Machine Learning from Schools about Energy Efficiency

Burlig, Knittel and Rapson, Working Paper, 2019

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Energy effiency

- A number of public policies–including efficiency standards, utility-sponsored rebate programs, and information provision requirements–aim to encourage more investment in energy efficiency.
- Challenges:
    - **Why consumers fail to avail themselves of profitable investment opportunities** (Allcott and Greenstone, 2012; Gillingham and Palmer, 2014; Gerarden, Newell, and Stavins, 2015) — Market Failure
    - **Real-world savings and costs of energy efficiency investments:** accurately measuring the savings from energy efficiency investments is difficult as it requires constructing a counterfactual energy consumption path from which reductions caused by the efficiency investments can be measured.

Contributions

- High-frequency data in electricity market from the ”smart metering”.
- Regularization methods (LASSO) to reduce the high-dimension covariate spaces in the pre-treatment period and predict the counterfactual energy consumption in the post-treatment period.
- School-by-school counterfactual in a panel fixed effects model to estimate causal effects.

Context and Data

- Why school?
  - similar activities
  - same wide-ranging trends in education
  - clustered within distinct neighborhood and towns
- Engineering estimates suggest that commercial buildings, including schools, may present important opportunities to increase energy efficiency.
  - not profit-maximizing
  - less likely to take cost-effective investments
  - encourage energy-efficiency investment may yield high returns
- Schools that participated in Pacific Gas and Electric Companys (PG&E's) energy efficiency programs.
- School districts identified opportunities for improvements at their schools and then applied to PG&E for rebates to help cover the costs of qualifying investments.

Data sources

- High-frequency electricity consumption and account information with data on energy efficiency upgrades, school characteristics, community demographics, and weather.
- Hourly interval electricity metering data for the universe of public K-12 schools in Northern California served by PG&E from 2008-2014.
  - PG&E retrieved all meters associated with ”education” customers
  - macthing schools using the GPS coordinates of smart meters.
- Number of students, demographic composition of each school’s students, the type of school.
- Census blocks to incorporate additional neighborhood demographic information, such as racial composition and income.

Summary Stats

Table 1: Average characteristics of schools in the sample

Characteristic	Untreated	Any intervention		HVAC interventions		Lighting interventions	
		Treated	T-U	Treated	T-U	Treated	T-U
Hourly energy use (kWh)	33.1	57.5	24.4	63.1	29.9	61.0	27.9
	(34.4)	(73.0)	[<0.01]	(82.2)	[<0.01]	(87.5)	[<0.01]
First year in sample	2012	2010	-2	2009	-2	2010	-2
	(1.7)	(1.8)	[<0.01]	(1.6)	[<0.01]	(1.8)	[<0.01]
Total enrollment	538	730	192	769	230	745	207
	(363)	(488)	[<0.01]	(515)	[<0.01]	(523)	[<0.01]
Acad. perf. index (200-1000)	789	794	6	794	6	785	-4
	(99)	(89)	[0.21]	(88)	[0.28]	(79)	[0.51]
Bond passed, last 2 yrs (0/1)	0.3	0.2	-0.0	0.3	-0.0	0.2	-0.0
	(0.4)	(0.4)	[0.33]	(0.4)	[0.80]	(0.4)	[0.22]
Bond passed, last 5 yrs (0/1)	0.4	0.4	0.0	0.4	0.0	0.4	0.0
	(0.5)	(0.5)	[0.91]	(0.5)	[0.24]	(0.5)	[0.21]
High school graduates (%)	23.4	23.3	-0.1	23.6	0.3	24.3	0.9
	(12.2)	(11.6)	[0.89]	(11.7)	[0.66]	(10.6)	[0.18]
College graduates (%)	20.0	20.3	0.3	19.5	-0.5	19.4	-0.6
	(12.3)	(12.0)	[0.55]	(11.9)	[0.46]	(11.8)	[0.41]
Single mothers (%)	20.5	19.3	-1.3	19.8	-0.7	20.6	0.0
	(19.1)	(18.4)	[0.17]	(18.8)	[0.48]	(18.9)	[0.97]
African American (%)	5.6	6.1	0.5	5.4	-0.3	6.2	0.6
	(9.3)	(8.0)	[0.25]	(6.0)	[0.56]	(7.4)	[0.27]
Asian (%)	8.8	11.7	2.9	12.6	3.8	9.7	0.9
	(12.9)	(16.2)	[<0.01]	(17.1)	[<0.01]	(12.1)	[0.23]
Hispanic (%)	42.4	43.4	1.1	45.3	2.9	46.4	4.0
	(28.8)	(26.8)	[0.41]	(27.1)	[0.05]	(25.3)	[0.01]
White (%)	34.7	30.8	-3.9	29.9	-4.8	29.4	-5.3
	(27.0)	(24.4)	[<0.01]	(23.9)	[<0.01]	(24.2)	[<0.01]
Average temp. ($^{\circ}$ F)	60.1	60.8	0.7	61.3	1.2	61.0	0.9
	(4.1)	(3.5)	[<0.01]	(3.4)	[<0.01]	(3.5)	[<0.01]
Latitude	37.7	37.5	-0.2	37.4	-0.3	37.4	-0.2
	(1.2)	(1.0)	[<0.01]	(1.0)	[<0.01]	(1.1)	[<0.01]
Longitude	-121.6	-121.2	0.4	-121.0	0.6	-121.2	0.4
	(1.0)	(1.1)	[<0.01]	(1.1)	[<0.01]	(1.1)	[<0.01]
Number of schools	958	912		564		435	

Trends in school characteristics

Selection into treatment as possible threat to econometric identification

Figure 1: Locations of untreated and treated schools

Notes: This figure displays the locations of schools in our sample. "Untreated" schools, in gray on the left, did not undertake any energy efficiency upgrades during our sample period. "Treated" schools, in blue on the right, installed at least one upgrade during our sample. There is substantial overlap in the locations of treated and untreated schools. The light gray outline shows the PG&E service territory.

Trends in school characteristics

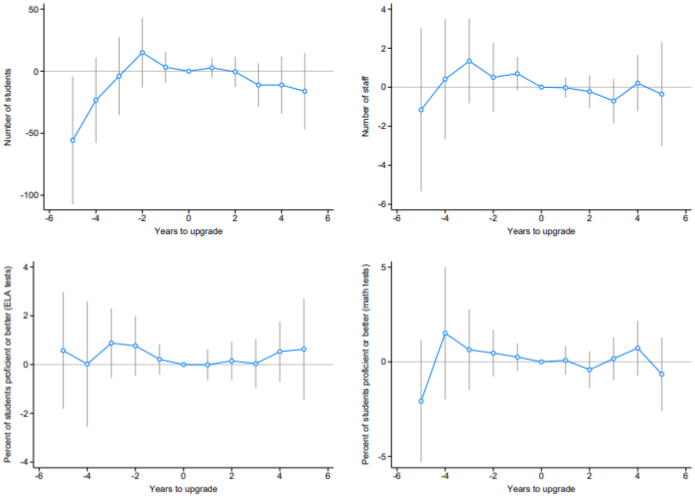
Time-varying differences between treated and untreated schools which correlate with the timing of energy efficiency upgrades.

- Number of enrolled students
- Number of staff members
- Percentage of students performing ”proficient” or better

$$Y_{it} = \sum_{y=-5}^{5} \beta^{y} \mathbf{1}[\textit{Year to upgrade} = y]_{it} + \alpha_i + \gamma_t + \epsilon_{it}$$

Trends in school characteristics

Figure 2: School demographics before and after treatment



Empirical strategy and results

- Standard panel fixed effects strategy
- Highly sensitive to both specification and the set of untreated schools that we include in the analysis
- Bias

$$Y_{ith} = \beta D_{it} + \alpha_{ith} + \epsilon_{ith}$$

  - school i on date t during hour-of-day h
  - D_{it} is a dummy indicating that school i has undertaken at least one energy efficiency upgrade by date t
  - first collapsing the data to school-by-month-of-sample-by-hour-of-day level
  - school and hour-of-day FE, school-by-hour fixed effects, month-of-sample FE
  - cluster at the school level
  - identification comes from within-school-by-hour and within-month-of-sample differences between treated and untreated schools

Results from event studies

Table 2: Panel fixed effects results

	(1)	(2)	(3)	(4)	(5)
Treat $\times$ post	-2.90	-2.90	-3.50	-2.23	-1.30
	(0.45)	(0.45)	(0.45)	(0.48)	(0.47)
Observations	55,818,652	55,818,652	55,817,256	55,817,256	55,818,652
Realization rate	0.68	0.68	0.81	0.90	0.54
School FE, Hour FE	Yes	Yes	Yes	Yes	Yes
School-Hour FE	No	Yes	Yes	Yes	Yes
School-Hour-Month FE	No	No	Yes	Yes	No
Month of Sample Ctrl.	No	No	No	Yes	No
Month of Sample FE	No	No	No	No	Yes

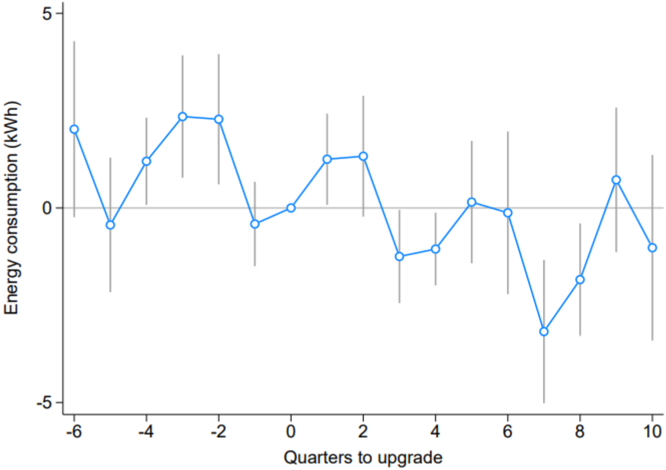
Robustness check

Table 3: Sensitivity of panel fixed effects results to outliers

	(1)	(2)	(3)	(4)	(5)
Panel A: Trim outlier observations					
Realization rate	0.45	0.47	0.59	0.42	0.11
Point estimate	-1.88	-1.96	-2.49	-1.10	-0.28
	(0.38)	(0.37)	(0.37)	(0.36)	(0.36)
Observations	54,701,384	54,701,384	54,699,856	54,699,856	54,701,384
Panel B: Trim outlier schools					
Realization rate	0.71	0.71	0.85	0.81	0.44
Point estimate	-2.70	-2.70	-3.27	-1.91	-1.02
	(0.42)	(0.42)	(0.42)	(0.42)	(0.42)
Observations	55,058,188	55,058,188	55,056,816	55,056,816	55,058,188
Panel C: Trim observations and schools					
Realization rate	0.48	0.50	0.63	0.44	0.11
Point estimate	-1.83	-1.91	-2.43	-1.07	-0.26
	(0.38)	(0.38)	(0.38)	(0.36)	(0.36)
Observations	54,037,088	54,037,088	54,035,584	54,035,584	54,037,088
School FE, Hour FE	Yes	Yes	Yes	Yes	Yes
School-Hour FE	No	Yes	Yes	Yes	Yes
School-Hour-Month FE	No	No	Yes	Yes	No
Month of Sample Ctrl.	No	No	No	Yes	No
Month of Sample FE	No	No	No	No	Yes

Robustness check

Figure 3: Panel fixed effects event study



Machine learning approach

Capturing heterogeneity could interact covariates with school and hour-of-day, generating millions of candidate covariates

- create unit-specific models of an outcome of interest, train these models using pre-treatment data only
- out-of-sample prediction of our outcome of interest in the post-treatment period -> compare the machine learning predictions to real data to compute prediction errors for each unit

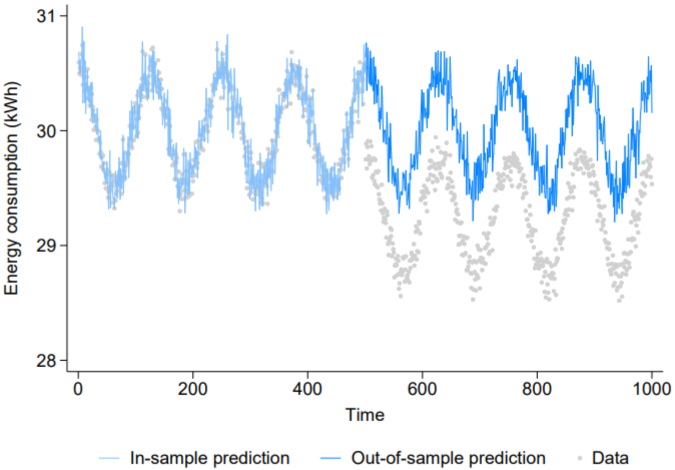
$$Y_{ith} - \hat{Y_{ith}} = \beta D_{it} + \alpha_{ith} + \gamma posttrain_{ith} + \epsilon_{ith}$$

Step1: Predicting counterfactuals

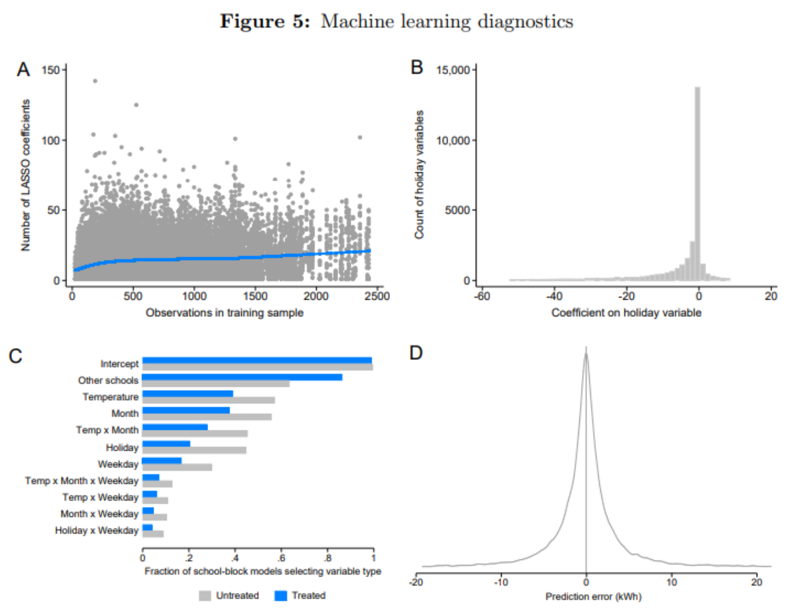
- Using machine learning to construct school-by-hour-of-day specific prediction models.
    - Treated schools: define the pre-treatment period as the period before any intervention occurs.
    - Untreated schools: randomly assign a ”treatment date” to define the ”pre-treatment” period.
- LASSO method to search over a large set of potential covariates: day of the week, holiday, month FEs, temperature spline, maximum/minimum tempeature, interaction between these variables/school FEs
- Cross-validation

Validity checks

Figure 4: Machine learning approach: graphical intuition



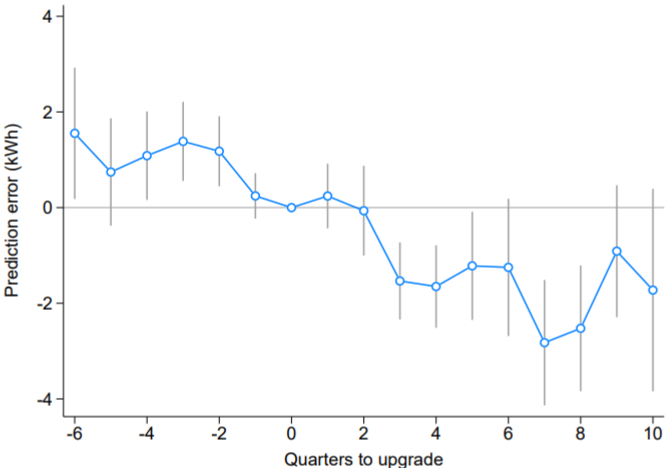
Validity checks



Step2: Panel regressions with prediction errors

$$Y_{ith} - \hat{Y_{ith}} = \beta D_{it} + \alpha_{ith} + \gamma posttrain_{ith} + \epsilon_{ith}$$

Figure 6: Machine learning event study



Step2: Panel regressions with prediction errors

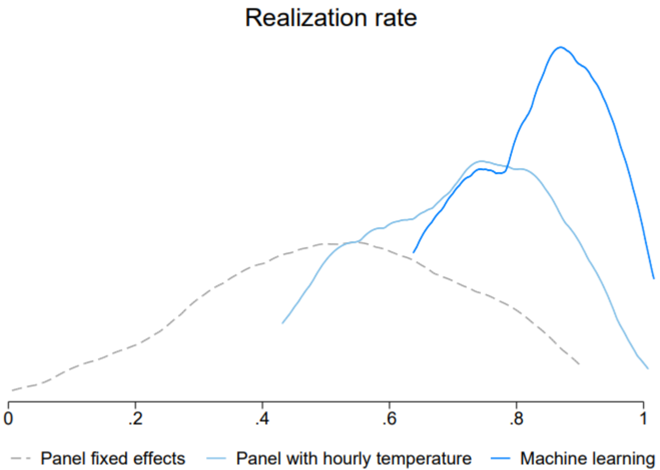
Table 4: Machine learning results

	(1)	(2)	(3)	(4)	(5)
Treat $\times$ post	-3.86	-3.86	-4.17	-3.43	-2.24
	(0.51)	(0.51)	(0.53)	(0.50)	(0.48)
Observations	55,822,576	55,822,576	55,821,180	55,821,180	55,822,576
Realization rate	0.90	0.90	0.96	1.01	0.70
School FE, Hour FE	Yes	Yes	Yes	Yes	Yes
School-Hour FE	No	Yes	Yes	Yes	Yes
School-Hour-Month FE	No	No	Yes	Yes	No
Month of Sample Ctrl.	No	No	No	Yes	No
Month of Sample FE	No	No	No	No	Yes

Comparing approaches

Realization rate: β divided by the average expected savings for upgrades (engineering estimates)

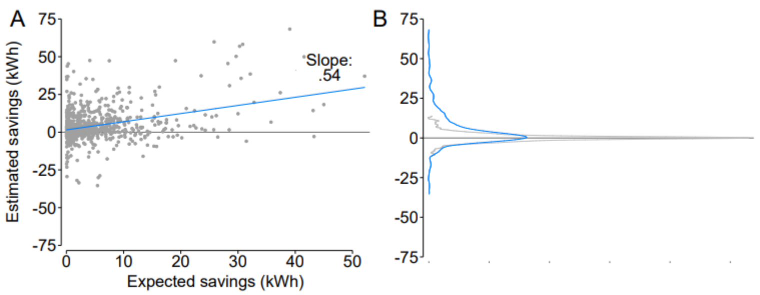
Figure 7: Comparison of methods across specifications and samples



Heterogeneity and targeting

- Whether these realization rates are heterogeneous based on observables for both schools and types of upgrades -> informative for policymakers deciding which upgrades to subsidize.
- school-specific treatment effects

Figure 8: School-specific effects



Heterogeneity and targeting

Table 6: Predicting heterogeneous effects

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.78	0.36	0.52	0.59	0.57	0.55
	(0.12)	(0.28)	(0.22)	(0.24)	(0.35)	(0.30)
HVAC only (0/1)		0.70	0.69	0.51	0.76	0.86
		(0.34)	(0.27)	(0.29)	(0.42)	(0.37)
Lighting only (0/1)		0.70	0.50	0.41	0.47	0.60
		(0.37)	(0.29)	(0.32)	(0.46)	(0.39)
HVAC and lighting (0/1)		0.37	0.19	0.10	0.02	0.40
		(0.35)	(0.28)	(0.31)	(0.45)	(0.39)
Longitude			-0.09	-0.10	-0.26	-0.25
			(0.21)	(0.23)	(0.33)	(0.29)
Latitude			0.28	0.30	0.23	0.32
			(0.15)	(0.16)	(0.24)	(0.21)
Average temperature (° F)			0.15	0.16	0.30	0.33
			(0.18)	(0.20)	(0.28)	(0.24)
Total enrollment				0.34	0.23	0.32
				(0.09)	(0.12)	(0.11)
Academic perf. index (200-1000)					-0.23	-0.24
					(0.16)	(0.14)
Poverty rate					-0.15	-0.10
					(0.16)	(0.14)
Expected savings (kWh)						-0.20
						(0.09)
Number of schools	903	903	881	838	776	776

Conclusions

- Estimate causal treatment effects in high-frequency panel data settings
- Heterogeneity in realization rates -> policy implication and targeting
- Energy efficiency upgrades deliver lower saving than expected ex ante.