



HOME ENERGY REPORTS – WHO IS DRIVING THE SAVINGS?

Using Multi-Level Models To Identify High,
Medium and Negative Savers

Olivia Patterson

Research Objective

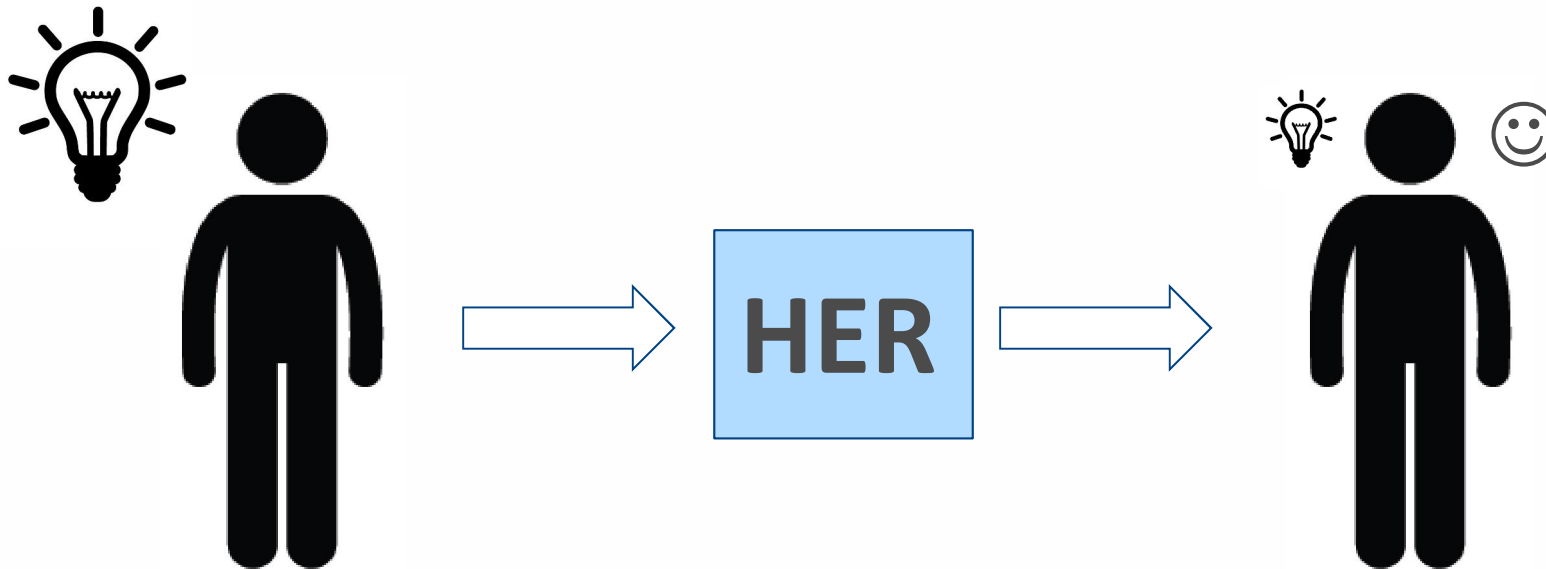


Overview of Home Energy Reports (HER) and Energy Efficiency

- Customers receive reports with:
 - Historical usage
 - Social norming (i.e. comparisons to neighbors)
 - Savings recommendations
- Most evaluations show small but consistent household-level savings
- Typically very large programs, up to hundreds of thousands of participants

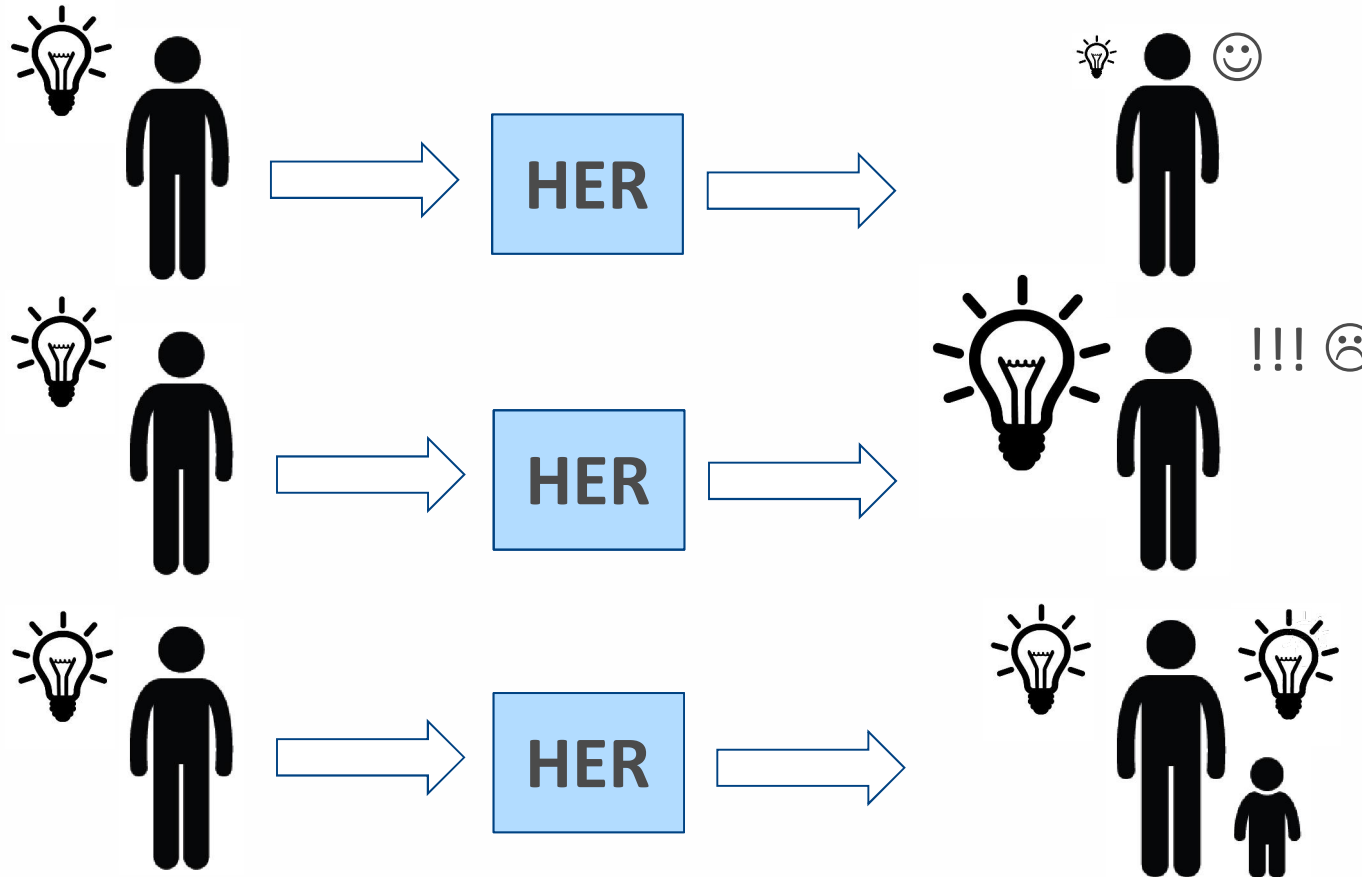
HER reports in theory

- Reduce energy consumption by changing customer behaviors and choices...



HER reports in practice...

- ...but customers may not respond the same way



If each individual responds differently, should we be asking different questions?

- Who were the high savers, low savers, and negative savers?
- Can we isolate top-tier savers and lower-tier savers, to better understand who is driving savings, and potentially, through leveraging secondary data, what their characteristics are?

What will these questions answer?

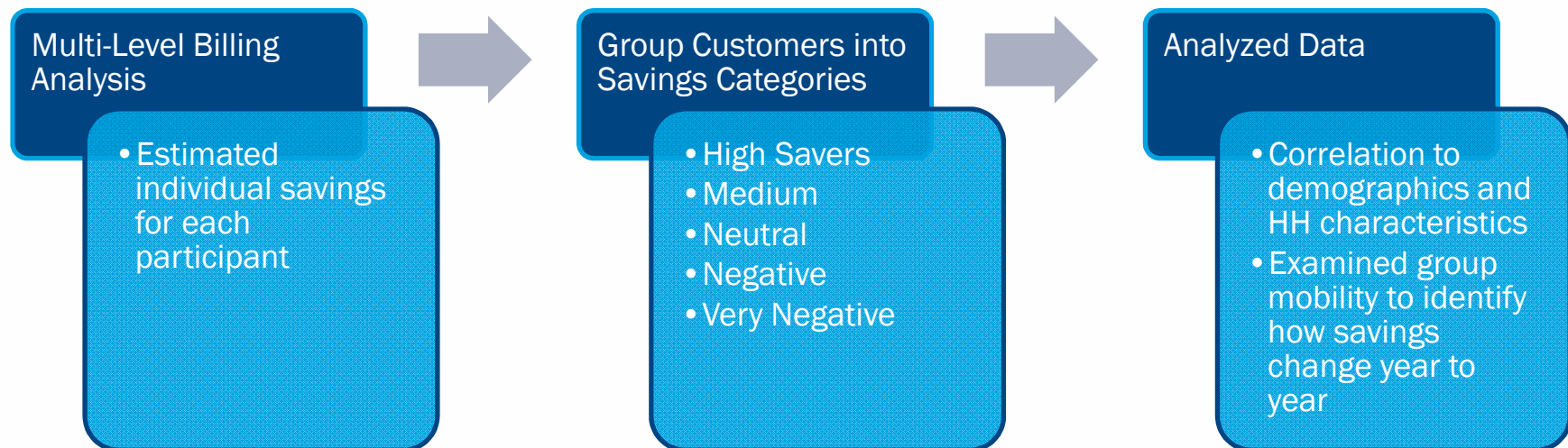
- Understanding household-level differences in response could:
 - Improve program targeting
 - Increase savings for some customers
 - Inform program reach and goals
- For this to happen, we must be able to:
 - Identify subgroups of customers with different savings
 - Understand *why* these customers behave differently

Approach & Results

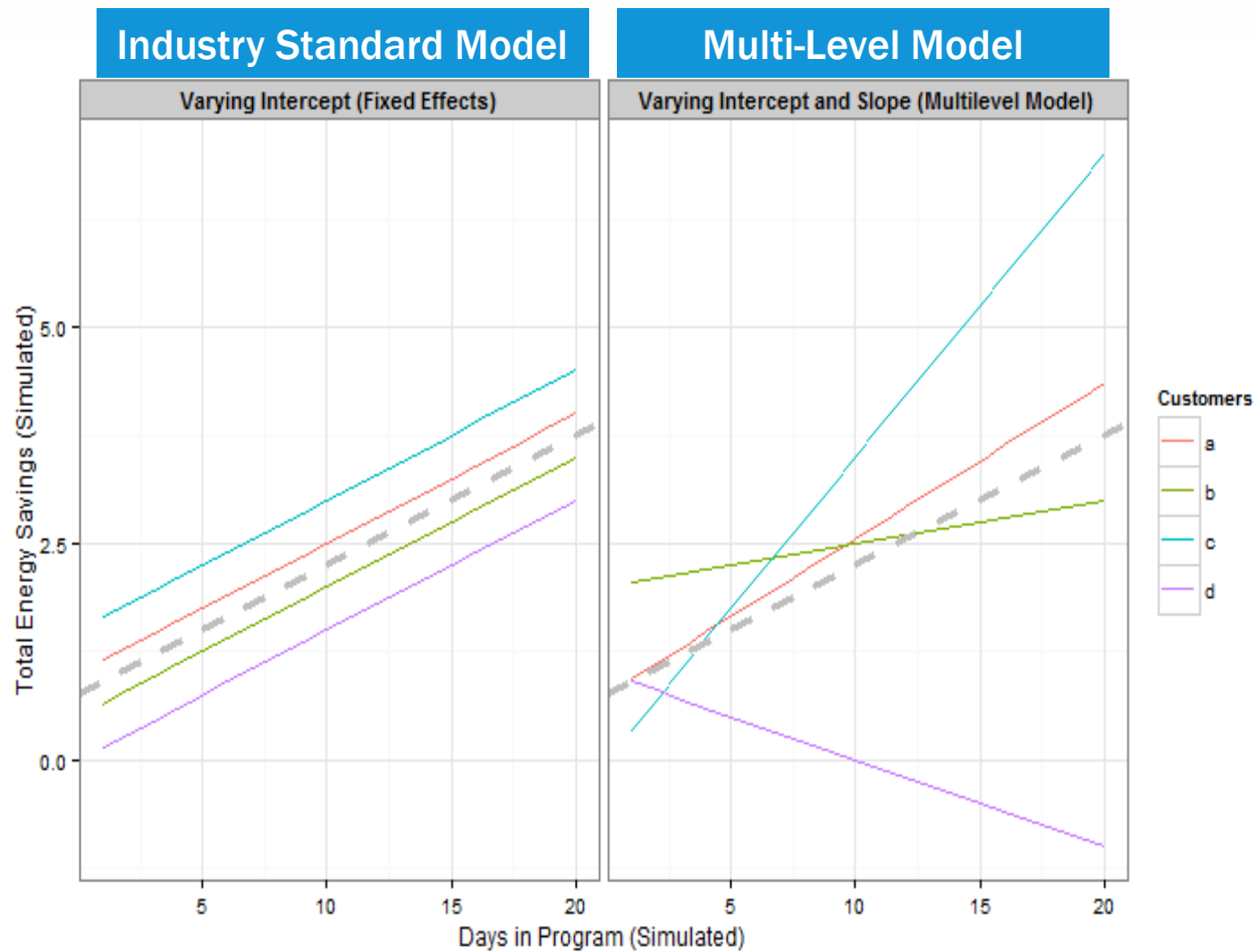


Conduct multilevel modeling to garner customer insights

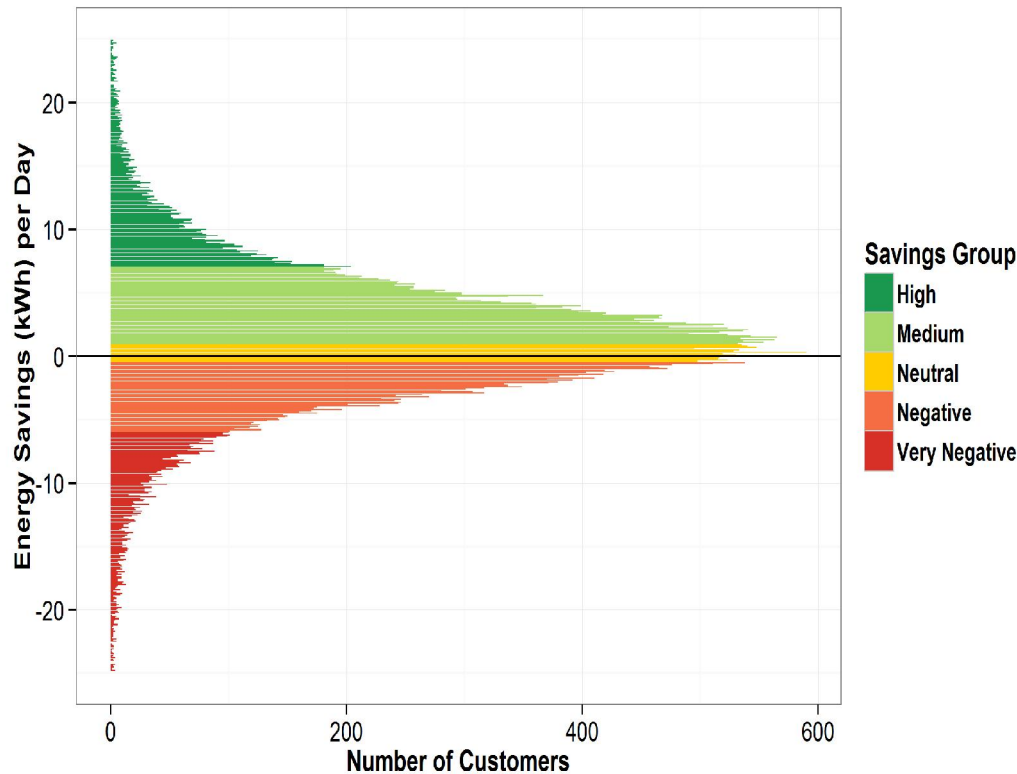
- Evaluated long-running HER program with ~250k customers
- Developed model to understand the responses of different types of customers to the HERs in addition to calculating total savings attributable to the program



Multilevel modeling estimates individual customer savings



On average, customers have positive energy impacts, but 40% of customers are increasing their energy usage

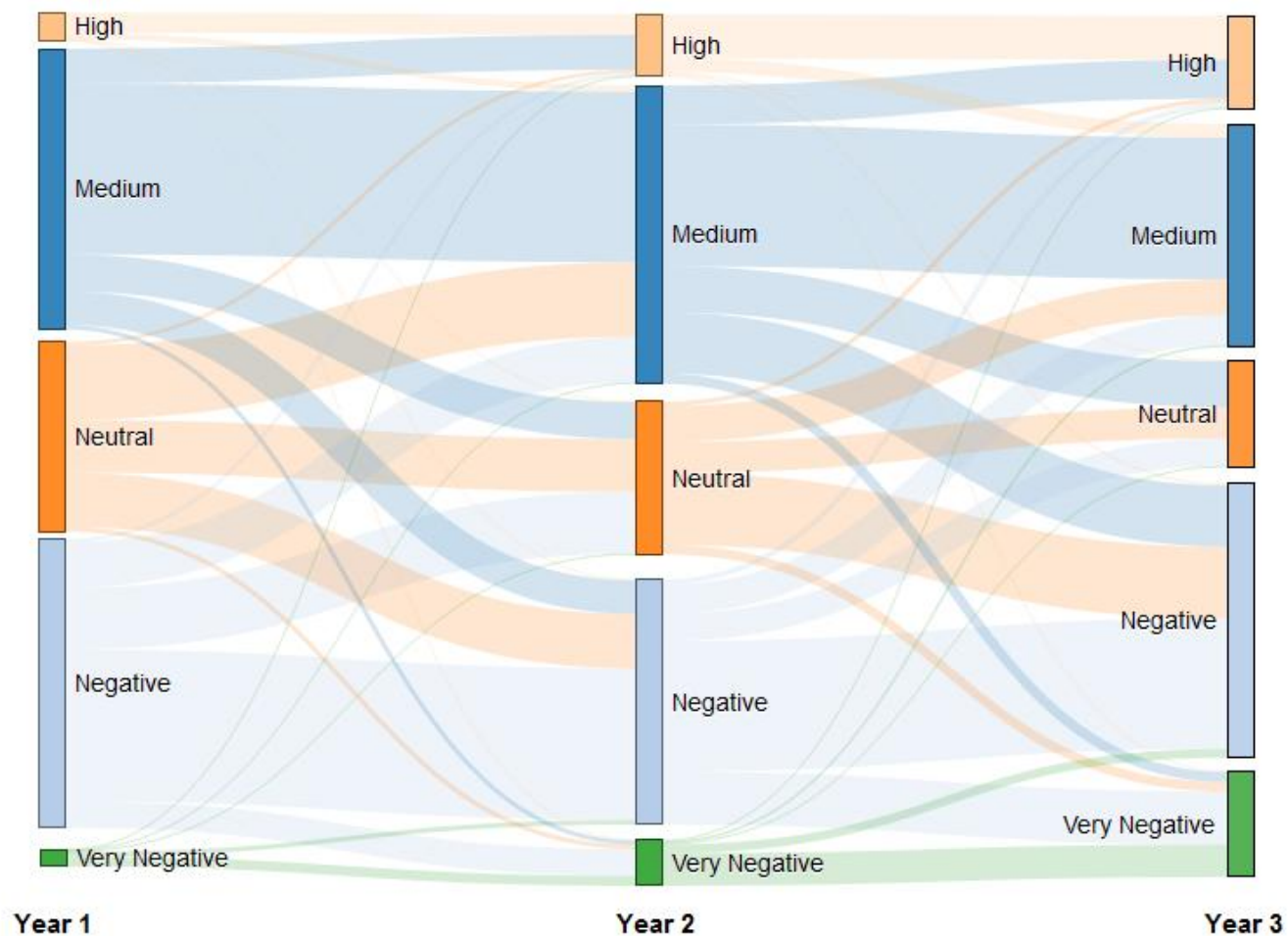


Group	Percent of Population	kWh Savings / Day
High	Top 10%	> 7 kWh
Medium	Next 30%	> 1 & ≤ 7 kWh
Neutral	Middle 20%	> - 0.5 & ≤ 1 kWh
Negative	Next 30%	> -6 & ≤ -0.5 kWh
Very Negative	Bottom 10%	≤ -6 kWh

Relationship to housing characteristics and demographics

- The most predictive characteristics after pre-treatment usage were:
 - *All fuel types*: age of the house, the customer's age, educational level, occupation, and number of people living at the residence
 - *Electric cohorts*: older participants, and those with fewer people living at the residence
 - *Gas cohorts*: participants with older houses, shorter time in home
- The size of the relationship between housing characteristics and savings varies by pre-treatment usage and interactions with other characteristics

Surprising results from mobility in savings groups



Conclusions

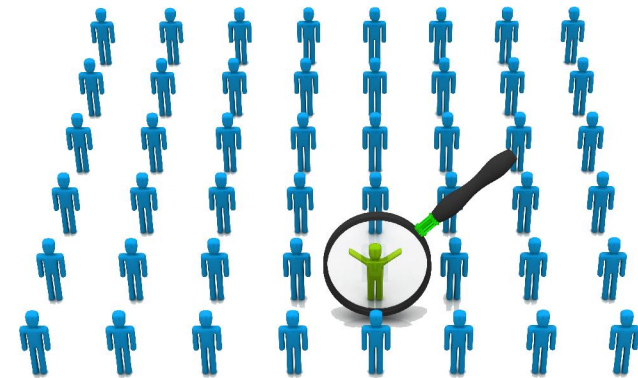
- On average, HER program produces positive savings
 - However, a little under half of participants are negative savers (e.g., increase energy consumption)
- Specific characteristics are associated with energy savings
 - These may not be generalizable to other populations
- Customers do not tend to change groups over time
 - Negative savers rarely become positive savers

Considerations Moving Forward



Predictive modeling can support program implementation changes

- Identify participants that would benefit from alternative intervention strategies:
 - *Very Negative Savers*: Stop or modify reports for participants in the very negative savings group could increase program impact (either frequency or messaging)
 - *Very High Savers*: Push them further into additional programs, heavily promote utility sponsored programs
 - *Middle of the Pack*: Use the report as an engagement tool (or for other online platforms)
- Remove customers predicted to be negative savers from future cohorts



Outstanding Questions & Next Steps

Why do participants save more or less?



Detailed survey to understand attitudes, behaviors, life changes

Can we predict the likely savings of new participants?



Models to predict participant savings



Thanks for listening!

Contact:

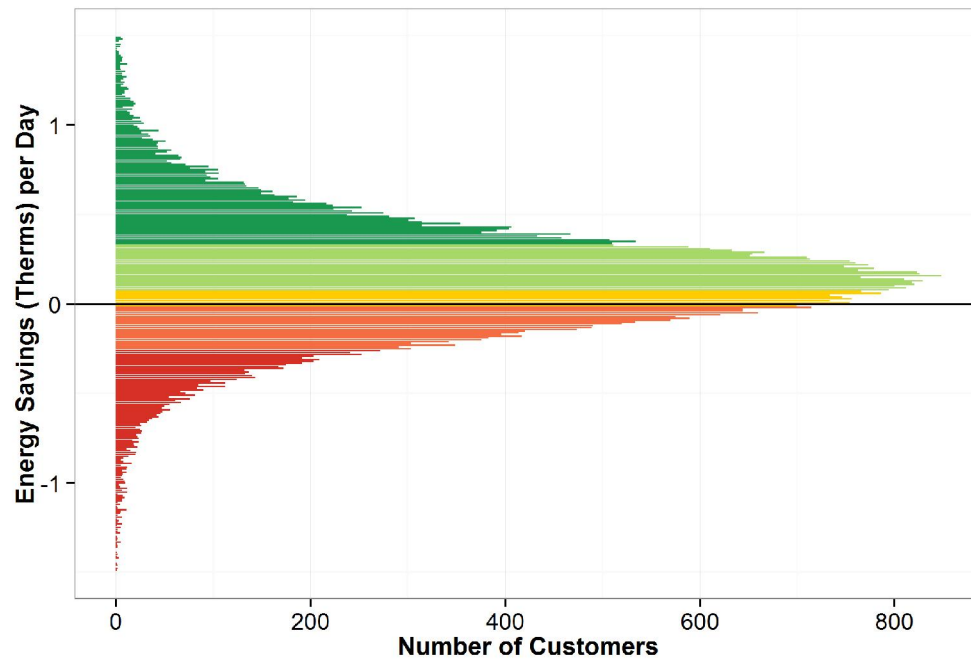
Olivia Patterson
Director, Data Science
Opinion Dynamics

opatterson@opiniondynamics.com



Opinion **Dynamics**

MLM Example: Daily Household-Level Gas Savings



Savings Group
High
Medium
Neutral
Negative
Very Negative

High: > 0.33 thm

Medium: > 0.08 & < 0.33 thm

Neutral: > -0.02 & ≤ 0.08 thm

Negative: > -0.25 & < -0.02 thm

Very Negative: ≤ -0.25 thm

MLM Example: Gas Savings Group Evolution

