Empirical Methods for the Analysis of the Energy Transition

Slide Set 8

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Energy demand: several response margins

We will separate between two strategies:

- **Energy efficiency**: becoming better at consuming the same goods, e.g., LEDs, building retrofit, better appliances, etc.
- **Demand response**: reducing our consumption if prices are high.

Today we will discuss energy efficiency interventions.

Energy Efficiency: Concepts and Evidence

Energy efficiency

We do not consume energy directly

- We consume "energy services" produced with energy inputs

Energy efficiency refers to the productivity of energy inputs:

$$\text{Energy efficiency} = \text{energy services} \; / \; \text{energy input}$$

Examples

- Example 1: keep room at 65F for an hour
- Example 2: run a washing machine at 4pm
- Example 3?

Energy efficiency - stock and flow

- Energy efficiency involves several strategies:
  - New better technology (e.g., heat pumps, better appliances, LEDs).
  - New better buildings (building codes, standards).
  - Improving energy efficiency of existing existing buildings (refurbishing).

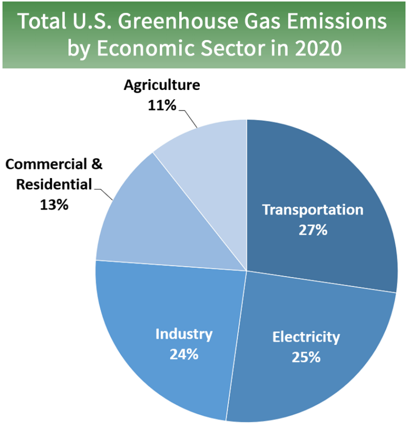
Energy Efficiency **Could** Be Essential to Decarbonization

1. Not enough battery storage for peak electricity demand
   - Consumption growing ahead of storage capability
   - **Reducing consumption lowers GHG emissions while grid mix of renewable and (mostly) non-renewable**

Energy Efficiency **Could** Be Essential to Decarbonization

2. Transitioning away from natural gas in buildings will take time

- Significant upfront costs
- Equity concerns with mandates

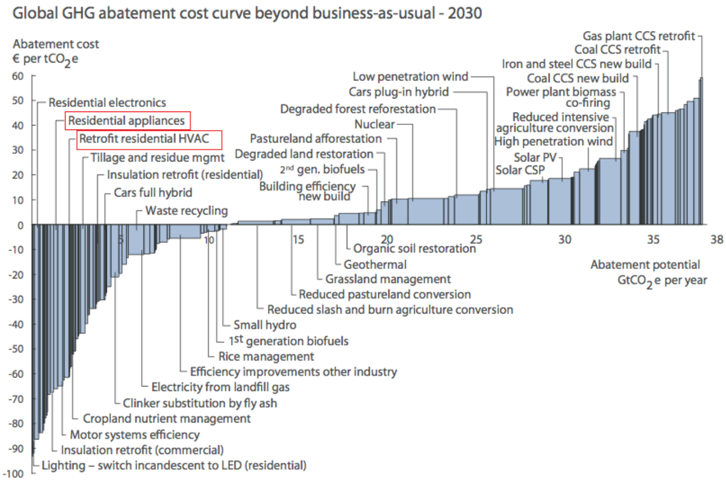


U.S. Environmental Protection Agency (2022). Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2020

Energy Efficiency **Could** Be Essential to Decarbonization

3. If done cost-effectively, one of lowest cost forms of carbon abatement

Unexploited Investment Opportunities?



Source: McKinsey and Company, "Pathways to a Low-Carbon Economy", 2010

The energy efficiency gap

- The energy efficiency gap refers to potential underinvestment in energy efficient technologies (typically by the part of consumers) – second channel of inefficiency.
- Defined as "a wedge between the cost-minimizing level of energy efficiency and the level actually realized."
- Suggests there are other market failures at play.

The energy efficiency gap – Debate

“Energy efficiency offers a vast, low-cost energy resource for the U.S. economy—but only if the nation can craft a comprehensive and innovative approach to unlock it.”

McKinsey & Co. (2009), Unlocking Energy Efficiency in the U.S. Economy

”When one tallies up the available empirical evidence from different contexts, it is difficult to substantiate claims of a pervasive energy-efficiency gap... the empirical magnitudes of the investment inefficiencies appear to be smaller, indeed substantially smaller, than the massive potential savings calculated in engineering analyses such as McKinsey & Co. (2009).”

Alcott and Greenstone (2012), Journal of Economic Perspectives

The energy efficiency gap – Evidence

There is somewhat of a debate on how much of an "energy efficiency puzzle" there is.

- Engineering view: typically more "optimistic"
- Economists view: typically more "pessimistic"

Studies find a wide range of estimates of costs of energy efficiency.

- A focus on percentage savings compared to "expected" engineering savings, with numbers as low as 10 to 20 percent.

Evidence – Empirical difficulties I

- Studies of energy efficiency gap are difficult:
  - Typically in non-randomized settings
  - Randomized experiments can be very expensive
- Ideal world:
  - Have two parallel universes with the same consumers
  - Offer energy-efficient appliance rebate in one and compare
- In practice, from observational data:
  - Consumers might be changing other things at the same time
  - Inframarginal consumers: they would have bought the better appliance anyway (should not count)
  - Noise to signal ratio quite high given the interventions

Evidence – Empirical difficulties II

- Engineering measurement to go around some of these difficulties:
  - Tries to get at the savings by formulating a model of energy consumption.
  - Circumvents the problem of households changing other consumption aspects at the same time
  - Does not deal with infra-marginal types
- In practice:
  - Model can have substantial biases
  - Consumers might change their behavior also with respect to the new appliance (e.g., better AC, use it more), known as "rebound affect"

Discrepancies Between Projected and Realized Savings

Large literature finds that empirical ex-ante estimates and realized ex-post savings differ substantially.

- Weatherization (WAP) and home retrofits (Fowlie et al. 2018, Allcott and Greenstone 2017)
- Appliance rebate programs (Houde and Aldy 2014, Davis et al. 2014)
- Building codes/efficient housing (Levinson 2016, Davis et al. 2018, Bruegge et al. 2019)
- General efficiency rebates (Burlig et al, 2021)

Are there opportunities to allocate resources differently to achieve reductions more cost-effectively? How to explain the gap?

Experiments on weatherization

- Fowlie, Greenston, and Wolfram (2018) explore an encouragement design to measure the value and savings from weatherization assistance programs (WAP) in low-income households.
- Encouragement used as an instrument for treatment (WAP).
- Findings:
  - Aggressive encouragement increased participation 5% points, but at high costs (>$1,000 per converted HH!) –see their P&P conference paper.
  - Energy savings are in the order of 10-20%, but only 30% the engineering projected savings.
  - In-home temperature does not seem to improve, limited evidence for rebound.

Recent paper on WAP decomposes the difference

- Christensen, Francisco, Myers, and Souza (2022) decompose the performance wedge:
  1. Engineering measurement and model bias (43%)
  2. Workmanship (41%)
  3. Occupant behavior (6%)
- 2. Modifying worker incentives
  - Randomized study paying workers based on building envelope tightness– quite cost-effective
- 3. Addressing model bias
  - Predictions based on realized savings at similar homes outperform current engineering model approach
  - Targeting funds differently could improve cost-effectiveness

Examples from non-experimental settings

We will cover two papers that use "natural experiments," exploiting policy interventions without randomization.

- Cash for coolers: rebate program for new fridges and AC in Mexico
- Machine learning from schools: efficiency program for public schools in CA

Example – “Cash for Coolers”

Since 2009 over 1.5 million refrigerators and air-conditioners have been replaced through Mexico’s “Cash for Coolers” Program.

C4C program details

Includes both refrigerators and room air-conditioners

- To date 90% refrigerators, 10% air-conditioners
- Direct cash subsidies of up to $185
- Also low-interest credit against future electric bills

Old appliance must be 10+ years old

- Verified by the retailer to be working at time of replacement
- Then permanently disassembled in recycling centers

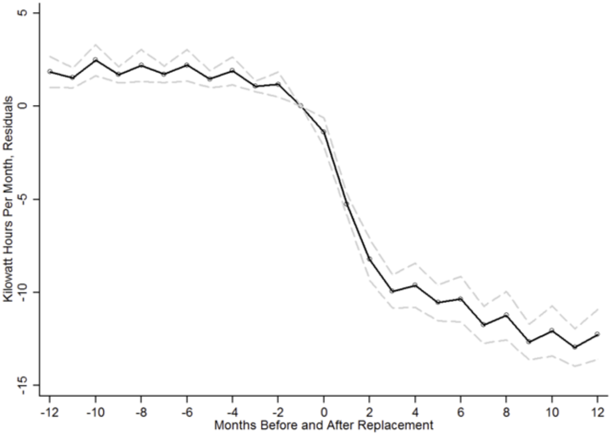
New appliance must meet exceed 2002 standard by 5%.

C4C assessment

- Lucas Davis, Alan Fuchs, and Paul Gertler, “Cash for Coolers”.
- What is the effect of C4C on electricity consumption?
  - What is the implied cost per “megawatt”?
  - What is the implied cost per ton of carbon dioxide abated?
  - How does this compare to ex ante predictions?
- What broader lessons can be learned from C4C for the design of energy efficiency programs?

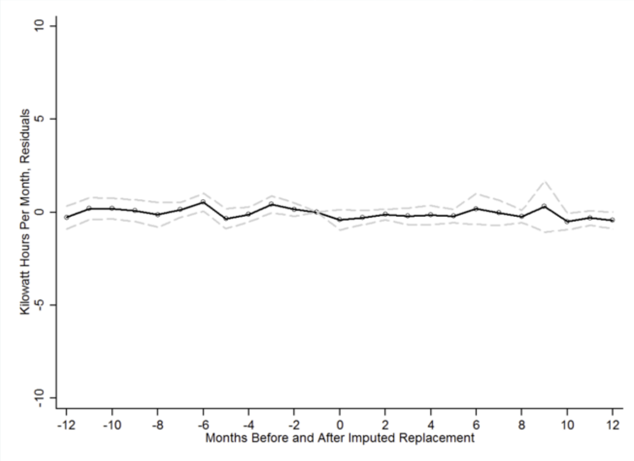
C4C impacts

FIGURE 2
The Effect of Refrigerator Replacement on Household Electricity Consumption



C4C impacts

FIGURE 3
Assessing the Validity of the Control Group



C4C and rebound

TABLE 2
The Effect of Appliance Replacement on Household Electricity Consumption

	(1)	(2)	(3)	(4)	(5)	(6)
1[New Refrigerator]$_{it}$	-11.2**	-11.0**	-11.0**	-11.5**	-11.5**	-11.4**
	(0.5)	(0.4)	(0.4)	(0.4)	(0.5)	(0.5)
1[New Air Conditioner]$_{it}$	8.5*	6.6**	-0.2	-0.7	1.2	1.2
	(3.6)	(2.2)	(0.8)	(0.8)	(0.8)	(0.9)
1[New Air Conditioner]$_{it}$ x 1[Summer Months]$_{it}$			16.5**	16.6**	12.6**	14.5**
			(4.2)	(4.2)	(3.9)	(4.1)
Household By Calendar Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-Sample By County Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Including Linear Time Trend for Participants	No	No	No	Yes	No	No
Including Treatment Households Only	No	No	No	No	Yes	Yes
Dropping Month of Replacement	No	No	No	No	No	Yes
Number of Households	1,914,160	1,914,160	1,914,160	1,914,160	957,080	957,080

C4C and rebound – Potential causes

1. The new appliances tended to be larger and have more features.
   - These features are valued by households, but use more electricity
   - For example, through-the-door ice adds 80 kWh per year
2. The old appliances tended to be close to the minimum age threshold.
   - Refrigerators average age 13.2 years
   - Air-conditioner average age 10.9 years
3. Households likely increased utilization of air-conditioners.
   - Valued by households, but increased electricity consumption.
   - This may have been amplified by the increasing block rates
4. Some of the old appliances were probably not working.

C4C cost effectiveness

TABLE 4
Electricity Consumption, Carbon Dioxide Emissions, and Cost-Effectiveness

	Refrigerators (1)	Air Conditioners (2)	Both Appliances Combined (3)
C. Cost-Effectiveness			
Total Direct Program Cost (U.S. 2010 dollars, millions)	\$129.9	\$13.3	\$143.2
Program Cost Per Kilowatt Hour (U.S. 2010 dollars)	\$0.25	--	\$0.30
Program Cost Per Ton of Carbon Dioxide (U.S. 2010 dollars)	\$427	--	\$506

Machine learning and policy evaluation

- Several papers now highlight the usefulness of machine learning in the context of panel regressions (e.g., see work by Athey).
- Electricity consumption data at high frequency lends itself very well to the use of ML.
- See Christensen, P., Francisco, P., Myers, E., & Souza, M. (2021) for another example of this.
- Can it really help? How?

Burlig Knittel Rapson Reguant Wolfram (2020)

How effective are energy efficiency upgrades at reducing electricity consumption?

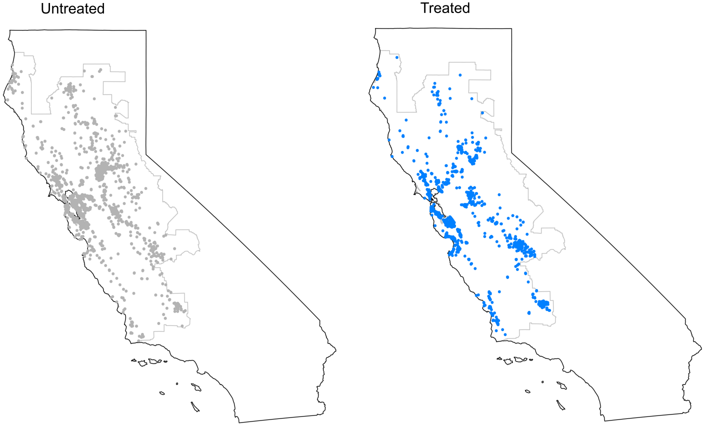
- **Context:** $1 billion EE subsidy program in CA's K-12 schools
- **Data:** 15' interval electricity consumption
- **Research design:** Panel fixed effects meets machine learning

This question is difficult to answer empirically

Central challenge: Energy efficiency upgrades are not randomly assigned.

- It is difficult to disentangle energy efficiency from other factors.
- We must construct a counterfactual energy consumpton path.

Our sample spans the PG&E territory



Can machine learning help?

- Panel FE models are often not properly specified.
- Schools are very heterogeneous (e.g., climate, size, school calendar).
  - Ideally, introduce school-specific coefficients and trends in a very flexible manner.
- We easily came up with $\sim$6,000,000 candidate control variables by making them school-hour specific!
- No clear *ex ante* optimal choice.

Machine Learning: Advantages in this application

- Exogenous weather variation and predictable weekly and seasonal patterns drive variation in electricity consumption.
- Schools are relatively stable consumption units:
  - as opposed to single households that move around, unobservably buy a new appliance, expand family size, etc.
  - as opposed to businesses and manufacturing plants, exposed to macroeconomic shocks.

Prediction can do well!

Machine Learning: Approach

Step 1

- Use *pre-treatment data* to predict electricity consumption as a function of flexible co-variates, *for each school separately*.
  - For control schools, determine a "pre-treatment period" randomly.
  - Use LASSO method (penalized regression).
    - Minimizing the sum of the squared errors plus $\lambda \cdot \sum_{j=1}^{p} |\beta_j|$.
    - Larger "tuning parameters" lead to fewer coefficients.
    - Use bootstrapped cross-validation with training and holdout samples *within pre-treatment*.
  - Include a wide range of school-specific variables, and also consumption at control schools (a la synthetic control).
  - Also consider other alternatives (random forests).

Machine Learning: Approach

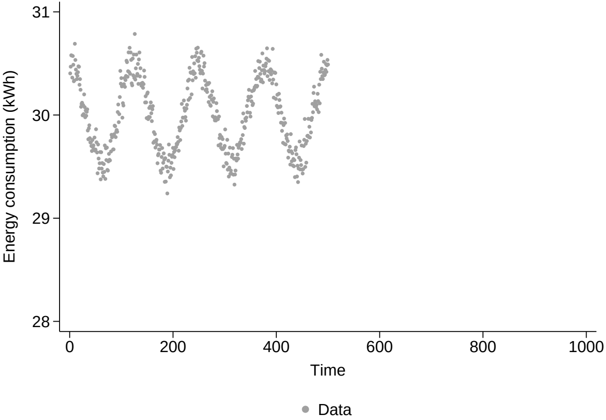
Step 2

- Regress *prediction errors* on treatment and controls.

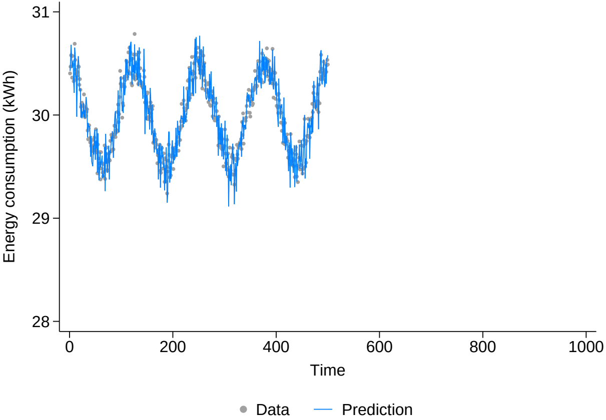
$$Y_{ith} = \beta D_{it} + \alpha_i + \kappa_h + \gamma_t + \varepsilon_{ith}$$

  - Data pooled across schools.
  - Replicates diff-in-diff approach, but Y variable is now the prediction error.

Machine Learning: Graphical intuition



Machine Learning: Graphical intuition



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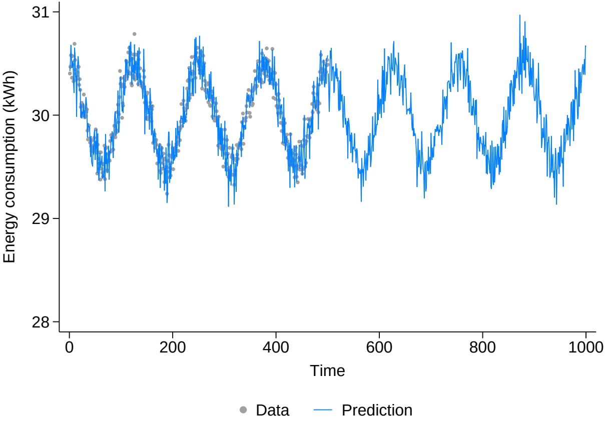

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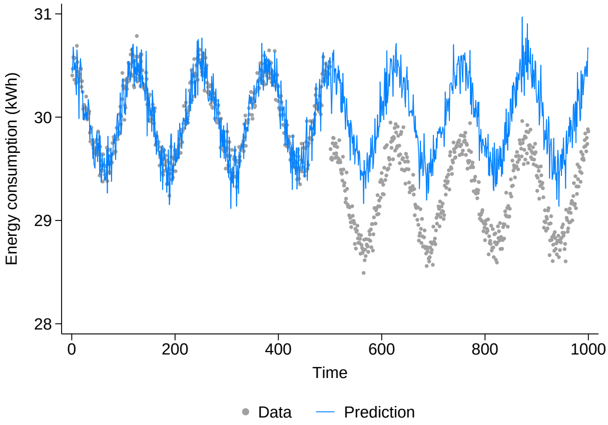
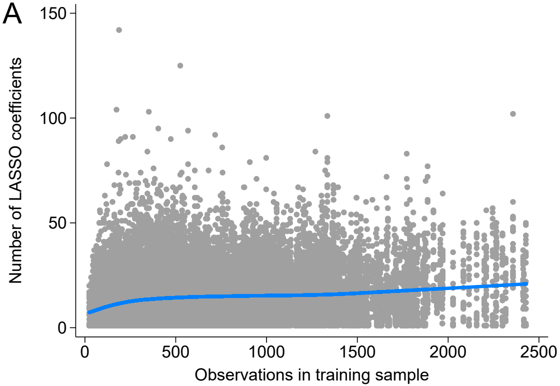


ML check: model complexity scales with observations

Step 1: Each dot is a school-hour model

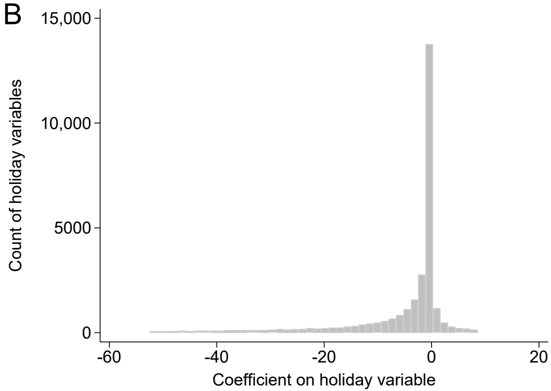
- The more data, the more controls.



ML check: holidays negatively correlated with energy use

Each observation is a school-specific holiday coefficient

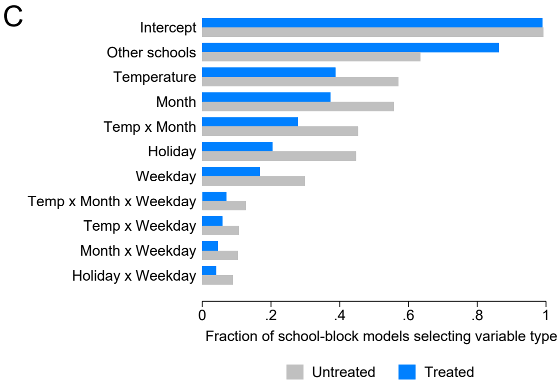
- Sanity check on sign of controls.



ML check: a wide range of variables in model

Each school-block model has different predictors

- Better taylored than a "normal" regression.



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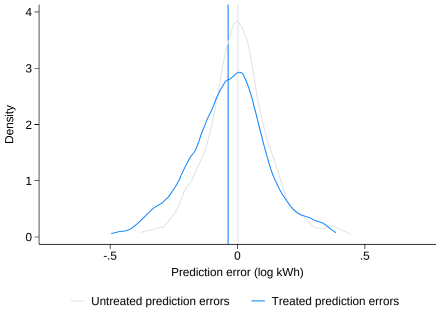
ML check: comparison across methods

	p10	p25	p50	p75	p90
LASSO optimal Lambda	-0.23	0.18	0.44	0.61	0.72
LASSO 1SE Lambda	0.08	0.21	0.43	0.58	0.69
LASSO + Synth optimal Lambda	-0.12	0.30	0.62	0.86	0.93
LASSO + Synth 1SE Lambda	0.13	0.33	0.64	0.86	0.93
LASSO Synth only optimal Lambda	-0.08	0.28	0.61	0.85	0.93
LASSO Synth only 1SE Lambda	0.12	0.32	0.63	0.85	0.93
Forest by school-block	0.09	0.30	0.52	0.67	0.76
Forest by school	-1.70	-0.15	0.42	0.63	0.71

The LASSO with control schools appears to do well out-of-sample

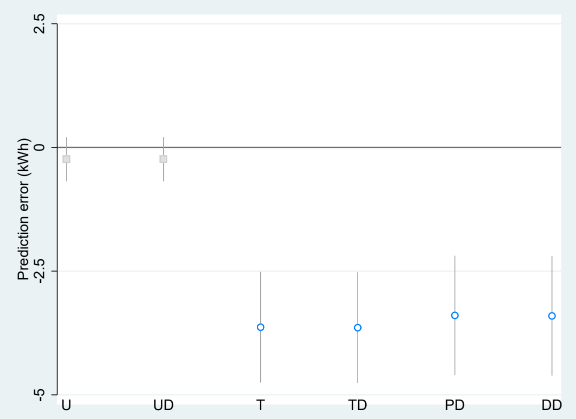
Control and treated school estimates suggest savings

- Controls: Prediction errors centered around zero well out-of-sample
- We see a shift in the distribution for schools with upgrades



ML results are stable across estimators

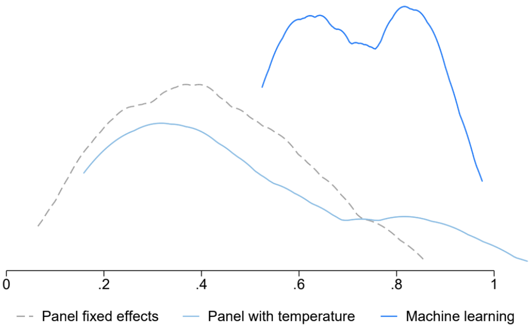
- Prediction errors suggest a reduction in energy consumption of around 2.5 KWh per day.
- However, still lots of noise across school measurements.



Implications for energy efficiency gap

- Estimates suggest savings around 0.5-0.7 of energy efficiency savings.
- Regressions are more noisy and can lead to very low estimates (0.1-0.6).
- Important to consider measurement problems when assessing the effectiveness of energy efficiency.

Figure 4: Comparison of methods across specifications and samples



Discussion: Why low realized savings?

Several potential explanations:

- General measurement error in expected savings?
  - Errors ins savings engineering model.
  - Timing of savings for which we have additional info.
- Large heterogeneity in realized savings?
  - Average effectiveness vs intervention-by-intervention.
  - Some interventions more effective than others.
  - Some interventions harder to predict.

Modeling: Adding demand-side policies to the model

Adding demand side policies and energy efficiency to model

- In today's practicum, we will incorporate demand-side policies into the model to analyze its benefits.
- We will go back to our model with investment, so that we have "dynamic" benefits from demand response.

Incorporating flexible vs. inflexible demand

- In our simple simulation, we will assume that there are two types of consumers:
  - Sensitive consumers: they respond to market prices.
  - Insensitive consumers: they pay a fixed tariff (or respond as if the price were fixed, even if it isn't).
- There will be a share α of insensitive consumers.

In the demand functions

- As in Borenstein and Holland (2005), total demand will be equal to:

$$\begin{aligned} demand_t &= demand\_insensitive_t + demand\_insensitive_t \\ &= (1-\alpha)(a_t - b_t tariff) + \alpha(a_t - b_t p_t) \\ &= a_t - b_t\left((1-\alpha)tariff + \alpha p_t\right) \end{aligned}$$

- *What are the challenges with having insensitive demand?*

Inefficiencies from lack of response

- Static
  - Demand is high in moments of scarcity (high prices), and does not get reduced efficiently.
- Dynamic
  - High demand in moments of scarcity leads to overinvestment.

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