Managing an Energy Crises
Large-Scale Evidence of Residential Natural Gas Savings Through Financial Rewards

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Energy crises require energy saving efforts

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World is in its 'first truly global energy crisis' - IEA's Birol

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U.S. Power Crisis Leaves Millions Cold, Dark as Blackouts Expand

- Blackouts are hitting states from North Dakota to Oklahoma
- Texas shortages continue with millions cut off amid freeze

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Winter is coming: All you need to know about the EU's 15% gas reduction plan

The New York Times

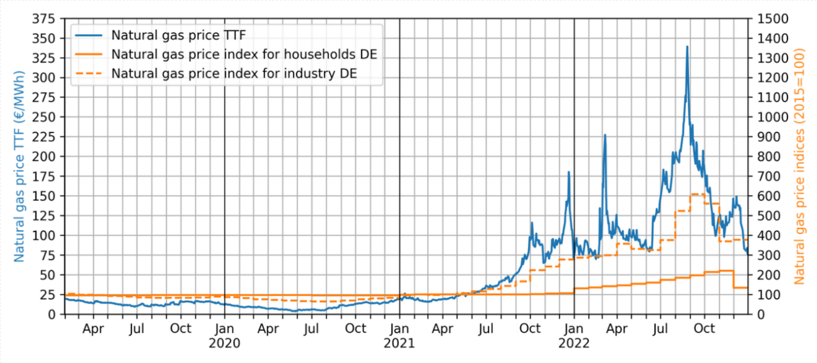
Biting Cold Sweeping U.S. Hits the South With an Unfamiliar Freeze

In Texas, where a 2021 storm killed 246 people and knocked out electricity for millions, officials urged residents to conserve power.

'Less water means more gas': how drought will test California's stressed power grid

California's diminishing water supply is cutting down hydropower, causing the state to rely more on fossil fuels

Retail prices unlikely to reflect societal costs



Development of natural gas wholesale and end-consumer prices during the European Energy Crises 2022/23 (Ruhnau et al., 2022)

Energy saving reward programs could provide an alternative financial incentive.

What is an energy saving reward?

- payment by a utility (government) to the customer
- conditional upon achieving a reduction in energy consumption over a specified period

How does the analyzed program work?

- 100 EUR conditional on
- saving 10% in the 2022/23 heating season compared to consumption in the previous heating season
- Self-reporting of meter reading at beginning and end of program

We study the causal effect of the reward on the natural gas consumption.

Research questions

- Is the program effectively reducing gas consumption of participating customers during the crises (target of inference: ATT)? yes, by 5%
- Which customers are attracted to saving reward programs? those with the highest elasticity/financially motivated customers
- Which customer segment saves most? wip
- What is the mechanism behind the causal effect, financial incentive or information treatment? wip
- Could the program have been improved? wip

We have access to the universe of residential gas consumer data

Utility owned data

- $170,000$ residential natural gas customers from a large German utility
  - Treatment group: $10,000$ voluntary participants
  - Control group: $160,000$
- rich set of customer information

Additionally

- census data (100x100m)
- degree of urbanization
- socio-economic data

We use meter readings unrelated to the reward to determine the control group's consumption.

- Irregular meter readings challenging
- Often present in the utility sector (e.g. heating, water, gas, electricity)
- Need for an innovative solution

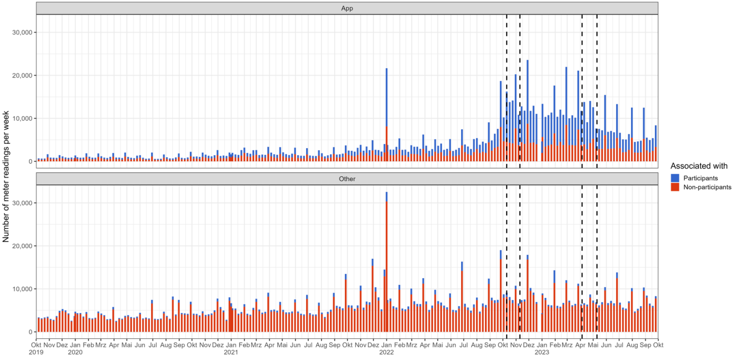
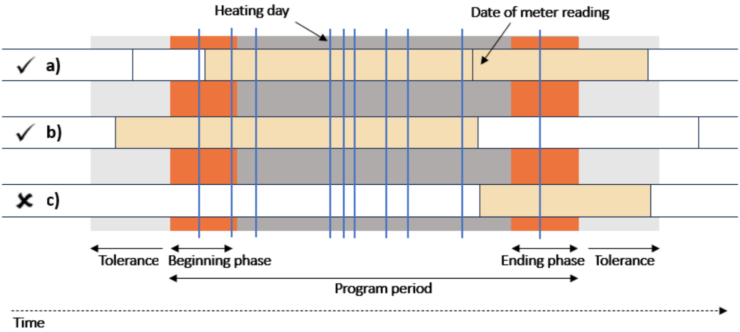


Figure 1: Number of meter readings, divided between App users (above) and non-app users(below)

We select customers with unrelated readings during a comparable time period.

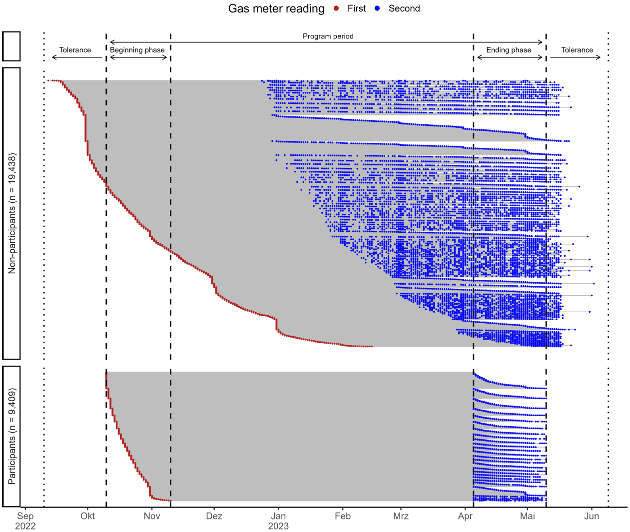
Criteria for "comparability"

- Tolerance: Customer's meter must not be taken more than X days before or after the end of the period.
- Coverage: The entire metering period must cover at least Y percent of the heating days.



We get a control group of over 20k customers for which we construct the outcome variable y_i

Impact on N



Selection bias is a threat to identification

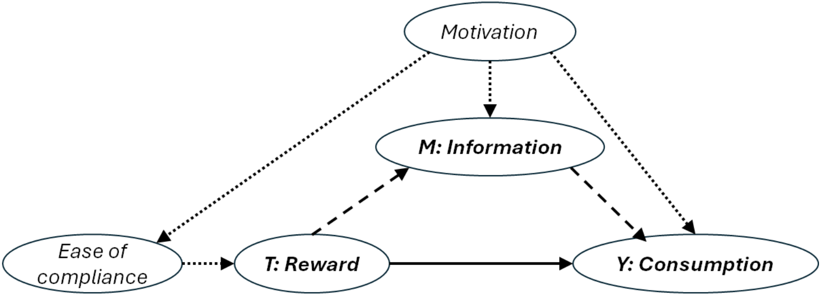


Figure 2: The core identification challenge

Selection bias is a threat to identification

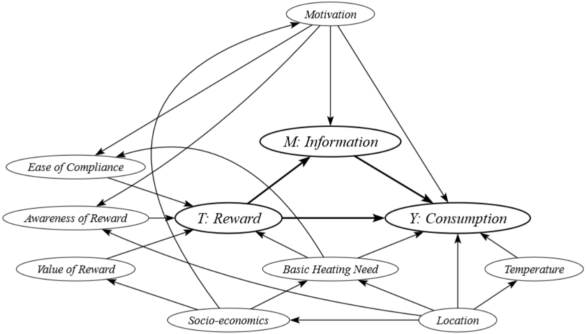


Figure 3: The Causal Effect of the Program on Consumption represented by a DAG

*Source:*Own illustration created via causalfusion.net (see Bareinboim and Pearl, 2016).

We overcome selection bias by conditioning/matching on proxy variables for confounders.

Empirical strategy

- Outcome variable: gas consumption per heating degree day $y_i = \frac{\sum_j C_j}{\sum_t [\mathbb{1}\mathrm{HDD}_t]}$
- Regression equation

$$y_i = \beta \mathbb{1}[\mathrm{Reward}_i] + \alpha \mathrm{B}_i + \mathbf{M}_i \cdot \gamma + \mathbf{L}_i \cdot \delta + \mathbf{S}_i \cdot \rho + \epsilon_i, \tag{1}$$

- Matching Matching variants Effective sample size

Table 1: Variables and proxies

	Variable	Proxies/Units
y_i	Individual Gas Consumption	Cubic meters per heating day
$\mathbb{1}[\mathrm{Reward}_i]$	Program Participation	full participants (1) vs. non-participants (0)
B_i	Basic Heating Need	Annual consumption forecast in 1,000 kWh
$\mathbf{M}_i$	Motivation	i) App use for meter readings ii) Newsletter receipt iii) Contract via comparison portal iv) Competitive customer segment v) Marginal price paid in ct/kWh
$\mathbf{L}_i$	Location	i) Part of utility's default supply area ii) County × degree of urbanization
$\mathbf{S}_i$	Socio-economic Status	Zipcode-specific shares of social status classes
ϵ_i	Error Term	Captures unobserved differences

The program reduced consumption by an additional 5.4% compared to the control group

The Effect of the Program on Consumption

	Unadjusted sample			Matched samples	
	U-0	U-1	U-2	M-1	M-2
$\mathbb{1}$[Reward]	-0.59***	-0.40***	-0.40***	-0.35***	-0.32***
	(0.04)	(0.02)	(0.02)	(0.04)	(0.04)
Matched sample				[1]	[2]
Control sets as defined in · Basic heating need (B_i)		✓	✓	✓	✓
· Motivation ($\mathbf{M}_i$)		✓	✓	✓	✓
· Location ($\mathbf{L}_i$)		✓	✓	✓	✓
· Socio-economics ($\mathbf{S}_i$)			✓		✓
Effect estimate (in %)	-9.5	-6.6	-6.6	-5.9	-5.4
N	28 847	28 847	28 847	12 312	12 314
R^2	0.01	0.75	0.75	0.77	0.77
R^2 within		0.73	0.73	0.75	0.75

Notes: (i) ***, **, *, and . represent 0.1%, 1%, 5%, and 10% significance levels, respectively; (ii) robust standard errors in parentheses; (iii) the dependent variable is the gas consumption measured in m^3 per heating day.

The results hold against a wide range of robustness checks

1. Control group selection: tolerance and coverage results
2. Pseudo-treatments results
3. War motivation and age controls results
4. Other matching algorithms results
5. Not-including control variables after matching results
6. Inclusion of temperature controls results

Conclusion

Energy saving rewards are an effective, additional tool to manage energy crises by reinforcing saving behavior:

- Attractive for a small fraction of customers, mostly already motivated segments
- ATT: reduction of gas consumption by 5.4% compared to control group

But getting the magnitude of the premium right requires more research

- Role of uncertainty
- Improve treatment assignment given heterogeneity
- Understand mechanism better

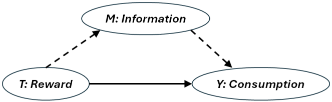
Outlook

Double Machine Learning (DML)

- Analysing heterogeneity between individuals
- Better targeting of intervention

(Chernozhukov et al., 2018; Knaus, 2022; Bach et al., 2023)

Mechanism analysis (Pearl, 2000)



Feedback

Thanks for listening!

Comments? Questions? Suggestions?

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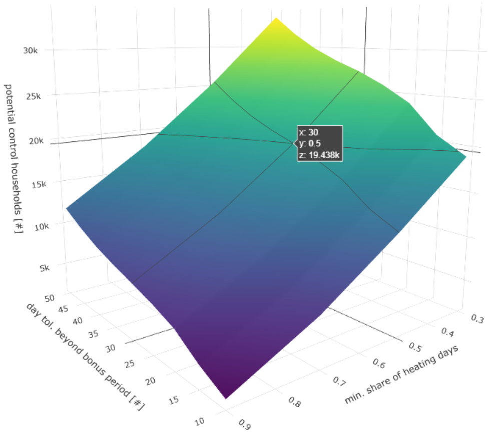
Outcome variable

Figure 4: The Construction of the Outcome Variable:
Potential Control Households (3D-animation)



Pseudo-Treatments

Table 2: The Effect of the Program on Consumption: Pseudo-treatment Estimates

	Unadjusted sample			Matched samples	
	U-0	U-1	U-2	M-1	M-2
$\mathbb{1}$[Reward]	0.063 (0.058)	0.003 (0.032)	0.003 (0.032)	0.019 (0.047)	0.001 (0.041)
Matched sample				[1]	[2]
Control sets as defined in equation (2):					
· Basic heating need (B_i)		✓	✓	✓	✓
· Motivation ($\mathbf{M}_i$)		✓	✓	✓	✓
· Location ($\mathbf{L}_i$)		✓	✓	✓	✓
· Socio-economics ($\mathbf{S}_i$)			✓		✓
Effect estimate (in %)	1.01	0.04	0.05	0.30	0.01
N	19 438	19 438	19 438	13 756	13 827
R^2	0.00	0.73	0.73	0.72	0.72
R^2 within		0.71	0.71	0.69	0.69

Notes: (i) ***, **, *, and . represent 0.1%, 1%, 5%, and 10% significance levels, respectively; (ii) robust standard errors in parentheses; (iii) the dependent variable is the gas consumption measured in m^3 per heating day.

Outcome model

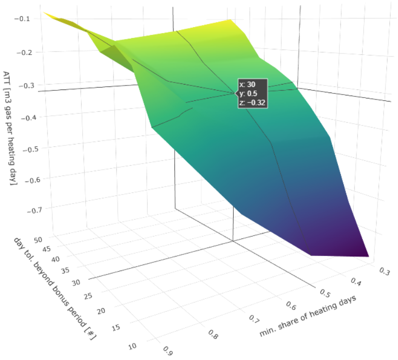
Table 3: The Effect of the Program on Consumption: Estimates from Different Outcome Models

		Fewer controls			
	1	2	3	4	5
$\mathbb{1}$[Reward]	−0.32***	−0.31***	−0.31***	−0.32***	−0.28***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.07)
Matched sample	[2]	[2]	[2]	[2]	[2]
Control sets as defined in equation (2):					
· Basic heating need (B_i)	✓	✓	✓	✓	
· Motivation ($\mathbf{M}_i$)	✓	✓	✓		
· Location ($\mathbf{L}_i$)	✓	✓			
· Socio-economics ($\mathbf{S}_i$)	✓				
Effect estimate (in %)	-5.4	-5.3	-5.3	-5.4	-4.9
N	12 314	12 314	12 314	12 314	12 314
R^2	0.77	0.75	0.75	0.75	0.00
R^2 within	0.75				

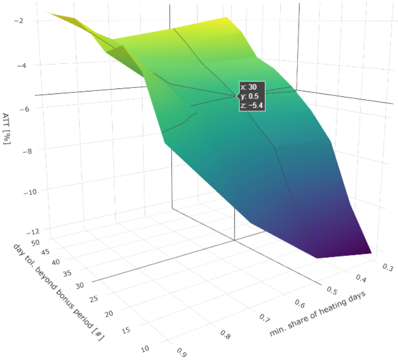
Notes: (i) ***, **, *, and . represent 0.1%, 1%, 5%, and 10% significance levels, respectively; (ii) robust standard errors in parentheses; (iii) the dependent variable is the gas consumption measured in m^3 per heating day.

Dependent variable

Figure 5: The Effect of the Program on Consumption: Outcome Variable (3D-animation)



(a) In m^3 per heating day



(b) In percent

Additional controls

Table 4: The Effect of the Program on Consumption: Main Estimates (Reduced Sample)

	Unadjusted sample			Matched samples	
	U-0	U-1	U-2	M-1	M-2
$\mathbb{1}$[Reward]	-0.65^{***}	-0.36^{***}	-0.36^{***}	-0.32^{***}	-0.27^{***}
	(0.05)	(0.03)	(0.03)	(0.04)	(0.04)
Matched sample				[1]'	[2]'
Control sets as defined in equation (2):					
· Basic heating need (B_i)		✓	✓	✓	✓
· Motivation' ($\mathbf{M'}_i$)		✓	✓	✓	✓
· Location ($\mathbf{L}_i$)		✓	✓	✓	✓
· Socio-economics' ($\mathbf{S'}_i$)			✓		✓
Effect estimate (in %)	-10.1	-5.9	-5.9	-5.4	-4.6
N	20 736	20 736	20 736	8252	8258
R^2	0.01	0.77	0.77	0.80	0.81
R^2 within		0.75	0.75	0.78	0.79

Notes: (i) ***, **, *, and . represent 0.1%, 1%, 5%, and 10% significance levels, respectively; (ii) robust standard errors in parentheses; (iii) the dependent variable is the gas consumption measured in m^3 per heating day; (iv) ' indicates that $\mathbf{M'}_i$ and $\mathbf{S'}_i$ (and thus also our first and second matched sample) are slightly adapted by including additional covariates with a non-negligible number of missings.

Temperature

Table 5: The Effect of the Program on Consumption: Estimates with Temperature Controls

	1	2	3	4	5
		Temperature controls			
$\mathbb{1}$[Reward]	-0.32***	-0.36***	-0.31***	-0.27***	-0.31***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Matched sample	[2]	[2]	[2]	[2]	[2]
Control sets as defined in equation (2):					
· Basic heating need (B_i)	✓	✓	✓	✓	✓
· Motivation ($\mathbf{M}_i$)	✓	✓	✓	✓	✓
· Location ($\mathbf{L}_i$)	✓	✓	✓	✓	✓
· Socio-economics ($\mathbf{S}_i$)	✓	✓	✓	✓	✓
Type of further temperature controls		$\bar{T}_o$	HD_{15}	HDD_{15}	$DDN_{20/15}$
Effect estimate (in %)	-5.4	-6.1	-5.2	-4.7	-5.2
N	12 314	12 314	12 314	12 314	12 314
R^2	0.77	0.78	0.77	0.77	0.77
R^2 within	0.75	0.75	0.75	0.75	0.75

Notes: (i) ***, **, *, and . represent 0.1%, 1%, 5%, and 10% significance levels, respectively; (ii) robust standard errors in parentheses; (iii) the dependent variable is the gas consumption measured in m^3 per heating day; (iv)

Different comparison groups

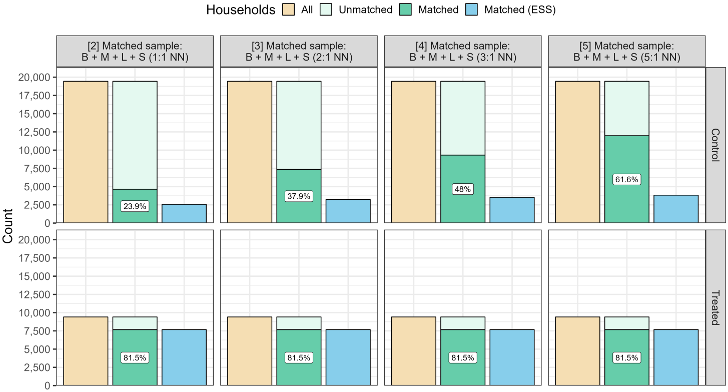
Table 6: The Effect of the Program on Consumption: Further Matching Estimates

		Further matched samples		
	M-2	M-3	M-4	M-5
$\mathbb{1}$[Reward]	-0.32***	-0.31***	-0.32***	-0.32***
	(0.04)	(0.03)	(0.03)	(0.03)
Matched sample	[2]	[3]	[4]	[5]
Matching attributes:				
· **NN!** matching ratio	1:1	2:1	3:1	5:1
· With replacement	✓	✓	✓	✓
Control sets:				
· Motivation	✓	✓	✓	✓
· Location	✓	✓	✓	✓
· Basic heating need	✓	✓	✓	✓
· Socio-economics	✓	✓	✓	✓
Effect estimate (in %)	-5.4	-5.3	-5.4	-5.5
N	12 314	15 034	16 993	19 651
R^2	0.77	0.76	0.76	0.76
R^2 within	0.75	0.74	0.73	0.73

Notes: (i) ***, **, *, and . represent 0.1%, 1%, 5%, and 10% significance levels, respectively; (ii) robust standard errors in parentheses; (iii) the dependent variable is the gas consumption measured in m^3 per heating day; (iv) the distance measure used to match within exact matching strata is the Mahalanobis distance.

Sample Sizes

Figure 6: Sample Sizes (Matched Households):
Further Matching Variants



Readings over time

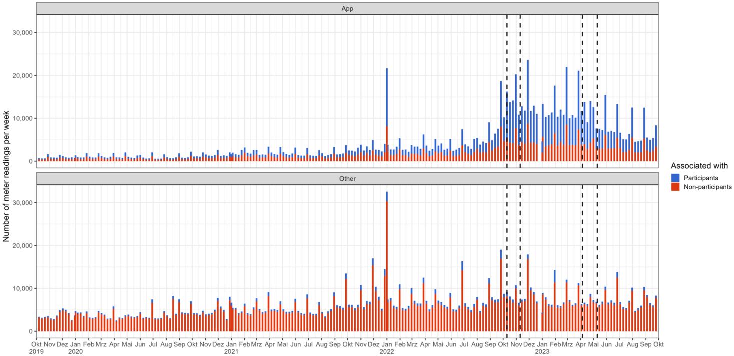


Figure 7: Number of meter readings, divided between App users (above) and non-app users(below)

Descriptive Statistics

Table 7: Descriptive Statistics: Main Variables

Variable name	Means: Treated	Means: Control	Mean diff.: Raw	Mean diff.: Std.
(A) Contract and customer details (in-house)				
Motivation				
App usage (before) (Y/N)	0.50	0.07	0.43	
Competitive customer segment (Y/N)	0.80	0.68	0.11	
Newsletter received (Y/N)	0.23	0.13	0.10	
Comparison portal (Y/N)	0.53	0.44	0.09	
Marginal price (ct/kWh)	8.39	8.59		-0.11
Location				
Default supply area (Y/N)	0.42	0.50	-0.08	
Basic heating need				
Predicted demand (1k kWh/p.a.)	17.86	18.36		-0.05
Others				
Fixed price (€/year)	140.51	135.10		0.14
Customer age (years)	53.09	54.48		-0.10
(B) Soc.-eco. variables (Acxiom)				
Social status class: Very low (%)	0.05	0.04		0.00
Social status class: Low (%)	0.06	0.05		0.03
Social status class: Rather low (%)	0.09	0.08		0.04
Social status class: Intermediate (%)	0.13	0.12		0.06
Social status class: Rather high (%)	0.20	0.22		-0.09
Social status class: High (%)	0.23	0.25		-0.07
Social status class: Very high (%)	0.25	0.24		0.04
(C) Soc.-dem. variables (German Census 2011)				
Age of inhabitants (avg. year)	42.43	42.72		-0.03
Family size (avg. #)	2.72	2.69		0.07
Household size (avg. #)	2.27	2.19		0.13
Age of buildings (avg. year)	58.76	63.57		-0.20
Flats per building (avg. #)	2.49	2.96		-0.21
Living space per flat (avg. m^2)	100.95	95.15		0.20
Rooms per flat (avg. #)	4.81	4.58		0.21

Notes: We use the standard deviation of the covariate in the group of participants as the standardization factor to ensure comparability across continuous covariates. Acxiom's (2020) social status classes are measured in percent per zipcode. The socio-demographic variables from the German Census 2011 (DESTATIS, 2020) are all reported as average statistics per 100x100m grid cell.

We overcome selection bias by conditioning/matching on proxy variables for confounders.

Regression equation

Matching variants | Effective sample size

$$y_i = \beta \mathbb{1}[\text{Reward}_i] + \alpha \text{B}_i + \mathbf{M}_i \cdot \gamma + \mathbf{L}_i \cdot \delta + \mathbf{S}_i \cdot \rho + \epsilon_i, \quad (2)$$

Variables and proxies

	Variable	**Proxies/Units**
y_i	Individual Gas Consumption	Cubic meters per heating day
$\mathbb{1}[\text{Reward}_i]$	Program Participation	full participants (1) vs. non-participants (0)
B_i	Basic Heating Need	Annual consumption forecast in 1,000 kWh
$\mathbf{M}_i$	Motivation	i) App use for meter readings ii) Newsletter receipt iii) Contract via comparison portal iv) Competitive customer segment v) Marginal price paid in ct/kWh
$\mathbf{L}_i$	Location	i) Part of utility's default supply area ii) County $\times$ degree of urbanization
$\mathbf{S}_i$	Socio-economic Status	Zipcode-specific shares of social status classes
ϵ_i	Error Term	Captures unobserved differences

Control group selection via matching

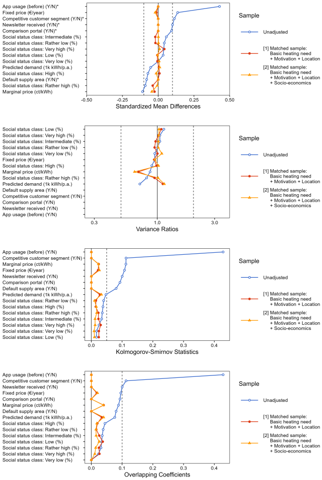
Why match?

- achieve unconfoundeness
- guarantee common support
- account
  for non-linear relationships

How?

- First matched control group:
  - Exact matching on motivation proxies and location
  - 1:1 NN
    within exact matching strata
    using Mahalanobis distance
    for basic heating need
- Second matched control group
  - additionally:
    1:1 NN Mahalanobis
    distance matching
    on socio-economic classes
    within exact matching strata.

Figure 8: Covariate Balance:
LOVE Plots on Main Variables



Effective Sample Size

We find matching partners for 82% of participants.

Figure 9: Sample Sizes (Matched Households): Main Matching Variants