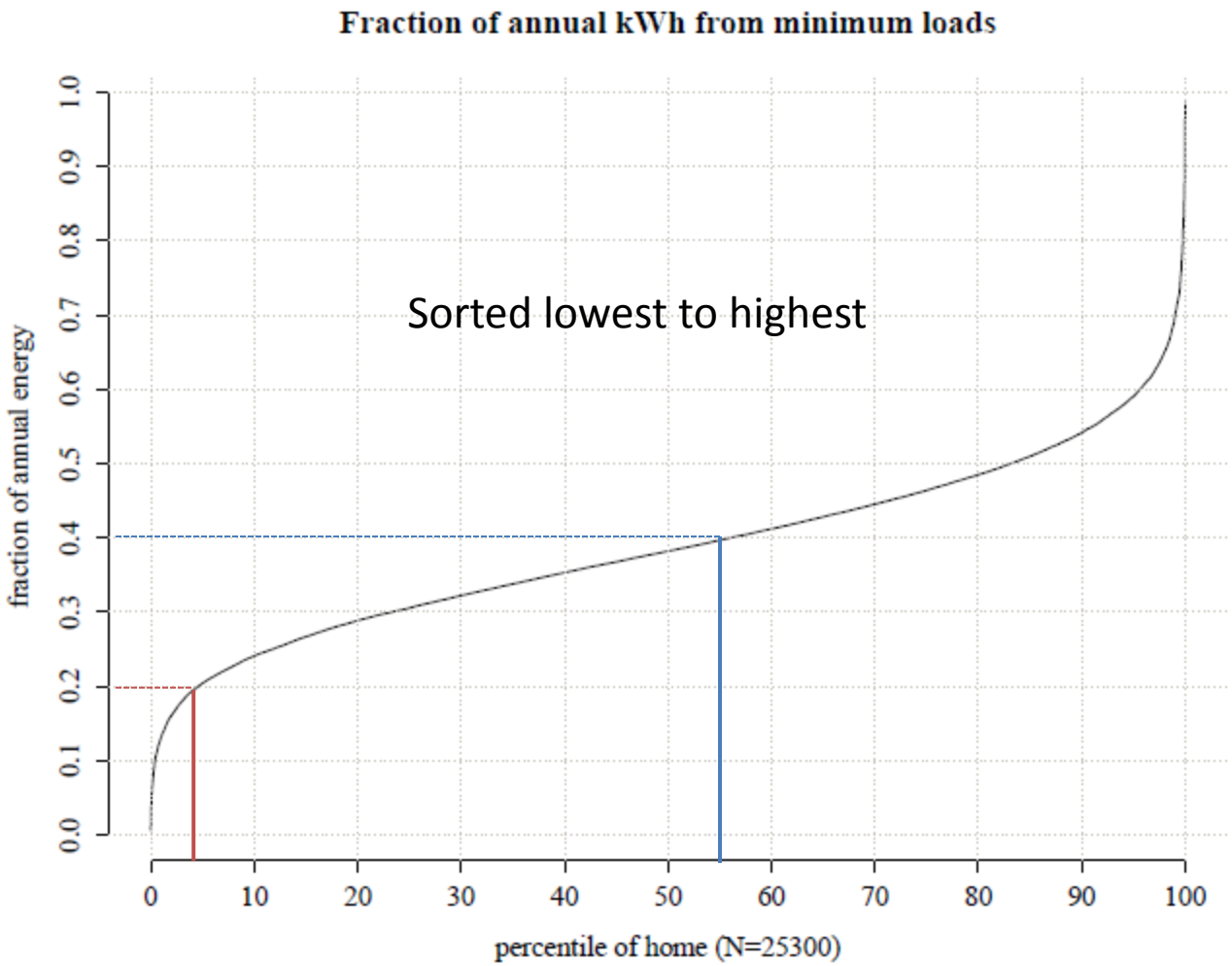
Ex 1: Baseload

Estimating energy consumption of always on equipment

New with hourly data: Load shapes!



Annual fraction of energy attributable to base load energy



Minimum loads contribute:

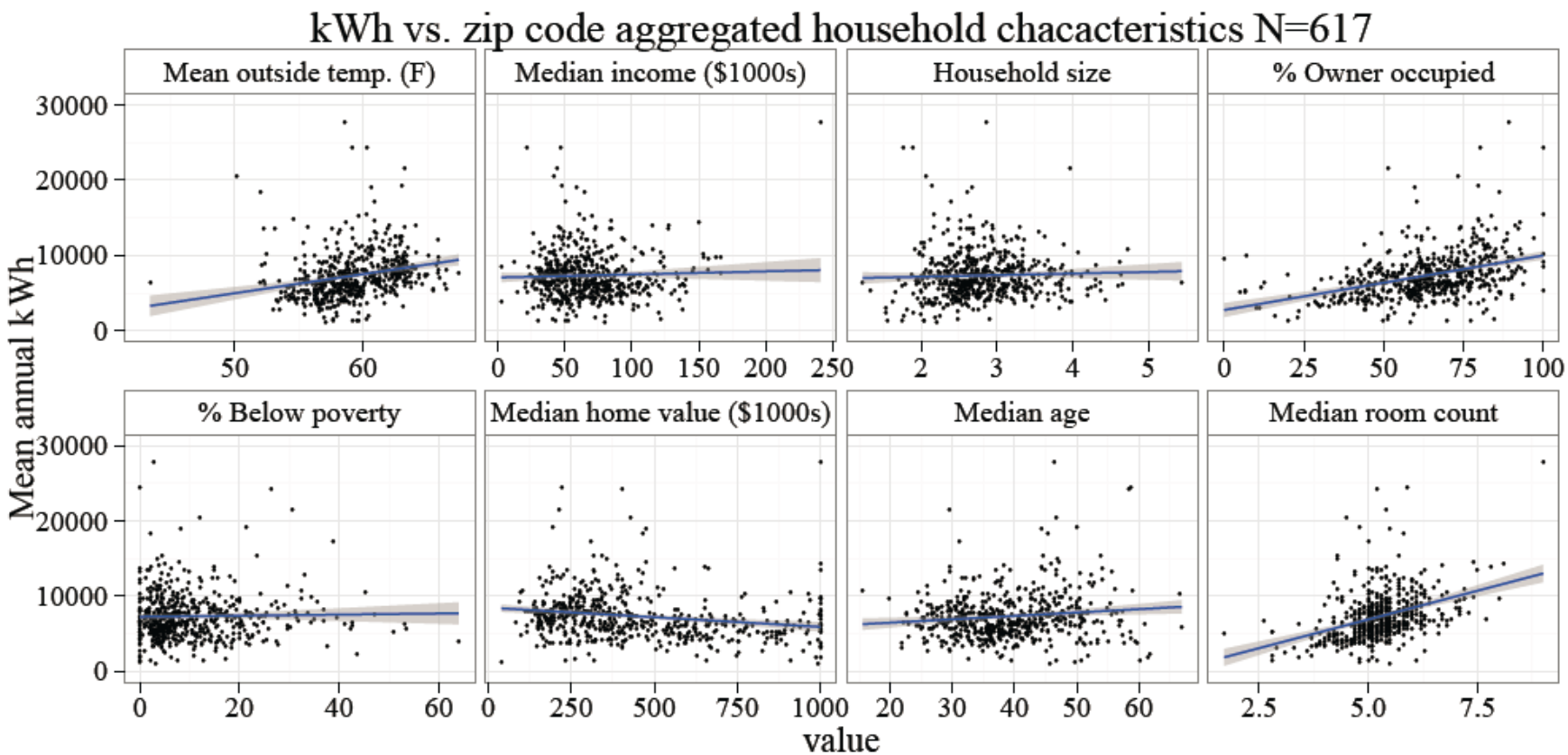
<20% of annual energy use in fewer than 5% of homes.

>40% of annual energy use for 45% of all homes.

Ex 2: Targeting

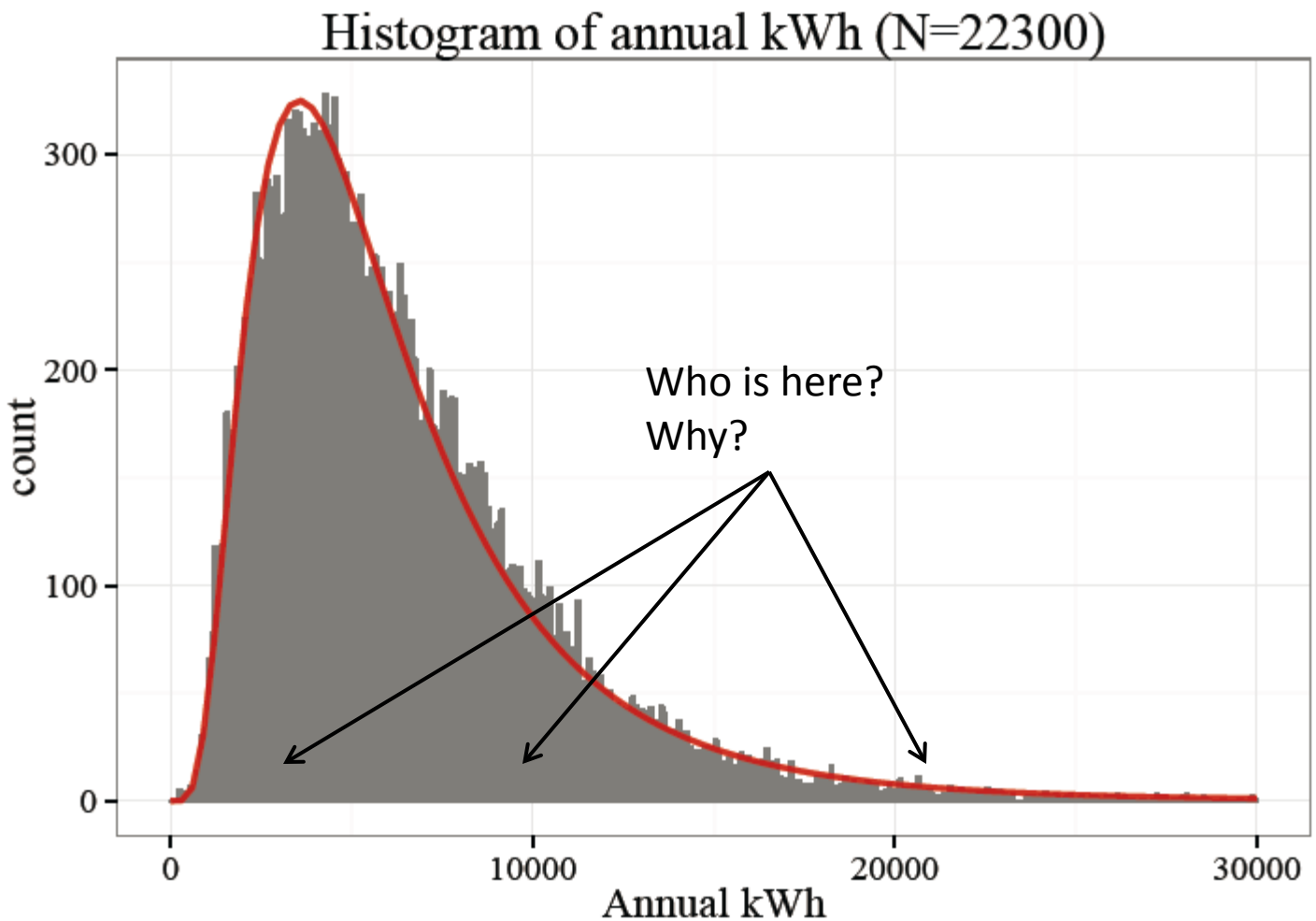
Differentiation of program implementation opportunities across premises and within each premise

Electricity usage correlation with demographics

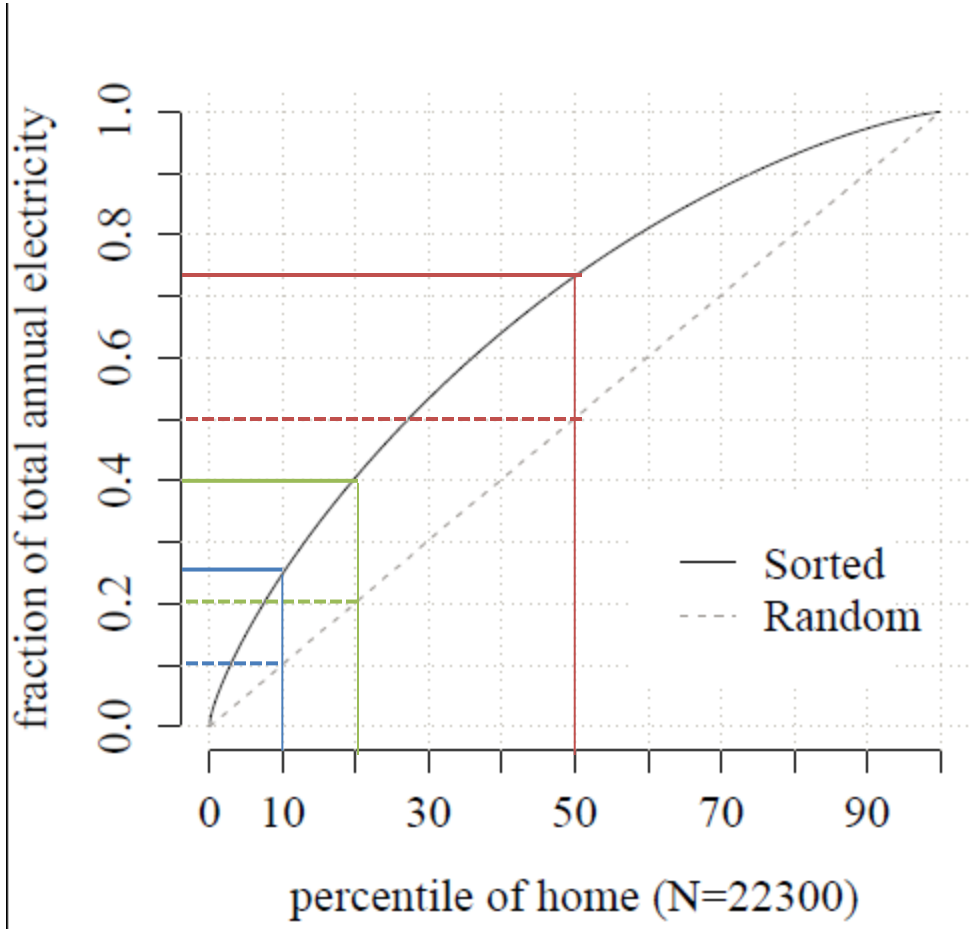


Often non-zero, but explain a small fraction of variance.

Distribution of annual kWh demand



Cumulative sum of ranked vs. randomly selected annual energy



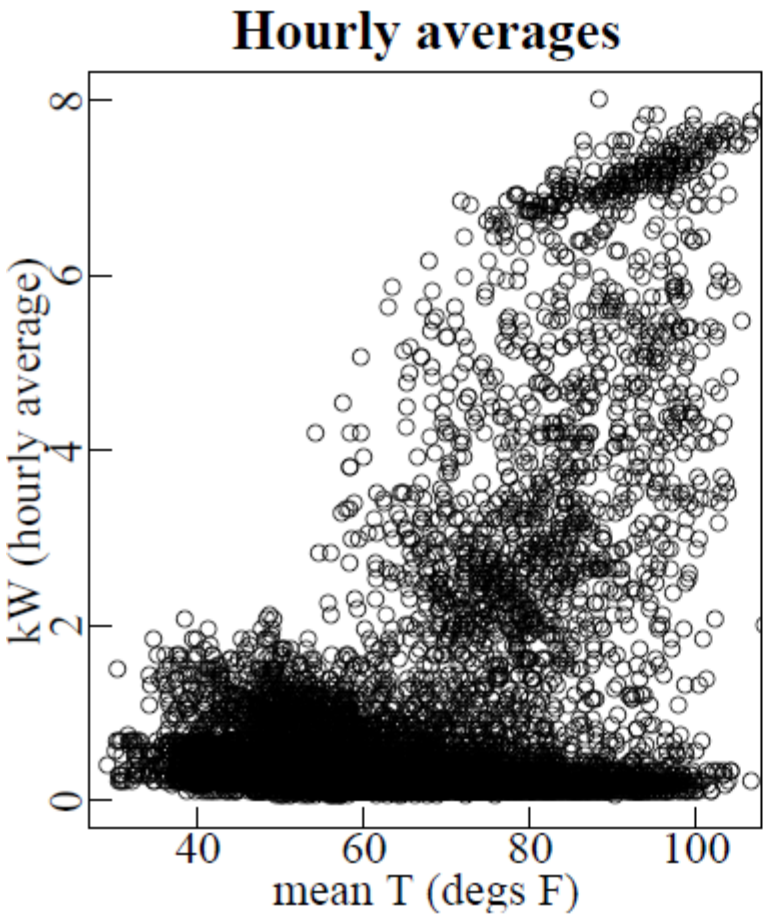
Sorted vs. random participation

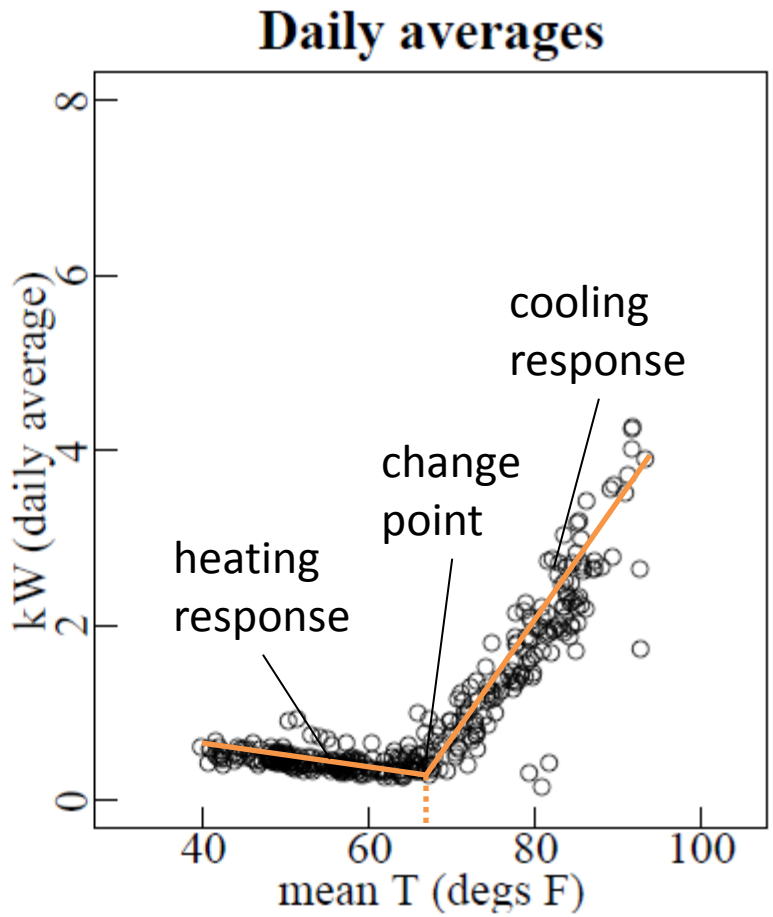
%ile	Ranked fract.	Random fract.	Ratio
10	0.25	0.10	2.5
20	0.4	0.2	2
50	0.75	0.50	1.5

Ex 3: Thermal data analysis

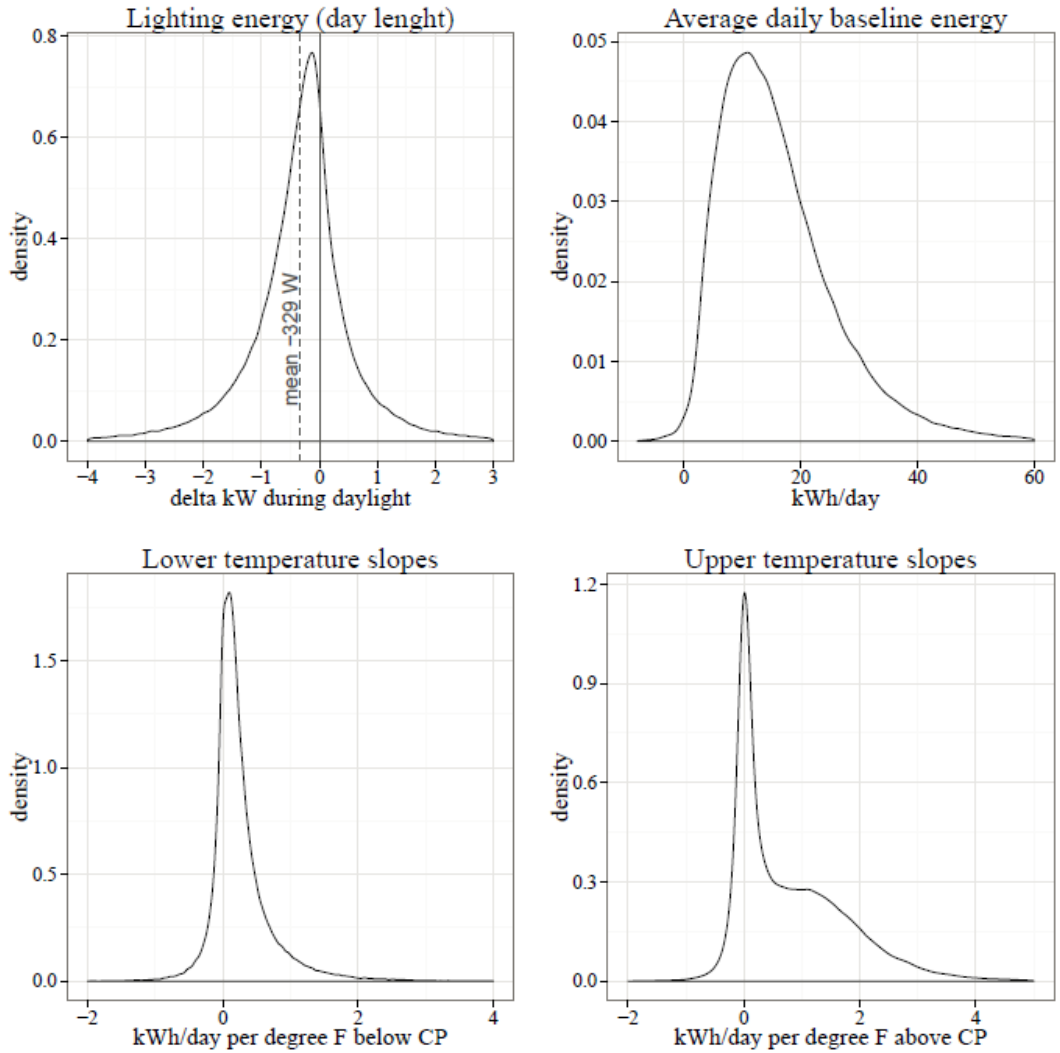
- **Regression modeling** to fit drivers of home energy demand
- Several **competing models** describe different operational strategies
- Model selection determines the **best model per household** and overall
- Model parameters can be interpreted as **physically meaningful** customer attributes

Hourly vs. daily averaging of demand

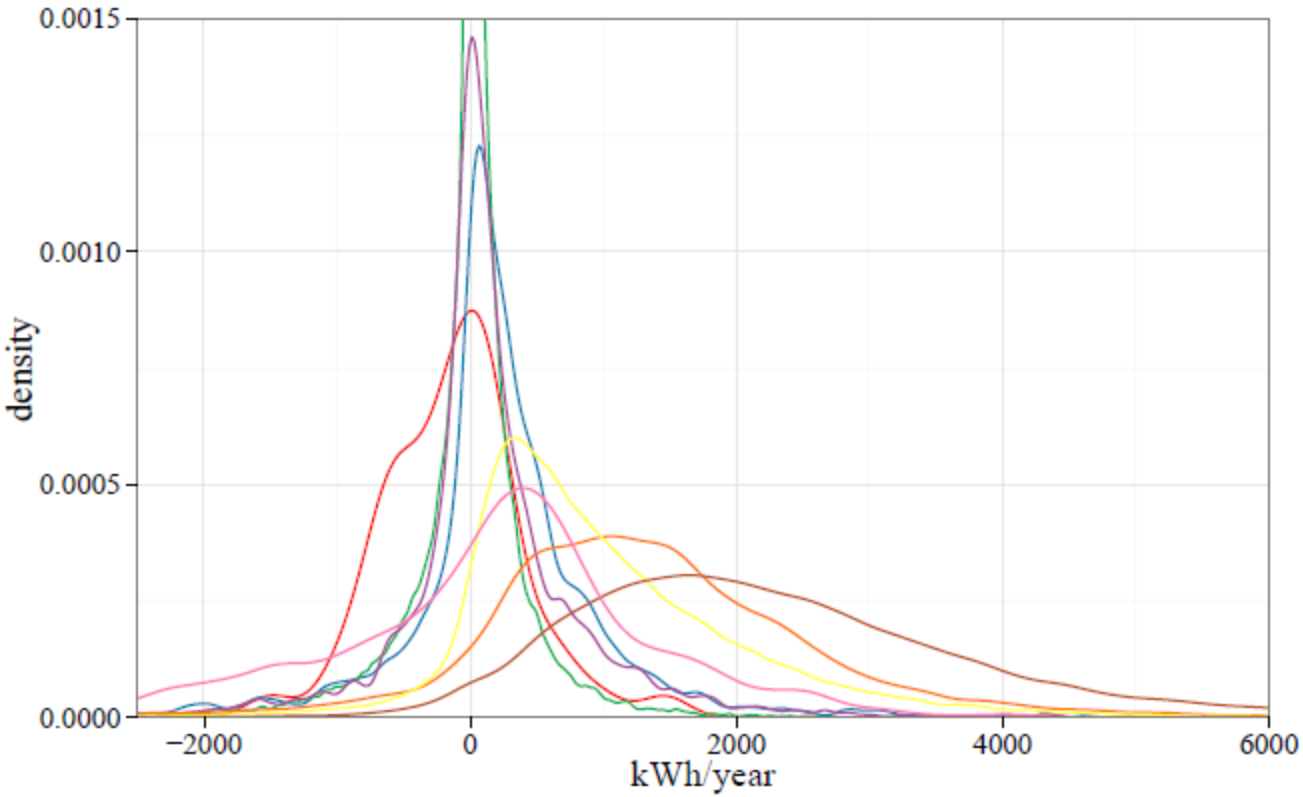


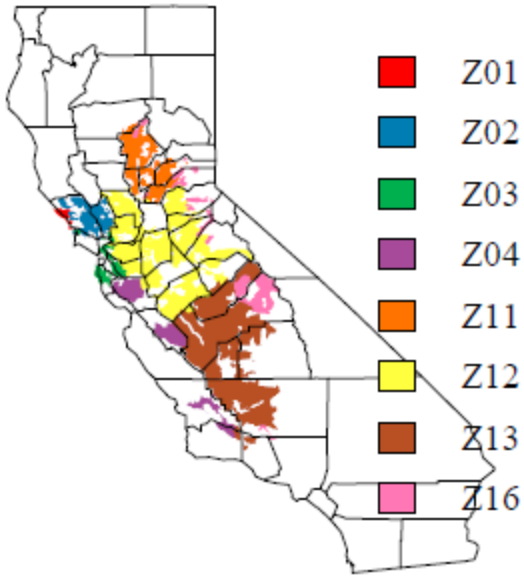


Distributions of model coefficient estimates (N=160,000)

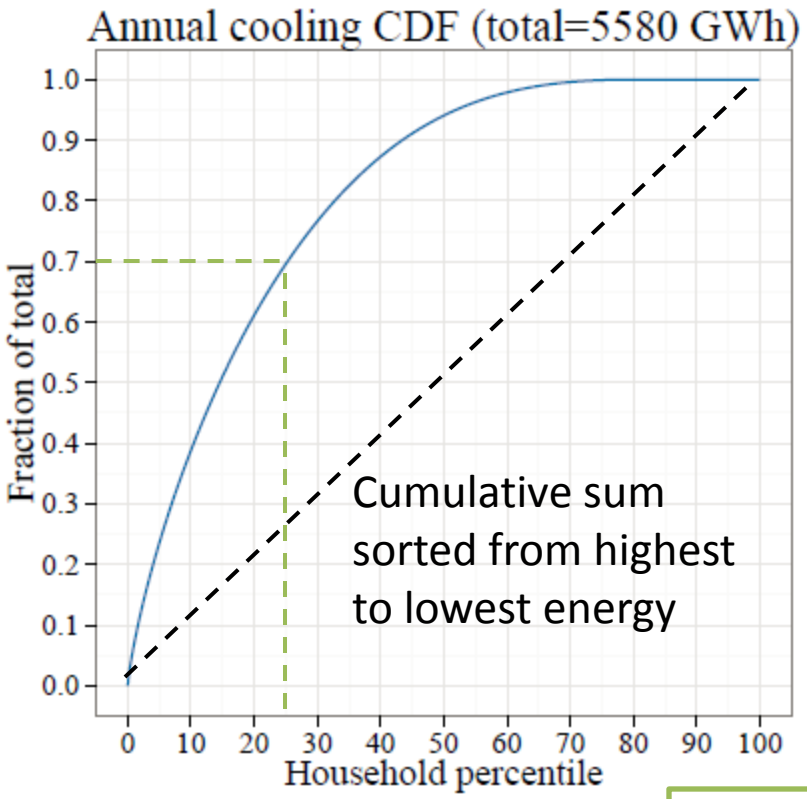


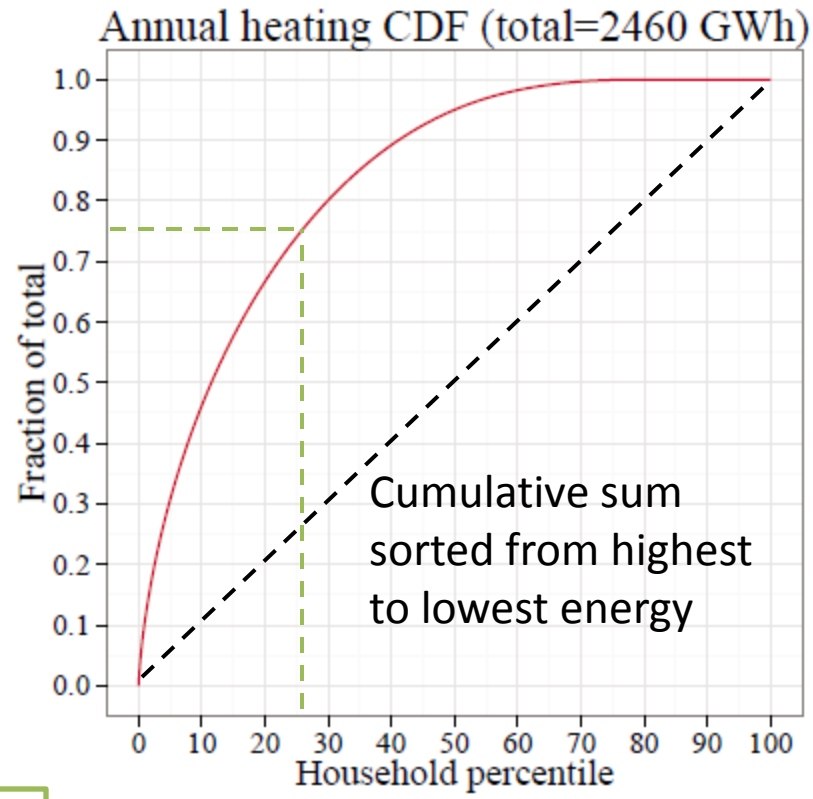
Modeled annual cooling energy





Cumulative estimated electric cooling and heating energy



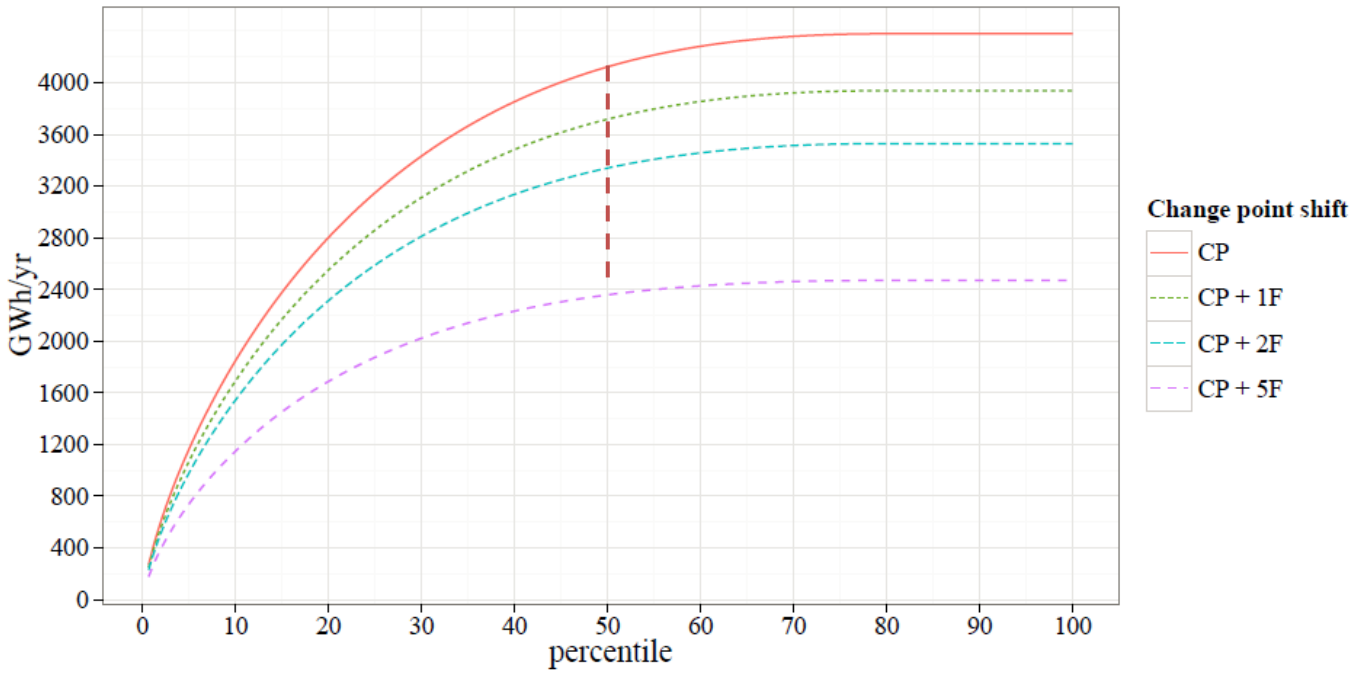


percentile	5th		10th		25th		50th		75th		100th	
	GWh	%	GWh	%	GWh	%	GWh	%	GWh	%	GWh	%
cooling	1315	24%	2166	39%	3881	70%	5247	94%	5574	100%	5579	100%
heating	755	31%	1136	46%	1820	74%	2336	95%	2457	100%	2459	100%

Changing set points

Re-calculate annual estimates with modified change points

Cumulative distributions of annual cooling energy with modified cooling set points



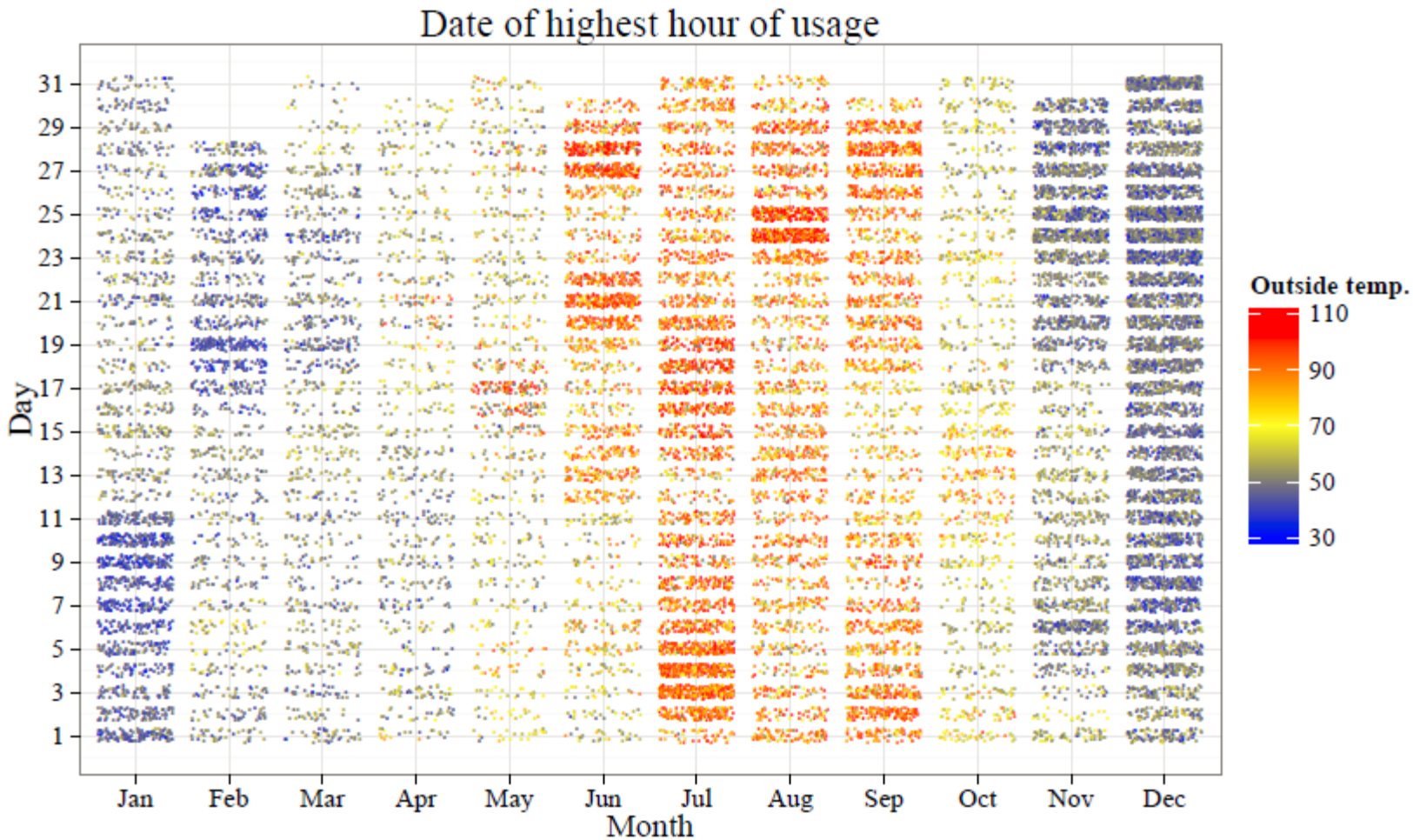
Savings from set point increases by ranked percentile of the population

percentile	5th		10th		25th		50th		75th		100th	
$\Delta^\circ F$	GWh	%	GWh	%	GWh	%	GWh	%	GWh	%	GWh	%
$+1^\circ F$	95	8%	157	8%	289	9%	406	10%	440	10%	440	10%
$+2^\circ F$	185	16%	306	17%	561	18%	784	19%	849	19%	850	19%
$+5^\circ F$	425	36%	702	38%	1276	40%	1766	43%	1906	44%	1909	44%

Ex 4: Peak demand

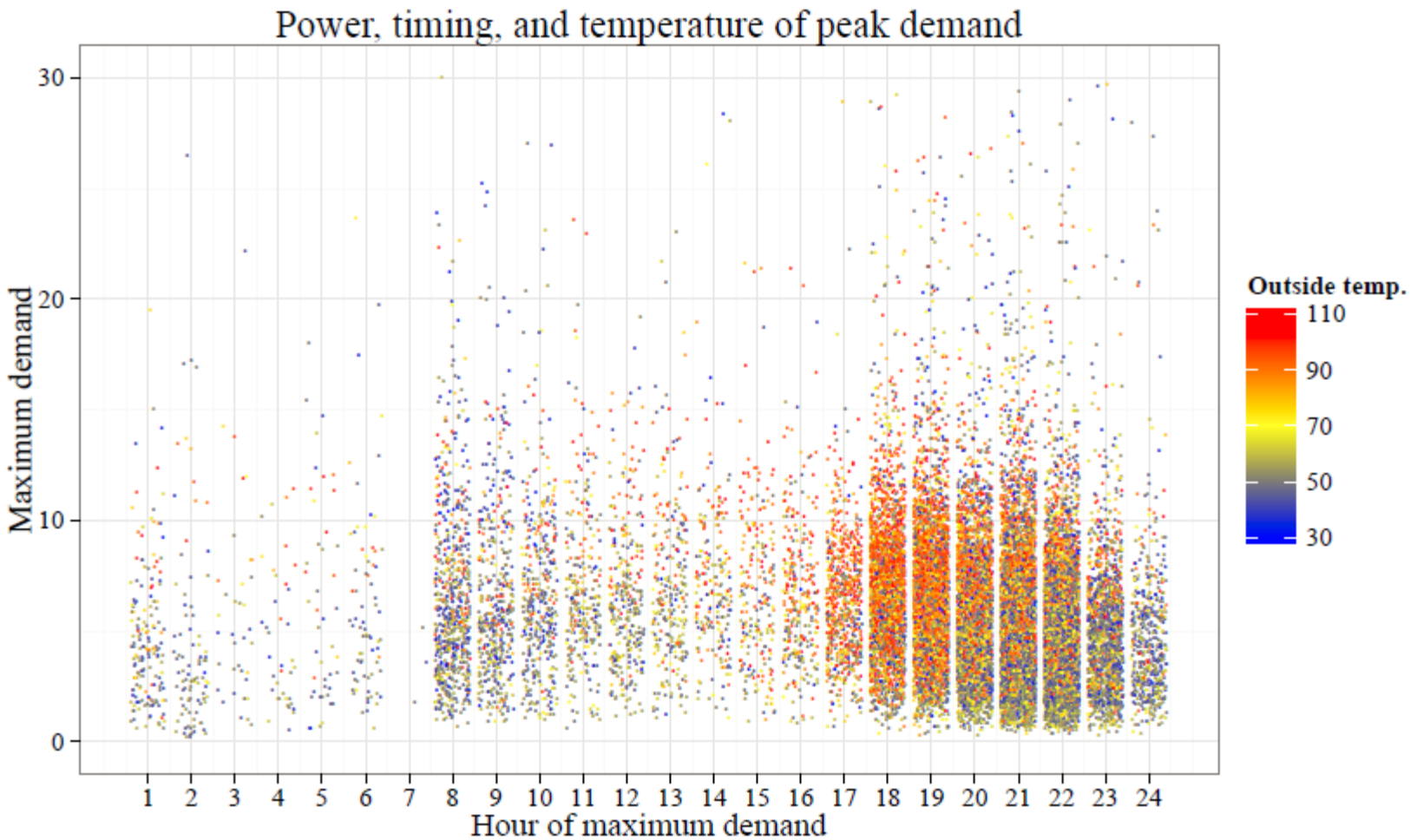
Characterizing the timing and magnitude of household annual peak demands and their relationship to grid peak demand

Calendar of peak demand hours for every household

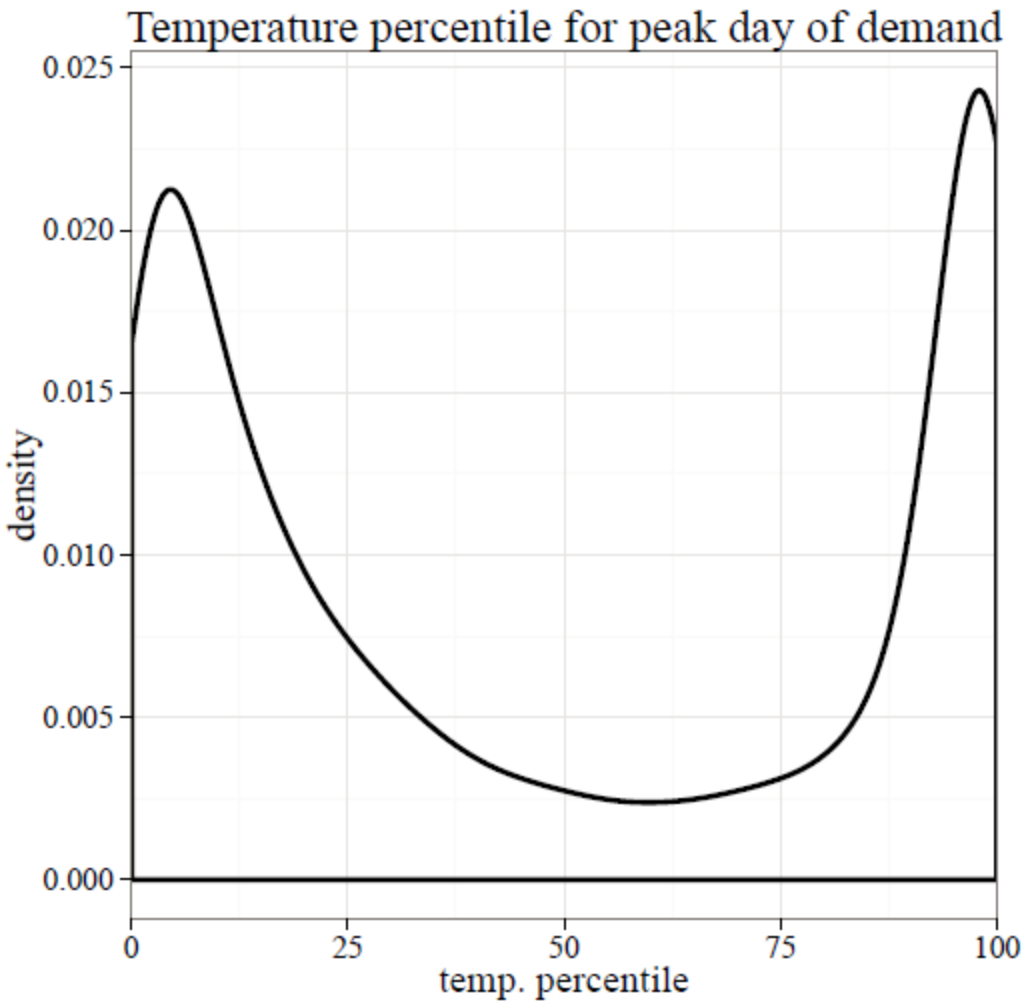


Highest usage correlates with hottest and coolest temperatures; also influenced by holidays.

Time of day of peak demand hours for every household

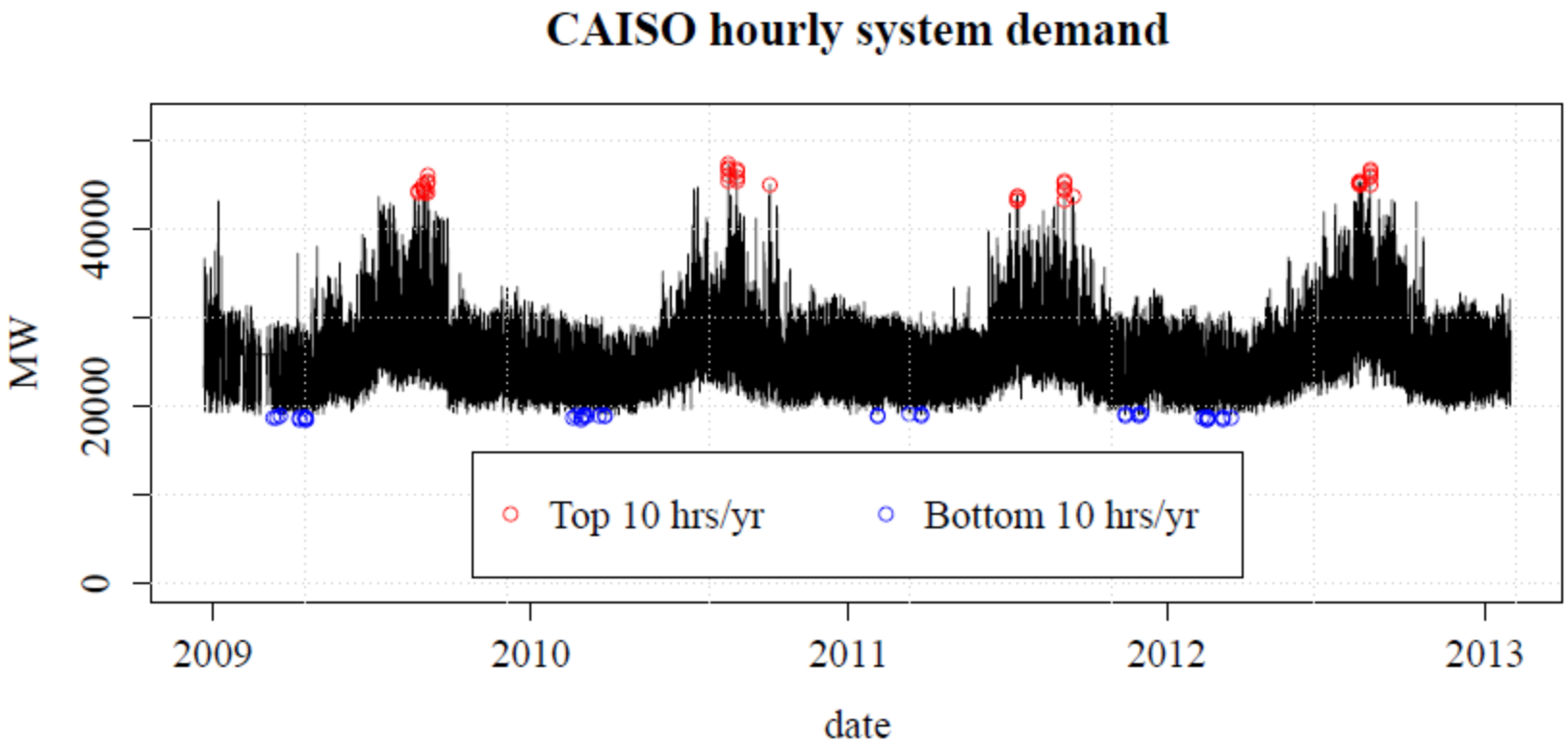


Density of outside temperature percentile for peak demand day



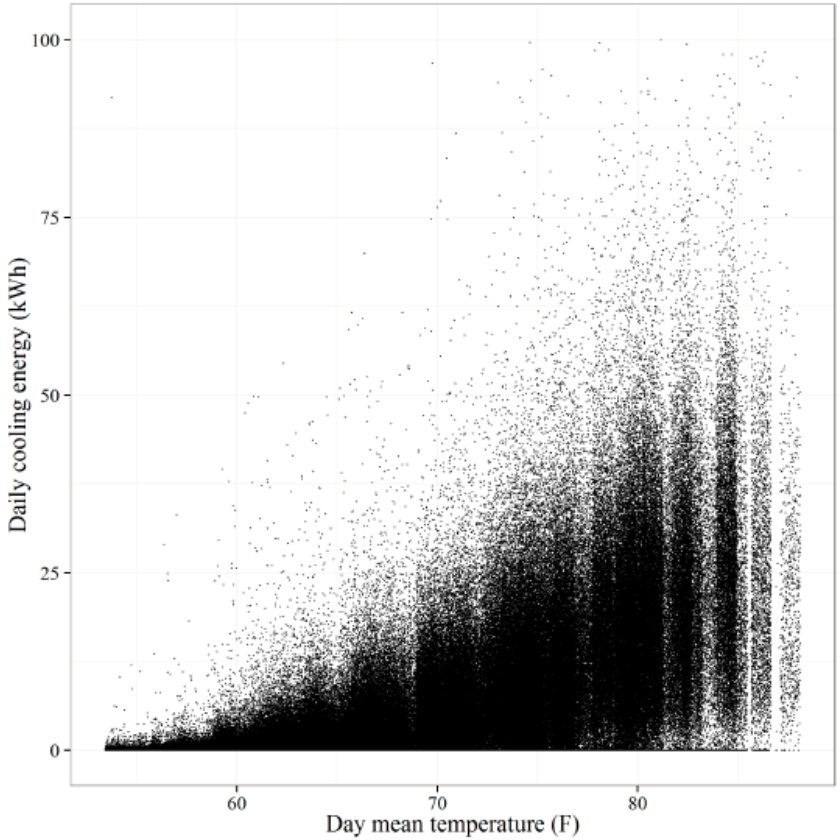
Temperature percentile for peak day of demand is strongly bimodal.

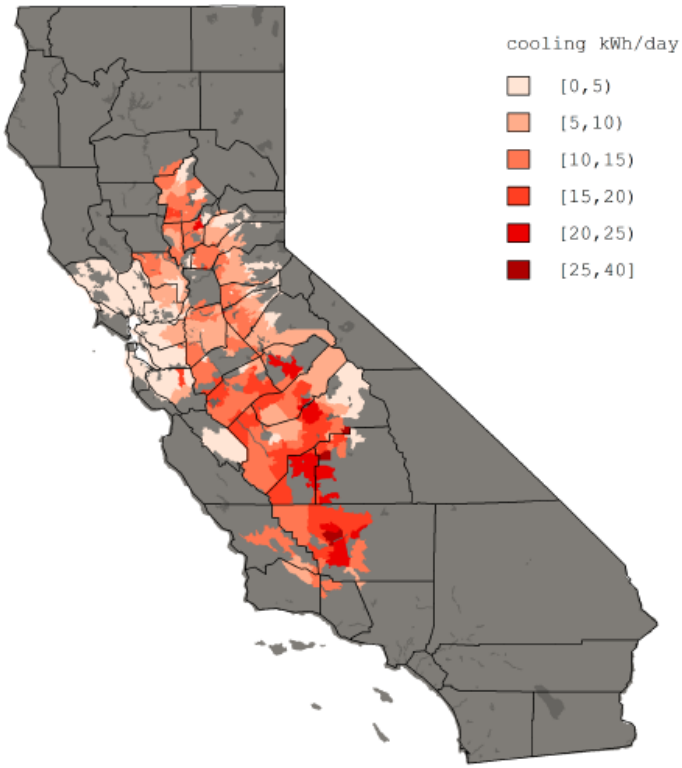
Top hours of CAISO demand



Peak cooling by outside temperature and location

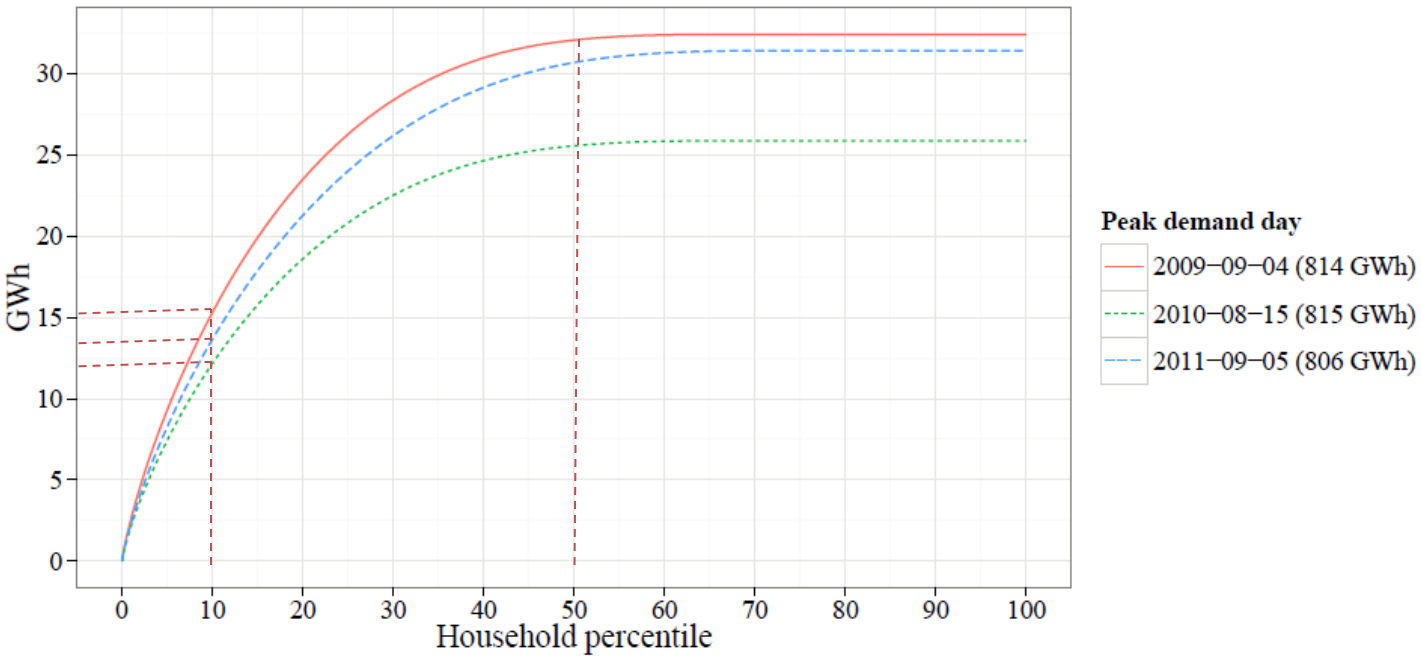
Residential cooling for peak demand day by outside temperature and zip code





Peak coincident cooling

Cumulative residential cooling energy on peak demand days



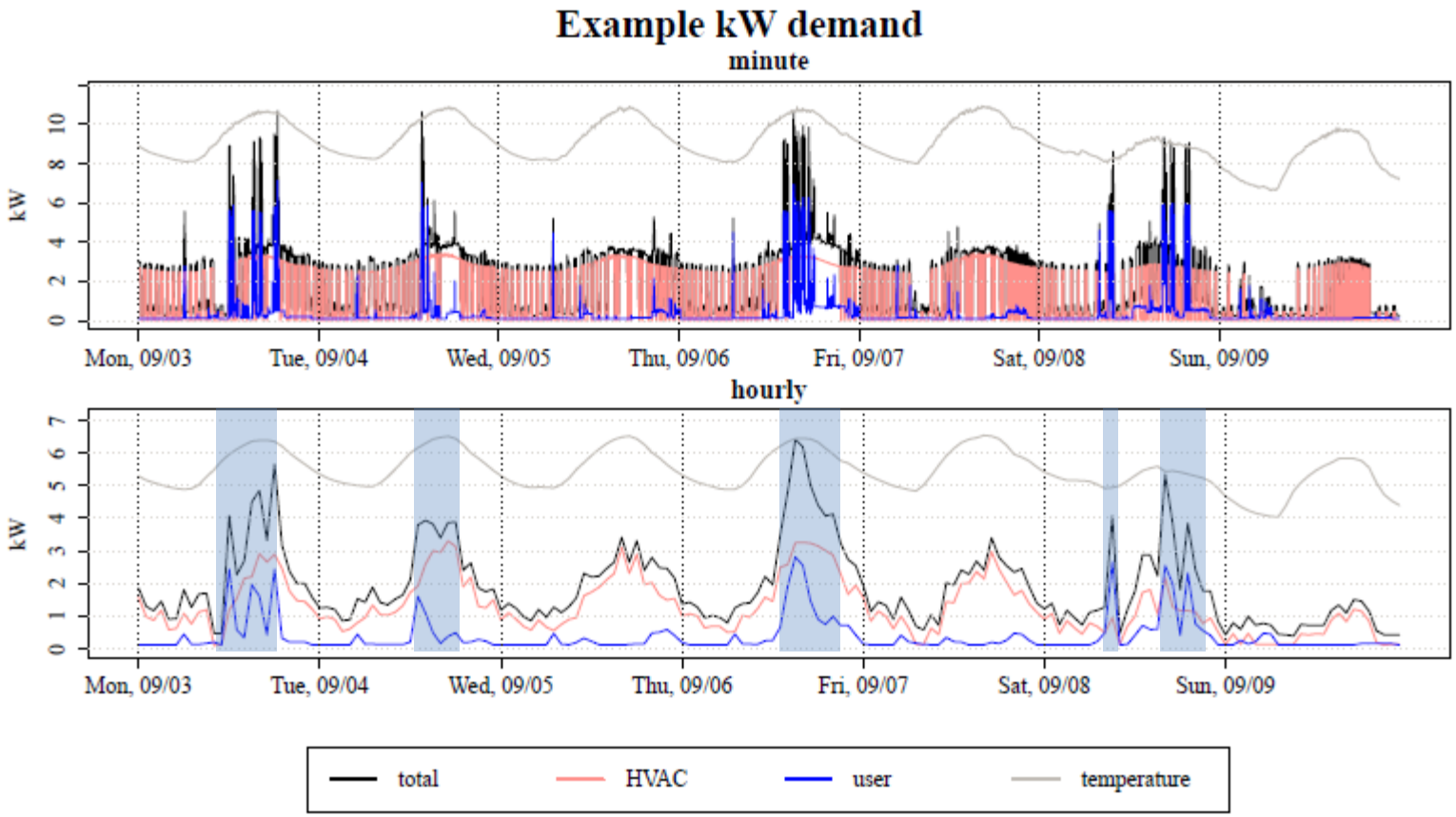
Cumulative peak demand day cooling energy by ranked percentile of the population

percentile	5th	10th	25th	50th	75th	100th
	GWh	GWh	GWh	GWh	GWh	GWh
2009-09-04 (814 GWh)	9	15	26	32	32	32
2010-08-15 (815 GWh)	7	12	21	26	26	26
2011-09-05 (806 GWh)	8	14	24	31	31	31

Ex 5: Direct occupant control

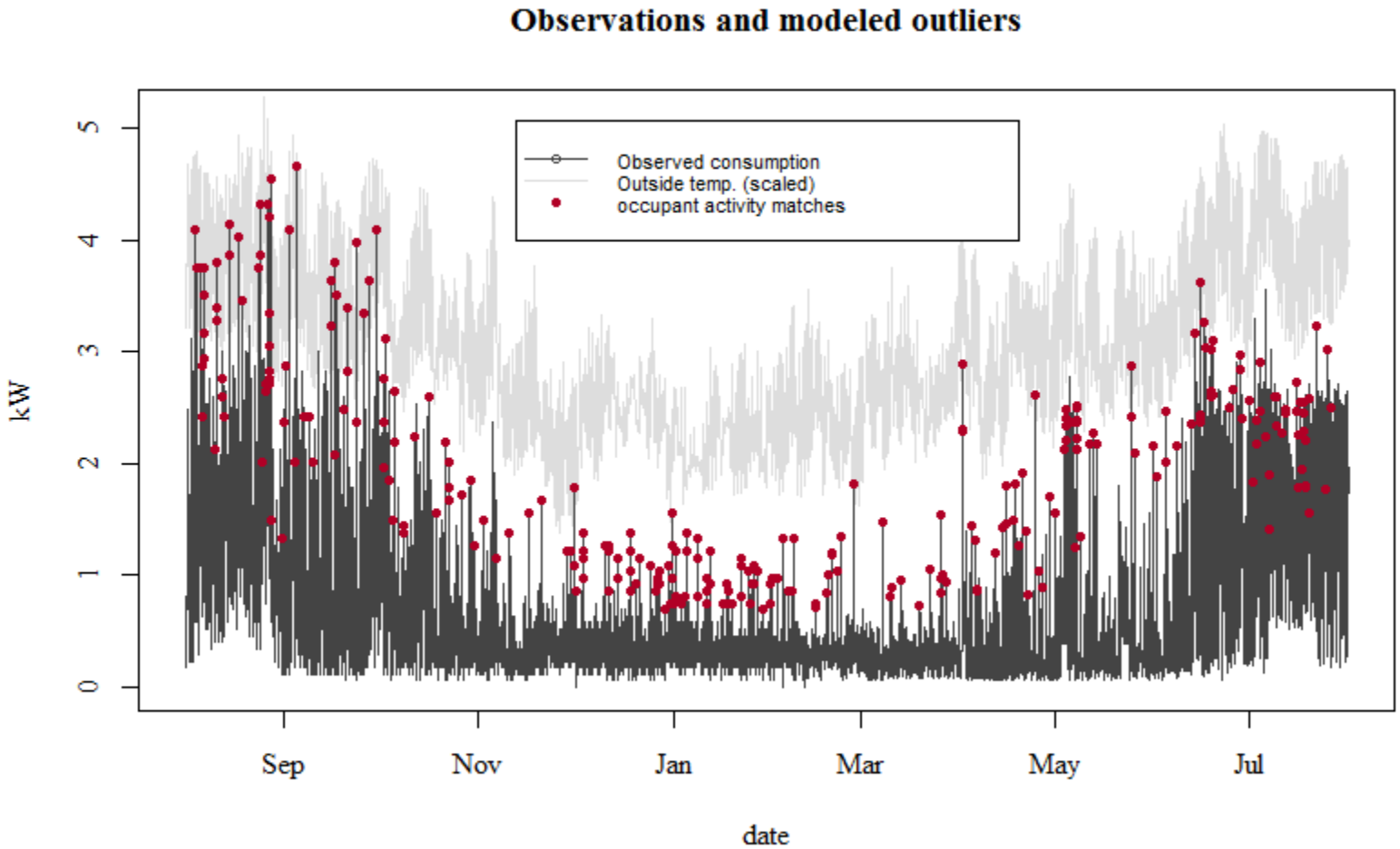
- Direct control leads to **unscheduled variation** in energy use
- It involves important end uses like laundry, TVs, microwaves, hair dryers, electric ranges, etc.
  - It can be seen as an **indication of occupancy** (and activity)
- It will create **transient modeling errors** that wind up in the residuals of a predictive model
  - Large residuals likely to contain contribution from occupant controlled load
- We can **estimate the timing** of occupant control based on large, transient residuals
- We can place **similar timing patterns** into "lifestyle" groups and infer targeting criteria from group characteristics

Inspiration for defining *occupant controlled loads*

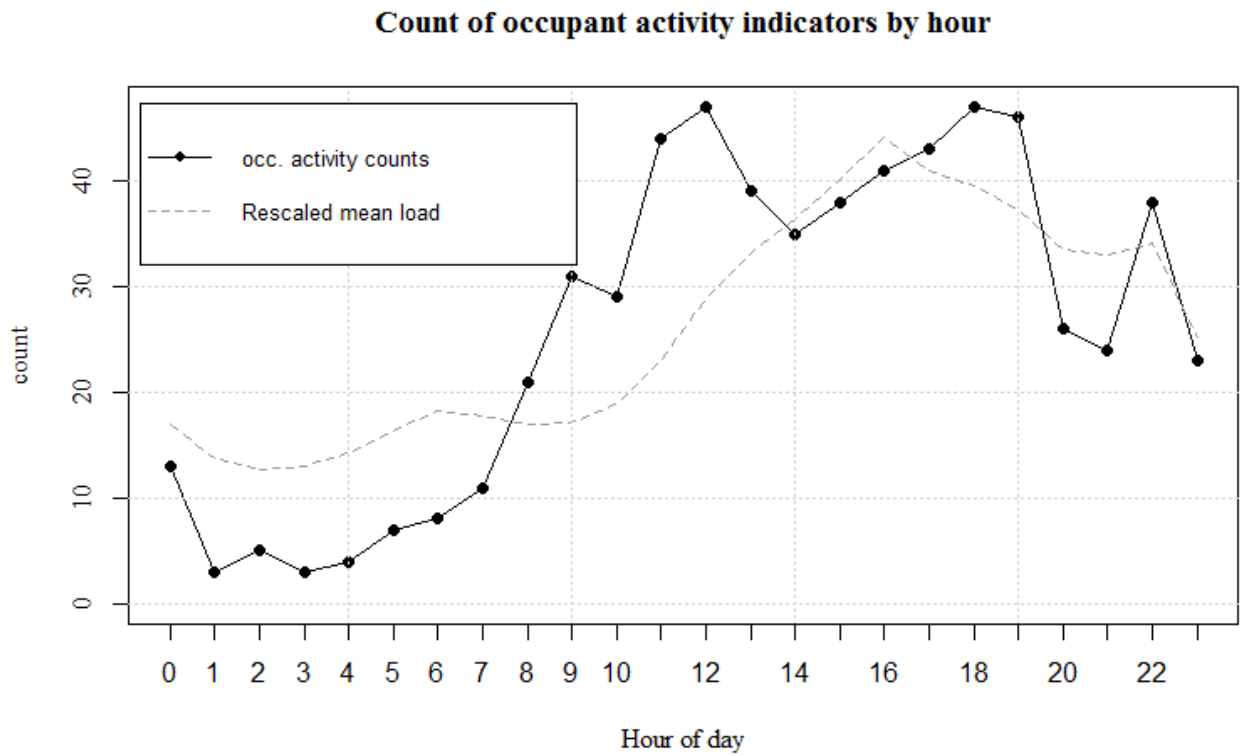


Occupant controlled loads is when loads directly controlled by occupants are operated (blue above). This is actual sub-metered data (not from PG&E). Our work requires *estimation* of the timing of occupant controlled loads.

Observations with estimated occupant activity



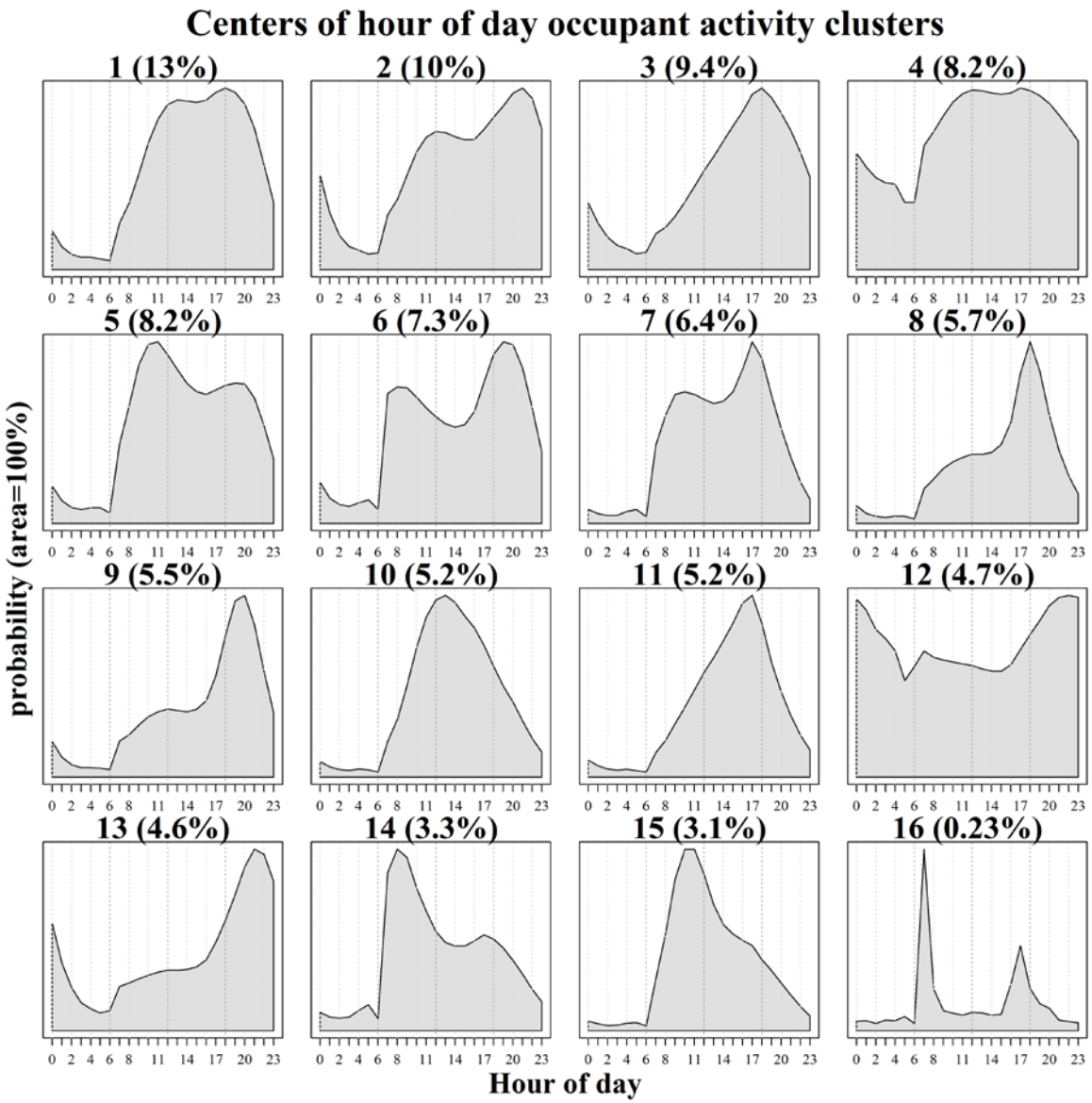
Count of *occupant activity* by hour of day



Pattern in timing of occupant activity creates an empirical distribution of probabilities of occupant activity by time of day. It is independent of simple mean load fixed effects.

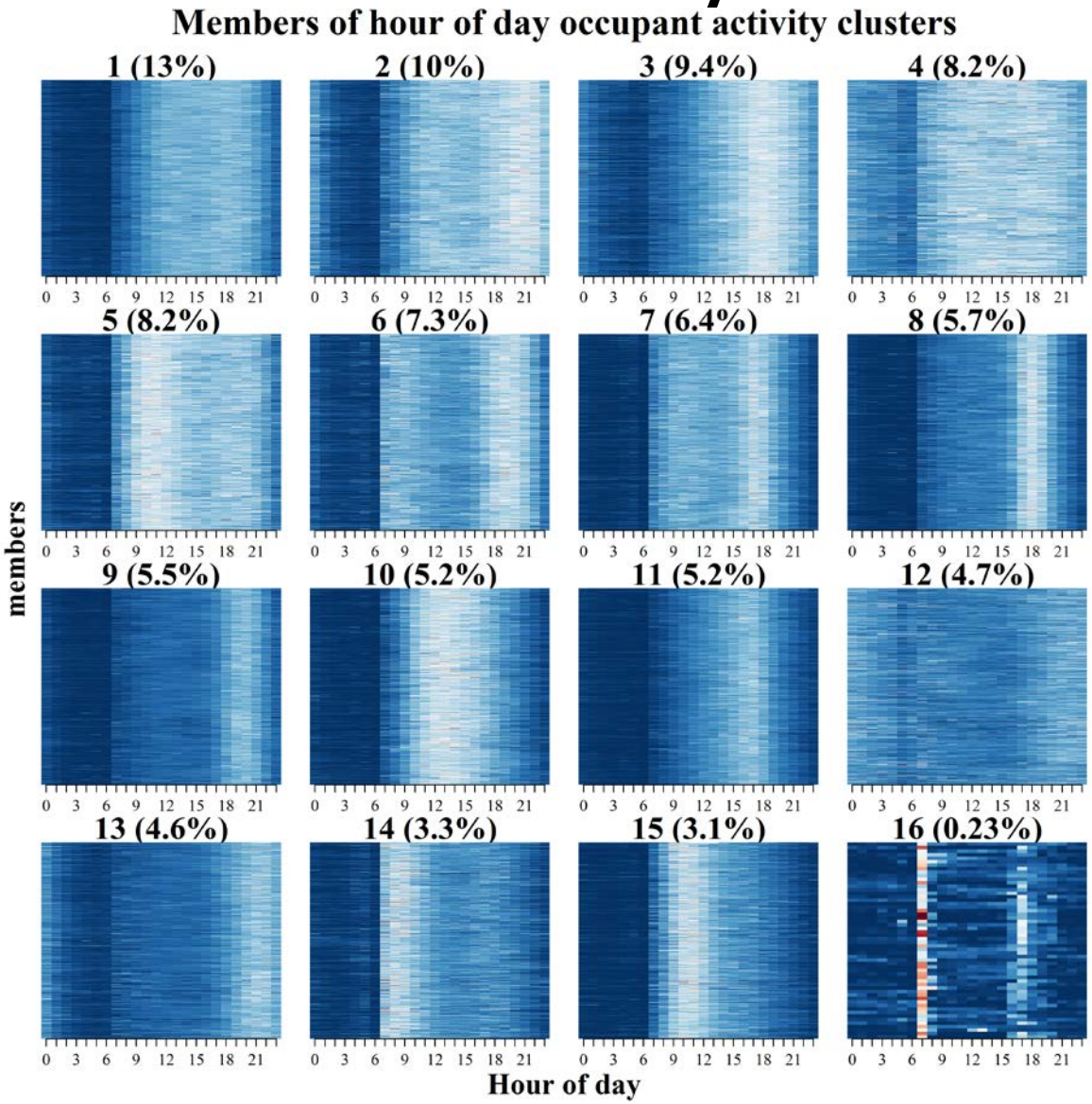
I computed similar empirical distributions for all 24,000 households whose data supported them. The following slides depict the results of clustering those distributions into groups by similarity.

Weekday occupant activity cluster centers



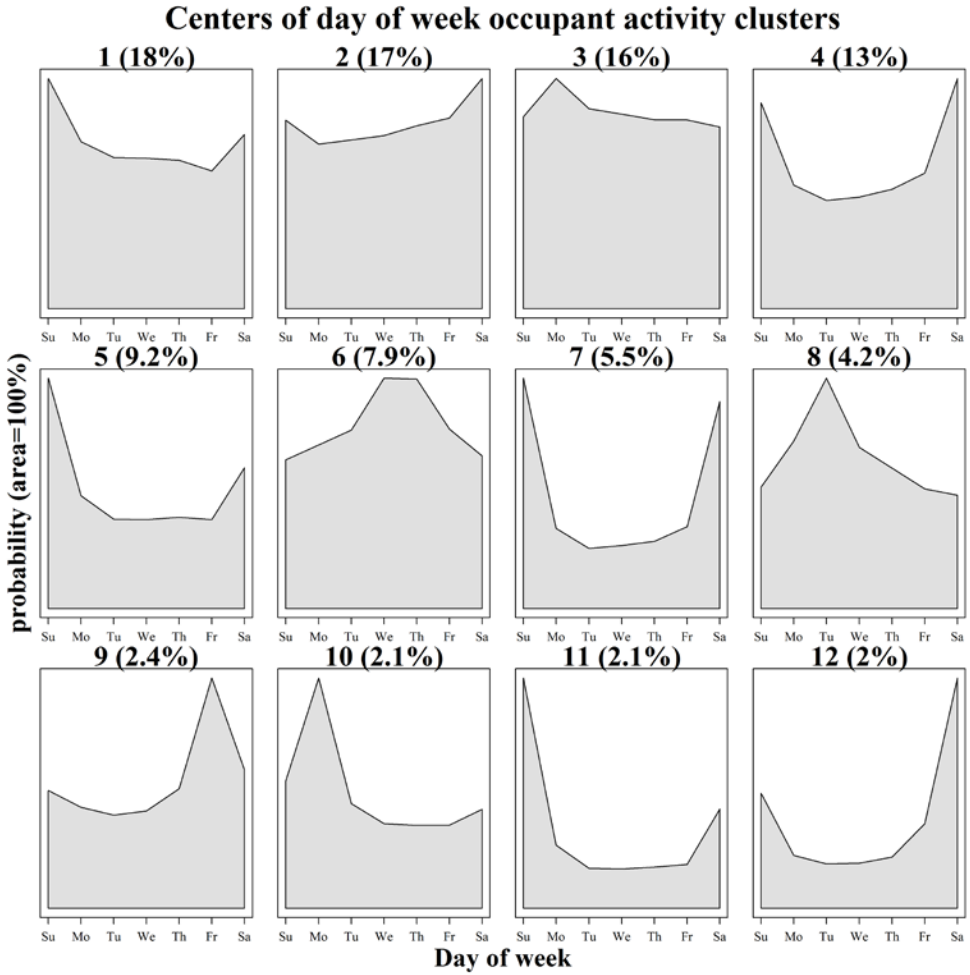
K-means cluster centers (N=24,000; K=16) of hour-of-day empirical probabilities of occupant controlled loads, sorted from largest to smallest membership.

Hour-of-day cluster members



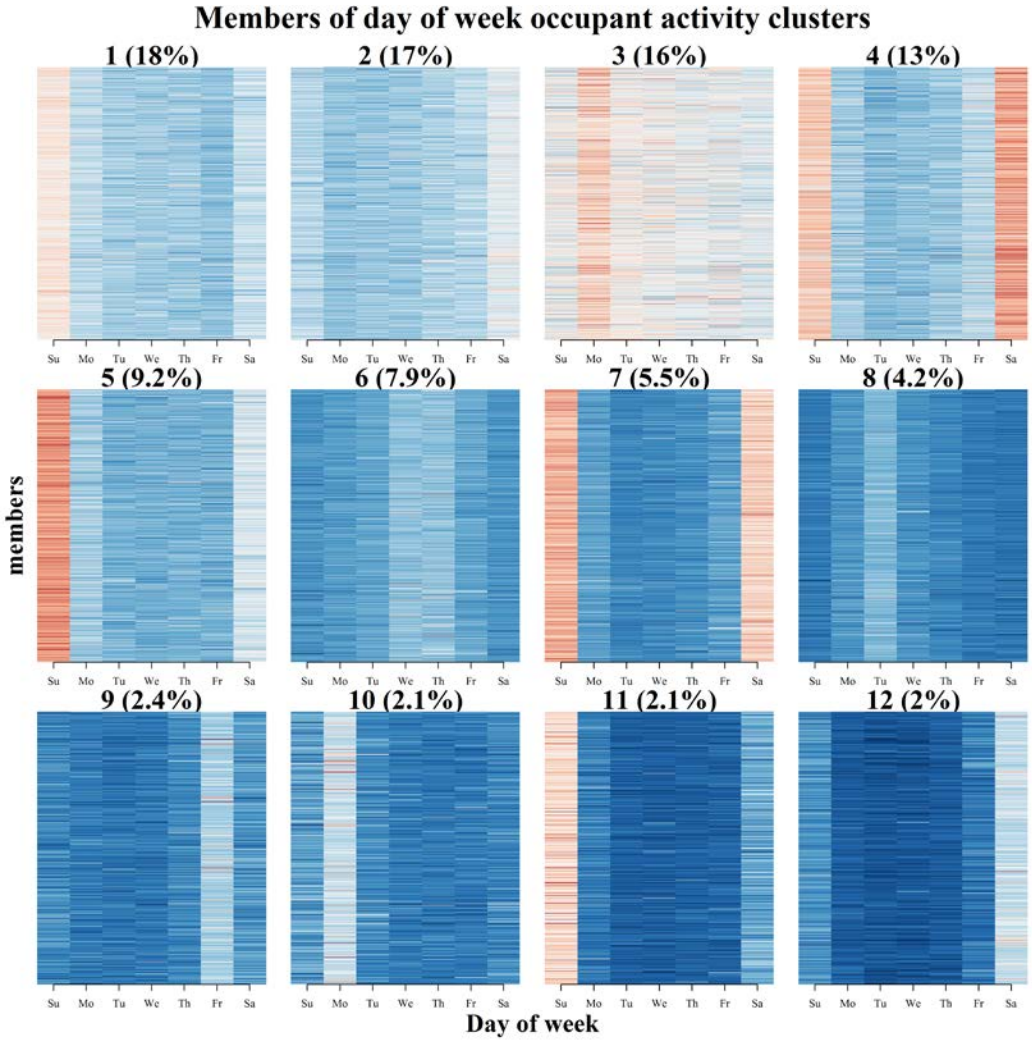
Membership of K-means hour-of-day clusters (K=16), with each row representing a single household. Relative magnitude of probabilities are color coded from blue (low) to white (mid) to red (high). Consistency of patterns across rows suggest good cluster performance.

Day-of-week cluster centers



Cluster membership and cluster centers for empirical distributions of occupant driven load probabilities by day of week (Su through Sa). Note the prevalence of higher relative probabilities on weekends – and that some households are lower on weekends.

Day of week cluster members



Politics of smart meters

- Large up front costs, long payback – rate payer advocates are worried
  - In CA, roughly $4B for 11.4M meters, about $350 per meter
- Largest official benefits accrue to utilities, rather than customers
  - reduced meter reading budgets and DR benefits from real-time pricing
- Significant opposition to meter installation
  - Stated concerns include privacy, utility control of loads, and EMF emissions
- All point **to lack of trust** and **low expectations for benefits**

- **Customers need to have their concerns addressed and see benefits for themselves**

Future work: EE and DR programs

- Testing empirical **targeting outcomes** for real programs
  - Retrospective natural experiments to see if targeting methods can predict successful program participation
  - Randomized control trials to quantify empirical targeting benefits over current practice
- Improving **program evaluation**
  - Baseline and savings estimates based on meter data
  - Savings estimates based on identifying the fingerprints of specific measures
  - Evaluation using randomized controlled trials
- Holistic **grid planning**
  - Using meter data to form a more spatially and temporally detailed model of demand
  - Strategic targeting of EE and DR to reduce congestion, support renewable energy integration, etc.

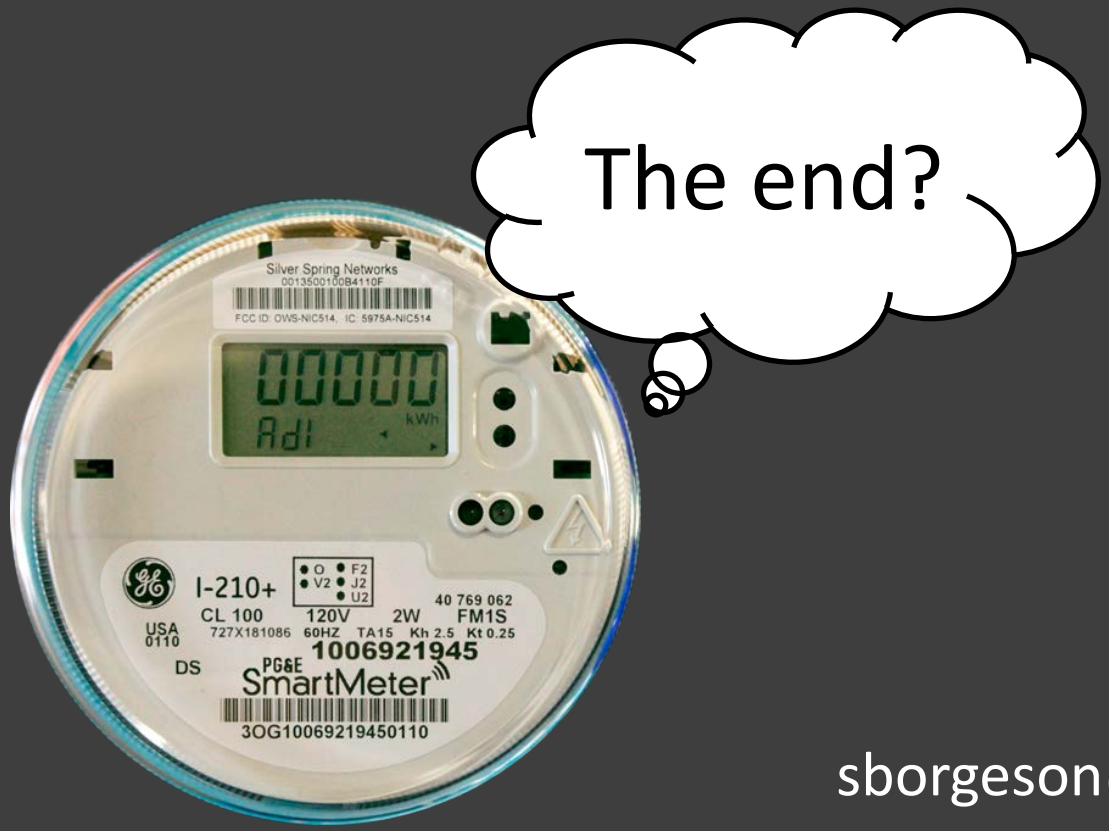
Future work: Research agenda

- Apply similar techniques to **commercial customers**
- Tools to **educate and inform customers**: **visualization and analysis**
- Comparing customers and cultures across service territories
- Investigation of **behavioral factors** that influence consumption
- More precise quantification of **targeting potential**
- Market **segmentation** studies using meter data
- Change and **fault detection** to find problems as they happen
- End-use **disaggregation** from whole home data
- Estimating **appliance ownership**
- Combined study of **communicating thermostat and smart meter data** to model household thermal properties, patterns of occupancy, etc.
- Applying similar techniques to **water consumption**

Conclusions

- Climate change mitigation in buildings is **significantly different** from traditional energy efficiency and demand response program motivations and will require **significant changes to programs**
- Smart meter data can provide information to support **more aggressive** and **more personalized** energy efficiency and demand response programs
- Examination of overnight minimum consumption corroborates the growing **role of plug loads** and vampire loads in total energy consumption
- Meter data reveals **spatial and temporal** patterns in cooling
  - The cooling efficiency and demand response potential is dominated by a **minority of now identifiable** households
  - Modest **set point changes** can produce very significant energy savings
- The differences **within** temperature bands or demographic categories can exceed differences **across** those groups
- Current practice is not capturing some of the **most promising** potential benefits of meter data
- Creative uses of meter data for public benefit are compatible with practical **privacy protections**, but **require support** from policy makers

Questions & Discussion



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