NREL 40
NATIONAL RENEWABLE ENERGY LABORATORY
1977 - 2017

Webinar: Using Machine Learning and Data Analysis to Improve Customer Acquisition and Marketing in Residential Solar

July 20th, 2017

NREL is a national laboratory of the U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy, operated by the Alliance for Sustainable Energy, LLC.

Logistics

- Participants are joined in listen-only mode.
- Use the Q&A panel to ask questions during the webinar. We will have time for Q&A at the very end.

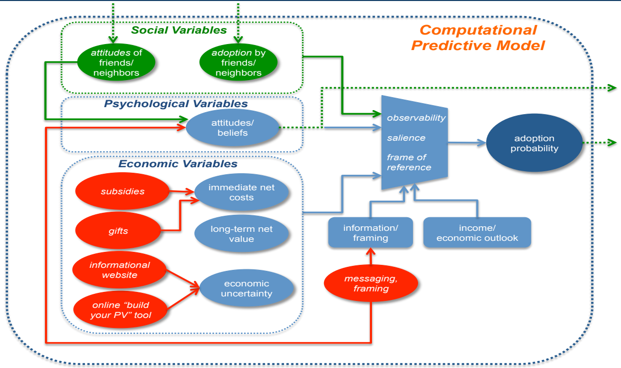
➢ To ask a question:
  - Click Q&A box in the gotowebinar toolbar
  - Type your question in the Q&A box
- For any technical difficulties during the webinar, contact the GoToWebinars Help Desk at 888.259.3826 for assistance.

Presenters

- Kiran Lakkaraju – Sandia National Laboratories
- Yevgeniy (Eugene) Vorobeychik – Vanderbilt University
- Michael Rossol – National Renewable Energy Laboratory

Exceptional service in the national interest

Sandia National Laboratories



Promoting Solar Technology Diffusion Through Data-Driven Behavior Modeling

Co-PI: Dr. Kiran Lakkaraju, Sandia National Laboratories

Co-PI: Prof. Eugene Vorobeychik, Vanderbilt University

Team: University of Pennsylvania, California Center for Sustainable Energy, National Renewable Energy Laboratory, Vote Solar

Sandia National Laboratories is a multi-program laboratory managed and operated by Sandia Corporation, a wholly owned subsidiary of Lockheed Martin Corporation, for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-AC04-94AL85000.

SAND2014-18601 PE

Residential Photovoltaics and Soft Costs

- DOE SunShot Goal: Reduce cost of installed solar energy systems to $.06/kWh by 2020[3.]
- Residential energy use is 21% of consumption in the US (as of 2013)[1.]
- PV prices going down but 67% of total residential system price going to "soft costs"[2]:
  - **Customer acquisition ~ 9.2%**
  - Installation labor ~ 10.5%
  - Supply chain costs ~ 11.7%
- If we can reduce customer acquisition costs, we reduce costs of PV.

1. http://www.eia.gov/beta/MER/?tbl=T02.01#/?f=A&start=1949&end=2013&charted=3-6-9-12

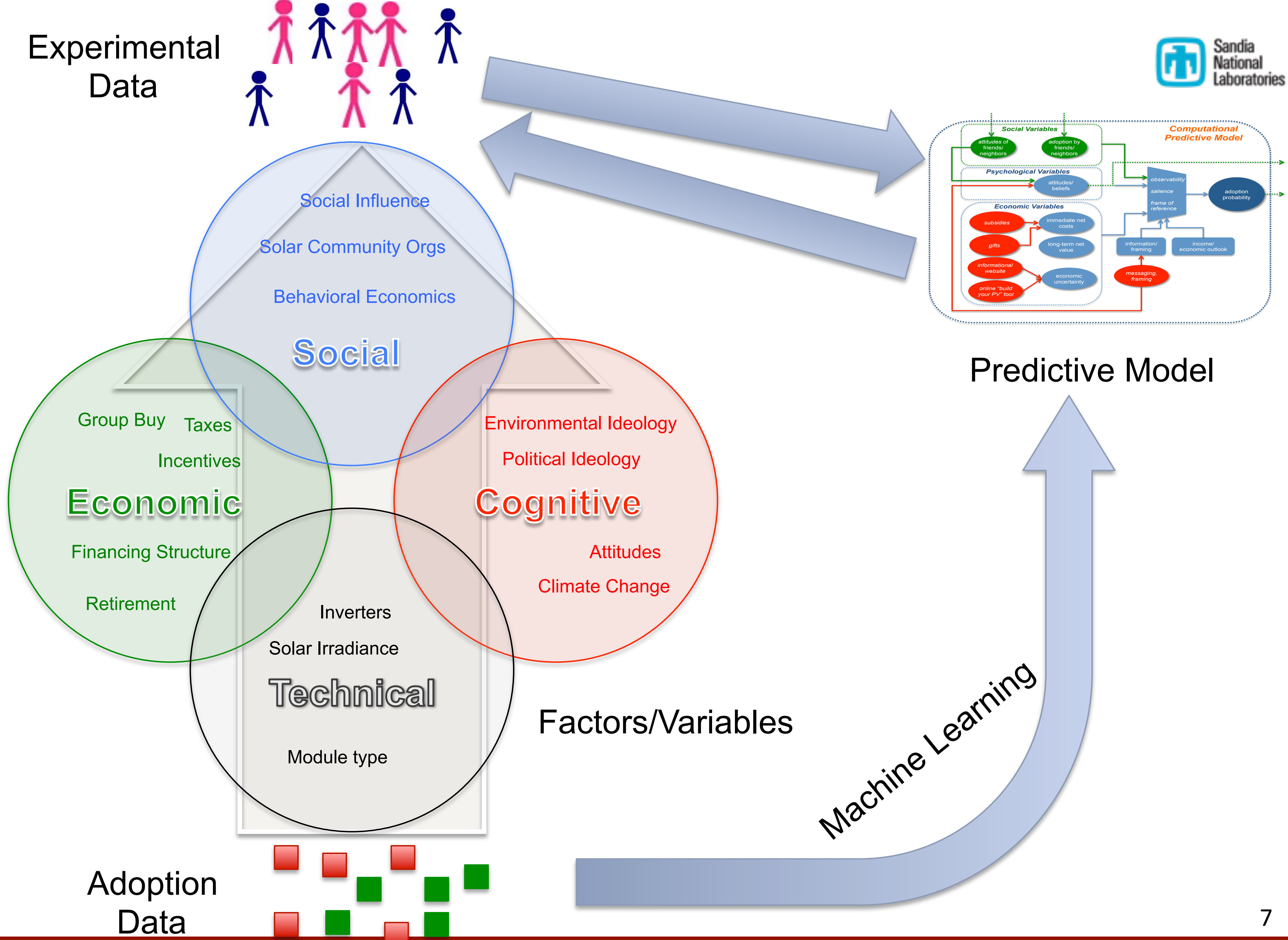
2. Friedman, Ardani, Feldman, Citron, Margoli, Zuboy, "Benchmarking Non-Hardware Balance-of-System (Soft) Costs for U.S. Photovoltaic Systems, Using a Bottom-Up Approach and Installer Survey – Second Edition"

3. http://energy.gov/eere/sunshot/mission

Overarching Research Questions

How can we determine residential solar PV adoption tendencies and trends, at the individual and aggregate level?

GOAL: Develop a model to test and identify incentive policy structures that increase adoption



Experimental Data
Social Variables
attitudes of friends/ neighbors
adoption by friends/ neighbors
Computational Predictive Model
Psychological Variables
attitudes/ beliefs
observability
salience
frame of reference
adoption probability
Economic Variables
subsidies
immediate net costs
gifts
long-term net value
informational website
economic uncertainty
online "build your PV" tool
information/ framing
income/ economic outlook
messaging, framing
Predictive Model
Social Influence
Solar Community Orgs
Behavioral Economics
Social
Group Buy
Taxes
Incentives
Economic
Financing Structure
Retirement
Environmental Ideology
Political Ideology
Cognitive
Attitudes
Climate Change
Inverters
Solar Irradiance
Technical
Module type
Factors/Variables
Machine Learning
Adoption Data

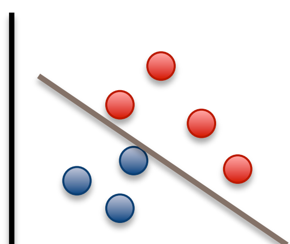
Overarching Research Questions

How can we determine residential solar PV adoption tendencies and trends, at the individual and aggregate level?

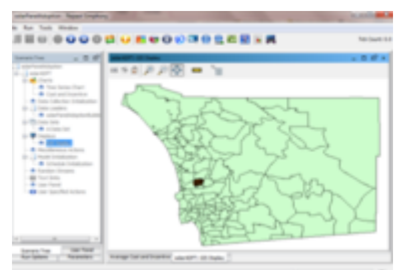
Approach:

Agent-based model (ABM) development through **data-driven machine learning**

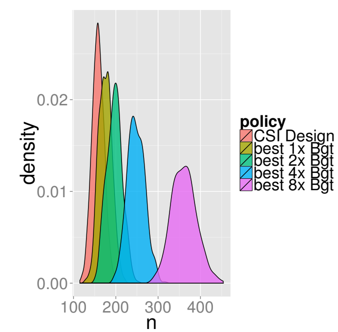
Data gathering



Predictive Model



ABM Modeling



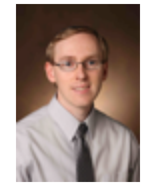
Policy Testing

GOAL: Develop a model to test and identify incentive policy structures that increase adoption

Sandia National Laboratories

Lead Organization

Dr. Kiran Lakkaraju (PI)



Prof. Eugene Vorobeychik (Co-PI)

Ben Sigrin

Prof. Howard Kunreuther

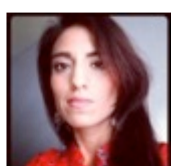
Prof. Arthur van Benthem

Prof. Ruben Lobel

Dr. Dena Gromet

Tim Treadwell

Georgina Arreola

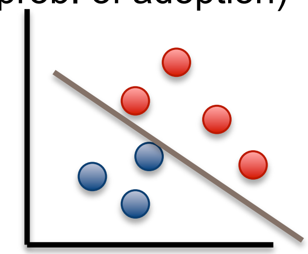


Jesse Denver

Kevin Armstrong

Predictive Model

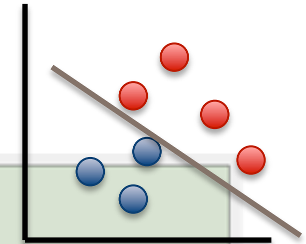
Predictive Model
(prob. of adoption)

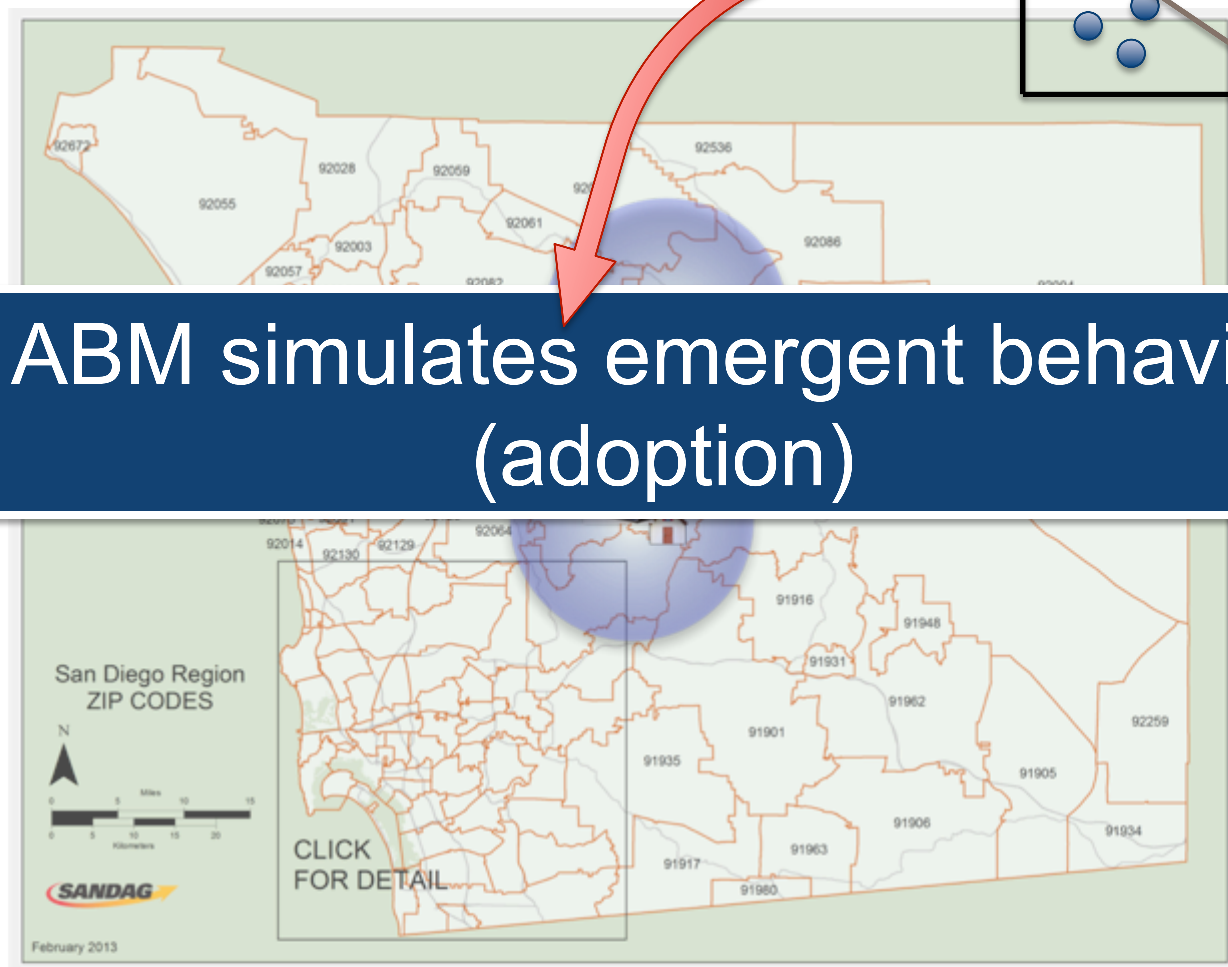


- Predict probability of an individual adopting at a particular time.
- Identify important features.

Agent Based Model (ABM)

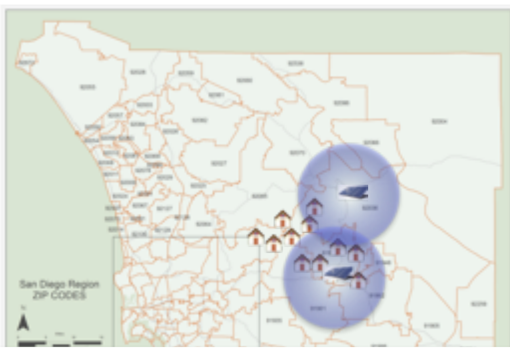
Predictive Model



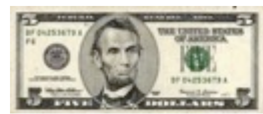


ABM simulates emergent behavior (adoption)

Interventions

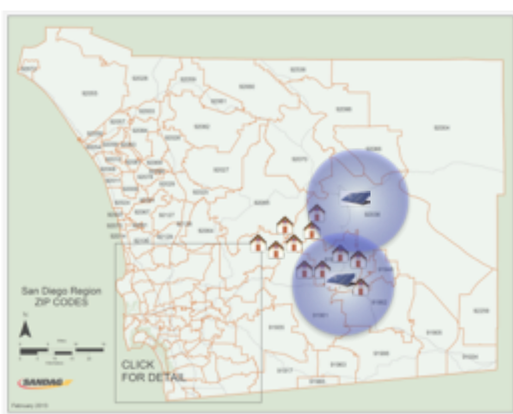


+



Incentive Structure

ABM allows analysis of policy interventions



+

Incentive Structure

What have we learned from the data?

- Retirement spurs thoughts about adoption (Survey).
- Monthly bill savings is an important factor (Survey).
- Liberals respond more favorably to a "reduce" electricity usage message; conservative more favorably to "increase" savings message (Experiments).

- Step-wise incentive structures (like the California Solar Initiative structure) do not increase adoption with increased budgets. More useful to give away free system in our ABM model (ABM simulations).

ALGORITHMIC MARKETING

YEVGENIY (EUGENE) VOROBEYCHIK

Assistant Professor, EECS
Director, Computational Economics Research Laboratory
Vanderbilt University

PROMOTION OF INNOVATION

- Four important questions:
  - Causality: which variables *causally* influence adoption of innovation
  - Forecasting: how can we accurately forecast adoption trends, both individual and aggregate
  - Impact: what is the impact of changes in environment/ policy variables on attitudes, adoption decisions, and trends
  - Optimization: how to we choose policy to optimally promote innovation (subject to cost/budget constraints)

PROMOTION OF INNOVATION

- **Econometrics, social science research**
  - **Causality**: which variables *causally* influence adoption of innovation
  - Forecasting: how can we accurately forecast adoption trends, both individual and aggregate
  - **Impact**: what is the impact of changes in environment/ policy variables on attitudes, adoption decisions, and trends
  - Optimization: how to we choose policy to optimally promote innovation (subject to cost/budget constraints)

PROMOTION OF INNOVATION

- **Computer Science**
  - Causality: which variables *causally* influence adoption of innovation
  - **Forecasting**: how can we accurately forecast adoption trends, both individual and aggregate
  - Impact: what is the impact of changes in environment/ policy variables on attitudes, adoption decisions, and trends
  - **Optimization**: how to we choose policy to optimally promote innovation (subject to cost/budget constraints)

PROMOTION OF INNOVATION

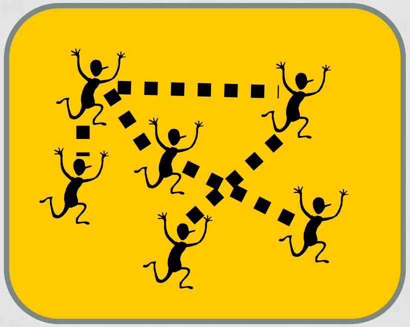
- **Computer Science**
  - Causality: which variables *causally* influence adoption of innovation
  - **Forecasting**: how can we accurately forecast adoption trends, both individual and aggregate
    - Optimize model accuracy in predicting unseen data
    - *Crucial*: embed known causal models and controls
    - Constrain models to make economic sense
  - Impact: what is the impact of changes in environment/ policy variables on attitudes, adoption decisions, and trends
  - **Optimization**: how to we choose policy to optimally promote innovation (subject to cost/budget constraints)

PROMOTION OF INNOVATION

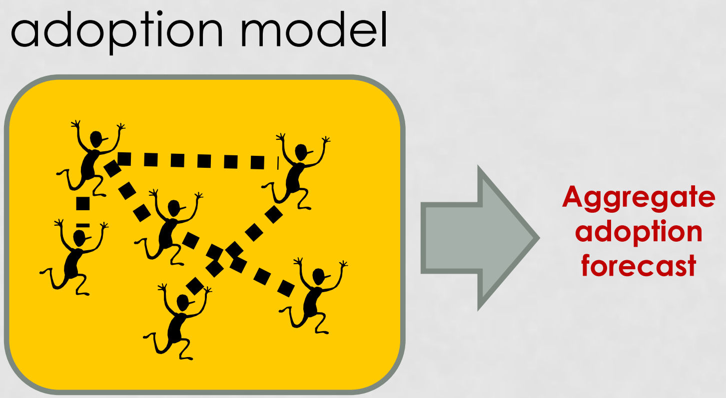
- **Computer Science**
  - Causality: which variables *causally* influence adoption of innovation
  - **Forecasting**: how can we accurately forecast adoption trends, both individual and aggregate
  - Impact: what is the impact of changes in environment/ policy variables on attitudes, adoption decisions, and trends
  - **Optimization**: how to we choose policy to optimally promote innovation (subject to cost/budget constraints)
    - Assuming that causality of policy variables is correctly captured

ALGORITHMIC PERSPECTIVE ON PROMOTION OF INNOVATION

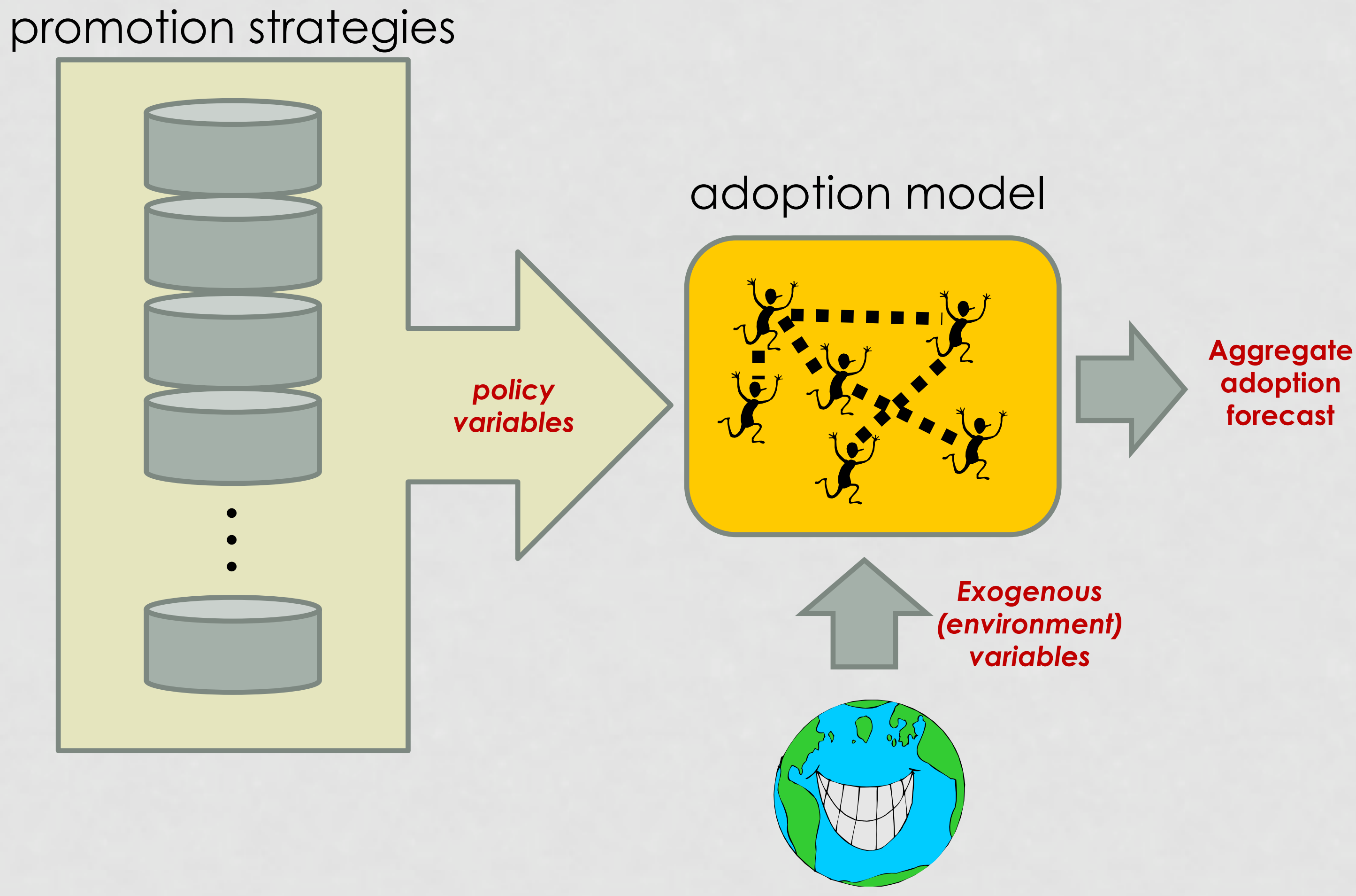
adoption model



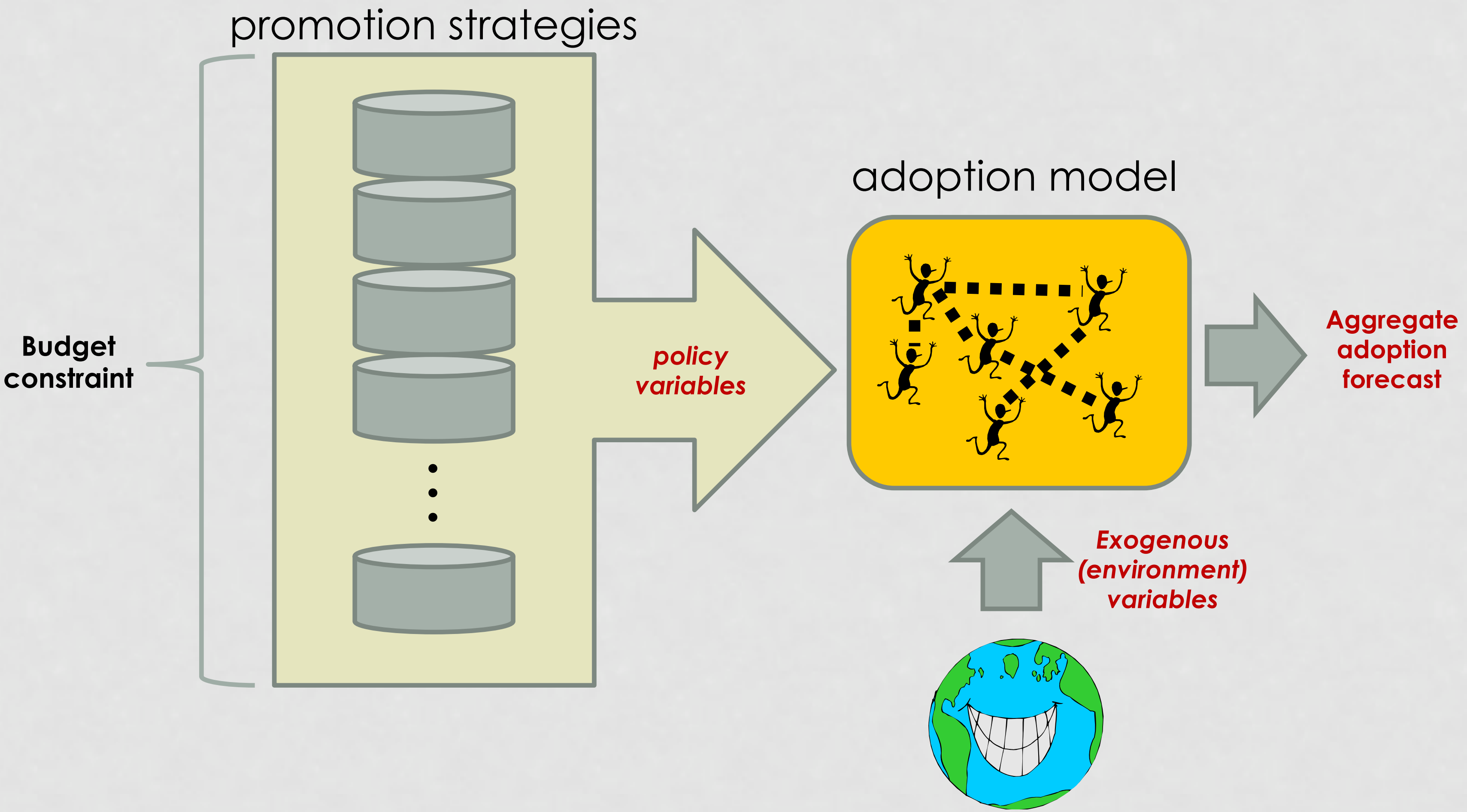
ALGORITHMIC PERSPECTIVE ON PROMOTION OF INNOVATION



ALGORITHMIC PERSPECTIVE ON PROMOTION OF INNOVATION



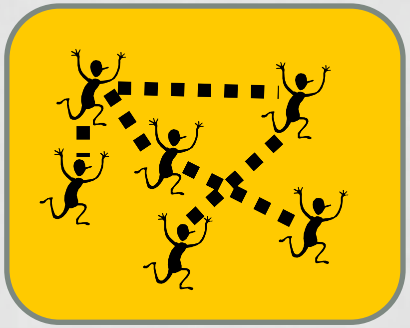
ALGORITHMIC PERSPECTIVE ON PROMOTION OF INNOVATION



ALGORITHMIC PROBLEM: FORECASTING

- Problem:
  - Use prior individual-level adoption data to develop a model for forecasting individual decisions, and aggregate adoption trends
  - ***Technical challenges***: scalable model calibration, model validation at multiple scales
- Approach:
  - Data-driven agent-based modeling (DDABM)
  - Scalable calibration: using machine learning (ensuring features are causally grounded)
  - Validation: cross-validation (measure effectiveness of individual behavior); forecasting validation (split data along time dimension into calibration and validation sets)

adoption model



DDABM[1]

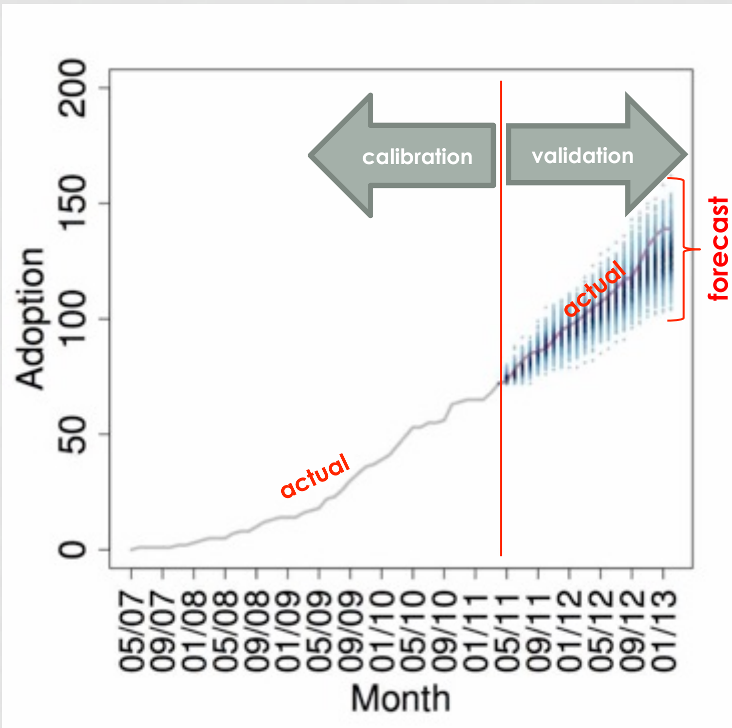
- **Individual agent behavior**: probability that individual (household) adopts solar PV, as a function of a collection of variables (including policy variables)
  - Learn from a ***large individual-event dataset*** of past adoption decisions
  - Include social influence: capture interactions among agents; leverage previous causal modeling method (Bollinger & Gillingham, 2012)
- Agent-based model: learned agent models instantiated as households, given household/ demographic parameters from data

[1] H Zhang, Y Vorobeychik, J Letchford, K Lakkaraju. Data-driven agent-based modeling, with application to rooftop solar adoption. *International Conference on Autonomous Agents and Multiagent Systems (AAMAS)*, 2015.

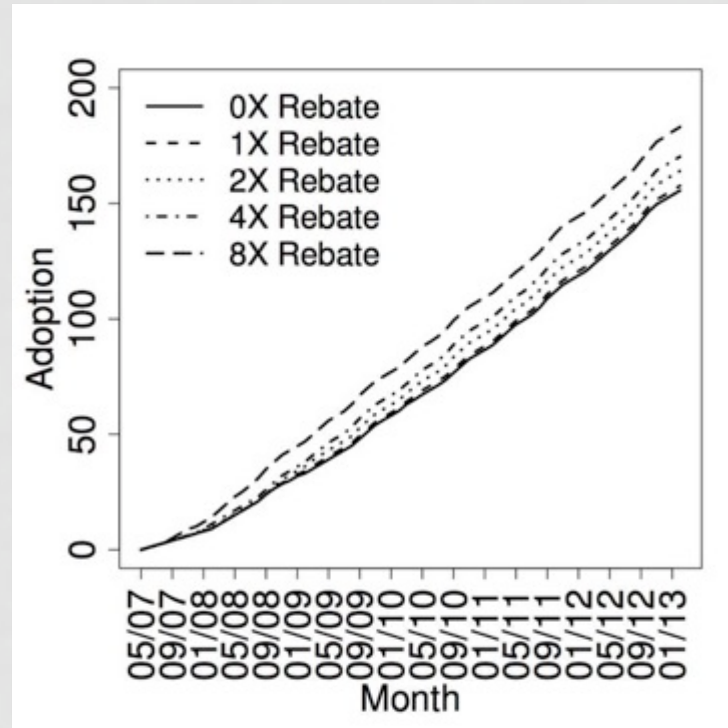
DATA

- **Adopters**: adoption (incentive reservation) time, installation time, lease vs. own, system size, assessor data (property characteristic: square footage, etc), energy use data for 12 months prior to adoption (*obtained from Center for Sustainable Energy*)
- **Owners**: cost of ownership
- **Leasers**: cost of leases (based on a subsample of actual lease contracts)
- **Non-adopters**: assessor data
- Climate data (solar insolation/geographic location)

DDABM[1]



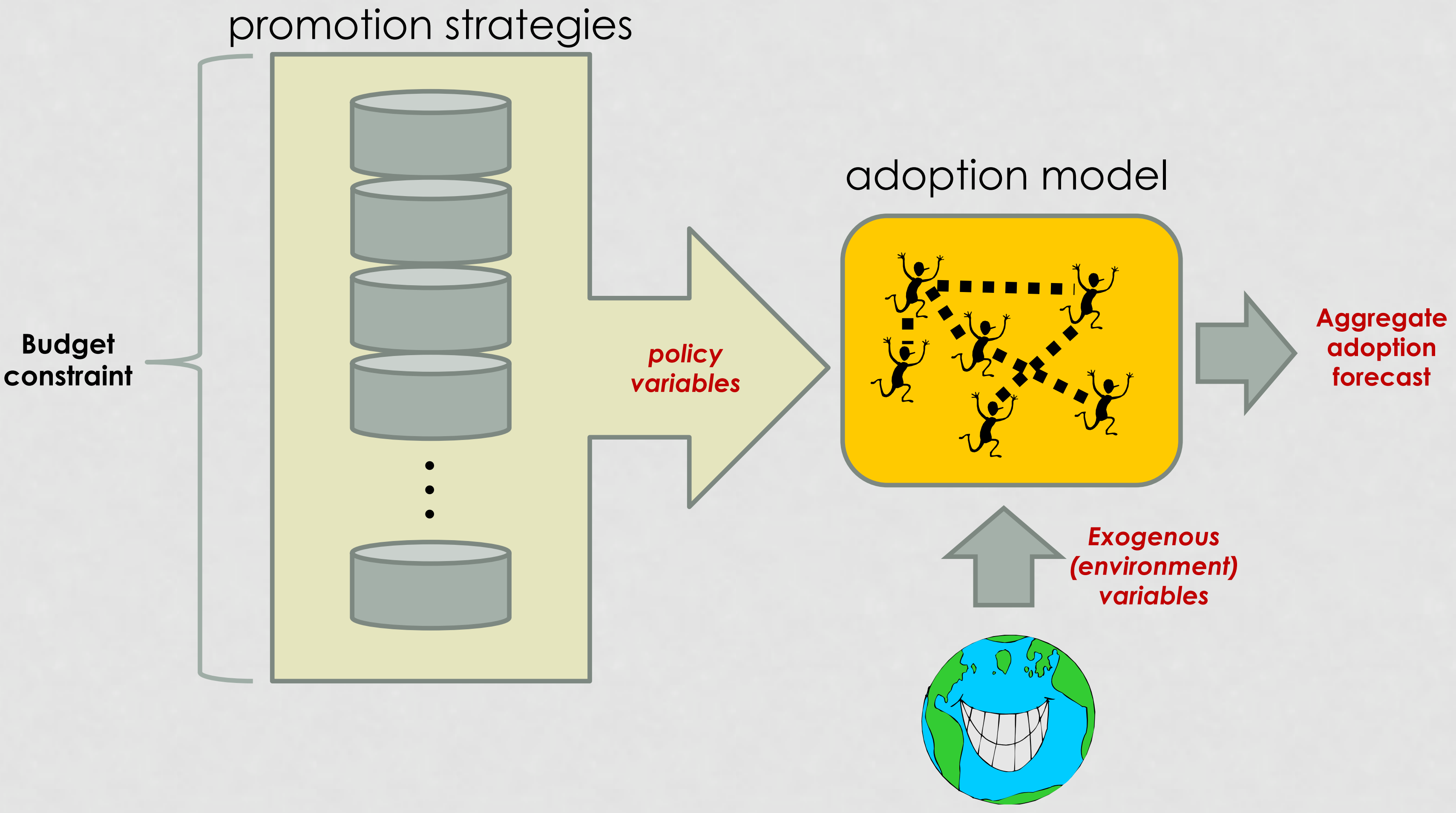
Model captures actual adoption patterns



Incentives have weak impact on adoption trends

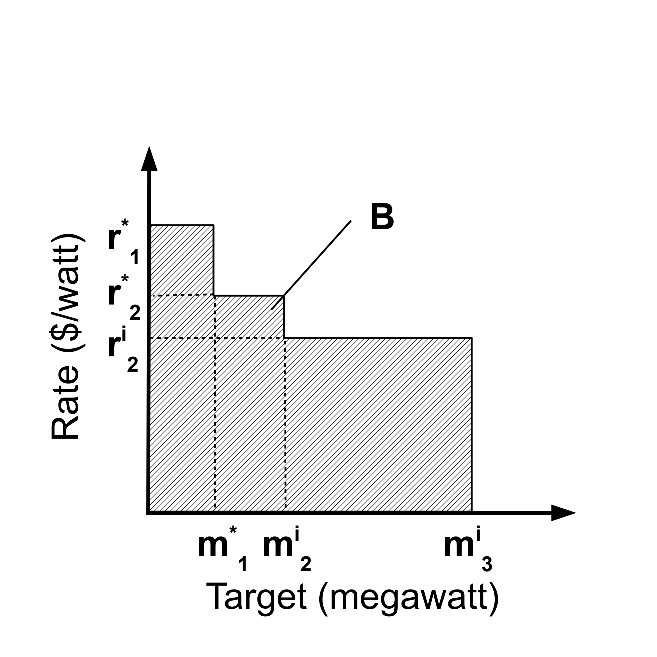
[1] **H Zhang, Y Vorobeychik, J Letchford, K Lakkaraju. Data-driven agent-based modeling, with application to rooftop solar adoption. *International Conference on Autonomous Agents and Multiagent Systems (AAMAS)*, 2015.**

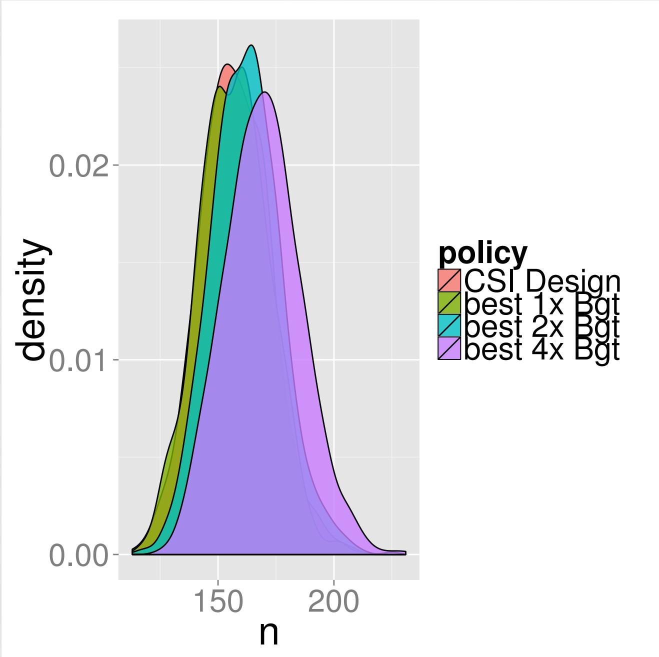
ALGORITHMIC PROBLEMS: PROMOTION



OPTIMIZING INCENTIVES[2]

- Problem: given a budget and a time horizon, how to optimally choose incentive policy
  - Amount of incentive / watt
  - MW transition points to lower incentives





[2] H Zhang, Y Vorobeychik, J Letchford, K Lakkaraju. Data-driven agent-based modeling: framework and application. *Journal of Autonomous Agents and Multiagent Systems, 2016.*

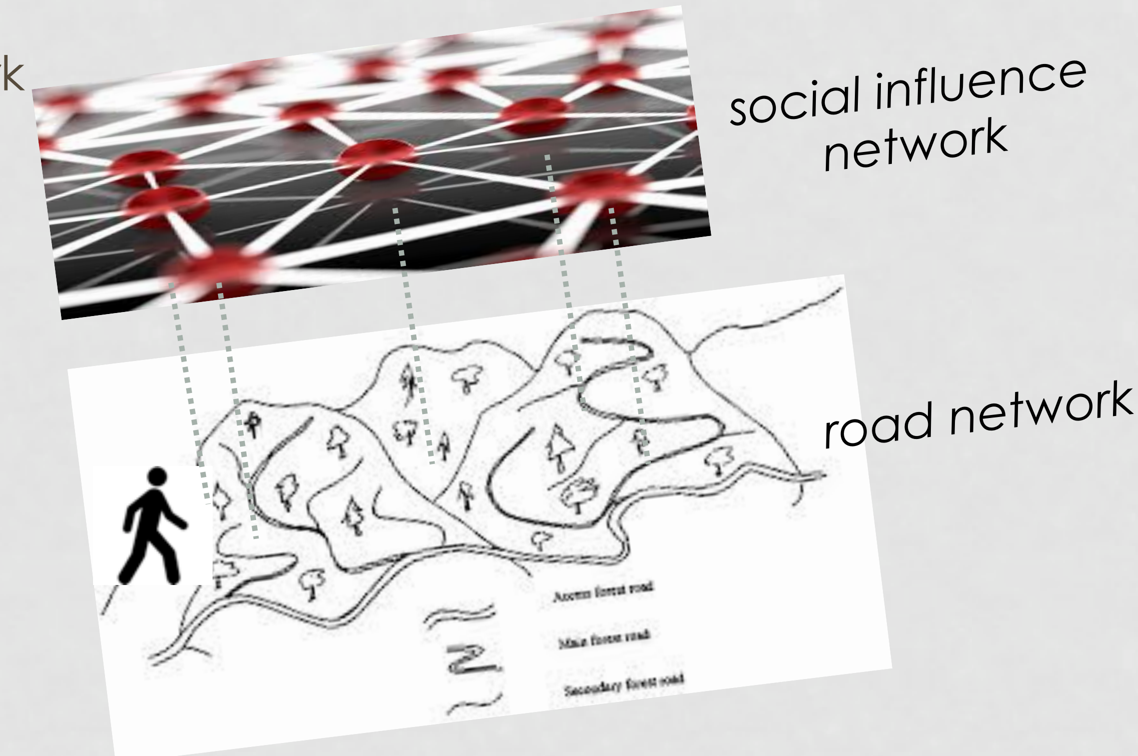
DOOR-TO-DOOR MARKETING[4]

- Door-to-door marketing has been shown effective, but is also quite expensive
- How can we effectively decide where to focus marketing efforts?
  - Target individuals who are likely to adopt, and who are in the best position to influence others to adopt
  - Traveling to individual households is time consuming; wish to do this efficiently

[4] **H Zhang, Y Vorobeychik. Dynamic influence maximization under increasing returns to scale. *AAAI Conference on Artificial Intelligence (AAAI)*, 2016.**

DOOR-TO-DOOR MARKETING MODEL

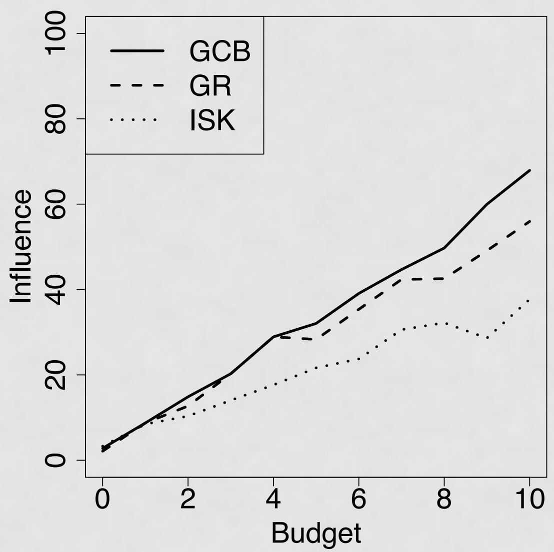
- Walk door-to-door along a road network
- Goal: maximize # of adopters, subject to the constraint that your walk takes at most H hours

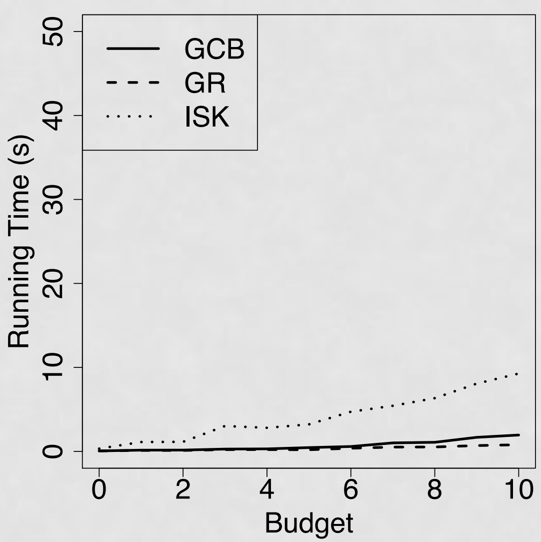


[4] **H Zhang, Y Vorobeychik. Dynamic influence maximization under increasing returns to scale. *AAAI Conference on Artificial Intelligence (AAAI)*, 2016.**

ALGORITHMS FOR DOOR-TO-DOOR MARKETING

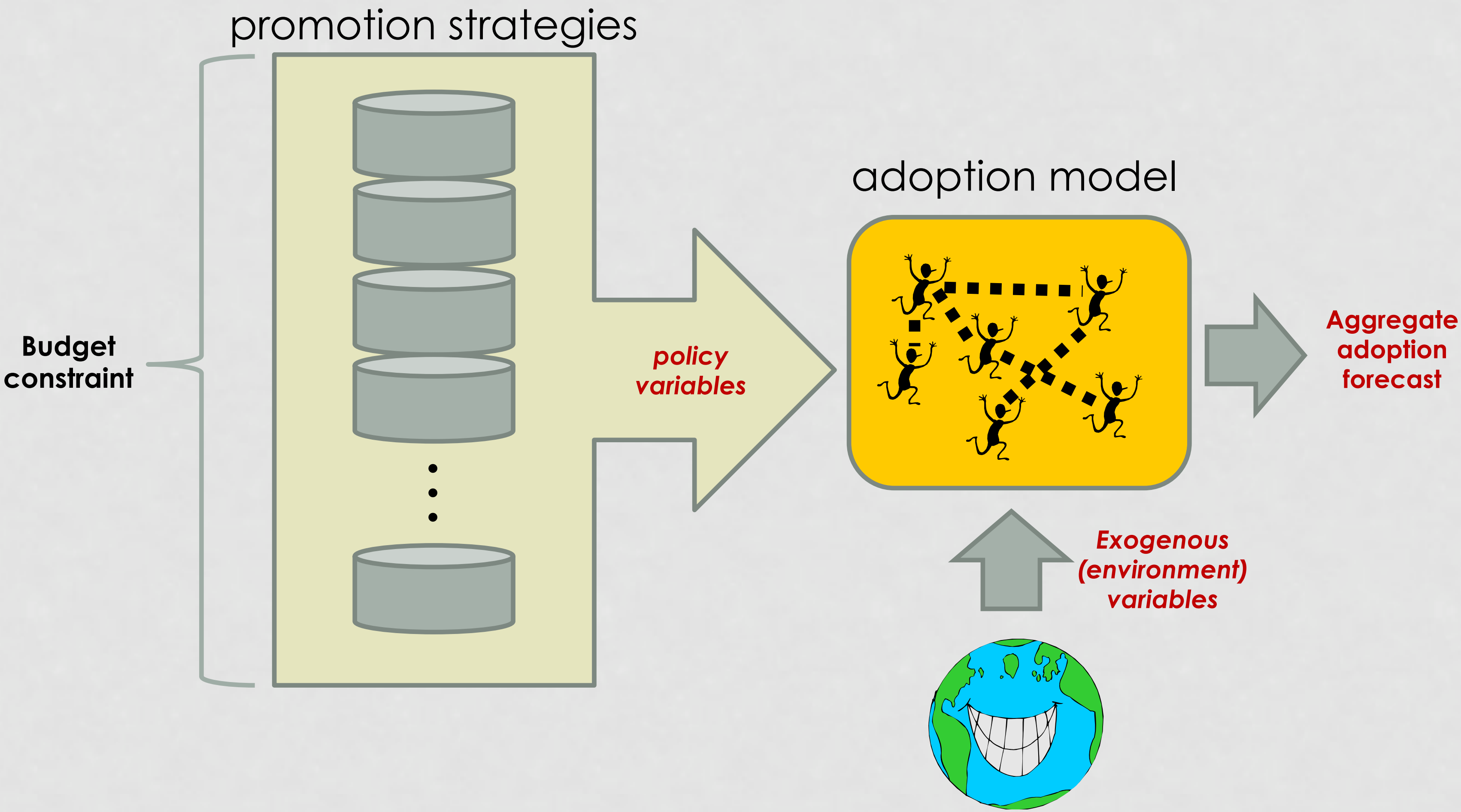
- Developed a new greedy algorithm (GCB), adding households to visit based on marginal impact on influence per unit marginal cost of visiting
- Proved that it's near-optimal and much faster than state-of-the-art alternatives





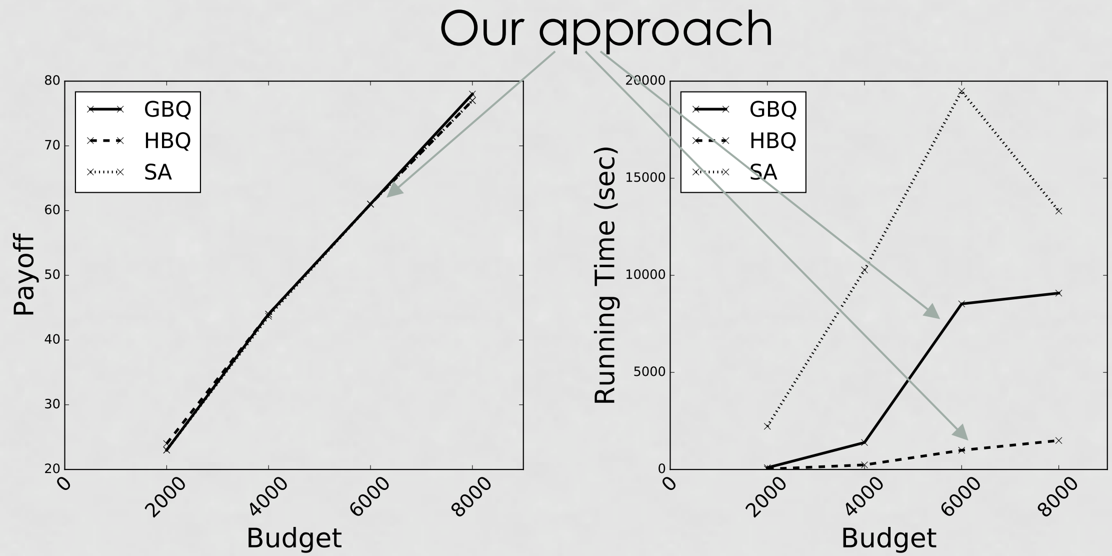
[4] H Zhang, Y Vorobeychik. Dynamic influence maximization under increasing returns to scale. *AAAI Conference on Artificial Intelligence (AAAI)*, 2016.

ALGORITHMIC PROBLEM: DIVIDE BUDGET AMONG MANY MARKETING ACTIVITIES



ALGORITHMIC PROBLEM: DIVIDE BUDGET AMONG MANY MARKETING ACTIVITIES

- Problem: have a collection of marketing activities, with varying costs and impact on adoption
- Approach: can formulate as an approximate multi-Knapsack problem
  - Developed new algorithms for efficient query strategies when channel response is represented using simulations (e.g., ABM)



BOTTOM LINE

- Many algorithmic problems arise in the context of innovation diffusion
  - Modeling and big-data analytics of adoption decisions (human behavior modeling)
  - Computational (often, combinatorial optimization) methods for optimizing marketing decisions
- We made progress addressing some of these in the context of solar PV adoption, using individual-level CSI data for San Diego county
  - Uncovered and addressed some fundamental computational problems in the process

NATIONAL RENEWABLE ENERGY LABORATORY

1977 - 2017

Willingness to Adopt Solar: An investigation into Ad design

Michael Rossol[1]

Kimberly Wolske[2], Annika Todd[3]

James McCall[1], and Ben Sigrin[1]

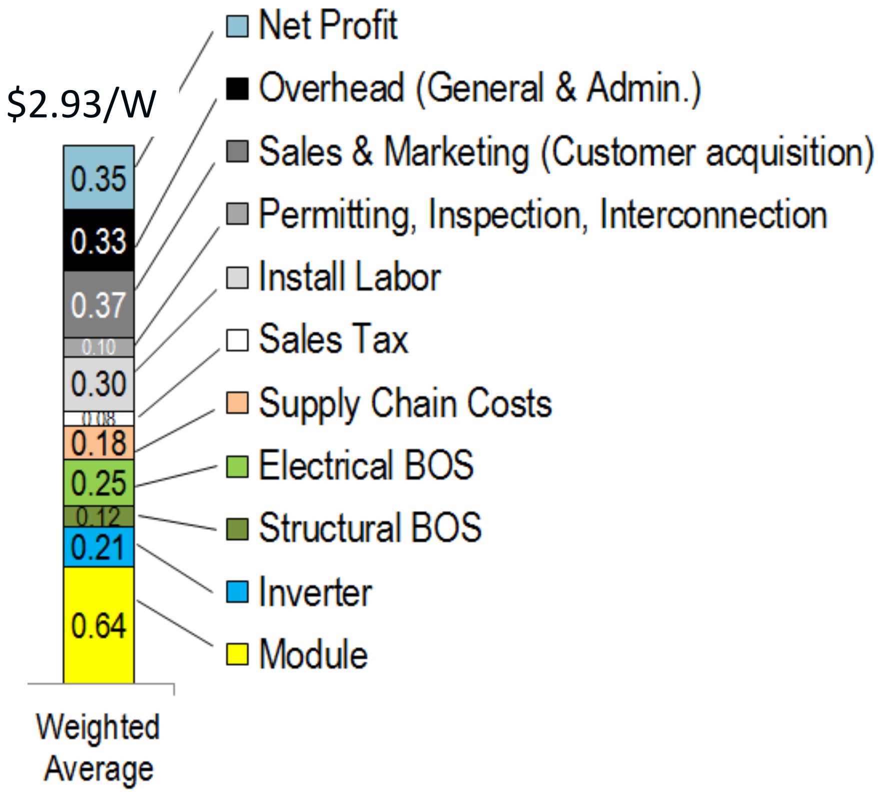
July 20th, 2017

[1] National Renewable Energy Laboratory

[2] Harris Public Policy, University of Chicago

[3] Lawrence Berkeley National Lab

Customer acquisition is a substantial portion of the cost of PV



Fu et al. 2016
U.S. Solar Photovoltaic System Cost Benchmark

- Environment Primarily: 3-5%
- Environment + Money: 33%
- Both, but Money over Environment: 39%
- Money and not Environment: 6%
- Opportunistic: ~20%

Moezzi et al. In-preparation
A Non-Modeling Exploration of Residential Solar Photovoltaic (PV) Adoption and Non-Adoption

Research Questions

H1: Consumers will respond more favorably to loss frames than gain frames

- The literature suggests that losses loom larger than potential equivalent gains, so loss framing should be more motivating

H2: Ads that present the benefits of PV in the near term will be more effective than ads that frame the benefits in the long-term

- The literature suggests that people discount the future and thus near term financial benefits may be more effective

H3: Ads that present the benefits of PV in terms of net savings (i.e. savings net of the system payment) will be more effective than those in terms of gross savings (i.e. doesn't include system payment)

- Prior work has suggested customers assume the savings are gross, which understates the potential benefits

H4: Ads that present higher monetary savings from PV will be more effective than those with lower monetary savings.

- Assesses market potential as a function of the bill savings amount

Outline

- Surveys
  - Ads
  - Measures used
  - Demographics
- Results
  - Gain/Loss by Time Frame
  - Net/Gross by Saving Amount
  - Role of Ad Skepticism
  - Role of pre-existing psycho-social constructs
- Conclusions

Survey 1: Gain/Loss by Time Frame

Gain Faming

Loss Framing

CA	NY
$67 each month	$28 each month
$804 each year	$336 each year
$20,100 over the next 25 years	$8,400 over the next 25 years

Savings are based on a May 2016 assessment of likely solar savings for residential customer in CA or NY with a 5kW system.

Survey 2: Net/Gross by Saving Amount

Gross savings: Ambiguous

Net savings: Unambiguous

Amount of savings:

- Low = $300 per year
- Mid = $625 per year
- High = $925 per year

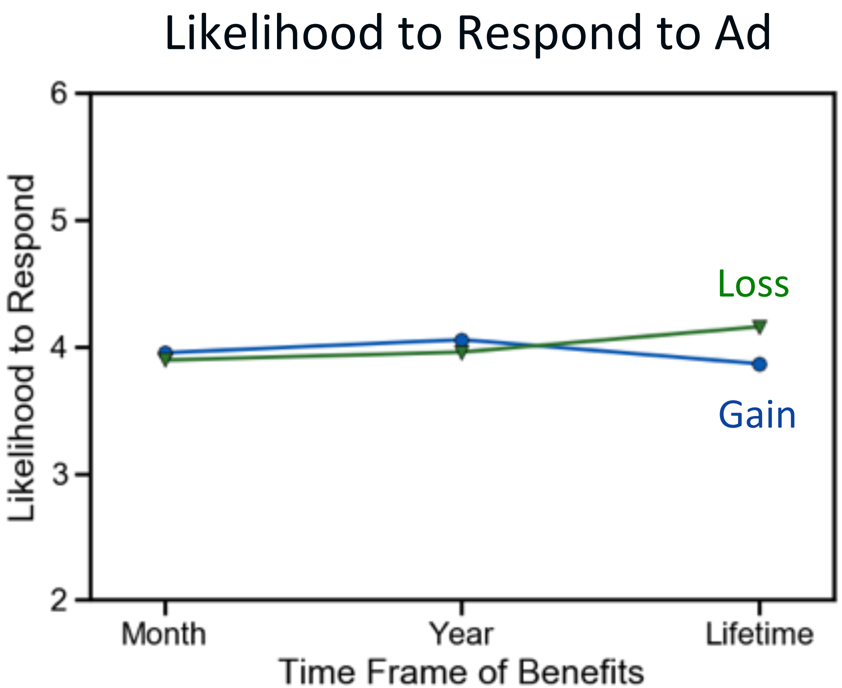
Mid savings are based on a May 2017 assessment of likely solar savings for residential customer in MA with a 5kW system.

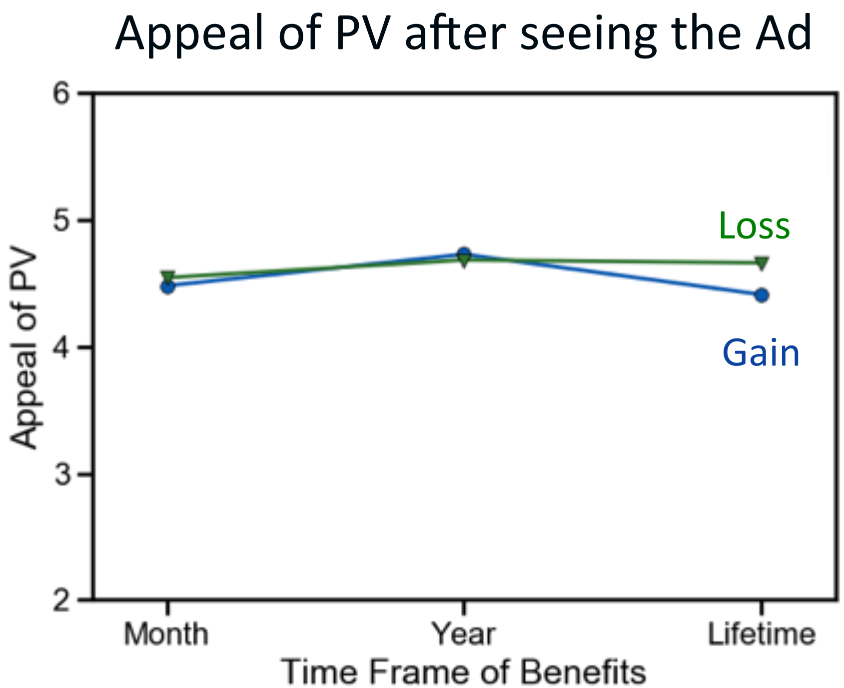
Survey Measures

- Dependent Variables:
  - Likelihood to respond to the ad
  - Based on the ad how appealing is PV
    - Appeal of Solar Panels
    - Cost benefit of PV
    - Financial Impact of PV
  - How skeptical are you of the benefits of PV
- Covariates:
  - Psycho-social
    - Environmental Norms
    - Perceived Social Support
    - Customer Innovativeness CNS, CUM
    - Home in-suitability
  - Socioeconomics
    - Age
    - Gender
    - Education
    - Household size
    - Home Square Footage
    - SES Rung (Income)

Gain/Loss and Time Framing did not significantly influence the appeal of PV or likelihood of responding to the ad

Study 1 – Gain/Loss by Time Frame

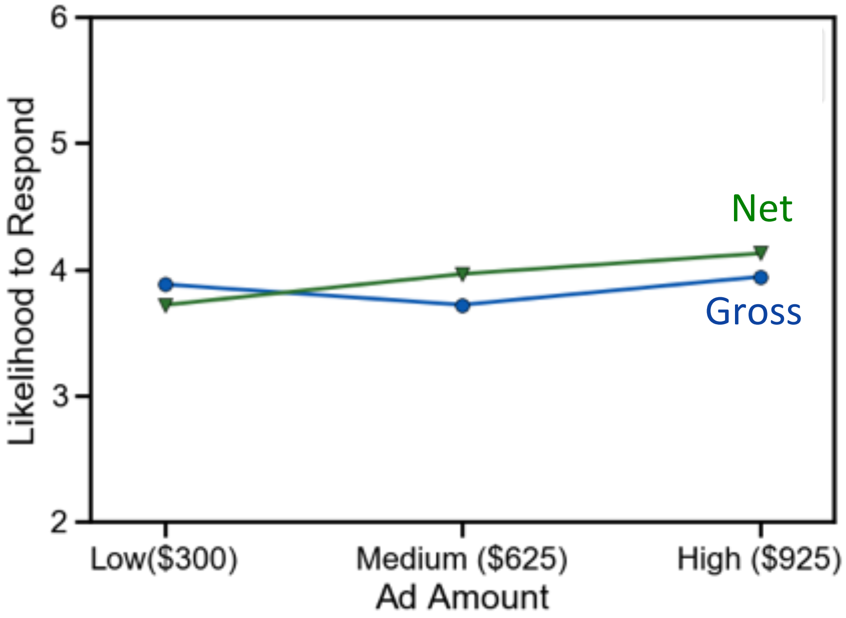




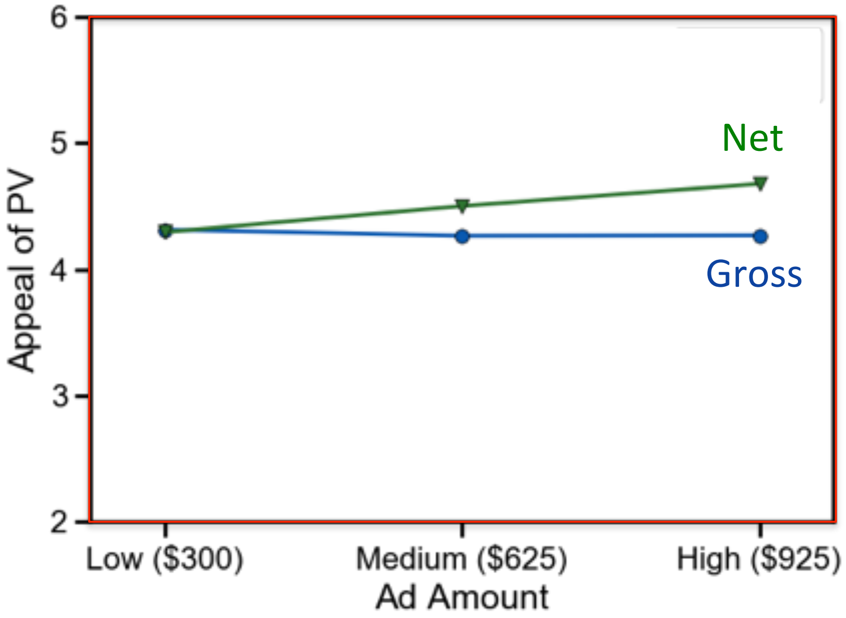
Higher amounts framed as net savings increased the appeal of PV, but did not increase likelihood to respond to the ad

Study 2 – Net/Gross by Saving Amount

Likelihood to Respond to Ad

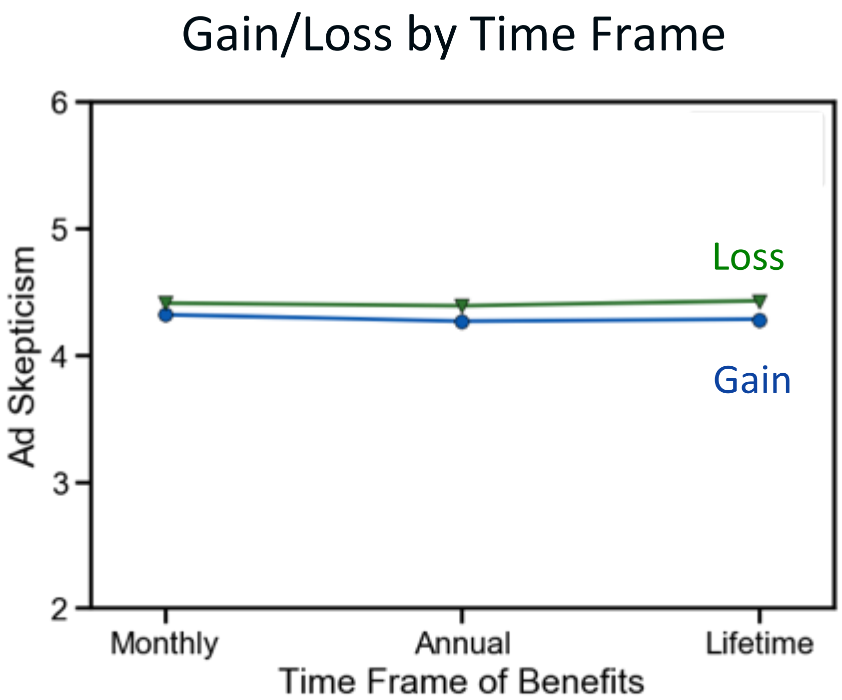


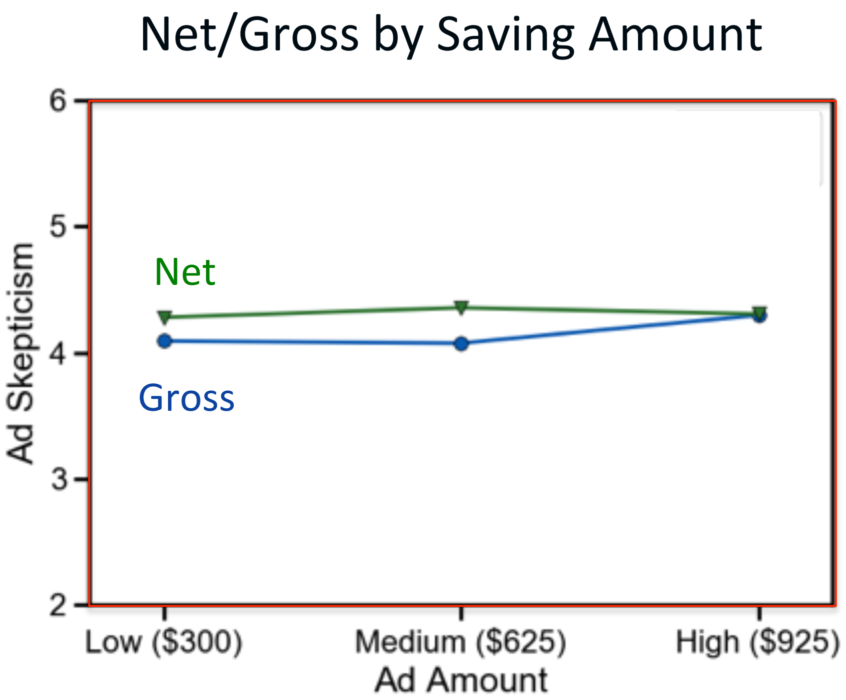
Appeal of PV after seeing the Ad



Net/Gross X Amount *p = 0.02*

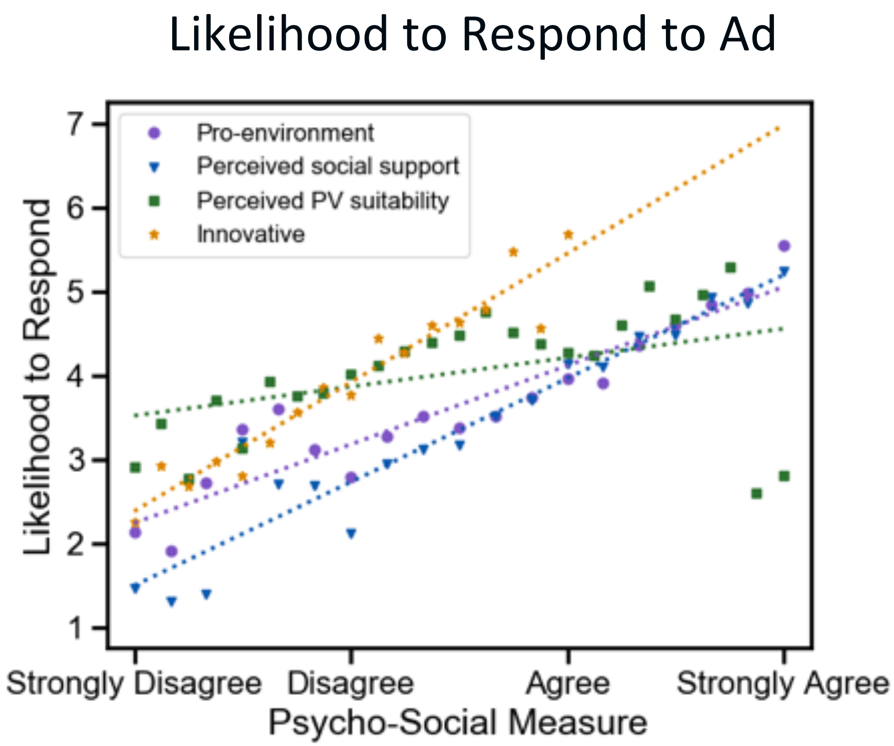
Surprisingly Net ads indicate greater skepticism

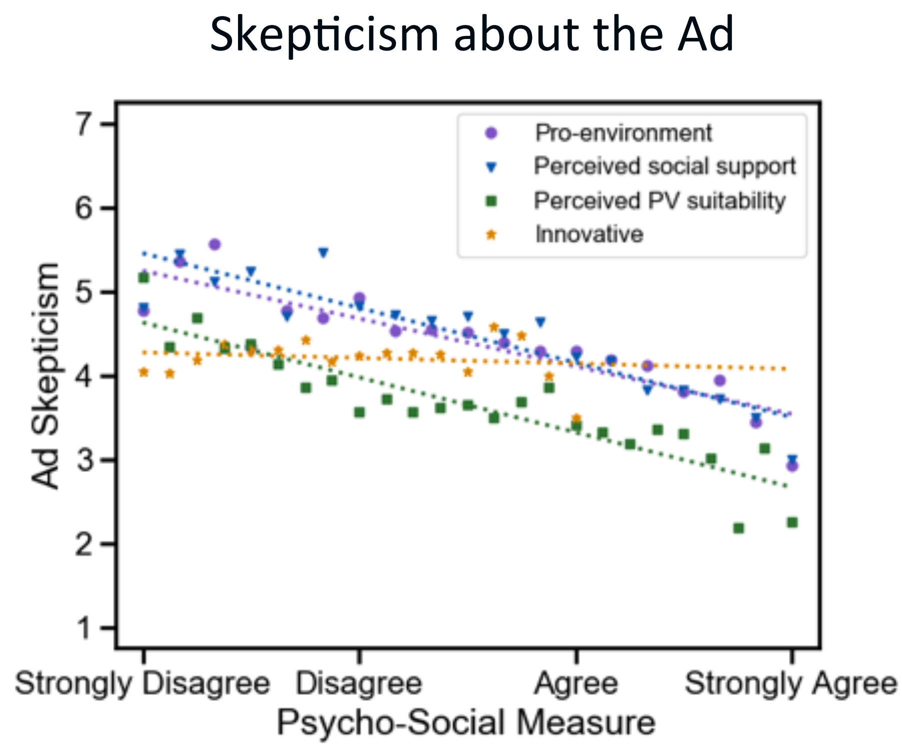




Net/Gross *p = 0.018*

Results: Psycho-Social Variables strongly influence WTA





Hypothesis

H1: Consumers will respond more favorably to loss frames than gain frames

- Respondents responded similarly to both gain and loss frames

H2: Ads that present the benefits of PV in the near term will be more effective than ads that frame the benefits in the long-term

- Respondents responded similarly regardless of time frame for savings/losses

H3: Ads that present the benefits of PV in terms of net savings (i.e. savings net of the system payment) will be more effective than those in terms of gross savings (i.e. doesn't include system payment)

- Net ads resulted in greater appeal for PV but did not lead to a greater likelihood to respond to the ad

H4: Ads that present higher monetary savings from PV will be more effective than those with lower monetary savings.

- Respondents responded similarly regardless of ad amount

Conclusions

- Efforts to make the financial benefits of PV seem more appealing do not appear to strongly influence interest in PV:
  - Time frame for savings has little effect
  - Gain and loss framing are equally effective
  - Greater savings does not increase likelihood to respond
  - Providing greater financial detail leads to greater skepticism
- Instead pre-existing psycho-social constructs appear to drive interest in PV
  - Being pro-environment
  - Having social support to adopt PV
  - Perceiving your home to be well suited for PV
  - Being innovative
- Targeted marketing has the potential for greatest return
  - Find the proper audience
  - Target ads to said audience

Questions?

Questions?