Empirical Methods for the Analysis of the Energy Transition

Slide Set 8

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Roadmap

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

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: cooling a home during a heatwave

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).

- It can have big implications for decarbonization.
  1. Make transition easier by lowering demand
  2. Make transition use of fossil fuels more efficient
  3. Estimated to be relatively cheap

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**

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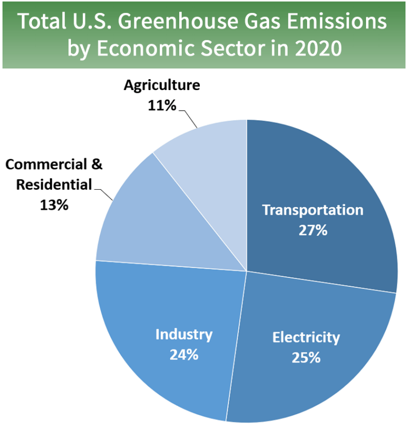
Energy Efficiency **Could** Be Essential to Decarbonization

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

- Significant upfront costs
- Equity concerns with mandates

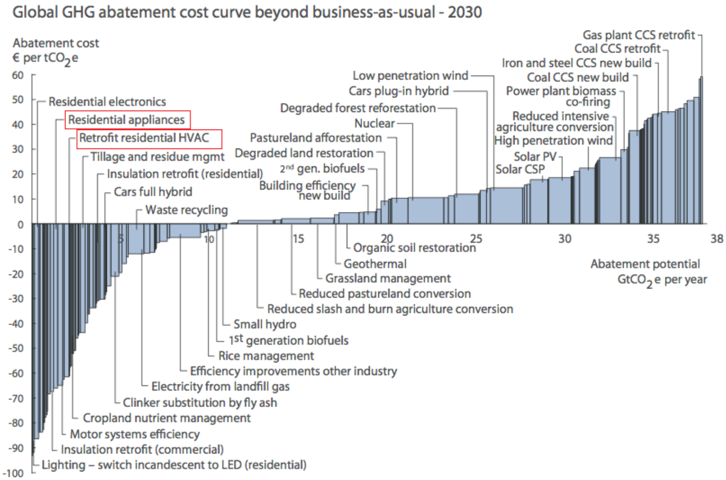


U.S. Environmental Protection Agency (2022). Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2020

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."
- This wedge appears even without an externality cost.
- 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.

Discrepancies Between Projected and Realized Savings

- 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?

Discrepancies replicated in the literature – Summary by Enrich (2025)

Study	Location	Intervention	Outcome	Result
Davis et al. (2014)	Mexico	Subsidy ~10% and 40% to replace fridges	Percentage of realized vs projected savings	30%
		Subsidy ~10% and 40% to replace AC		0%
Jacobsen i Kotchen (2013)	Florida (US)	Building codes		100%
Levinson (2016)	California (US)	Building codes		0%
Fowlie et al. (2018)	Michigan (US)	WAP ($4000 in average)		30%
Christensen et al. (2023)	Illinois (US)	WAP		50%
Zivin i Novan (2016)	California (US)	WAP ($1700 in average)		50%

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Accounting for the performance wedge

- Christensen, Francisco, Myers, and Souza (2022) decompose the performance wedge in WAP:
  1. Engineering measurement and model bias (43%)
  2. Workmanship (41%)
  3. Occupant behavior (6%)

Some solutions explored in paper

- Modifying worker incentives
  - Randomized study paying workers based on building envelope tightness– quite cost-effective
- Addressing model bias
  - Predictions based on realized savings at similar homes outperform current engineering model approach
  - Targetting funds based on improved predictions can increase benefits

Further evidence on WAP – Enrich (2025)

Study	Location	Intervention	Outcome	Result
Fowlie et al. (2018)	Michigan (US)	Encouragement to receive energy audit	Increase in participation	From 1% to 6%
		Energy audit + retrofit ($4000 in average)	Energy consumption	-20% (mostly from gas)
Ministeri d'Inclusió, Seguretat Social i Migracions (2024)	Catalonia (Spain)	Energy Audit + info on conservation strategies + retrofit (5000€ in average)	Energy consumption	Not significant
			Energy expenditures	Info: -15% Retrofit: Not significant
			Perceived quality of housing conditions	Info: Not significant Retrofit: +4%
Myers et al. (2022)	Austin (Texas, US)	Mandatory certified audits	Housing prices	Increase in the correlation between energy efficiency and price
			Investments in energy efficiency	+30%
Peñasco i Díaz (2023)	UK (England and Wales)	Subsidy to insulation equipment	Gas consumption	-0.3% / -5%
Zivin i Novan (2016)	California (US)	Energy audit + info on conservation strategies + retrofit ($1700 in average)	Electricity consumption	-7% for retrofit
				-31% adding conservation strategies

Further evidence on building codes – Enrich (2025)

Study	Location	Intervention	Outcome	Result
Aroonruengsawat et al. (2012)	US	Building codes	Electricity consumption	-0.3% / -5%
Jacobsen i Kotchen (2013)	Florida (US)		Electricity consumption	-4%
			Gas consumption	-6%
Kotchen (2017) – review of previous study	Florida (US)		Electricity consumption	Zero long term effects
			Gas consumption	Persistent long term effect
Levinson (2016)	California (US)		Electricity consumption	Not significant
			Gas consumption	Not significant
Bruegge et al. (2019)	California (US)		Electricity consumption	-1%
			Gas consumption	-0.6%
			Square footage	-5% for bottom quintiles
			Housing prices	-10% for bottom quintiles +2% for top quintile
Novan et al. (2022)	California (US)		AC Electricity consumption	-8% / -13%

Key findings

- Building codes contribute to reducing gas consumption and, to a lesser extent, electricity consumption (medium). The effects on electricity consumption will increase as we electrify the residential sector.
- Evidence on the distributional effects is scarce, but one study finds that the existence of building codes could lead to a reduction in the size and attributes of smaller homes, affecting disproportionally lower-income groups (medium).
- Interventions encouraging voluntary energy audits have limited effects (high). However, making audits mandatory can be an effective measure to promote investment and provide information so that both sellers and buyers make optimal decisions (high).
- For both building codes and retrofit subsidies, studies differ on the period to recover upfront costs. This is due to the long lifespan of these investments, and assumptions about energy prices and environmental benefits (high).

We will cover a couple of examples

All of them are “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" – Davis et al. (AEJ, 2014)

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

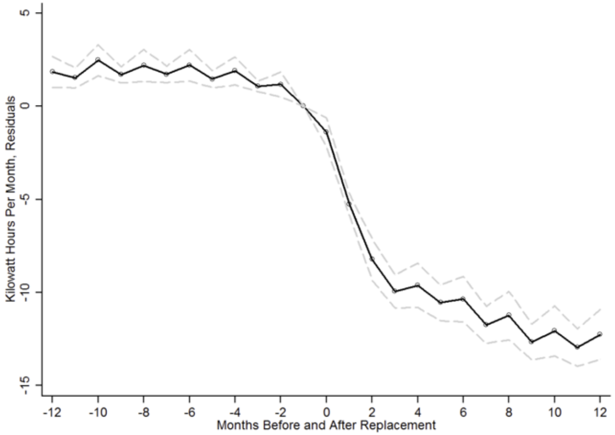
New appliance must meet exceed 2002 standard by 5%.

C4C assessment

- 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?

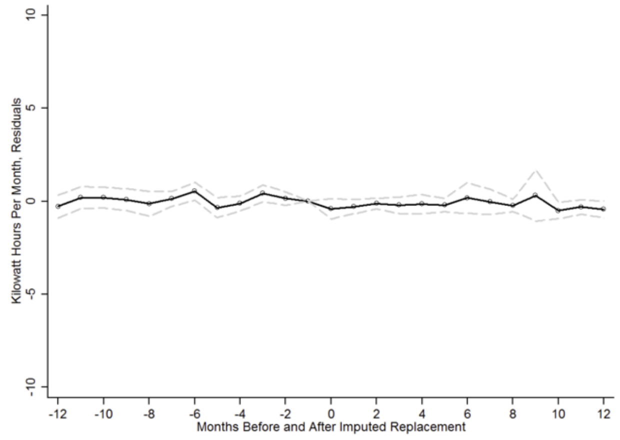
C4C impacts

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)
$1[\text{New Refrigerator}]_{it}$	-11.2**	-11.0**	-11.0**	-11.5**	-11.5**	-11.4**
	(0.5)	(0.4)	(0.4)	(0.4)	(0.5)	(0.5)
$1[\text{New Air Conditioner}]_{it}$	8.5*	6.6**	-0.2	-0.7	1.2	1.2
	(3.6)	(2.2)	(0.8)	(0.8)	(0.8)	(0.9)
$1[\text{New Air Conditioner}]_{it} \times 1[\text{Summer Months}]_{it}$			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

C4C Inframarginal participation (Boomhower and Davis, 2014)

- Energy-efficiency (EE) programs typically pay rebates to households that adopt an upgrade, typically popular.
- A key public-finance concern: many participants may be **inframarginal** (they would have upgraded anyway).

Evaluation challenge

Observed post-upgrade savings among participants combine:

- **True additionality**: marginal adopters induced by the program
- **Selection / inframarginality**: adopters even absent the rebate

These can substantially affect the **marginal value of public funds**.

Identification: subsidy thresholds isolate the *marginal* participant

- In *C4C*, rebate amounts (or eligibility) change discretely at observable cutoffs.
  - **Level** of participation ⇒ total take-up (includes inframarginal households)
  - **Jump at the threshold** ⇒ induced take-up (the marginal response)

Key insight

- **Discontinuity in take-up** measures the causal effect of a higher subsidy on adoption.
- A large level but small jump implies substantial **inframarginal** participation.
- No jump at some thresholds may reflect either offsetting program components or limited responsiveness at the margin.

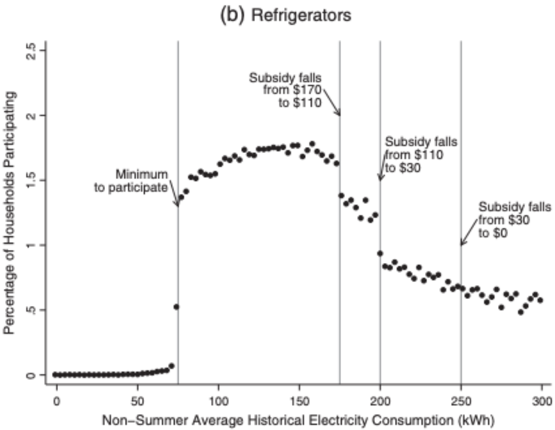


Fig. 5. Program participation.

Main takeaway: how inframarginal are EE rebates?

- A substantial share of program participation is estimated to be **inframarginal** (free-riding is economically meaningful).
- As a result, **average** savings among participants can be a misleading object for welfare and cost-effectiveness.
- The welfare case for EE rebates depends on:
  - externalities (CO_2, local pollution),
  - distributional objectives, and
  - targeting/eligibility rules that increase marginal take-up.

Machine learning and policy evaluation

- For many energy efficiency papers, there is a need to have a clear counterfactual but selection into the energy efficiency programs can make comparisons difficult.
- 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 application of energy efficiency and ML.

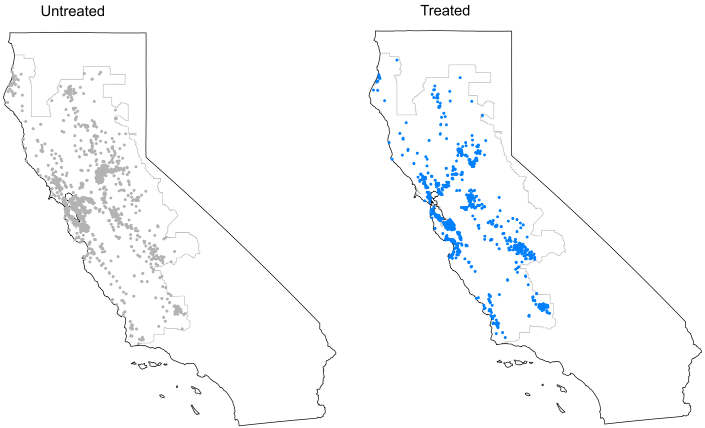
Can it really help? How?

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 **Central challenge:** Energy efficiency upgrades are not randomly assigned, 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 ~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

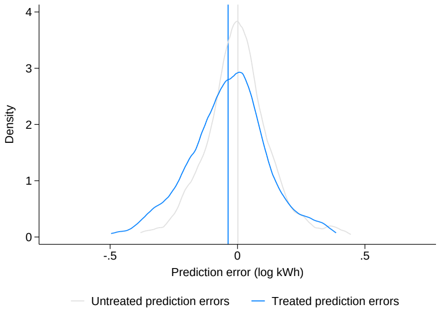
- Regress *prediction errors* on treatment and controls.

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

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

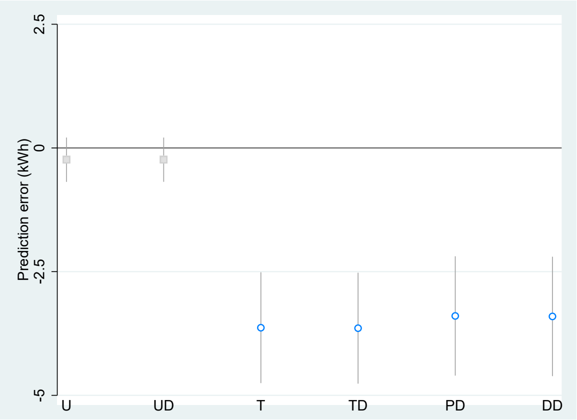
Control and treated school estimates suggest savings but small

- 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

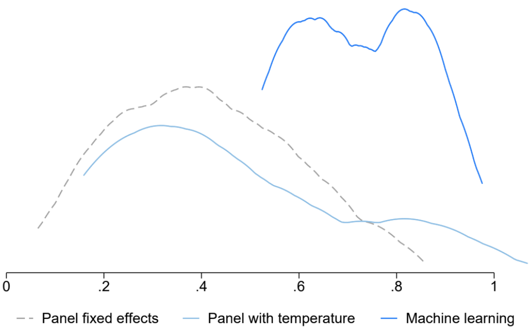
- Prediction errors suggest a reduction in energy consumption of around 2.5 KWh per day.
- However, still lots of noise across school measurements.



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.

Interactions of energy efficiency and climate impacts

- Evidence of energy efficiency is mixed: reductions in energy consumption are significant, but less than under ideal conditions.

- Energy efficiency it is yet crucial for the energy transition:
  - Reducing demand can be cheaper than reducing emissions for many settings!
  - Energy efficiency protects households from extreme events: better infrastructure, less gradient in consumption needs.

Roadmap

I. Energy Efficiency

- Energy Efficiency: Concepts and Evidence
- Natural experiment example (Mexico)
- Natural experiment example with ML (California)

II. Adding demand behavior 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.
- This will allow us to understand the value from **demand-side policies** accounting for prices and investment.

- Note: We will focus on demand response/demand flexibility, and examine the complementarities with renewable power.

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:

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

- *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 in gas plants
  - Lack of flexible demand leads to underinvestment in renewable power

Solving the model

- We will use the social planner approach, but we need to be **careful on how we define it**.
- True surplus from the "insensitive" consumers needs to be ignored to avoid the social planner trying to achieve second-best by distorting the market equilibrium.
  - Thm 2 in Borenstein and Holland (2005) suggests a social planner might want to distort the signals to inattentive consumers).
  - We will only include the surplus of sensitive consumers in the objective function – but careful that total surplus should be larger.

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