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Using Machine Learning for Policy Evaluation: The UK Carbon Tax

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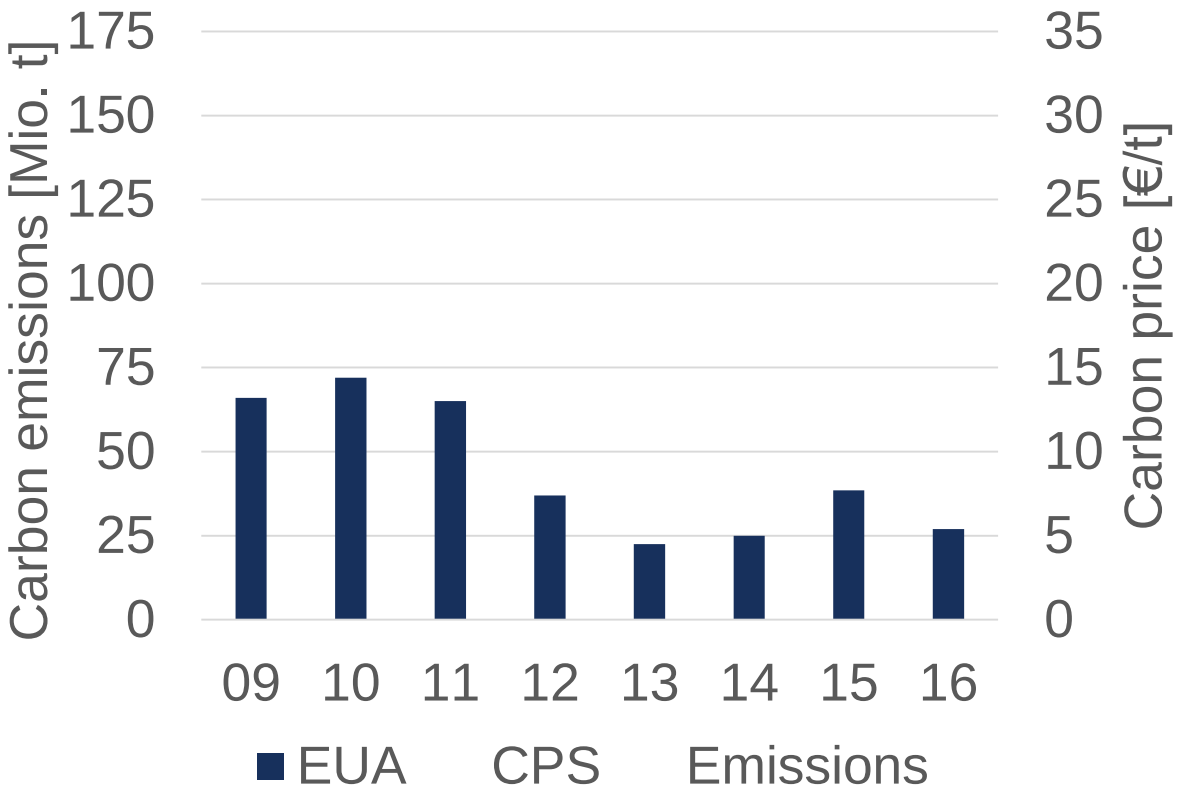
Background and research question



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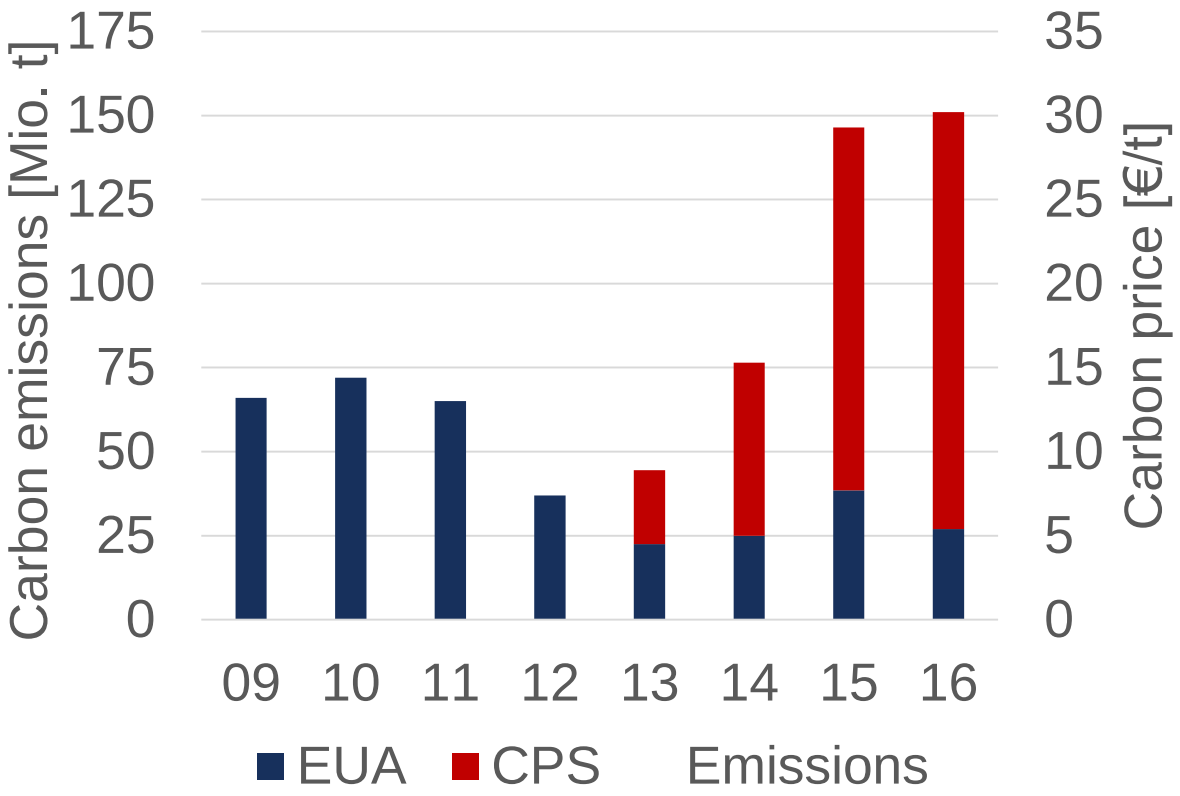
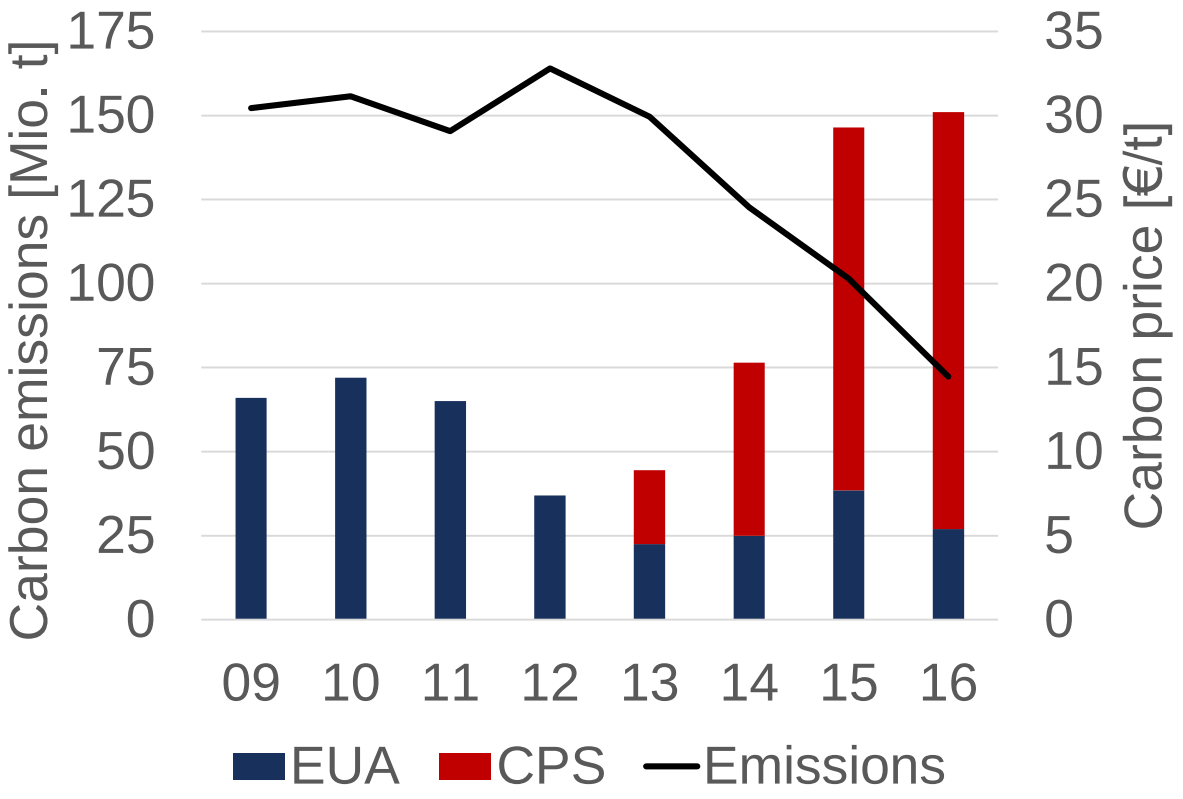


- Carbon price support (CPS) introduced in 2013 by UK government
  - Tax on electricity sector emissions
  - Varies by year

Background and research question



Sources: EEX (2017), Hirst (2017), EC (2016)

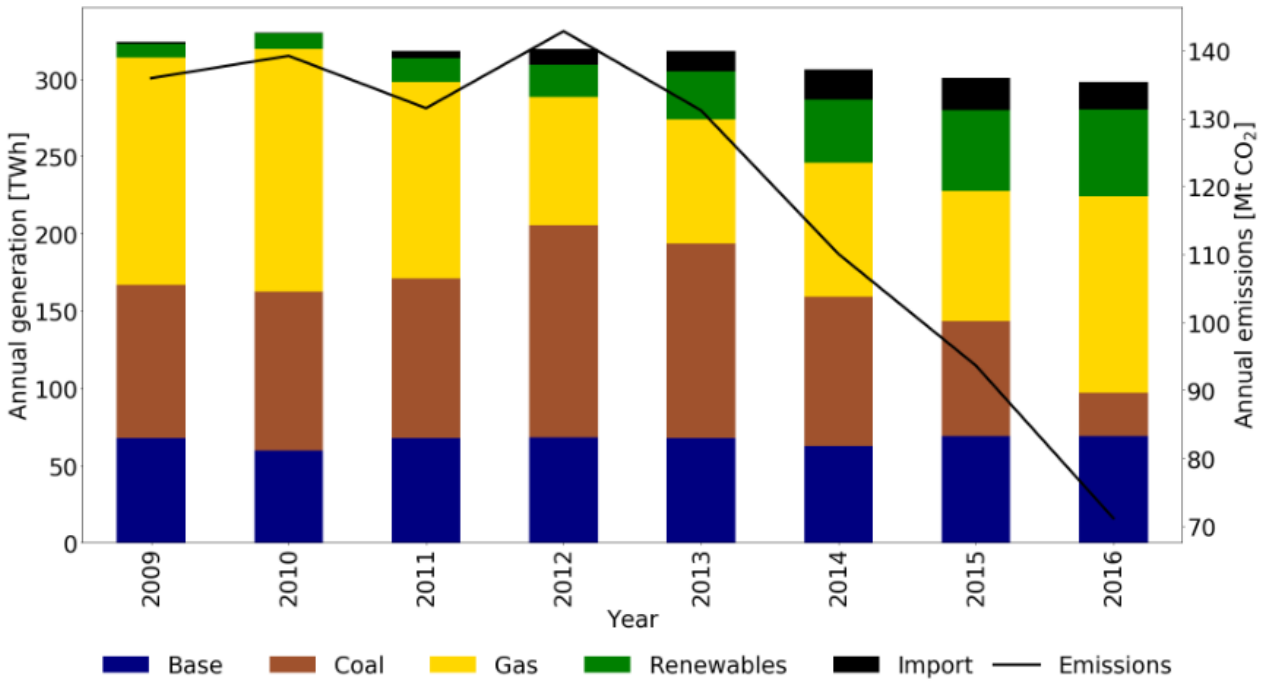
- Carbon price support (CPS) introduced in 2013 by UK government
  - Tax on electricity sector emissions
  - Varies by year
- What was the impact of the CPS on
  - coal and gas generation?
  - emissions?
- What were the abatement costs?

Reasons for decreasing emissions

Two major reasons for lower emissions in power sector:

- Lower total fossil generation
  - Lower demand
  - More renewables
  - More imports
- Coal-to-gas switch
  - Change in installed capacities
  - Change of relative fuel prices

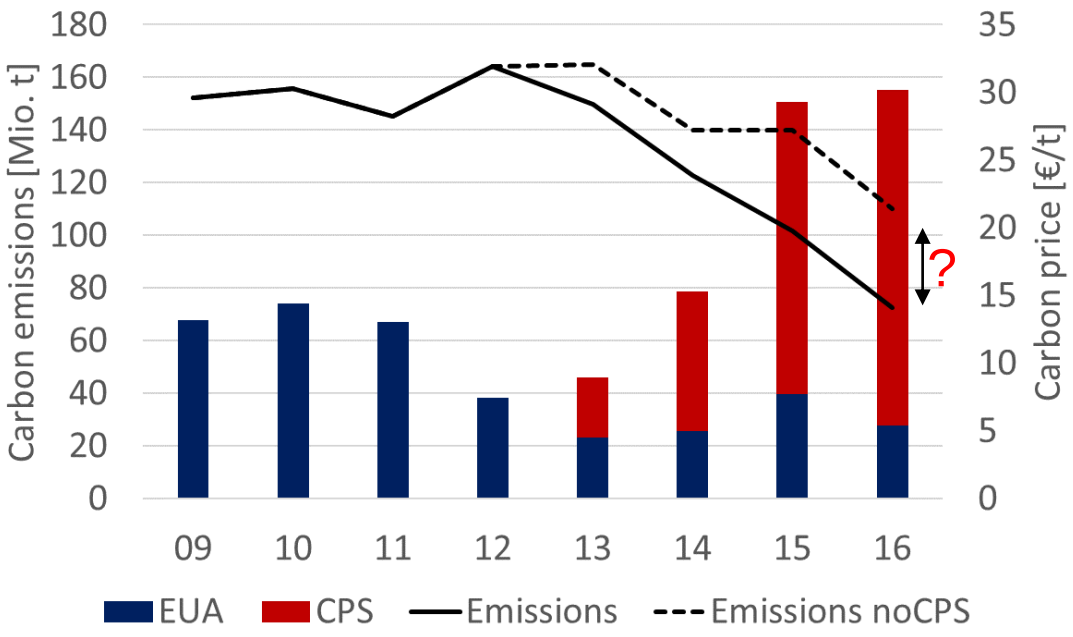
FIGURE 2. Annual electricity generation and emissions



How would emissions have evolved without CPS?

- Methodological challenges
  - Missing control group
  - No variation in treatment

- Methodological Approach
  1. Estimate prediction model using machine learning
  2. Predict unobserved counterfactual
  3. Treatment effect: Difference between observed outcome and «no policy» counterfactual



Literature and contribution

- Literature
  - Impact of fuel and carbon prices on emissions
    Empirical studies: *Martin et al. 2016; McGuiness & Ellerman 2008; Cullen & Mansur 2017*
    Simulation studies: *Delarue et al. 2008, 2010*
  - Machine learning for policy evaluation
    Burlig et al. 2017; Cicala 2017

- Contribution
  - Ex-post assessment of carbon price impacts in electricity sector and how they depend on fuel prices
  - Evaluation of treatment effect in the absence of a control group using machine learning

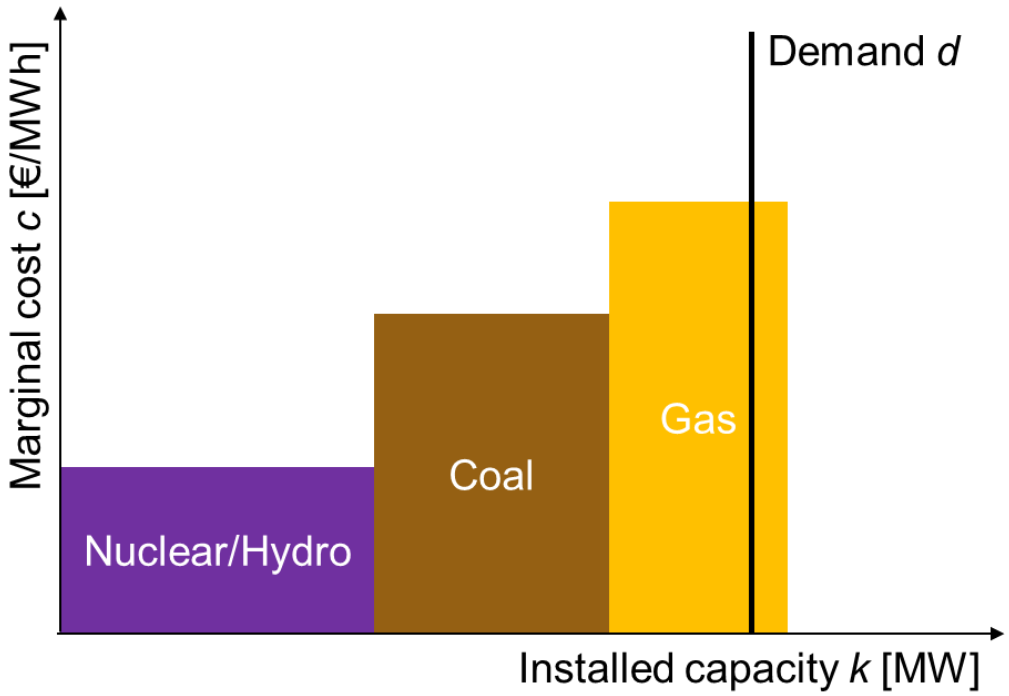
Empirical Implementation

Short-run electricity model

- Outcome of conventional (i.e., gas, coal) unit:

$$y_{it} = f\left(c_i, c_{-i}, k_i, k_{-i}, d\right)$$

- Main assumptions:
  - Inelastic demand
  - Perfect competition



Data

- Data
  - Hourly generation of each unit and demand (2009 – 2016)
  - Hourly available capacity
  - Fuel, EUA, CPS prices
  - Daily temperature

- Challenges
  - Marginal cost are not observed

  ➔Use fuel prices and temperature
  - No variation in CPS prices

  ➔Use carbon price inclusive fuel price ratio

$$r_t := \frac{p_t^{coal} + \theta^{coal}\left(p_t^{EUA} + p_t^{CPS}\right)}{p_t^{gas} + \theta^{gas}\left(p_t^{EUA} + p_t^{CPS}\right)}$$

Prediction Model

$$y_{it} = f_i\left(c_i, c_{-i}, k_i, k_{-i}, d\right) \quad \rightarrow \quad \hat{y}_{it} = \hat{f}_i\left(r_t, temp_t, k_i, k_{-i}, d, \mathbf{D}\right)$$

- Output as function of
  - Carbon price inclusive fuel price ratio
  - Temperature
  - Available capacities
  - Demand
  - Time fixed effects

- Prediction problem: $\widehat{f_i}$ is estimated from data using machine learning algorithms
- In our case: LASSO (penalized OLS)

Method

- Methodological Approach
  1. Estimate prediction model using machine learning

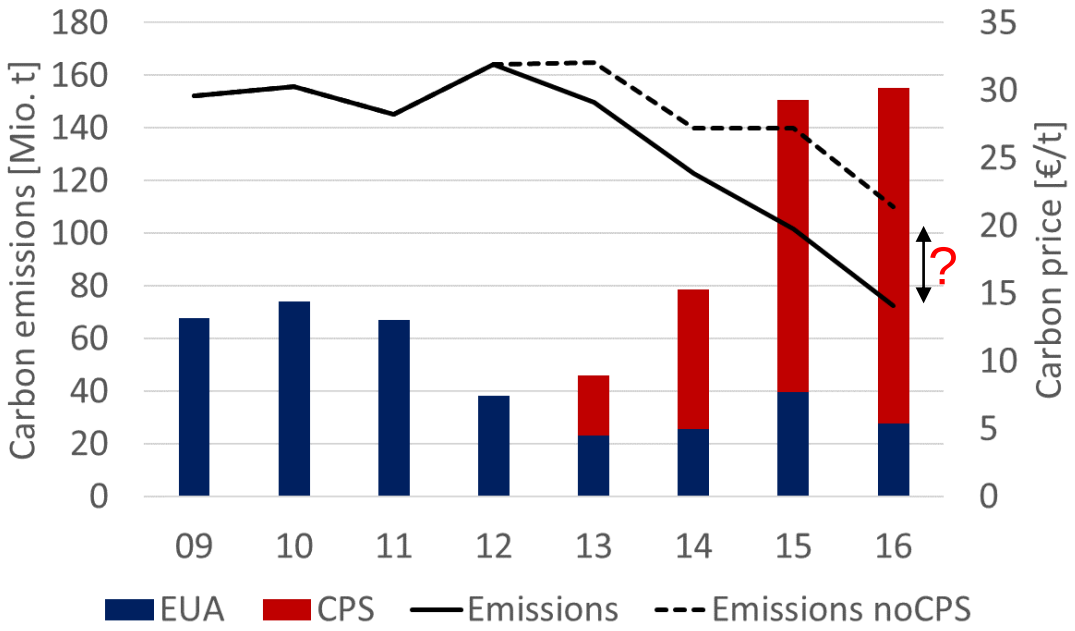
$$\hat{y}_{it} = \hat{f}_i\,(r_t, temp_t, k_i, k_{-i}, d, \mathbf{D})$$

  2. Predict unobserved counterfactual Fuel price ratio without CPS:

$$\bar{r}_t = \frac{p_t^{coal} + \theta^{coal} p_t^{l}}{p_t^{gas} + \theta^{gas} p_t^{E}}$$

  3. Treatment effect

$$\hat{\delta}_{it}^{CPS} = \hat{f}_i(r_t, temp_t, d_t, k_{it}, k_{-it}, \boldsymbol{D_t}) - \hat{f}_i(r_t = \bar{r}_t, temp_t, d_t, k_{it}, k_{-it}, \boldsymbol{D_t})$$



From generation to emissions and cost…

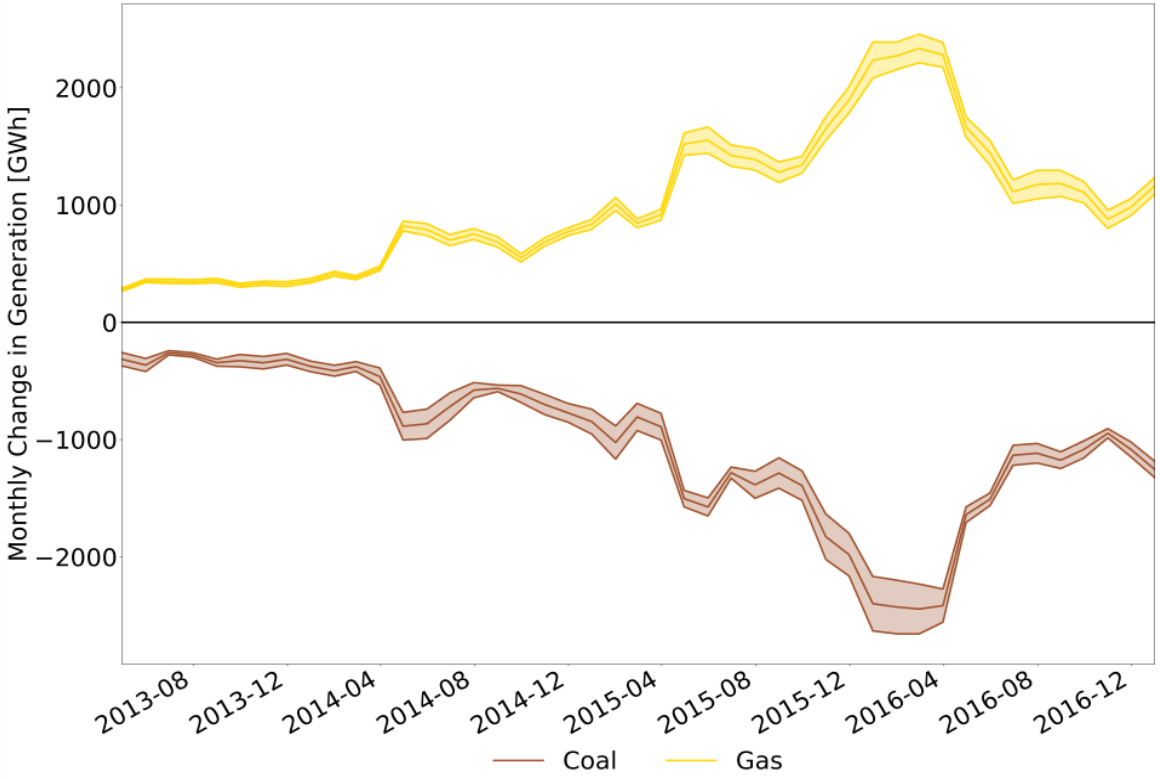
- Estimate impact of CPS on each coal and gas plant

- Impact on emissions: $\Delta E = \sum_{it} \hat{\delta}_{it}^{CPS} e_i$
- Short-run technical abatement cost: Change in fuel cost

Results

Impact of the CPS on coal and gas generation

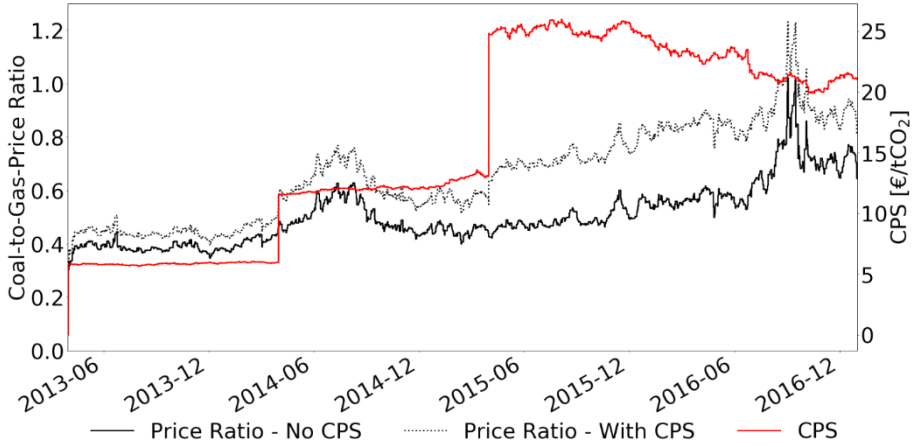
FIGURE 4. Monthly impact of CPS on generation

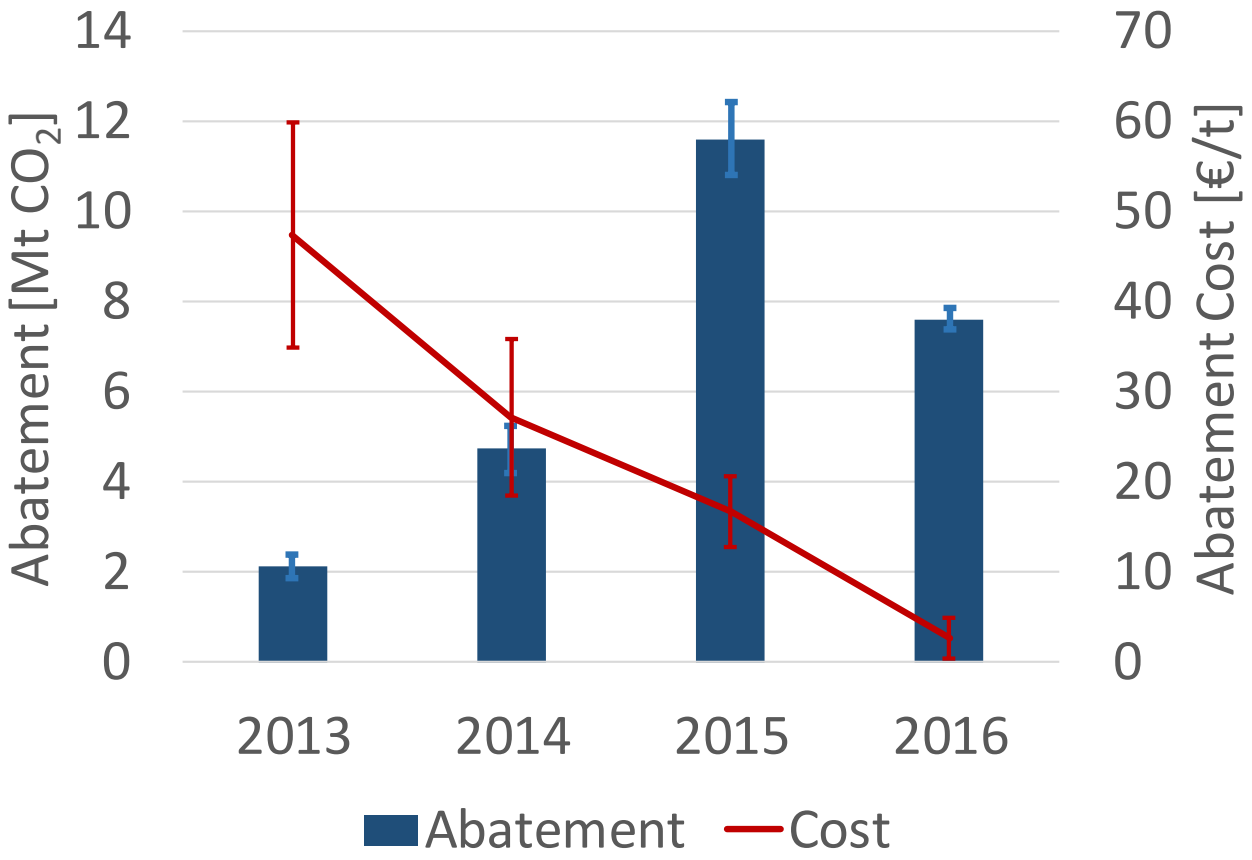


Notes: Shaded areas represent 95 % confidence intervals.

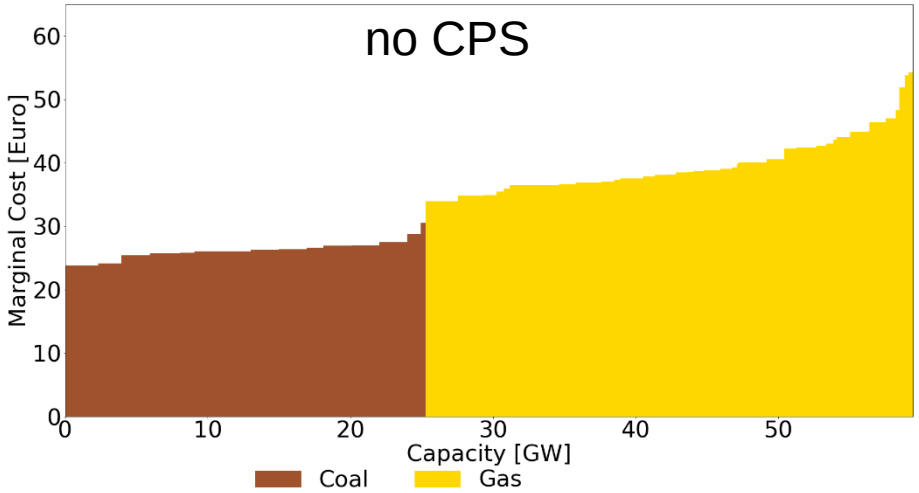
Impact of CPS on abatement and cost

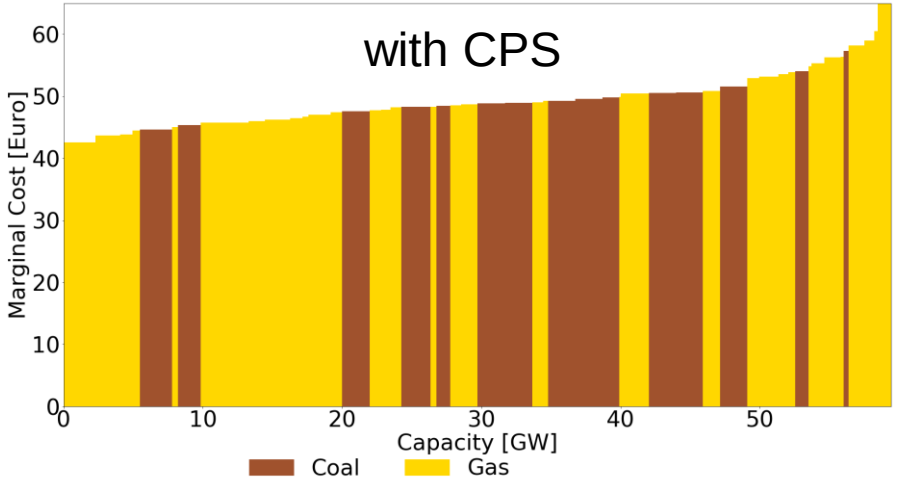
- Total abatement: 24.2 Mt (6.2%)
- Average cost: 18.2 €/t
- What drives CPS impacts?
  - level of CPS
  - coal-to-gas price ratio

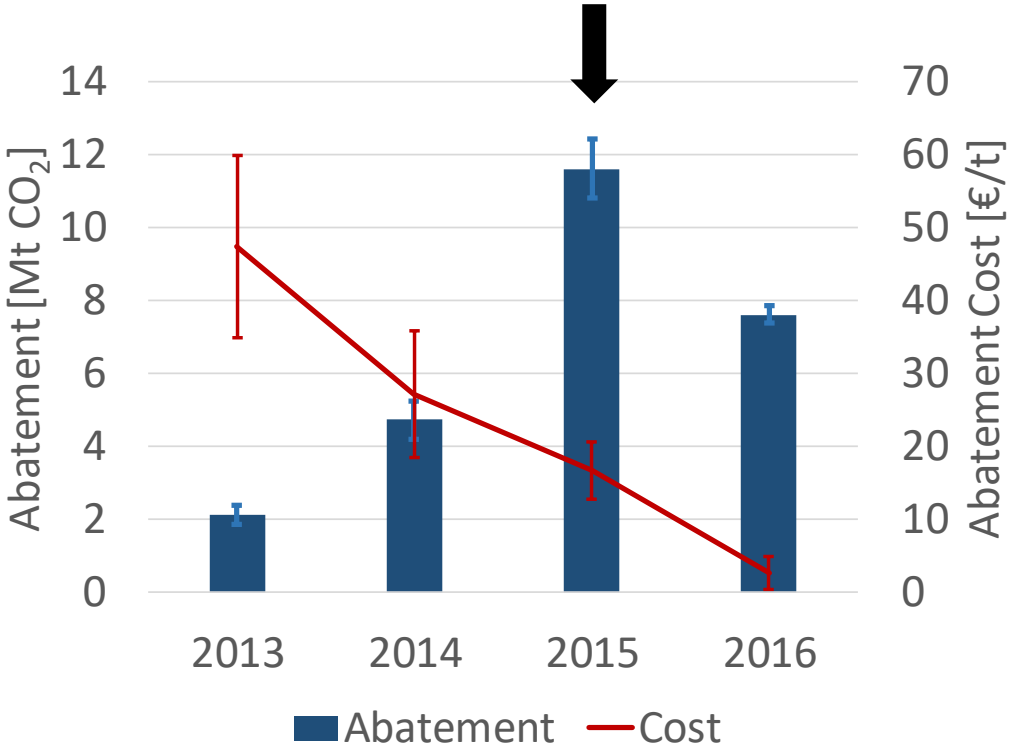




What affects CPS impacts? Fuel price ratio - 2015



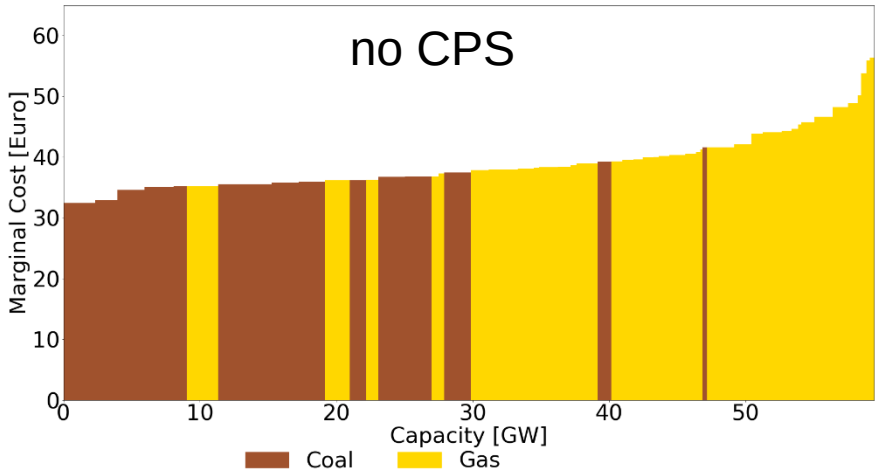


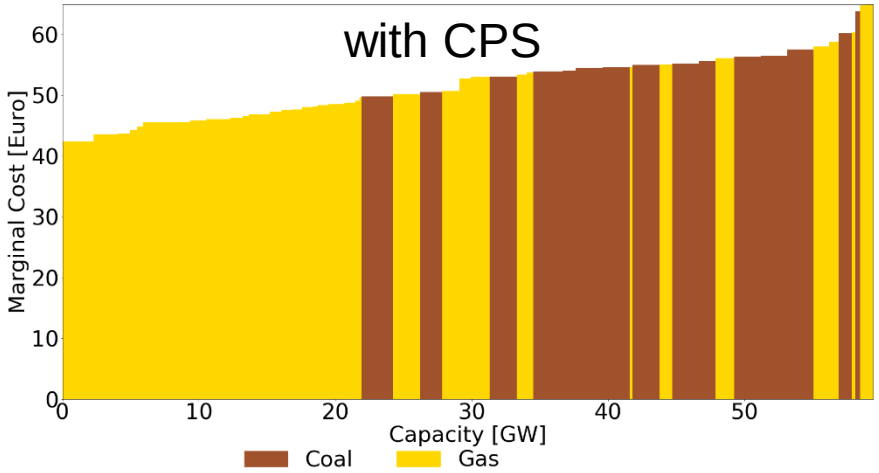


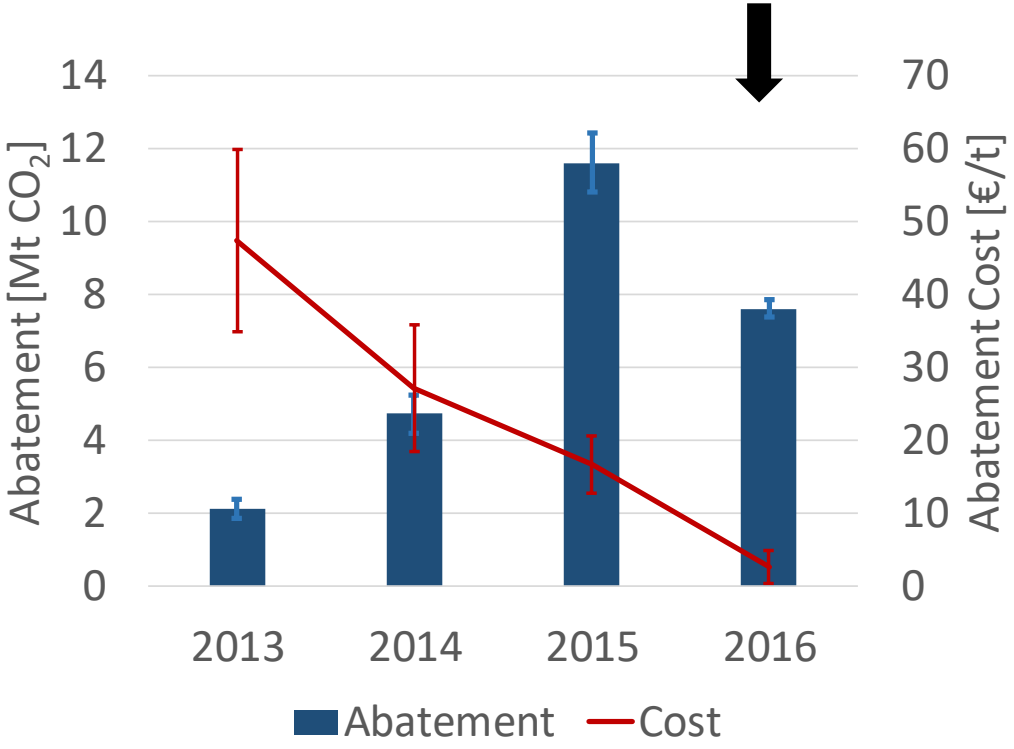
- Gas nearly as cheap as coal

➔ High abatement at relatively low cost

What affects CPS impacts? Fuel price ratio - 2016



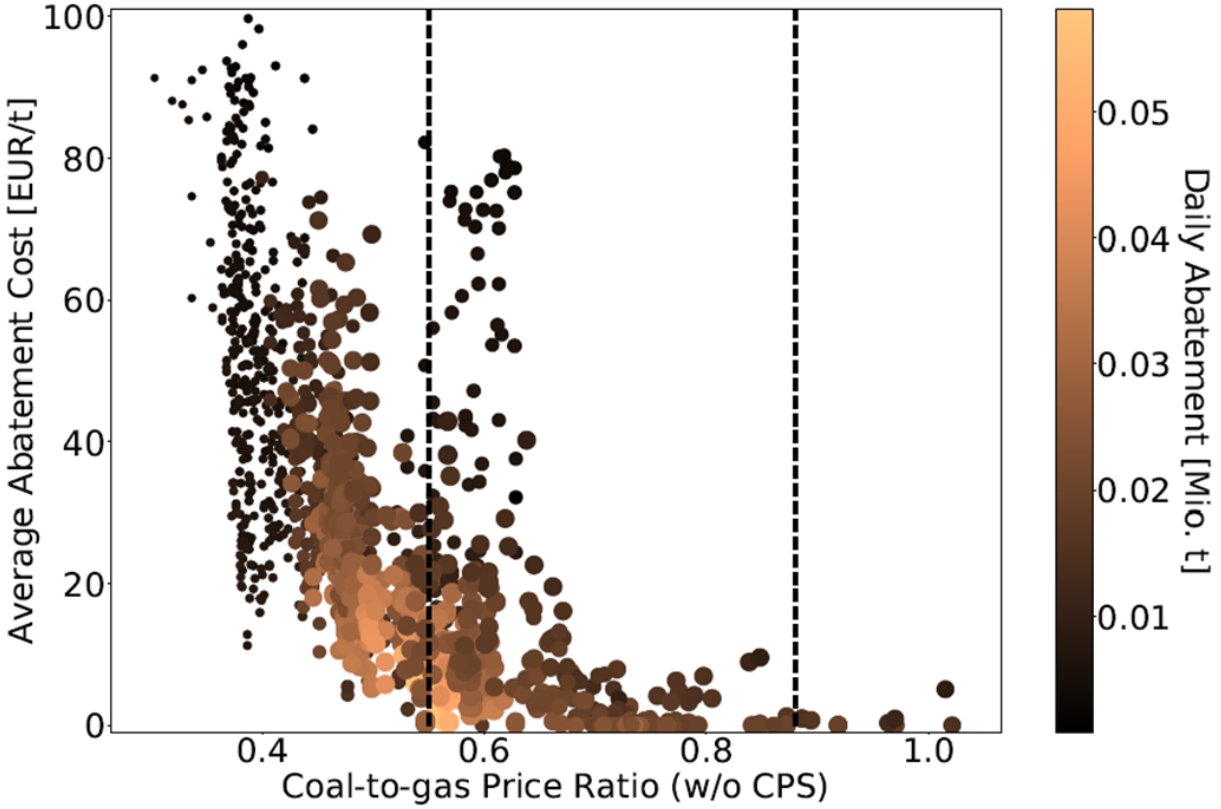


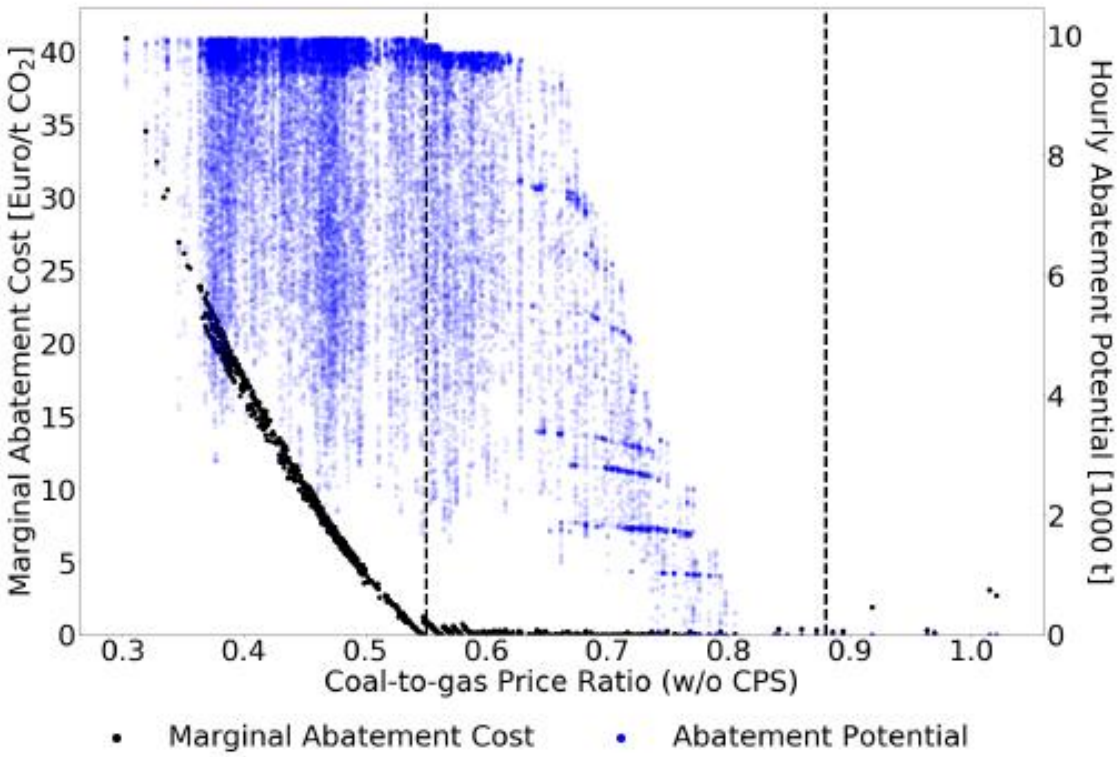


- Gas competitive without CPS

➔ Low abatement cost but also low abatement potential

Impact of carbon and fuel prices: Summary





Bubble size: Level of CPS

Summary

Summary: Impact of UK Carbon Price Support

- What was the impact of the CPS on UK carbon emissions?
  - 45 TWh coal generation replaced by gas
  - 24 $MtCO_2$ abated
  - 18 €/tCO_2 on average

- Impact and cost of CPS are affected by
  - level of CPS
  - coal-to-gas price ratio

  ➔Higher coal prices decrease abatement cost but also decrease abatement potential

Literature

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Backup

How to estimate the treatment effect?

- Treatment effect

$$\delta_{it}^{\bar{z}} = y_{it} - f_i\left(x_{it}, h_{it}, z_t = \bar{z}\right)$$

- Function f_i not known
  ➔ <u>Predictor</u> needed

$$\hat{\delta}_{it}^{\bar{z}} = y_{it} - \hat{f}_{it}\left(x_{it}, z_t = \bar{z}\right)$$

- Not a problem of parameter estimation but outcome prediction problem
  ➔ Machine learning approach

Machine learning for predictions

$$\hat{f}_i^{\alpha} := \arg\min_{f_i \in \mathcal{F}} \sum_t \left[\left(y_{it} - f_i^{\alpha}\left(x_{it}, z_t\right) \right) \right]^2$$

- Choose f_i^{α} to minimize <u>in-sample</u> mean-squared error
- Cross-validation to choose hyperparameters (α) to minimize <u>out-of-sample</u> prediction error
- By design, in-sample bias to improve prediction performance

Estimating treatment effects

$$\hat{\delta}_{it}^{\bar{z}} = \hat{f}_i^{\alpha*}(x_{it}, z_t) - \hat{f}_i^{\alpha*}(x_{it}, z_t = \bar{z})$$

- Treatment estimator: Difference between
  - predicted outcome under treatment
  - predicted outcome under no-treatment (counterfactual)

- Need to account for machine learning induced bias
  ➔ Use of difference estimator

When is this the correct treatment effect?

- Treatment effect $$\delta_{it}^{\bar{z}} = y_{it} - f_i\left(x_{it}, h_{it}, z_t = \bar{z}\right)$$
- Condition 1
  Observed controls independent of treatment $$x_{it} \perp\!\!\!\perp z_t$$
- Condition 2
  Unobserved controls are independent of treatment (conditional on observed ones) $$h_{it} \perp\!\!\!\perp z_t | x_{it}$$

Do we estimate the correct treatment effect?

- Treatment effect $$\hat{\delta}_{it}^{\bar{r}} = \hat{f}_i\left(r_t, temp_t, k_i, k_{-i}, d, \mathbf{D}\right) - \hat{f}_i\left(r_t = \bar{r}_t, temp_t, k_i, k_{-i}, d, \mathbf{D}\right)$$

- Condition 1
  Observed controls independent of treatment $$(p_t^{Coal}, p_t^{Gas}, p_t^{EUA}, k_{it}, temp_t, d_t) \perp\!\!\!\perp CPS_t$$

- Condition 2
  Unobserved controls are independent of treatment (conditional on observed ones) $$h_{it} \perp\!\!\!\perp CPS_t | (p_t^{Coal}, p_t^{Gas}, p_t^{EUA}, k_{it}, temp_t, d_t)$$