The incentive to invest in thermal plants in the presence of wind generation

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Abstract

In a deregulated market, the decision to add generation rests with private investors. This paper evaluates how generator profits are affected by increasing wind generation. Using hourly historical data for the Irish Single Electricity Market, we simulate new series of electricity prices, representative plant bids and wind generation. We calibrate the model based on the negative correlation between electricity prices and wind generation. This allows us to determine that increasing wind generation induces lower profits for all baseload plants. Additionally, it decreases profits for baseload natural gas plants more than for less flexible coal-fuelled plants, which might encourage investment in less flexible plants.

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Keywords: electricity; generation incentives; simulation; wind generation; Ireland.

1. Introduction

This paper analyses how increasing wind generation affects the incentives to invest in thermal power plants.

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Investment in thermal plants is critical for the reliability of electricity systems, especially in countries facing a large renewal of their electricity generation portfolios. The growing share of renewable (often intermittent) sources of electricity generation means that there is a particular interest in flexible plants.

Wind generation has the advantage of relying on free fuel and the disadvantage of depending on a fuel source that is variable: wind does not blow all the time, and when it blows it is not constant.

An active and growing literature has analysed the effect of wind on electricity prices; for example see Newbery (2010), Perez Arriaga and Batlle (2012), Troy et al. (2010), and Devitt and Malaguzzi Valeri (2011).

Increased wind generation tends to decrease the price of electricity in any system based on merit order, since wind-powered plants displace plants that have positive fuel costs and carbon dioxide emissions. On the other hand, extensive investment in wind generation is fostered by subsidies, which are generally recovered through additional fees tacked on to the final price of electricity, pushing electricity prices up. Additionally, as wind generation increases, traditional thermal plants (operated by natural gas, coal or oil) have to accommodate the fluctuations in wind to meet a fairly inelastic demand. Thermal plants therefore vary the amount they produce more often in situations where there is a large variation in the amount of wind. The result is that these plants start up (and shut down) more often.[3]

This paper focuses on the implications of these findings on expected profits and therefore on investment incentives in conventional generation with varying degrees of flexibility. We show that while all baseload plants are penalized by the presence of larger amounts of wind, more flexible plants incur larger losses.

The results are driven by two factors. First, profits of all plants are reduced with lower wholesale electricity prices. Second, less flexible baseload plants turn on and off less often than more flexible plants. The latter effect is due to a combination of technical constraints, with less flexible plants designed to run

[3]See Perez Arriaga and Batlle (2012) for a general discussion of this topic.

and remain off for longer stretches of time, and the need to rely on baseload plants to maintain reliability of the system. If the output of baseload plants is needed at times of peak demand they will have to run for a few hours prior (or after) the peak demand periods.

We study a specific electricity system: the Irish Single Electricity Market (SEM). The SEM encompasses the electricity systems of both the Republic of Ireland and Northern Ireland, making it a unique cross-jurisdiction, cross-currency system.

To determine how power plants' expected profits change as wind generation capacity increases, we compare the revenue and cost streams of three types of thermal generation plants: a coal plant, a combined cycle gas turbine plant (CCGT) and an open cycle gas turbine plant (OCGT). This allows us to determine if investment in new power plants is likely to be sustained over time, given current retribution schemes and expected increases in wind penetration. The biggest challenge we face is the estimation of robust parameters that determine how costs and prices evolve with higher wind generation.

Steggals et al. (2011) present an overview of how wind generation may affect electricity prices and its implications for investment decisions in other generation technologies. The authors do not quantify the effects of wind, but discuss which policies would encourage investment in the presence of wind, with a particular focus on Great Britain. Traber and Kemfert (2011) consider both the dampening effect of wind generation on wholesale prices and how it increases costs of conventional plants. Using a simulation model of Germany's electricity plant portfolio, they find that investment in relatively flexible plants is likely to be suboptimal, since they generate less frequently in the presence of large amounts of wind. We adopt a different methodology in this paper, but obtain a similar result for flexible natural gas plants: their returns decrease in the presence of more wind. However, Traber and Kemfert (2011) also conclude that non-flexible coal plants are gradually displaced by 2020 as wind increases over time, whereas our results show that a lack of flexibility might be rewarded under certain circumstances. The German market is a single-price market, but unlike the SEM it is not compulsory and a large part of the market operates through bilateral contracts (Möller et al., 2011).

Gross et al. (2010) analyse the British electricity market and argue that the incentives to invest depend in part on the risks associated with fluctuations in electricity prices. Plants that tend to set the marginal price hedge automatically against fluctuations in energy prices. In our paper we explicitly simulate price fluctuations as a function of wind generation.

Garcia et al. (2012) are primarily interested in analysing the effects of different regulatory schemes on the incentives to invest in renewable capacity. Using a stylised theoretical model, they find that designing incentives to invest in renewable capacity without affecting investment in conventional capacity is challenging.

Other studies have focused on the effect of wind on electricity prices, for example Nicholson and Porter (2012) and Woo et al. (2011). They report a negative relation between electricity prices and wind.[4] These papers study the balancing market of the Texas ERCOT system, which accounts for about 5% of all electricity exchanges.

The Irish system displays a few favorable characteristics from the point of view of this study: first, it has limited interconnection with other systems allowing us to identify the effect of wind more easily. Second, wind capacity is relatively large, increasing from about 900MW at the end of 2007 to more than 2000MW at the end of 2011. Third, it is a compulsory pool system with central dispatch that publishes most of the system data.

The contribution of renewable energy to overall energy demand for the Republic of Ireland was around 5% in 2010 (SEAI, 2011) and Ireland's target under the European Directive (2009/28/EC) is to achieve a 16% penetration

[4] Woo et al. (2011) highlight that rising wind generation reduces spot prices but amplifies the spot price variance.

by 2020.[5] Similar numbers hold for Northern Ireland, where renewables accounted for about 3% of total energy consumption in 2009 (based on DECC, 2011). The Government plan of 2011 asserts that electricity generation from renewable sources is effective in reducing Ireland's electricity-related greenhouse gas emissions (GHGs).[6] The same document declares that renewables will have to account for about 40% of electricity demand if Ireland is to meet its overall targets. Installed wind capacity, the largest source of renewable energy in Ireland and Northern Ireland, is therefore expected to continue rising in the near future.

The rest of the paper is organised as follows. Section 2 describes the SEM and presents a stylised framework outlining how less flexible plants might be better off than more flexible ones with large amounts of wind generation. Section 3 describes the data and Sections 4 gives details of the empirical methodology. Section 5 reports the simulation results and Section 6 concludes.

2. Introducing the SEM and an analytical framework

2.1. The SEM

The SEM was established in November 2007 and is a gross mandatory pool with a single System Marginal Price (SMP) in each period. All generation with capacity greater than 10MW must bid in the pool directly and all buyers must buy from the pool.

The SMP is based on a market schedule that does not account for transmission constraints. Each period's SMP is determined by the marginal bid provided by the marginal plant – defined as shadow price– plus the value of the uplift. Plants are stacked according to their marginal bid, from cheapest to most expensive, and are called to generate in that order until they produce enough to

[5] The Directive is available at `//eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2009:140:0016:0062:en:PDF`. The Irish renewable targets and commitments are outlined in several documents available on the TSO website (`http://www.eirgrid.com/renewables/policyandtargets/irelandandnorthernireland/`).

[6] Available at: `www.taoiseach.gov.ie/eng/Publications/Publications_Archive/Publications_2011/Programme_for_Government_2011.pdf`.

serve demand. The uplift measures any additional amount generators have to be paid to avoid short-run losses, including the no load costs, which are generation costs that are independent of the level of output, and any start up costs.

Marginal bids reflect the short run marginal costs of a plant and include the costs of fuel, carbon dioxide emission permits and operation and maintenance costs needed to generate an additional megawatthour (MWh) of electricity. On top of the SMP, power plants also receive capacity payments, designed to help cover capital costs and encourage plant availability.

Power plants are required to submit offers into the pool by 10 a.m. of the day ahead. The offers include both commercial and technical characteristics, addressed in more detail in the data description section. Power plants are constrained to bid their short run marginal cost, in line with the bidding code of practice.[7] The Market Monitoring Unit monitors the market to make sure that generators are bidding within the rules.

As a further check of market power, there is a system of forward contracts in the form of contracts for differences, created to enhance competition in both the Republic of Ireland and in Northern Ireland. This market is however not very developed.

The presence of substantial amounts of wind on the system raises some interesting questions for security of supply. The system cannot rely on wind alone due to its large and sudden variations and the fact that thermal plants are unable to change their production instantly. In order to guarantee reliability, the System Operator (SO) curtails wind when its share of demand exceeds 50%.[8] If transmission, wind curtailment or other constraints arise, plants that are constrained off still obtain the SMP for the period but have to return the equivalent of the costs they did not incur. Plants that are called to generate even if they were not included in the unconstrained market schedule will be

[7] The bidding code of practice is available at: http://www.allislandproject.org/GetAttachment.aspx?id=52931422-c47f-498b-b520-8bf7ef7e956f.

[8] For details on the curtailment of wind for security of supply reasons see EirGrid (http://www.eirgrid.com/media/47958_EG_Summary09.pdf; (http://www.eirgrid.com/media/Annual%20Renewable%20Report%202010.pdf).

compensated for their generation costs, but do not receive that period's SMP. A side effect of being constrained on is that thermal power plants end up increasing or decreasing generation (and turning on and shutting down) less frequently. Ramping and start up costs of thermal power plants are therefore reduced by wind curtailment (and its associated payments).

2.2. A model of generator returns in the presence of wind

The goal of this section is to present a stylised model of how less flexible plants can be better off than more flexible plants in the presence of large amounts of wind generation in a compulsory pool market with a binding code of practice. We start by assuming that plants are infinitely flexible and in section 2.3 refine the results under the more realistic assumption that starting a plant is costly and cannot occur instantly. Less flexible plants are subject to stronger constraints on the number of consecutive hours they have to be on or off. This effectively limits the number of times they can start up in any given period. In this section, however, we focus on the indirect effect of wind on baseload plants if the latter are needed to ensure the reliability of the system at peak demand times.

We assume that there are three types of generating plants: wind, baseload and peakload. Firms have capacity constraints. Each can produce a maximum of K^i MegaWatts (MW) in each period, where $i = \{H, L, W\}$ indexes technologies, which differ in their costs. K^i represents total installed capacity for a plant using technology i. Peak plants (indexed by H) generate electricity at the highest marginal cost (MC), followed by baseload (indexed by L) and wind (indexed by W), which is assumed to have 0 short-run marginal costs since wind itself is free.

Given a demand D_t in every period t (which we assume varies over time but is inelastic to price), and wind generation W_t, with $0 \geq W_t \geq K^W$, the price is determined as follows:

$$P_t = \begin{cases} 0 & if\ D_t \leq W_t \\ MC^L & if\ W_t < D_t \leq K^L + W_t \\ MC^H & if\ W_t + K^L < D_t \leq W_t + K^L + K^H \\ P_{max} & otherwise \end{cases} \tag{1}$$

Generators are only allowed to bid actual costs, related to their fuel, carbon permit use and operation and maintenance, which leads to the wholesale price reported in Equation 1. However, baseload plants incur an additional cost, represented by $\phi(D_t, W_t)$, which affects their profits. This cost arises when a baseload plant has to start up and shut down or increase and decrease output to accommodate variations in wind. This will happen when demand is greater than available wind, but less than the sum of wind and baseload capacity, and wind varies over time. Put more concisely, when $0 < D_t - Wt \leq K^L$ and $|\Delta W_t| > 0$, where $\Delta W_t = W_t - W_{t-1}$. Peaking plants are designed to be more flexible and therefore do not incur any additional cost when required to turn on and change their output quickly.[9]

We characterise the cost ϕ as follows:

$$\phi(D_t, W_t) = \begin{cases} g \cdot |\Delta W_t| & if\ 0 < [D_t - W_t] \leq K^L \\ 0 & otherwise \end{cases} \tag{2}$$

where g is a parameter that determines the size of additional costs associated with starting up and varying output.

Generators also receive capacity payments. In the SEM, the regulators establish a capacity 'pot' at the beginning of every year and allocate it across periods as a function of the margin between available generating capacity and expected demand. In this analysis we will simplify and assume that capacity payments are allocated equally across all periods.[10]

[9] While this is a simplification, costs associated with starting the plant and varying output are going to be much smaller for peaking plants than for baseload plants.

[10] The actual allocation methodology is more complex. Part of the allocation is done ex-

For a plant that lasts T periods, generator i receives the following stream of payments for 1 MW of installed capacity over the lifetime of the plant, gross of capital costs:

$$\pi^i = \sum_{t=0}^{T} [P_t - (MC^i + \phi(D_t, W_t)) + C_t] \cdot q_t^i \tag{3}$$

where C_t are the capacity payments per MW of available generation paid out at time t and q_t is 1 if the plant is generating in period t and 0 otherwise.

Based on equations 1 and 3, the expected returns to a generator depend on the distribution of D_t and W_t. We assume that D_t and W_t are distributed independently. While this is a simplification, it is consistent with the hourly data we use in our analysis. The correlation coefficient between hourly wind generation and electricity demand from 1 January 2008 to 31 December 2011 is equal to -0.05.[11] To keep the example simple, the distribution of demand is assumed to be as follows:

$$D_t = \begin{cases} \bar{D} & \text{with probability p} \\ \underline{D} & \text{with probability 1-p} \end{cases} \tag{4}$$

with demand always higher or equal to baseload capacity, or $0 < K^L \leq \underline{D} < \bar{D}$. Wind, on the other hand, is distributed as a Weibull distribution, as is common in the literature, with scale parameter α and shape parameter β.[12] Given the

ante, and part is ex-post. There is therefore a possibility of strategic behaviour on the part of firms, but we abstract from it in this paper.

[11] This figure is based on historical electricity generation data by wind, which depends on wind's total installed capacity. To evaluate if the correlation would be higher for constant installed wind capacity, we also calculate the correlation coefficient between electricity demanded and the wind generation profile, where the profile is calculated as the hourly electricity generated by wind, divided by total installed. The result indicates even less correlation, with the coefficient equal to -0.004. The empirical correlation depends on the level of aggregation applied. While there is no correlation with hourly information, aggregating all the data to the monthly level would result in a positive correlation.

[12] See Weisser (2003), Yeh and Wang (2008), Yu and Tuzuner (2008) and Yu and Tuzuner (2009) for some examples.

cumulative distribution function of a Weibull distribution, the following holds:

$$prob[W_t \leq D_t - K^L] = \begin{cases} 1 - e^{-((D_t - K^L)/\beta)^\alpha} & if D_t - K^L \geq 0 \\ 0 & otherwise \end{cases} \tag{5}$$

For $D_t - K^L \geq 0$ the expected value of the additional start-up and ramping costs ϕ is therefore going to be:

$$E_t(\phi) = g \cdot |\Delta W_t| \cdot \Big\{ p[1 - e^{-((\bar{D} - K^L)/\beta)^\alpha}] + (1-p)[1 - e^{-((\underline{D} - K^L)/\beta)^\alpha}] \Big\} \tag{6}$$

2.3. A case with non-flexible baseload plants

Now let's make the example slightly more complex (and somewhat more realistic). In the previous section we assumed that the baseload plant will be able to adapt instantly to wind generation fluctuations. In this section we explore what happens if the baseload plant is not perfectly flexible. If it has to produce at high levels in period $t+1$, it must be already operating at time t. To facilitate the operation of the baseload plant, wind at time t will be curtailed if needed. Wind curtailment is already taking place in the SEM (Pöyry (2010), pg.30 and Gorecki (2011)) and in other systems with large amounts of wind (e.g. Spain; for a review see Rogers et al., 2010).

When the plant is constrained on for operational safety reasons, it will not turn on and off and the start-up costs associated with ϕ will be equal to zero. We also set the cost of varying output once the plant is on to 0. Including them would increase the costs of forcing non-flexible plants to vary output, but would not change the qualitative findings reported here. We formalise this in the following example.

If wind and peak plants are not sufficient to meet expected demand at time t + 1, or $E_t[D_{t+1} - W_{t+1} - K^H] > 0$, the baseload plant will be constrained on at time t. Note that E_t is the expectation at time t of events that take place at future dates. When a plant is constrained on, it receives a payment to cover its cost of production, but does not receive the electricity market price. As before, firms have capacity constraints. They can each produce a maximum of K^i MegaWatts in each period. To simplify the presentation we also assume that for every period t, $D_t > K^H$, or that demand is always larger than the capacity of peaking plants.

The price is determined as in equation 1. If the baseload plant is needed to meet demand in period $t+1$, the system operator dispatches it in period t as well, even if $D_t \leq W_t$. This changes the costs for baseload plants. We will show that $\phi(\cdot)$ unambiguously decreases, and therefore baseload plant profits unambiguously increase when compared to the results in section 2.2. The expected value of ϕ from equation 6 has to be adjusted for the probability that the plant will be needed at time $t+1$ and therefore dispatched at time t as well, or $E_t[D_{t+1} - W_{t+1} - K^H] > 0$. More formally, if we define the updated ϕ as ϕ':

$$E_t(\phi') = E_t(\phi) - E_t[D_{t+1} - W_{t+1} - K^H] \tag{7}$$

As before, D_t and W_t are independently distributed, so we can rewrite the second term on the right hand side of Eq.(7) as $prob\left[E_t(W_{t+1}) < E_t(D_{t+1}) - K^H\right]$, which is the cumulative distribution function of W_{t+1} calculated at $E_t(D_{t+1}) - K^H$. If, as we assumed above, the expected value of $D_{t+1} - K^H$ is positive, it is also true that:

$$E_t[D_{t+1} - W_{t+1} - K^H] > 0 \tag{8}$$

and substituting Equation 8 in 7 we obtain the following result:

$$E_t(\phi') = E_t(\phi) - E_t[D_{t+1} - W_{t+1} - K^H] > E_t(\phi) \tag{9}$$

thereby proving that $E_t(\phi') < E_t(\phi)$, where $E_t(\phi)$ comes from equation 6.

What changes for peaking plant profits? Not much. They might be called on to produce more often, since they are capable of adjusting quickly to changes in wind generation, but every time they are called to produce out of the theoretical merit order, they are remunerated exactly for their costs, leaving their profits unvaried.

This section has described how profits of less flexible plants can end up decreasing less than those of more flexible ones in the presence of wind generation and reliability constraints.

In the empirical work we present in the following sections, we determine if a plant generates or not by comparing its bid to that period's marginal price of electricity. As we explain in Section 4 we do not simulate electricity demand explicitly, although demand levels are implicit in electricity marginal prices. A higher demand is associated with higher electricity prices, all else being equal.

3. Data description

Data on daily bids of gas, coal and distillate power plants come from the market operator's website (`http://www.sem-o.com`). We use data from 1 January 2008 to 31 December 2011.

Each power plants bids two sets of information: commercial and technical data. Technical data includes details such as availability, minimum and maximum generation amounts, ability to change the quantity generated and minimum number of hours of generation and of down time. The information on minimum down and up times and heat rates comes from the model validation information published by the regulators at `www.allislandproject.org`.

Commercial data provide prices at which the generator is willing to produce electricity. The bids include a fixed portion (the no load cost), a series of quantity-price pairs and up to three start-up costs, depending on the plant being cold, warm or hot.

Plants are allowed to bid up to 10 price-quantity pairs valid for each period of the day, although they rarely submit more than 3 different combinations. Commercial bids encompass all of a plant's costs: fuel, carbon dioxide permits and maintenance and operation. They therefore implicitly account for each plant's efficiency and each fuel's carbon content.

We build a single bid price per participant per day for this variable portion of the bid. Specifically, for each day we choose the price associated with the efficient generation level of each plant. Market rules dictate that the price in quantity-price pair bids cannot decrease with quantity, so our representative price will be the higher bid price available.[13]

We obtain daily bid series for 3 typical power plants: a relatively new combined cycle gas turbine (CCGT), a standard coal and a peaking open cycle gas turbine (OCGT) running on distillate fuel.[14]

Table 1: *Summary statistics on shadow price and bids, (2008-2011), nominal*

			Obs	Mean	St. Dev.	Min	Max
Marginal Bid €/MWh		*Coal*	1461	46.80	10.16	30.27	88.09
		Gas	1461	39.80	7.16	25.89	55.92
		Distillate	1461	162.85	33.45	85.12	224.58
Fixed Bid €/MW	**No Load**						
		Coal	1461	2.73	0.59	1.68	4.34
		Gas	1461	10.77	3.28	4.34	18.04
		Distillate	1461	28.01	5.53	15.61	38.64
	Start-up warm						
		Coal	1461	228.05	43.87	148.52	350.95
		Gas	1461	299.73	91.89	124.14	572.45
		Distillate	1461	26.75	1.55	23.06	29.80
	Start-up hot						
		Coal	1461	144.97	27.64	94.85	222.40
		Gas	1461	269.54	90.92	87.47	510.35
		Distillate	1461	26.75	1.55	23.06	29.80
Shadow Price €/MWh			35040	49.81	23.53	0	494.56

Data on shadow prices are on an hourly basis. Data on bids are on a daily basis.
All data come from www.sem-o.com

Table 1 summarises the data for the daily bids of each representative power plant and the shadow price in nominal terms. Bid data are daily, whereas the shadow price series is on an hourly basis, accounting for the difference in the number of observations.[15] The marginal bid information refers to the variable price-quantity bids. The second group of rows shows the statistics over this period for the fixed elements of the bids, which are also daily. We calculate the per MW value of each part of the fixed bids by dividing by each plant's capacity,

[13]However, once the fixed no load portion of the bids is included in the calculation, complete bids per MWh of electricity generated decrease with quantity.

[14]In particular, we take Huntstown I as representative of a baseload CCGT natural gas plant, Moneypoint I for coal and Rhode I for a distillate peaking plant.

[15]The coal plant has 43 observations recorded as 0 for each of the no load, hot and warm start-up costs. The natural gas plant has 14 observations recorded as zero for each series. We set them equal to the value of the previous day.1 observation for the shadow price was negative. We set it to 0.

defined as the maximum quantity plants offer in their bids (285MW for the coal plant, 352MW for the CCGT and 52MW for the distillate plant). In the rest of the paper we estimate the fixed portions of the bids using their historical average. The peak distillate plant has relatively small start-up costs. Because we focus on the changes in baseload costs we approximate start-up costs for the peak distillate plant with 0 in the rest of the paper for simplicity.

One clarification is needed here. The coal plants in the SEM are relatively old. Moneypoint I, used here, was commissioned in 1987 and was retrofitted with scrubbers between 2004 and 2008. It has a relatively low efficiency, around 0.34, which means that it needs to burn about three units of energy of coal to produce one unit of electricity. Moreover, after the 2009 drop in natural gas prices, coal prices remained high for a few months. This contributes to the relatively high coal costs seen in Table 1. Huntstown, used as the CCGT plant, has a much higher efficiency of 0.56.

Plants incur additional costs if they have to turn on and off. The cost of starting up depends on the length of time elapsed since the last generation period, with the largest costs occurring when the plant has cooled off completely. In our model we consider only hot starts (when the plant has been shut down for fewer than 12 hours) and warm starts (when the plant has been shut down between 12 and 72 hours), as in the past cold starts (with the plant shut down for longer than 72 hours) have proven rare. We do not explicitly account for ramping costs, the additional costs incurred when varying output once the plant is already generating.

Historical wind generation for the Republic of Ireland and Northern Ireland comes from EirGrid and SONI respectively.

We build a series describing the monthly capacity of installed wind based on system operator files that specify the size and initial connection date of all wind farms in the Republic of Ireland and Northern Ireland.

Finally, we calculate average capacity payments in €/MW. Each year the regulator determines a capacity pot to be allocated across all plants as a function of their availability. We calculate the average payment per available MWh by dividing the annual pot by the amount of plant available during that year across the whole SEM. We adjust this number by each plant's average availability during the 2008-2011 period to obtain plant-specific average capacity payments.[16]

After collecting the data, we deflate all monetary series to 1 January 2008 using the eurozone harmonised consumer price index from the European Central Bank. In the SEM bids should equal costs, given the bidding code of practice. We assume this equivalency in the rest of the paper, in particular when calculating plants' profits.

4. Methodology

For each plant we compare profits per MW installed under two scenarios. The first scenario is set as the baseline, with wind capacity equal to the average 2011 amount, or 1889MW. The second scenario features 3000MW of installed wind capacity.

In each hour revenue is given by the sum of the shadow price, which we simulate for the two scenarios, an uplift portion and capacity payments. The latter two elements are approximated by their historical average. Total hourly costs are the sum of variable bids, defined in the previous section and simulated for the two scenarios, fixed no load and start up costs. The no load cost is again approximated by its historical level. The value of warm and hot start up costs are also taken as their historical average. Note however that they will be added to the cost in each period only if the plant switches from off to on in that period.

We first allow each plant to run only if its variable bid is lower than (or equal to) that period's shadow price.[17] We then impose technical and system security constraints. If the coal plant generates, it has to generate for at least 6 consecutive hours and it has to be off at least 5 consecutive hours. Minimum

[16] Moneypoint I (coal) was available on average 88% of the time, Huntstown I (CCGT) 89% and Rhode I (peaking plant) 97% of the time during the 2008-2011 period.

[17] This is in line with the merit order rule used in the SEM, outlined in sections 4.16 and following of the Trading and Settlement Code, available at `www.sem-o.com`.

on and off hours for the CCGT plant are 4 hours.

To simulate the effect of having to maintain system reliability, we impose that if the baseload plants (both coal and CCGT) generate at any point during their minimum 'on' window (6 hours for coal and 4 hours for the CCGT plant) they are constrained on for all periods during the relevant window.[18]

Note that any time a plant deviates from its initial running pattern (i.e. if it is constrained on or off for technical or security of supply reasons) we set the profits for that period equal to zero.[19] The less flexible a plant, the more likely it will be to be constrained on or off and therefore experience fewer starts during the simulation horizon.

This approach allows us to avoid making explicit assumptions on how the plant portfolio or electricity demand evolve. In practice we are implicitly assuming that the relation between available capacity and electricity demanded remains stable. Note that we do not make explicit assumptions on prices of fuels, carbon dioxide permits or the level of demand. These variables underlie, and are encompassed by, the bid and shadow price simulations.

In the SEM generators are forced to bid their marginal costs, so we take bids as representative of their fuel, carbon and operation costs. More complex hypotheses should be considered in different markets (see Wolak, 2001).

In order to define the best simulation process for shadow price and bids we must first determine the optimal calibration period.

4.1. Calibration period

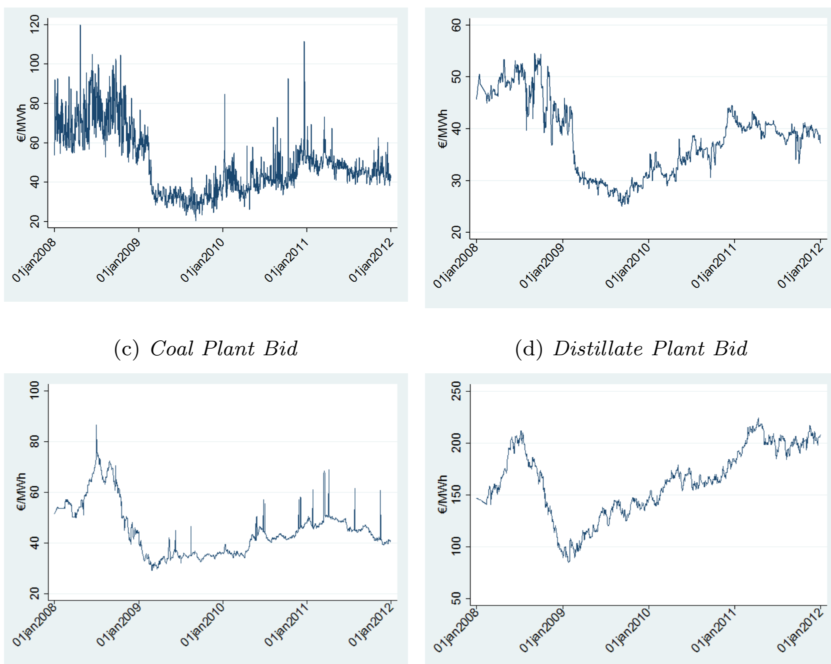
Figure 1 presents graphs of the daily power plant bids in real terms. All figures are deflated to 1 January 2008. There is a dramatic downturn of all the bids in early 2009, which reflects a large decrease in brent oil prices in mid 2008,

[18]Varying this rule to constrain the plan on only if it is on for at least 50% of the periods in the first run does not change the main results, as we discuss in footnote 24.

[19]In the SEM a plant that is constrained on will be compensated only for its costs, so its profits will be zero. If transmission constraints cause a plant to be constrained off, it keeps the SMP but has to return the equivalent of the costs not incurred. We ignore the latter case since we do not model transmission constraints.

followed by a decrease in natural gas prices in early 2009. This might be a sign of a structural break in the series.

Figure 1: *Shadow price, coal, gas and distillate bid prices, (2008-2011), 2008 currency €/MWh*



(a) *Shadow Price*

(b) *Natural Gas Plant Bid*

(c) *Coal Plant Bid*

(d) *Distillate Plant Bid*

The same break potentially affects the shadow price, as the electricity price in the SEM follows natural gas prices fairly closely, as reported in SEM (2010).

A vast literature (see Zivot and Andrews, 1992; Baum, 2001; Muñoz and Dickey, 2009) stresses that the presence of structural breaks can affect the result of stationarity tests. We therefore test for the presence of structural breaks in our sample to identify an optimal calibration period for which to test for stationarity. The Clemente and Rao test detects the presence of a structural break in the shadow price series on the 8th of February 2009, whereas the Zivot and Andrews test finds a break on the 12th of the same month. A Chow test performed on the same series rejects the null hypothesis of absence of structural breaks in the shadow price series for the 12th of February 2009 with an F statistic equal to 3454.95.[20]

The same tests on natural gas and coal power plant bids show that both series have a structural break at the end of September of 2008.[21] No structural breaks are detected for the distillate bid series, which is not stationary when evaluated during the whole period between 1 January 2008 and 31 December 2011.

We therefore set the calibration period for the shadow price from 13 February 2009 to 31 December 2011; for the natural gas plant bids from 28 September 2008 to 31 December 2011 and for the coal plant bids from 21 September 2008 to 31 December 2011. Bids of the distillate power plant are taken from 1 January 2008.

4.2. Model choice

We remove the 3, 6 and 12 month seasonality by applying a moving average technique described in Weron (2006). We also preprocess the price series eliminating all the spikes, defined as price changes that are farther than two standard deviations from the average price. After the calibration and simulation procedures, the final series is obtained by adding seasonality and spikes back in.

4.2.1. Distillate power plant bids

Which process best fits the historical data depends on the series' properties. The bids of the distillate-fuelled OCGT follow a persistent (non-stationary) process and are therefore simulated with a Geometric Brownian Motion process (GBM from now on) that increases at a constant rate. A GBM process can be

[20]To perform both the Clemente and Rao and the Zivot tests we follow the procedure presented in Baum (2001).

[21]The t-statistics associated with the Clemente and Rao test for coal and gas power plant bids are -3.68 and -3.06 respectively. The Chow test statistic for the same series, performed at the end of September 2008 is 3.96 for the coal and 14.09 for the gas plant. The Dickey-Fuller test performed on the gas series after the structural break rejects the presence of a unit root at the 1% probability level with the test statistic equal to -2.15. The Phillips-Perron test rejects the presence of a unit root at the 5% level, with a statistic equal to -15.85. The same statistic for the coal bids rejects the null hypothesis at the 1% level, with a value of the statistic of -33.15.

described as

$$dX_t = \mu X_t dt + \sigma X_t dW(t) \tag{10}$$

with solution

$$dx_t = (\mu + \frac{1}{2}\sigma^2)dt + \sigma dW_t \tag{11}$$

in which $x_t = log(X_t)$. We use the MLE estimator to estimate μ and σ, following Brigo et al. (2007).

4.2.2. Electricity prices, coal and gas power plant bids

The electricity shadow price, coal and natural gas plant bids are stationary after the structural break and are simulated by mean reverting processes with jumps. To control the size and the frequency of the jumps, we follow Weron (2008) and model the jump as a Poisson process of the form $J_t dq_t$ where J_t is a (truncated) random variable responsible for the size of the spike and q_t is a Poisson process with intensity λ. The process can be described as follows:

$$dX_t = \alpha X_t(\theta - X_t)dt + \sigma X_t dW_t + J_t dq_t \tag{12}$$

Applying the Ito formula, the process solution can be characterised as:

$$dx_t = \theta(1 - e^{-\alpha dt}) + x_{t-dt}e^{-\alpha dt} + \sigma e^{-\alpha t}\int_{t-dt}^{t} e^{\alpha u}\,\mathrm{d}W_u + J_t dq_t \tag{13}$$

in which $x_t = log(X_t)$. We estimate the parameters of this model by standard OLS.

4.2.3. Modelling the effect of wind

As mentioned above, the shadow price is stationary. Equation (13) does not account for the specific effect of wind on the shadow price and we account for this separately. We identify the correlation coefficient between wind and shadow price using the following relation between hourly historical data:

$$SP_{Simul} = MRP_{Simul} - \rho_{Wind,SP} * Wind_{Hist} * WindCapacity_{Hist} \tag{14}$$

where the simulated shadow electricity price SP_{Simul} is a function of the mean reverting process MRP described in equation (13), historical wind load curves

($Wind_{Hist}$) and total installed wind capacity ($WindCapacity_{Hist}$). We determine the empirical correlation coefficient between the shadow price and wind ($\rho_{Wind,SP}$) by minimising the difference between the simulated shadow price series SP_{Simul} and its realised values SP_{Hist} , for the period from 13 February 2009 to 31 December 2011.

$$\rho_{Wind,SP} = argmin(SP_{Hist}, SP_{Simul}) \tag{15}$$

The minimisation above leads to $\rho_{Wind,SP}$ equal to -0.002.

Wind simulation. As is common in the literature (see references in Section 2.2), we assume that wind follows a Weibull distribution, the parameters of which are estimated using the historical wind series from January 2008 to December 2011. We add a jump to the Weibull process to simulate the effect of wind on the shadow price, which in the recent past has on occasion reached zero. The Weibull distribution is characterised by two parameters: scale parameter α, estimated to be 1.234, and shape parameter β, estimated equal to 0.307.

The mean of the simulated wind series is slightly higher than its historical average (0.287 instead of 0.281). Overall variability is higher for the historical series (with a standard deviation of 0.21 versus 0.07 for the simulated series). The simulated wind series does not replicate the weather-driven clusters of wind that occur in reality.[22] The lack of persistence of the Weibull distribution increases the hour-to-hour variability of the shadow price and therefore the number of times baseload plants start up in the simulations and it does so for both the baseline and the 3000MW scenario.

5. Results

5.1. Shadow prices and bids

The baseline features 1889 MW of installed wind capacity, equal to the average wind capacity installed in 2011. Differences between the baseline and

[22]We thank an anonymous referee for emphasising this point.

history can be ascribed to the specific simulation methodologies we use for each series. We then run a scenario with 3000MW of installed wind. Comparing the results between the two scenarios allows us to identify the effects of higher wind on thermal plant profits, net of modelling choices which remain the same across the scenarios.

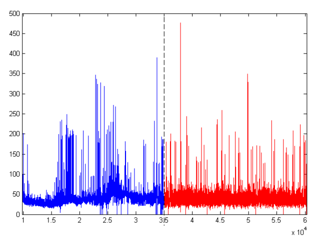
The simulation runs for 25225 periods. This is the same duration as the shadow price calibration horizon, which is between February 13 2009 and 31 December 2011.

In order to simulate power plant bids and electricity prices correctly, we run 1000 draws of each simulated process and report the average of these draws.

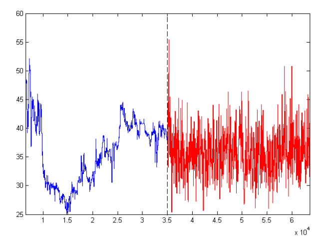
5.1.1. Comparing Scenario 1 (baseline) to history

Figure 2: *Electricity prices and bids (historical and simulated), 2008 currency, €/MWh*

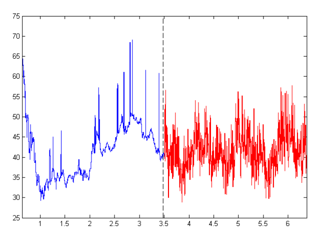
(a) *Shadow Price*



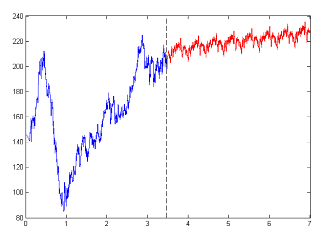
(b) *Natural Gas Bids*



(c) *Coal Bids*



(d) *Distillate Bids*



Historical series in blue, simulated series in red. Simulated data runs for 25225 periods (equivalent to the number of periods between 13 February 2009 and 31 December 2011). The number of observation for the historical values depends on the structural breaks of the series. The shadow price series starts from February 13th, 2009. Natural gas bids start from the 28th of September 2008, coal bids from the 21st of September 2008 and distillate bids from the 1st of January 2008.

We compare the baseline to history to illustrate how our specific modelling choices influence the properties of the simulated series.

Figure 2 shows the historical and simulated shadow price and generation bids side by side. Table 2 compares the characteristics of the baseline to the historical series, from their structural break to the end of December 2011.

Table 2: *Summary statistics: historical vs baseline, hourly data. Real 2008 €/MWh*

(a) *Shadow price*

MIL €	Historical	Baseline	% change
Mean	39.74	39.33	-1.0%
St.Dev.	15.44	16.74	7.8%
Skewness	6.67	5.85	-13.9%
Obs	25225	25225	

(b) *Bids* : *Gas*

MIL €	Historical	Baseline	% change
Mean	35.89	35.88	0.0%
St.Dev.	5.47	3.80	-44.0%
Skewness	0.08	0.31	74.9%
Obs	1190	1190	

(c) *Bids* : *Coal*

MIL €	Historical	Baseline	% change
Mean	41.57	41.95	0.9%
St.Dev.	6.74	4.76	-41.6%
Skewness	0.82	0.35	-132.7%
Obs	1197	1197	

(d) *Bids* : *Distillate*

MIL €	Historical	Baseline	% change
Mean	192.40	240.96	20.2%
St.Dev.	20.25	6.41	-216.1%
Skewness	-0.05	-0.01	-631.5%
Obs	1460	1460	

The number of observations for the historical series depends on where the structural break falls. The shadow price series starts from February 13th, 2009. Gas bids start from the 28th of September 2008, coal from the 21st of September 2008 and distillate from the 1st of January 2008. Data for prices are hourly, data for bids are daily.

One thing to note is that the variable bid for coal is on average larger than the variable bid for the natural gas plant. This is a consequence of the relatively low efficiency of the coal plant and means that the coal plant will on average generate fewer periods than the natural gas plant, as shown in the next section.

The mean of the simulated shadow price is slightly lower than it was historically. This is partially due to the use of the Weibull distribution to model wind.

The bid of the distillate-fuelled plant is simulated as a GBM with a positive trend and therefore increases over time, explaining why the mean of the simulated series is larger than its historical counterpart.

To measure the effect of using the Weibull distribution for wind, we compare the number of generation periods of the natural gas and the coal plant in the baseline scenario versus the number of periods the plants would have generated if the shadow price had been equal to the historical outcome. For both types of plants the number of generation periods is lower with the simulated shadow price, both before and after constraints are added (results available from the authors). The final results will therefore underestimate profit levels. This is one important reason for which we focus on the difference in profits in the 3000MW versus the baseline scenario and do not analyse the absolute level of profits.

5.1.2. Comparison of Scenario 2 (3000MW of wind) with the baseline

In this scenario, we increase wind capacity to 3000MW and compare the results to the baseline, as shown in Table 3.

Wind has a direct effect on the shadow price and an indirect effect on the costs of thermal power plants. When wind blows, the shadow price decreases, as wind generation displaces more expensive plants: thermal power plants reduce their production on average. The indirect effect arises since additional wind increases the number of times power plants start up, even if less then proportionally.[23]

[23] Note that start up costs do not include other costs that plants might incur when changing their output, such as wear and tear costs that tend to be larger for less flexible plants (Denny and O'Malley, 2009).

As expected the shadow price in this scenario decreases, by 1.51%. Table 3b reports the changes in the average costs of the power plants per unit of capacity, including no load and start up costs. The increase in costs is driven by the change in the number and type of start ups since by assumption wind does not affect any other cost component. Start up costs increase for both the gas and the coal power plants, but the effect on the coal power plant is more muted.

Table 3: *Summary statistics: Baseline and 3000MW Wind Scenarios*

(a) *Shadow price, €/MWh*

	Baseline	3000MW	% change
Mean	39.33	38.74	-1.51%
St.dev.	16.74	16.63	-0.62%
Skewness	5.85	5.58	-4.97%

(b) *Avg.cost changes with noload and start-up costs, €/MWh*

	Baseline	3000MW	Δ
Mean Gas	48.17	48.41	0.5%
Mean Coal	46.10	46.17	0.1%
Mean Distillate	248.39	248.39	0.0%

(c) *Number of start-up periods*

	Gas	Coal	Distillate
Baseline	320	342	12
3000MW	338	353	11
Δ	18	11	1
% change	5.6	3.2	0.1

(d) *Generation periods*

	Gas	Coal	Dist
Baseline	21124	18078	6
3000MW	20760	17598	6
Δ	364	480	0
% change	1.4	1.9	0

More wind causes lower shadow prices on average. This implies that all plants will end up generating for fewer periods, as their bids will be higher than the shadow price more often. This is confirmed by Table 3d showing that both the coal and the CCGT natural gas plant generate on fewer occasions with greater wind, but the effect is larger for the coal plant. The coal plant ends up generating for 480 fewer hours, or a decrease of about 1.9%. The natural gas plant generates 364 fewer hours, or 1.4% less.

The Weibull distribution for wind introduces more hour-to-hour variability of the shadow price, which would make perfectly flexible plants turn on and off repeatedly. Imposing the technical and security of supply constraints cuts down on these artificial start ups and shut downs. In particular coal generation periods more than double after the constraints, to a total of 18078 in the baseline and natural gas periods of generation increase by more than 50% to 21124 in the baseline. The lack of flexibility of the coal plant, and the need to maintain system reliability, means that it also ends up starting up fewer additional times between the baseline and the 3000MW scenario. Table 3c shows that more wind causes the natural gas plant to start up 5.6% more times versus a 3.2% increase for the coal plant.

As wind penetration increases, it might well be that market rules will have to be modified to allow thermal plants to maintain viable generation patterns. It is unclear how baseload plants could operate strictly on their merit order while maintaining profitability unless there are major changes in technology and/or the plant portfolio. More flexible plants or improvements in storage technology could help alleviate the problems.

5.2. Profits

We aggregate all the findings on revenues and costs from the previous sections to determine how the wind increase affects profits.

The expected profits are gross of capital costs and are calculated as the difference between the electricity price plus capacity payments received by plants and their simulated costs (the sum of their bids, no load and any start-up costs), and should therefore be interpreted as short-run profits. As mentioned earlier, they are reported per MW of installed capacity.

The average historical values for uplift and start-up costs are taken for the period 13 February 2009 to 31 December 2011. Capacity payment averages are calculated for the years between 2009 and 2011 and are equal to €7.48/MW for coal, €7.58/MW for the CCGT and €8.20/MW for the distillate power plant.

As a result, the profit equation for each power plant i is given by:

$$\pi^i = \sum_t (SP_{Simul,t} + Uplift + CapPayments^i - Bid_t^i - NoLoad^i - Startup_t^i) \tag{16}$$

where all series indexed by t are simulated on a daily or hourly basis, and the rest are taken as historical averages. When installed wind capacity increases, all power plants face lower profits. As shown earlier, they face a lower shadow price and incur generation costs that are higher per MW of installed capacity due to the greater incidence of start up costs.

Table 4: *Profits, €(mill.)/MW* in 2008 currency

€ mill.	Gas	Coal	Distillate
Baseline	461.74	517.40	414.70
3000MW	445.25	505.84	414.58
% change	-3.5	-2.2	0.0

Profits are aggregated over 25,225 periods.

The CCGT gas power plant profits decrease in the 3000MW scenario by 3.5% with respect to the baseline, whereas coal power plant profits decrease by 2.2%. There is no change for the distillate-fuelled OCGT power plant, as it is the peaking plant and we assume that its start-up costs are negligible.

We therefore obtain the main results of the analysis. Profits decrease for both types of baseload plants, but they decrease less for the less flexible plant. This result is driven by the sum of technical and system constraints imposed to guarantee the reliability of the electricity system.[24]

[24] As a robustness check we also run the analysis limiting the effect of system reliability. We impose that a baseload plant will be turned on for the minimum number of consecutive periods for which it has to be on only if it already generates for at least 50% of the minimum 'on' periods after the first simulation run. The main results (not reported) do not change: all baseload plants end up with lower profits and the profits of the more flexible CCGT plant

This result suggests that less flexible plants may be at an advantage as wind increases with the set of rules under which the SEM currently operates.

Profit changes are likely to be even more significant for larger wind increases than those studied in this paper. We should however note that the correlation between shadow price and wind might vary in a non-linear way as installed wind capacity increases. This implies that applying the current correlation coefficient to larger increases in wind could lead to inaccurate results.

6. Conclusions

In this paper we analysed the effect of increased wind generation on the incentives to invest in thermal plants in the context of a deregulated market. In a deregulated market, the decision to build new plants rests with private investors, who will evaluate the situation based on expected profits. To measure how profits change with more wind we build two different scenarios with varying amounts wind generation capacity and compare them.

We set the correlation coefficient between wind and shadow price equal to -0.002, the value that minimises the difference between historical and simulated shadow price. Power plant profits are calculated as the difference between simulated revenue and simulated costs. Revenue is given by the sum of the SMP and capacity payments, whereas costs are the sum of both fixed and variable components of fuel, carbon emission permits, operation and maintenance costs, in addition to start-up costs, if any.

We build a baseline where we assume that the wind in the system is the same as the average wind installed in 2011. The difference in the results between this scenario and the past can be ascribed to differences introduced by the specific simulation methodologies.

In the second scenario we consider the effects of 3000MW of installed wind capacity. This causes shadow prices to be lower and generation costs to be

decrease more than those of the coal plant. The difference in profits between the CCGT and the coal plant narrows slightly.

slightly higher for baseload plants due to an increase in the number of times plants start up during the simulation period. Consequently all baseload generators obtain lower total profits.

Interestingly, the natural gas baseload plant's profits decrease more than for the coal plant. In our analysis this outcome arises because the system operator constrains the less flexible plant on or off more often to respect its technical constraints and maintain reliability of the system. As a result, the less flexible plant increases the number of times it starts up proportionally less than the more flexible one. A similar result could hold under different market rules, for example if plants enter bilateral contracts based on their overall costs, including the costs associated with switching on and off more often due to higher levels of wind. This suggests that under certain market rules, the incentive might be to invest in less flexible plants with more wind, a result that would make the electricity system more difficult and costly to balance.

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