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

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In a deregulated market, the decision to add generation rests with private investors. This paper evaluates how generator profits are affected by increasing wind. Using hourly historical data for the Irish Single Electricity Market, we simulate future series of electricity prices, representative plant bids and wind generation. We estimate a negative correlation between electricity prices and wind generation. This allows us to determine that increasing wind generation capacity causes a larger decrease in profits for baseload gas plants and a smaller decrease for less flexible coal-fuelled plants, suggesting that investment incentives might not be aligned with stated environmental goals.

JEL: C15; L94; Q40

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This paper analyses the effects of increasing wind generation on the incentives to invest in thermal plants and offers insights on how increased wind generation affects the wholesale cost of electricity. Continued investment in thermal plants is critical for the reliability of electricity systems, especially for countries that face a large renewal of their electricity generation portfolios.

An active and growing literature has analysed the effect of wind on electricity

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prices, for example see Newbery (2010),Perez Arriaga and Batlle (2012), Troy et al. (2010), and Devitt and Malaguzzi Valeri (2011). 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. Increased wind generation tends to decrease the price of electricity in any system based on merit orders, since wind-powered plants displace plants that have positive fuel costs (and positive carbon dioxide emissions). On the other hand, extensive investments in wind generation have been fostered by subsidies, which are generally recovered through additional fees tacked on to the final price of electricity, pushing towards higher electricity prices. 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 amounts of wind. The result is that these plants start up (and shut down) more often and are subject to larger ramping costs (costs incurred when increasing or decreasing generation). This issue has been analysed in Troy et al. (2010) for Ireland and discussed more in general in Perez Arriaga and Batlle (2012).

This paper focuses on the implications of these findings for investment incentives in conventional generation in deregulated systems. In deregulated systems, the decision to invest in a certain size and type of generating plant rests with investors and is therefore driven by expected profits. 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 assess how electricity systems are likely to evolve over time and 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 drive 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, but focus on discussing potential policies to encourage investment in the presence of wind, with a particular focus on Great Britain (GB). Traber and Kemfert (2011) consider both the dampening effect of wind generation on wholesale prices and how they increase the costs for 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 approach in this paper, simulating many years of future prices, but we 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 displaced by wind over time, whereas our results show that the lack of flexibility might be rewarded under certain circumstances. Gross et al. (2010) analyze the GB 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 and are therefore price makers automatically hedge 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.

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. The Irish system also 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, it has experienced a large increase in installed wind capacity, more than doubling 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 has been estimated around 5% in 2010 (SEAI, 2011), but Ireland's target under the European Directive (2009/28/EC) is to achieve a 16% penetration.[1] Similar numbers hold for Northern Ireland, where renewables accounted for about 3% of total energy consumption in 2009 (calculated from the information presented in DECC, 2011). Wind generation is the largest single source of renewables available in Ireland.[2] The Government plan of 2011 (http://www.taoiseach.gov.ie/eng/Publications/Publications_Archive/Publications_2011/Programme_forGovernment_2011.pdf) asserts that electricity generation from renewable sources offers effective ways to reduce the contribution of power generation to Ireland's greenhouse gas emissions (GHGs). 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 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 of the setup. Section 3 describes the data and Sections 4 gives details of the empirical methodology. Section 5 reports the simulation results and Section 6 concludes.

[1] The Directive is available at (http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2009:140:0016:0062:en:PDF)

[2] The Irish renewables targets and commitment are outlined in several documents available from the TSO website (http://www.eirgrid.com/renewables/policyandtargets/irelandandnorthernireland/)

I. Introducing the SEM and an analytical framework

A. The SEM

In the Irish system, the system marginal price (SMP) is determined by the bid provided by the marginal plant – defined as shadow price– plus the value of uplift. Plants are stacked according to their bid, from cheapest to most expensive, and are called to generate in that order until they produce enough to service existing demand. The uplift measures any additional startup costs generators have to be paid to avoid short-run losses. Bids reflect the short run marginal costs of a plant and include the costs of fuel and carbon dioxide emission permits needed to generate a megawatthour (MWh) of electricity. On top of the SMP, power plants also receive capacity payments, designed to help cover capital costs.

Power plants are required to bid their short run marginal cost in line with the bidding code of practice.[3] The Market Monitoring Unit monitors the market to make sure that generators are bidding within the rules. Extensive system data are available from the start of SEM, in November 2007. The SEM is a compulsory pool system, where every generator with a capacity larger than 10MW has to offer electricity and generation is centrally dispatched. Similarly, all buyers have to buy from the pool. We are therefore able to simulate our model based on complete system data. This is different from other studies, such as Nicholson and Porter (2012) and Woo et al. (2011), that report results for the balancing market of the Texas ERCOT system, which accounts for only 5 per cent of all electricity exchanges.[4]

As a further check of market power, there is a system of future contracts in the

[3]The bidding code of practice is available on the Commission of Energy Regulation website: http://www.allislandproject.org/GetAttachment.aspx?id=52931422-c47f-498b-b520-8bf7ef7e956f.

[4]Both these works focus on the historical estimation of the relation between electricity spot prices and wind in ERCOT. Nicholson and Porter (2012) show that wind generation is negatively related to the electricity price, and that wind has a stronger effect on the balancing-energy price during the day than it does at night. Woo et al. (2011) highlights that rising wind generation tends to reduce spot prices and amplify the spot-price variance. Both these studies, however, focus on the estimation of the relation between existing wind and electricity prices, and not on the simulation of the effects of different installed wind capacities.

form of contracts for differences (CFD), created to enhance competition between generators both in the Republic of Ireland and in Northern Ireland. However, a centrally dispatched market and the regulation that forces generators to bid their marginal cost limit the incentives to develop forward electricity markets. As result, the CFD market is not well developed.

The presence of wind on the system raises some interesting questions related to 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 ensure that a sufficient amount of thermal electricity generation is always available, in any given period the System Operator (SO) curtails up to 50% of wind capacity. If wind is curtailed and thermal plants that would not otherwise be called to generate have to produce electricity, they receive "constraint payments" that cover their cost of generation. A side effect of being constrained on is that thermal power plants end up increasing or decreasing generation less frequently. Ramping costs of thermal power plants are therefore reduced by wind curtailment (and its associated payments).

B. *A model of generator returns in the presence of wind*

In a deregulated electricity system, any new investment depends on the level of expected monetary returns to private investors, which in turn depends on market prices and the costs associated with generation.

The following sections illustrate the main aspects of this investment problem by providing a stylised example of how wholesale prices are set in a compulsory pool market with a binding code of conduct. We start by assuming that plants are infinitely flexible and in section I.C refine the results under the more realistic assumption that ramping is both costly and cannot occur instantly.

We assume 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 costs related to their fuel and carbon permit consumption, 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 increase or decrease its output (often referred to as ramping) to accommodate variations in wind, which 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 change their output quickly.[5]

We characterise the cost ϕ as follows:

[5]While this is a simplification, costs associated with changes in output are going to be much smaller for peaking plants than for baseload plants.

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

where g is a parameter that determines the size of additional ramping costs.

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 in response to the existing margin between available generating capacity and expected demand. In this analysis we will simplify and assume that they are allocated equally across all periods.[6]

For a plant that lasts T periods, generator i receives the following payments, gross of capital costs over the lifetime of the plant:

$$(3) \qquad \pi^i = \sum_{t=0}^{T} (1+r)^{-t}[P_t - (MC^i + \phi(D_t, W_t)) + C_t] \cdot q_t^i$$

where r is the discount rate and C_t are the capacity payments per MW of available generation paid out at time t.

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. To keep the example simple, the distribution of demand is assumed to be as follows:

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

[6]The actual allocation methodology is more complex. Part of the allocation is done ex-ante, and part is ex-post. There is therefore a possibilty of strategic behaviour on the part of firms, but we abstract from it in this paper.

with $0 < K^L \leq \underline{D} < \bar{D}$. Wind, on the other hand, is distributed as a Weibull distribution, as is common in the literature, [7] with scale parameter α and shape parameter β. Given the cumulative distribution function of a Weibull distribution, the following holds:

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

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

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

C. 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. This means that 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)).[8]

When the plant has to stay on for operational safety reasons, it will not ramp

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

[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`.

on and off and its associated ϕ will be equal to zero. 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 (which might be zero, if it is set by wind in that period). 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. However, the system operator applies adjustments to the generation schedule to maintain system reliability. In particular, 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 Equation 7 as $prob\left[E_t(W_{t+1}) < E_t(D_{t+1}) - K^H\right]$, which can be measured as 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, really. 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.

II. Data description

Information on daily bids of gas, coal and distillate power plants come from the market operator's website (`http://www.sem-o.com`). We calculate the short run costs of the different power plants starting from the bid/quantity pairs declared by each market participant for each day from January 2008 (two months after the market started, in November 2007). On the basis of the data, we calculate the average cost of 3 typical power plants: a natural combined cycle gas turbine, a coal and a distillate oil peaking one.[9] Table 1 summarises the data for the average costs of each representative power plant.

Plants bid their fuel and carbon permit price costs. They incur additional costs if they have to vary the amount of electricity generated and/or turn on and off.

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

Table 1—: *Summary statistics (2008-2011), €/MWh*

	Gas	Coal	Distillate	Shadow price
Mean	36	46.7	163.3	49.8
Max	60.1	88.7	224.6	494.6
Min	15	30.3	85.1	0
St. Dev	10.8	10.1	34.6	23.5

Note: The series for the distillate-fuelled plant (an open cycle gas turbine) starts in January 2009 instead of January 2008 due to availability of historical data.

We refer to these additional costs as cycling costs. When the plant turns on or off, cycling costs vary depending on the length of time since the last generation period. The largest costs occur when the plant has not been generating for long periods and 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 proved rare. Data on ramping costs have been taken from the All-Island Project website, set up by the electricity regulator (CER).[10]

Historical wind generation for the Republic of Ireland and Northern Ireland comes from EirGrid and SONI respectively.[11]

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.

III. Methodology

We specify a dynamic system to evaluate generators' profits over time. Many studies have simulated the effect of wind by creating unit-commitment models and varying the amount of wind. In this paper we take the historical data on

[10]This data come from the 2011 Plexos validation report data.

[11]EirGrid records data on wind farms that bid into SEM. They estimate that smaller wind farms (i.e. producing less than 10MW) account for an additional 20% of wind generation and add this amount to published data.

electricity prices and costs, use them to estimate parameters, and build a time series of future costs and revenues based on the simulated series.

The main advantage of our approach lies in its simplicity. Using data on bids and electricity prices, and making some straightforward hypotheses on the distribution of wind, we are able to replicate generators' costs and profits without having to make explicit assumptions on how the portfolio mix evolves, and especially without having to model the short-run lumpiness of investment that arises when a new (large) plant is set up in a relatively small system. This allows us to isolate the effect of increasing renewables on the system, net of the effect of lumpy changes in the generation mix.

This exercise is somewhat easier for the SEM as generators are forced to bid exactly their marginal costs. More complex hypotheses should be considered in different markets (see Wolak (2001)).

We start by studying the relation between wholesale electricity prices (specifically the shadow price) and wind. This allows us to estimate parameters that describe how electricity prices evolve as a function of installed wind capacity. The other component of the SMP, the uplift, is not correlated with wind, as shown in Di Cosmo and Malaguzzi Valeri (2012).

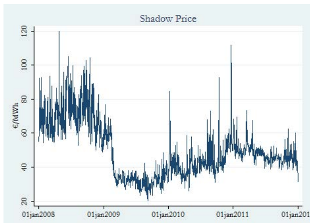
We then analyse how power plant costs and electricity prices have evolved over time and use the findings to simulate the profits of potential new thermal power plants. The power plant costs are defined as the sum of their bids and their ramping costs, as described in the previous section.

A. Calibration period

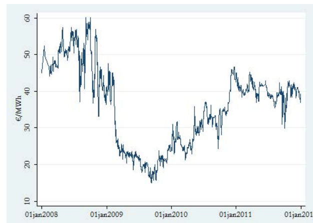
We test a number of specifications to check the best fitting process for each price series. In order to determine whether electricity and energy prices follow stationary processes we apply both the standard augmented Dickey-Fuller(ADF) and the Phillips Perron (PP) unit root tests. These tests reject the null hypothesis of presence of a unit root in the considered sample for all the series with the exception of the oil power plant bids.[12] However, as argued by Muñoz and Dickey (2009), financial series can show a (spurious) unit root in the presence of structural breaks.

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

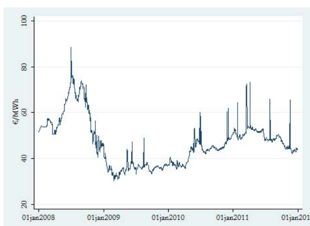
(a) *shadow price*



(b) *cost for PP with gas*



(c) *cost for PP with coal*



(d) *cost for PP with distillate*

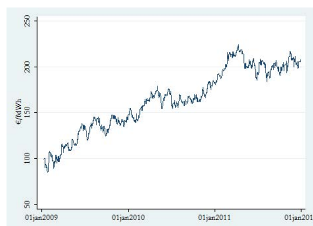


Figure 1 shows an obvious downturn in oil prices and natural gas prices in early 2009, which might have affected the bids of the power plants that use these fuels as their main input. We therefore test for the presence of structural breaks in our sample. This allows us to identify an optimal calibration period and estimate the parameters of the mean reverting process that drives the simulated prices. The Chow test 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. Both Zivot and Andrews (1992) and Baum (2001) have introduced tests to identify unit roots in the presence of structural breaks. The Clemente and

[12]For the shadow price series the ADF test statistic is -9.680 with a 1% critical value equals to -3.430. The PP statistic is -9.827 and the 1% test statistic is equal to -3.960. For the gas-fueled power plant the ADF test statistic is -2.581. For the coal power plant the ADF is -5.289 and for distillate power plants the ADF is -3.491.

Rao test detects the presence of a structural break in the shadow price series on the 8th of February 2009, whereas the Zivot test finds a break on the 12th of the same month. All the tests suggest a structural break in a similar period in February 2009; however these tests reject the hypothesis of the presence of a unit root in the series. The same tests on the natural gas power plant bids show that the presence of the structural break cannot be rejected at the 5% level for the end of December 2008. This is plausible, as the shadow price in the SEM follows natural gas prices (including the implicit carbon cost of a standard CCGT) fairly closely, as reported in SEM (2010).[13] We therefore estimate the parameters of the simulated series on the subsamples identified by these tests.

B. Model choice

We first remove the seasonality by applying a moving average technique as suggested by Weron (2008). We also preprocess the price series eliminating all the spikes, which are defined as price changes that are farther than two standard deviations from the average price. After the calibration and simulation processes, both seasonality and spikes are added back to simulated series, to obtain the final series.

Oil power plant costs. — Which process best fits the historical data depends crucially on the series' properties. As the bids of the oil-fuelled OCGT power plant follow a persistent (non-stationary) process, we simulate the future values of this series with a geometric Brownian motion process (GBM thereafter). This process reflects the non-stationarity of the series, which increases at a constant rate. A GBM process can be described as

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

[13]The Clemente and Rao test statistics for gas and coal power plants are -3.684 and -3.341 respectively, with the test statistic equal to -3.893. We then reject the hypothesis of the presence of a unit root in these series at the 5% level

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).

Electricity prices, gas and coal power plant costs. — Electricity, coal and gas bids proved to be stationary in the calibration period and we simulate these series with 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 follows:

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

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

Modelling the effect of wind. —

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

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

where the simulated electricity price is a function of the mean reverting process described in equation (13), historical wind load curve ($Wind_{Hist}$) and total installed wind capacity ($WindCapacity_{Hist}$). We determine the correlation coefficient between the shadow price and wind ($\rho_{Wind,SP}$) by minimizing the difference between the simulated series SP_{Simul} and its realised values SP_{Hist} , for the period 2009-2011.

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

The minimization above leads to $\rho_{Wind,SP}$ equal to -0.0020. This correlation parameter is consistent with the one found by Di Cosmo and Malaguzzi Valeri (2012), who use an econometric analysis of SEM data to estimate the relation between wind and shadow price.

Wind simulation. — Wind is introduced as a shock that affects the system and follows a Weibull distribution, the parameters of which are estimated from the historical wind series. We add a jump to the Weibull process in order to simulate the effect of wind on the shadow price, which in the recent past has on occasion reached zero. Wind capacity on the island of Ireland is expected to increase to up to 6000MW in the next 10 years, as discussed previously. In this paper we assume that wind capacity will rise from 2000MW to 3000MW within the next 3 years.

IV. Results

A. Shadow prices and fuel costs

Each power plant runs only if it bids less than (or up to) the shadow price, since SEM is a merit order dispatch system. We impose this condition in our simulation.

We simulate three different scenarios in order to assess the effect of wind on the system. In the first scenario we reproduce the same level of wind capacity installed in 2011. In the second scenario, wind capacity is set equal to zero. Without wind generation, we expect generation costs to be lower (as the ramping costs will be lower) and shadow price and profits to be higher than in the past, during which the installed capacity of wind was equal to 1889MW on average. Finally, in the third scenario, we calculate electricity prices and generation costs when installed wind capacity is equal to 3000MW. In order to simulate power plant costs and electricity prices correctly, we run 1000 draws of each simulated process and report the average of these draws.

Scenario 1 (baseline): wind capacity installed on the system from 2009 to 2011. — In this scenario we assume that the capacity of wind installed in the system is fixed at the average 2011 capacity of 1889MW.This scenario is designed to provide an appropriate baseline for our analysis. By focusing on the difference of the results from the baseline, we are able to eliminate any effect of the simulation methodology and therefore isolate the genuine effect of increasing wind generation.

We use the correlation coefficient identified by the minimisation process described by equation (15). We assume that wind follows a Weibull distribution with shape and slope parameters estimated from historical data.

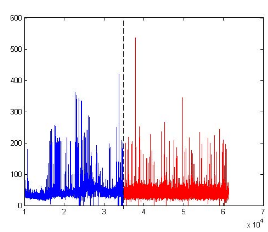
Figure 2 shows the results of the shadow price and generation costs (bids) simulations and Table 2 compares the characteristics of the simulated and historical series.

The difference between simulated and historical shadow prices is partially due to the use of the Weibull distribution to model wind. Although this distribution is widely used in the literature, the simulated series has a lower variance than its historical counterpart. The historic mean of the wind distribution is matched by shifting the whole simulated distribution downward instead of just increasing the frequency of the downward spikes. As a result, the simulated prices shift downwards with respect to their historical values.

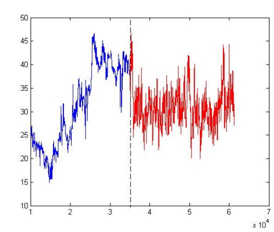
Note however that the specific distribution chosen to simulate wind affects the shadow price mean, but not the direction of the changes we measure in the rest of the analysis.

Figure 2. : *Electricity and energy prices (2009-2014), €/MWh*

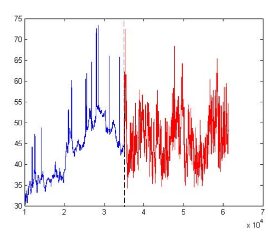
(a) *shadow price*



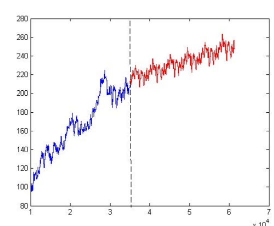
(b) *cost for PP with gas*



(c) *cost for PP with coal*



(d) *cost for PP with distillate*



Note: Historical series in blue, simulated series in red.

The simulated series for natural gas and coal bids have means that are comparable to their historical levels, but a slightly higher standard deviation. This result is typical for this type of studies (see e.g. Benth et al. (2012)). The bid of the distillate-fuelled plant is simulated as a non-stationary geometric brownian motion and increases over time, so the mean of the simulations is going to be larger than the historical base. In Table 2 we compare the simulated period with the most recent historical month of observations (i.e. 720 observations). As expected, the simulation bid is larger, due to the ongoing positive trend. If we focus on the standard deviation in the historical and simulated periods, Table 2 suggests that they are very similar.

Table 2—: *Summary statistics: historical and simulated, €/MWh*

(a) *Shadow price*

	Simulated	Historical	Δ
Mean	40.96	41.77	-1.9%
St. Dev	16.91	16.39	3.2%
Skewness	5.35	6.47	-17.3%

(b) *Marginal costs : mean*

	Simulated	Historical	Δ
Mean Gas	31.04	31.39	-1.1%
Mean Coal	46.26	46.24	0.0%
Mean Distillate	233.31	203.82	14.5%

(c) *Marginal costs : standard deviation*

	Simulated	Historical	Δ
St.Dev Gas	4.24	8.44	-49.8%
St.Dev Coal	5.79	10.33	-44.0%
St.Dev Distillate	11.50	11.00	4.6%

(d) *Marginal costs : skewness*

	Simulated	Historical	Δ
Skew Gas	0.67	-0.06	-1147%
Skew Coal	0.62	0.75	-17%
Skew Distillate	0.08	-13.73	-101%

Scenario 2: 3000MW of wind capacity installed in the system. — In this scenario, we assess the effect of a large investment in wind capacity on the Irish

system. The wind capacity target in 2020 is close to 6000MW, so we investigate the effect of wind increasing to 3000MW by 2014.

Table 3 reports the results of our analysis. The presence of wind consistently reduces average shadow prices. As wind has priority dispatch, the increase in installed wind capacity reduces the number of profitable hours for thermal power plants. A problem also arises in terms of system reliability. Baseload thermal plants need several hours to turn on and shut off. As mentioned earlier, wind is variable over time. These two facts mean that in order to maintain system reliability, if a system operator foresees increases in demand at times of low wind availability, it will have to allow unflexible baseload plants (and specifically coal-fuelled plants) to continue generation during times of high(er) wind generation.

There are thus two possible cases: *i*. the system operator exports any excess wind or curtails it in order to leave coal power plants running at their minimum stable capacity even at times of high wind generation. In this case, coal plants' cycling costs will be based on hot start costs; *ii*. wind is forecast to generate consistently for more than 8 hours, and coal plants are turned off. In this scenario, coal plants' cycling costs will be larger, and equal to their warm start costs.

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 power plants' ramping costs, even if less then proportionally. Troy et al. (2010) highlight that ramping costs vary for different power plants. In particular, these costs are quite large for baseload gas and coal power plants, whereas an OCGT can easily ramp up and ramp down following variations in electricity prices and wind generation. However, the OCGT is the most expensive power plant on the system, in terms of marginal cost, and is therefore not an efficient substitute for baseload plants.

Table 3 compares the characteristics of the series in the 3000MW scenario with those defined in the baseline, focusing on the baseload power plants: coal and CCGT. As expected, Table 3 shows that the shadow price in this scenario decreases, by 1.4%. Table 3b reports the changes in the ramping costs between the baseline and the 3000MW scenario for coal and gas plants. Ramping costs increase, as expected, but minimally. Note that ramping 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). Finally Table 3 calculates the change in the number of generating periods for coal and gas plants respectively. The last line summarises the results by aggregating the hourly periods into days. It shows that in all scenarios the coal plant generates for fewer periods than the natural gas plant. However, the number of generation periods decreases less for coal than for gas plants with increased wind penetration.

It is particularly interesting to observe the behavior of the coal plant, the least flexible plant we consider. As mentioned earlier, it has technical constraints that limit its ability to ramp frequently. Given the SEM operating rules discussed in Section 2.1, when wind sets the shadow price (i.e. there is sufficient wind to meet all the demand), the System Operator (SO) is still forced to keep less flexible plants in operation if their output is needed when demand increases and/or wind dies down. Note that the coal plant runs for a relatively short number of periods overall, but this is mostly driven by the set of fuel and carbon dioxide simulated costs.

Scenario 3: no wind capacity installed. — In the scenario without wind generation the shadow price is higher than in the baseline, as expected. Table 4 shows that the CCGT power plant's ramping costs are lower. Somewhat counterintuitively, the coal plant's ramping costs are marginally higher. This result emerges because in this scenario coal plants generate more often and consequently turn on and off (slightly) more frequently.

In general the results of this section are the mirror image of the ones presented

Table 3—: *Summary statistics: historical and simulated*

(a) *Shadow price, €/MWh*

	Simulated	Baseline
Mean	40.38	40.96
St.Dev	16.91	16.91
Skewness	5.34	5.35

(b) *Cost changes due to ramping, €/MWh*

	Gas	Coal
Baseline	31.0425	46.2629
3000MW	31.0533	46.2601
Δ	0.011	- 0.003

(c) *Generation periods*

	Gas	Coal
Baseline	19671	6838
3000MW	19196	6557
Δ	- 475	- 281
(number of days)	**-20**	**-12**

for the case where wind capacity is set to 3000MW.

B. Profits

This section compares future estimated profits with their historical levels and evaluates how investment incentives change as wind generation grows. In order to investigate the choices made by investors, we determine the necessary conditions under which a power plant must run. We then add the ramping costs that derive from generation patterns of each plant and calculate future expected profits for each representative power plant, assuming a yearly discount rate of 2 per cent (nominal) per year.

The expected profits do not include fixed costs, but are calculated as the difference between the electricity price plus capacity payments and power plants' simulated costs (inclusive of ramping costs), as stated in Equation 6. They should therefore be interpreted as short-run profits.

We use the yearly average of the capacity payments paid out per MWh of available plant from 2008 to 2011 to approximate the level of capacity payments for future years.

Table 4—: *Summary statistics: historical and simulated*

(a) *Shadow price, €/MWh*

	Simulated	Baseline	Δ
Mean	42.03	40.96	2.6%
St.Dev	17.20	16.91	1.7%
Skewness	5.39	5.35	0.9%

(b) *Cost changes due to ramping, €/MWh*

	Gas Plant	Coal Plant
Baseline	31.043	46.263
Simulated	31.022	46.269
Δ	-0.1%	0.0%

(c) *Generation periods*

	Gas	Coal
Gen. periods Baseline	19671	6838
Gen. periods 0MW	20491	7379
Δ	820	541
(number of days)	**34**	**23**

We follow a similar procedure to determine uplift costs. Di Cosmo and Malaguzzi Valeri (2012) show in their analysis that there is no statistical relation between the amount of wind generation and uplift costs. We therefore assume here that uplift costs are fixed and equal to their average between 2008 and 2011.

The present value of the profit stream is calculated according to the following expression for each plant type:

$$E(\pi Future) = \sum_{i=0}^{T} \left(\frac{1}{(1+r)^i} \right) \pi^i \tag{16}$$

in which T is the number of simulation periods, π^i represents profits in period i, and r is the discount rate. We compare these results to the profits realised in the baseline by the same power plants. Future profits are calculated from 1 January 2012 for approximately 3 years. Presenting the results as differences from the simulated baseline allows us to clearly identify the effect of wind.

Comparing 3000MW of wind capacity installed in the system with the baseline. — 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 (marginally) higher. The other generation revenue sources, capacity payments and uplift, are unaffected by wind. Overall, profits decrease by the amounts displayed in Table 5. Note that for the thermal plants profits should be interpreted as the profits for each MW of installed capacity.

Table 5—: *Realised and expected profits, present value in €(thousands)/MW*

	Gas	Coal	Distillate
Profit Baseline	476.13	282.36	219.56
Profit Future	464.90	278.26	219.59
Difference	-2.36%	-1.45%	0.01%

Note: All profit streams refer to a 3-year period

The profitability of CCGT gas power plants with respect to the calibration period decreases by 2.36%, and the profitability of the coal power plant decreases by 1.45%. The situation does not vary for the distillate-fueled OCGT power plant, as it is the peaking plant and we assume that its ramping costs are negligible.

Profits of the fairly unflexible coal power plant decrease less than the profits of the CCGT power plant. This result is driven by the constraints imposed on the system in order to guarantee its reliability. With more wind, traditional plants will not generate as much. At the same time, to maintain system reliability, thermal plants remain on standby in case wind stops blowing.

In our model, we impose that power plants get zero profits for all the periods in which wind generation is high enough to determine the marginal price, as during these periods the power plants only receive constraint payments (equal to their marginal costs). This also means that the least flexible power plant (coal) is less affected by the high wind penetration than the CCGT power plants, as it ramps less due to its ramping inability and low marginal costs. This in turn limits the losses that this power plant faces in the high wind scenario with resect to the CCGT plant, although in all the simulation scenarios the coal plant runs significantly less than the CCGT plant.

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 is likely to vary in a non-linear way as installed wind capacity increases. This implies that applying the current correlation coefficient to even larger increases in wind would lead to inaccurate results.

Scenario 3: no installed wind. — In the scenario without wind generation results are symmetric: the shadow price is higher and generation costs are lower. Thermal power plants therefore realise higher profits, compared to the simulated baseline.

As the distillate power plant doesn't benefit from lower ramping costs, its profits do not vary significantly.

The following Table summarises these results:

Table 6—: *Realised and expected profits, present value in €(thousands)/MW*

	Gas	Coal	Distillate
Profit Baseline	476.13	282.36	219.56
Profit Future	498.47	290.89	219.58
Difference	4.69%	3.02%	0.01%

Note: All profit streams refer to a 3-year period

V. Conclusions

In this paper we have analysed the effect of increased wind generation on the incentives to invest in new 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 decide on the basis of expected profits. To measure how profits change with more wind we build three different scenarios in which the installed capacity of wind varies.

We set the correlation coefficient between wind and shadow price equal to -0.002, as this is the value that minimizes the difference between the historical and the simulated shadow price. The profits of the power plants are calculated by simulated future fuel costs, ramping costs, uplift costs and capacity payments.

We build a baseline where we assume that the wind in the system is the same as in 2011. The difference in the results between this scenario and the past can be ascribed to differences introduced by the specific simulation methodologies used here. In particular the use of the Weibull wind distribution lowers the simulated shadow price in the baseline with respect to its historical record. Comparing the increasing wind generation scenario to the baseline allows us to abstract from these problems.

In the second scenario we consider the effects of 3000MW of installed wind capacity. This is associated with lower shadow prices, slightly higher generation costs for baseload plants and consequently lower profits for all generators. The third scenario considers no wind on the system; this induces higher electricity prices and lower ramping costs than in the baseline. As a result, power plants' expected profits are higher.

Interestingly, changes in the natural gas baseload plant's profits are higher than the changes for the coal plant. In our analysis this outcome arises because the system operator keeps the cheaper and less flexible plants in the system to guarantee supply reliability. However a similar result could hold under different market rules, for example if plants bid their overall costs, including the wear and tear costs associated with ramping and switching on and off.

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