The Economics of Energy Efficiency

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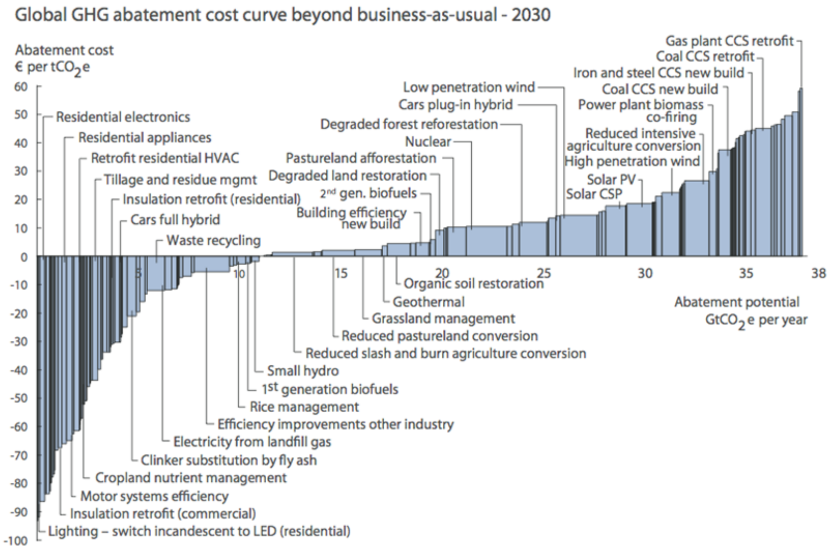


Source: McKinsey and Company, “Pathways to a Low-Carbon Economy,” 2010

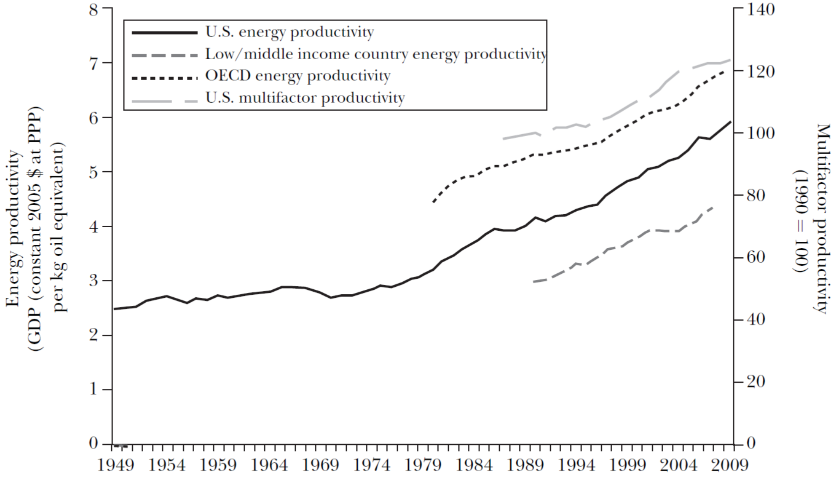
Motivation

Is energy efficiency a "win-win" for climate policy?

Energy efficiency is at the core of CO_2 mitigation strategies:

- **EU's Recovery and Resilience Facility:**
  - Germany: "€2.5 billion will be spent on a large-scale renovation programme to increase the energy efficiency of residential buildings."
  - Spain: "The plan supports the green transition through investments of over €7.8 billion in the energy efficiency of public and private buildings..."
- **US Inflation Reduction Act of 2022:**
  - "$9 billion in consumer home energy rebate programs, focused on low-income consumers, to electrify home appliances and for energy efficient retrofits"
  - "10 years of consumer tax credits to make homes energy efficient and run on clean energy..."

What is Energy Efficiency?



Source: (Allcott and Greenstone, 2012)

So What is the Problem?

- **Energy Efficiency Gap** (Allcott and Greenstone, 2012; Gerarden, Newell, and Stavins, 2017)
- Some investments in energy efficiency not happening in absence of policy

- Some possible reasons:
  - Market failures
  - Modeling flaws
  - Behavioral effects

Market Failures and Energy Efficiency

- **Innovation market failures**
  - R+D and learning effects
  - Market power
- **Information market failures**
  - Learning by using or experience goods
  - Asymmetric information (lemons problem)
  - Principal-agent incentive issues (owner/renter) (Myers, 2015)
- **Capital market imperfections**
- **Energy market failures**
  - Pricing
  - Externalities

Modeling Flaws and Energy Efficiency

- **Unobserved or understated adoption costs**, including unaccounted for product characteristics
- **Overstated benefits** of adoption, (e.g. due to inferior project execution and/or poor policy design)
- Incorrect **discount rates**
- **Heterogeneity** across end users in the benefits and costs of energy-efficiency

Behavior and Energy Efficiency

(Covered in previous lecture)

- **Prospect Theory**
- **Myopia** (short-sightedness)
- **Rebound Effect**
- **Peer Effects**
- **Inattentiveness and Salience**
- **Social Norms**

Wedge Between Projected and Realized Savings

Realized savings often fall short from what was expected

- Weatherization and home retrofits (Fowlie, Greenstone, and Wolfram, 2018; Allcott and Greenstone, 2012)
- Appliance rebate programs (Houde and Aldy, 2014; Davis, Fuchs, and Gertler, 2014)
- Building codes/efficient housing (Levinson, 2016; Davis, Martinez, and Taboada, 2018; Bruegge, Deryugina, and Myers, 2019)

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Could mean carbon mitigation goals are much more expensive than anticipated or will not be achieved

An Application

- **"Decomposing the Wedge Between Projected and Realized Returns in Energy Efficiency Programs."** Peter Christensen, Paul Francisco, Erica Myers, and Mateus Souza
- Decompose 'performance wedge': (1) engineering measurement and model bias, (2) workmanship, and (3) rebound effect
  - Mechanisms affect policy implications

Policy Implications

Decompose the performance wedge: mechanisms affect policy implications

- Engineering models: analyze and calibrate these models
- Workmanship: are there market failures we can correct?
- Occupant behavior: train occupants to use equipment and other nudges

The Paper

- Estimate heterogeneity in savings and wedge using machine learning: Weatherization Assistance Program (WAP)
  - Largest U.S. energy efficiency program (over 7 million served since 1976)
  - Funds allocated using modeling tools employed for wide-range of retrofit programs (i.e National Energy Audit Tool: NEAT)
- Quantify effects of major proposed channels: measure-specific savings, contractor heterogeneity, rebound effect

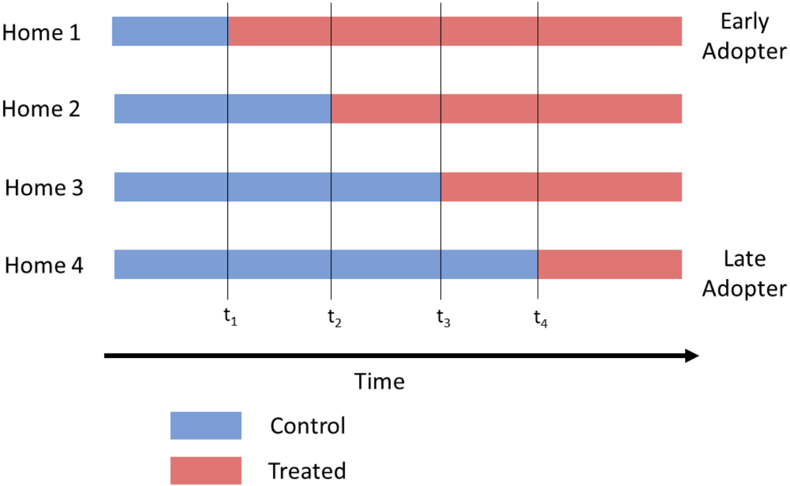
Data

- Around 9,000 low-income homes from the Illinois Weatherization Assistance Program (WAP)
  - Program years 2009-2016
  - Rich data on: energy audits, housing structure, demographics, upgrades performed, and job costs
  - We know who performed the jobs in each home
  - Engineering projections of savings
- Monthly electricity/gas consumption
- PRISM daily weather data

Empirical Strategy

- Our setting constitutes an event study with staggered adoption
- Use machine learning to recover heterogeneous treatment effects
- Subtract our estimated effects from engineering projections (wedge)
- Describe systematic heterogeneity in wedge to investigate mechanisms

An Event Study With Staggered Adoption



Machine Learning Approach

- Machine learning for counterfactual predictions (Burlig et al., 2020; Abadie, 2005)
  - Use data from not-yet-treated homes to predict counterfactual usage post-treatment
  - Compare true usage vs. counterfactual to obtain effect of the program

Machine Learning Approach

- Machine learning for counterfactual predictions (Burlig et al., 2020; Abadie, 2005)
  - Use data from not-yet-treated homes to predict counterfactual usage post-treatment
  - Compare true usage vs. counterfactual to obtain effect of the program
- Identifying assumption is parallel trends, similar to DID
  - Not-yet-treated homes account for time-varying relationships between usage and rich controls on for time, weather, house, and households

Why Machine Learning

- Flexibility to capture nonlinear relationship between housing structure, weather and energy usage
- Efficient for recovering treatment effect heterogeneity
- Do not suffer from near-term bias (Souza, 2019)
- Chose ML algorithm based on lowest out-of-sample RMSE
  - Highly flexible tree-based model (gradient boosted trees)
- Special concern about **out-of-sample** performance
  - Cross-validation

Illustration of a Regression Tree

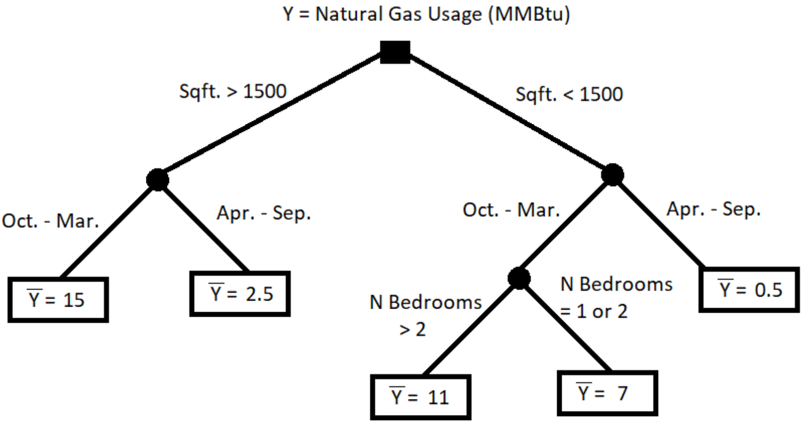
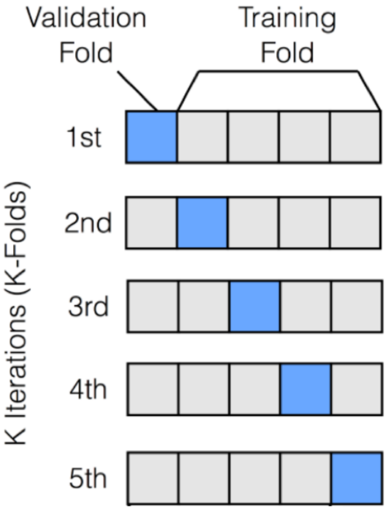


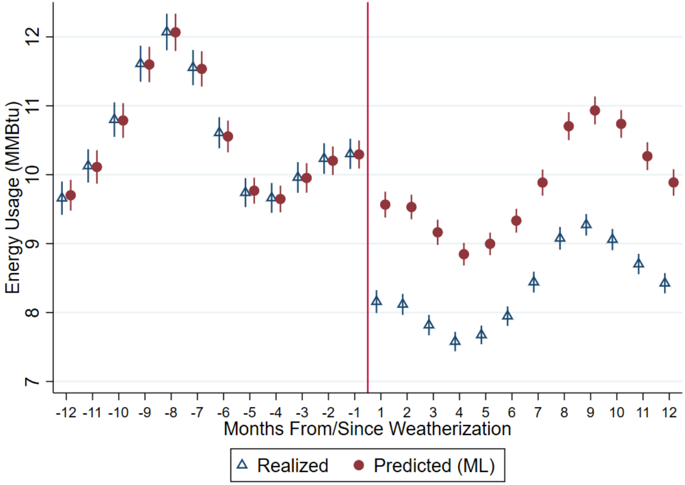
Illustration of 5-Fold Cross-Validation



Source: ML tutorial by Ethen Liu

Predicting Counterfactuals

Machine learning predictions versus true energy usage



Program Average Treatment Effects on Energy

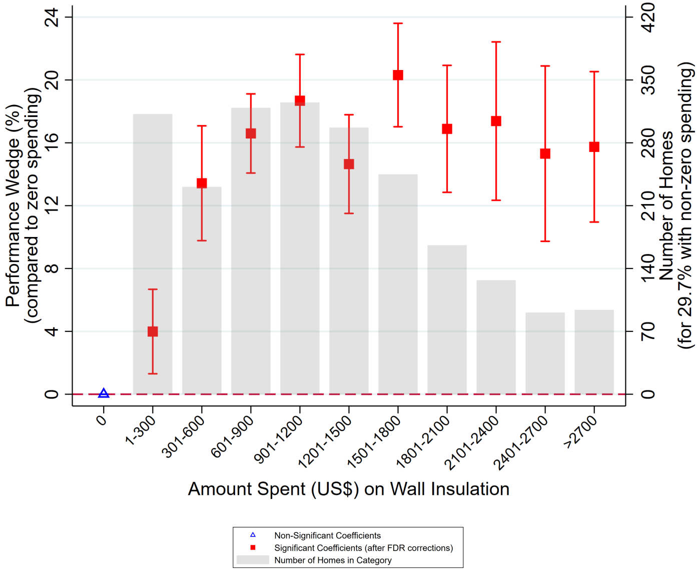
Outcome: *Percent Energy Savings*	Engineering Projections	Machine Learning
WAP Treatment	-0.2903***	-0.1483***
	(0.0020)	(0.0037)
Realization Rate		.5108
Observations	22,394	142,327

Empirical Strategy – decomposing the wedge

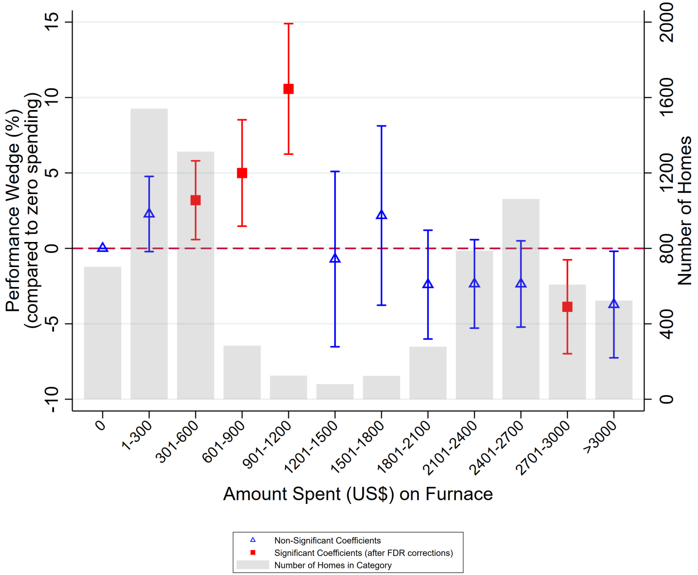
$$[\hat{b}^{p}_{it} - \hat{b}^{ml}_{it}] = \alpha_0 + \eta_j + \sum_{k=1}^{K} \beta_k C^k_{it} + \sum_{g=1}^{G} \gamma_g X^g_{it} + \varepsilon_{it}$$

- ⇒ $\hat{b}^{p}_{it}$ are engineering projected savings
- ⇒ $\hat{b}^{ml}_{it}$ are realized savings
- ⇒ C^k_{it} are binned variable for K categories of program spending (such as spending in Wall Insulation), and β_k correlates those variables with the performance wedge
- ⇒ X^g_{it} are binned covariates related to housing structure and demographics
- ⇒ η_j are contractor specific fixed effects

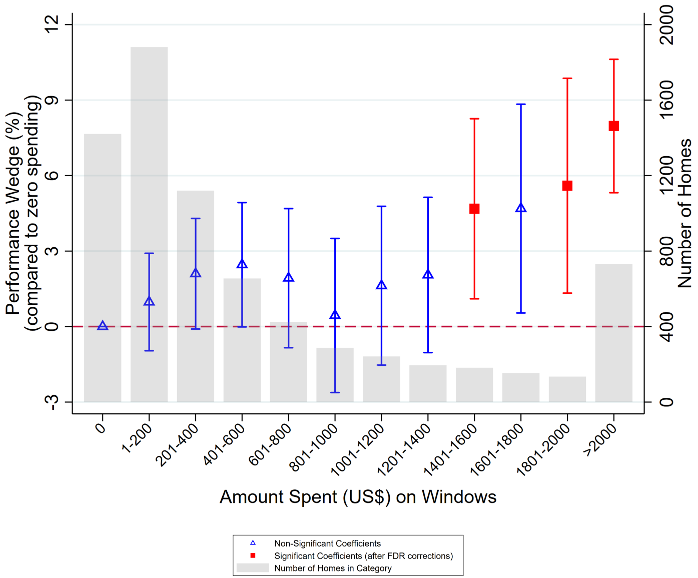
Results – estimated Wedge by Wall Insulation spending



Results – estimated Wedge by Furnace spending



Results – estimated Wedge by Window spending



Workmanship – Contractor Quality

- Regress savings on contractor fixed effects and controls?
  - Requires no unobserved or uncontrolled for determinants of savings – unlikely
  - Some contractors may have been "lucky" in a given year
- Use contractor's mean savings from previous year to isolate variation in performance due to quality
- We assume that homes are unobservably easier to weatherize "at random", uncorrelated with contractors over time
  - This is likely the case, since contractors receive work orders based on a queue

Contractor Quality Measure

Contractor quality can be defined as:

$$\eta_j = q_j + \varepsilon_j$$

where η_j is observed quality, q_j is true quality, and ε_j is an idiosyncratic error

We estimate η_j based on:

- First Step: calculate average savings η_{jy} for homes served by contractor j in year y
- Second Step: regressed η_{jy} on lagged savings plus other controls

$$\eta_{jy} = \alpha_0 + \delta\eta_{jy-1} + \sum_{k=1}^{K} \beta_k C_{it}^{k} + \sum_{g=1}^{G} \gamma_g X_{it}^{g} + \varepsilon_{it} \quad \forall\, t > t_i\ ,$$

Use the above equation to predict $\hat{\eta_{jy}}$, as our measure of contractor quality

Simulation: Effect of Workmanship on the Wedge

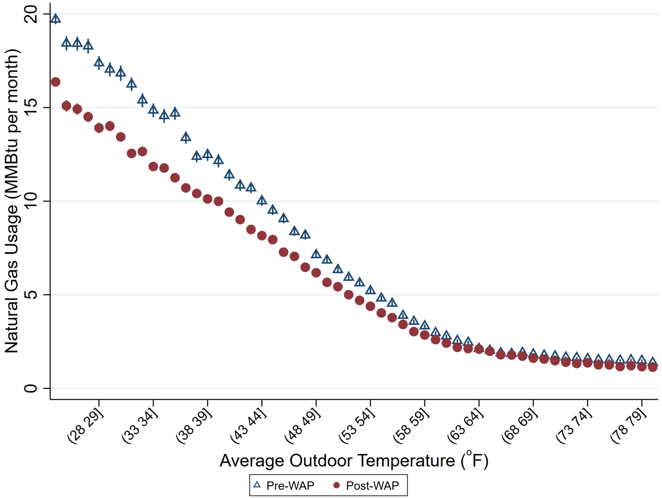
	Baseline	"Best" Contractor Percentile			
		50th	75th	90th	95th
Avg. Pct. Point Wedge	15.357	15.406	12.871	10.452	**8.806**
	(0.621)	(0.638)	(0.734)	(0.977)	(1.205)
Wedge Reduction		0.315%	-16.190%	-31.939%	**-42.658%**
		(1.599)	(3.169)	(5.623)	(7.542)
Observations	84,404	84,404	84,404	84,404	84,404

Rebound Effect

We explore one of the main behavioral channels which can affect energy savings in this context: the rebound effect

- Households may increase thermostats after weatherization, given the lower cost burden
- Recent evaluations suggest that rebound is close to 0.4^{o}F (Pigg et. al., 2014; Fowlie et. al. 2018)
- Our thought experiment: how does the rebound affect our estimates of the performance wedge?

Energy Consumption and Outdoor Temperature



Simulation: Effect of Rebound on the Wedge – Results

	Baseline	Varying the balance point		
Balance Point (^{o}F)	61.8	61.6	**61.4**	61.2
Removed Rebound Effect (^{o}F)	0	0.2	**0.4**	0.6
Average Percentage Point Savings	-11.391	-11.874	**-12.352**	-12.824
	(0.543)	(0.542)	(0.540)	(0.539)
Savings Increase Compared to Baseline		4.246%	**8.442%**	12.585%
		(0.198)	(0.393)	(0.585)
Average Percentage Point Wedge	15.098	14.619	**14.140**	13.673
	(0.583)	(0.581)	(0.580)	(0.579)
Wedge Reduction Compared to Baseline		-3.177%	**-6.347%**	-9.443%
		(0.090)	(0.178)	(0.261)
Observations	128,670	128,655	128,644	128,631

Conclusions From Application

- We provide insight about how the engineering models are biased in this context
- Overestimated savings imply that climate policies may be less cost-effective than expected
- This does not mean that we should ignore energy efficiency
- Heterogeneity analysis finds that several homes indeed benefit a lot from the program
- So there are opportunities to improve allocation of program funds (Christensen, Francisco, Myers, Shao, and Souza, 2021)
- Other policy implications:
  - WAP and similar programs can benefit from ex-post analyses to improve predictive models of home-specific savings
  - Role for addressing contractor performance/incentives (Christensen, Francisco, and Myers, 2020)

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