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The Impact of the North Atlantic Oscillation on Electricity Markets: A Case Study on Ireland

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Abstract: The North Atlantic Oscillation (NAO) is a large-scale circulation pattern driving climate variability in north-western Europe. As the deployment of wind-powered generation expands on electricity networks across Europe the impacts of the NAO on the electricity system will be amplified. This study assesses the impact of NAO, via wind-power generation, on the electricity market considering thermal generation costs, wholesale electricity prices and wind generation subsidies. A Monte Carlo approach is used to model NAO phases and generate hourly wind speed time-series data, electricity demand and fuel input data. A least-cost unit commitment and economic dispatch model is used to simulate an island electricity system, modelled on the all-island Irish electricity system. The impact of NAO obviously depends on the level of wind capacity within an electricity system. Our results indicate that NAO phases can affect thermal generation costs by up to 8%, wholesale electricity prices by as much as €1.5/MWh, and that wind power generators receive on average 12% higher remuneration.

Keywords: North Atlantic Oscillation, NAO, Electricity, prices, subsidy

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1 Introduction

The North Atlantic Oscillation (NAO) is a large-scale circulation pattern driving climate variability in north-western Europe (Hurrell et al., 2013). Its influence is far reaching, including impacts on wave height (Trigo et al., 2008), solar energy (Colantuono et al., 2014), rainfall and hydropower production (Cherry et al., 2005; Munoz-Díaz and Rodrigo, 2003), crop yields (Tian et al., 2015) and fishery catches (Gamito et al., 2015; Teixeira et al., 2015). There is also a literature about its impact on the wind resource (Pirazzoli et al., 2010; Jerez and Trigo, 2013; Jerez et al., 2013; Burningham and French, 2013; García-Bustamante et al., 2013) drawing a range of conclusions. In an analysis of data from Iceland and northwestern Europe, Pirazzoli et al. (2010) conclude that while NAO affects wind activity, its impact is not uniform. More specifically, Jerez et al. (2013) find that negative NAO phases (NAO^{-}) enhance wind speeds, precipitation and cloud cover on the Iberian Peninsula. Burningham and French (2013) find that positive NAO phases (NAO^{+}) are associated with increased intensity and frequency of high wind events in the UK and Ireland. These outcomes are not surprising as NAO has simultaneous opposite effects in the regions affected by its northern and southern centres of action. While the NAO plays a major role it is not the only large-scale circulation pattern that affects local wind conditions, as both the East Atlantic (EA) and the Scandinavian (SCAND) modes also play a part (Trigo et al., 2008). With NAO known to have an effect on wind speeds it follows that there is likely to be a consequential impact on renewable electricity generation from wind farms.

In recent years, research on the NAO has investigated the impact on the electricity sector (e.g. Brayshaw et al. (2011); Ely et al. (2013)). Früh (2013) uses a simple illustrative example to show how relatively small changes in the wind resource can lead to large deviations in wind farm incomes. Therefore, a clear understanding of how the wind resource evolves, either due to NAO or otherwise, is very important, as it can affect the profitability of existing wind farms, which in turn can affect the level of future investment in renewable energy. Brayshaw et al. (2011) makes the point that the representation of wind speed data, incorporating either NAO^{+} or NAO^{-} phases, during investment planning could potentially lead to substantial under or over estimates of wind power output. Both Brayshaw et al. (2011) and Ely et al. (2013) investigate technical implications of NAO variability on the operation of the power grid. Brayshaw et al. (2011) find that the NAO state has a noticeable impact on the power output from wind turbines, which has implications for wind resource forecasting, as well as electricity system planning and operation. Ely et al. (2013), investigating the implications of NAO variability on interconnected UK and Norway power grids, finds that a highly interconnected grid may be more affected by the NAO than a less interconnected network. However, there is no published research about the impact of NAO on electricity prices, though there is an extensive literature on the wider topic of the impact of wind energy on electricity prices (e.g., Ketterer (2014); Amor et al. (2014); Shcherbakova et al. (2014); Woo et al. (2013); Würzburg et al. (2013)).

The literature has clearly established that NAO affects wind turbine output, though the relationship is non-linear, varies by location, is influenced by other large-scale circulation patterns, and is subject to further research. What is also of relevance but not well understood is the NAO's impact on the economics of electricity generation. While NAO affects wind turbine output, it is not straightforward or obvious what is the consequential impact, if any, on electricity prices or generator profitability. Electricity market design, the share and type of thermal generation, as well as fossil fuel prices will all determine wholesale market prices of electricity. The aim of this paper is to examine the effect of NAO on the electricity market, and particularly wholesale electricity prices, using a simulation analysis case study based on the

Single Electricity Market (SEM) on the island of Ireland. A motivation for this analysis was the unusually calm wind speeds experienced in the UK and Ireland in the winter of 2009/2010. While December through February normally includes some of the windiest times of the year, during 2009-2010 there were extended periods with very low wind speeds and wind farms were not productive. The implication for the electricity sector was that it had to call on thermal generation to a much greater extent than might have been expected in a 'normal' year, which lead to significant additional fuel costs. The impact of low winds was exacerbated by very low temperatures, leading to a situation of high electricity demand and a consequent spike in wholesale electricity prices. Thus, basing an analysis on the events of winter 2009/2010 alone one cannot draw general conclusions about the impact of NAO on the electricity market. A simulation case-study enables an investigation of many realisations of the effect of NAO on wind, coupled with its interaction with the electricity market (including technical and market constraints) plus other stochastic variables such as electricity demand, fuel and carbon prices.

The literature on the effect of wind on electricity prices has not yet extended to the specific impact of the NAO. In general wind has both positive and negative effects on generating system costs and prices due to the characteristics of wind energy. For example, wind may displace and cause more frequent cycling of baseload generating plant, which in turn can affect system costs and merit order (inflexible plant may fall down the merit order) (Troy et al., 2010). Wind displacing thermal plants reduces fuel cost, which contributes to a downward pressure on electricity prices. Due to its intermittency, wind may also add additional costs associated with providing reserve, or transfer costs to uplift or capacity payment mechanisms (Felder, 2011; Denny and O'Malley, 2007). A number of previous studies have estimated the impact of increased wind generation on electricity costs and prices. Studies covering Germany, Austria, Korea, Canada and the United States find that additional wind generation capacity reduces prices (Ketterer, 2014; Würzburg et al., 2013; Amor et al., 2014; Shcherbakova et al., 2014; Woo et al., 2013). On the contrary, Swinand and O'Mahoney (2015) summarise the results of 22 studies from Europe and the USA that conclude that additional wind penetration increased costs. While these studies do not consider NAO, their results may be sensitive to its impact and may explain why some studies find that wind increases prices while others find the reverse. The current analysis compares whether Irish electricity prices under NAO^{+} phases are less than prices under NAO^{-} phases.

The contribution of this paper is to determine whether the impact of the NAO on the wind resource passes through the electricity market into an impact on electricity prices. This has relevance to wind farm developers because it is likely to affect the profitability of wind farm investments or, depending on the design of wind subsidies, affect the total costs of government subsidy support. It also has direct relevance for renewable energy targets and energy policy makers. The EU's Renewable Energy Directive (2009/28/EC) specifies a mandatory target of 20% for all energy to come from renewable energy sources by 2020. Ireland has established a national target of a 40% contribution from renewables to gross electricity consumption (RES-E) by 2020 as part of its contribution to the EU target. In 2013 20.9% of gross electricity consumption was from renewable sources, primarily wind (Howley et al., 2014). Ireland, like other EU countries, is likely to continue its investment in renewable electricity generation into the future and it is of relevance to both electricity consumers and regulators whether and to what extent the variability of NAO affects electricity prices as wind capacity on the electricity network increases.

The rest of the paper continues with a review of relevant literature. That is followed by Section 2, which describes the models used and Monte Carlo inputs. Section 3 presents and discusses the simulation results organised by NAO phase and by wind subsidy mechanism, and also includes a section on preferences for risk. Section 4 concludes the paper with a brief summary.

2 Methodology

The objective in this section of the paper is to derive a series of wind speed parameters that are applicable to Ireland and associated with variations in the NAO index. These parameters will be used in the simulation case study to generate synthetic wind speed data, which will be used as input into an electricity dispatch model based on the Single Electrictiy market (SEM) in Ireland.

2.1 NAO and wind speed

Instrumental monthly NAO indices have been calculated and made available on-line by the Climate Research Unit (CRU) of the University of East Anglia, dating back to 1821. This index is calculated as the difference between normalised sea level pressure over Gibraltar and South-west Iceland. It was first published in Jones et al. (1997) and has since been extended to the present by Tim Osborn.[1] The NAO index cover the range -6.05 to +6.66; we split this range into 15 'bins', 0.847 units wide each, and calculated the proportion of months that the NAO index falls within each bin, as shown in Figure 1. The analysis focuses on the extended winter months, October to March. During simulations we use these distributions to draw an NAO index bin for each winter month.

The next stage uses the ERA-Interim re-analysis dataset and fits Irish wind speed data to a Weibull distribution. ERA-Interim global reanalysis database was released in 2011 by the European Centre for Medium-Range Weather Forecasts (ECMWF) and has the highest spatial resolution (0.75 degree horizontal) covering a range of parameters, describing weather as well as ocean-wave and land-surface conditions, and upper-air parameters covering the stratosphere and the troposphere. The model results span from 1979 to present and are calculated across a 0.75 x 0.75 degree spatial grid. Wind data at 10 metre height and 6 hourly resolution were retrieved covering 51 N to 56 N and 11.25 W to 5.25 W for the period January 1979 to December 2014. Using this data we fit a Weibull distribution to these wind speed data for each month. Mean values for the Weibull scale and shape parameters (μ) for each month-NAO bin combination were estimated and collated by NAO bin as below:

$$\mu^{j}_{i,m}, \; i = 1 \dots 15, \; j = c, k \tag{1}$$

where i is the NAO bin, m refers to the month, c and k are the Weibull scale and shape parameters. Across all month-NAO bin combinations the calculated relative standard deviation (RSD) (i.e. ratio of the standard deviation to the mean) for both the shape and scale parameters were approximately 0.25. Because we are interested in the impact of NAO on wind turbine power generation we re-scaled the data from 10 metre height to 60 metres using a wind shear profile (Zoumakis and Kelessis, 1991), as show in equation 2:

$$V_{60} = V_{10} \frac{log(60/\omega)}{log(10/\omega)} \tag{2}$$

where V refers to wind speed and ω to roughness length for which we use the European Wind Atlas roughness class 1.5 (ω = 0.055 metres), defined as agricultural land with some houses

[1] See http://www.cru.uea.ac.uk/ timo/datapages/naoi.htm

Figure 1: NAO Index Frequency, Winter Months 1979-2014

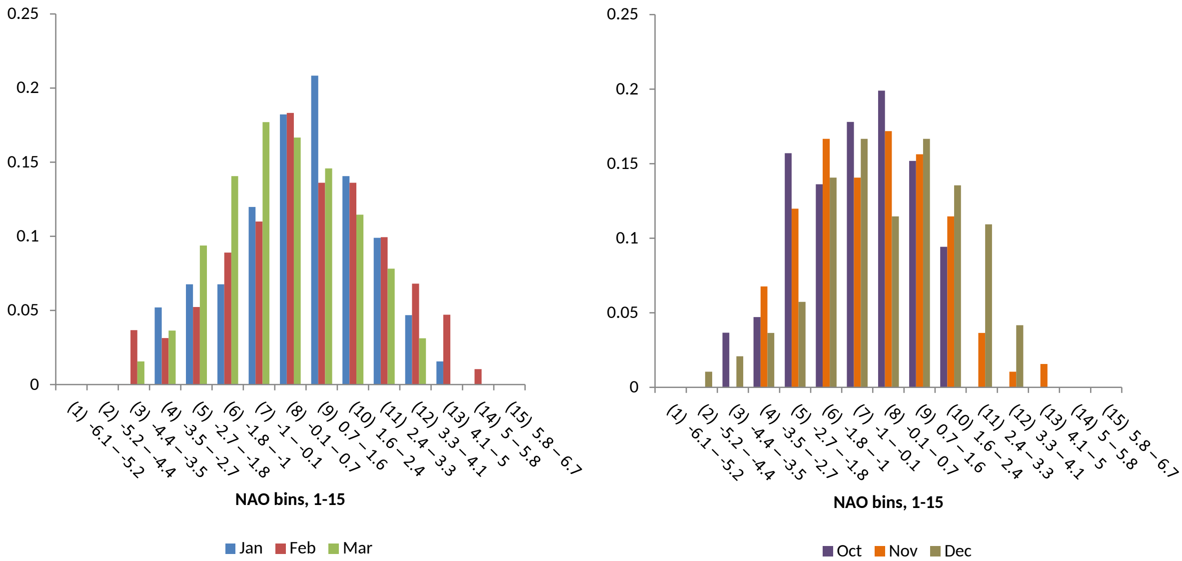
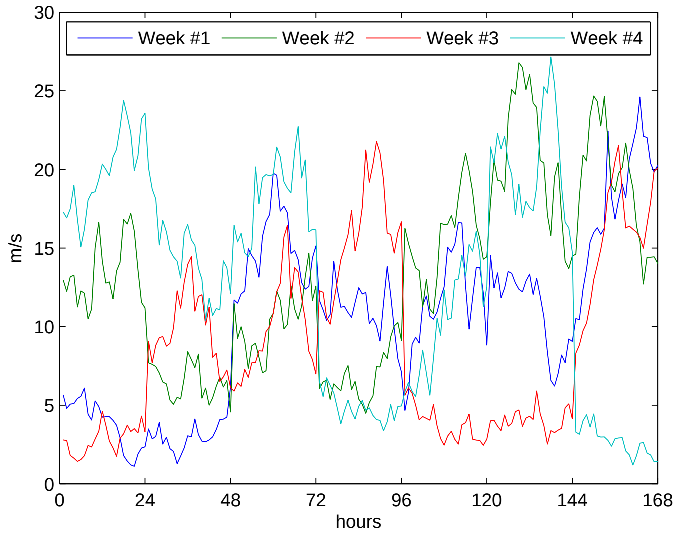


Figure 2: Sample synthetic January wind speed data (+2.431 $\leq$ NAO index $<$ 3.2711)



and 8 metre tall sheltering hedgerows with a distance of approximately 1250 metres (Troen and Petersen, 1989). While newly installed wind turbines can be in excess of 100 metres, rescaling to 60 metres height allows for the fact that many installed wind turbines are substantially smaller.

2.2 Synthetic wind speed time series

For each winter month (October–March) we draw a random NAO bin and for that month-NAO bin combination use the associated Weibull scale and shape parameters, as discussed above. We use that information to generate hourly synthetic wind speed time series for each month using a method proposed by Carapellucci and Giordano (2013). Their methodology is based on the assumption that wind speed comprises deterministic elements incorporating diurnal patterns and monthly variation through the year, a stochastic component, and a time series component generated through an autoregressive process. Figure 2 provides an example of the synthetic wind speed data for the first four weeks in January. The NAO bin randomly drawn for the example in Figure 2 covered the NAO index range +2.431 to +3.2711. The estimated Weibull scale and shape parameters associated with the month of January and NAO bin +2.431 to +3.2711 are 15.647 and 2.017 respectively. However, as mentioned earlier, the scale and shape parameters are estimates with a standard deviation roughly equivalent to 25% of the estimates of the mean. This is implemented during simulations by independently drawing shape and scale parameters from a truncated normal distribution, $N(\mu^j_{i,m}, (0.25 \times \mu^j_{i,m})^2)$, with truncation occurring at +/- 1 standard deviation from the mean. Drawing from a normal distribution allows for the variance in the shape and scale parameter estimates, whereas truncation seeks to impose the structure of the 15 NAO bin types during simulation. The scale and shape parameters drawn to generate the times series in Figure 2 (i.e. January and NAO bin +2.431 to +3.2711) are 13.2785 and 1.7872 respectively.

2.3 Wind power model

A generic wind turbine output model was used to characterize the relation between wind speed and wind turbine electricity output (Liu, 2012; Hetzer et al., 2008):

$$WP = \begin{cases} 0, & (V < v_{in} \text{ or } V \geq v_{out}) \\ w_r, & (v_r \leq V < v_{out}) \\ \frac{(V - v_{in}) w_r}{(v_r - v_{in})}, & (v_{in} \leq V < v_r) \end{cases} \tag{3}$$

where WP is power generated, v_r, v_{in}, and v_{out} are rated, cut-in, and cut-out wind speeds; w_r is the rated power of a wind turbine, and V is wind speed. While a wide range of turbine types exist, we assume just three, as outlined in Table 1. We assume shares by turbine category are 33%, 38% and 29% respectively. These turbine types and shares broadly match the installed wind generation capacity in the island of Ireland electricity market in 2012. Within the wind power model this means that for a low wind speed of eg. 3.5 m/s, only turbine types A and C operate accounting for 62% of installed wind generation capacity. For wind speeds 25 m/s $< V \leq$ 34 m/s, only category C turbines are operational, accounting for 29% of installed capacity.

Table 1: Turbine wind speed characteristics, metres/second

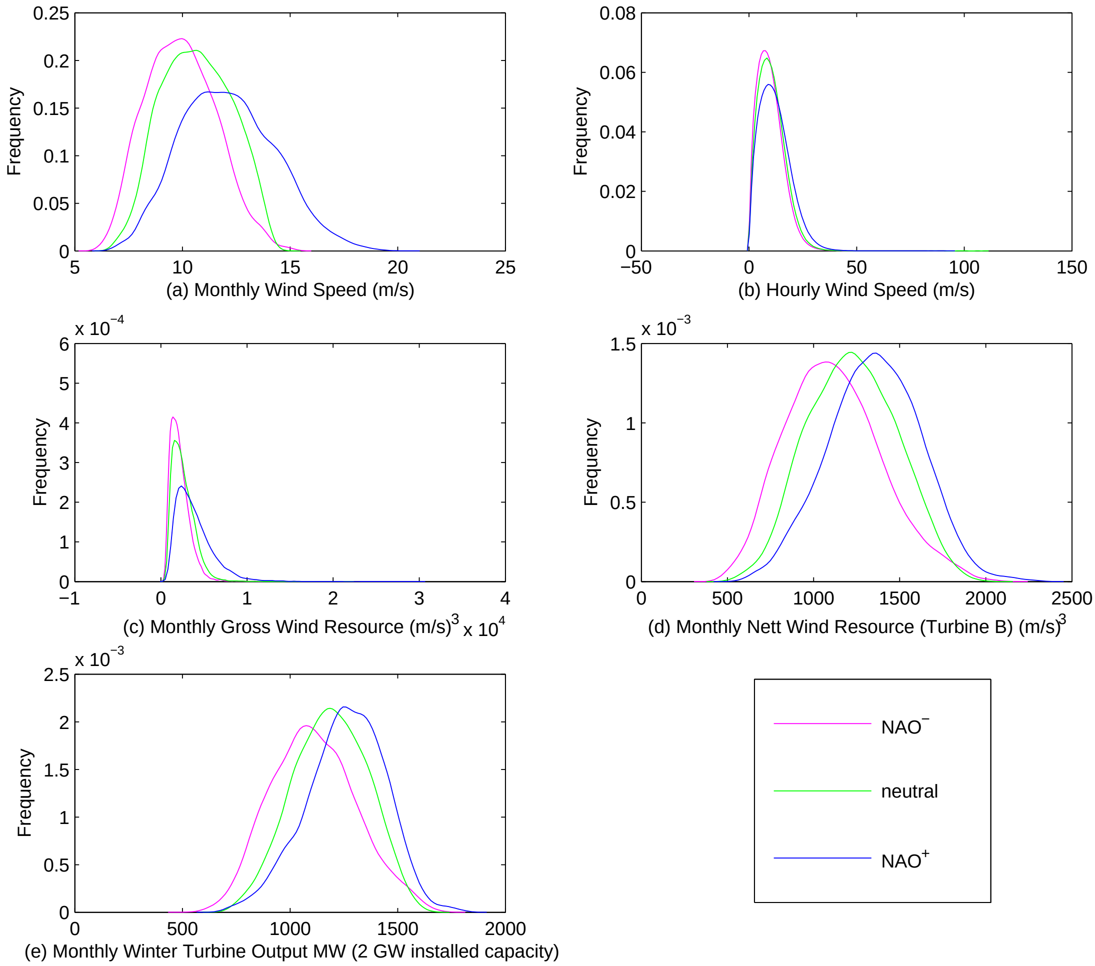
	Type A	Type B	Type C
Cut-in speed	3	4	3
Rated speed	12	14	13
Cut-out speed	25	25	34

Hourly simulation data was generated for the 6 winter months across 10,000 replications (i.e. 10,000 winters). Probability density estimates produced using a kernal smoothing function on wind speed, wind resource and wind turbine output data are presented in Figure 3. Similar to Brayshaw et al. (2011) and Munoz-Díaz and Rodrigo (2003), variability of NAO is divided into three phases for illustrative purposes: NAO$^-$ (NAO < -0.966), NAO neutral ($-0.966 \leq$ NAO < 0.7287), and NAO$^+$ (NAO$\geq$ 0.7287). Panels (a) and (b) of Figure 3, which show the distribution of monthly and hourly mean wind speeds, illustrate how positive NAO phases shifts the distribution of mean wind speeds to the right during winter months compared to neutral or negative NAO phases. Higher wind speeds invariably mean a greater wind resource. The available power of wind crossing rotors of a wind turbine, P, is

$$P = \frac{1}{2} A \rho v^3 \tag{4}$$

where A is the rotor area, ρ is the air density, and v is the wind speed (Burton et al., 2011). Assuming constant A and ρ we can plot available power as proportional to v^3, as in panel (c) in Figure 3. The plot in panel (c) assumes that all the available wind resource can be harnessed and in that sense is the gross wind resource available. However, from the wind power model (equation (3)) we know that power generation only occurs within specified wind speed ranges. Panel (d) plots the distribution of the mean nett wind resource that is accessible for generation using wind turbine type B in Table 1. Panels (c) and (d) illustrate a greater wind resource associated with NAO$^+$ phases compared to other phases but also show how the technical constraints of wind turbines limits the wind resource usefully available, especially higher wind speeds during NAO$^+$ phases. Panel (e) shows the probability density of mean monthly wind turbine output assuming an installed capacity capacity of 2GW across the three wind turbine types. Similar to the earlier panels, NAO$^+$ phases are associated with higher mean turbine output compared to neutral or NAO$^-$ phases. We fail to reject the null hypothesis that mean turbine output under NAO$^+$ is greater than under both neutral and NAO$^-$ phases ($p < 0.0001$) using t-tests for equality of means. This result on the synthetic data is in line with earlier research that NAO affects wind turbine output (e.g. Jerez et al. (2013).

Figure 3: Wind Speed, Wind Resource and Wind Turbine Output



The next stage is to investigate the impact of NAO under stochastic electricity demand, fuel and carbon prices, within the complexity of a centrally dispatched electricity market. The methodology for that analysis is described in the remainder of this section.

2.4 Electricity dispatch model

Several approaches are used in the literature to simulate electricity generation schedules depending on the application. Some instances use linear dispatch models, which consider the output of generation units as a continuous linear variable between zero and the unit's rated capacity (Hirth, 2013; Chattopadhyay, 2010; Godby et al., 2014; De Jonghe et al., 2012). Some models add a further simplification, considering demand as a load duration curve (Chaudry et al., 2013). This approach fails to include the 'on-off' state of units, cannot incorporate start and no load costs of units, and cannot implement technical restrictions such as minimum up/down times and minimum outputs. As variability increases from renewable generation such as wind and solar, the dispatch arrived at by linearised dispatch-only models diverges significantly from reality (Shortt et al., 2013). The inclusion of these technical constraints requires mixed-integer programming (MIP), which is widely utilised in generation planning and operation research (van der Weijde and Hobbs, 2011; Ela and O'Malley, 2012; Hargreaves and Hobbs, 2012; Pereira et al., 2014). However the computational requirements of mixed-integer programming tend to rule out running a large number of scenarios of such models.

The Flexible Algorithm for Scheduling Technologies (*FAST*) was developed as a response to this problem of providing electricity generation schedules that mimic system decisions in real time, while meeting demand and respecting technical constraints. The *FAST* algorithm mimics the input-output relationship of a mixed-integer unit commitment model but does so in orders of magnitude faster, which is of practical relevance when simulating many scenarios. The algorithm is described in Lynch et al. (2013) and Shortt and O'Malley (2014) and seeks to determine least-cost schedules for generation dispatch, considering start-up and no load costs, as well as variable costs and technical constraints. The *FAST* solution produces unit-commitment and economic dispatch schedules whose costs are on par with those from the MIP under a relatively tight optimality gap.

In order to increase computational speed while respecting technical constraints, *FAST* splits generation into flexible and inflexible units. Inflexible units whose size or cycling characteristics are such that a linear representation of their costs would not yield accurate schedules have been given a mixed-integer formulation. Flexible units (which tend to be numerous, small and more flexible) are represented by linear costs. *FAST* solutions bear a strong degree of similarity across a number of metrics with equivalent mixed-integer programmes except for computation time, where *FAST* on average determines schedules several thousand times more quickly (Lynch et al., 2013). *FAST*'s computational efficiencies are achieved through a number of simplifications. For instance, it does not include minimum up and down times, start times or transmission constraints. Unit outages are not considered but uncertainty associated with unit outages is considered by enforcing a spinning reserve target that at each hour must be at least as great as the largest installed unit. There is no explicit limit on the maximum level of instantaneous wind generation but *FAST* will curtail wind energy where doing so will reduce total costs. *FAST*'s quick computational times is particularly important when considering unit-commitment issues across a long time horizon, such as 4,368 hours (i.e. 6 winter months of data), for many scenarios (e.g. several thousand).

2.5 Installed generation capacity

The installed conventional generation capacity modelled is a simplification of the generation units installed on the Irish system and the total capacities of each technology are given in Table 2. We consider four inflexible types of generation, two coal fired and two Combined Cycle Gas Turbine (CCGT) technologies. The flexible technologies considered here are Open Cycle Gas Turbines (OCGTs), one gas-fired and one using distillate. The characteristics of each technology in terms of the fuel requirements for starting, no load running and incremental output increases are given in gigajoules in Table 2. These figures are based on the characteristics of units on the Irish system at present, as reported in the inputs for the PLEXOS model which has been validated by the regulatory authorities in the Irish market for modelling the Irish system (CER and NIAUR, 2013).

Table 2: Parameters for generation capacity based on 2013 installed generation

	Fuel Type	Start fuel (GJ)	No-load fuel (GJ/hr)	Incremental fuel (GJ/MWh)	Total capacity (GW)
Coal 1	Coal	6920	193	10.9	1200
Coal 2	Coal	6200	394	8.75	600
CCGT 1	Gas	393	667	4.81	2800
CCGT 2	Gas	1800	592	5.2	2400
OCGT 1	Gas	na	na	9.82	1000
OCGT 2	Distillate	na	na	9.21	1500

Note that the *FAST* model does not allow for load-shedding, and so there must be sufficient generation capacity installed to meet the demand and reserve requirement at every hour. Thus the total installed capacity considered here is higher than the total installed on the Irish system at present, as there are some outlying high-demand hours in the input data considered.

2.6 Electricity demand data

Electricity demand is a function of various factors, such as the season, the weather, the time of day, day of the week, public holidays and social events. Thus electricity demand has a predictable pattern and is also subject to unpredictable variations. In addition to wind, the NAO may also affect temperatures (Sen and Ogrin, 2015), which in turn may affect electricity demand for space heating. The effect of NAO on electricity demand is not modelled here. Instead we generated hourly electricity loads based on historical hourly demand from the five years 2008–2012. For each simulation one of the five calendar years was randomly selected and the entire demand series was scaled by a randomly-generated factor of between 0.8 and 1.2. The high variation in the scaling factor is to examine the impacts of unusually high or low demand. We also impose hourly random noise of up to +/- 10% variation from the hourly load profile. Consequently, the demand profile in each simulation preserves temporal characteristics of electricity demand as observed in previous years but introduces randomness to allow for variation in demand that in reality could be attributed to factors such as high/low economic activity or mild/severe weather.

2.7 Fuel and carbon prices

Fuel and carbon prices are generated from a lognormal distribution. The mean and standard deviation for each are given in Table 3. We used daily coal, gas and oil price data from Deane et al. (2014) for the years 2008 to 2011 to estimate the parameters of lognormal price distributions, from which we calculate the relative standard deviation (RSD) (i.e. ratio of the standard deviation to the mean) for each price series. We draw random prices from lognormal distributions with means equivalent to 2012 fuel and carbon prices from Clancy et al. (2015), which are in turn obtained from the IEA. We then use the historical RSD to calculate standard deviation. For carbon we assume an RSD of 0.25. To allow for correlation in fuel prices we use the variance-covariance matrix of daily fuel prices between 2008 to 2011 given in Table 4. For the Monte Carlo simulation we draw one vector of fuel and carbon prices for each scenario, meaning that prices are constant across the 4,368 hours (6 winter months) within each scenario. This assumption is not unreasonable as generation firms sign long-term contracts for fuel supply.

Table 3: Statistical parameters of fuel prices based on 2012 Irish prices

	Coal (€/GJ)	Gas (€/GJ)	Distillate (€/GJ)	CO_2 (€/tonne)
Mean	2.91	7.99	21.59	7.45
Standard deviation	0.72	2.80	5.78	1.86

Table 4: Fuel price variance-covariance maxtrix

	Gas	Oil	Coal
Gas	2.74	1.16	1.19
Oil	1.16	6.74	0.81
Coal	1.19	0.81	0.73

2.8 Welfare and risk aversion

To examine the welfare implications for electricity generators and consumers we propose using a utility framework. Electricity generators, whether thermal or wind, derive welfare from production revenues net of costs but have an aversion to risk. Consumers derive welfare from their consumption of electricity and disutility from the cost of same, and are also averse to variation in the payments they make for their electricity. We consider utility, U, per megawatt (MW) as a linear function of both welfare (W) and risk (ϑ) measures.

$$U_i = W_i - \beta_i * \vartheta_i, \ i \in (c, p) \tag{5}$$

where c is consumers and p is producers, and β is the coefficient of risk aversion. We calculate utility per megawatt hour consumed for consumers (MWh_c) and per MW installed wind capacity for producers (MW_p). Only short-term effects are considered and not the costs or effects of investment.

2.8.1 Welfare measures

We define electricity generators' welfare as their producer surplus, given as the total quantity of electricity supplied ($Generation_t$) at each time period t multiplied by the price of electricity at that period ($Price_t$), minus the production cost of electricity at that period. Production costs are defined as fuel and carbon costs only. Wind generators have production costs of zero and their $Generation_t$ is equivalent to WP in equation 3. Thus producer welfare (W_p), assuming no market power, is the sum of producer surpluses from electricity production at each time period.

$$W_p = \sum_t Price_t * Generation_t - Costs_t \tag{6}$$

For our purposes, we define consumer welfare, W_c, as the negative of electricity payments. Wind generation impacts on consumer payments in two ways. The first is any subsidy consumers must pay to wind generators, and the second is the impact wind generation may have on electricity prices (both their level and the variance thereof). Thus consumer welfare is given by

$$W_c = \sum_t -(Payment_t * Demand_t + Subsidy_t * WP_t) \tag{7}$$

where WP_t is the quantity of electricity consumed at time t from equation 3. The value of the subsidy payment, $Subsidy_t$, varies depending on the design of the wind subsidy and is discussed later in Section 3.3.

2.8.2 Risk measures

An increasingly popular measure of risk is Conditional Value-at-Risk (CVaR) developed by Rockafellar and Uryasev (2000). CVaR is an estimate of the expected loss incurred in the $(1-\alpha)\%$ worse cases of possible outcomes and is a coherent measure of risk in the sense of Artzner et al. (1999). A particular advantage of CVaR as a measure of risk is that it is easy to calculate using linear programming and does not require knowledge of the underlying distribution (Rockafellar and Uryasev, 2000, 2002). For producers we calculate CVaR in relation to their surplus, $\vartheta(\tau_p)$, and for consumers in relation to electricity payments, $\vartheta(\tau_c)$.

We perform a Monte Carlo analysis for K realisations of demand, input prices and wind, defining our CVaR variable as

$$\vartheta(\tau_{ik}) = \vartheta\left(metric_{ik} - \frac{1}{K}\sum_{k=1}^{K} metric_{ik}\right), \ i \in (c,p) \tag{8}$$

where $metric_{ik}$ is either consumer payments or producer surplus in scenario k. By Rockafellar and Uryasev (2000) equation 8 may be calculated by minimising

$$\vartheta(\tau_{ik}) + \frac{1}{K(1-\alpha)}\sum_{k=1}^{K} u_k \tag{9}$$

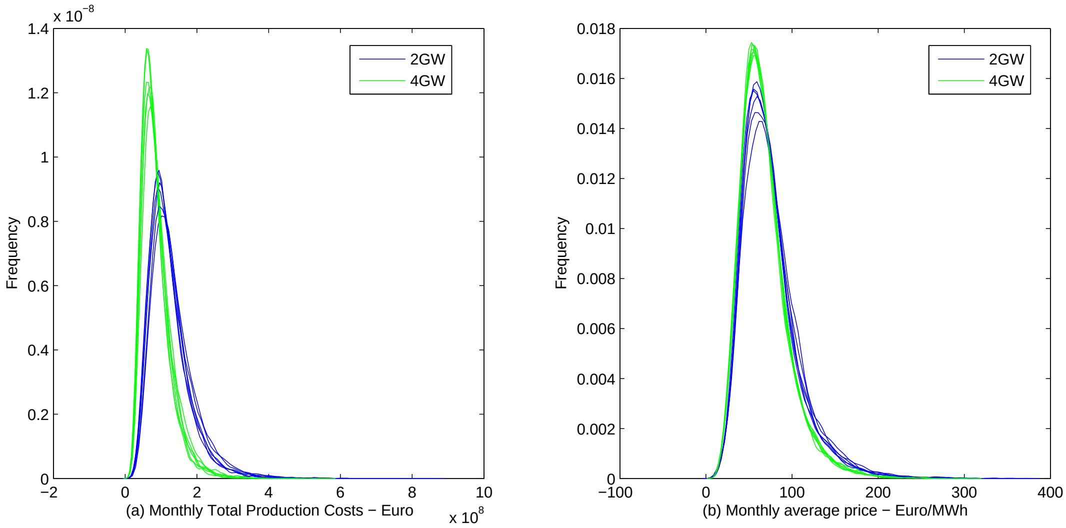
subject to constraints $u_k \geq 0$ and $\tau_{ik} + \vartheta(\tau_i) + u_k \geq 0$, where u_k is an auxiliary real variable. For this study we set $K = 10{,}000$ scenarios, where each scenario contains 4,368 hours worth of data (i.e. 6 winter months), and $\alpha = 0.95$.

3 Results and discussion

3.1 By Winter

We first present results by winter season showing how electricity production costs and prices vary with installed wind capacity. Figure 4 plots prices and production costs associated with 2GW and 4GW of wind capacity. Production costs relate to thermal generation, as wind generation has a marginal cost of zero. The plot distributions reflect the modelled variability in input prices, electricity demand and wind speed across the 10,000 simulations. On average production costs are lower with higher wind capacity. With 2GW wind capacity mean monthly production costs are €125 million falling to €87 million with 4GW capacity, a 30% reduction. Similarly,

Figure 4: Total Production Costs and Electricity Prices



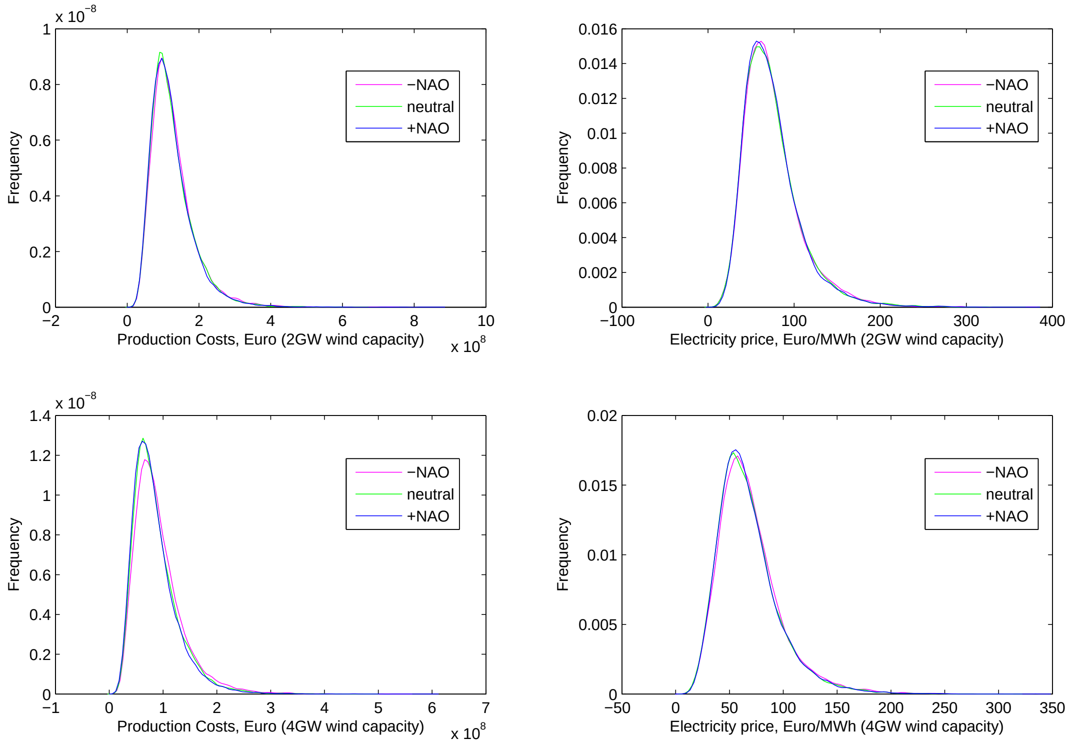
wholesale electricity prices decline from €74.6/MWh with 2GW capacity to €68.2/MWh when wind capacity is doubled. Figure 4 shows how greater levels of installed wind capacity can, on average, reduce electricity costs and prices across a wide range of input cost, load, and wind scenarios.

3.2 By NAO phase

The question of interest here is the effect of varying levels wind resource associated with NAO$^+$ and NAO$^-$ phases (for a given level of wind generation capacity). The different coloured plots in Figure 4 are related to a scaling of the output from the wind power model in section 2.3 (e.g. from 2GW to 4GW), whereas the effect of NAO on the wind resource changes the output from the wind power model for a given wind generation capacity. Consequently, the impact on electricity costs and prices is likely to be more subtle. Figure 5 plots the distributions of production costs and electricity prices by NAO phase for two levels of installed wind generation capacity. On first sight the distributions appear graphically similar but they do differ, as indicated by the statistics describing the distributions in Table 5. At 2GW installed wind capacity total thermal production costs are 3% lower under NAO$^+$ compared to NAO$^-$, with the reduction in the median slightly less. When wind capacity is 4GW there is a proportionately greater reduction in thermal generation costs, which fall by 8.2% compared to NAO$^-$. Electricity prices are 1.1% lower in NAO$^+$ compared to NAO$^-$ phases at 2GW wind capacity and 2.1% lower at 4GW wind capacity. Statistical tests on equality of means of electricity prices reject the null ($p = 0.012$) in favour of the alternative that mean price during NAO$^+$ phases is less than mean price under NAO$^-$ phases ($p = 0.006$). The greater wind resource under NAO$^+$ phases is also associated with a lower variance in costs and prices. Previous work shows how increased wind capacity reduces the mean and the variance of annual production costs (Lynch and Curtis, 2016). The statistics measuring skewness indicate that the distributions of both costs and prices are marginally less right-skewed during NAO$^+$ phases or when wind capacity increases, i.e. the probability of very high prices or costs is lower. A high kurtosis value indicates a sharper peak (or heavy tails) in the distribution, which is the case under NAO$^+$ phases.

The effect of NAO is not usually considered when assessing the impact of additional wind generation on electricity prices but the results here show that ignoring NAO could lead to

Figure 5: Monthly Thermal Production Costs and Electricity Prices



unexpected significant financial gains or losses. At 2GW wind generation capacity, which broadly matches the installed wind capacity in the island of Ireland electricity market in 2012, there is on average a €0.8/MWh difference in electricity prices comparing NAO$^+$ and NAO$^-$ phases. The difference increases to €1.5/MWh with 4GW generation capacity. As indicated earlier, these differences are between 1-2% of the electricity price and therefore could represent a substantial component of a generator's profit margin. Investment decisions in new generation plant that is not mindful of the distribution of NAO phases and its impact on the wind resource could lead to unexpected deviations from expected revenue, either positive or negative.

We examine revenue and profit streams in Table 6 for two wind generation capacity scenarios and a stylised thermal generation capacity mix, which was described in section 2.5. The *FAST* algorithm only incorporates operational fuel costs, including start costs. Therefore, estimates of thermal generation plants' profit levels represents an approximation of gross profits before overhead or capital costs. Wind revenues are market revenues and exclude subsidy support. Across all the wind, fuel cost and demand scenarios, wind generation capacity receives on average 12% higher remuneration under NAO$^+$ compared to NAO$^-$ phases. If wind capacity doubles from 2GW to 4GW, wind generation revenues will grow by roughly 55%. This reflects the curtailment of wind within the model, which does not include interconnection capacity. As wind has priority dispatch, when wind generation increases thermal plant is displaced, and consequently fuel costs decline. When comparing positive and negative NAO phases, fuel costs fall on average by 3.2% under 2GW installed wind capacity, but proportionately more at higher levels of installed wind capacity. This reflects lower levels of cycling of thermal plants. Because the effect of NAO is on wind speed, one might assume that its impact is confined to wind generators; however there is an indirect financial impact on thermal generators. Their monthly profit levels are on average between 3–7% lower in NAO$^+$ compared to NAO$^-$ phases.

Table 5: Monthly Thermal Production Costs and Electricity Prices

		Total Costs, €m			Price €/MWh		
		2GW	4GW	% ∆	2GW	4GW	% ∆
Mean	NAO⁻	127.7	92.0	-28.0%	75.1	69.2	-7.8%
	NAO⁺	123.9	84.4	-31.9%	74.2	67.8	-8.7%
	%∆	-3.0%	-8.2%		-1.1%	-2.1%	
Median	NAO⁻	115.0	82.3	-28.4%	68.6	64.2	-6.3%
	NAO⁺	112.1	75.6	-32.6%	68.2	62.6	-8.2%
	%∆	-2.5%	-8.2%		-0.6%	-2.6%	
Std Dev	NAO⁻	61.8	46.3	-25.2%	33.7	29.8	-11.7%
	NAO⁺	59.3	41.6	-29.8%	33.0	29.0	-12.0%
	%∆	-4.1%	-10.0%		-2.3%	-2.7%	
Skewness	NAO⁻	1.9	1.9	0.6%	1.6	1.5	-3.9%
	NAO⁺	1.9	1.9	-1.7%	1.6	1.6	-2.9%
	%∆	-0.3%	-2.5%		2.5%	3.5%	
Kurtosis	NAO⁻	10.2	10.2	-0.2%	7.8	7.5	-3.3%
	NAO⁺	11.0	10.7	-2.4%	8.2	8.4	2.8%
	%∆	7.9%	5.6%		4.7%	11.3%	

Table 6: Mean Monthly Revenues and Profits, €million

		2GW	4GW	%∆
Wind Revenue	NAO⁻	56.0	86.8	54.9%
	NAO⁺	62.7	96.7	54.2%
	%∆	12.0%	11.5%	
Thermal Revenue	NAO⁻	192.2	144.6	-24.8%
	NAO⁺	186.0	133.2	-28.4%
	%∆	-3.2%	-7.8%	
Thermal Profits[a]	NAO⁻	64.5	52.6	-18.4%
	NAO⁺	62.2	48.8	-21.4%
	%∆	-3.6%	-7.2%	

[a] Thermal profits equal to electricity price less operational fuel costs.

3.3 Wind Generation Subsidies

Most wind generation receives subsidy support. In Ireland a support floor applies, equivalent to approximately €80/MWh in 2015.[2] A consumer's exposure to the cost of wind subsidies is unknown[3], partly due to the vagaries of the wind resource, which includes the NAO, but also due to the design of wind subsidy support schemes. Using our simulation data we calculate three types of wind subsidy to gauge the sensitivity of wind generation subsidies to NAO phases. The first is a floor subsidy similar to that which applies in Ireland (A); the second a flat premium of €26.12 (B); and the third is a fixed price for wind electricity of €95.31/MWh (C). The value of the premium in subsidy type B, €26.12/MWh, is equivalent to the mean subsidy per MWh generated from wind under NAO$^-$ wind. Consequently the mean monthly cost of subsidy types A and B are equal under NAO$^-$ phase. In the third option the subsidy is a fixed price and unlike option A there is no upside for wind generators. The fixed electricity price of €95.31/MWh is such that the total revenue to wind producers (subsidy plus market revenue) is equivalent to the total revenue to wind producers under subsidy type A or B.

Table 7 reports the results for 2GW of installed wind capacity. With subsidy type A under NAO$^+$ the cost of the subsidy is 14.5% higher than under NAO$^-$, which is proportionately more than the increased revenue wind generators receive from the electricity market (12% in Table 6). Under subsidy type B, which is a flat premium of €26.12/MWh, the mean cost of subsidy scheme is 13% higher under NAO$^+$ versus NAO$^-$. More wind increases the cost of both subsidy types, but the cost of subsidy floor in type A is more expensive during windy periods. This occurs because NAO$^+$ phases lead to lower electricity prices, which means that the subsidy support to reach the price floor increases. With a fixed premium, the total subsidy cost depends on the amount of wind generation and is independent of the electricity price.

Because there is no market up-side for wind producers under subsidy type C, the direct cost of the subsidy scheme is between €9.7–11 million per month higher than subsidy A, depending on NAO phase. However, as wind producers' price is capped at €95.31/MWh, any electricity prices above the cap can be used to offset the gross cost of subsidy. The value of the electricity produced when the price is above €95.31/MWh exactly matches the additional direct cost of the subsidy such that net cost of subsidy type C is equal to the cost of subsidy type A. The consumer's exposure to additional net subsidy costs in windy periods is equivalent in subsidy types A and C.

From a wind producers' perspective the mean of total revenue (market+subsidy) is the same under all three subsidy types under NAO$^-$ wind phases. From the consumer's perspective the net cost of the three subsidy types under NAO$^-$ wind phases are also equivalent. However, under NAO$^+$ phases subsidy type C is most lucrative to wind producers and type B the lease lucrative, whereas type B is the least costly to consumer and the subsidy type with the lowest standard error. For more discussion on the issues surrounding subsidy design and exposure to electricity price uncertainty see Farrell et al. (2013) or Devine et al. (2014).

3.4 Risk

So far discussion has mostly referred to mean values but there is considerable risk inherent in the analysis. The simulation analysis modelled the stochastic nature of wind, demand, fuel prices, and carbon price and it would be careless to focus only on the mean values. While

[2] See http://www.dcenr.gov.ie/Energy/Sustainable+and+Renewable+Energy+Division/REFIT.htm

[3] We assume all subsidy costs are bourne by the final consumer, without going into detail on whether that is through a levy on electricity bills, through general taxation, or some other means.

Table 7: Wind Subsidy Scenarios by Month

Subsidy type		Mean Subsidy, €m			Std Dev, €m		Total Wind Revenue, €m		
		NAO⁻	NAO⁺	%Δ	NAO⁻	NAO⁺	NAO⁻	NAO⁺	%Δ
A	€80/MWh floor	21.1	24.2	14.5%	12.1	13.4	77.1	86.9	12.7%
B	€26.12 flat premium	21.1	23.9	13.0%	3.7	3.6	77.1	86.6	12.2%
C	€95.31/MWh fixed price	30.8[a]	35.2[a]	14.2%[a]	14.9	16.5	77.1	87.1	13.0%

[a] Direct or gross subsidy cost. Net subsidy cost is equivalent to subsidy A. For further details see text.

Table 6 discussed mean electricity prices in the region of €75/MWh, the probability of prices substantially higher or lower is quite high. For instance, electricity prices within one standard deviation of the mean vary between €40–110/MWh approximately, irrespective of NAO phase. We employed the simple utility framework and CVaR to assess preferences in the presence of the risk associated with the electricity market.

3.4.1 Wind producers' utility

The metric taken for wind producers' utility is the total payments they receive for their energy, which includes the subsidy payment and any market revenues, divided by the total wind capacity; in other words, we consider the return per MW installed capacity. We consider the revenues under the three different subsidy mechanisms and calculate the utility of the wind producer, as a function of both their revenues and their associated Conditional Value at Risk, according to equations 5 and 6. Figure 6 shows the utility for each level of risk aversion under the three different subsidy payment mechanisms (i.e. price floor, flat premium, fixed price) for both NAO$^+$ and NAO$^-$ phases.

From wind producers' perspective, lower installed wind capacity levels yield higher payments per MW installed, as the output of wind farms inceases nonlinearly with wind capacity. A fixed price subsidy yields the highest utility per MW for every level of risk aversion. However, wind producers' preferred order of other subsidy mechanisms differs by NAO phase depending on the level of risk aversion. For example, under NAO$^+$ phases for all levels of risk aversion a price floor and a flat premium yield practically equivalent levels of utility. Under NAO$^-$ phases utility under a price floor or flat premium diverge depending on the level of risk aversion. Above a risk aversion level of approximately 0.3, a price floor subsidy yields higher utility irrespective of installed capacity. Thus NAO changes the order in which wind producers would rank their preferred subsidy mechanisms, but the most preferred option of a fixed price does not change irrespective of installed capacity, risk aversion or NAO phase.

3.4.2 Consumers' utility

For consumers we consider the total payment made for electricity, both to thermal and to wind producers, in order to account for any effects wind may have on the market price[4]. Thus the metric in question is consumers' disutility, and consumers will wish to minimise their risk-adjusted payments for a given level of risk aversion, as specified in equations 5 and 7. Figure 7

[4]Consumers of course are generally shielded from wholesale market price fluctuations, and it is supply companies who purchase directly from generation companies. Such companies also frequently enter into long term forward contracts to hedge their risk. We do not model these effects here.

Figure 6: Wind producers' utility under each payment mechanism

(a) NAO^{+} (b) NAO^{-}

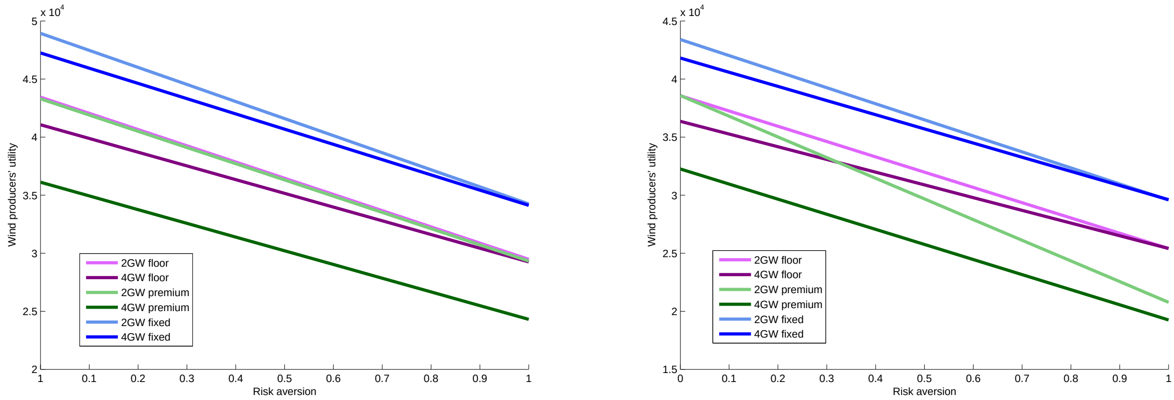
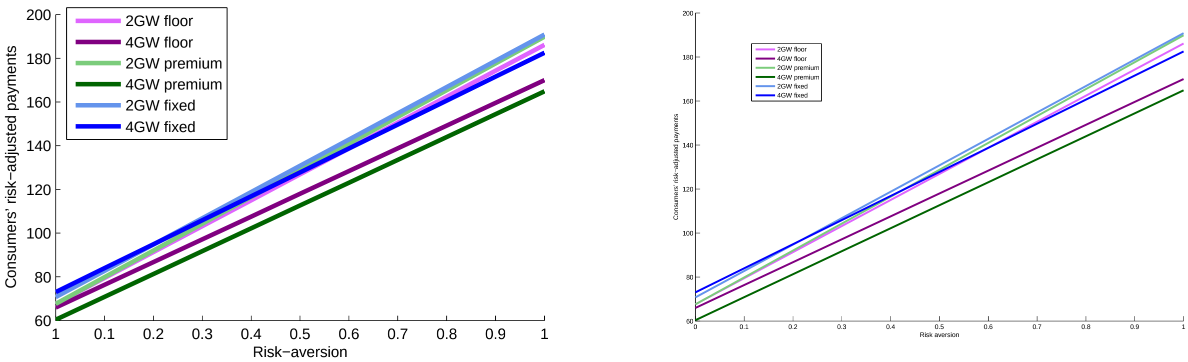


Figure 7: Consumers' risk-adjusted payments under each payment mechanism

(a) NAO^{+} (b) NAO^{-}



shows consumers' disutility for both NAO^{+} and NAO^{-} phases under the three different subsidy payment mechanisms (i.e. price floor, flat premium, fixed price).

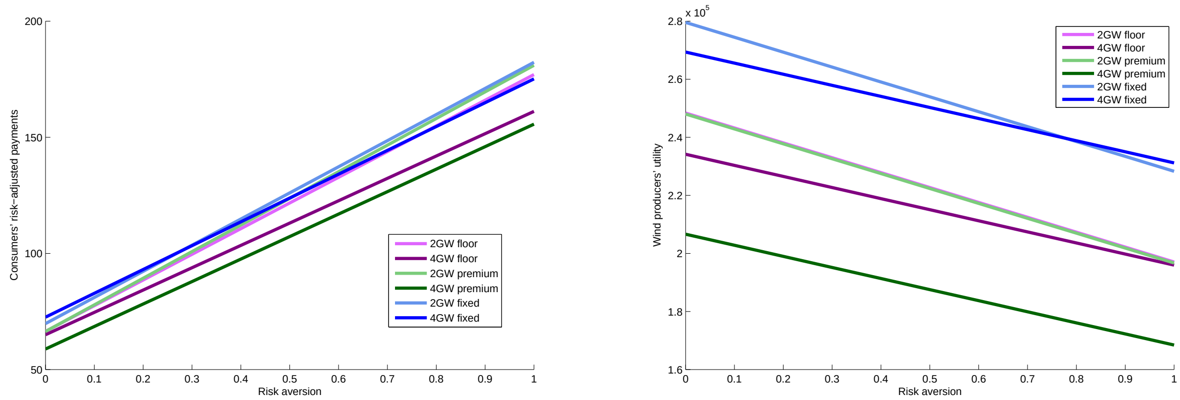
Consumers' subsidy mechanism of choice, i.e. the mechanism which minimises their risk-adjusted payment per MWh of electricity consumed, is the opposite to wind producers' preference ordering. Consumers' optimal mechanism, under every level of risk aversion and irrespective of NAO phase, is a flat premium when 4GW of wind capacity is installed. At 2GW of installed wind capacity, consumers' preference for subsidy mechanism varies depending on risk aversion. Under NAO^{+} phases and low levels of risk aversion, a flat premium subsidy yields the highest utility, whereas a price floor yields the highest utility at high levels of risk aversion. Whether at 2GW or 4GW installed wind capacity and irrespective of NAO phase, a fixed price is consumers' least preferable subsidy mechanism to support wind producers.

3.4.3 Consumers' and Wind Producers' utility across all wind phases

Finally Figure 8 considers the utility implications for both consumers and producers under all wind phases, NAO^{+}, NAO neutral and NAO^{-}. Given the fact that NAO^{+} phases are more frequent than NAO^{-} phases, the total utility of consumers and producers is similar to that of NAO^{+} phases. As the specification of the flat premium subsidy, i.e. €26.12/MWh, was designed to provide wind producers with the same revenue as the price floor mechanism with 2GW of

Figure 8: Consumers' and wind producers' utility under each payment mechanism

(a) Consumers' disutility (b) Producers' utility



installed wind, it is unsurprising that the wind producers' utility for the two mechanisms is the same. However, consumers are not indifferent between the two, preferring the floor price subsidy mechanism, particularly at high levels of risk aversion. Producers' preferred subsidy mechanism across all NAO phases is a fixed price, though depending on level of risk aversion the level of preferred installed capacity varies. Consumers' preferred subsidy mechanism across all NAO phases varies depending on installed wind capacity and the level of risk aversion. At 4GW installed capacity a flat premium is the subsidy mechanism that gives the lowest risk-adjusted payment per MWh of electricity consumed. At 2GW installed capacity the flat premium is preferred at very low levels of risk aversion but a price floor otherwise.

Across the three subsidy mechanisms the difference in utility, whether in NAO$^+$ or NAO$^-$ wind phases, is relatively small in the case of consumers but much larger in the case of wind producers, which highlights that the effects of NAO on electricity prices impacts much more on wind producers than on consumers. As a consequence a policy-maker, using conditional value at risk as a measure of risk, may consider a fixed price subsidy as the best policy measure to support investment in renewable wind generation capacity. Whereas a policy-maker who wishes to balance the interests of both consumers and producers might select a floor price mechanism, as the 'second best' option for both consumers and producers. However, this leaves wind producers exposed to the variation of NAO, which consumers are largely indifferent towards (regarding electricity generation). Furthermore, the impact of NAO$^-$ phases on a wind producers' utility depends on their appetite for risk, with wind producers with a low appetite for risk preferring a flat premium and 2GW installed wind to a floor price with 4GW installed.

4 Conclusions

The influence of NAO on wave power, solar energy, and rainfall among others has been widely documented. Many studies examine its impact on the wind resource (e.g. Pirazzoli et al. (2010); Jerez and Trigo (2013); Jerez et al. (2013); Burningham and French (2013); García-Bustamante et al. (2013)). There is also an extensive literature examining how wind energy affects electricity prices (e.g., Ketterer (2014); Amor et al. (2014); Shcherbakova et al. (2014); Woo et al. (2013); Würzburg et al. (2013)). But there is no published research that examines the effect of NAO on electricity markets. This paper investigates that specific issue by developing a simulation methodology using synthetic wind speed data and an electricity dispatch model.

While the magnitude of the empirical results in the paper are specific to the model, which is based on the SEM market in Ireland, they are likely to be indicative of magnitude of the effect of NAO on electricity costs and prices in other similar electricity markets. The results are also conditional on the level of installed wind capacity. In 2012 there was 2.1GW of installed wind capacity on the Irish system with instantaneous wind penetration regularly exceeding 40% of demand (Clancy et al., 2015). By 2017 4GW of installed wind capacity is anticipated (EirGrid and SONI, 2015) and hence the analysis centres around 2GW and 4GW of installed wind capacity.

The analysis found that NAO phase has a statistically significant effect on both thermal generation costs and wholesale electricity prices. At 2GW installed wind capacity the mean of total thermal production costs are 3% lower under NAO^+ compared to NAO^- phases, as wind is displacing thermal generation. When wind capacity doubles to 4GW there is a proportionately greater reduction in thermal generation costs, which fall by 8.2% in NAO^+ versus NAO^- phases.

Mean electricity prices are 1.1% lower in NAO^+ compared to NAO^- phases at 2GW wind capacity, equivalent to €0.8/MWh. At 4GW wind capacity the difference in mean electricity prices between NAO^+ and NAO^- phases is 2.1% or €1.5/MWh. These differences are between 1-2% of the electricity price and therefore could represent a substantial component of a generator's profit margin. Investment decisions in new generation plant that is not mindful of the distribution of NAO phases and its impact on the wind resource could lead to unexpected deviations from expected revenue, either positive or negative. While windier NAO^+ phases result in lower wholesale prices, wind capacity factors increase and the net result is that on average revenues to wind generators increase by 12%. Revenue and profits of thermal generators decline inversely proportional to the level of installed wind capacity.

Most wind generation receives subsidy support and the design of the subsidy mechanism can influence the level of capacity deployment (for example, see Farrell et al. (2013); Devine et al. (2014)). The analysis compared whether NAO had an impact on either the cost of the subsidy support or wind producers' total revenue. Three subsidy mechanisms were examined (floor price, fixed price or flat premium) and specified in such a way that the total subsidy cost and wind producers' total revenue were equivalent across the three mechanisms during NAO^- phases. During NAO^+ phases on average a fixed price subsidy is most lucrative to wind producers and a flat premium lease lucrative. A flat premium is, on average, the least expensive from a consumer's perspective. Using Conditional Value at Risk as a measure of risk we considered how consumers' and producers' preferences for a subsidy mechanism might vary depending on NAO. From consumers' perspective the difference in their utility across the three wind support subsidy mechanisms is small, irrespective of NAO phase, though in most circumstances a flat premium is preferred. From wind producers' perspective a fixed price subsidy yields the highest utility per MW for every level of risk aversion and irrespective of NAO phase.

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