The Implicit Cost of Carbon Abatement During the COVID-19 Pandemic

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Motivation

Impact of pandemic on electricity consumption and carbon emissions:

- Is there a silver lining?

EU Green Deal:

- By 2050, reach net zero CO2 emissions by 2050
- By 2030, reduce emissions by at least 55% vs 1990 levels

Debate on how to achieve those goals:

- Is it possible without sacrificing **economic growth**?
- What are the implicit costs of different strategies?

Research Question

What are the implicit costs of abatement according to alternative strategies?

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1. **Slowing down economic activity**:
   - Pandemic as a natural experiment
   - Caveat: Pandemic was a shock, not planned "degrowth"
   - Pandemic is proxy of slow down, holding economic structure fixed

Research Question

What are the implicit costs of abatement according to alternative strategies?

1. **Slowing down economic activity**:
   - Pandemic as a natural experiment
   - Caveat: Pandemic was a shock, not planned "degrowth"
   - Pandemic is proxy of slow down, holding economic structure fixed
2. **Decoupling strategy**:
   - Invest in energy efficiency and low-carbon technologies
   - How much investment in renewables would we need to achieve same carbon abatement as the pandemic?

Steps of the analysis

1. We measure the effects of the pandemic on **emissions reductions**.
   - Counterfactual **electricity** usage in absence of the pandemic
   - Counterfactual power-sector **emissions**
   - Counterfactual **emissions** from other sectors
2. We measure the effects on the Spanish economy (GDP).
   - Counterfactual **GDP**
3. Simulate counterfactual **investments** in renewables to achieve CO2 reductions similar to those observed in the power sector during the pandemic.
4. Compare the implicit cost of carbon abatement from pandemic versus decoupling.

Predicting Counterfactual Electricity Demand

- **Objective:**
  - Predict counterfactual electricity demand in absence of the pandemic
    - Obtain precise hourly predictions, which will be used later in electricity market simulations
    - Use only covariates that are not affected by the pandemic
- **Data:**
  - Hourly demand in Spain from 2015-2020
  - Weather variables: temperature, precipitation, wind speed, and wind direction
  - Holidays
  - Date/time fixed effects (seasonality)
  - Time trends

Predicting Counterfactual Electricity Demand

- **Predictive machine learning model of demand:**

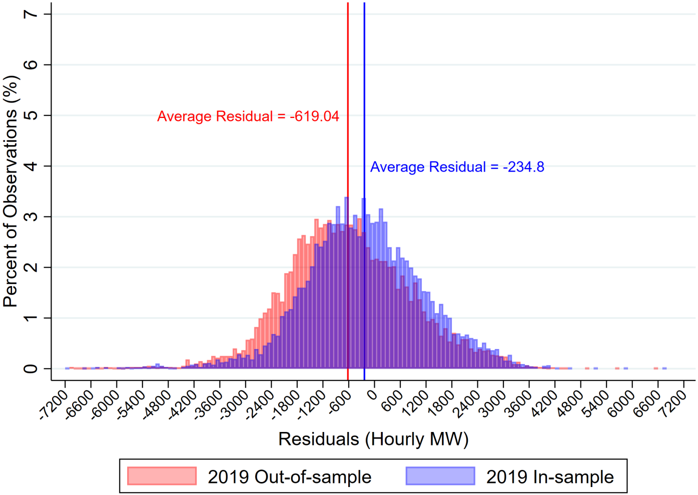
$$Y_t(0) = g(\mathbf{X}_t) + \varepsilon_t$$

- Covariates $\mathbf{X}_t$: weather and date/time fixed effects
- Model trained and cross-validated with past data (2015-2019)
  - Model selected based on **out-of-sample** performance
  - Using forward chaining cross-validation (Hyndman and Athanasopoulos, 2018):
- $g()$: Gradient Boosted Trees (Chen and Guestrin, 2016)

- Impact of the pandemic on electricity demand:

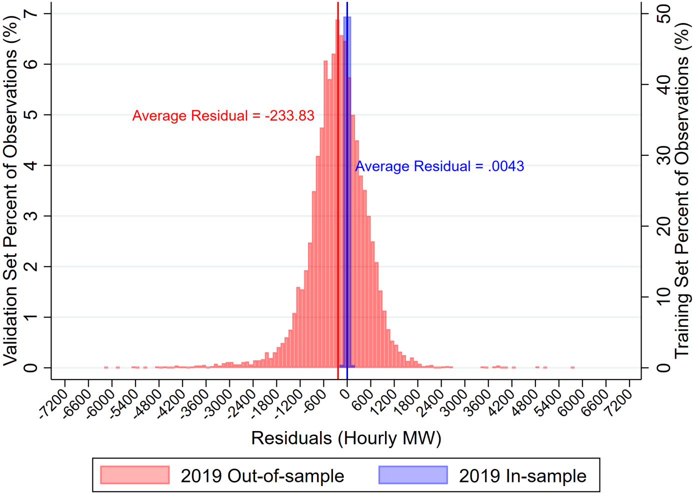
$$\hat{b}_t = Y_t(1) - \hat{Y}_t(0) = Y_t(1) - \hat{g}(\mathbf{X}_t)$$

Cross-Validation Results – fixed effects model



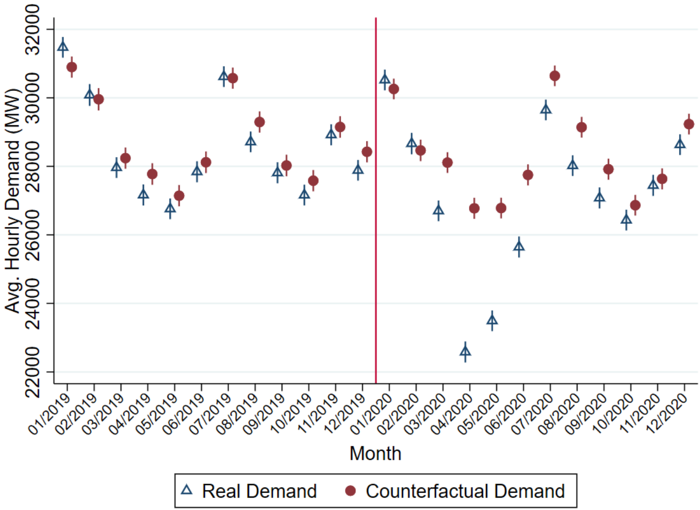
Day of year FE; hour of day interacted with weather; lagged (up to 3) weather

Cross-Validation Results – ML



Average out-of-sample residual is less than 1% of mean hourly demand

Counterfactual Demand in the Power Sector



Counterfactual Emissions in the Power Sector

- Use the hourly demand estimates to **simulate the hourly electricity market outcomes** with and w/o the pandemic
- Simulations based on De Frutos and Fabra (2012)
- Identify which plants would have been dispatched $\longrightarrow$ obtain carbon intensity of the market

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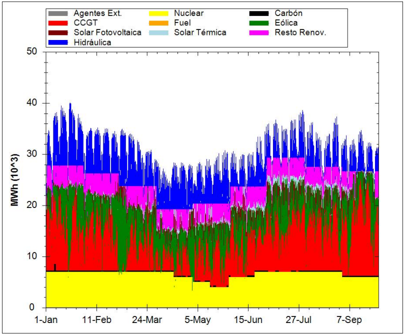
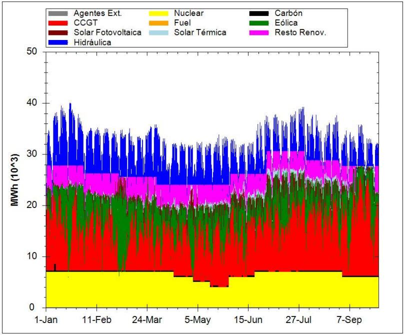
- We take all else as given:
  - Hourly availability of renewables
  - Monthly hydro availability
  - Existing capacity of gas/coal/nuclear plants
  - Daily prices of gas/coal/CO2
  - Caveats: nuclear availability and gas/coal/CO2 prices may have changed

Emissions in the Power Sector (up to Sep. 2020)



(a) Using realized demand



(b) Using counterfactual demand

Note: Simulations need to be updated. Currently showing results up to Sep. 2020.

Change in Generation Mix and Emissions

Emissions in Spanish Power Sector (up to Sep. 2020)

	MtCO2 Emissions		
	Realized	Counterfactual	Difference
Coal	0.48	0.52	0.03
Gas	13.01	16.40	3.39
Cogen + Others	9.26	9.67	0.41
Total	22.75	26.59	3.83

Notes: Assuming competitive market structure. Results from strategic equilibrium presented in the paper.

Almost 90% of abatement due to reduced gas usage.

Emissions from Other Sectors

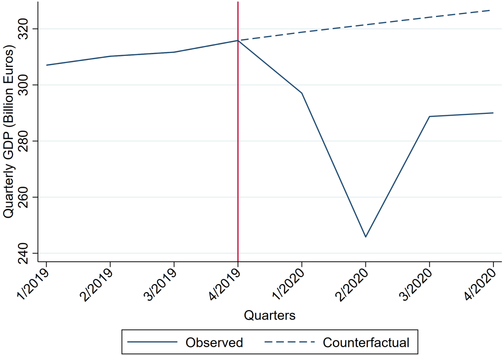
Other Sectors' CO_2 Emissions

	MtCO2 Emissions			
	2019	2020	Diff.	Pct. Diff.
Domestic Aviation	5.64	3.00	-2.63	-46.68
Ground Transport	84.83	75.40	-9.43	-11.12
Industry	62.25	55.63	-6.62	-10.64
Residential	36.70	36.14	-0.56	-1.53

Source: (Carbon Monitor; Liu et al., 2020)

Counterfactual economic activity

- Counterfactual GDP based on forecasts from Bank of Spain
- Forecasts made at the end of 2019 (no info. about pandemic)



- Total GDP loss in 2020: 169.37 Billion Euros
- Implicit cost of carbon = 6.510 €/Ton CO_2

Decoupling Strategy

- Simulate the market, varying types of investments
- Keep simulations that yield the same emissions reductions in the power sector as the pandemic

	Emission Reductions (M Tons CO2)	Investment Costs (M €)		Implicit Cost of Carbon (€/Ton CO2)
		Total	Investment+O&M (Q1-Q3)	
Solar Investments	4.01	5,917.5	230	57.4
Wind Investments	3.80	10,486.7	482	126.9
Hybrid Investments	3.93	8,202.1	356	90.5

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The implicit cost of carbon under each strategy is:

1. Slowing down economic activity: 6.510 €/Ton CO2
2. Decoupling: 57.4 €/Ton CO2

Conclusions

Carbon abatement may be obtained by slowing down economic activity and/or investing in renewables

1. Our results suggest that simply halting growth may be too costly
   - The pandemic has weakened economic activity more than what is reflected in aggregate electricity consumption data
   - Carbon abatement was short-lived, while economic losses are expected to be long-lasting
2. Investments in renewables can achieve abatement at relatively lower cost
   - Renewables could even provide more benefits in terms of economic stimulus
3. Of course, these strategies should be complemented with:
   - Improving energy efficiency, revolutionizing transport and mobility, etc.

Thank You!

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Comments? Feedback? Questions?

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European Research Council

Established by the European Commission

References

- De Frutos, María-Ángeles and Natalia Fabra (2012). "How to allocate forward contracts: The case of electricity markets". *European Economic Review* 56(3), pp. 451–469.
- Hyndman, Rob J and George Athanasopoulos (2018). *Forecasting: principles and practice*. OTexts. Chap. 5.10 - Time series cross-validation.
- Liu, Zhu, Philippe Ciais, Zhu Deng, Steven J Davis, Bo Zheng, Yilong Wang, Duo Cui, Biqing Zhu, Xinyu Dou, Piyu Ke, et al. (2020). "Carbon Monitor, a near-real-time daily dataset of global CO 2 emission from fossil fuel and cement production". *Scientific data* 7(1), pp. 1–12.

Appendix: Why Machine Learning?

- ML flexibly accounts for nonlienarities and high-order interactions
- Agnostic about which variables are most important
- Agnostic about functional forms
- Best **out-of-sample** performance
  - Will compare to fixed effects models

Appendix: Cross-Validation Results – ML

Using RMSE as accuracy metric. Values are in MW.

	Panel A: Validation Year RMSE			
	2016	2017	2018	2019
Model 1	1155.88	934.42	856.18	809.13
Model 2	1160.67	984.78	871.45	815.45
Model 3	1517.53	1219.22	1165.42	1063.05
Model 4	1532.10	1266.84	1152.23	1083.03

	Panel B: Hyperparameters			
	ntrees	max_depth	shrinkage	minobspernode
Model 1	2000	10	0.05	20
Model 2	2000	30	0.05	20
Model 3	2000	10	0.5	20
Model 4	2000	30	0.5	20

Hourly demand in 2019: mean 28527.69 MW; Std. dev. 4524.94.

Appendix: Inference With Machine Learning

Let b_t be the effect of the pandemic.
$Y_t(1)$ is realized demand, and $Y_t(0)$ is counterfactual demand

$$\hat{b}_t = Y_t(1) - \hat{Y}_t(0)$$
$$\hat{b}_t = Y_t(0) + b_t - \hat{Y}_t(0)$$
$$\longrightarrow b_t = \hat{b}_t + \hat{Y}_t(0) - Y_t(0)$$
$$\longrightarrow b_t = \hat{b}_t - \hat{r}_t$$

Where $\hat{r}_t$ are residuals from the prediction of $Y_t(0)$

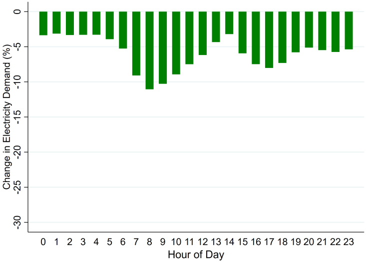
Then we also have (assuming $\hat{b}_t$ and $\hat{r}_t$ independent):

$$Var(b_t) = Var(\hat{b}_t) + Var(\hat{r}_t)$$

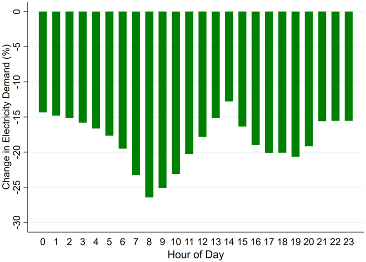
Note that $\hat{r}_t$ cannot be observed, so we proxy it with the variance of the (out-of-sample) residuals from 2019

Effect of the Pandemic on Electricity Consumption

Reduced electricity demand by hour of the day



1st Partial Lockdown
(March 11 - March 28)



Full Lockdown
(March 29 - April 10)

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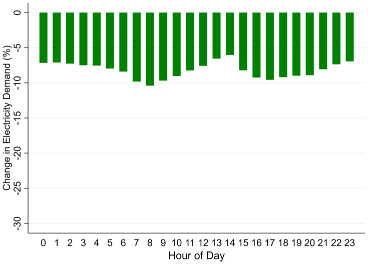
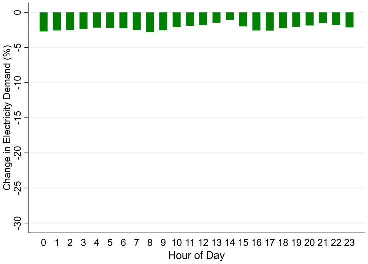


Partial Lockdowns
(April 11 - August 14)



Rest of Year
(August 15 - December 31)