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How Effective was the UK Carbon Tax?
A Machine Learning Approach to Policy Evaluation

Jan Abrell, **Mirjam Kosch,** Sebastian Rausch

IAEE, 25.8.2019

Two main questions

1. What was the impact of the UK carbon price support on emissions?

2. How can we use machine learning for policy evaluation in the absence of a control group?

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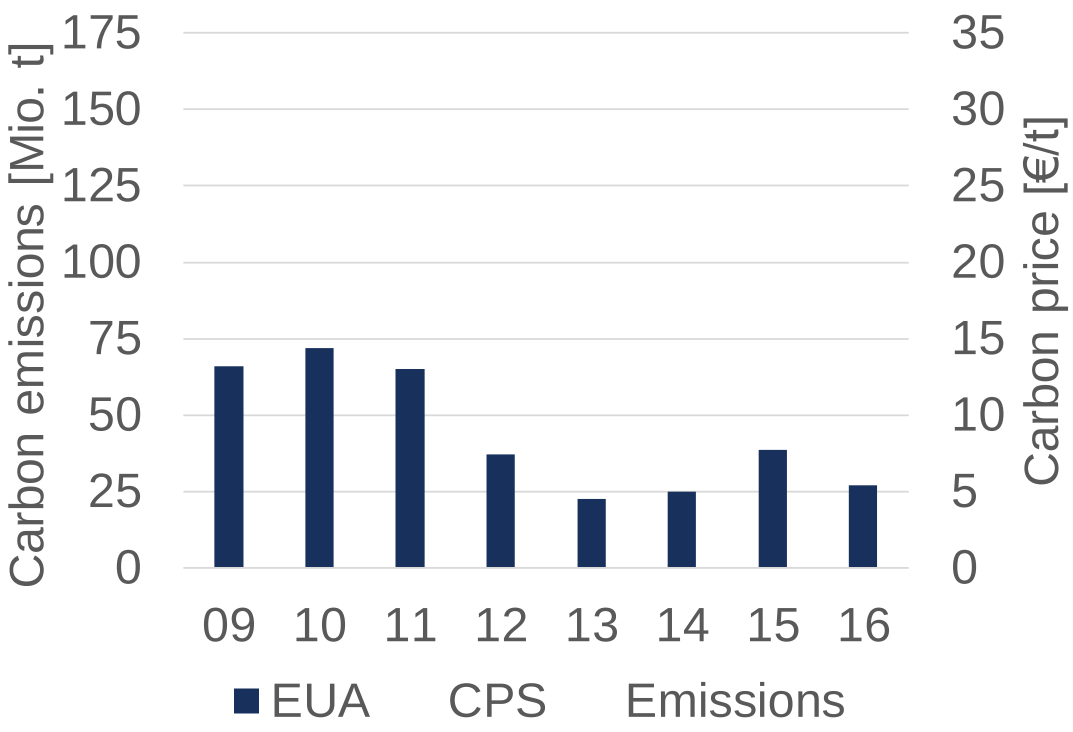
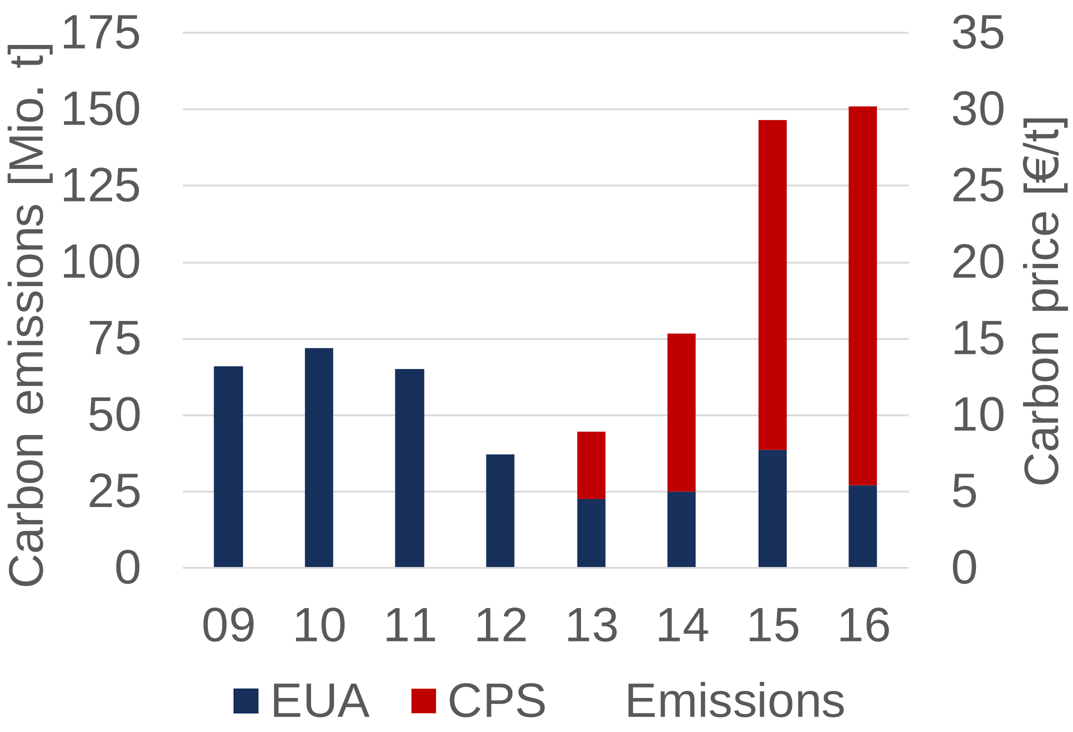
Low CO_2 price…

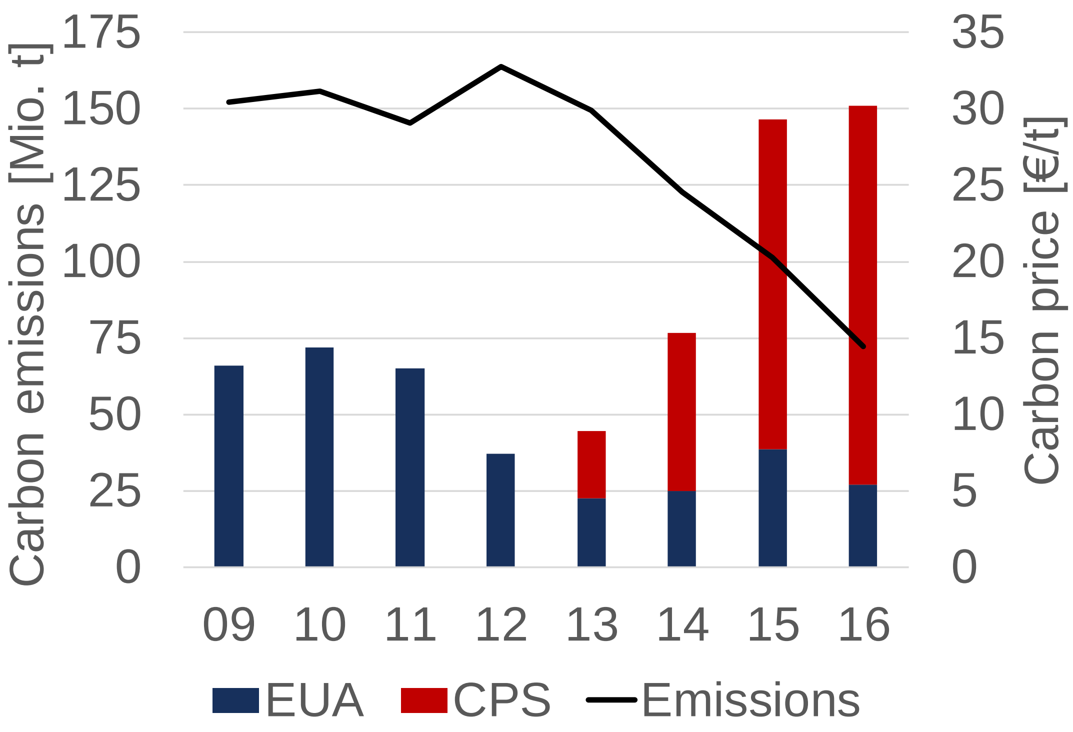


Low CO_2 price leads to introduction of UK carbon tax



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

Low CO_2 price leads to introduction of UK carbon tax



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?

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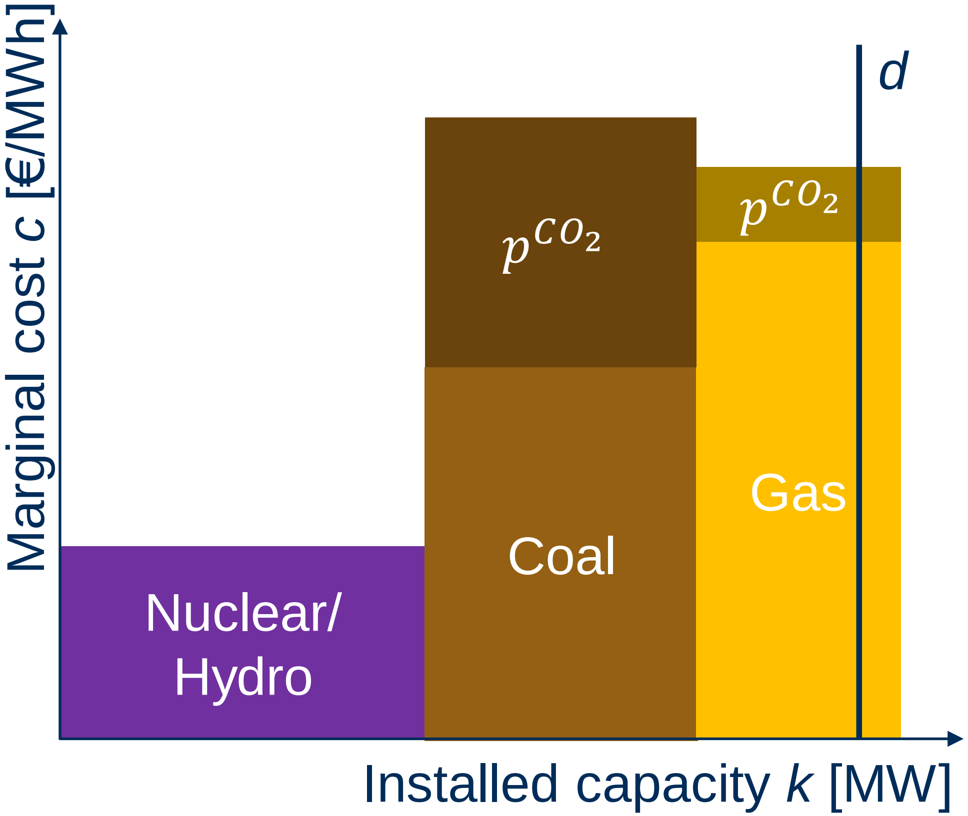
Coal-to-gas switch

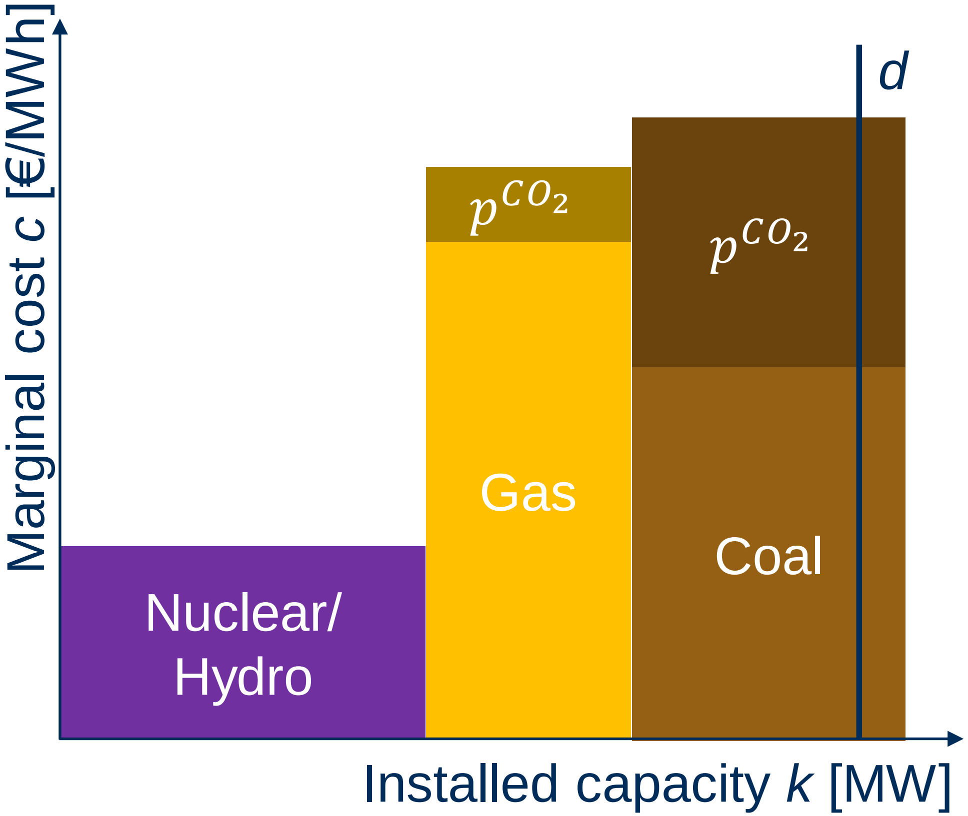
Impact of CPS on power market?



Coal-to-gas switch – and other reasons for lower emissions

Impact of CPS on power market?

→ Coal-to-gas switch

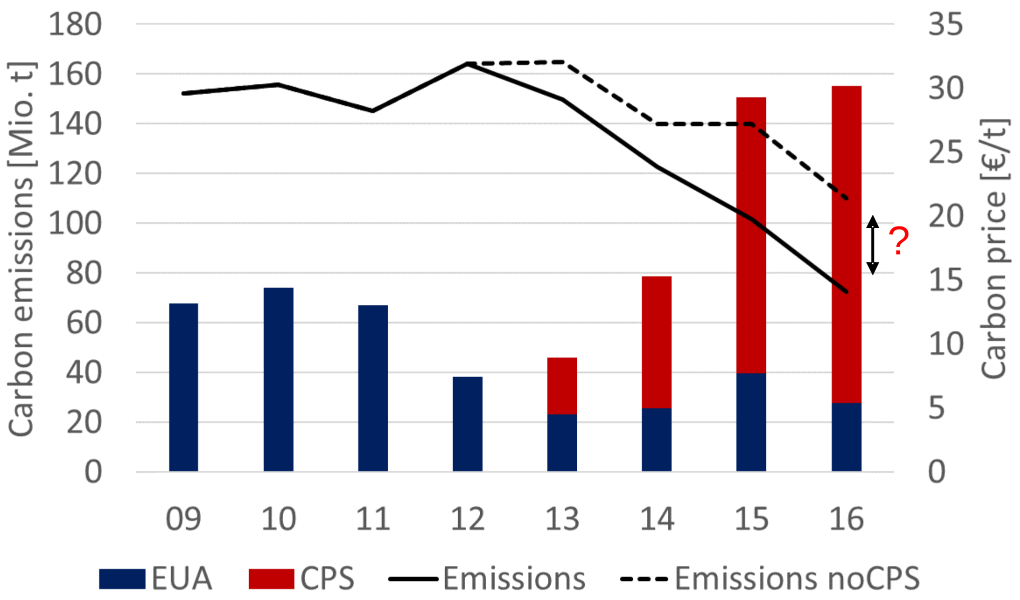


Other reasons for lower emissions?

- More renewables
- Lower demand
- More imports
- Less fossil capacity

→ How to isolate effect of CPS?

How would emissions have evolved without CPS?



– Methodological challenge: No control group

– Methodological Approach

1. Predict unobserved counterfactual
   (using machine learning)

2. Treatment effect: Difference between observed and «no policy» counterfactual

Literature and contributions

Literature

– Impact of fuel and carbon prices on electricity sector emissions
  – Empirical studies: *Martin et al., 2016; McGuiness & Ellerman 2008; Martin et al. 2014;* Jaraite and Di Maria, 2015; *Cullen & Mansur 2017; Leroutier, 2019*
  – Simulation studies: *Delarue et al. 2008, 2010*

– Machine learning for policy evaluation
  Burlig et al. 2019; (Cicala 2017)

Contributions

  – Ex-post assessment of carbon price impacts in electricity sector and how they depend on fuel prices
  – Program evaluation in the absence of a control group using machine learning

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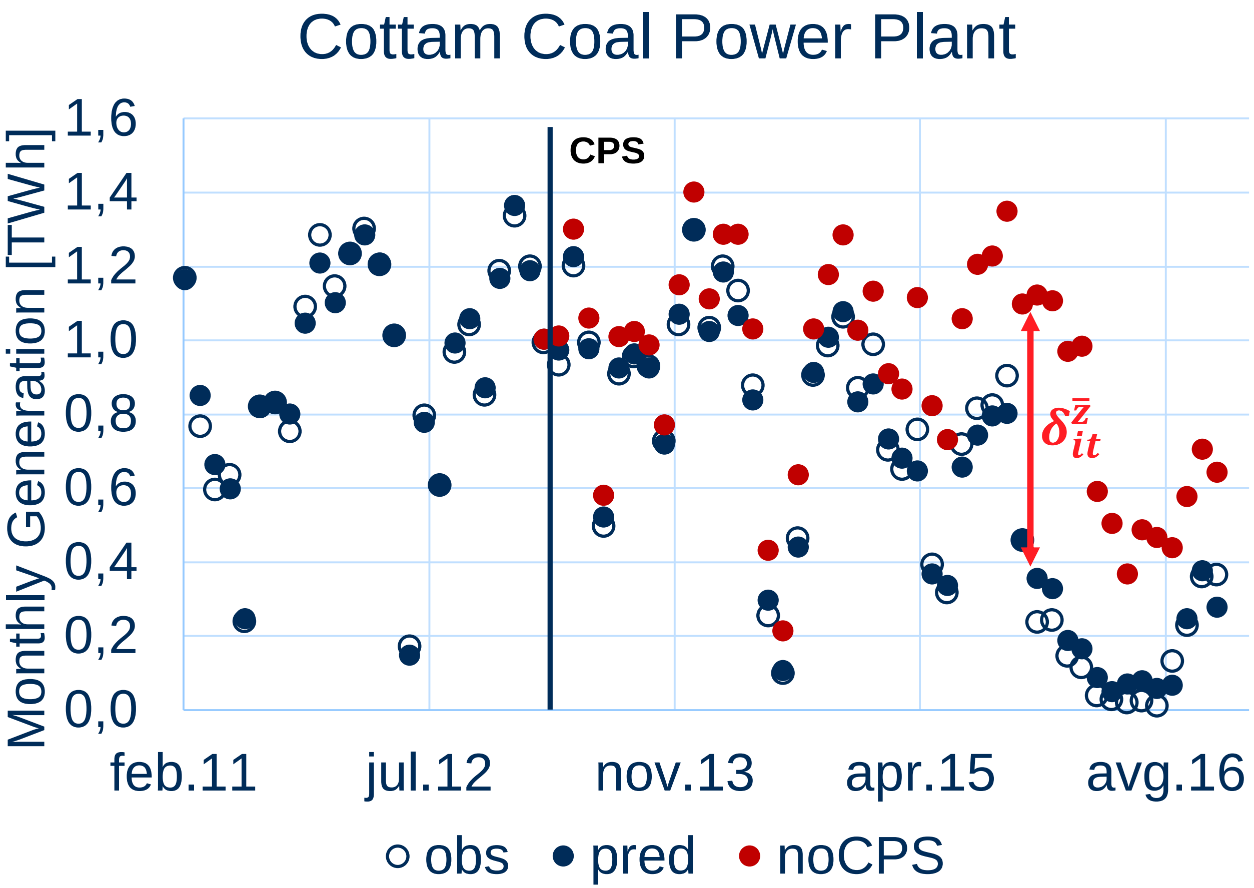
Methodological Approach in a Nutshell



Proposed procedure

1. Theoretical model

$$y_{it} = f_i(x_{it}, z_t) + \epsilon_{it},$$

$$\epsilon_{it} \sim (0, \sigma_\epsilon^2); \epsilon_{it} \perp (x_{it}, z_t)$$

x_{it} controls

z_t treatment variable

2. Train prediction model *f*

➔ Machine Learning approach

3. Counterfactual prediction

$$y_{it}^{\bar{z}} = f_i(x_{it}, z_t = \bar{z}_t)$$

$\bar{z}_t$ counterfactual treatment

4. Derive treatment effect

$$\delta_{it}^{\bar{z}} = y_{it} - y_{it}^{\bar{z}}$$

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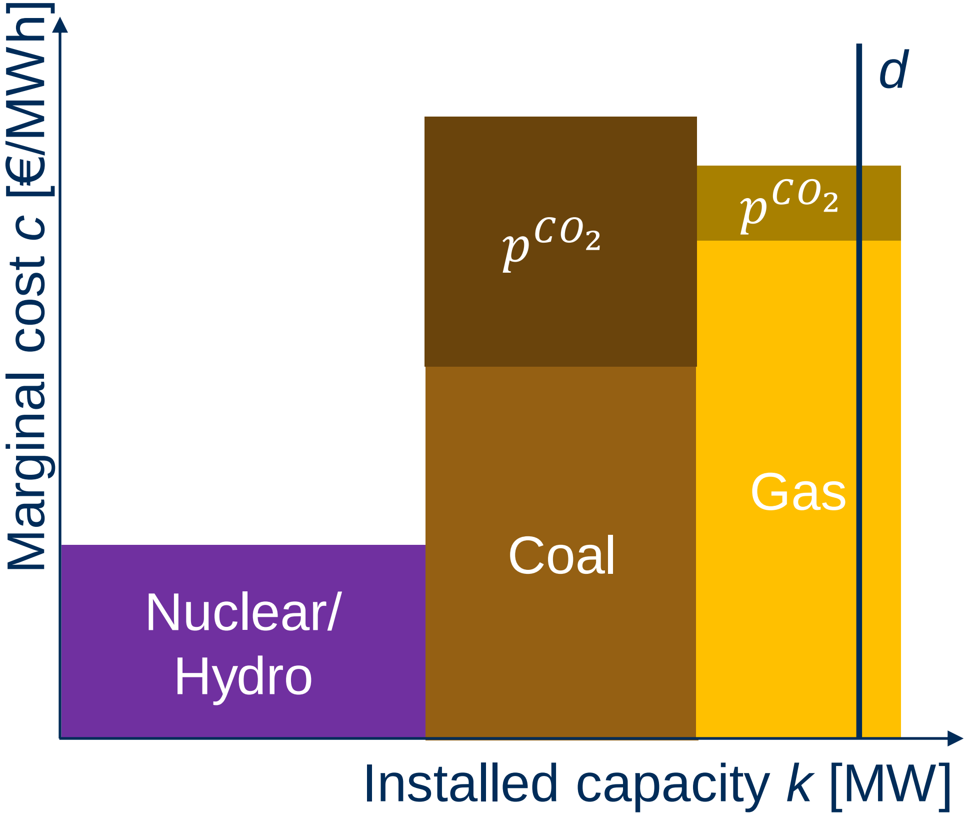
1 Theoretical Model: Short-run Electricity Market



Generation Capacity

$$y_{it} = f_i\,(D_t, c_{it}, K_{it}, c_{-it}, K_{-it})$$

Demand Marginal cost

2 Train prediction model with data

Hourly generation of each unit

Hourly available capacity

$$y_{it} = f_i\left(D_t, c_{it}, K_{it}, c_{-it}, K_{-it}\right) \rightarrow y_{it} = f_i\left(r_t, temp_t, D_t, K_{it}, K_{-it}, \boldsymbol{\phi}_t\right)$$

Hourly demand

Hourly marginal cost per unit

Two challenges

1. Marginal cost not observed

$$c_{it} = f_i(p_t^{gas}, p_t^{coal}, p_t^{EUA}, p_t^{CPS}, temp_t)$$

Daily fuel and carbon prices

Daily mean temperature

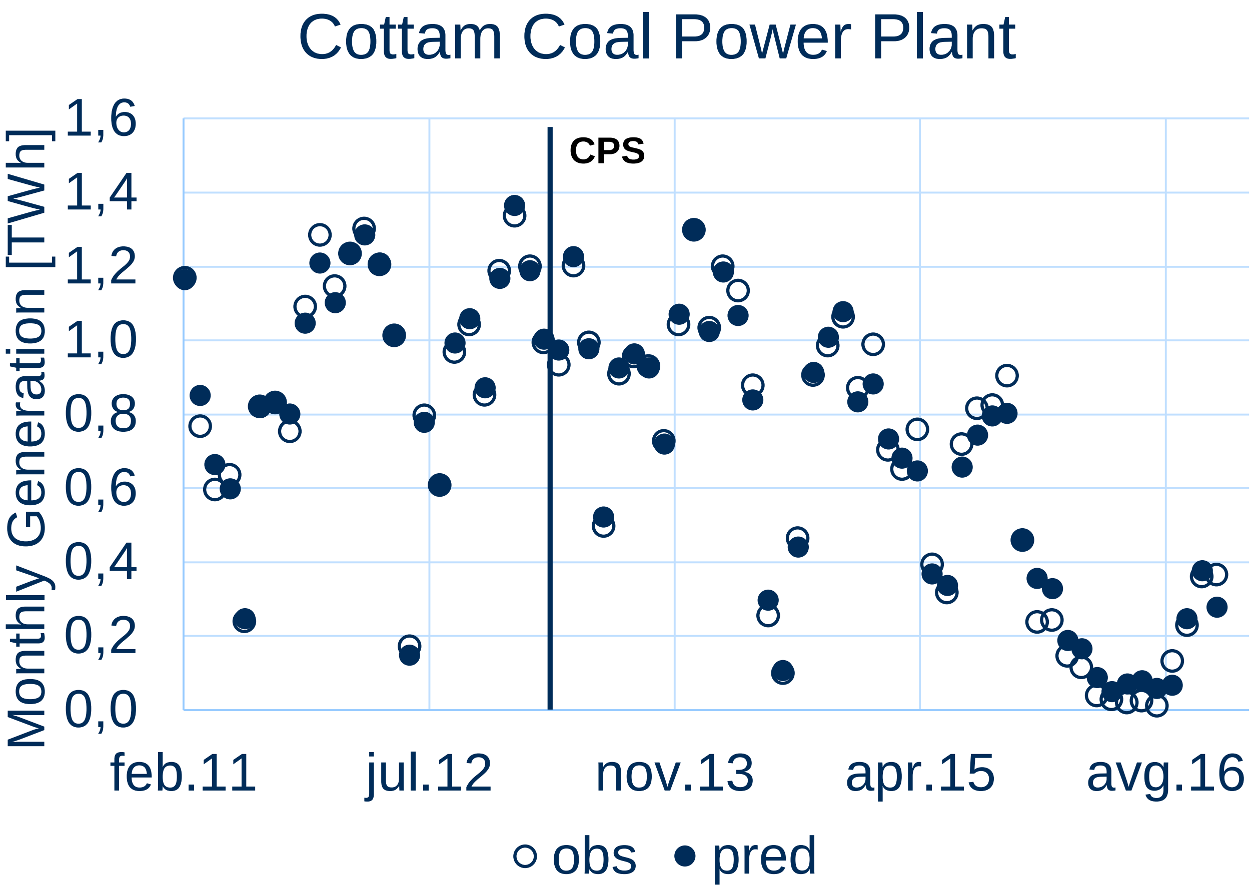
2. Little variation in CPS prices

➔ Use carbon price inclusive fuel price ratio as treatment variable

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

Sources: ELEXON (2017), EIKON (2017)

2 Train prediction model with data



- Estimate $\widehat{f}_i$ from input data using machine learning
  $\hat{y}_{it} = \hat{f}_i\,(r_t, D_t, K_{it}, K_{-it}, temp_t, \boldsymbol{\phi_t})$
- In our case:
  LASSO (penalized OLS)

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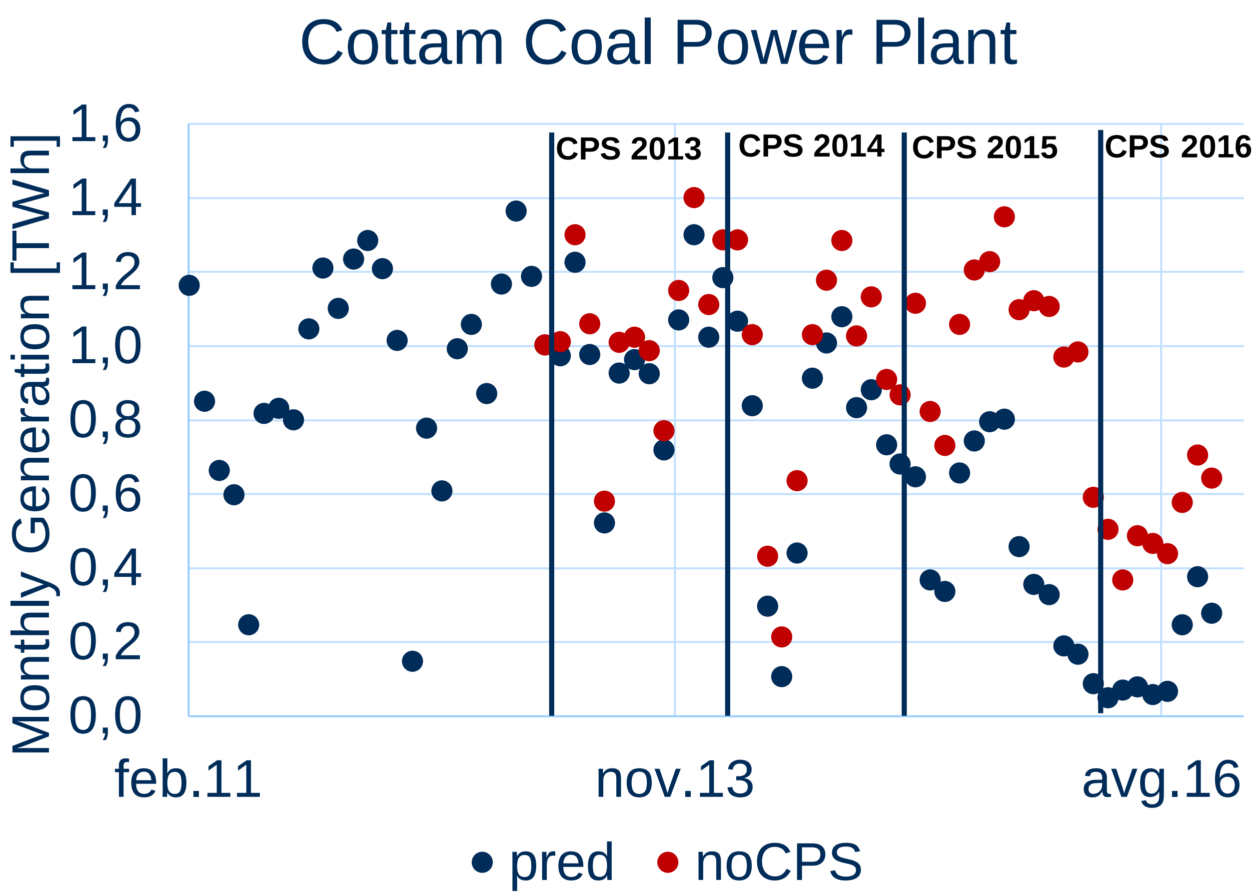
3 Counterfactual prediction

What would have happened without the CPS?

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

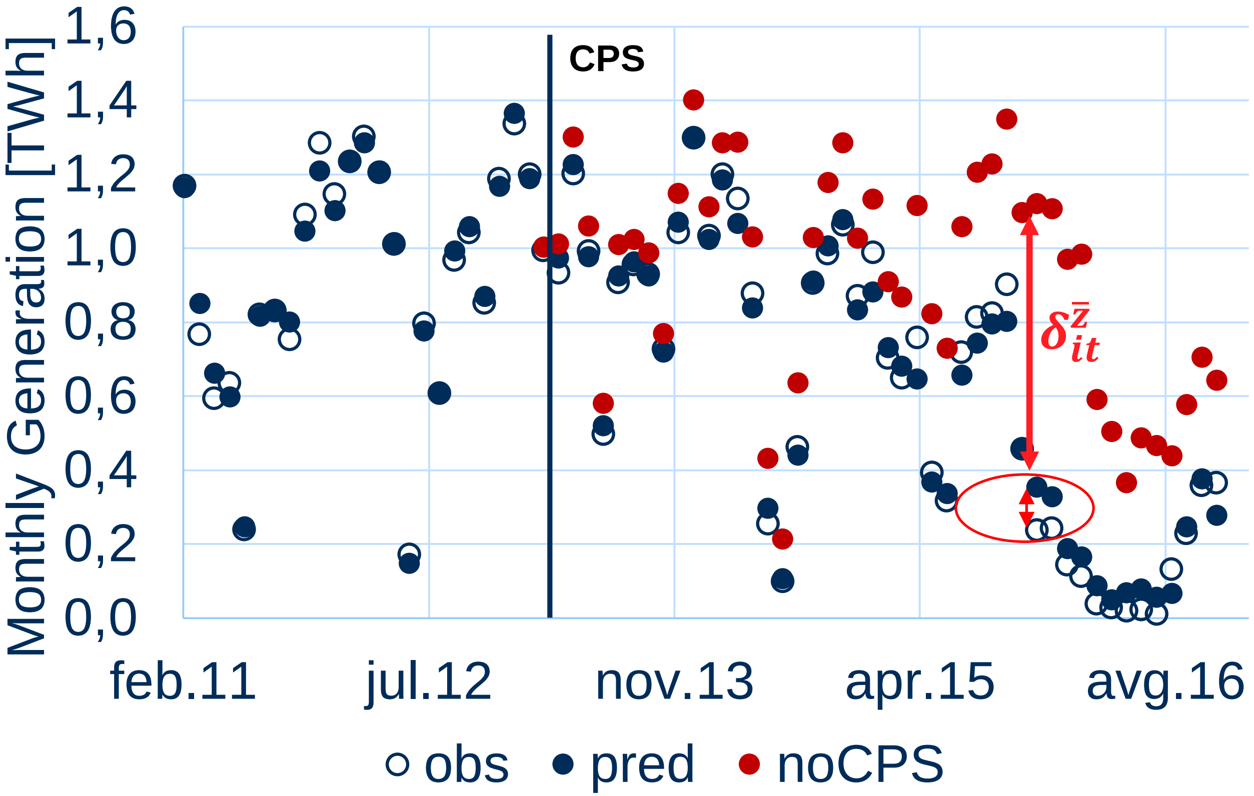
Set CPS to zero for counterfactual: $\hat{y}_{it}{}^{noCPS} = \hat{f}_i(r_t(CPS = 0), D_t, K_{it}, K_{-it}, temp_t, \boldsymbol{\phi_t})$



- Cheaper coal
- More coal (and less gas) generation

4 Derive Treatment Effect

Cottam Coal Power Plant



$$\hat{\delta}_{it}{}^{CPS} = \hat{y}_{it} - \hat{y}_{it}{}^{noCPS}$$

Why not:

Observed – Counterfactual?

➔ prediction errors lead to biased estimate of treatment

➔ eliminate bias by comparing predictions

Results

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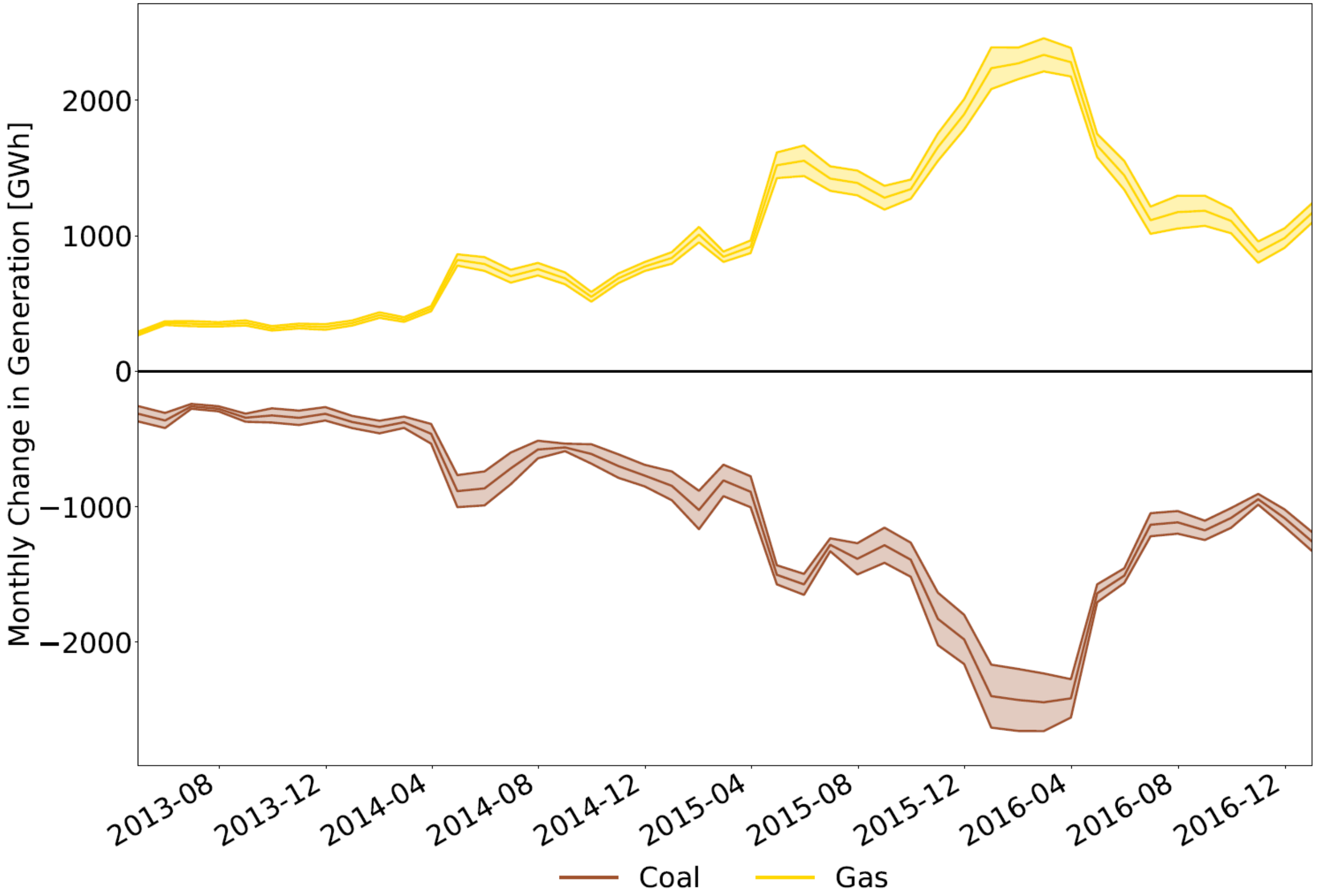
Impact of CPS on coal and gas generation

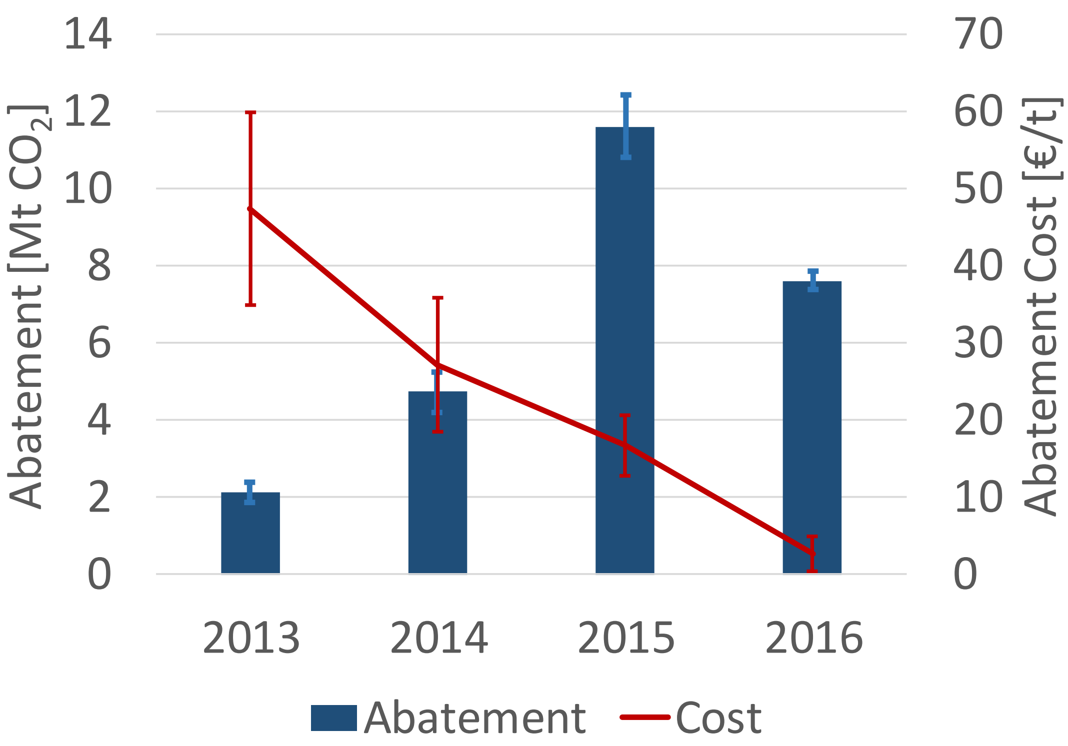


- Coal (gas) generation decreased (increased) by 45 TWh
- Generation impacts robust to inclusion of fixed effects
- Generation impacts sum up to zero

CPS reduces emissions – at relatively low cost

- Abatement: $\Delta E_i = \sum_t e_i \hat{\delta}_{it}$

- Technical abatement cost: Change in fuel cost



Avg. abatement: 24.2 Mt (6.2%)

Avg. cost: 18.2 €/t

➔What drives the impact?

- ➔Level of CPS
- ➔Coal-to-gas price ratio

Summary

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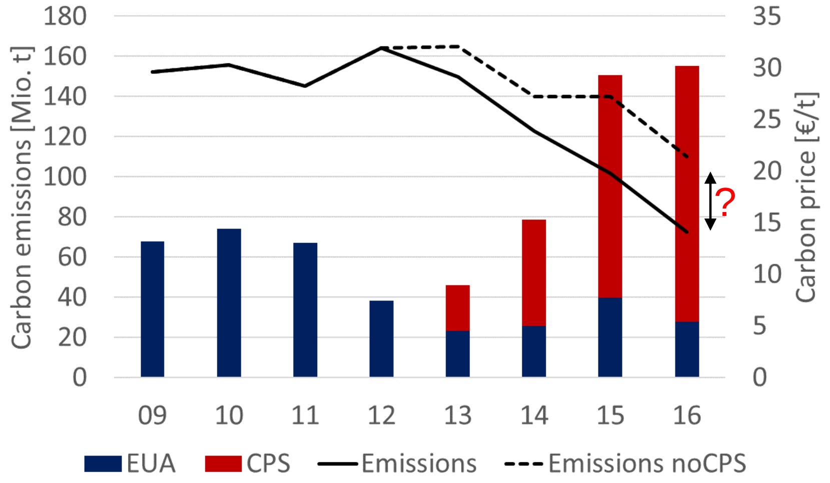
Summary

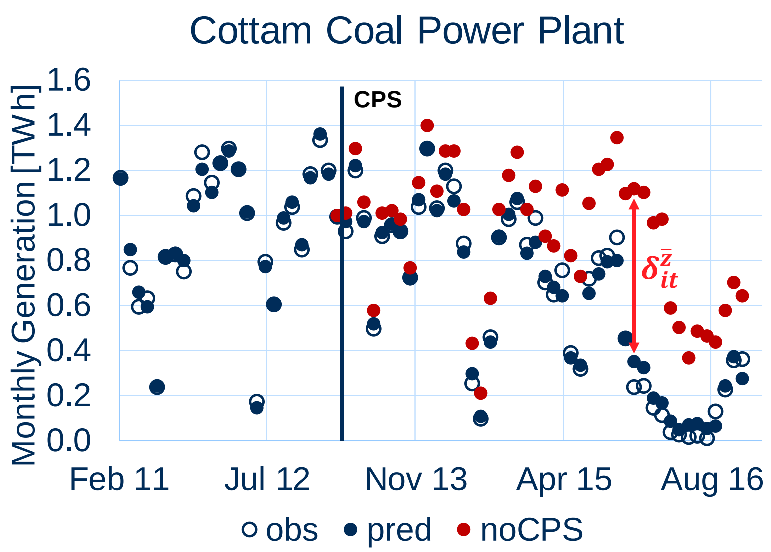
1. What was the impact of the UK carbon price support on emissions?

   ➔ Between 2013 and 2016, CPS lead to an emission reduction of around 6% at average cost of 18.2€/t.

2. How can we use machine learning for policy evaluation in the absence of a control group?

   ➔ Estimate unobserved counterfactual.





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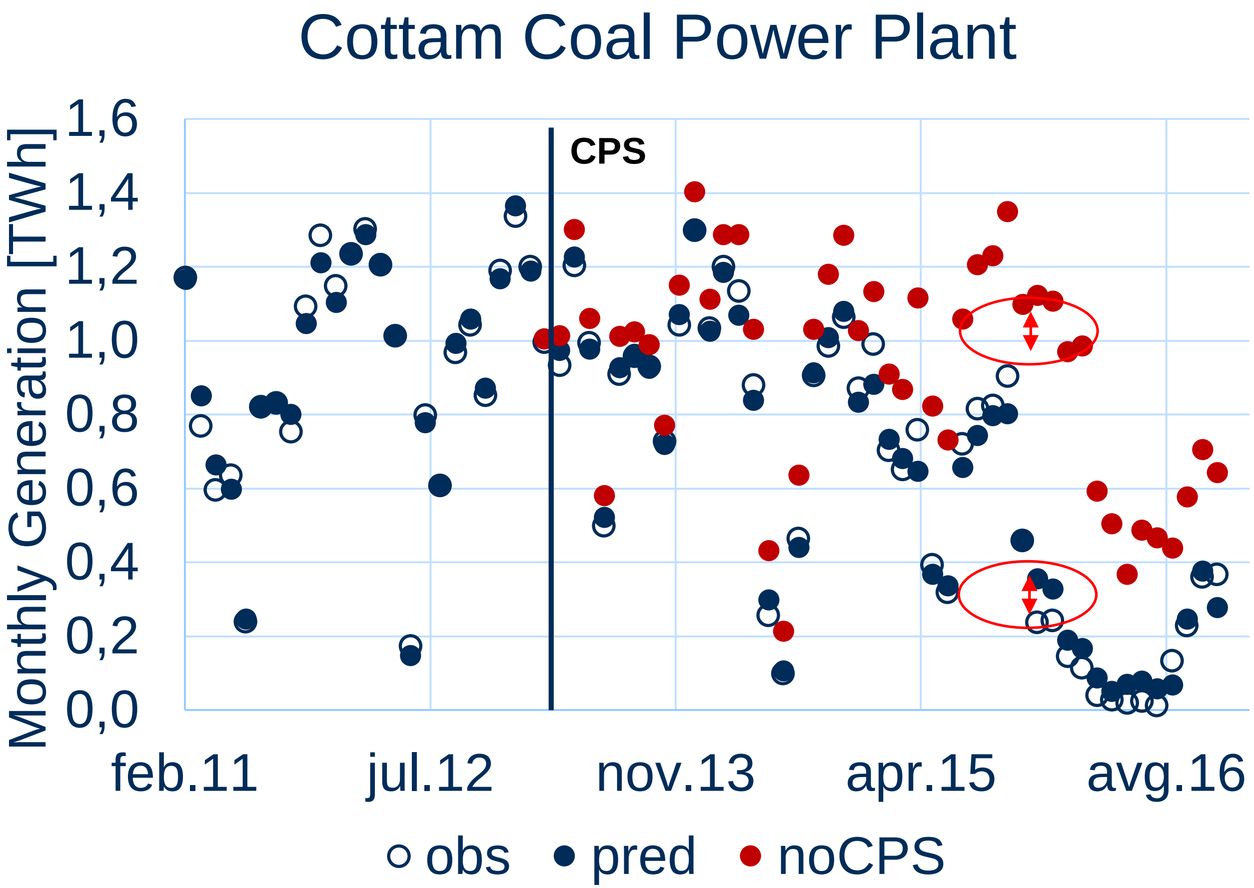
Backup Slides

When does the approach work?



- Prediction errors independent of treatment

➢ Observed prediction errors do not depend on treatment level

➢ Do not predict "too far" out of sample (covariate overlap; positivity) $\Pr[r_t | K_i, temp_t, D_t] > 0$

- Independence of observed covariates $\left(p_t^{coal}, p_t^{gas}, p_t^{EUA}, K_{it}, temp_t, D_t\right) \perp p_t^{CPS}$
- Conditional independence of unobserved covariates (h_{it}) $\mathrm{h_{it}} \perp p_t^{CPS} | \left(p_t^{coal}, p_t^{gas}, p_t^{EUA}, K_{it}, temp_t, D_t\right)$

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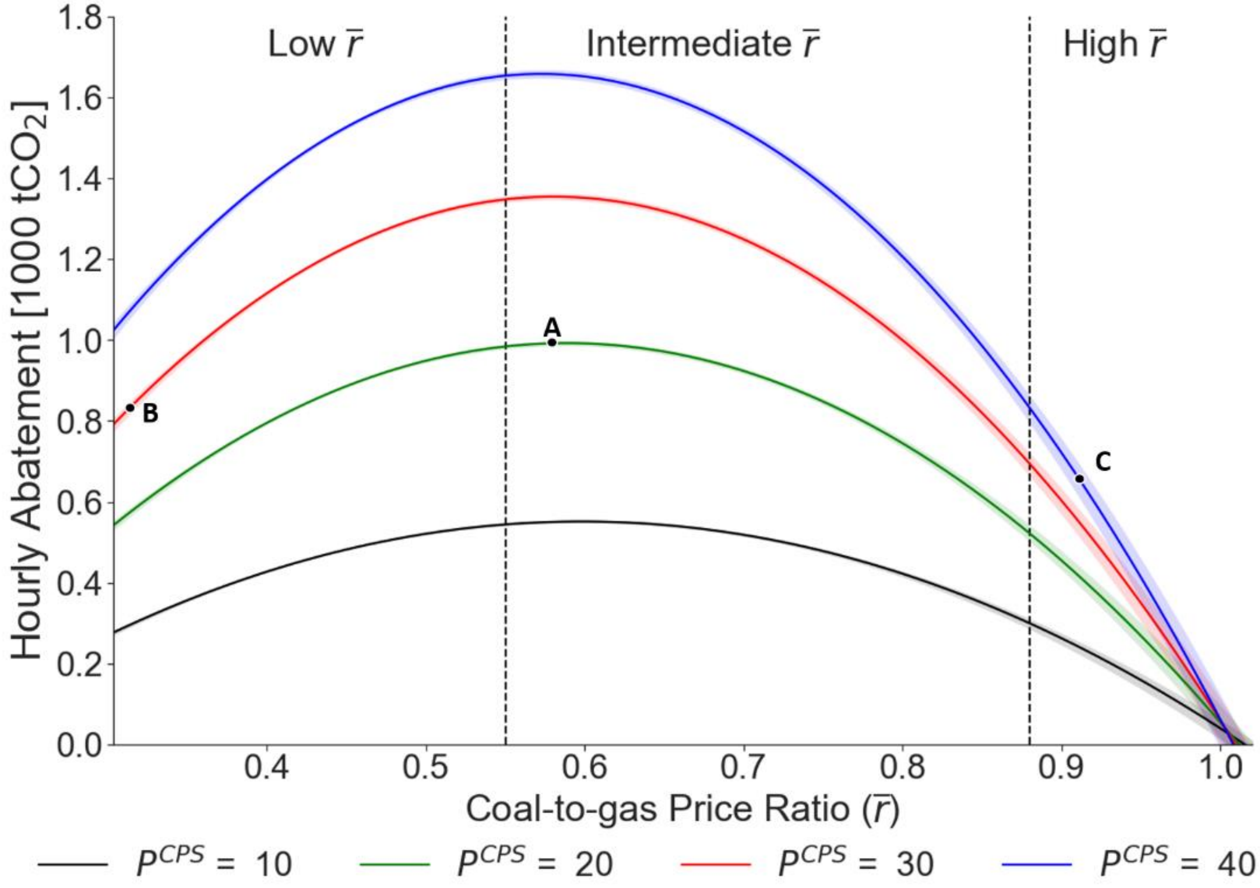
The Impact of Fuel Prices on Abatement

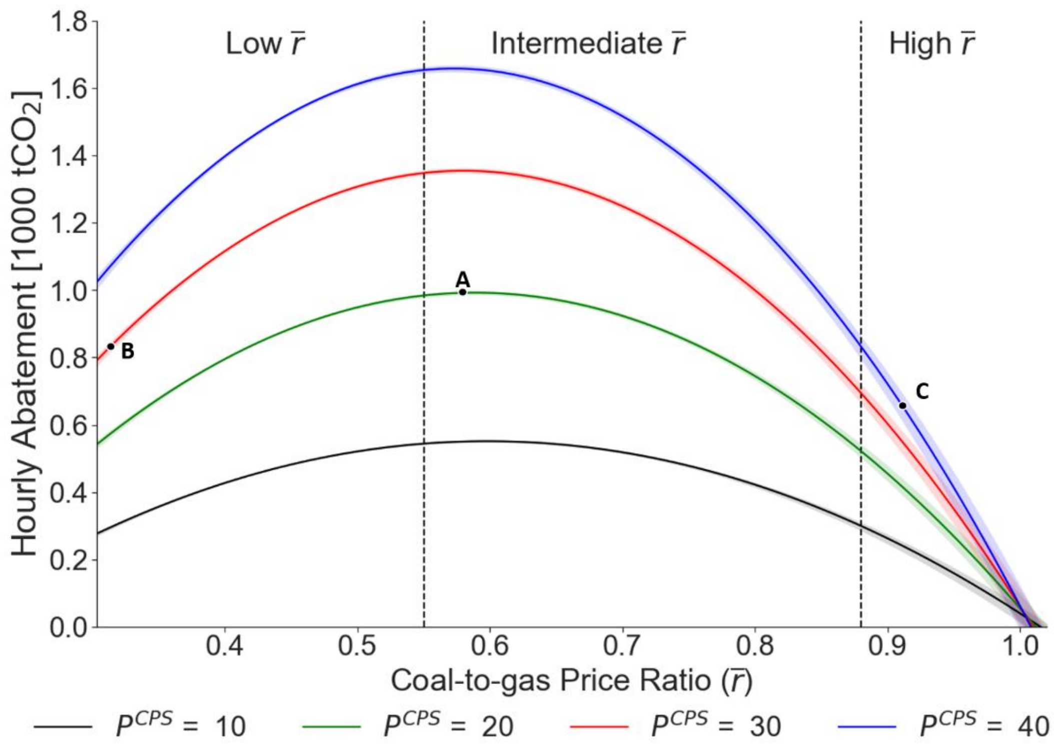
Low r	Intermediate r	High r
$p^{coal} < p^{gas}$	$p^{coal} \sim p^{gas}$	$p^{coal} > p^{gas}$

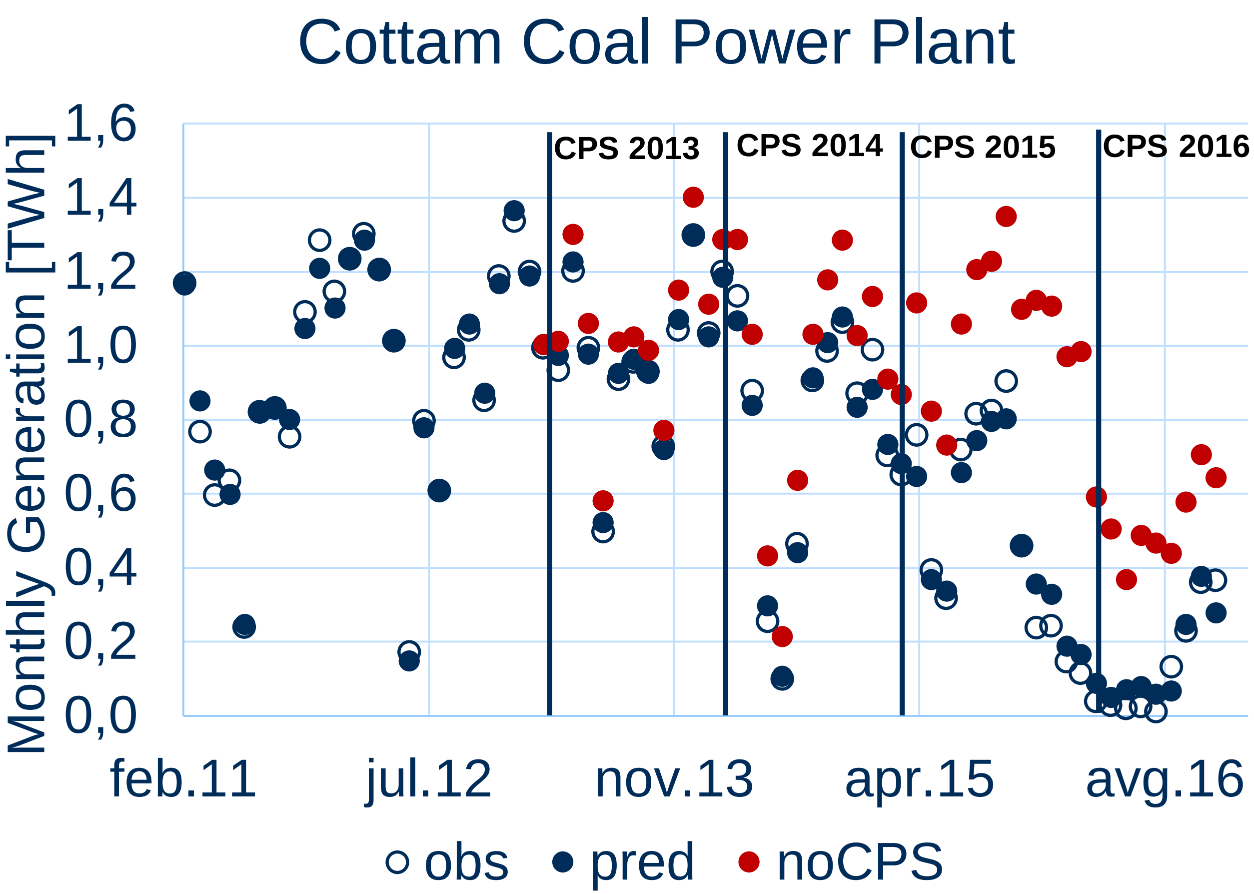


→ Higher tax does not necessarily imply higher abatement

The Impact of Fuel Prices on Abatement

Low r	Intermediate r	High r
$p^{coal} < p^{gas}$	$p^{coal} \sim p^{gas}$	$p^{coal} > p^{gas}$
High abatement potential	Decreasing abatement potential	No abatement potential
High technical cost	Moderate technical cost	Zero technical cost
Low abatement	High Abatement	Low abatement





Proposed procedure

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x_{it} observed controls

z_t treatment variable

(2) Estimate predictor of process *f*

➔ Machine Learning approach

(3) Counterfactual prediction

$$y_{it}^{\bar{z}} = f_i(x_{it}, z_t = \bar{z}_t)$$

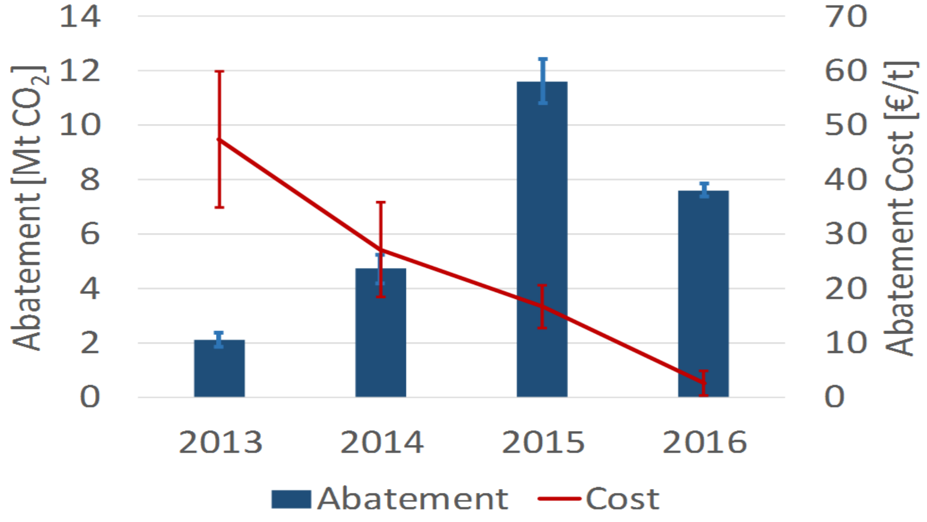
$\bar{z}_t$ counterfactual treatment

(4) Derive treatment effect

$$\delta_{it}^{\bar{z}} = y_{it} - y_{it}^{\bar{z}}$$

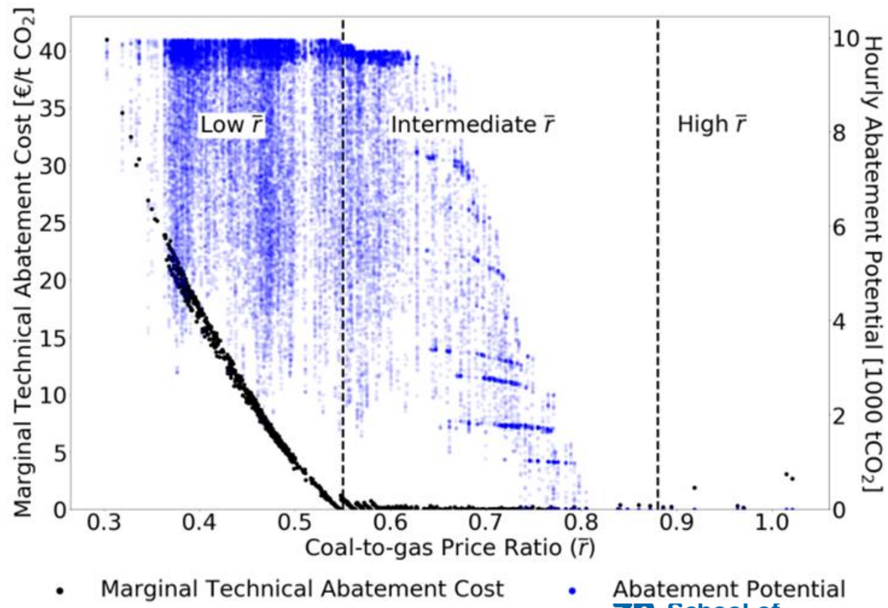
Impact of UK Carbon Price Support

- What was the impact of the CPS on UK carbon emissions?
  Coal-to-gas switch: 45 TWh
  Total carbon abatement: 24 $MtCO_2$ (6.2%)
  Average abatement cost: 18 €/tCO_2



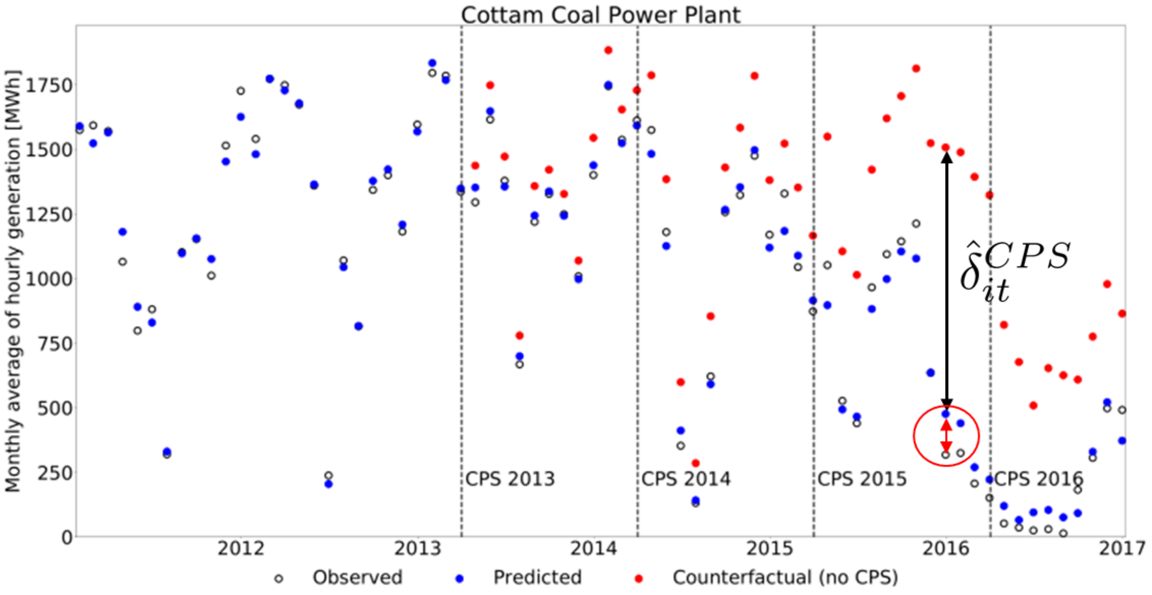
- CPS impact/cost affected by
  - level of CPS
  - coal-to-gas price ratio

    ➔Higher coal prices decrease
    (1) abatement cost
    (2) abatement potential



Methodology: How to evaluate impacts of a broad based tax?

- Proposed procedure
  (1) Use theory to learn about underlying process
  (2) Estimate predictor of process
  (3) Derive treatment effect based on counterfactual prediction



- Basic framework
  - Autonomous process
    $$y_{it} = f_i\left(D_t, c_{it}, K_{it}, c_{(-i)t}, K_{(-i)t}\right)$$
  - Variation in treatment sufficient to identify causal impact

- Prediction error independent of treatment

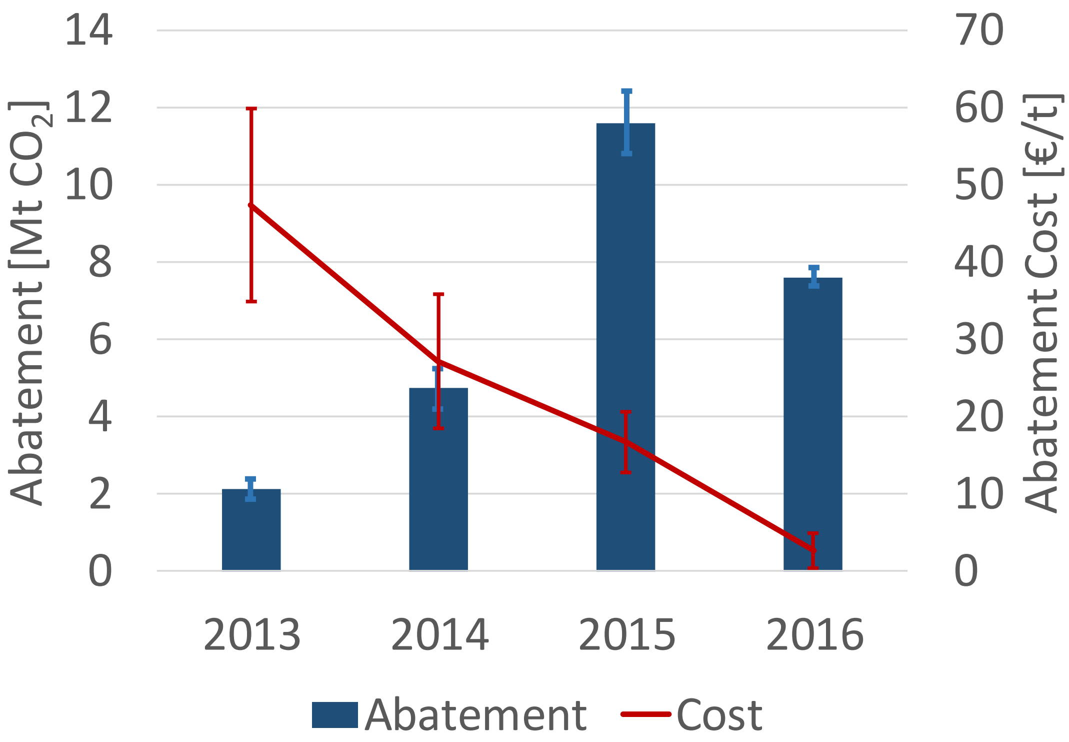
Impact of CPS on abatement and cost

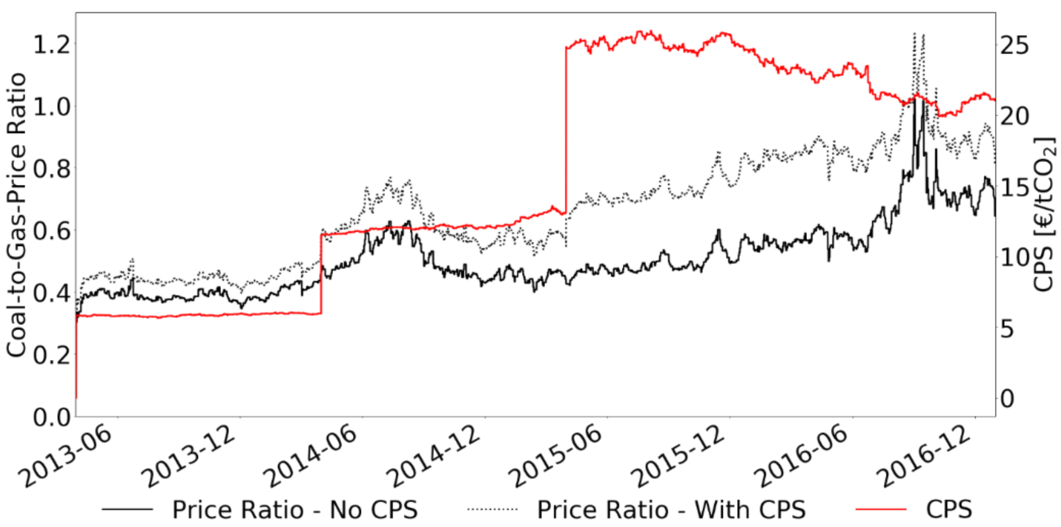
- Abatement: 24.2 Mt (6.2%)

$$\Delta E_i = \sum_t e_i \hat{\delta}_{it}$$

- Average cost: Change in fuel cost 18.2 €/t

- What drives CPS impacts?
  - level of CPS
  - coal-to-gas price ratio





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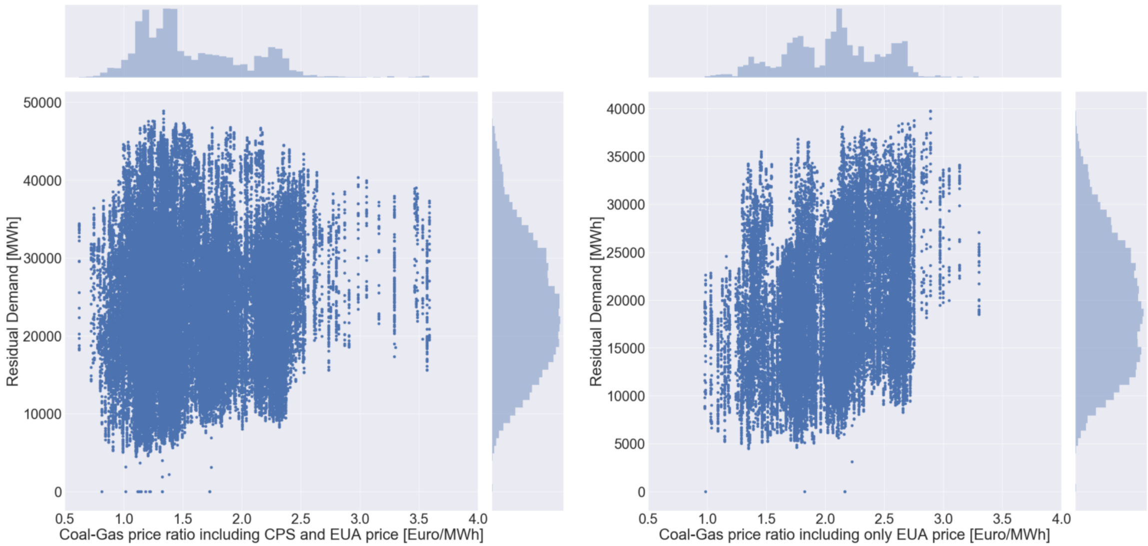
When does the approach work?

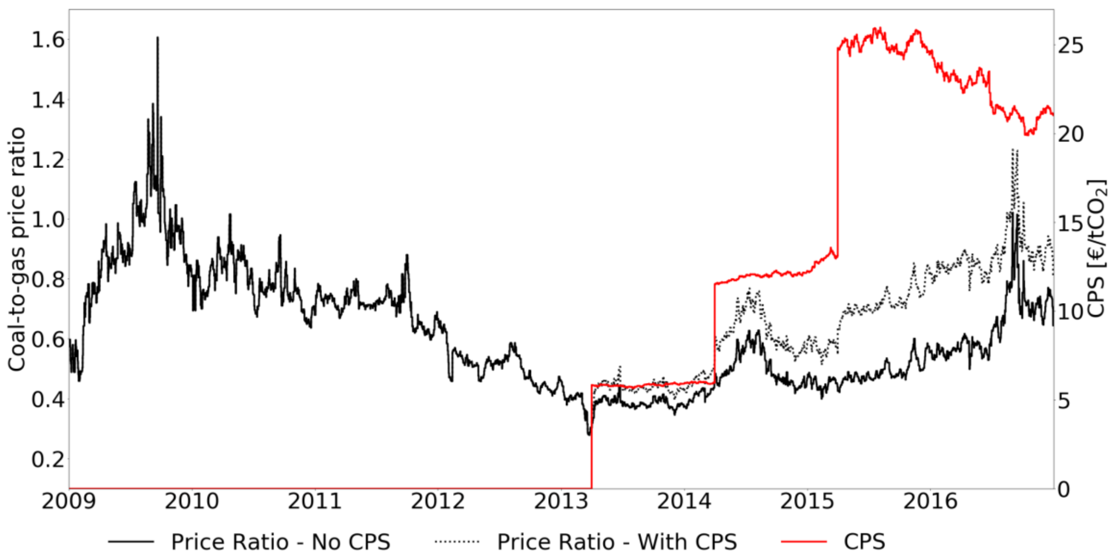
4. Do not predict “too far” out of sample (covariate overlap; positivity)

$$Pr\left[\overline{r}_t | K_{it}, temp_t, D_t\right] > 0$$



(a) Observed r_t over full sample (b) Counterfactual $\overline{r}_t$ over CPS period

5. Variation in treatment sufficient to identify treatment impact



Machine learning for predictions

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

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

Machine learning for predictions

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- Cross-validation to choose hyperparameters (α) to minimize out-of-sample prediction error
- By design, in-sample bias to improve prediction performance

Abatement and Cost Impact

TABLE 5. Impacts of the UK carbon tax (CPS) on aggregate emissions and abatement costs

	Period				Total impact
	2013	2014	2015	2016	2013-2016
CPS [€/t]	5.85	12.17	24.70	21.60	–
Emissions without CPS ($\overline{E}$) [Mt]	125.8	112.0	98.0	71.3	407.1
CO_2 abatement					
ΔE_t [Mt]	2.1	4.7	11.6	7.6	26.1
	(0.25)	(0.53)	(0.81)	(0.24)	(1.60)
% of total emissions	1.7	4.2	11.9	10.7	6.4
Abatement cost $\Psi_t = T_t + R_t$					
Technical cost T_t [mio. €]	101.1	129.1	195.1	20.5	445.0
	(9.2)	(18.4)	(29.1)	(16.6)	(58.7)
Avg. tech. cost $T_t/\Delta E_t$ [€/t]	47.5	27.2	16.8	2.7	18.2
	(12.5)	(8.7)	(4.0)	(2.3)	(4.0)
Tax payments R_t [mio. €]	725.7	1309.6	2129.4	1372.8	5194.3

Notes: Values shown refer to estimated plant-level impacts $\hat{\delta}_{it}^{CPS}$, based on model specification M1 and equation (17), aggregated by period. As the CPS is adjusted in April of every year, all reported variables refer to the period from April to March of the subsequent year. As data is available until December 2016, we can only estimate the impacts of the CPS for a nine month period. To ensure comparability with previous years, we scale model values for 2016 to a 12-month basis. Bootstrapped standard errors are shown in parentheses.

Simulations

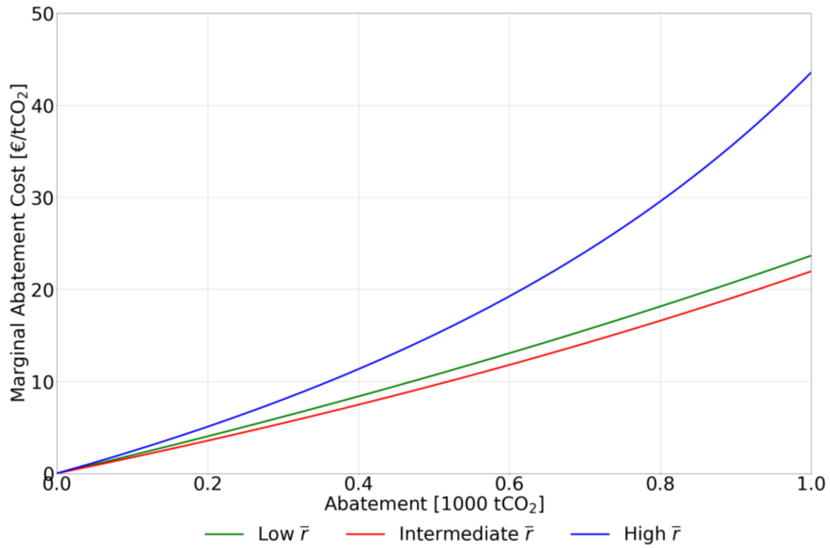
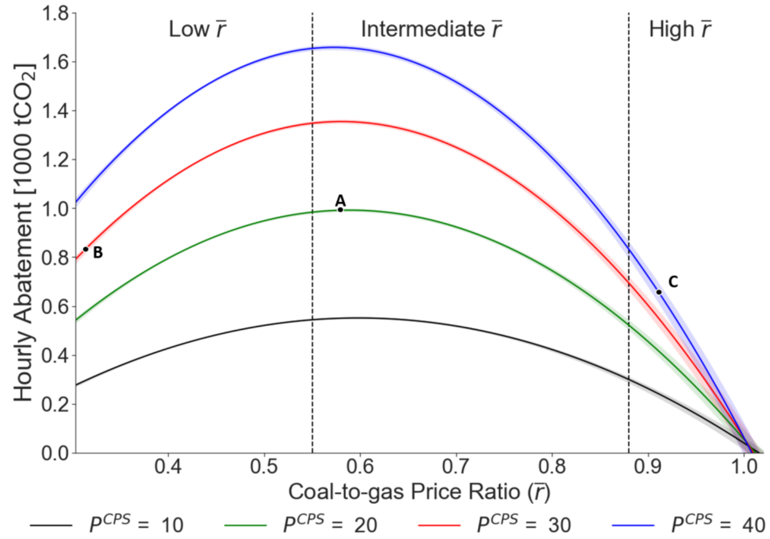
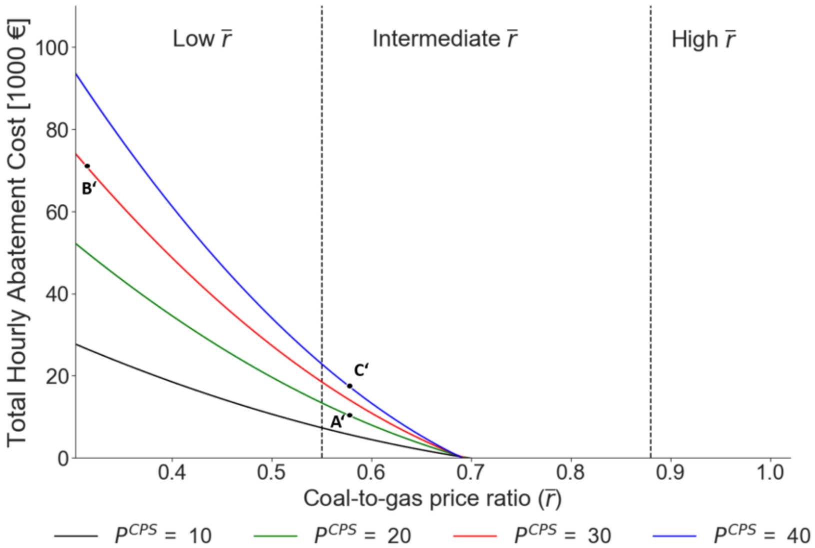


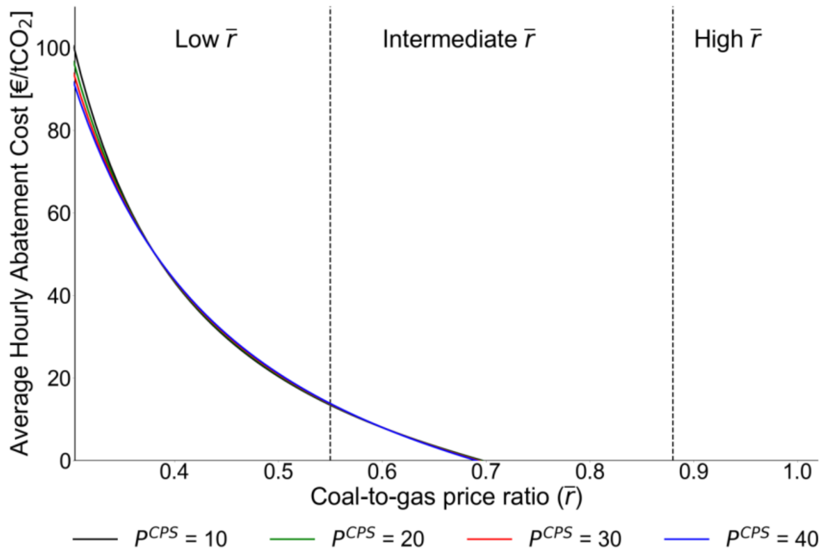
FIGURE 9. Empirical MAC curves for different carbon tax-exclusive fuel price ratios $\bar{r}_t$



(a) CO_2 abatement (ΔE_t)



(b) Total technical abatement costs (T_t)



(c) Average abatement costs ($T_t/\Delta E_t$)

Plant Characteristics

TABLE 2. Power plant characteristics.

Plant	Installed capacity [MW]	Average heat efficiency η_i [–]	Emissions rate e_i [ton of CO_2/MWh]	Opening/ closing date[a]
Natural gas plants				
Pembroke	2269	0.60	0.34	end 2012/–
Peterhead	2134	0.55	0.36	–/March 2014
Staythorpe	1792	0.58	0.34	2010/–
Didcot CCGT	1404	0.55	0.36	–/–
Connahs Quay	1380	0.48	0.42	–/–
West Burton CCGT	1332	0.51	0.40	–/–
Grain CHP	1305	0.56	0.36	–/–
South Humber	1239	0.50	0.40	–/–
Seabank	1169	0.55	0.36	–/–
Saltend South	1164	0.52	0.38	–/–
Teesside	1155	0.45	0.44	–/Feb. 2013
Immingham CHP	1123	0.44	0.46	–/–
Barking	945	0.46	0.44	–/Dec. 2012
Langage	905	0.55	0.37	–/–
Marchwood	898	0.58	0.34	–/–
Killingholme	854	0.48	0.42	–/March 2015
Severn	850	0.54	0.37	–/–
Spalding	830	0.54	0.37	–/–
Rocksavage	800	0.53	0.38	–/–
Sutton Bridge	796	0.52	0.39	–/–
Damhead Creek	783	0.53	0.38	–/–
Coryton	770	0.52	0.38	–/–
Little Barford	740	0.54	0.37	–/–
Rye House	715	0.43	0.46	–/–
Keadby	700	0.47	0.42	–/Feb. 2013
Medway	680	0.53	0.38	–/–
Baglan Bay	520	0.57	0.35	–/–
Deeside	498	0.47	0.42	Dec. 2011/–
Great Yarmouth	420	0.56	0.35	–/–
Shoreham	420	0.54	0.37	–/–
Enfield Energy	408	0.53	0.38	–/–
Corby	401	0.39	0.51	–/Oct. 2015
Cottam CCGT	395	0.55	0.36	-/-
Kings Lynn	325	0.52	0.39	-/March 2012
Peterborough	316	0.37	0.54	-/Dec. 2011
Average natural gas plant[b]		0.51	0.40	

Notes: Installed capacities, fuel type, and plant opening and closure dates are provided by Variable Pitch (2016) and Nationalgrid (2011). For data sources and calculations of heat efficiencies and emission rates see text. [a]"–" indicates that the plants' opening or closure date lies outside of the sample period 2009–2016. [b]Calculated using installed capacities as weights.

TABLE 2. Power plant characteristics.

Plant	Installed capacity [MW]	Average heat efficiency η_i [–]	Emissions rate e_i [ton of CO_2/MWh]	Opening/ closing date[a]
Coal plants				
Longannet	2304	0.42	0.81	–/March 2016
Didcot COAL	2108	0.39	0.88	-/March 2013
Cottam	2000	0.39	0.86	–/–
Ratcliffe	2000	0.38	0.89	–/–
West Burton COAL	1972	0.38	0.90	–/–
Fiddlers Ferry	1961	0.37	0.92	–/March 2016
Ferrybridge	1960	0.38	0.89	–/March 2016
Drax COAL	1947	0.38	0.90	–/–
Kingsnorth	1940	0.36	0.94	–/Dec. 2012
Eggborough	1932	0.37	0.92	–/–
Aberthaw	1641	0.41	0.82	–/–
Cockenzie	1200	0.38	0.91	–/March 2013
Rugeley	996	0.39	0.88	–/June 2016
Ironbridge	964	0.35	0.98	–/March 2012
Uskmouth	363	0.33	1.04	–/–
Average coal plant[b]		0.38	0.89	

Notes: Installed capacities, fuel type, and plant opening and closure dates are provided by Variable Pitch (2016) and Nationalgrid (2011). For data sources and calculations of heat efficiencies and emission rates see text. [a]"–" indicates that the plants' opening or closure date lies outside of the sample period 2009–2016. [b]Calculated using installed capacities as weights.