Uncertainty in energy efficiency: Technologies, strategies, behavior, and policy

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Overview of Two Studies

1. How effective are demand-side management programs at reducing energy consumption, given studies of varying quality?
2. How do decisions about energy efficiency compare to what people “should” do?

Main Results

1. Effectiveness of demand-side management
   – Reported effects are likely biased and may overestimate true effects by a factor of 2
2. Energy efficiency decisions
   – Rational analysis captures some important features: uncertainty and time preferences
   – Misses others: debt aversion and insensitivity to split incentives

Study One

1. How effective are demand-side management programs at reducing energy consumption, given studies of varying quality?
2. How do decisions about energy efficiency compare to what people "should" do?

Assessing Uncertainty in Demand-side Management (DSM) Programs

- Utilities are moving toward wirelessly communicating smart-meters, with a promise of helping people conserve energy and reduce peak demand
- Pilot studies of technologies/programs enabled by smart meters vary in their quality and reporting, leading to significant uncertainty in expected effects

Risk-of-Bias Uncertainty Assessment

- Medical researchers must assess uncertainty in clinical trials
- The Cochrane Collaboration provides guidance on systematic reviews (meta-analyses) of clinical medical trials
- Those methods were applied to DSM field trials, where there are no currently accepted standards

Meta-Analysis

All studies examining effectiveness of three smart-grid enabled programs up to 2012:

- In-home displays
- Dynamic pricing
- Automation

32 studies in total

Meta-Analysis: Biases

- Volunteer bias
- Intervention selection bias
- Sequence generation bias
- Allocation concealment bias
- Blinding bias
- Attrition

Volunteer Selection Bias

- People who volunteer for a study might respond differently than the general population
- BC Hydro Power Smart Study
  - Those with higher education and income were more likely to volunteer for a pilot test of dynamic pricing and in-home displays

Sulyma *et al*. 2008. Experimental evidence: A residential time of use pilot. In: American Council for an Energy-Efficient Economy Summer Study on Energy Efficiency in Buildings, pp. 292–304.

Intervention Selection Bias

- Participants who select their own treatment group might systematically differ from non-selectors
- Olympic Peninsula Project
  - Participants could choose their favored tariff group (fixed rate, time-of-use with critical peak pricing, real-time pricing)

Hammerstrom *et al.* 2007. Pacific Northwest Gridwise Testbed Demonstration Projects. Part I. Olympic Peninsula Project. Technical Report, Pacific Northwest National Laboratory.

Sequence Generation Bias

- Researchers might assign participants using non-random methods
- Baltimore Gas and Electric Smart Energy Pricing Pilot
  - Customers recruited sequentially to real-time pricing, then peak rebate, etc. (24 study conditions)
  - Most eager respondents will be given the first condition, etc.

Faruqui, A., Sergici, S., 2009b. BG&E Smart Energy Pricing Pilot (SEPP). Technical Report, Baltimore Gas and Electric Company and The Brattle Group.

Schulz, K. F., & Grimes, D. A. (2002). Generation of allocation sequences in randomised trials: Chance, not choice. *The Lancet*, *359*(9305), 515-519.

Allocation Concealment Bias

- Researchers or participants can manipulate random assignment if they know it beforehand
  - Believe someone would really benefit from treatment
  - Give someone in a larger house a smart thermostat, expecting greater savings
  - Medical researchers have tried to decipher random assignment by holding sealed envelopes up to a light to see the contents

Schulz, K. F. (1995). Unbiased research and the human spirit: the challenges of randomized controlled trials. *Canadian Medical Association Journal*,*153*(6), 783-786.

Blinding Bias

- If participants or researchers know what treatment a person received they may act differently, or be treated differently
  - People can guess treatment based on the taste of a pill, leading to differential symptom reporting (knowing they got a placebo)
  - Consumers told they were in an energy consumption study reduced their electricity use by ~ 3% (Hawthorne Effect)

Schwartz, D., Fischhoff, B., Krishnamurti, T., & Sowell, F. (2013). The Hawthorne effect and energy awareness. *Proceedings of the National Academy of Sciences*, *110*(38), 15242-15246.

Attrition Bias

- Participants who withdraw or are excluded after the study begins might differ systematically from those who remain
  - If those who do not benefit drop out, results among those who are left in the study will seem more effective
  - Connecticut Light & Power's Plan-it-Wise study found a 1% monthly dropout rate for unknown reasons

Faruqui, A., Sergici, 2009a. Connecticut Light and Power (CL&P) Impact Evaluation of CL&P's Plan-it-Wise energy program. Technical Report, Connecticut Light and Power and The Brattle Group.

Bias Classification Criteria

Table 1
Criteria for classifying studies as high or low risk-of-bias.

Bias type	High risk	Low risk
Volunteer	Opt-in design	(1) Opt-out design (2) Mandatory participation (3) Heckman correction[a]
Intervention	(1) Random assignment before volunteering (allowing withdrawal) (2) Participant or researcher choice (3) Availability of intervention (4) Assignment based on pretests or baseline data	(1) Random assignment after volunteering (2) Propensity score adjustment[b]
Generation	Alternating, day of birth, sequential, other non-random sequence	Truly random sequence
Concealment	Not central randomization or similar procedure	Central randomization[c]
Blinding	Participants knew about other intervention groups when recruited	Participants were not informed about alternative intervention or control groups
Attrition	Data exclusions or withdrawals, and data not missing at random	(1) No dropouts or exclusions (2) Intention-to-treat analysis[d] (3) Appropriate imputation[e]

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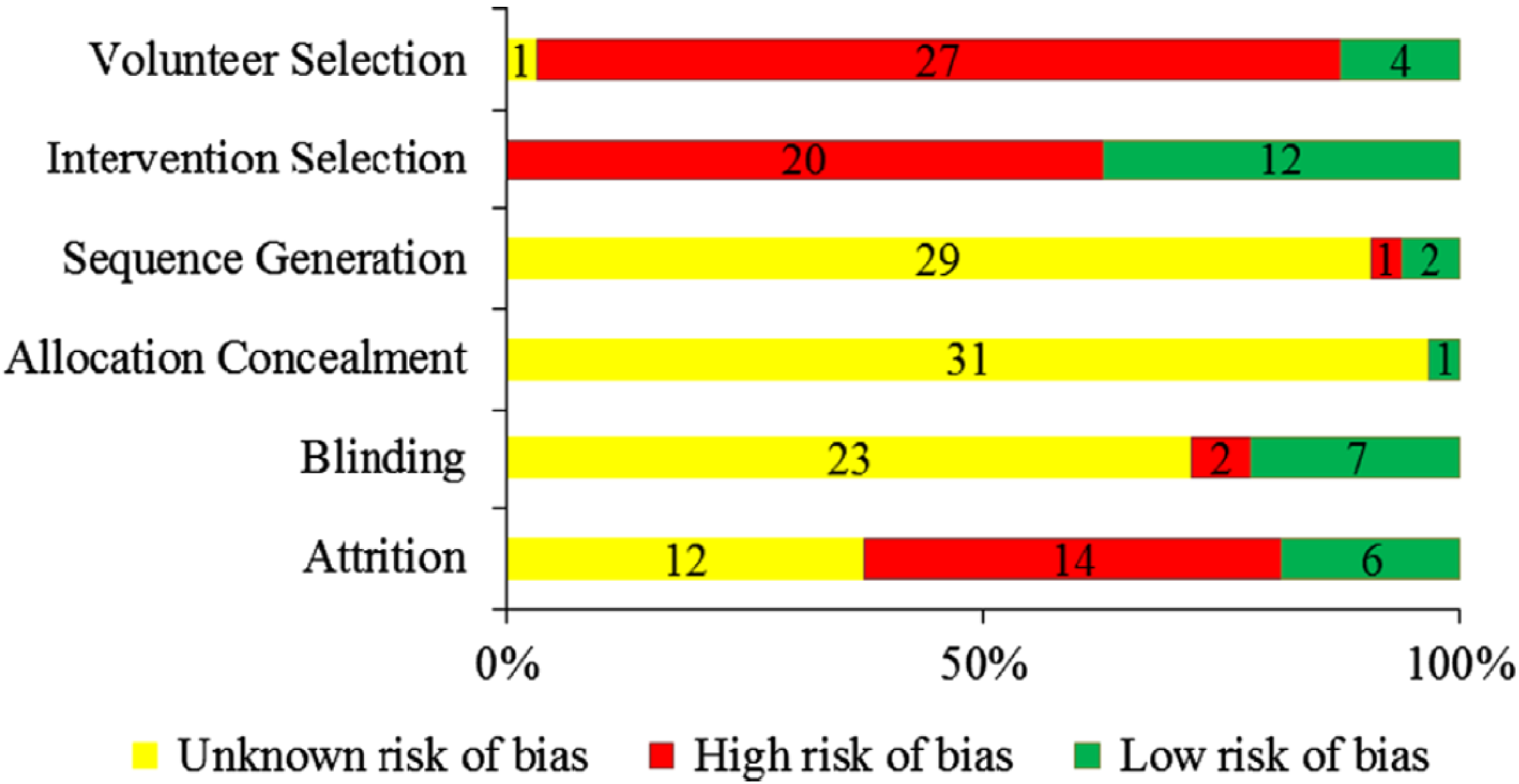
Volunteer Selection
Intervention Selection
Sequence Generation
Allocation Concealment
Blinding
Attrition
1
27
4
20
12
29
1
2
31
1
23
2
7
12
14
6
0%
50%
100%
Unknown risk of bias
High risk of bias
Low risk of bias

Cochrane Adjustments for Bias

Table 2
Estimates of bias for each of the six types of bias.

Source	Bias type	Bias estimate[a] (%)	95% CI	Variance[b] (%)
–	Volunteer	–	–	–
Stukel et al. (2007)	Intervention	44	[19, 69]	156
Jüni et al. (2001)	Generation	19	[−9, 40]	196
Jüni et al. (2001)	Concealment	30	[20, 38]	25
Jüni et al. (2001)	Blinding	14	[1, 26]	43
Kjaergard et al. (2001)	Attrition	−8	[−21, 6]	49
Schulz et al. (1995)				

[a] *Bias estimate* is the expected value of the bias estimate.
[b] *Variance* is the variance of the bias estimate based on the 95% confidence intervals.

$$\mu_i = \prod_j E[\mu_{ij}]$$

$$\hat{\theta}_{i;adj} = y_i = \text{true effect of study i} = \frac{\text{reported effect of study i}}{\text{overall bias of study i}} = \frac{y_i^*}{\mu_i}$$

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Peak Shaving: Reported and Adjusted Estimates

Generic inverse variance (GIV) and hierarchical linear model (HLM) estimates of reported and adjusted effects on peak reduction for four of the five intervention combinations.[a]

Intervention	Generic inverse variance			Hierarchical linear model		
	Reported	Adjusted	Groups[b]	Reported	Adjusted	Groups[c]
Pricing only	**6.93***	**2.49***	11	**10.83***	**5.92***	28
	(1.74)	(0.64)	(17)	(1.77)	(1.21)	(3)
IHD and pricing	6.30	3.06	1	**12.91***	**6.17***	10
	(4.34)	(4.44)	(10)	(4.44)	(2.11)	(1)
Pricing and automation	**32.80***	**16.81***	3	**25.35***	**13.83***	16
	(5.50)	(3.60)	(16)	(4.44)	(2.65)	(3)
All three	–	–	0	**31.30***	**12.56***	3
			(4)	(1.41)	(3.30)	(1)

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Conservation: Reported and Adjusted Estimates

Generic inverse variance (GIV) and hierarchical linear model (HLM) estimates of reported and adjusted effects on overall reduction for the five intervention combinations.

Intervention	Generic inverse variance			Hierarchical linear model		
	Reported	Adjusted	Groups	Reported	Adjusted	Groups
IHD only	**3.76*** (1.27)	1.12 (1.11)	12 (5)	**5.10*** (2.33)	**2.99*** (1.20)	16 (0)
Pricing only	**2.84*** (0.92)	0.30 (0.35)	10 (18)	1.73 (1.17)	0.91 (0.61)	21 (10)
IHD and pricing	2.17 (3.51)	1.05 (2.94)	1 (9)	2.30 (1.41)	1.32 (0.87)	8 (3)
Pricing and automation	**3.60*** (1.58)	0.09 (0.14)	4 (14)	3.84 (2.21)	2.81 (1.92)	11 (7)
All three	**3.00*** (0.323)	1.28 (2.18)	1 (3)	3.00 –	1.28 –	1 (3)

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Summary

Risk of Bias in Study Outcomes

- High risk-of-bias from volunteerism, intervention selection, and attrition
- Bias could plausibly reduce observed effects by half

Reporting Standards

- Almost no reporting of random assignment, how people were informed of assignment, and whether people knew about alternative treatments
- Poor reporting of uncertainty
- Standardized conduct and reporting would allow assessment of uncertainty and bias (CONSORT)

Main Results

- Effectiveness of demand-side management
  - Reported effects are likely biased and may overestimate true effects by a factor of 2
- Best estimates of peak shaving effects
  - Dynamic pricing: 3-6%, +/- 1%
  - Dynamic pricing + Automation: 14% +/- 3%
- Best estimates of conservation effects
  - Any treatment: 1-3% +/- 1% (~ a Hawthorne effect)

Study Two

1. How effective are demand-side management technologies at reducing energy consumption, given studies of varying quality?
2. How do decisions about energy efficiency compare to what people “should” do?

Pittsburgh B/C offices

Class A

- Above average rents
- High quality finishes
- State of the art systems

Class B

- Average rents
- Fair to good finishes
- Adequate systems

Class C

- Below average rent
- “Functional” space

22M ft^2 in downtown/Oakland

Uptake of programs in Duquesne Light territory

Program:	CPITD Verified Gross MWh/yr Savings	Percent of Portfolio CPITD Verified Gross MWh/yr Savings	CPITD Verified Gross MW Reductions	Percent of Portfolio CPITD Verified Gross MW Reductions
Residential: EE Program - Upstream Lighting	106,611	35%	5.578	16%
Residential: Low-Income EE - Upstream Lighting	20,561	7%	1.141	3%
Residential: EE Program (REEP) - Rebate Program	10,508	3%	0.864	3%
Residential: Appliance Recycling	10,271	3%	1.421	4%
Residential: School Energy Pledge	3,920	1%	0.818	2%
Residential: Low-Income EE	2,995	1%	0.383	1%
Public Agency/Non-Profit	30,576	10%	4.173	12%
Office Building - Large – EE	30,059	10%	4.288	13%
Primary Metals EE	24,074	8%	2.951	9%
Chemical Products EE	14,869	5%	2.005	6%
Mixed Industrial EE	13,417	4%	2.175	6%
Retail Stores - Small – EE	12,876	4%	3.094	9%
Retail Stores - Large – EE	10,123	3%	1.526	4%
Office Building - Small – EE	5,424	2%	1.459	4%
Commercial Sector Umbrella EE	5,003	2%	0.937	3%
Healthcare EE	3,905	1%	0.527	2%
Industrial Sector Umbrella EE	3,224	1%	0.711	2%
TOTAL	**308,416**	**100%**	**34.051**	**100%**

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Research Question

1. How do decisions about energy efficiency among class B/C office building owners compare to what people "should" do?

Behavioral Decision Research Approach

Behavioral Decision Research Approach

1. **Normative analysis** of investment decision problem

Behavioral Decision Research Approach

1. **Normative analysis** of investment decision problem
2. **Descriptive analysis** using interviews and a survey

Normative Analysis

Energy savings should outweigh the costs, subject to:

1. Uncertainty in energy savings
2. Time discounting
3. Capital constraints
4. Split incentives

Normative Analysis Summary

$$\sum_{j=1}^{J} \frac{ES_j}{(1+\delta^* + \delta^o)^j} > \sum_{j=1}^{Q} \frac{AC}{(1+\delta^*)^j}$$

1. Provides rate of return with enough certainty
2. Provides rate of return better than alternatives
3. Owner has enough cash to pay (or available financing)
4. Energy savings flow to owner, not tenant

Descriptive Analysis

- Comprehensive list of 327 B/C office building owners (504 buildings) in Pittsburgh
  - CoStar, Allegheny County Records, deed searches
- Recruited 132 owners (40%)
  - 1) Mail, 2) postcard, 3) phone/email, 4) in-person, 5) second mailing
- Mostly owner occupiers (98/120 reporting)

Descriptive Analysis

What is the perceived:

1. Uncertainty in energy savings
2. Time discounting
3. Capital constraints
4. Split incentives

Policy Preferences

"Suppose the following services could be provided to help you improve the energy use of your building's lighting systems. Tell us what you think about each of them using a rating from -3 to $+3$ described in the scale below."

"very unhelpful" (-3) "very helpful" ($+3$)

Uncertainty and Information

- *Energy Saving Comparables*: Data on the energy savings in buildings comparable to yours that improved their lighting systems.
- *Energy Savings Assessment*: Assessment by an engineer or architect about the energy saving potential of improved lighting systems.
- *Economic Assessment*: A cost-benefit analysis of lighting system improvements most relevant for your building.
- *Contractor Vetting*: Vetting of potential contractors based on quality, reliability, and customer satisfaction.
- *Energy Tracking*: Assistance in tracking your building's energy use with energy management software.
- *Contractor Scorecard*: A public scorecard showing how well potential lighting contractors have performed in the past.
- *Guarantee*: A guarantee that you will save a certain percent on your electricity bills if you improve your lighting systems.
- *Lease Structuring*: Assistance in creating a lease structure that allows tenants to pay for part of the cost of the lighting systems. (skip this question if your building is not multi-tenant)

Table 4: Attitudes Toward Decision-Making Services

Service	−3	−2	−1	0	+1	+2	+3	Mean	SD	n
Guarantee	1	1	1	14	12	27	69	2.1[a]	1.2	125
Economic Assessment	1	1	0	12	13	39	61	2.1[a]	1.1	127
Energy Assessment	1	1	1	13	25	34	52	1.9[b]	1.2	127
Energy Comparables	4	2	0	19	25	29	47	1.7[c]	1.5	126
Energy Tracking	1	3	1	35	28	20	38	1.4[d]	1.4	126
Contractor Vetting	2	3	3	36	20	22	38	1.3[d]	1.5	124
Contractor Scorecard	1	1	1	41	29	21	33	1.3[d]	1.3	127
Lease Structuring	5	4	1	33	12	14	23	1.3[e]	1.3	92

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Table 6: Factor analysis of service attitudes

Item	Factor 1	Factor 2	Uniqueness
Guarantee	0.11	**0.50**	0.74
Economic Assessment	**0.88**	0.14	0.21
Energy Assessment	**0.86**	0.16	0.23
Energy Comparables	**0.53**	0.37	0.58
Energy Tracking	**0.42**	0.35	0.70
Contractor Vetting	0.27	**0.60**	0.57
Contractor Scorecard	0.15	**0.90**	0.18
Eigenvalue	2.1	1.7	
% Variance Explained	0.3	0.24	
Cumulative Variance	0.3	0.54	

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Uncertainty and Information

- Respondents wanted a guarantee and economic cost-benefit assessment
- Guarantee reflected concern about project performance, uncertainty in savings
- Cost-benefit assessment reflected desire for information
- These two concerns were separable

Capital Constraints

1. How much do you think it would cost to buy and install new linear fluorescent lamps, ballasts, and fixtures in your entire building?
2. Could you pay for that without getting external financing?

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- 79% (87/110 responding) said they <u>could</u> pay out of pocket
- Capital availability may not be a major issue

Time Discounting

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$$\boxed{\sum_{j=1}^{q} \frac{AC}{(1+\delta^*)^j}} = \sum_{j=1}^{14} \frac{ES_j}{(1+\delta^* + \delta^o)^j}$$

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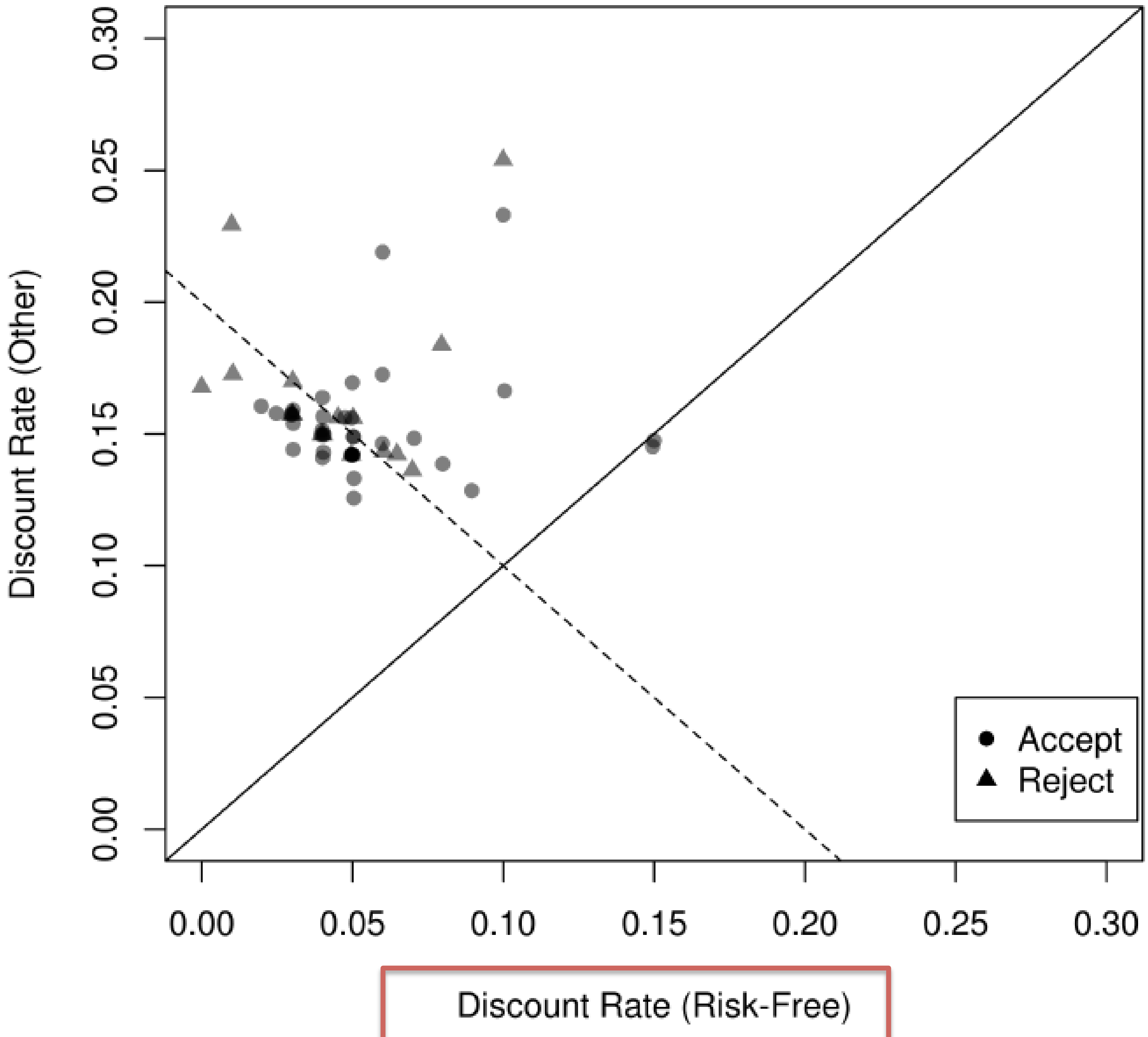
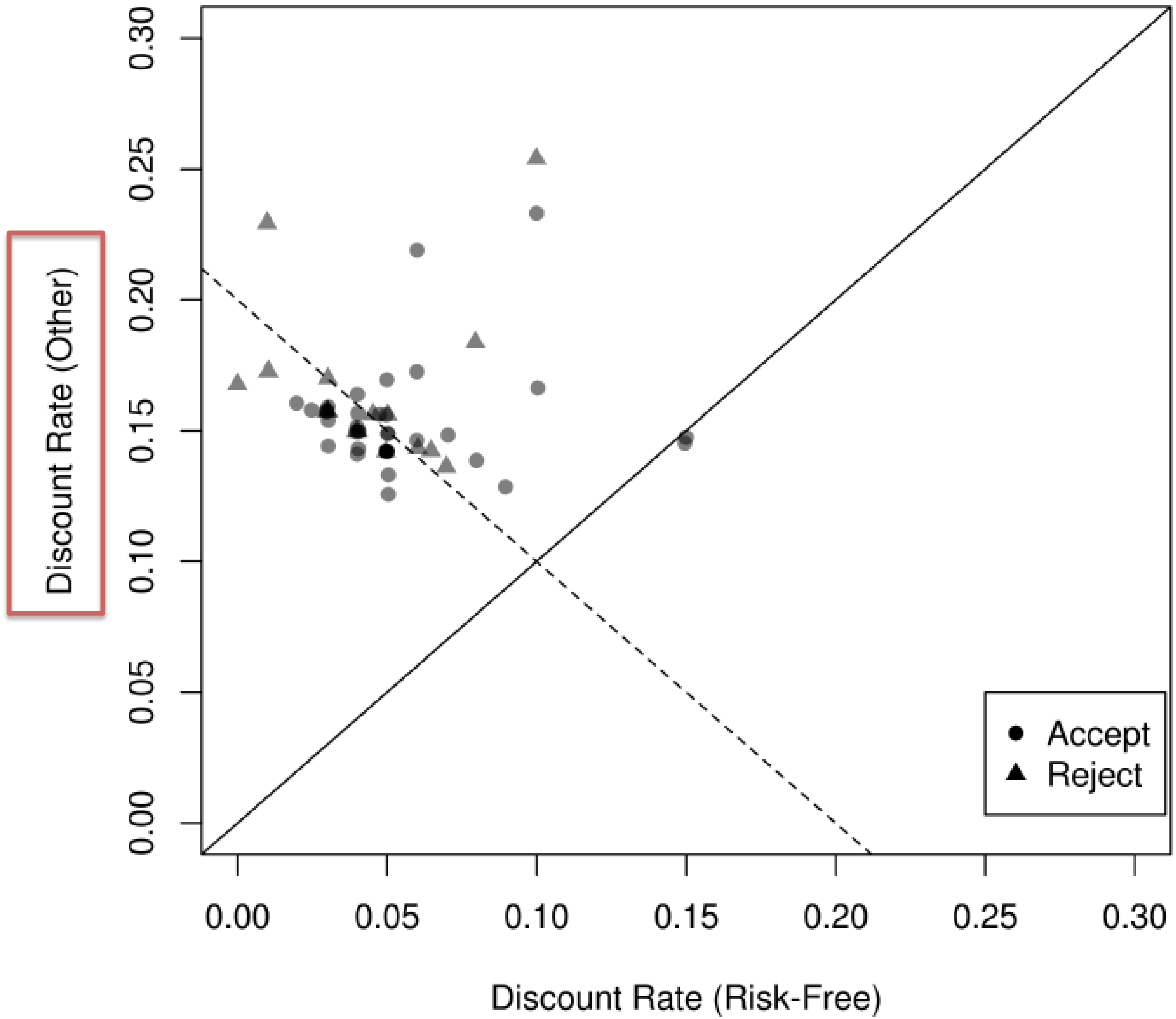

Discount Rate (Other)
0.00
0.05
0.10
0.15
0.20
0.25
0.30
Discount Rate (Risk-Free)
Accept
Reject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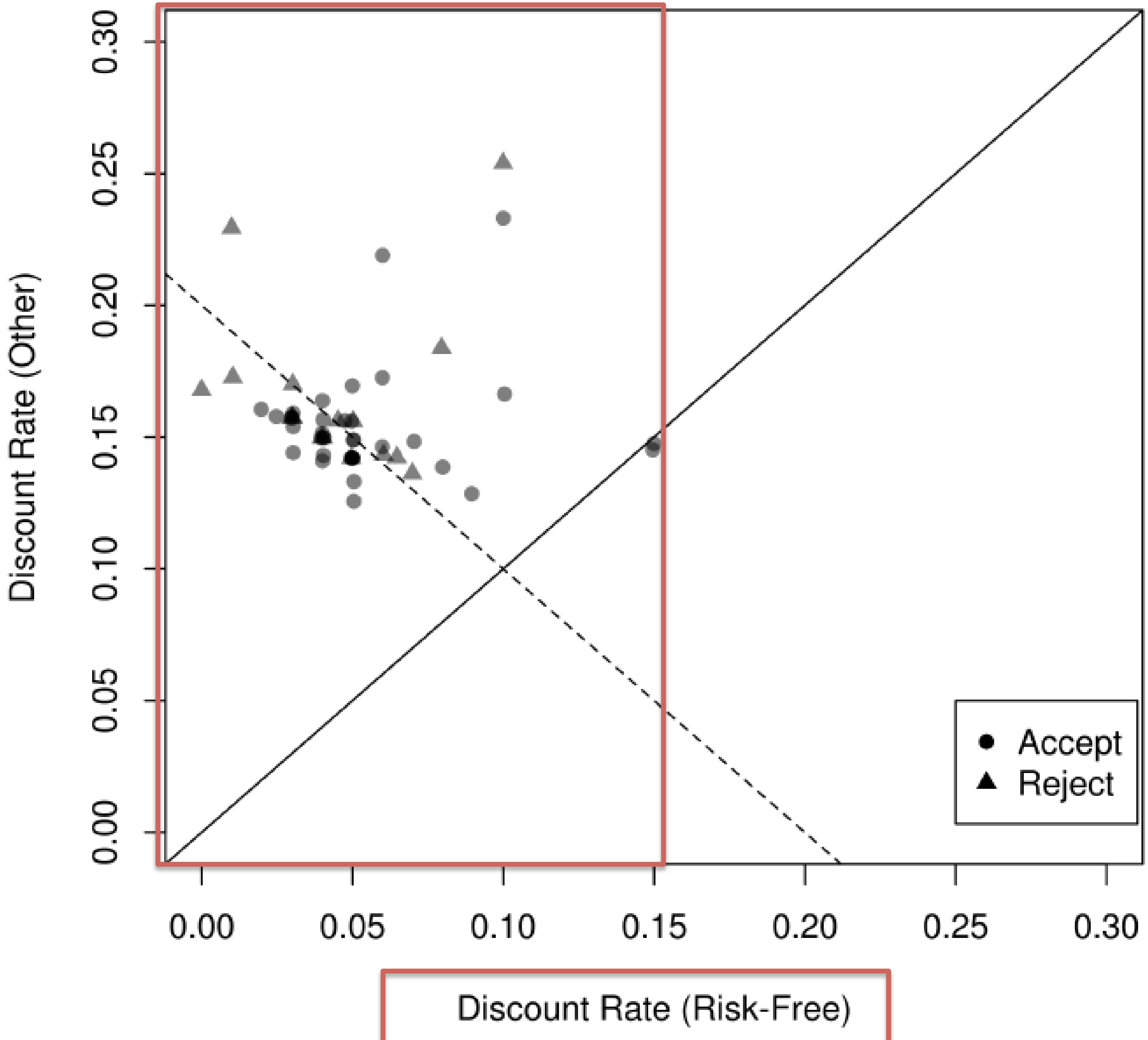
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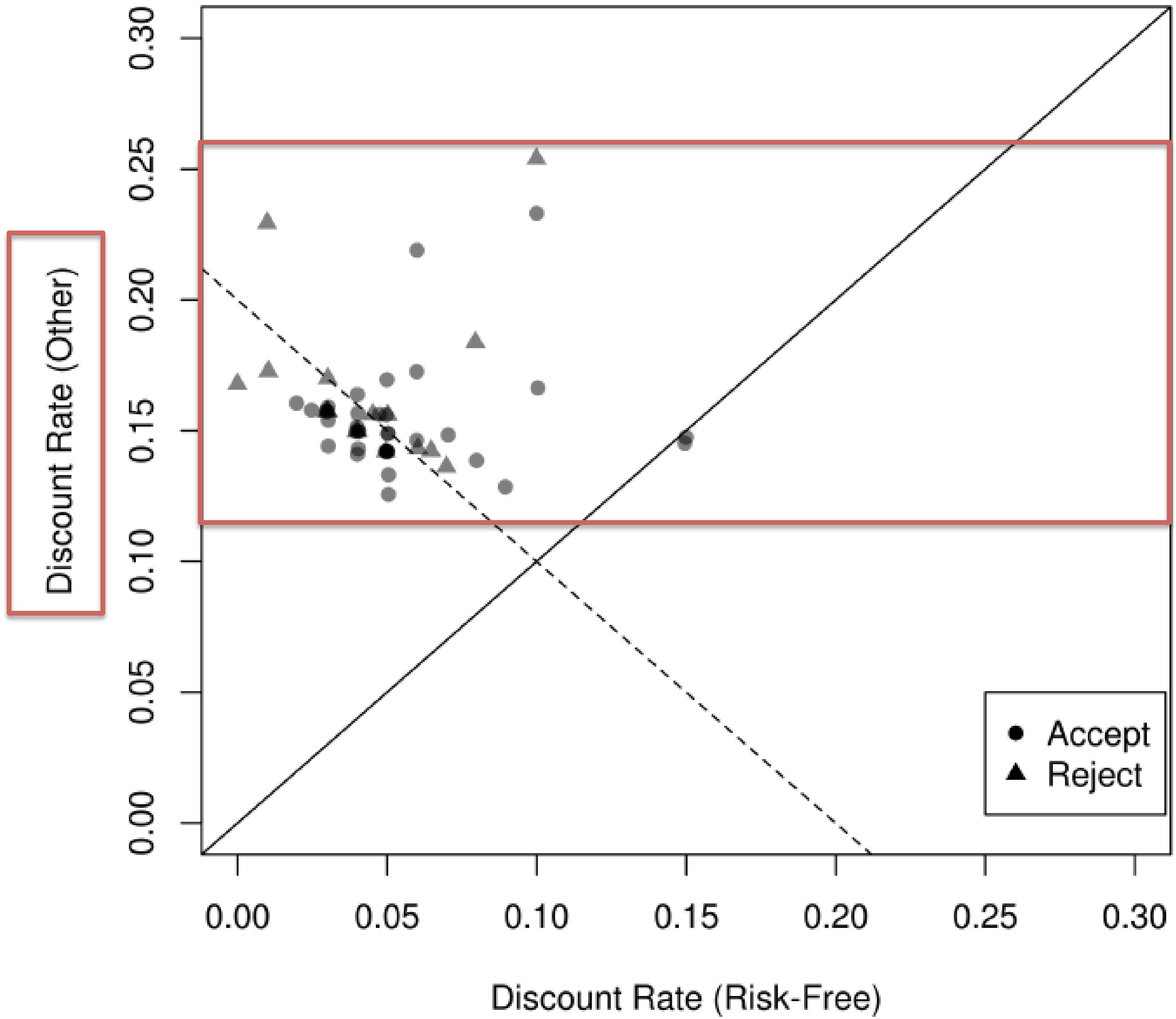

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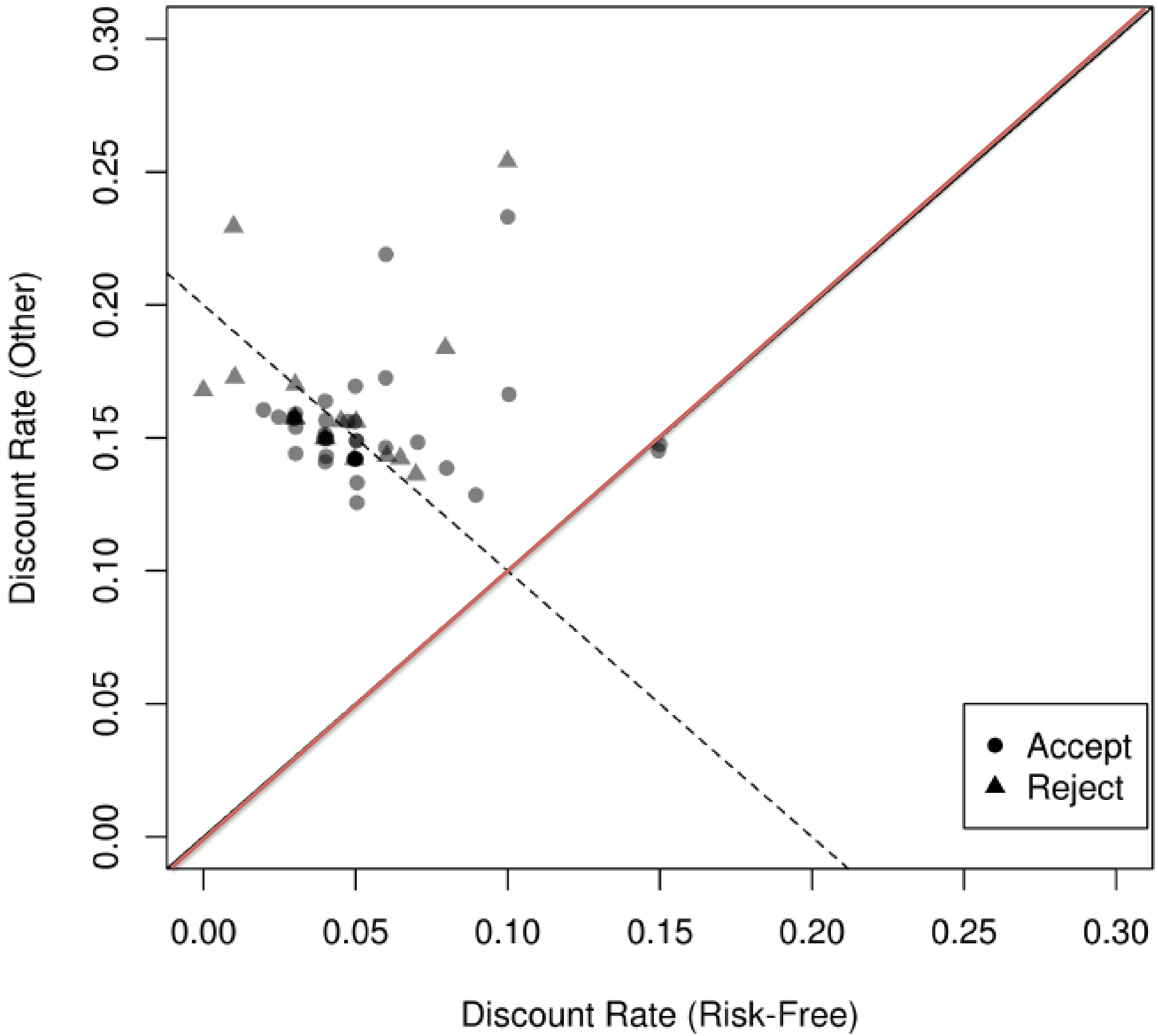

0.30
0.25
0.20
0.15
0.10
0.05
0.00
Discount Rate (Other)
Accept
Reject
0.00
0.05
0.10
0.15
0.20
0.25
0.30
Discount Rate (Risk-Free)

Time Discounting

- Most of the discounting of energy savings was not accounted for by time preferences
- Interestingly, many respondents refused to give a WTP or WTA for loans

Debt Aversion

"Imagine that you have enough money to pay the full cost of the lighting improvements up front, but also have the option of making payments evenly divided across a fixed number of years. Assume there is 0% interest on the delayed payments. Which would you prefer? (Full cost up front or even payments over several years)."

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- $\boxed{\text{Full cost up front: [35]}}$
- Even payments over several years: [80]

Debt Aversion

Table 8: Attitudes Toward Financing and Debt

Financing Mechanism	-3	-2	-1	0	$+1$	$+2$	$+3$	Mean	SD	n
Self Financing	16	6	7	17	17	15	46	0.95[a]	2.1	124
Utility Financing	24	10	5	29	21	16	19	0.1[b]	2	124
Energy Service Contract	28	13	8	22	21	20	12	-0.17[c]	2.1	124
Small Bank Loan	30	11	8	43	18	8	6	-0.55[d]	1.8	124
Commercial Bank Loan	35	13	6	38	18	8	6	-0.69[d]	1.8	124
Local Government Loan	58	6	12	21	13	4	10	-1.2[e]	2	124

Split Incentives

Table 10: Hypothetical choices to invest in occupancy sensors by split incentive

Option Chosen	No Split Incentive	Split Incentive	Total
Sensors	48	19	67
No Sensors	36	14	50
% Investing	57%	58%	

Split Incentives

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Table 11: Hypothetical choices to invest in linear fluorescents by split incentive.

Option Chosen	No Split Incentive	Split Incentive	Total
Linear Fl.	54	22	76
No Linear Fl.	31	9	40
% Investing	64%	71%	

Split Incentives

- Who pays the energy bills did not factor much into respondent hypothetical choices
- Many were owner-occupiers
- In pretest interviews, many were much more concerned about tenant retention than energy bills

Normative and Descriptive Analyses

- Uncertainty
  - Building owners should care about uncertainty in the energy savings and it is their biggest concern
- Time Discounting
  - The time value of money should make energy efficiency investments less attractive
  - For respondents this is true, but other factors account for more discounting than time preferences
- Capital constraints
  - Most respondents can pay and are debt averse
  - Some exhibit negative discount rates, preferring to pay the full cost up front
- Split incentives
  - Shouldn't care about energy efficiency unless they can make money off it, but split incentives didn't matter much to them

Research Team

- Tamar Krishnamurti

- Gabrielle Wong-Parodi

- Jay Apt

- Baruch Fischhoff

Research Assistants

- Dan Hochman

- Ranan Tanenbaum

- Xiyu Wang

- Yuvraj Kumar

Acknowledgements

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CEDM

Richard King Mellon Foundation

Research Partners

GREEN BUILDING ALLIANCE

TEN THE EFFICIENCY NETWORK

Plan for the day

08:30 – 09:15	Overview of >25 years of HDGC, CDMC and CEDM – Granger Morgan
09:15 – 10:00	Uncertainty in energy efficiency, Part 1: technologies, strategies, behavior and policy – Inês Azevedo
10:00 – 10:30	Uncertainty in energy efficiency, Part 2: technologies, strategies, behavior and policy – Alex Davis
10:45 – 11:15	Coffee break
11:15 – 11:45	Decision support for implementing the EPA Clean Power Plan Proposed Rule – Jeff Anderson
11:45 – 12:30	Marginal emissions factors, health and climate change co-benefits and trade-offs - Inês Azevedo
12:30 – 13:30	Lunch break
13:30 – 13:55	Insights from twenty years of work on expert elicitation and projections – Granger Morgan
13:55 – 14:05	Transitioning to a low carbon economy, Part 1: Insights from the RenewElec Project – Granger Morgan
14:05 – 14:30	Transitioning to a low carbon economy, Part 2: Insights from ITC and BC's Climate Policy – Hadi Dowlatabadi
14:30 – 15:10	Strategies for supporting investment decisions about large energy infrastructure in the face of regulatory and other uncertainty – Dalia Patiño
15:10 – 15:40	Coffee break
15:40 – 16:00	Reflections on Research and Governance wrt Albedo Modification – Granger Morgan
16:00 – 16:45	Insights From Our Experience in Building and Using ICAMs – Hadi Dowlatabadi
17:45 – 17:00	Muddling through on climate policy: good, but not good enough to avoid the risk of dead ends – Granger Morgan
17:00 – 17:30	Discussion and round table on what investigators in CEDM might best work on in the next several years to be most useful to the IA and energy modeling communities.

https://www.dropbox.com/sh/9skgog59wdd3m4x/AAAQzsPhamXaRmGOIOhyz7Dpa?dl=0