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THE IMPACT OF A CARBON TAX ON THE CO2 EMISSIONS REDUCTION OF WIND

Chi-Kong Chyong Bowei Guo David Newbery

19 January 2018

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Keywords Carbon pricing, fuel mix, wind, marginal displacement factors, unit commitment model, econometrics

JEL Classification H23, L94, Q48, Q54

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Publication January 2019
Financial Support

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Energy policy aims to reduce emissions at least long-run cost while ensuring reliability. Their effectiveness depends on the cost of emissions reduced. Britain introduced an additional carbon tax (the Carbon Price Support, CPS) for fuels used to generate electricity that by 2015 added £18/t CO_2, dramatically reducing the coal share from 41% in 2013 to 8% in 2018. This paper shows how to estimate CO_2 reductions, arguing that policies have both short and long-run impacts. Both need to be estimated and combined to measure carbon savings. The paper shows how to measure the Marginal Displacement Factor (MDF, tonnes CO_2 /MWh) for wind. The short-run MDF is estimated econometrically while the long-run MDF is calculated from a unit commitment model of the GB system in 2015. We examine counter-factual fuel and carbon price scenarios. The CPS lowered the short-run MDF by 7% in 2015 but raised the long-run MDF (for a 25% increase in wind capacity) by 33%. The CPS raised the 2016 wholesale price by £6.22/MWh with impacts on interconnector trade.

*This paper arose out of a paper commissioned by Iberdrola (Newbery, Reiner and Ritz, 2018). We are indebted to helpful comments from an EPRG referee

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Keywords: Wind, marginal displacement factors, carbon pricing, fuel mix, unit commitment model, econometrics

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1 Introduction

Energy policy aims to reduce emissions at least long-run cost while ensuring reliability. Policies to support wind or solar PV, improve efficiency, or shift peak demand need to be assessed on the cost of the emissions reduced. Ofgem (2018) in its *State of the market 2018* is a good example, comparing the cost effectiveness of various UK energy policies. Long-run cost reductions may require higher costs today to drive down future costs by innovation, demonstration and deployment. The EU *Renewables Directive* (2009/28/EC)[1] aims at these longer-term goals, as does *Mission Innovation* (Newbery, 2018). This paper shows how to estimate CO_2 reductions in electricity from specific policies, ignoring these longer run benefits. It argues that policies have both short and long-run impacts. Both need to be estimated and combined to measure carbon savings. The paper shows how to measure these savings.

We demonstrate this by looking at the CO_2 displaced by wind in Britain as the price of carbon varies. The UK Government introduced a Carbon Price Floor from 2013. This takes the form of a carbon tax (the Carbon Price Support, CPS) on fuels used to generate electricity. The CPS is added to the EU Allowance (EUA) price to give the total extra cost of the carbon content of fossil fuels. By 2015 this was sufficiently high to dramatically impact the fuel mix in generation, as shown in Figure 1. The share of coal fell from 41% in 2013 to 8% in 2018. Great Britain[2] therefore offers an excellent test-bed for the impact of a carbon tax (the CPS) as the fuel mix is likely to affect the carbon displaced by wind. Wind is hard to forecast with much accuracy day-ahead when the time comes to decide which types of generation to commit and run. As wind varies from moment to moment, the carbon displaced will depend on the plant operating, and which types of plant can adjust up or down at least cost. We study this short-run impact econometrically to find the main drivers of the short-run displacement achieved.

Policies are chosen for their long-run impact. Governments set targets for the future share

[1] See http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=CELEX:32009L0028:EN:NOT.

[2] Northern Ireland was exempt from the CPS as it forms part of the Single Electricity Market with Ireland, who declined to adopt a Carbon Price Floor.

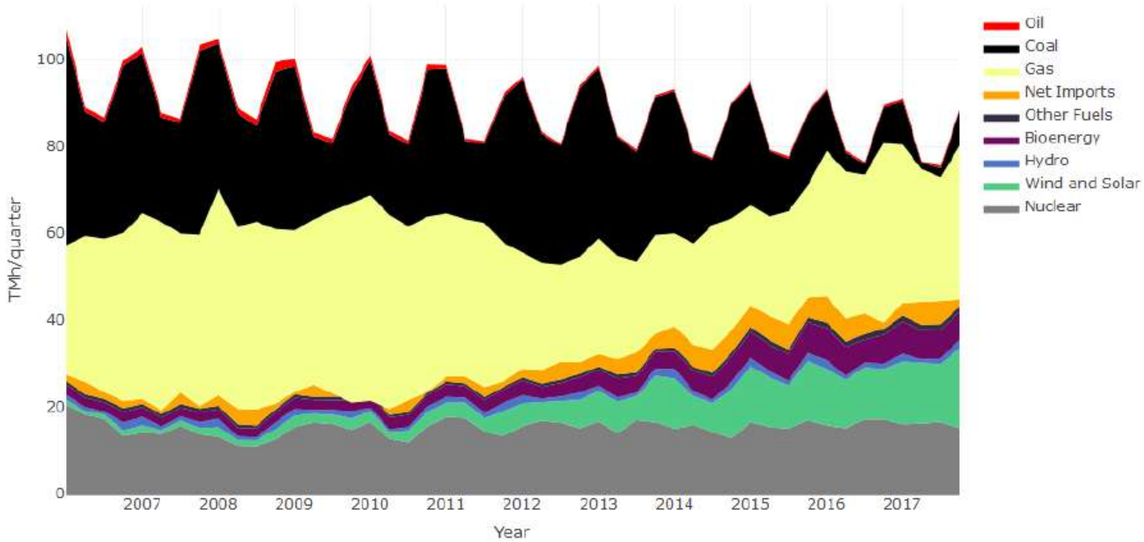


Figure 1: GB generation per quarter by fuel type

Source: Elexon Portal at https://www.elexonportal.co.uk/news/latest

of renewable electricity and 2050 carbon budgets. These policies will affect the future fuel mix, and hence the plant available to be dispatched day to day. We determine this long-run impact with a unit commitment dispatch model of the GB system in 2015. We use that to examine the effect of increasing wind capacity by 25%. Long run has the conventional meaning that it is a period over which capacity can change, in contrast to the short run in which the vagaries of wind can only be accommodated by the plant already committed and capable of responding. We study the impact of the CPS as it was in 2015. We also look at two counterfactuals. The first is no CPS, but just the EUA price, as it might have been without the policy intervention. The second looks to the middle of 2018, when the EU Emissions Trading System was reformed, which raised the GB total carbon price substantially above its 2015 level.

This paper argues that policies intended to reduce emissions in electricity require a weighted average of the short and long-run impacts. The weights will depend on the size of the forecast error at the time plant is committed. More uncertainty means that adjustments will depend more on the plant available, requiring a higher weight on the short-run impact. Other policies, such as a ban on coal-fired generation or contracts to reduce demand when requested, have predictable effects better measured with the long-run approach.

The Marginal Displacement Factor (MDF) measures the tonnes of CO_2 reduced by an extra 1 MWh of wind in that hour. The MDF depends on the plant mix of the system (coal and efficient gas in our case) as well as fuel and carbon prices. The MDF of renewables will therefore vary over countries and time. The MDF is useful for determining the extra support to offer low-carbon technologies if the market price of carbon is below its social cost. It can be (and is) used to measure the cost-effectiveness of policy interventions that displace fossil fuel.

The econometric estimates also give the short-run Marginal Emission Factor (SR-MEF) of demand — the change in emissions resulting from a change in demand of 1 MWh in that hour (tonnes CO_2/MWh). This is used to measure the impact of the CPS on wholesale prices and hence on trade over the existing interconnector to France. For future interconnectors, both the long-run and short-run impacts are needed.

The next section briefly reviews related literature before describing the British Carbon Price Floor and developments in the EU Emissions Trading System, their impact on GB carbon prices over time and the evolution of GB fuel costs. Section 4 summarises the merit order effect and its dependence on total fuel costs to motivate the dependence of the MDF of wind on relative fuel costs. Section 5 sets out the econometric analysis to derive the SR-MDF of wind. Section 6 explains the model used to measure the LR-MDF. Section 7 contrasts the SR and LR-MDFs and discusses their use in policy analysis. Section 8 measures the impact of the CPS on wholesale prices, allowing us to examine the impact on trade with France. Section 9 concludes.

2 Literature review

We have only found one *ex post* econometric analysis (Staffell, 2017) of the performance of the GB CPS - even though Britain's CPS has been in place for over five years. Staffell's paper has the broader aim of explaining why CO_2 emissions fell by 46% in the three years to June 2016, whereas our aim is to focus more narrowly on estimating the MDF for wind, and to explore the underlying mechanism driving changes in the MDF. The econometric methodology also allows us to identify the marginal plant setting the price in the day-ahead auction for interconnector use, so we can construct counterfactuals of the wholesale price without the CPS and the impact on interconnector flows.

Our SR-MDF estimates pick up from the period that Thomson et al. (2017) studied econometrically (2009-2014). They find that in 2010, a period of intermediate coal costs, the MDF was 0.61 tCO_2/MWh. Counterintuitively, this fell to 0.48 tCO_2/MWh in 2014 (when the CPS was introduced, although at a low level) and coal became more expensive. We aim to better understand these changes in the MDF, which Thomson et al. (2017) note might be due to the "unusual operation of the system in 2012-14". We confirm Thomson's findings and show the reason for the apparently counter-intuitive findings, which by 2015 go in the opposite direction to the LR-MDF.

Most studies make "instantaneous" CO_2 emissions as the dependent variable in regressions (for example, Gutiérrez-Martin et al., 2013; Wheatley, 2013; Thomson et al., 2017). Instead we use half-hourly coal and gas generation as dependent variables and develop non-linear econometric models to estimate the marginal fuel (coal and gas MWh) displacement per MWh of wind and its dependence on the fuel cost difference. With this we can estimate the MDF of wind. The conventional approach has the advantage that it gives the estimated MDFs directly. Our indirect estimate of the MDFs has two advantages. First, it explains the underlying mechanisms that drive the dynamics of the MDF. Second, it allows us to study the counterfactual in which the CFP is not implemented or carbon prices are set at a higher level. This would be difficult without knowing the underlying mechanisms.

3 The British Carbon Price Floor

The Carbon Price Floor (CPF) was announced in the 2011 Budget to come into effect in April 2013. The CPF was intended to bring the price of carbon in fuels used in the GB electricity supply industry up to £(2011)30/tCO_2 by 2020 and £(2011)70/tCO_2 by 2030 (the dashed line at current prices in Figure 2), sufficient to make mature zero-carbon generation competitive against fossil fuels. The CPF is administered by adding the Carbon Price Support (CPS, a carbon tax added to the EUA price) on fuels used to generate electricity. The CPS was set at £4.94/tCO_2 in September, 2010. By April 2013, the EUA price had fallen to just under £4/tCO_2 so the effective price was far below the desired level (the dashed line in Figure 2). It was raised in 2014 to £9.55/tCO_2 and again in 2015 to £18.08/tCO_2, to bring the price back to the desired CPF trajectory. In 2011, the UK Government hoped that other EU countries would be attracted by this fiscally attractive solution to the politically intractable problem of ETS reform. Other EU Member States declined to follow (until recently when the Dutch Government announced plans for a CPF).

Faced with a potentially large mismatch between the cost of generating electricity in Britain and on the Continent, the Chancellor froze the CPS at £18/tCO_2 from 2016-17 through 2020-21.[3] Figure 2 shows the increasing divergence between the EU and GB CO_2 prices. In November 2017 the EU finally agreed to reform the ETS, introducing a Market Stability Reserve that allows surplus EUAs to be cancelled (Newbery et al., 2018). In response the EUA price rapidly increased, and with it, the GB carbon price moved above the original CPF trajectory (Figure 2).

The impact of this considerable increase in the fossil fuel cost has been dramatic. Figure 3 shows the variable fuel costs from 2012-17, with and without the carbon price (EUA plus CPS). The CPS gradually increased the cost of coal, but it was not until April 2015, when the CPS was doubled, that the variable coal cost rose above the variable cost of more efficient CCGTs.

[3] See http://researchbriefings.files.parliament.uk/documents/SN05927/SN05927.pdf.

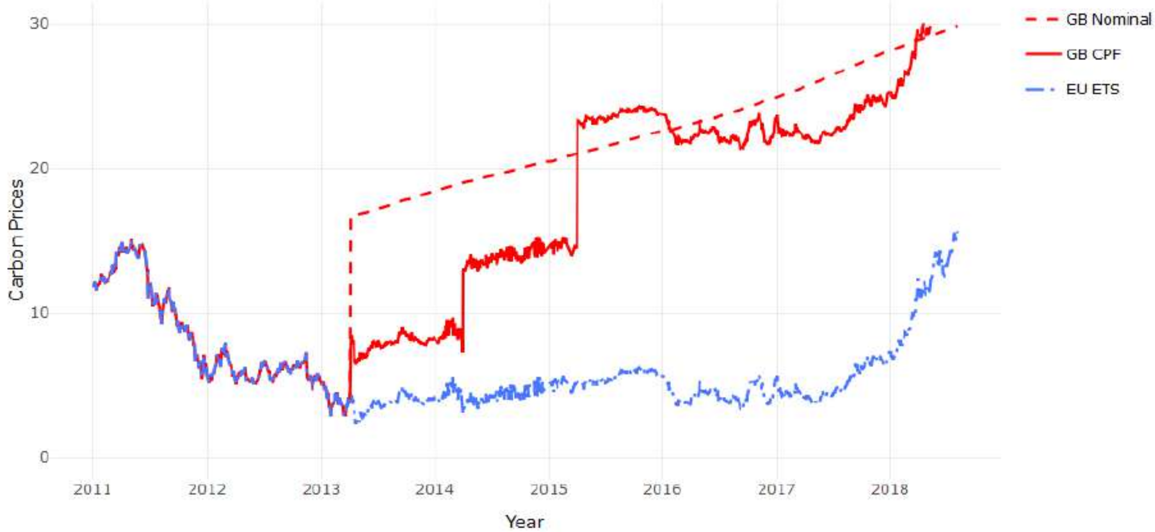


Figure 2: Evolution of the European Allowance (EUA) price and CPF, £/tCO_2

Source: https://www.investing.com/commodities/carbon-emissions

Figure 1 shows the massive switch from coal to gas, with renewables also rapidly taking share and further lowering carbon intensity.

The rest of this paper is primarily devoted to quantifying the impact of the CPS on the carbon savings from wind, which, as Figure 1 shows, has been increasing rapidly.[4] To do this we need to estimate both the short-run (SR) and long-run (LR) Marginal Displacement Factors (MDFs). The short-run impacts are studied econometrically over a period of varying fuel and CPS prices given the existing wind capacity, providing statistically highly significant estimates. We use a unit commitment dispatch model of British electricity to compute the long-run impact of the CPS by raising wind capacity by 25%, leaving the plant mix and fuel prices constant, and varying the level of the CPS. We expect the short-run MDF (SR-MDF) to differ from the long-run MDF (LR-MDF), as the SR-MDF estimates the impact of variable (imperfectly predicted) wind on the *existing* wind capacity. The LR-MDF estimates the impact of an increase in wind

[4]The same approach could in principle be applied to carbon savings from solar PV or smart charging of battery electric vehicles, but the necessary data are not currently readily available.

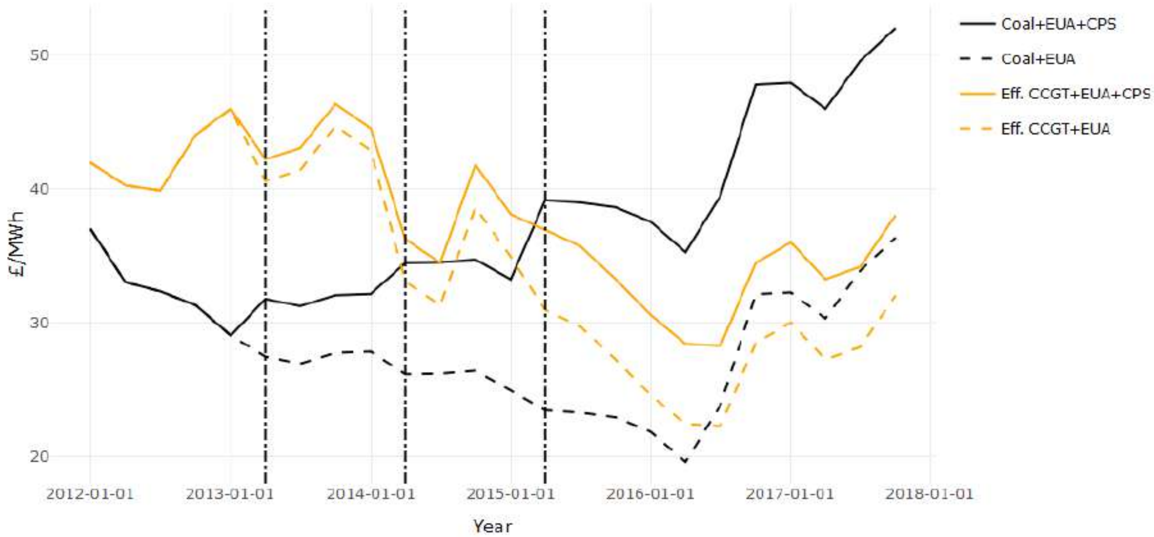


Figure 3: Electricity generation cost by fuels for generators

Source: BEIS *Quarterly Energy Prices* at https://www.gov.uk/government/statistical-data-sets/prices-of-fuels-purchased-by-major-power-producers

capacity and its accurately predicted output. The two estimates differ in important ways, and both estimates are needed to inform policy.

Table 1 gives the thermal efficiency of coal as 35.6% with emissions 0.871 tCO_2/MWh_e,[5] and the emission factors for the most efficient CCGTs in 2015 as 0.333 tCO_2/MWh_e, although the range is wide and includes less efficient (and largely unused) older CCGTs. Thus coal has more than twice the carbon intensity of gas. At a CPS of £18/tCO_2, the cost of coal-fired generation is increased by £15.7/MWh_e and efficient CCGTs by £6/MWh_e, giving gas an advantage of nearly £10/MWh_e, compared to the average baseload price from 2011-13 of £47/MWh_e.

The impact of the CPS can be clearly seen in the coal cost in Figure 3, although it is not until Q2 2015 when the coal cost exceeded efficient CCGT costs. Before then, the dark green spread (the average wholesale prices *less* the coal cost including the EUA *plus* CPS) was £7.7/MWh_e

[5] See https://www.statista.com/statistics/548964/thermal-efficiency-coal-fired-stations-uk/. Subscript $_e$ indicates per unit of *e*lectricity output.

Table 1: Characteristics of Fuel Types

	Fuel Price £/MWh$_{th}$	Capacity GW	Efficiency GCV	CO_2 t/MWh$_e$
Coal	£6.57	17.1	35.6%	0.871
CCGT new	£15.87	14.2	55.1%	0.333
CCGT older	£15.87	5.2	52%	0.352
CCGT oldest	£15.87	7.6	36%	0.511

Note: GCV is Gross Calorific Value (Higher Heat Value), subscripts $_{th}$ refer to thermal content, $_e$ electric output. Efficiencies are often quoted for the more impressive Lower Heat Value. For gas the LHV is 90% of the HHV, downgrading the 61.2% nominal efficiency to 55.1% HHV. The oldest CCGTs are often running inefficiently part-loaded or in open-cycle mode for fast balancing response.

while the clean spark spread (average wholesale prices *less* the cost of CCGT including carbon price) was £3/MWh$_e$, making coal the preferred base-load and gas mid-merit. From November 2015 to June 2017 the dark green spread fell to $-$£1.8/MWh (a loss if running at full capacity all the time, but higher priced hours would still give a positive spread), while the average clean spark spread rose to £8.9/MWh, shifting gas from mid-merit to base load, and coal to mid-merit or peaking load. Figure 1 shows the impact on the fuel mix of generation.

Coal has normally been the major swing fuel in winter months, and indeed on a cold winter day (09:30 February 27 2018) CCGTs were producing 19.4 GW but coal was producing 11.1 GW, its maximum.[6] On a calm sunny summer day (15:40 August 3, 2018), CCGTs were producing 17.8 GW, coal only 0.5 GW, wind down to 1.1 GW and solar up at 4.8 GW. Clearly the CPS has had a major impact on the GB fuel mix and hence on CO_2 emissions, and will likely have impacted the wholesale price and consequently the direction of interconnector trade with neighbouring countries lacking a CPF, (notably, the high priced island of Ireland).

[6] Real time data are available from http://gridwatch.co.uk/; the installed capacity for coal was 11.1 GW in 2017, (instead of the value of 17.1 GW in 2015 in Table 1,) see https://transparency.entsoe.eu/.

4 The Merit Order Effect and the Impact of Renewables

Renewables (wind, solar PV, run-of-river hydro) and nuclear power have zero variable carbon emissions and low variable costs, so if available, they will displace more expensive fossil generation. Exactly which fossil generation will be displaced depends on which are able to adjust their output. The merit order for conventional (dispatchable) plant ranks plant in increasing variable cost, with residual demand (total demand less renewable generation) determining the marginal conventional plant displaced by renewables. The merit order impact of renewables is well-understood (Clò et al., 2015; Cludius et al., 2014; Deane et al., 2017; Green & Vasilakos, 2012; Ketterer, 2014) but care is needed to account for plant dynamics.

Figure 4 shows the Q2 2016 merit order of GB nuclear, coal and CCGT plant (excluding biomass, CHP, pumped storage, interconnectors and renewables) with just the EUA or with the added CPS at £18/tCO_2. At EUA carbon prices coal is cheaper than all CCGTs. With the CPS, efficient CCGTs (shown as Eff. CCGT) displace coal, but that is still cheaper than the less efficient CCGTs (shown as Ineff. CCGT), some of which are probably operating as balancing units in open-cycle mode.

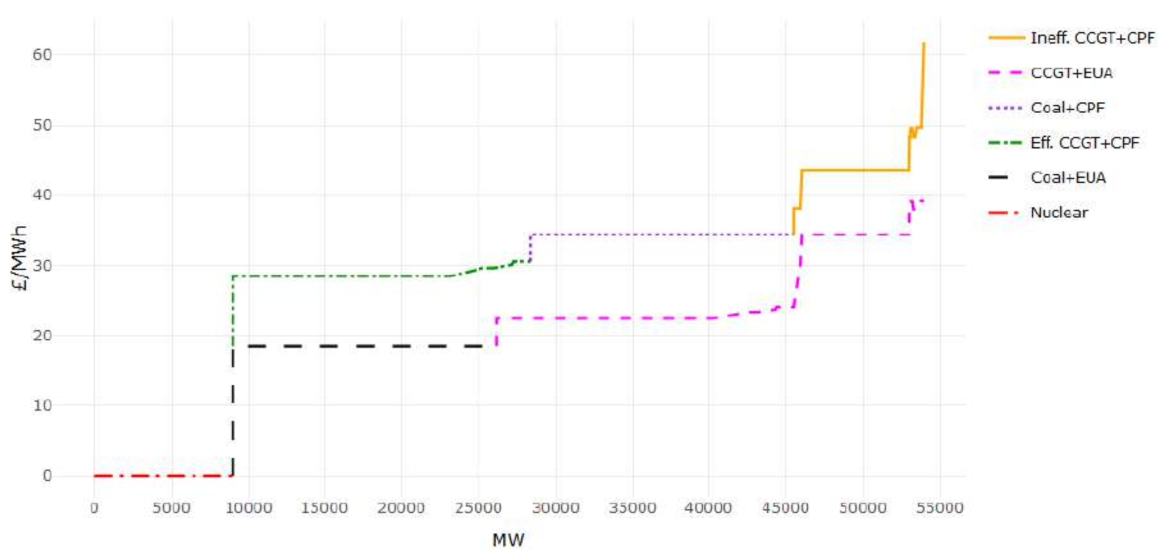


Figure 4: Merit order for conventional generation plant, Q2 2016

Figure 5 plots the generation costs for coal and efficient CCGTs, the spot market prices, and electricity generation for two consecutive days in one figure. The horizontal lines in the lower part show the costs of generating with gas in efficient CCGTs, including the CPS at £18/tCO_2, and above it, coal. The vertical lines in Figure 5 show where coal changes from having a negative dark green spread to positive or *vice versa* (where the spot market prices intersect with the coal cost). Coal plant is costly to restart, so if needed later in the day will run at minimum load, and start to ramp up in time to deliver when demand and prices rise. Wind varies considerably over this 48 hour period (between 6.7 GW and 4.3 GW) but this variation is dwarfed by the variation in demand (from 25-49 GW). As a consequence, coal and gas generation follow load and any adjustment in response to wind variations are swamped by load variations. However, while load is reasonably predictable, wind is less predictable and likely to rely more on the balancing market, for which flexible plant is at a premium (as noted by Thompson et al., 2017).

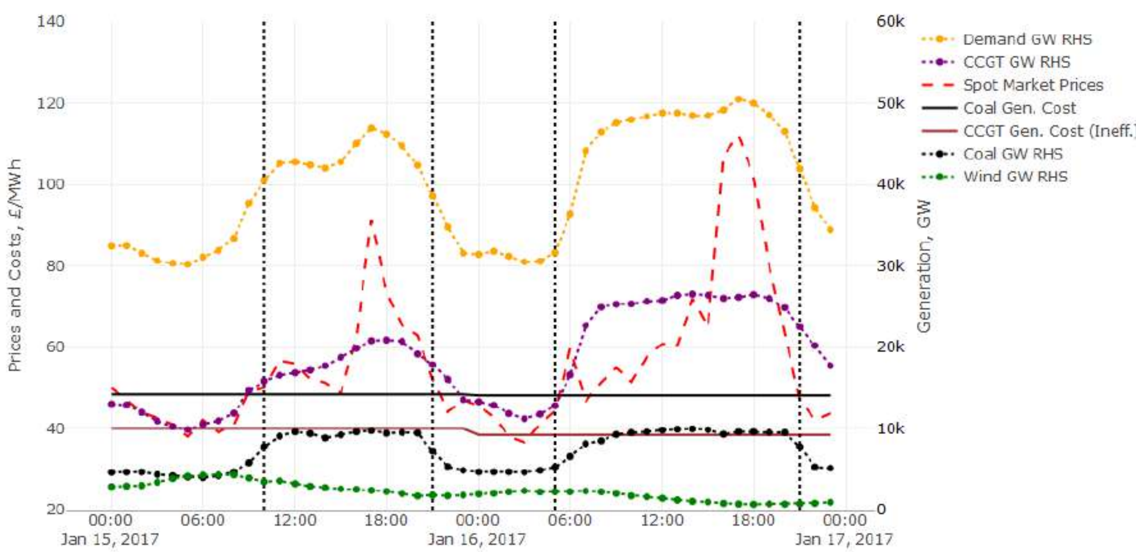


Figure 5: Generation, prices and costs by hour, 15th-16th Jan 2017

Note: includes CO_2 at £18/tCO_2.
Source: Elexon Portal

5 Econometric Analysis

The short-run marginal displacement factor (SR-MDF) measures the marginal CO_2 savings of wind *with the existing capacity of wind* using data from 2012 to 2017. This covers the period before the implementation of the CPS (pre Q2 2013), the period when it was implemented and raised twice (Q2 2013 - Q2 2016) and when it is fixed at £18/tCO_2 (post Q2 2016). Figure 3 shows the generation costs for coal and gas during the period with and without the CPS, where we observe a switch of merit order from Q2 2015, when the CPS reached its highest level. Thomson et al. (2017) estimate the SR-MDF from 2009 to 2014. Our data overlaps their period, allowing us to better understand the underlying mechanism driving changes in the SR-MDF. We then study the counterfactual SR-MDF without the CPS.

5.1 The short-run impact of wind

The conventional approach to estimate the SR-MDF (Hawkes, 2010; Thomson et al., 2017; Staffell, 2017) uses the following static model:

$$\Delta E_t = a\Delta D_t + b\Delta W_t + c_t, \tag{1}$$

where ΔE_t is the half-hourly first difference of the system CO_2 emissions (tCO_2), and ΔD_t (MWh) and ΔW_t (MWh) are the first differences of electricity demand and wind output respectively. Coefficient a is the marginal emission factor (MEF) (tCO_2/MWh) of demand and $-b$ is the SR-MDF (tCO_2/MWh) of wind. c_t is other system effects which can be half-hourly specific.

By definition,

$$\Delta E_t = e_C\Delta C_t + e_G\Delta G_t + e_O\Delta O_t, \tag{2}$$

where C_t, G_t and O_t are electricity generated from *C*oal-fired stations, *G*as (CCGTs) and *O*ther energy sources; e_C, e_G, and e_O are the CO_2 emission intensities for coal, gas (efficient CCGTs), and other fuel sources. O_t consists of energy sources which are negligible (open-cycle gas turbines (OCGTs) and oil), must-runs (combined heat and power and biomass), and imports, which do not count as GB sources of emissions.[7] Therefore, $e_O \Delta O_t$ is close to zero because either $e_O = 0$ (for imports) or $\Delta O_t \approx 0$ (for the must-run and negligible energy sources).

Given that coal and CCGT do not affect each other during half-hourly intervals, substituting ΔE_t in (1) by (2) gives

$$\Delta C_t = \alpha_0 + \alpha_1 \Delta W_t + \alpha_2 \Delta D_t + \boldsymbol{\theta'X_t} + \varepsilon_t, \tag{i}$$

$$\Delta G_t = \beta_0 + \beta_1 \Delta W_t + \beta_2 \Delta D_t + \boldsymbol{\delta'X_t} + \mu_t, \tag{ii}$$

where $\boldsymbol{X_t}$ is a vector that consists of hourly (or half-hourly) dummy variables. Having first differences (instead of levels) means that we do not need to worry about non-stationary processes. Consequently, we have:

$$e_C \alpha_2 + e_G \beta_2 \approx a = \text{MEF},$$

$$-(e_C \alpha_1 + e_G \beta_1) \approx -b = \text{SR-MDF}.$$

The SR-MDF is estimated indirectly from (i) and (ii) instead of Eq.(1). This indirect approach enjoys the following advantages. First, it identifies the underlying drivers of the dynamics of the SR-MDF (i.e. the shares of coal and gas displaced by wind). Second, the non-linear version of (i) and (ii) discussed below allows us to study the counterfactual in which the CFS is not implemented. That would be difficult without understanding the underlying mechanism. Staffell (2017) uses a similar approach, looking at the specific fuel types that are displaced by wind (and solar). Staffell's finding that only fossil plant and imports adjust their output to wind changes supports out analysis of the two-step estimation of the SR-MDF using regression (i)

[7] Nuclear, solar, wind, run-of-river hydro, and pumped storage supply during their release phase are not included in (2) because none of them generates GHG.

and (ii) and their non-linear versions. As wind supply depends on wind speed, ΔW_t can be treated as exogenous. As the half-hourly demand for electricity is inelastic to prices (Clò et al., 2015), ΔD_t is also treated as exogenous.[8]

The slope coefficients α_1 and β_1 are the marginal *fuel* displacement of wind, measuring the changes in coal and gas generation caused by a change in wind output, conditional on the change in demand and time dummies. We would expect both $\hat{\alpha}_1$ and $\hat{\beta}_1$ to be negative, and $|\hat{\alpha}_1 + \hat{\beta}_1|$ to be close to but smaller than 1 — in addition to coal and CCGT plants, a small but significant proportion of changes in wind can also be compensated by imports and pumped storage. The coefficients α_2 and β_2 measure the response of coal and gas generation to demand changes. We would expect both $\hat{\alpha}_2$ and $\hat{\beta}_2$ to be positive and $|\hat{\alpha}_2 + \hat{\beta}_2|$ to be less than 1 because a proportion of changes in demand can also come from other sources.

The magnitudes of α_1 and β_1 depend on total energy demand (hence the time of the day) as well as the actual merit order between coal and gas, which is determined by $\tilde{P}_t \equiv P_t^C - P_t^{G^e}$, the difference in variable energy generation costs between coal (P_t^C) and efficient CCGT plants ($P_t^{G^e}$) (hereafter the cost differential).[9] Each day is separated into two periods: off-peak (23:00-07:00) and peak (07:00-23:00)[10] based on Figure 4 and 5, which suggest that the base-load plant is sufficient for energy demand during (most of the) off-peak hours and the mid-merit plant is the marginal fuel for most of peak hours.[11] We further split the two sub-samples based on $\tilde{P}_t$, and denote the periods when $\tilde{P}_t < 0$ as COAL-BASE and the periods when $\tilde{P}_t \geq 0$ as GAS-BASE depending on which fuel is expected to run on base load, and run regressions (i) and (ii) on each sub-sample. (Details of the data sources and summary statistics are given in the Data

[8]Exceptions include pumped storage where demand depends on spot price differences over time, and interconnector flows, which depend on spot price differences across space.

[9]Because inefficient CCGT plants only count for a small proportion of energy supply and only supply energy in very cold winter days, we only consider the generation cost differential between coal and efficient CCGT plants, for which we use the short-hand gas.

[10]The definition on peak and off-peak is from https://customerservices.npower.com/app/answers/detail/a_id/179/~/what-are-the-economy-7-peak-and-off-peak-periods%3F based on London, Eastern and East Midlands. The results are not sensitive to changing the peak period to 08:00-23:00 or 07:00-22:00.

[11]In Figure 4, the boundary between base load and mid-merit load in GB should be slightly above 30GW, after taking CHP, biomass, and renewables into consideration.

Appendix.) The results are shown in Appendix Table 5.

5.2 The role of generation cost differentials between coal and gas

Appendix Table 5 shows that the impacts of ΔW_t and ΔD_t on ΔC_t and ΔG_t depend on the cost differential ($\tilde{P}_t$), especially for off-peak periods. During off-peak periods, a negative $\tilde{P}_t$ will boost the partial effect of ΔW_t and ΔD_t on ΔC_t; while during peak periods a negative $\tilde{P}_t$ will diminish the impact of ΔD_t on ΔC_t. The same is true for the impact of ΔW_t and ΔD_t on ΔG_t, but in the opposite direction.[12] We conclude that the partial effects of ΔW_t and ΔD_t on ΔC_t and ΔC_t depend on $\tilde{P}_t$, and assume the dependency is non-linear, suggesting the following regressions:

$$\Delta C_t = \alpha_0 + f(\tilde{P}_t)\cdot \Delta W_t + k(\tilde{P}_t)\cdot \Delta D_t + \boldsymbol{\theta' X_t} + \varepsilon_t, \tag{iii}$$

$$\Delta G_t = \beta_0 + g(\tilde{P}_t)\cdot \Delta W_t + l(\tilde{P}_t)\cdot \Delta D_t + \boldsymbol{\delta' X_t} + \mu_t, \tag{iv}$$

where $f(\tilde{P}_t)$, $k(\tilde{P}_t)$, $g(\tilde{P}_t)$, and $l(\tilde{P}_t)$ are non-linear functions of $\tilde{P}_t$, taken as polynomials of degree four.[13] For example,

$$f(\tilde{P}_t) = \alpha_{1,0} + \alpha_{1,1}\tilde{P}_t + \alpha_{1,2}\tilde{P}_t^2 + \alpha_{1,3}\tilde{P}_t^3 + \alpha_{1,4}\tilde{P}_t^4.$$

Regressions (iii) and (iv) are more robust because they are an improvement on the previous linear regressions, and non-linear relationships make more sense of the varying sensitivity of the merit order to the cost differential.[14]

From the the results shown in Appendix Table 5, we would expect the *magnitudes* of $f(\tilde{P}_t)$ and $k(\tilde{P}_t)$ during off-peak periods to be decreasing with $\tilde{P}_t$, meaning that as the coal generation

[12] We also find no evidence on the asymmetric partial effects when wind rises and falls ($\Delta W_t > 0$ *v.s.* $\Delta W_t \leq 0$), and when the demand on fossil generation increases and declines ($\Delta C_t + \Delta G_t > 0$ *v.s.* $\Delta C_t + \Delta G_t \leq 0$).

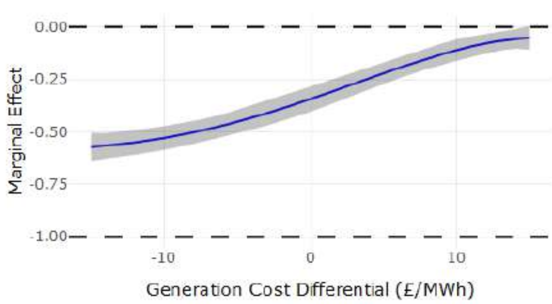
[13] We assume the polynomial forms to be degree four because some coefficients on the polynomial terms become insignificant when the order is higher, and a lower order also avoids over-fitting.

[14] In fact, the test for the joint significance of the polynomial terms are all statistically significant at the 0.1% level. For example, in $f(\tilde{P}_t)$, we test $H_0 : \alpha_{1,1} = \alpha_{1,2} = \alpha_{1,3} = \alpha_{1,4} = 0$.

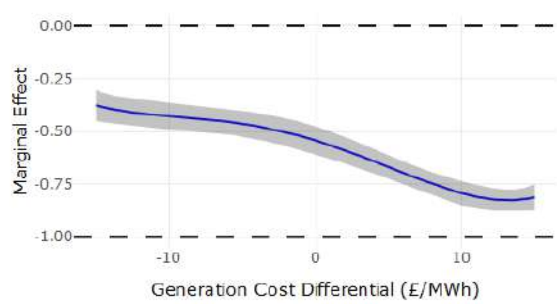
cost increases relative to gas, coal will be less sensitive to changes in wind and total demand in off-peak periods, and become less of the base load. Furthermore, $\tilde{P}_t$ is expected to have its highest influence on the partial effects when $\tilde{P}_t$ is close to zero, the tipping point that determines the base-load fuel. Therefore, we would expect the slope rates for $\hat{f}(\tilde{P}_t)$, $\hat{k}(\tilde{P}_t)$, $\hat{g}(\tilde{P}_t)$, and $\hat{l}(\tilde{P}_t)$ to be the highest at around $\tilde{P}_t = 0$. For the same reason, the *magnitudes* of $g(\tilde{P}_t)$ and $l(\tilde{P}_t)$ during off-peak periods are expected to be increasing with $\tilde{P}_t$, with the highest slope rate at $\tilde{P}_t = 0$.

In peak periods we expect $k(\tilde{P}_t)$ to be increasing with $\tilde{P}_t$, and $l(\tilde{P}_t)$ to be decreasing with $\tilde{P}_t$, with slope rates highest at $\tilde{P}_t = 0$. We also expect $\tilde{P}_t$ to have little impact on $\hat{f}(\tilde{P}_t)$ and $\hat{g}(\tilde{P}_t)$ as gas provides flexible response regardless of the cost difference,

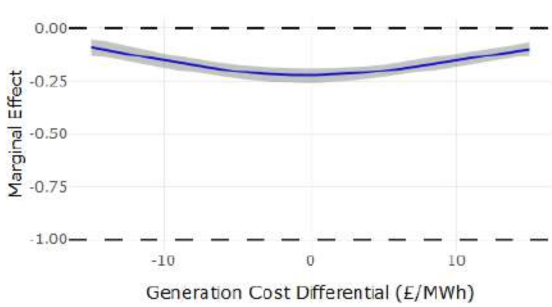
(a) partial effects of ΔW_t on ΔC_t, off-peak



(b) partial effects of ΔW_t on ΔG_t, off-peak



(c) partial effects of ΔW_t on ΔC_t, peak



(d) partial effects of ΔW_t on ΔG_t, peak

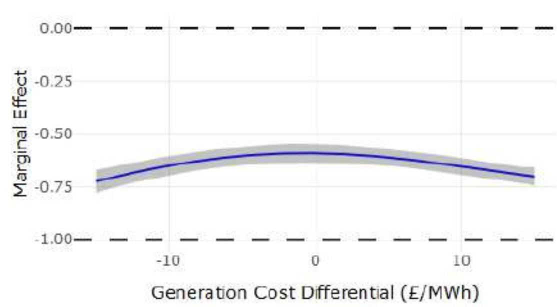
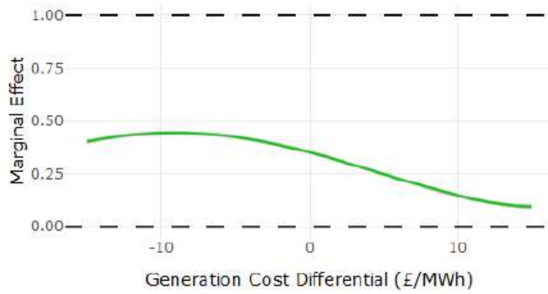


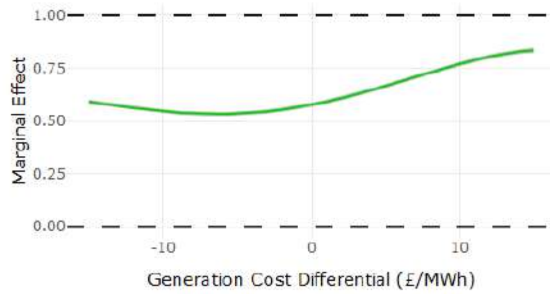
Figure 6: The estimated partial effects of ΔW_t on ΔC_t and ΔG_t, regressions (iii) and (iv)

The detailed estimation results are shown in the Appendix. The non-linear partial effects of

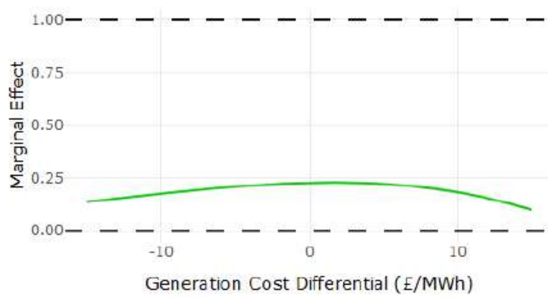
(a) partial effects of ΔD_t on ΔC_t, off-peak



(b) partial effects of ΔD_t on ΔG_t, off-peak



(c) partial effects of ΔD_t on ΔC_t, peak



(d) partial effects of ΔD_t on ΔG_t, peak

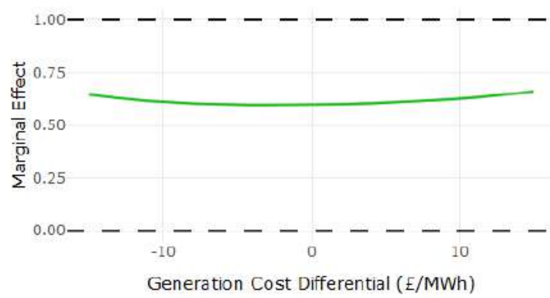


Figure 7: The estimated partial effects of ΔD_t on ΔC_t and ΔG_t, regressions (iii) and (iv)

ΔW_t on ΔC_t and ΔG_t (i.e. $\widehat{\partial \Delta C_t/\partial}\Delta W_t$ and $\widehat{\partial \Delta G_t/\partial}\Delta W_t$) and the corresponding 99% confidence intervals for are plotted in Figure 6, with the x-axis representing the cost differential $\tilde{P}_t$ and y-axis representing marginal effects. Overall, the partial effects are negative, and $|\widehat{\partial \Delta C_t/\partial}\Delta W_t + \widehat{\partial \Delta G_t/\partial}\Delta W_t|$ is close to but smaller than 1 for any given $\tilde{P}_t$ within the range considered.

FigureS 6a and 6b show the off-peak relationships. The slopes of the curves reflect the impact of $\tilde{P}_t$ on switching the merit order: the steeper the slope, the stronger the impact. The curvatures are indeed similar to expectations — upward (downward) sloping with the highest slope rates near $\tilde{P}_t = 0$, and with decreasing slope rates as $\tilde{P}_t$ moves away from zero, meaning that $\tilde{P}_t$ has little impact on the marginal fuel displaced by wind when the cost difference becomes large.

Thus in 2013 when $\tilde{P}_t^{2013} = -£13.5$, a 1 MW change in wind supply *in off-peak periods* is on average accompanied with a -0.56 MW change in coal generation and a -0.40 MW change in gas generation. In 2017 when $\tilde{P}_t^{2017}$ =£13.5, a 1 MW change in wind supply would on average result in a -0.06 MW change in coal generation and a -0.83 MW change in gas generation.

Figures 6c and 6d plot the peak relationships. The curvatures for the partial effects are more moderate than those in Figures 6a and 6b. This suggests that gas is always more responsive to wind variations during peak periods due to its flexibility. At the margin, wind displaces 9%-22% of coal and 59%-72% of gas.

Figures 7 shows the partial effects of ΔD_t on ΔC_t and ΔG_t (i.e. $\widehat{\partial \Delta C_t / \partial} \Delta D_t$ and $\widehat{\partial \Delta G_t / \partial} \Delta D_t$). Again, Figures 7a and 7b plot the off-peak partial effects, and 7c and 7d plot the peak partial effects. All partial effects are always positive, and $\widehat{\partial \Delta C_t / \partial} \Delta D_t + \widehat{\partial \Delta G_t / \partial} \Delta D_t$ is also close to but smaller than 1 for any given $\tilde{P}_t$ within the interval of study.

The curvatures for the off-peak partial effects meet our initial expectations — downward sloping for coal and upward sloping for gas. As the generation cost for coal becomes higher (i.e. $\tilde{P}_t$ increases), gas becomes more sensitive to demand changes during off-peak periods. Thus when $\tilde{P}_t^{2013} = -£13.5$, for 1 MW change in the energy demand, coal on average contributes 0.42 MW and gas on average 0.58 MW. When $\tilde{P}_t^{2017}$ =£13.5, 1 MW increase in demand would on average increase coal generation by only 0.10 MW and gas generation by 0.82 MW.

As with wind changes, in peak periods the marginal effects of demand changes do not vary much with $\tilde{P}_t$. At the margin, 10%-23% of demand change is met by coal and 59%-66% by gas.

5.3 Short-run Marginal Displacement Factor of Wind

In addition to wind displacing coal and gas, it can also influence other flexible power sources, especially pumped storage and imports, which explains why $|\hat{f}(\tilde{P}_t) + \hat{g}(\tilde{P}_t)| < 1$ and $|\hat{k}(\tilde{P}_t) + \hat{l}(\tilde{P}_t)| < 1$. However, when pumped storage is providing output it does not directly emit CO_2, nor do imports count as GB emissions, and we can confine attention to impacts on coal and gas for estimating the marginal CO_2 displacement factor of wind. (On average, the emissions caused by the pumping changes induced by wind changes will cancel out, as wind is as likely to increase as to decrease.)

The estimation results from Figure 6 and 7 allow us to calculate the marginal CO_2 displacement of wind for each quarter since 2012 as follows: for each half hour, given the generation cost differential, calculate the partial effects of ΔW_t on ΔC_t and ΔG_t; multiply the estimated partial effects by the emission coefficients of coal and efficient CCGTs respectively to obtain the (short-run) marginal CO_2 displacement of wind (the SR-MDF).[15] The calculation is done separately for peak and off-peak and then combined to give the final result.

Figure 8 plots the quarterly average SR-MDF of wind, where the dotted curve represents the generation cost differential between coal and gas ($\tilde{P}_t$), which is to be read from the right-hand y-axis. The two thick horizontal lines are the CO_2 emission coefficients (tCO_2/MWh) for coal and efficient CCGTs.

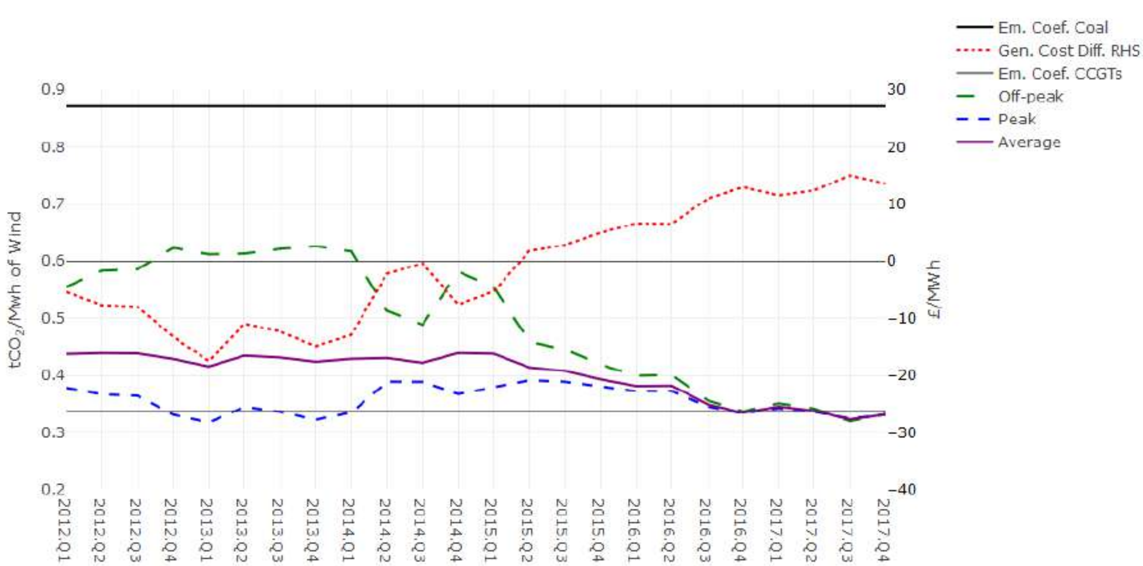


Figure 8: The short-run marginal displacement factors of wind

[15]We use the emission factor of 0.871 tCO_2/MWh for coal-fired power plants, and a weighted average of 0.337 tCO_2/MWh for efficient CCGTs.

Figure 8 shows that the SR-MDF of wind in off-peak periods is decreasing during the period, with no strong trend for peak periods. The reason is straight-forward from Figure 6 and 7. When coal is cheaper and on base load (before Q2 2015), coal responds more to wind changes during off-peak periods. Since coal has a higher emission intensity than gas, the marginal CO_2 displacement of wind is higher when coal is the marginal fuel (during off-peak before Q2 2015). In peak hours, however, demand is more variable, and CCGTs are better able in respond quickly to variations in wind, so the cost differential has little impact on the peak SR-MDF of wind. The solid curve is the average SR-MDF after combining peak and off-peak periods, which is also in general negatively correlated with the generation cost differential ($\tilde{P}_t$). The negative relationship is mainly driven by the dynamics of the SR-MDF during off-peak periods.

The CPS almost doubled after Q2 2015, causing efficient CCGTs to provide base-load power, displacing coal. Since then, wind primarily displaces gas in both peak and off-peak periods. causing the SR-MDF for off-peak periods to fall. Thus before Q2 2015, a 1 MWh short-run increase in wind supply would on average reduce CO_2 emissions by 0.43 tonnes; while from Q2 2015 to Q4 2017, it would on average only reduce CO_2 emissions by 0.36 tonnes.

The period 2012-2017 slightly overlaps with that studied (2009-2014) by Thomson et al. (2017), allowing a comparison of the results, shown in Figure 9 (the detailed numbers are shown in Table 9 in the Appendix). We used the best readily available data to replicate Thomson et al.'s results and extend their estimates to 2016.[16] (Details for the replication are given in the Appendix.)

Despite using a rather cruder (but more accessible) data set, the replicated results on the SR-MDF are very close to those from Thomson et al. (2017), especially for the years between 2010-2013. On the other hand, our estimates from non-linear regressions are overall smaller

[16] We use the five-minute average generation by fuel type data from the Elexon portal (https://www.elexonportal.co.uk/article/view/216?cachebust=p3a16b2n35) which is only available up to Q1 2017.

Figure 9: Comparisons on the patterns of annual MDFs, tCO_2(eq)/MWh

than those from Thomson et al. (2017) and the replicated results, because we are using completely different emission factors.[17] Despite that, the pattern for the dynamics of our estimated SR-MDF overlaps with the replicated results except for 2012, perhaps because we treat imports as overseas CO_2 emission and exclude their contribution.[18] Our results can be more intuitively explained by the merit-order effect given the fuel cost movements shown in Figure 3: in spite of introducing the CPS on April 1, 2013, efficient CCGTs did not become base load until Q2 2015; without a switch in the merit order there is no reason for any drastic change in the SR-MDF in 2013.

To compare the SR-MDF with the LR-MDF in the next section, we estimate the SR-MDFs under three difference carbon price scenarios — no CPS (full carbon price £6/tCO_2), base CPS (full carbon price £24/tCO_2), and high CPS (full carbon price £37/tCO_2). We choose these

[17]Thomson et al. (2017) use well-to-tank net calorific values (NCV) and as a result, the average emission factors for coal (with 35.6% efficiency) and efficient gas (with an average of 54.5% efficiency) are, respectively 1.12 tCO_2eq/MWh and 0.416 tCO_2eq/MWh, much higher than the carbon emission coefficients found by other studies. See https://www.parliament.uk/documents/post/postpn_383-carbon-footprint-electricity-generation.pdf.

[18]It would be possible, but challenging, to determine the marginal plant and hence emissions from the transmission-constrained Continental electricity market.

Table 2: Generation Costs by Fuels

	Cost £/MWh$_e$			
	no CO_2	zero CPS	base CPS	high CPS
Coal	£18.46	£23.68	£39.36	£50.68
CCGT new	£28.80	£30.80	£36.79	£41.12
CCGT older	£30.52	£32.63	£38.97	£43.54
CCGT oldest	£44.08	£47.15	£56.35	£62.99
CPS £/tCO_2		£6.00	£24.00	£37.00

three particular carbon prices because the average EUA price for 2015 is around £6/tCO_2,[19] therefore the zero and base CPS cases simulate the 2015 fuel mix with and without the CPS. £37/tCO_2 corresponds to the high 2018 EUA price induced by the *Market Stability Reserve*. Table 2 gives the electricity generation cost by fuels under the three proposed scenarios, based on the fuel price and plant efficiencies given in Table 1.

Table 3: SR-MDF for the Three Carbon Price Scenarios

	Carbon Prices		
	£6/tCO_2	£24/tCO_2	£37/tCO_2
$-d\Delta C/d\Delta W$	0.29	0.24	0.15
$-d\Delta G/d\Delta W$	0.56	0.60	0.69
SR-MDF	0.44	0.41	0.36
$d\Delta C/d\Delta D$	0.28	0.26	0.18
$d\Delta G/d\Delta D$	0.58	0.60	0.67
MEF	0.44	0.43	0.38

Notes: $-d\Delta C/d\Delta W$ is the coal Displacement Factor (DF, the decrease in Coal output for 1 MWh of Wind), $-d\Delta G/d\Delta W$ is the gas DF and SR-MDF = $-d\Delta CO_2/d\Delta W$ is the displacement of CO_2 in tCO_2/MWh of extra wind.

The SR-MDF and MEF under the three carbon price scenarios are given in Table 3. Note that here the partial effects are averaged over peak and off-peak periods. As the Carbon price

[19] The exact 2015 average was £5.85/tCO_2.

increases, both $-dC/dW$ and dC/dD declines, and both $-dG/dW$ and dG/dD increases. This is driven by the merit-order switch during off-peak periods — the CPS forces gas to displace coal during off-peak periods in response to wind (and demand) changes; whereas during peak periods gas has always been the major respondent to wind (and demand) changes thanks to its flexibility. Because coal has a much higher emission factor, both SR-MDF and MEF decline.

5.4 The SR-MDF without the CPS

By treating fuel prices as exogenous, we can calculate the marginal effects of ΔW_t on ΔC_t and ΔG_t without the CPS by adjusting the generation cost differential in the estimated regressions (iii) and (iv). We then multiply the marginal effects by the corresponding emission factors to derive the SR-MDF without the CPS. The patterns are shown in Figure 10.

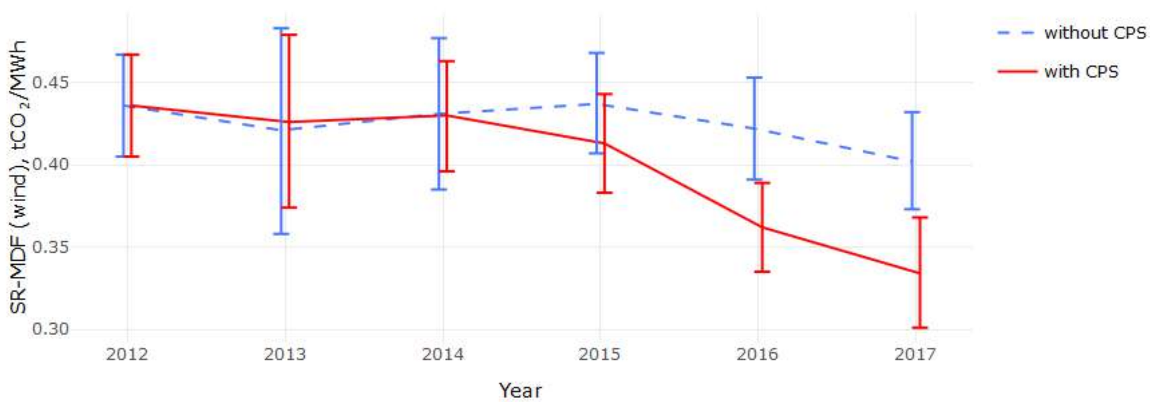


Figure 10: SR-MDF with and without the CPS

Without the CPS, the SR-MDF would stay relatively high, so the average SR-MDF in 2015 would be 0.44 tCO_2/MWh instead of 0.41 tCO_2/MWh, or 7% higher, while in 2017 it would be 0.40 tCO_2/MWh instead of 0.33 tCO_2/MWh, or 21% higher. The explanation is that without the CPS, both coal and gas costs would be lower, but the generation cost from coal would be much lower. Coal would continue on base load, being the marginal off-peak fuel until late 2017, when the gas and EUA prices increase and coal becomes mid-merit even without the

CPS, explaining why the SR-MDF stays high until late 2017. During this period, without the CPS, wind displaces more CO_2, although the CPS shifts supply from coal to gas, reducing overall emissions.

6 Modelling the Long-run Carbon Savings from Wind

The long-run carbon savings from additional wind capacity is studied using a simulation model to determine dispatch with and without a significant increase in wind capacity. Deane et al. (2015) do this for EU scenarios in 2030 and 2050, using Plexos to minimize total costs over a year, assuming inelastic time varying demand, and taking account of pumped storage and operational and technical constraints (presumably transmission capacities, ramping, minimum load and other plant characteristics). Ofgem (2018) in its *State of the market 2018* uses the LCP EnVision model to simulate not just dispatch but also investment and retirements from 2010-2017 to simulate counterfactuals with and without some or all of the policy interventions, including the CPS. Ofgem is interested in the increase in wholesale electricity costs and the policy costs, which together give the cost to consumers, excluding longer-run benefits (learning spill-overs inducing climate change mitigation elsewhere).

We use a simple hourly unit commitment model of the 2015 GB power system to examine the impacts of varying wind capacity on fuel mix and hence CO_2 emissions, for three carbon prices and two levels of wind capacity. In contrast to Ofgem (2018) we do not attempt to model plant entry and exit, although the plant we simulate in 2015 is the plant listed as then present (Ofgem, 2018, Figure A3, p9). Thus we can examine the impact of additional wind capacity on future carbon savings (although not including their impact on plant exit). All cases take the plant available in 2015, but hold demand and all outputs other than coal, gas, and pumped storage at their 2015 values.[20] The base case takes the actual wind output in each hour of 2015 (an average wind year), and holds fuel and carbon prices constant across the year, so

[20]From Elexon Portal at https://www.elexonportal.co.uk/news/latest.

that variations in fuel prices and trade do not confound the variations of interest. The assumed fuel and the three carbon prices (EUA price plus CPS) are shown in Table 1, with the installed capacities, efficiencies and carbon intensities of key generation units.

The simulation determines an optimal hourly dispatch with predictable future outputs of wind over the period of optimization. The simulations are re-run with 25% more wind in each hour (i.e. with 25% more installed capacity at each location) to see how much coal and gas output is displaced in each hour and the resulting carbon savings, which in turn depend on the carbon price. Pumped storage is endogenous but only in arbitrage mode. Its more valuable use is in short-term balancing but that cannot be handled in a deterministic model. The hourly resolution inevitably conceals short-run variations (the actual output data are given in 5-minute periods), and so should be thought of as simulating the main (day-ahead) impacts of wind on the generation mix, rather than actions in the balancing market. As wind forecasts improve and intra-day markets become more liquid these simulations will better model wind impacts. We discuss how to combine the longer and shorter run analyses below.

A proper but more complicated analysis would determine the plant mix including reserves for balancing as uncertainties in demand and wind are resolved, and then re-optimize dispatch in real time limiting plant to those available, and subject to their various operating constraints (ramp rates, minimum load, etc.). This will be left for future analysis. Our deterministic modelling reduces the need for more flexible plant, probably increasing the role of coal in adjusting to changes, and understates total system costs. As our interest is in the impact of a known increase in wind capacity, the short-run variations may be sufficiently similar in the two wind scenarios to cancel out when taking the difference between scenarios.

Table 4 gives the summary results that can be directly compared with the short-run results in Table 3. The first column shows that without the CPS and just the EUA of £6/tCO_2, the change (Δ) in wind output over the year of 8.11 TWh leads to a fall in CO_2 of 4.16 million tonnes, so the saving per MWh of wind, the LR-MDF (shown as $-dCO_2/dW$) is 0.51

tCO_2/MWh. With the CPS at its actual value of £18/tCO_2, the CO_2 price is £24/tCO_2, the LR-MDF ($-dCO_2/dW$) is 0.68 tCO_2/MWh, decreasing slightly to 0.63 tCO_2/MWh if the CO_2 price is £37/tCO_2. The impact of the increased wind capacity decreases base-load coal by 2.62 TWh at zero CPS, with the larger share of adjustment made by mid-merit gas which falls by 5.47 TWh, giving $-dG/dW$ = 0.67. At the actual CPS wind now mainly displaces mid-merit coal (by 5.09 TWh) while base-load gas falls by 2.97 TWh. As a result, $-dC/dW$ rises in and $-dG/dW$ falls ($-dC/dW = 0.63$; $-dG/dW = -0.37$). At the high CO_2 price, less coal runs on average so the change in coal is slightly less than in the base case and gas slightly more, with $-dC/dW = -0.55$ and $-dG/dW = -0.45$. Summarising, the LR-MDF of wind increases from 0.51 (tCO_2/MWh) at zero CPS, to 0.68 with a CPS of £18/tCO_2 and then decreases slightly to 0.63 at the highest carbon price as coal is squeezed out of the system.

Table 4: Displacement Factors for the Three Carbon Price Scenarios, 2015 Generation Mix

	Carbon Prices					
	£6/tCO_2		£24/tCO_2		£37/tCO_2	
	TWh	dCO_2	TWh	dCO_2	TWh	dCO_2
ΔC	-2.62	-2.28	-5.09	-4.07	-4.44	-3.87
ΔG	-5.47	-1.87	-2.97	-1.15	-3.67	-1.27
ΔW	8.11	-4.16	8.11	-5.22	8.11	-5.14
$-dC/dW$	0.32		0.63		0.55	
$-dG/dW$	0.67		0.37		0.45	
LR-MDF	0.51		0.68		0.63	
dC/dP_c TWh/£			-3.03		-0.81	
dG/dP_c TWh/£			2.98		0.82	
dCO_2/dP_c Mt/£				-1.63		-0.43

Notes: $-dC/dW$ is the coal Displacement Factor (DF, the decrease in Coal output for 1 MWh of Wind), $-dG/dW$ is the gas DF and SR-MDF = $-dCO_2/dW$ is the displacement of CO_2 in tCO_2/MWh of extra wind. dX/dP_c is the change in output of X (coal, gas or CO_2) for a £1 increase in the CO_2 price going from £6-24/tCO_2 or from £24-37/tCO_2, measured at the base level of wind.

The last three lines of Table 4 give the estimated impact of raising the carbon price P_c by

£1/tCO_2 on the output of coal, gas and CO_2.[21] The CPS switches the merit order, so that on average a £1/tCO_2 increase in the CPS (from zero CPS to £18/tCO_2) significantly lowers coal generation by 3.03 TWh/year, saving 1.63 million tCO_2/year. Increasing the total CO_2 price further to £37/tCO_2 has a more moderate impact on the fuel mix and emissions — a £1/tCO_2 increase in the CO_2 price results in 0.81 TWh decline in coal generation (displaced by gas) and 0.43 mt CO_2 reduction.

In the zero CPS case coal has a capacity factor (CF) of 87%[22] and a coefficient of variation (CV) of output of 23%, while gas has a CF of 26% (CV 75%), consistent with coal on base load and gas providing mid-merit variable output. As gas is displaced by the extra wind, its carbon benefit is low. The situation changes considerably with the CPS at £18/tCO_2. Coal output is lower and more variable (CF falls to 42% and CV rises to 57%), while gas CF rises to 52% (CV 32%), consistent with gas on base load with coal displaced by the extra wind, raising its carbon benefit.

Finally, at the highest carbon price, coal's CF falls to 32% (CV 57%) and is frequently not running, while gas is on base load at 57% CF (CV=31%), much as in the base case. As a result coal is more often displaced by wind, so the carbon benefit of wind again increases. More details are given in the Appendices.

It is also possible to identify which fuel responds to hourly (i.e. short-run) predicted changes in demand, determined by the optimum dispatch. To avoid complications caused by pumped storage and correlations of wind with demand, it is perhaps more helpful to compare changes in the share of fossil fuel response of coal (the remainder being gas). At a zero CPS, the share of response from coal to changes in demand on fossil fuel (i.e. coal and gas) is 36%, with 64% of the adjustment coming from mid-merit gas as expected. With the CPS coal falls

[21] Calculated by differencing the outputs at £6/tCO_2 and £24/tCO_2 and dividing by the £18/tCO_2 (=24-6) to give the first set of values (in the £24/tCO_2 column) and similarly differencing the outputs at £37/tCO_2 and £24/tCO_2 to give the final column.

[22] This is given by the average output relative to the maximum observed output, which is below the nominal capacity. This seems a more relevant measure for CCGTs, where there is a large tail of less efficient plant that would otherwise give a very low CF for gas as a whole.

to 23%, with 76% coming from gas, suggesting that gas is always more flexible, more so when it is cheaper than coal.

The econometric analysis discussed above strongly suggests that the displacement impact of wind and hence its carbon saving depends on the state of the system, and whether off-peak or peak, when plant may be at its maximum output and unable to increase output, or when minimum loaded and uneconomic to turn off. Five-minute or half-hourly changes in wind and demand may also cause one or other fuel to hit its ramp constraints, and hence determine which plant is required to respond; effects that are poorly captured by the model's hourly resolution. Pumped storage is endogenous in the simulations and will be driven by cost differentials, which will vary between different wind capacity scenarios. As pumped storage has a round trip efficiency of about 75%, if more storage is required, then losses will lead to more MWh of fossil generation, so the sum of the output changes of coal, gas and wind will not necessarily sum to zero.

6.1 The variation of LR-MDFs with Residual Demand

Figure 11 graphs a rolling average (over 672 non-consecutive hours ranked by residual demand) of the displacement of coal output ($-dC/dW$), gas output ($-dG/dW$), pumped storage output ($-dPS/dW$), and the implied carbon saving, the LR-MDF ($-dCO_2/dW$, tCO_2/MWh) as a function of residual demand (total demand net of renewables) for the 2015 constant fuel prices and actual 2015 CPS (total carbon price £24/tCO_2). It also shows the deviation of the average wind over these hours compared to the annual average.[23] Residual demand is averaged over the same number of hours (672) as the responses, and equal intervals show equal increments of

[23]The graphs are constructed by averaging the MWh of coal, gas and pumped storage displaced by the average wind increase over 672 ranked non-consecutive hours, and not the average of the instantaneous displacement factors. The reason is that comparing two different annual wind levels (but the same hourly pattern) leads to quite different plant dispatch and notably different pumped storage (we are holding interconnector flows constant as otherwise these would further complicate the analysis). Differences in pumped storage give rise to implausible hourly LR-MDFs, and are driven less by wind than by the need to minimize dispatch costs over the optimization period (70 hours). Over a sufficiently long window the impact of pumped storage cancels out (except for losses, which are significant, so there is net negative storage increasing residual demand).

net demand.

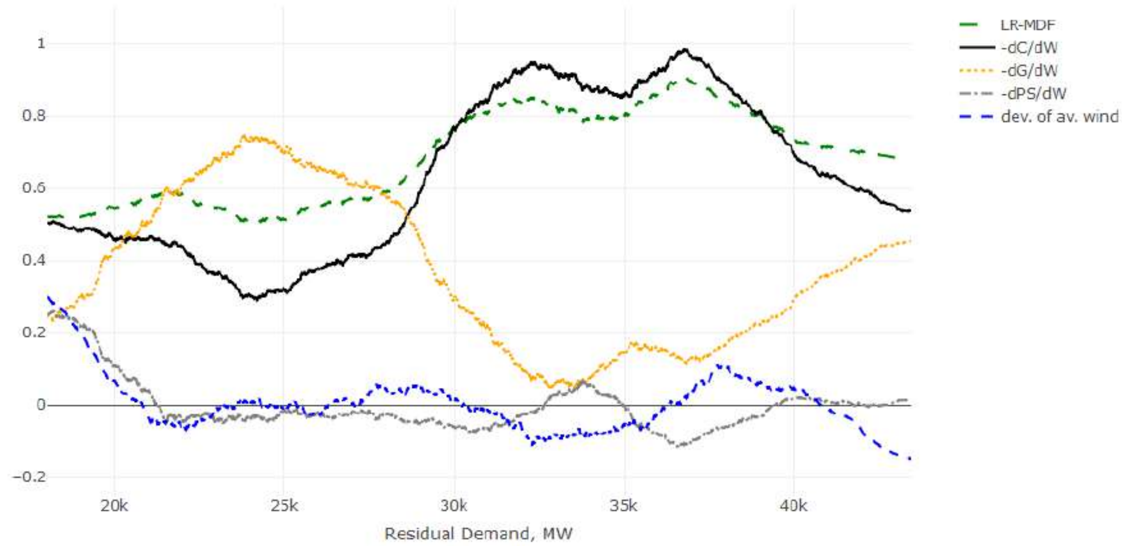


Figure 11: Displacement Factors v.s. Residual Demand, £24/tCO_2

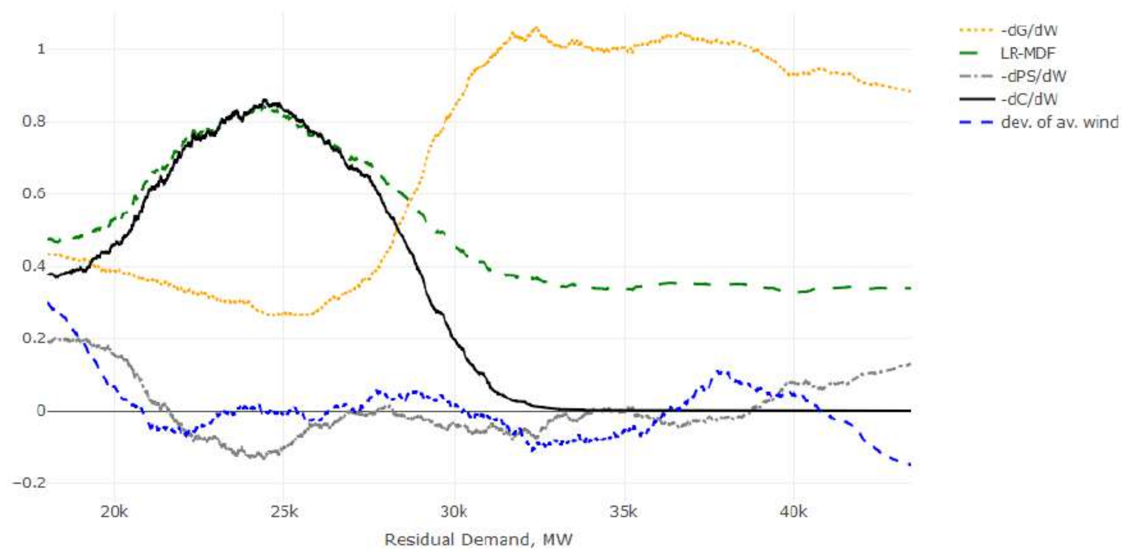


Figure 12: Displacement Factors v.s. Residual Demand, £6/tCO_2

In the base case (total CO_2 price £24/tCO_2) coal is mid-merit and gas base load, as Appendix Figure 19 shows. When residual demand is low, wind displaces mostly gas as coal is running at minimum stable levels, but at higher residual demand when prices are high enough to make coal profitable, coal can respond flexibly ($-dC/dW$ rises almost to unity until it reaches full capacity, then is replaced by gas) while gas is base load and hardly varying ($-dG/dW$ is very low but still responding to increased demand at very high RD). Coal (and CO_2) displacements move in counterpoint with gas, as $-dC/dW - dG/dW - dPS/dW = 1$, and averaged over many hours dPS/dW is small, as the graph show. Thus the LR-MDF for wind is smaller at low levels of residual demand (RD), and higher at higher RD. As a result the LR-MDF is larger than for the zero CPS case discussed below.

Figure 12 repeats this for the case with no CPS (just the EUA £6/tCO_2). This time coal does not respond at all at high residual demand when it is at base load, but does respond more strongly than gas at low RD, so the LR-MDF is high at low RD (off-peak) and lower for higher RD (peak periods) leading to a lower average LR-MDF. This is in sharp contrast to the short-run behaviour estimated econometrically, where the SR-MDF is *lower* with the CPS than without.

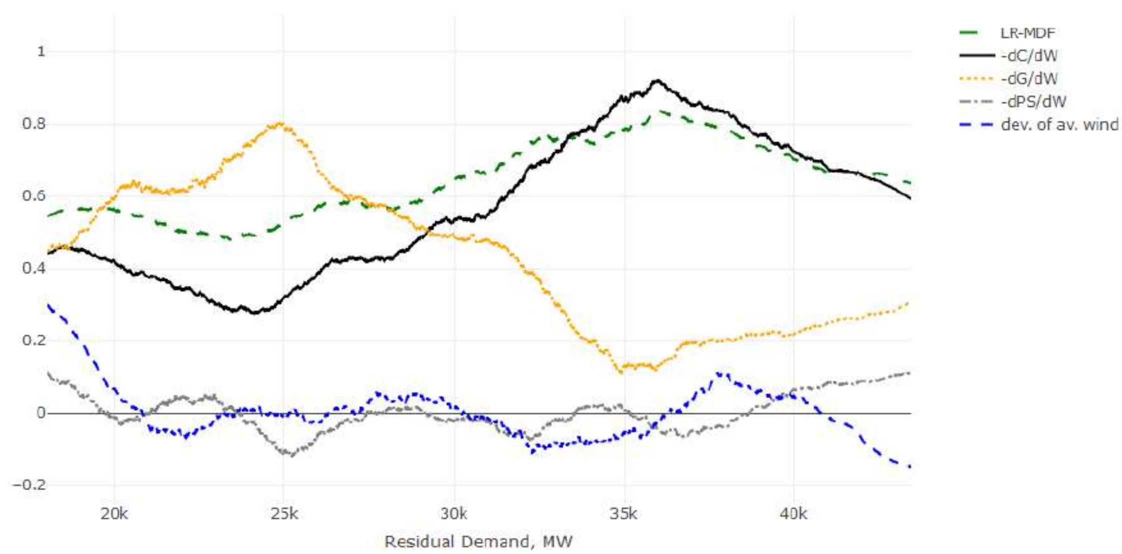


Figure 13: Displacement Factors v.s. Residual Demand, £37/tCO_2

Finally, Figure 13 shows responses at the very high carbon prices seen towards the end of 2018 (£37/tCO_2). Now coal is running at low load factors when RD is low and adjusts less than gas, but responds more strongly at higher levels of RD. The average LR-MDF falls slightly compared to the base case.

7 Measuring the carbon savings of wind from the LR and SR-MDFs

The LR-MDF measures the impact of more wind capacity on the merit order under different fuel and carbon prices. More wind turbines edge out the most expensive fuel, identified by the LR-MDF. A large increase in wind capacity is likely to force the closure of some coal stations, until average prices rise enough to make the remaining stations sufficiently profitable. As plant exit is not included, the LR model may over-estimate the maximum output that coal can supply, which may affect the LR-MDF at higher carbon prices, possibly reducing them as coal becomes a smaller share of the plant capacity.

In the short-run (the period in which plant is committed to deliver in future hours) the carbon savings will be affected by the types of plant that respond to the unpredictable part of wind changes. Which plant can increase or decrease output sufficiently rapidly will depend on its flexibility and whether operating away from minimum or maximum output, and this may not be the plant where the residual demand meets the merit order.

The LR-MDF *rises* (from 0.51 to 0.68 or by 33% for 2015 data) as the total carbon price rises from £6/tCO_2 to £24/tCO_2. The CPS moves coal from base-load to mid-merit where wind now displaces coal rather than gas. The short run responses, after plant is committed, are identified by the econometric analysis. The evidence above suggests that most of the variation in the SR-MDFs with the carbon price occur off-peak. In peak hours the marginal displacement of coal is low and relatively insensitive to the carbon price (more precisely, the cost difference) with most of the response coming from gas. When coal is cheaper than gas and coal is running on base-load it will run above its minimum output off-peak and hence be able to vary its output, although it will be at full output during peak hours and unable to increase output. Even when coal is more costly according to the merit order, it will only be committed if the peak prices are high enough to cover both variable costs at the peak and any losses running off-peak, when it is at minimum load to be in a position to ramp up for the profitable hours. Thus it will be less flexible off-peak and, as before, less flexible during the peak. High coal prices somewhat counterintuitively mean that coal is less responsive in the short run than gas. As a result, the CPS in 2015 lowered the SR-MDF from 0.44 to 0.41 (all tCO_2/MWh) or by 7%.

The econometric analysis shows that flexible CCGTs always respond to wind changes during peak periods; while for off-peak periods, the cheaper fuel is responding to wind changes (the more costly fuel is likely at minimum load). Therefore, the value for the SR-MDF mainly depends on which fuel source is the off-peak marginal fuel. Without the CPS, coal is cheaper and thus the marginal off-peak fuel. The CPS made coal more expensive than gas, shifting the marginal fuel for off-peak periods from coal to gas. As a result, the SR-MDF without CPS is higher than the SR-MDF with the CPS.

The relevant policy issue is whether increasing wind capacity reduces emissions, and the answer will be primarily driven by the LR-MDF, recognising that the actual operation of the electricity system in real time depends on forecast uncertainty, which will require flexible responses coming from possibly different plant than the apparently marginal plant suggested by the merit order. If the average error in wind forecasts at the commitment stage is 10% (Gonzlez-Aparicio and Zucker, 2015) then an appropriate MDF would be 10% x SR-MDF + 90% x LR-MDF, or in 2015 0.65t CO_2/MWh.

8 Estimating the impact of the CPF on wholesale prices

The marginal emission factor (MEF), a in (1), gives the marginal emissions from changes in demand, so if the carbon price P_c changes, so will the cost of emissions from marginal plants, C_{C}:

$$\Delta C_{\mathrm{C}} = \mathrm{MEF} \cdot \Delta P_c \approx [e_C k(\tilde{P}_t) + e_G l(\tilde{P}_t)] \cdot \Delta P_c \tag{3}$$

from nonlinear regressions (iii) and (iv).

The wholesale price is not necessarily equal to the variable cost of the marginal plant setting the price (not least because in a single price auction like EUPHEMIA plant needs to cover its start-up costs and may add a margin to cover fixed costs). Nevertheless, small changes in the variable cost of the marginal plant, ΔC_c, should translate into corresponding changes in the clearing price in the EU day-ahead auction platform EUPHEMIA that sets the price for interconnector trade.[24] With that in mind, Figure 14 shows the evolution over time in current £/MWh of the marginal cost of the CPS, ΔC_{CPS}, and hence allows us to predict the change in the prices that drive interconnector trade.

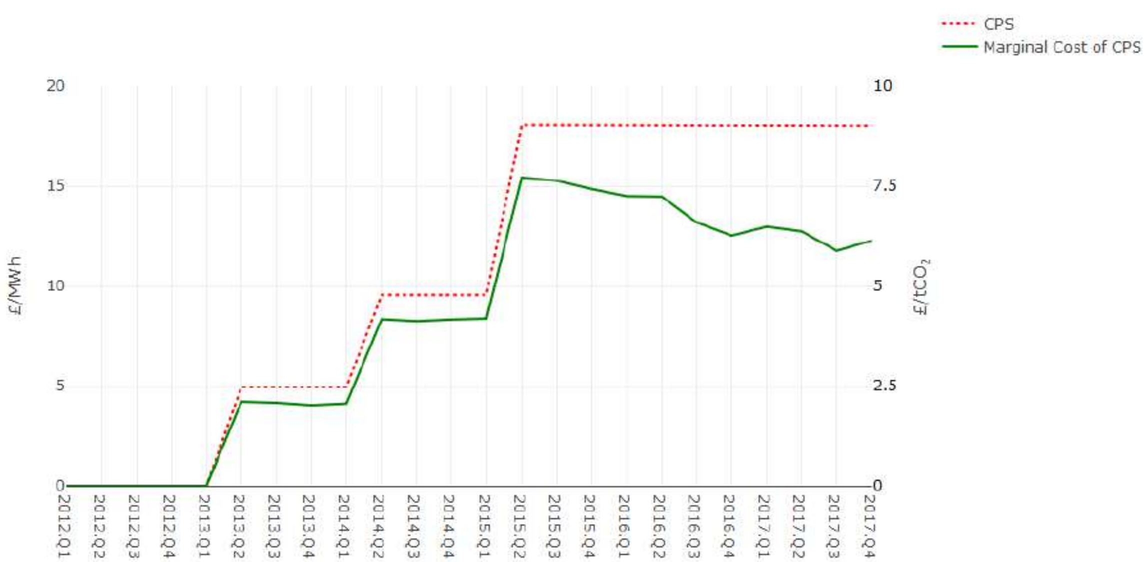


Figure 14: Marginal Cost of CPS on the Cost of Emission

As an example, we can ask what is the possible impact on trade with France over IFA in 2016 with and without the CPS. This is complicated by the fact that recorded trade is mainly determined by the day-ahead market, but can be subsequently changed by trades on the intraday and balancing markets, while our model only predicts price change from the day-ahead clearing price. The second complication is that the volume of the IFA flow can have further impacts on

[24]This assumes 100% cost pass-through, which is often rejected in oligopolistic markets, but the GB electricity market is considered workably competitive, and so this is a defensible assumption.

the spot market prices (SMPs) on both sides. Without the CPS the GB SMP will be lower. If from the (normal) position of importing the sign of the price difference between GB and France ($P_t^{\Delta} \equiv P_t^{\mathrm{GB}} - P_t^{\mathrm{FR}}$) changes, and with it the direction of the IFA flow, GB demand will increase. That will partly offset the fall in GB prices. Reduced imports or increased exports will drive the prices back towards equality, until the export capacity is fully used and GB prices are below French prices. (French prices will also fall somewhat as they reduce exports, but as France is connected to a much larger European market this effect will normally be considerable smaller.) The price change induced by each GW of extra exports (reduced imports) can be estimated from the price duration schedule. Newbery et al. (2016) using earlier data found this to be roughly €1/MWh/GW over the middle section of the schedule. Using just 2016 GB price data and ignoring scarcity prices above €100/MWh a linear estimate is closer to €1.25/MWh/GW, or €5/MWh for a complete change of direction of 4GW. If the French price impact is smaller (somewhat arbitrarily taken as €0.75/MWh/GW) then the total impact would be €2/MWh/GW.

To estimate the impact of removing the CPS, we first compute the notional price difference (P_t^{Δ}) assuming no trade over IFA, so that when GB would have imported P_t^{Δ} will now be higher (by up to €4/MWh depending on volumes[25]) and when GB would have exported P_t^{Δ} will now be lower. This gives the price difference (P_t^{Δ}) without the IFA shown as the dotted duration schedule curve in Figure 15. This schedule is adjusted down by the marginal cost of the CPS to the dashed schedule again assuming no trade. Finally, IFA trade is opened with the corresponding further price adjustment to give the predicted counterfactual price differences with IFA but no CPS. Notice there is now a flat section of price equality at $P_t^{\Delta} = 0$.

The results are a significant change in 2016 net imports over IFA from 10.9 TWh with the CPS to 5.6 TWh without the CPS, so that 5.3 TWh of net imports are because of the GB CPS. In 2016, GB is importing at the full available IFA capacity (nominally 2,000MW but can be

[25]using the actual capacity from Nord Pool given at https://www.nordpoolspot.com/Market-data1/GB/Capacities/UK/Hourly/?view=table.

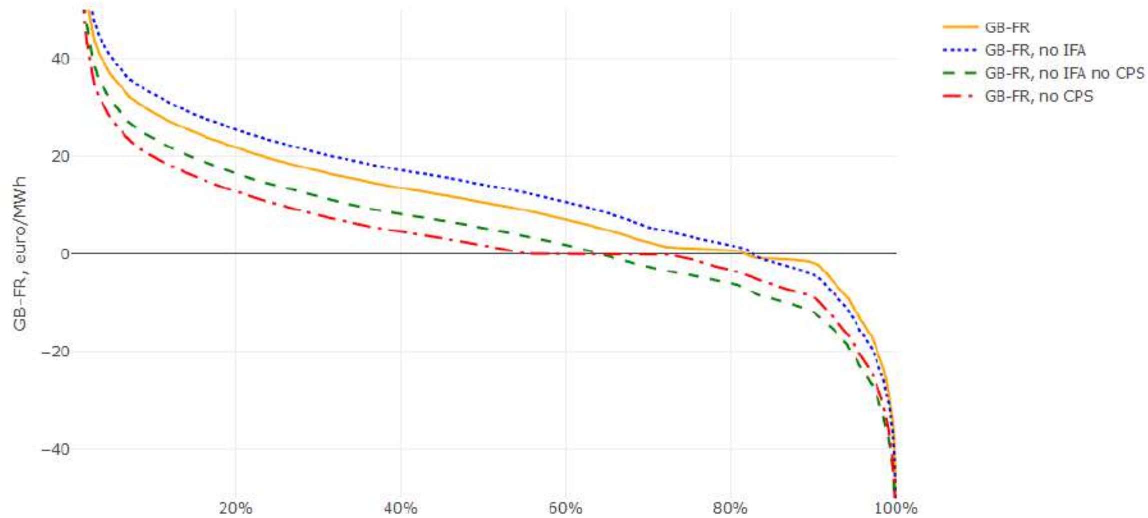


Figure 15: Actual and Counterfactual Loss-adjusted Price Differences

lower due to maintenance) 72% of the time, and exporting the full capacity 10% of the time; while without the CPS, it is estimated that the number would be reduced to 55% for import, and 28% for export but at a lower price. As France owns half of IFA, the CPS profited their share of IFA by roughly €38 million in 2016 (while UK consumers paid more, National Grid profited from its share of IFA, and the Government received extra CPS revenue).[26] These estimates are somewhat rough and ready, but give a reasonable estimate of the impact of the CPS on one interconnector, leaving a fuller study of all the interconnectors for a later paper.

9 Conclusion

This paper has investigated the effect of the Carbon Price Support (CPS) on the carbon saving from wind by examining the impact of wind on the more carbon-intensive coal and less carbon-intensive CCGT outputs. The evolution of the fuel mix from 2010-17 strongly suggests that gas has displaced coal, and that wind has displaced both, but as the clean spark and dark

[26]This is estimated from half the difference in trade revenue with and without the CPS.

spreads have varied substantially over this period with varying fuel and carbon prices, a more detailed examination was undertaken to tease out the various effects. The unit commitment simulation model explores the effect of different total carbon prices on the carbon savings from a significant increase (25%) in installed wind capacity, holding fuel prices constant. At 2015 gas and coal prices, the CPS at an additional £18/tCO_2 on an EUA price of £6/tCO_2 switches coal from base-load to mid-merit, so now coal rather than gas is displaced by extra wind capacity, *increasing* the carbon benefits of wind investment. At higher total carbon prices, coal output decreases and moves more to peak hours, resulting in a smaller carbon savings from wind investment.

The short-run impact of half-hourly varying wind on the fuel mix and emissions was explored econometrically. Variations in fuel and carbon prices as well as wind capacity and final demand over a longer time period (2012-2017) identify the drivers of the Marginal Displacement Factor (MDF) of wind quite precisely. The econometric study suggests that the short-run MDF depends on demand (i.e. which fuel type is running at the margin), the merit order, and the flexibility of fossil plants. Specifically, when demand is low (off-peak), base-load plant responds more strongly to short-run wind changes. However, when demand is high and so is its variability, more flexible CCGTs are better able to respond. Hence CCGTs are the marginal fuel during peak hours (07:00-23:00) regardless of the merit order, while coal would only be the marginal fuel during off-peak hours (23:00-07:00) when coal provides the base load. The CPS switches the merit order moving coal to mid-merit fuel, but the more flexible CCGTs become the marginal fuel for the entire day, *lowering* the MDF. We argue that the best estimate of the MDF of wind is a weighted average of the SR and LR-MDFs, with a weight on the SR-MDF equal to the mean forecast error of wind at the time of plant commitment (which we have taken as 10%).

Both the simulation and the econometrics confirm that the impact of wind depends quite sensitively on the state of the system — which plant are running and whether they are constrained by minimum loads, capacity, or ramping limits, which in turn depend on the time period over which wind varies. The fuel mix depends on fuel and carbon prices and the levels of residual demand. Different countries have very different plant mixes, and so the carbon benefits of additional renewables capacity will also vary, while over time, fuel and carbon prices as well as the plant mix will also vary. This paper shows how the emissions benefits can be measured for a given plant mix and set of fuel and carbon prices, implying that country level detailed modelling will be needed to understand their impacts.

The same econometric model can be used to estimate the price change caused by adding the CPS and that in turn can be used to estimate the impact on flows over interconnectors. In 2016 we estimate that the impact of the CPS was to transfer an extra €38 million to RTE, the owner of half of the France-England interconnector, IFA.

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Appendices

Appendix A: The linear SR-MDF econometric model

Table 5: Estimation results from linear regressions (i) and (ii)

(a) Off-peak period (23:00-07:00)

	ΔC_t		ΔG_t	
	COAL-BASE	GAS-BASE	COAL-BASE	GAS-BASE
(Intercept)	-5.19	-11.11^{*}	18.01^{*}	17.23^{*}
	(8.87)	(5.51)	(8.38)	(8.24)
ΔW_t	-0.52^{***}	-0.15^{***}	-0.41^{***}	-0.75^{***}
	(0.02)	(0.01)	(0.02)	(0.01)
ΔD_t	0.42^{***}	0.20^{***}	0.55^{***}	0.74^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
Time Dummies	YES	YES	YES	YES
R^2	0.66	0.51	0.79	0.87
Obs.	17441	17062	17441	17062

(b) Peak period (07:00-23:00)

	ΔC_t		ΔG_t	
	COAL-BASE	GAS-BASE	COAL-BASE	GAS-BASE
(Intercept)	251.22^{***}	-130.50^{***}	-115.21^{***}	180.63^{***}
	(9.83)	(8.28)	(12.53)	(11.68)
ΔW_t	-0.15^{***}	-0.15^{***}	-0.66^{***}	-0.65^{***}
	(0.01)	(0.01)	(0.01)	(0.01)
ΔD_t	0.14^{***}	0.21^{***}	0.64^{***}	0.61^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
Time Dummies	YES	YES	YES	YES
R^2	0.49	0.50	0.85	0.84
Obs.	34830	34072	34830	34072

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

The table shows that all estimates for the coefficients of ΔW_t and ΔD_t are statistically significant at the 0.1% level, and their signs follow our initial intuition. Specifically, during off-peak

Table 6: Estimate asymmetric partial effects, Off-peak (23:00-07:00)

	ΔC_t		ΔG_t	
	COAL-BASE	GAS-BASE	COAL-BASE	GAS-BASE
When wind rises, $\Delta W_t > 0$				
ΔW_t	-0.57^{***}	-0.16^{***}	-0.39^{***}	-0.76^{***}
	(0.04)	(0.02)	(0.04)	(0.03)
ΔD_t	0.42^{***}	0.19^{***}	0.56^{***}	0.75^{***}
	(0.01)	(0.00)	(0.01)	(0.01)
When wind falls, $\Delta W_t \leq 0$				
ΔW_t	-0.46^{***}	-0.17^{***}	-0.49^{***}	-0.73^{***}
	(0.04)	(0.02)	(0.04)	(0.03)
ΔD_t	0.42^{***}	0.21^{***}	0.53^{***}	0.73^{***}
	(0.01)	(0.00)	(0.01)	(0.01)
When fossil generation increases $\Delta C_t + \Delta G_t > 0$				
ΔW_t	-0.41^{***}	-0.16^{***}	-0.35^{***}	-0.55^{***}
	(0.04)	(0.02)	(0.03)	(0.02)
ΔD_t	0.33^{***}	0.21^{***}	0.61^{***}	0.69^{***}
	(0.01)	(0.00)	(0.01)	(0.01)
When fossil generation increases $\Delta C_t + \Delta G_t \leq 0$				
ΔW_t	-0.43^{***}	-0.12^{***}	-0.49^{***}	-0.75^{***}
	(0.02)	(0.01)	(0.02)	(0.02)
ΔD_t	0.40^{***}	0.17^{***}	0.48^{***}	0.69^{***}
	(0.01)	(0.01)	(0.01)	(0.01)

periods it is normally the base-load plant that responds to changes in wind supply and/or electricity demand. Table 5a shows that when coal is the base load, coal responds more strongly to wind and demand changes — if ΔW_t increases by 1 MW, ΔC_t would on average drop by 0.52 MW while ΔG_t would on average only drop by 0.41 MW. This changes when $\tilde{P}_t$ becomes positive — a 1 MW increase in ΔW_t will only reduce ΔC_t by 0.15 MW, much less than the 0.75 MW reduction in ΔG_t. The story is similar for the impact of ΔD_t on ΔC_t and ΔG_t when coal supplies the base load, where a 1 MW increase in ΔD_t would increase ΔC_t by 0.42 MW and

Table 7: Estimate asymmetric partial effects, Peak (07:00-23:00)

	ΔC_t		ΔG_t	
	COAL-BASE	GAS-BASE	COAL-BASE	GAS-BASE
	When wind rises, $\Delta W_t > 0$			
ΔW_t	-0.15^{***}	-0.15^{***}	-0.67^{***}	-0.69^{***}
	(0.02)	(0.01)	(0.03)	(0.02)
ΔD_t	0.14^{***}	0.21^{***}	0.63^{***}	0.60^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
	When wind falls, $\Delta W_t \leq 0$			
ΔW_t	-0.12^{***}	-0.14^{***}	-0.64^{***}	-0.61^{***}
	(0.02)	(0.02)	(0.03)	(0.02)
ΔD_t	0.14^{***}	0.21^{***}	0.65^{***}	0.62^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
	When fossil generation increases $\Delta C_t + \Delta G_t > 0$			
ΔW_t	-0.12^{***}	-0.12^{***}	-0.55^{***}	-0.55^{***}
	(0.02)	(0.01)	(0.02)	(0.01)
ΔD_t	0.15^{***}	0.16^{***}	0.54^{***}	0.54^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
	When fossil generation increases $\Delta C_t + \Delta G_t \leq 0$			
ΔW_t	-0.14^{***}	-0.15^{***}	-0.58^{***}	-0.56^{***}
	(0.02)	(0.01)	(0.02)	(0.01)
ΔD_t	0.10^{***}	0.25^{***}	0.69^{***}	0.56^{***}
	(0.00)	(0.00)	(0.01)	(0.00)

ΔG_t by 0.55 MW. However, when gas supplies the base load, a 1 MW increase in ΔD_t would only increase ΔC_t by 0.20 MW while increasing ΔG_t by 0.74 MW.

From Table 5b, the magnitude of changes in the coefficients of ΔW_t for peak periods for coal is negligible. Gas has always been dominant in responding to wind changes during peak periods — a 1 MW increase in ΔW_t is on average accompanied by 0.66 MW fall in ΔG_t when coal is the base load, and by 0.65 MW otherwise. This might be because demand is both high and more variable during peak periods; therefore flexible gas plants are better able to adjust to

Table 8: Estimation results from non-linear regressions (iii) and (iv)

	Off-peak (23:00-07:00)		Peak (07:00-23:00)	
	ΔC_t	ΔD_t	ΔC_t	ΔD_t
(Intercept)	-2.57	11.27	59.08^{***}	38.57^{***}
	(5.22)	(5.76)	(6.48)	(8.72)
ΔW_t	-0.34^{***}	-0.54^{***}	-0.22^{***}	-0.59^{***}
	(0.02)	(0.03)	(0.01)	(0.02)
ΔD_t	0.35^{***}	0.58^{***}	0.23^{***}	0.60^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
$\Delta W_t \times \tilde{P}_t$	$2.39 \times 10^{-2***}$	$-2.13 \times 10^{-2***}$	0.05×10^{-2}	-0.09×10^{-2}
	(0.27×10^{-2})	(0.29×10^{-2})	(0.16×10^{-2})	(0.21×10^{-2})
$\Delta W_t \times \tilde{P}_t^2$	3.26×10^{-4}	$-10.47 \times 10^{-4*}$	$8.30 \times 10^{-4***}$	$6.47 \times 10^{-4*}$
	(4.12×10^{-4})	(4.55×10^{-4})	(2.41×10^{-4})	(3.24×10^{-4})
$\Delta W_t \times \tilde{P}_t^3$	$-2.91 \times 10^{-5*}$	$3.04 \times 10^{-5*}$	-0.36×10^{-5}	0.74×10^{-5}
	(1.37×10^{-5})	(1.51×10^{-5})	(0.79×10^{-5})	(1.07×10^{-5})
$\Delta W_t \times \tilde{P}_t^4$	-0.82×10^{-6}	$3.62 \times 10^{-6*}$	-1.15×10^{-6}	0.48×10^{-6}
	(1.48×10^{-6})	(1.63×10^{-6})	(0.86×10^{-6})	(1.15×10^{-6})
$\Delta D_t \times \tilde{P}_t$	$-1.86 \times 10^{-2***}$	$1.38 \times 10^{-2***}$	$0.16 \times 10^{-2***}$	$0.10 \times 10^{-2***}$
	(0.03×10^{-2})	(0.04×10^{-2})	(0.02×10^{-2})	(0.03×10^{-2})
$\Delta D_t \times \tilde{P}_t^2$	$-6.65 \times 10^{-4***}$	$9.84 \times 10^{-4***}$	$-4.80 \times 10^{-4***}$	$1.81 \times 10^{-4***}$
	(0.50×10^{-4})	(0.55×10^{-4})	(0.30×10^{-4})	(0.40×10^{-4})
$\Delta D_t \times \tilde{P}_t^3$	$3.71 \times 10^{-5***}$	$-2.50 \times 10^{-5***}$	$-1.30 \times 10^{-5***}$	-0.21×10^{-5}
	(0.19×10^{-5})	(0.21×10^{-5})	(0.11×10^{-5})	(0.15×10^{-5})
$\Delta D_t \times \tilde{P}_t^4$	$0.90 \times 10^{-6***}$	$-1.68 \times 10^{-6***}$	-0.03×10^{-6}	$0.30 \times 10^{-6*}$
	(0.18×10^{-6})	(0.20×10^{-6})	(0.11×10^{-6})	(0.14×10^{-6})
R^2	0.64	0.84	0.48	0.84
Num. obs.	34503	34503	68902	68902

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

wind variations. In off-peak periods when coal provides the base load, CCGTs are likely to run at their minimum stable output and hence have limited ability to respond to an increase in wind supply.[27]

In addition, we also use the linear regressions to study the asymmetric partial effects when

[27] In spite of the negligible change in the coefficients of ΔW_t, the direction of changes in the coefficients of ΔD_t still suggests that as coal becomes more expensive (from COAL-BASE to GAS-BASE), coal shifts to mid-merit. Specifically, during peak periods, a 1 MW change in energy demand is on average accompanied by 0.14 MW change in coal generation when coal is the base load but by 0.21 MW otherwise.

wind rises and falls, and when the demand on fossil generation increases and declines. To do this, we run the regressions conditional on the sign of ΔW_t and $\Delta C_t + \Delta G_t$, and the results are shown in Figure 6 and 7. It is suggested that the rise and fall of wind generation, as well as the increase and decline of fossil generation has no significant impact on the partial effects, especially for peak periods.

The non-linear regression results are shown in Table 8.

Appendix B: Comparisons with Aggregate Demand

Figure 16 shows the same base case CPF as Figure 11 but against total demand. Note that the wind is now much higher in high (mainly winter) demand periods so there is a seasonal shift in the graphs as well as variations over the day. The highest wind corresponds to the highest total demand (in winter months) and the lowest wind occurs at times of lowest demand, while there is much less correlation of wind with residual demand. Again coal responds more to wind in lower demand hours, and there is a trend to respond less in high demand hours, but less pronounced than for the residual demand graphs of Figure 11. This graph can also be directly compared with the SR displacement factors in Table 5 for the GAS-BASE case, where off-peak $-dC/dW = 0.15$ and $-dG/dW = 0.75$. In Figure 16 $-dC/dW$ varies between 0.3 and 0.6 for aggregate demand up to 36 GW, with $-dG/dW$ moving inversely between 0.3 and 0.7. While the Table 5 peak values are almost the same as the off-peak values ($-dC/dW = 0.15$, $-dG/dW = 0.65$) in Figure 16 $-dC/dW$ varies between 0.6 and 0.9 while $-dG/dW$ varies inversely between 0.4 and zero.

Figure 17 repeats this for the zero CPS case and shows that the MDFs change across levels of demand in a rather more muted way than over changes in residual demand (which is what drives the merit order), but are otherwise rather similar. Again we can compare this with the COAL-BASE case of Table 5, in which the off-peak values -dC/dW = 0.52 and -dG/dW = 0.41, while in Figure 17 -dC/dW varies between 0.5 and 0.8 while -dG/dW varies inversely between

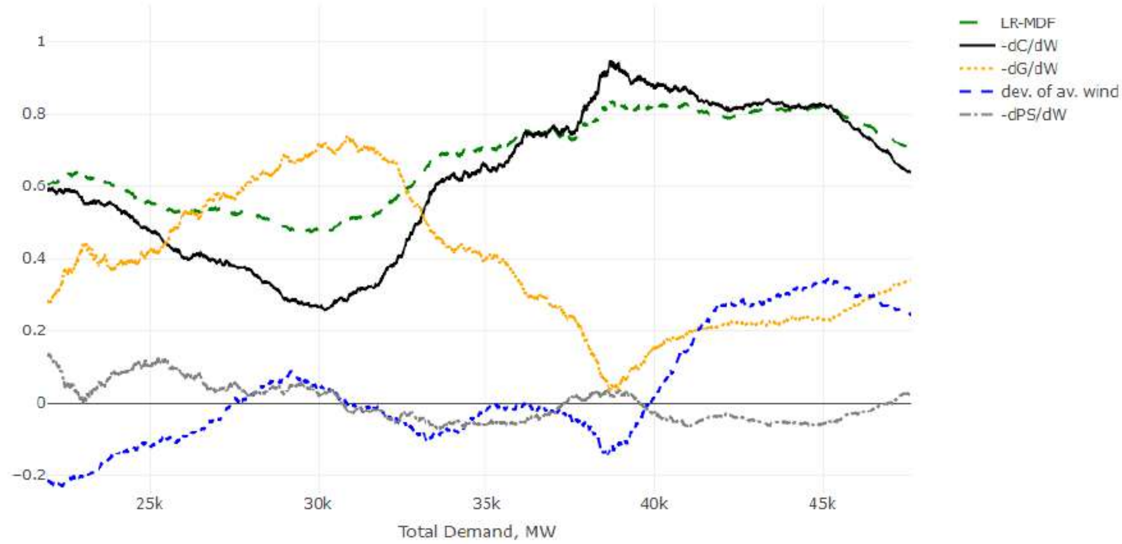


Figure 16: Displacement Factors v.s. Total Demand, £24/tCO_2

0.3 and 0.4, a closer match. The peak values in Table 5 have -dC/dW = 0.15 and -dG/dW = 0.66 while in Figure 17 -dC/dW falls steadily with rising demand from 0.4 to zero and -dG/dW rises from 0.6 to 1, arguably with similar averages as the SR displacement factors. Finally Figure 18 repeats the exercise for the high carbon price case, again showing similar but more muted changes.

Appendix C: Replicating Thomson et al. (2017)

We use the five-minute average generation by fuel data from the Elexon Portal[28] for the year 2009-2016. The replication process can be summarized as follows:

1. Use the same fuel intensity values for coal (0.39988kg CO_2/kWh_{th}) and gas (0.22674kg CO_2/kWh_{th})[29] as Thomson et al. (2017), and the average thermal efficiency of 36% and 55% respectively for coal and gas plants, to calculate the emission factor for coal

[28] See https://www.elexonportal.co.uk/article/view/216?cachebust=72iua05a54.
[29] NCV *plus* well-to-tank NCV

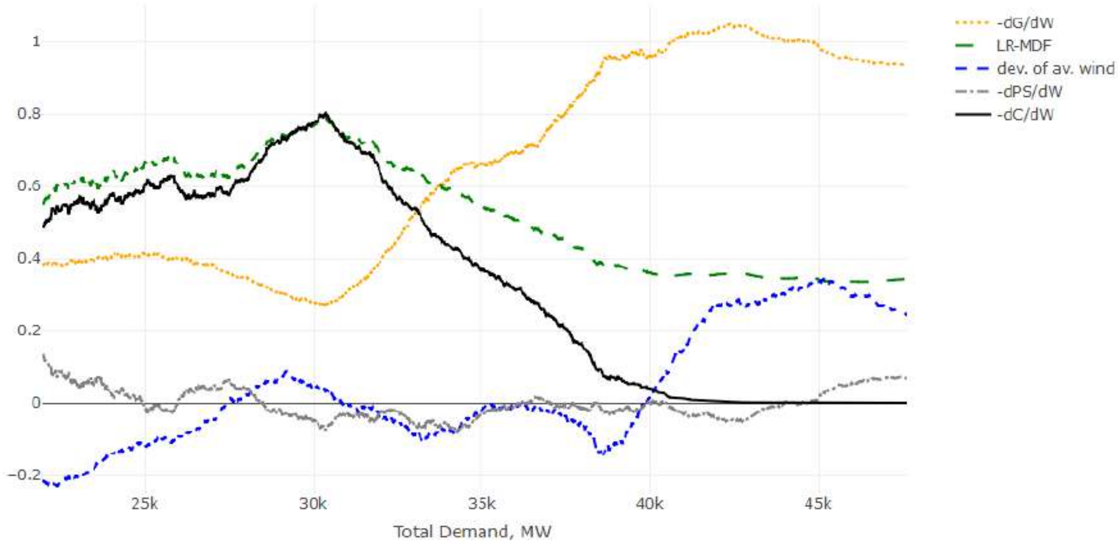


Figure 17: Displacement Factors v.s. Total Demand, £6/tCO_2

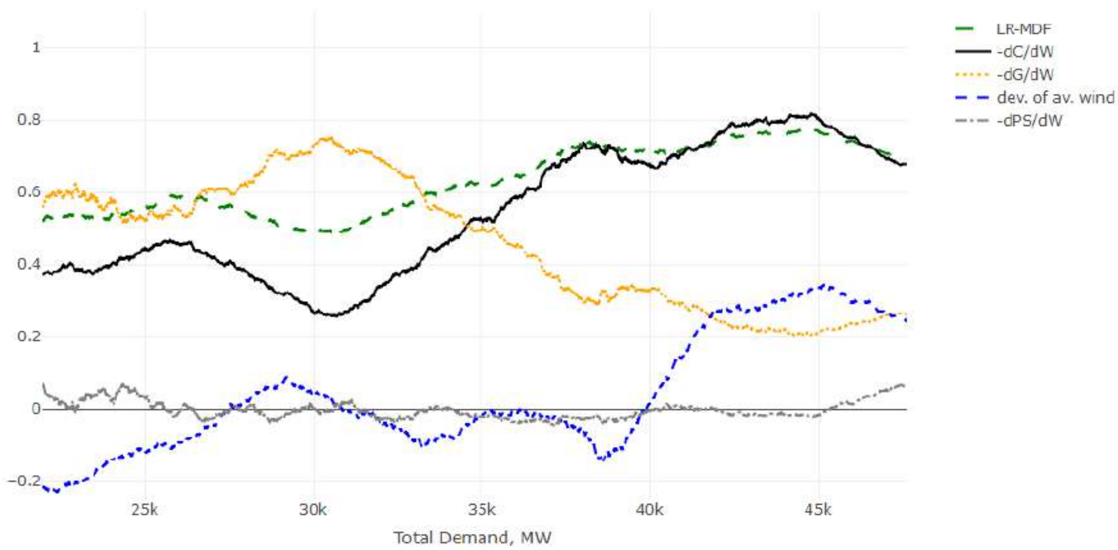


Figure 18: Displacement Factors v.s. Total Demand, £37/tCO_2

(1.111kg CO_2/kWh) and gas (0.412kg CO_2/kWh).[30]

2. We use the same emission factors for other generation types as Thomson et al. (2017),

[30]Thomson et al. (2017) argue that the thermal efficiency of a generating unit should be varying with the relative load (i.e. actual load relative to its full capacity), while we are unable to obtain the data for generating units, hence we used the average efficiency.

and extend their Table 2 to 2016. However, although the emission factors for overseas electricity can be found at the IEA website[31], it is expensive, hence we use the overseas emission factors for 2014 to proxy the overseas emission factors for 2015 and 2016.

3. Now that we have the emission factors for all fuel types, we can calculate CO_2 emissions for each five-minute interval. As in Thomson et al. (2017), we set negative imports to zero. However, for simplicity, we ignore pumped storage.

4. The five-minute changes in wind output (ΔP_w), total system supply (ΔP_s) and total system emissions (ΔC) are calculated as the difference between successive values.

5. After removing outliers, we run the following regression for each year:

$$\Delta C = k_0 + k_1 \Delta P_s + k_2 \Delta P_w + \boldsymbol{h'X_t} + \varepsilon,$$

   where k_1 is the marginal emission factor (MEF) and k_2 is the marginal displacement factor (MDF).

The results are shown in Table 9 and Figure 9. The numbers following "±" are standard errors multiplied by 1.96.

Data Appendix

The values for the Carbon Price Support (CPS) are published by the Government (HoC, 2018). The carbon content of natural gas is well-defined at 0.1839 tCO_2/MWh_{th}, but coal is more heterogenous and so one can work back from the CPS to infer its carbon intensity as 0.310 tCO_2/MWh_{th}. Table 10 gives the carbon prices used.

[31] http://data.iea.org//payment/products/115-co2-emissions-from-fuel-combustion-2018-edition-coming-soon.aspx

Table 9: Comparisons of annual MDFs, $tCO_2(eq)/MWh$

	MDF (wind)		
Year	Our Estimates	Replicated Results	Thomson et al.
2009		0.650 ± 0.039	0.597 ± 0.065
2010		0.628 ± 0.023	0.611 ± 0.049
2011		0.562 ± 0.022	0.553 ± 0.032
2012	0.436 ± 0.031	0.564 ± 0.018	0.547 ± 0.025
2013	0.426 ± 0.063	0.480 ± 0.012	0.487 ± 0.017
2014	0.430 ± 0.046	0.455 ± 0.010	0.483 ± 0.014
2015	0.413 ± 0.030	0.438 ± 0.009	
2016	0.362 ± 0.031	0.382 ± 0.008	
2017	0.334 ± 0.029		

Table 10: CPS rates in fiscal years beginning

	01/04/2013	01/04/2014	01/04/2015	01/04/2016
gas /MWh_{th}	£0.91	£1.75	£3.34	£3.31
coal /MWh_{th}	£1.59	£2.95	£5.65	£5.57
CPS £/tCO2	£4.95	£9.52	£18.16	£18.00

Source: https://www.envantage.co.uk/carbon-management/climate-change-levy-agreement/climate-change-levy-rates.html

The quarterly prices of fuels into power stations are published by BEIS (previously by DECC) as Table 3.2.1 and give gas and coal prices per kWh_{th}. Both include delivery and other costs from the spot prices (NBP for gas, various for coal but often ARA west Europe prices). The margin from NBP to power station can be estimated from the quarterly averages and that margin added to the day-ahead NBP price to give the opportunity cost of burning gas (which might otherwise be traded spot) but coal is more illiquid once delivered and stocked at the power station. It is less likely to be marked to market each day although the Bloomberg coal futures price will give an indication of restocking costs and hence the current value of coal (again including the margin to power station).

Generation Costs by Fuels

The gas price is less constant than the coal price as coal is more illiquid and storable, while the fuel prices published by BEIS only varies quarterly. It is fine to use quarterly prices but prices at higher frequency would provide more variation hence less variance on the estimates. Therefore, the daily spot natural gas futures price is downloaded from investing.com;[32] we then average the daily spot price by years and quarters, and take difference between the BEIS quarterly prices and the quarterly averaged spot prices to calculate the delivery and other costs for each quarter of each year; finally, we top up the daily spot price by the delivery and other costs and obtain the daily gas price, which includes delivery and other costs. The daily coal price is obtained by smoothing the BEIS quarterly coal price to avoid sudden rises and falls at the boarder of two consecutive quarters.

The average thermal efficiency for coal-fired power plants is fixed at 35.6%, and the *weighted* average thermal efficiency for efficient CCGTs is fixed at 54.5% (ranging from 51.4% to 55.1% for efficient CCGTs). Given this, the carbon emission factor for coal is

$$0.31(\mathrm{tCO_2/MWh}_{th}) \div 0.356 = 0.871(\mathrm{tCO_2/MWh}_e),$$

and for efficient CCGTs is

$$0.1839(\mathrm{tCO_2/MWh}_{th}) \div 0.545 = 0.337(\mathrm{tCO_2/MWh}_e).$$

Then the generation costs for coal and efficient gas are respectively calculated using the formula:

$$\text{Generation Cost} = \text{Fuel Price} \div \text{Thermal Efficiency} + (\text{CPS} + \text{EUA}) \times \text{Emission Fatcor}.$$

Generation by Fuel Types Data

The half-hourly generation by fuel types data is downloaded from the Elexon Portal.[33] Al-

[32] https://www.investing.com/commodities/natural-gas
[33] https://www.elexonportal.co.uk/article/view/7324?cachebust=zvf6ghgjwi

though there is no missing data, for each year there are some (half-)hours with misrecorded data. Specifically, whenever the CCGT generation is lower than 1000MW, we treat it as misrecording and replace it by "NA"; we also remove the data where the half-hourly change in total electricity supply is above 3000MW — this ensures the removal of outliers even though this sacrifices a very small proportion of the "normal" data.

EUA Price Data

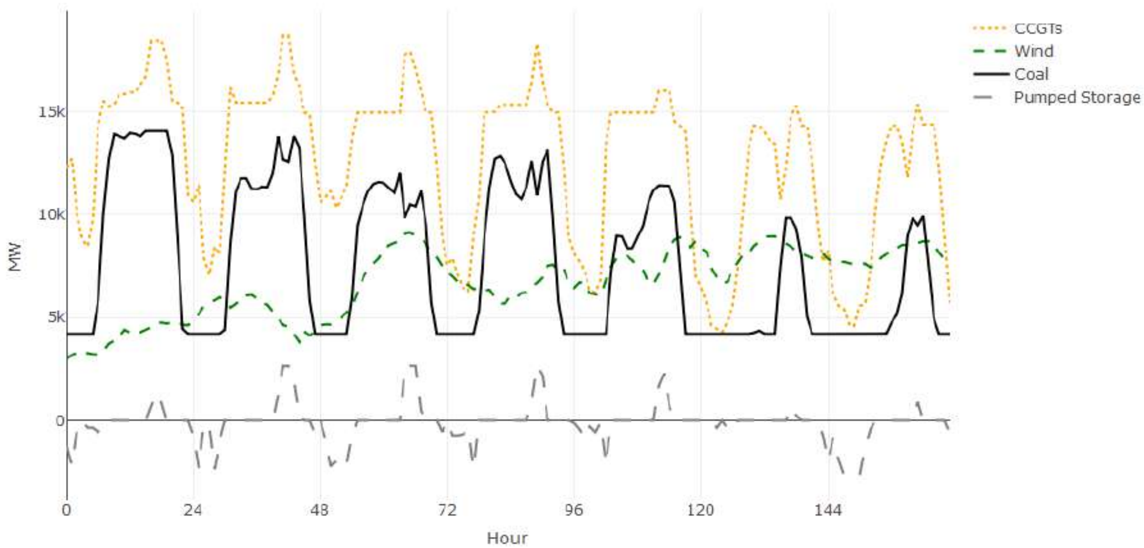
The EUA prices are downloaded from investing.com[34] and are converted to GBP using the exchange rate from the same website.[35]

Figure Appendix

Figure 19a shows simulated generation output over a week (Monday-Sunday) in January. Coal is profitable in peak hours and runs at its minimum stable output off-peak, varying with installed wind capacity more in response to changing residual demand (driven by changes in wind as final demand in any hour does not change with the counterfactual wind capacity increase), while Pumped Storage (PS) pumps off-peak and delivers at peak. Figure 19b shows an August week with lower total and residual demand and coal running most of the time at minimum load, but responding to peak demand, particularly when wind falls.

[34] https://www.investing.com/commodities/carbon-emissions
[35] https://www.investing.com/currencies/eur-gbp

(a) Simulated Generation, 5th Jan - 11th Jan



(b) Simulated Generation, 3rd Aug - 9th Aug

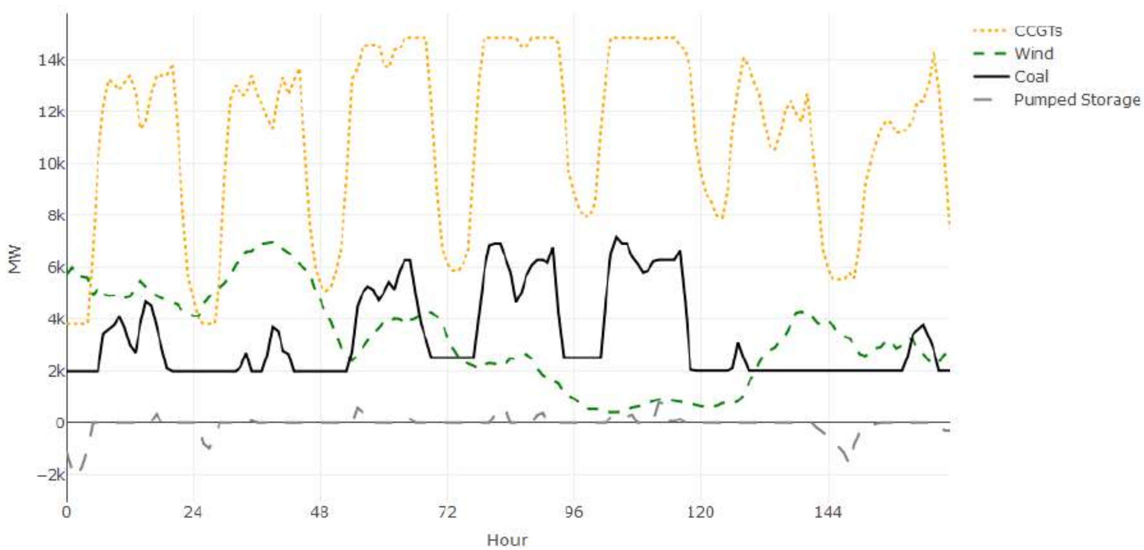


Figure 19: Plant Dispatched over a January and August week, £24/tCO_2