The effects of wind generation capacity on electricity prices and generation costs: a Monte Carlo analysis

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Abstract

We use Monte Carlo analysis to examine the potential of increased renewable generation to provide a hedge against variability in energy prices and costs. Fuel costs, electricity demand and wind generation are allowed to vary and a unit commitment and economic dispatch algorithm is employed to produce cost-minimising generation schedules under different levels of installed wind capacity. Increased wind capacity reduces the mean and the variance of production costs but only the variance of electricity prices. Wind generators see their market revenues increase while consumer payments and fossil generator profits do not considerably vary as wind capacity increases. Risk aversion is captured by considering the Conditional Value-at-Risk for both consumers and producers. The optimal level of wind generation increases as risk aversion increases due to the potential of wind to act as a hedge against very high electricity prices in high fuel price scenarios.

Keywords: Electricity, Monte Carlo analysis, wind generation, utility framework, Conditional Value-at-Risk, simulation

1 Introduction

Electricity prices are subject to a wide range of risks and uncertainties. Volatility in fuel prices, security of fuel supply, extreme weather events and network faults can all significantly affect the final cost of electricity supplied. Rising electricity prices may reflect a conflation of these issues (or numerous others) or may simply reflect strong global demand for primary fuels, such as fossil fuels or biomass. To reduce vulnerability to extreme movements in costs associated with input fuels (e.g. rising gas prices), electricity systems usually rely on diversity within the generation mix (e.g. coal, gas, oil, hydro, renewable generation, nuclear). Security of supply considerations may contribute towards the political desire for a diversified portfolio of generation assets, but the actual mix of generation plant within a liberalised electricity market will depend on numerous factors, not least the expected profitability of individual companies' specific investments. The fuel choice (e.g. coal, gas, wind, etc.) for a private utility considering investment in new generation plant will be influenced by variables such as market supports (e.g. for renewables), long term fuel price expectations, system operation and the expected capacity factor, as well as the company's own portfolio diversity and profitability. Consequently, under specific conditions and expectations, an electricity system can become heavily reliant on a narrow fuel mix and policy interventions may be necessary to effect generation mix diversity. For generators, when a system relies on a narrow fuel mix, they are insulated from risks as their costs and revenues are closely correlated. The risk is thus passed on to consumers in the form of varying electricity prices, augmenting a preference for a diversified fuel mix.

A question for policy makers and regulatory authorities is whether the generation capacity in a given electricity system is robust to economic shocks, such as fuel or carbon price spikes. Short duration electricity price spikes represent a risk for electricity retailers where consumer prices are heavily regulated but are a normal feature of liberalised electricity markets (Christensen et al., 2012). A greater policy concern is how the development of generation capacity within a market affects electricity prices, which has implications for market competitiveness and energy affordability. Targets for renewable energy penetration is one policy response intended to ameliorate the impacts of dependence on fossil fuel imports, though energy security of supply and climate change considerations are also driving forces for such policy measures (European Commission, 2009). Variable renewable generation such as wind and solar has zero or negligible marginal costs, and so can provide an effective hedge against variability in conventional fuel prices (Awerbuch, 2000, 2005; Awerbuch and Berger, 2003). New additions to the electricity system change the operation of the system and associated costs of electricity production but this will only lead to benefits for consumers if prices decrease. For various reasons, primarily market power, electricity generation costs may decrease but not necessarily electricity prices. In addition, a reduction in electricity prices when fuel costs are high benefits consumers but not producers, and so any hedge that renewable generation can provide against high fuel prices may not bring about benefits for both producers and consumers. As renewable investments are typically paid for (at least in part) by subsidies which are funded by energy consumers (Fouquet and Johansson, 2008; Hiroux and Saguan, 2010), the distributional effects of increased renewable generation are of interest to policy makers and regulatory authorities.

When evaluating investment strategies for the electricity market it is important that risk and uncertainty is fully assessed. There are innumerable risks in the electricity system but some of the main risks relate to the fuel and carbon prices, variable renewable generation and electricity demand. A frequent modelling approach for such risks is scenario analysis, where analysis is based on a limited number of possibilities that are usually within historical precedent. For example, generation capacity statements are based on a number of demand scenarios (EirGrid and SONI, 2013; National Grid, 2013). Such analyses are prone to converging to the median and it is not obvious whether a limited range of scenarios is sufficient to reflect the full set of possibilities. If scenario analysis is incremental to historical precedent it will not provide information on what will occur in the presence of large changes in the underlying variables. For example, what are the implications of a year with gas supply interruptions, a cold winter (i.e. high demand), and a low wind resource? Only when a wide range of risks are assessed can the robustness of the electricity system to economic shocks, particularly fuel prices, be fully assessed. Furthermore, scenario analyses with a small number of scenarios cannot provide any insight into the effects of variability on the welfare of risk-averse agents. While analysis of an 'extreme' event can reveal the potential of a given generation mix to mitigate the effects of very high prices, there is no possibility to examine the effects of volatility in general. Therefore, it is necessary to examine not only the expected value of prices and profits, but their variance as well.

While many risks within the electricity market can be modelled as draws from known probability distributions, in other instances such an approach is not suitable because with limited knowledge it is not possible to describe current or future outcomes. Uncertainty surrounding future energy policy directions is one such example. Policy measures are intended to affect the market but the scale and timing of such interventions are discrete and difficult to model. Consequently in our analysis of risk we concentrate on the main risks that can be easily incorporated using stochastic models.

1.1 Contribution of this paper

This paper explores the impact of wind generation on electricity prices using Monte Carlo methodologies. We simulate both unit commitment and economic dispatch from a least-cost system perspective. The inclusion of full unit commitment rather than economic dispatch alone avoids many of the pitfalls associated with the increased variability in net demand which arise when significant levels of wind generation are considered (Shortt et al., 2013). The hourly electricity price is calculated endogenously from the marginal cost of electricity provision at each hour. In this way the impact of wind generation under least-cost dispatch and marginal-cost pricing, i.e., an ‘energy-only’ market, is determined. We use Monte Carlo techniques to develop a mechanism for quantifying the potential volatility in electricity prices due to risk in fuel and carbon prices, the wind resource, and electricity demand. A utility framework incorporating risk aversion is used to investigate the potential impact of increased wind generation capacity both from consumer and producer welfare perspectives.

The contributions of this paper are therefore both theoretical and applied. We propose a theoretical framework for calculating the utility of risk-averse consumers and producers as renewable generation increases, considering a full range of inputs. This framework requires knowledge of electricity generation costs and market-clearing prices which are a function of power system operation, the solution to which cannot in general be derived analytically. However, a numerical solution for a test system using a utility framework can be solved allowing the optimal level of renewable investment for both producers and consumers to be calculated, considering both the level and the volatility of electricity prices and profits. A second contribution of this paper is to propose a method for determining the parameters required to compute the utility effects, and thus the societally-optimal level of wind generation. Our final contribution is to apply this methodology to a test case using a mix of historical and simulated data, and to explore the interactions of costs, prices, and their related risks. This gives considerable insight into short-run utility and welfare effects in competitive liberalised electricity markets, and provides a useful starting point against which further work considering long run effects on investment, or the effects of market power, can be considered.

1.2 Literature

There is an extensive literature examining the effects of fuel mix, risk, and renewable technologies in electricity generation on a range of engineering issues such as curtailment of renewable generation and investment in backup capacity, as well as on electricity prices (see Hirth (2013) for a synopsis). Our primary focus is the impact of variable renewable capacity (in our case wind) on electricity costs and prices considering variability in electricity demand, wind generation, fuel and carbon prices.

One approach investigating the impact of variable renewable energy on average electricity prices entails *ex-post* analyses utilising econometric methods, which is a literature that for the most part concludes that electricity prices decline with higher renewable capacity. For instance, in Germany in the years between 2006–2011 wind, solar and photovoltaic generation had a downward impact on prices (Cludius et al., 2014; Tveten et al., 2013; Ketterer, 2014). In the United States Woo et al. (2013, 2011) find both in the Pacific northwest and in Texas that increased wind generation reduced prices. In Denmark Munksgaard and Morthorst (2008) find that higher levels of wind generation reduced wholesale prices but increased consumer prices (including consumer contribution to renewables subsidy). Elsewhere, Gelabert et al. (2011) show that an expansion in Spanish renewables electricity generation, predominantly wind, reduced electricity prices, while Forrest and MacGill (2013) find that wind had a negative impact on price in the Australian National Energy Market between 2009 and 2011. There is some evidence to the contrary, i.e. that additional wind capacity increases electricity prices.

Milstein and Tishler (2011) show that increased renewable generation, in the form of photovoltaic, can increase average price and volatility, for which they find evidence in the Israeli electricity market. What is common to most of the empirical studies cited above is that they relate to a small number of years. In a Monte Carlo sense only a small number of potential data points are analysed and consequently the results from recent history might not be replicable *ad infinitum*. In addition, renewable generation in most systems examined represents a low level of total generation, and so it is unlikely that the price-reducing effects of renewable generation will increase linearly as renewable capacity increases to much higher levels. Indeed, Ciarreta et al. (2014) find that in Spain from 2010, when renewable production reached a relatively high level, a positive net cost was imposed on the system.

The econometric studies have also estimated the effect of increased renewable generation on electricity price volatility but there is less consensus in the results. For example, Tveten et al. (2013) find that renewables reduced maximum prices and variability overall in Germany, whereas Ketterer (2014) conclude the opposite. Woo et al. (2011) also find that increasing levels of wind increases price variance in the US. The issue of price volatility is also examined by Roques et al. (2010) using mean-variance portfolio (MVP) theory in a study of optimal wind power portfolios across Europe. Roques et al. (2008) additionally use Monte Carlo methods to obtain a distribution of generation plant investment returns to determine a private investor's optimal generation portfolio. Monte Carlo methods are especially useful for generating distributions of outcomes associated with volatility in prices, wind, demand, costs and capital facing the electricity generation sector. For example, in developing a portfolio model for future generation mix Min and Chung (2013) incorporate stochastic inputs for electricity demand, fuel prices, and capital costs. To assess the economics of wind energy developments, Valenzuela and Wang (2011) compute probability distributions of market clearing prices and wind farm revenues, whereas Xu et al. (2013) show how the distribution of consumer payments can vary under different market bidding rules. Mari (2014) use Monte Carlo techniques to generate fuel and carbon prices in a study that finds that both renewable energy and nuclear power can be used to hedge against rising electricity prices.

A number of electricity dispatch models have been used to examine a range of issues surrounding expanding renewable generation capacity (recent examples include Simoglou et al. (2014); Chattopadhyay (2014); Jaehnert and Doorman (2014); Pereira et al. (2014); Ciarreta et al. (2014); Clancy et al. (2015); Diffney et al. (2009)). The analyses take a number of approaches. One is to develop one or more scenarios surrounding the electricity market in a particular year, with 2020 a frequent choice, particularly in Europe given its associated policy targets for renewable electricity (European Commission, 2009). Pereira et al. (2014) use the Portuguese electricity system as a case study to examine the impact of increasing wind capacity for the year 2020, concluding that wind reduces marginal costs. Diffney et al. (2009) evaluate the cost of increasing wind generation on the Irish electricity system in the context of a policy target of 40 per cent of electricity from renewables by 2020. In the Irish system consumers are likely to benefit from a high level of wind generation, assuming 2020 fuel and carbon prices do not fall significantly. Simoglou et al. (2014) extend the analysis across multiple years when they examine the implications of a transition to the Target Model for the Greek electricity market. While market design issues are projected to lead to an unambiguous increase in prices, the expansion in renewables capacity in anticipated to result in a reduction in prices.

Ciarreta et al. (2014) take a different approach, building an algorithm that computes the outcome of the hourly wholesale auction under wind and no-wind scenarios in the Spanish electricity market and concludes that additional renewable generation reduced prices. Clancy et al. (2015) follow a similar methodology for Ireland in 2012 calculating fossil fuel cost and CO_2 emission savings under wind/renewables and no-wind/no-renewables scenarios.

Monte Carlo methods have been used to extend the analysis beyond a limited number of deterministic scenarios. Chattopadhyay (2014) in their research on the Indian electricity system note that power system planning is more complex than simply adding renewables; the analysis needs to incorporate the variability of resources (e.g. wind, hydro, solar) and their implications for dispatch, congestion, and pricing in the electricity system. Chattopadhyay focuses on a single year, 2017, but uses simulations of climate data to allow for the inter-annual variability of solar and wind resources in examining the impact of different penetrations of renewable generation capacity. Their analysis focuses on a range of issues such as congestion and security but in the context of price conclude that the effect of additional renewable generation on price is complex. Higher renewable capacity is associated with both higher average price peaks and lower price troughs depending on the season. In addition, they note that average prices conceal high volatility in prices with considerable numbers of very high price spikes. Jaehnert and Doorman (2014) undertake a similar analysis for north European electricity systems for the year 2020 in the context of increased penetration of renewables, strengthening of interconnection capacity, and an expected change in the portfolio of thermal power plants. Their simulations are based on 75 years of climatic data and show the impact of wind power production on a system with a substantial hydro resource, finding that average electricity prices are likely to decline under such circumstances but volatility increase.

1.3 Paper layout

The rest of the paper is organised as follows. The next section sets out the utility framework for electricity consumers and producers, with utility being a function of both welfare and risk measures. Section 3 describes the unit commitment and economic dispatch algorithm used. The design of the algorithm makes it particularly useful for Monte Carlo analyses. Our approach for measuring risk is also outlined in that section. The test system we use for our analysis is based on the electricity market on the island of Ireland. This system, and the method for generating data on the wind resource, prices and demand, is described in section 4. The results of our analysis are presented in the subsequent section and the paper concludes with a summary.

2 Welfare effects of increased wind generation

To examine the welfare implications for both electricity generators and consumers we propose a utility framework where U is utility, c is consumers and p is producers. We define an agent's utility as a linear function of both welfare and risk measures. Note throughout the paper we consider short-term effects only and do not consider the costs or effects of investment.

$$U_i = W_i - \beta_i * \vartheta_i,\ i \in (c, p) \tag{1}$$

where β is the coefficient of risk aversion and ϑ is a measure of risk.

2.1 Welfare measures

For electricity generators, welfare is defined as their producer surplus, given as the total quantity of electricity supplied at each time period multiplied by the price of electricity at that period, minus the production cost of electricity at that period. We define production cost as their fuel and carbon costs, and do not consider fixed costs or operation and maintenance (O&M) costs. Thus annual producer welfare is the sum of producer surpluses from electricity production at each time period.

For electricity consumers, welfare is often defined in terms of the integral of the demand curve minus the equilibrium price between zero and the market quantity demanded, i.e. consumer surplus. However, for the purposes of this model, demand in the short run is considered to be inelastic, which means consumer surplus is infinite. There can, however, be finite changes in surplus brought about by the addition of new technologies (including renewable technologies) on the system which shift or change the merit order of the system. Changes in surpluses are therefore calculated as the change in price multiplied by the (fixed) quantity consumed.[1] For our purposes, we consider the energy payments made in each time period as a proxy for calculating consumer welfare, where higher payments (for a fixed quantity demanded) lead to lower welfare, and vice versa. Hence we define consumer welfare, W_c, as the negative of electricity payments. The welfare of all producers, assuming no market power, is given in equation 2 and consumer welfare is given in equation 3:

$$W_p = \sum_t Price_t * Demand_t - Costs_t \tag{2}$$

[1] This of course assumes a competitive market where changes in price are passed on to consumers, as described above.

$$W_c = \sum_t -(Price_t * Demand_t) \tag{3}$$

2.2 Risk measures

The finance literature has developed a number of methods to measure risk. Mean-variance portfolio (MVP) theory developed by Markowitz (1952) has been used in finance and elsewhere. In the energy literature the MVP approach has been used in examining a broad range of issues including wind deployment and optimal generation mixes (Jansen et al., 2006; Doherty et al., 2006; Roques et al., 2008, 2010). However MVP has a number of important limitations, including the fact that it equally penalises desirable upside and undesirable downside outcomes.

A more extensively used measure of risk in financial markets is Value-at-Risk (VaR) (see Alexander (2009)), which allows the decision maker to specify the confidence level for attaining a certain level of wealth. VaR is defined as the maximum losses of a portfolio under a given confidence level, i.e., for a given confidence level α, the probability that expected maximum losses exceed the VaR value is $1 - \alpha$. Although broadly used, the VaR approach "suffers from being unstable and numerically difficult to calculate when losses are not 'normally' distributed, which is often the case because loss distributions tend to exhibit 'fat tails' or empirical discreteness" (Rockafellar and Uryasev, 2002).

An increasingly popular measure of risk is Conditional Value-at-Risk (CVaR) developed by Rockafellar and Uryasev (2000). Examples from the energy literature include Moazeni et al. (2014) who investigate optimal energy storage under risk and transaction costs within the power grid. Yau et al. (2011) and Carrión et al. (2007) model procurement decisions under spot price uncertainty in electricity markets, whereas Carneiro et al. (2010) model strategic planning of the supply chain to oil refineries. CVaR is derived from VaR, and is defined as the expected value of excess losses. CVaR answers the question: what is the expected loss incurred in the $(1 - \alpha)\%$ worse cases of possible outcomes? CVaR is not limited to symmetric loss distributions and unlike VaR, it is a coherent measure of risk in the sense of Artzner et al. (1999). A particular advantage of the CVaR measure is that it is easy to calculate for non-normal distributions. Furthermore linear programming can be used to calculate the CVaR of samples drawn from a distribution without requiring information about the parameters of the underlying distribution (Rockafellar and Uryasev, 2002).

For our purposes we employ CVaR as a measure of risk. In the case of producers we calculate CVaR in relation to their surplus, $\vartheta(\tau_p)$, and for consumers in relation to electricity payments, $\vartheta(\tau_c)$. The utility of producers and consumers, considering risk, is thus a function of the welfare metrics discussed above and their respective CVaRs. These utility functions are calculated as specified in equation 4, and the calculation of $\vartheta(\tau_i)$ is discussed in section 3.2.

$$U_i = W_i - \beta_i * \vartheta(\tau_i), \; i \in (c, p) \tag{4}$$

3 Methodology

We propose a method for deriving the cost and price parameters used in the utility framework outlined above and apply the framework and methodology to a test system. The energy payments made by consumers, and the surplus afforded to generators, are both functions of the cost of operating the power system. Power system operation is subject to many technical constraints and so cannot be derived analytically with accuracy. We therefore take advantage of numerical simulation to quantify these costs. Generating a distribution of inputs, such as electricity demand, wind generation and fuel prices, allows a distribution of corresponding outputs, such as costs, prices and profits, to be generated. From this distribution the conditional value at risk can be calculated, and these outputs can be combined with different levels of risk aversion in the framework outlined above to determine societally-optimal levels of wind. The determination of these outputs for each set of inputs, through numerical simulation, is outlined below.

3.1 *FAST*: Flexible Algorithm for Scheduling Technologies

In simulating electricity generation schedules, many models 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; Green, 2007; De Jonghe et al., 2012). Some add further simplifications, considering demand as a load duration curve (Chaudry et al., 2013). This approach, which fails to include the 'on-off' state of units, cannot incorporate the start costs and no load costs of units and their 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). However the computational requirements of mixed-integer programming tend to rule out running a large number of scenarios of such models.

The *FAST* algorithm was developed as a response to this problem of providing electricity generation schedules that mimic system or market operator decisions in real time, while respecting technical constraints. This algorithm mimics the input-output relationship of a mixed-integer unit commitment model, such as that employed in Shortt et al. (2013), but does so orders of magnitude faster. This allow consideration of a full year's worth of data, i.e. 8760 hours, while other MIP models often use 'representative' days or weeks (Pereira et al., 2014) due to the computational complexities involved. The algorithm is described in Lynch et al. (2013) and Shortt and O'Malley (2014). The algorithm 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. *FAST* can also be used to determine market-clearing prices, by setting the price of electricity generation equal to the variable cost of the marginal unit, as in Lynch et al. (2013).

FAST's computational efficiencies are augmented through a number of simplifications. For instance, *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 are given a mixed-integer formulation. Flexible units are represented by linear costs. *FAST* 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. This means there will always be at least one thermal unit online and so prices can never go to zero. 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. Policy applications using the *FAST* algorithm to date include Lynch et al. (2013), which investigates risk-return incentives in electricity markets.

3.2 Calculation of conditional value-at-risk

To examine the effects of risk aversion, we consider the conditional value-at-risk (CVaR) of the producer and consumer gains. Rockafellar and Uryasev (2000) propose a methodology for calculating CVaR without first needing to calculate value-at-risk (VaR) or requiring knowledge of the underlying distribution. Zhang and Wang (2009) employ this method to calculate optimal levels of participation in risk-hedging with supply companies for electricity consumers. As we are employing numerical simulation methods to compute the welfare effects of increased wind, this approach of determining CVaR by means of linear programming given outputs drawn from a sampling distribution is particularly suitable for this paper's application.

In order to consider consumers' and producers' aversion to volatile prices, we consider the metric of difference from mean surplus, in the case of producers, and from mean payments, in the case of consumers. Thus, we perform a Monte Carlo analysis for K realisations of demand, fuel prices and wind. We define our CVaR variable as

$$\vartheta(\tau_{ik}) = \vartheta\left(metric_{ik} - \frac{1}{K}\sum_{k=1}^{K} metric_{ik}\right),\ i \in (c, p) \tag{5}$$

where $metric_{ik}$ is either consumer electricity payments or producer surplus in scenario k. By Rockafellar and Uryasev (2000) equation 5 may be calculated by minimising

$$\vartheta(\tau_{ik}) + \frac{1}{K(1-\alpha)} \sum_{k=1}^{K} u_k \tag{6}$$

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 $K = 5{,}000$ scenarios, where each scenario contains 8760 hours worth of data, and $\alpha = 0.95$.

4 Input data and case study

We apply the above methodology to a case study based on the Single Electricity Market (SEM) of Ireland. This market comprises the systems of the Republic of Ireland and Northern Ireland. Several simplifications are made for the purposes of our study. The installed capacity is amalgamated into six 'types', as described in subsection 4.4, and several generation technologies are omitted.

The Irish electricity market has two interconnectors to Great Britain which we do not model. This is partly because modelling their effects would prove beyond the scope of this model, but also because we wished to isolate the effect of increasing wind on a single system. Interconnection could allow export in times of low prices and imports in times of high prices, and could in itself decrease the volatility of electricity prices. Thus the omission of interconnection from our analysis means that the model may overstate the benefits of wind in terms of reducing price variance compared to an interconnected system, as an interconnected system will have lower variability in any event. Actual SEM interconnector flows have not responded to contemporaneous prices, as highlighted by McInerney and Bunn (2013), implying that the overstatement of benefits in our model may not be a significant issue in practice at present. The Irish system also has 292MW of pumped storage generation which we do not model. Storage technologies in general behave similarly to interconnection (with an energy-limitation) and so the effects of wind are also likely over-stated compared to a system which includes storage.

4.1 Wind speed data

Rather than use historical values for the wind energy resource or wind generation capacity factors we have modelled wind speed at hourly intervals as a stochastic variable. Depending on installed wind generation capacity and turbine characteristics a potential wind generation output is calculated for a given wind speed.

A synthetic hourly wind speed time series was generated using the approach proposed by Carapellucci and Giordano (2013). The approach is based on the assumption that wind speed comprises deterministic elements incorporating diurnal patterns and monthly variation through the year, as well as a stochastic component. The time series element is generated through an autoregressive component. Following earlier research (e.g. Patel (2012), Usta and Kantar (2012)) the Weibull distribution is used as the probability density function that generally best fits wind speed data at a given location. However, we follow Harrison et al. (2008) in using the Rayleigh distribution, which is a special case of the Weibull with the value of the shape parameter $k = 2$, as it is often found to best fit wind speed data for Northern European wind sites. The mean of a Weibull distribution is given by $c\Gamma(1 + 1/k)$, where Γ is the gamma function. Therefore, for a given mean wind speed (mws) we can recover the scale parameter $c = mws * 1.1284$. Then for a given annual mean wind speed we draw hourly wind speed values from a Weibull distribution with parameters $c = mws * 1.1284$ and $k = 2$.

There is no recently-published figure for the annual mean wind speed across all wind farms in Ireland. ESBI (2003) estimate an average mean wind speed at 50 metres height of 8.3 metres/second (m/s) based on a sample of wind farms and meteorology sites covering the period 1990–1999, which is now out of date. Based on analysis of wind capacity factors in 2012 and turbine characteristics, discussed in the next section, our estimate of mean wind speed across all wind farms in 2012 was somewhat lower at 6.2 m/s. In our simulations we allow for high and low wind years by adjusting annual mean wind speed (i.e. 6.2 m/s) by a scaling factor drawn from $N(1, 0.03)$. By the 3-sigma rule 99.7% of all annual mean wind speeds are specified in the range 6.2 $m/s \pm 9\%$.

The wind speed time series introduces randomness in the amount of wind resource available both across a year (i.e. high and low wind years) and also the time of day and week. Figure 1 plots three separate weeks of generated wind speed time series using this approach.

4.2 Wind power output

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):

$$WP = \begin{cases} 0, & (V < v_{in} \text{ or } V \geq v_{out}) \\ w_r, & (v_r \leq V < v_{out}) \\ \frac{(V - v_{in})w_r}{(v_r - v_{in})}, & (v_{in} \leq V < v_r) \end{cases} \tag{7}$$

where WP is power generated, v_r, v_{in}, and v_{out} are rated, cut-in, and cut-out wind speeds; and w_r is the rated power of a wind turbine. While a wide range of turbine types exist, we assume just three, as outlined in Table 1. We assume shares by turbine

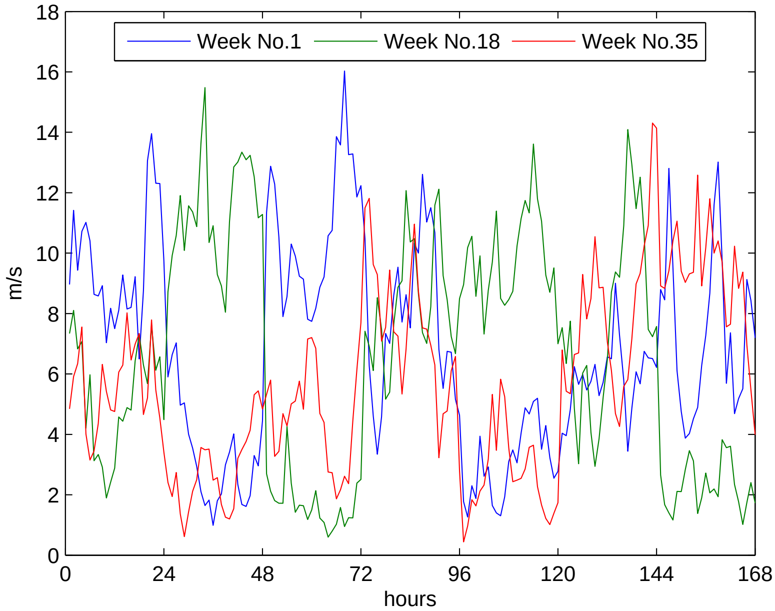

Figure 1: Sample synthetic wind speed data

category are 33%, 38% and 29% respectively. These turbine types and shares broadly match the installed wind generation capacity in the SEM in 2012. In practice the shares by turbine category are likely to evolve as new wind capacity is installed but the assumption of constant shares is unlikely to affect the substantive results of the analysis. Within the wind turbine model this means that for a low wind speed of say 3.5 m/s only turbine types A and C operate accounting for 62% of installed capacity. For wind speeds 25 $m/s < V \leq 34$ m/s only category C turbines are on line, accounting for 29% of installed capacity. For the scenario analysis, installed wind generation capacity is assumed to vary between 0 and 6GW in 1GW increments.

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

Table 1: Turbine wind speed characteristics, metres/second

4.3 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. We generated hourly electricity loads based on historical hourly demand from the 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. Consequently, the demand profile in each simulation preserves temporal characteristics of previously observed electricity demand but introduces randomness to allow for variation that could be attributed to factors such as high/low economic activity or mild/severe weather.

4.4 Installed generation capacity

The installed conventional generation capacity modelled is a simplification of the generation units installed on the Irish system. 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 are Open Cycle Gas Turbines (OCGTs), one gas-fired and one distillate. The characteristics of each technology in terms of 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). The CO_2 emissions per gigajoule are assumed to be 0.0946 tonnes for coal, 0.0571 for gas and 0.076 for oil.

	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

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

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.

4.5 Fuel and carbon prices

Fuel and carbon prices are generated from a lognormal distribution, as in Lynch et al. (2013). The mean and standard deviation for each are given in Table 3. We used daily coal, gas and oil prices data from Deane et al. (2014) for the years 2008 to 2011 to estimate the parameters of a lognormal price distributions and the variance-covariance matrix of fuel prices (given in Table 4). We then 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 a multivariate lognormal distribution with means equivalent to 2012 fuel and carbon prices from Clancy et al. (2015). We use the historical RSD to calculate standard deviation. For carbon we assume an RSD of 0.25. For the Monte Carlo simulation we draw one vector of fuel and carbon prices for each scenario, meaning that prices are constant across the 8760 hours within each scenario. This assumption is not unreasonable as generation firms sign long-term contracts for fuel supply.

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

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

Table 4: Fuel price variance-covariance maxtrix

5 Results and discussion

We analyse the output of the *FAST* algorithm, for the varying inputs, on an annual basis (e.g. average annual rather than hourly electricity prices) and present the results as a distribution of potential outcomes. It should also be emphasised that while we base the test case on the Irish electricity market, the model is developed as a representation of a stylised market and the simulation results are neither intended to represent the Irish system nor be a forecast of future outcomes.

5.1 Production costs and electricity prices

The distribution of average electricity costs, defined as average of total production costs divided by total demand in each hour, is given in Figure 2.[2] Two points are easily discerned. As installed wind capacity increases average production costs decline. The variance of average production costs also declines, with substantially less support in the upper tail as installed wind capacity increases. This is an anticipated result, as renewable wind generation is often advocated as a hedge against volatile fossil fuel prices (e.g. Little (2005)).

We had anticipated that higher levels of wind would lead to a reduction in electricity prices but in our simulations this did not occur. Average electricity prices are calculated as the average price at each hour for each scenario studied, with price defined as the marginal cost of production. This is analogous to the Shadow Price in the SEM[3]. Prices do not decline as more wind generation capacity is installed, as shown in Figure 3. On the contrary there is a small increase in average prices. This may be a consequence of the small number of technologies modelled (seven, including wind). Thus a very large amount of instantaneous wind generation is required in order to reduce net demand (given by demand minus wind) sufficiently for net demand to intersect the merit order curve at a lower point.

The impact of higher wind capacity on prices and costs is more transparent in Table 5, which provides some summary statistics both for average prices and costs. Average production costs decrease while the average electricity price increases as wind capacity

[2]We confine production costs to only include fossil fuel and carbon input costs.

[3]Note 'Shadow Price' in this context, in keeping with SEM terminology, means the incremental cost of the marginal generator, rather than the conventional understanding as the value of the Lagrange multiplier at the optimal solution.

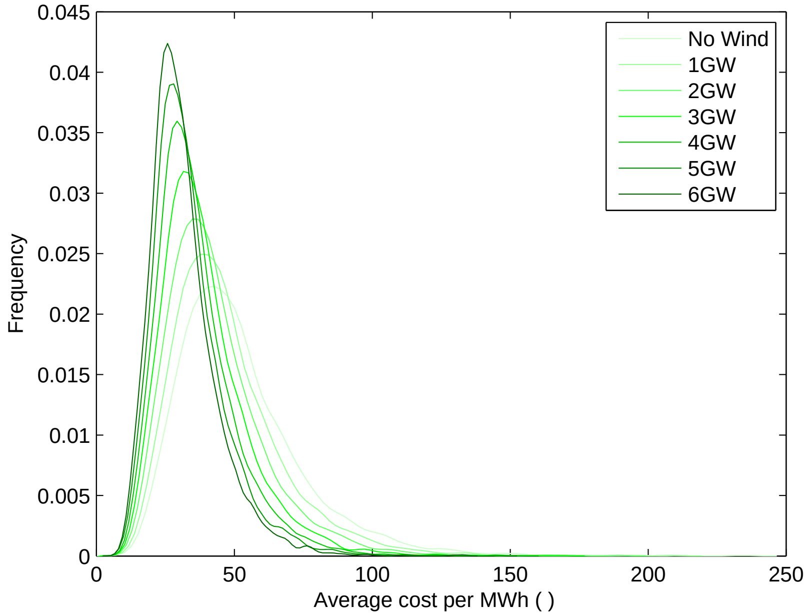

Figure 2: Distribution of average production costs per MWh

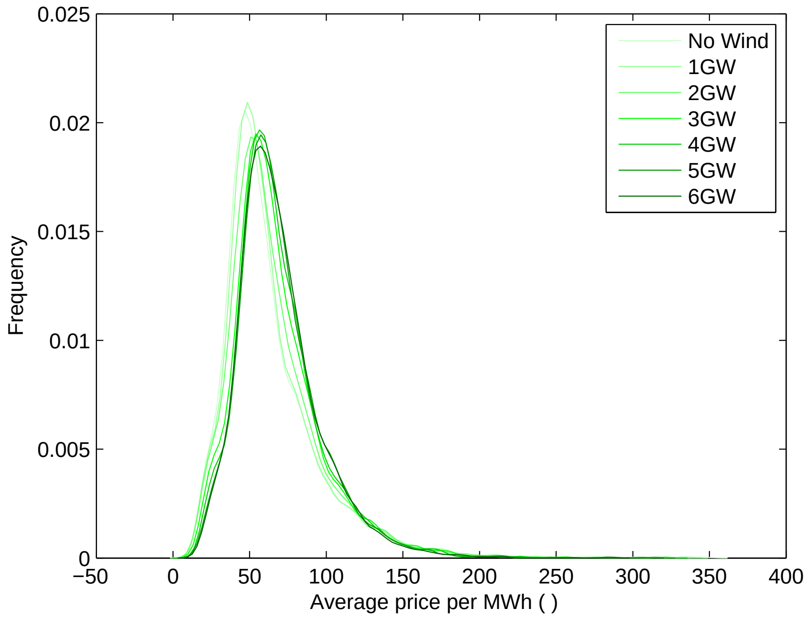

Figure 3: Distribution of average electricity prices

increases. However, the maximum of both costs and prices decline with higher wind generation capacity. Wind appears to be a hedge against upside risk on electricity prices but does not reduce average prices. One reason for this could be that wind does not necessarily displace the marginal unit, which determines the price, but instead displaces generation lower down the merit order curve. At higher levels of wind the frequency and duration of peaks in net demand decreases. This reduces the number of times an inflexible unit can remain online for a sufficiently long time to justify its start cost, and so flexible units, which have a higher marginal cost, are used more frequently, increasing shadow prices. Figure 4 shows the distribution of start costs as a proportion of total costs. Start costs are higher for higher levels of wind generation, due to the higher level of variability on the system from wind generation. There is also much greater variability in the level of start costs as a proportion of overall costs. This is a consequence of the greater variability in net demand at higher levels of wind generation.

In terms of variability, the variance of costs and prices decline as wind capacity increases. In the case of costs, support moves from the right into the left tail of the distribution as wind capacity increases and consequently mean costs decline. The same change in support across the distributions of prices does not occur, instead there is less support in the extreme right tail when wind capacity is high. The standard deviation of average cost falls from 43% to 39% of the mean as wind rises from 0GW to 6GW. In the case of prices, the standard deviation falls relatively more, from 50% to 39% of the mean. High levels of wind do not reduce average prices but can reduce electricity prices in very high fuel price scenarios.

It is interesting to note that average costs and electricity prices do not respond

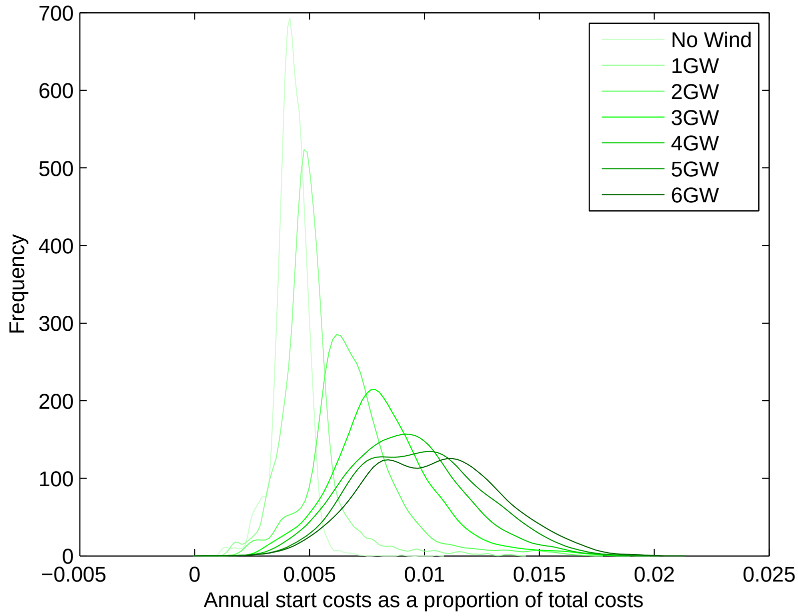

Figure 4: Distribution of annual start costs as a proportion of total costs

	Min Cost	Max Cost	Mean Cost	St. Dev. Cost	Min Price	Max Price	Mean Price	St. Dev. Price
0GW	11	236	52	23	12	349	63	32
1GW	10	210	47	20	11	337	64	31
2GW	9	191	43	18	11	332	66	31
3GW	9	170	39	16	12	323	68	30
4GW	9	154	36	14	17	315	69	28
5GW	8	146	34	13	15	308	69	28
6GW	8	132	32	12	16	285	69	27

Table 5: Summary statistics of costs and prices

linearly as additional wind capacity is installed. The scenario with the lowest fuel and carbon prices experienced the lowest electricity costs across all wind capacity levels, but only experienced the lowest electricity prices at 0–3GW of installed wind. At higher installed wind capacities the lowest electricity costs and prices occurred during different scenarios, which had higher fuel prices (albeit slightly). Higher levels of wind weaken the correlation between fuel and electricity prices.

To further examine the effect of wind and fuel prices on electricity production costs and prices, Figures 5 and 6 display the average production cost and average shadow price in each scenario respectively against the gas price in each scenario. For each level of gas price there is a clear reduction in average production costs as wind increases. For electricity prices however, there is no clear reduction at each gas price. This is because gas units, with greater installed capacity, are far more likely to be the marginal unit and therefore determine the electricity price. Thus for a given gas price any level of wind capacity will displace fossil generation and therefore will save on production costs but will not necessarily reduce prices.

As installed wind increases, the level of curtailment as a proportion of overall wind generation also increases. Figures 7 and 8 show frequency plots of the average wind available in each time period and the average wind generation available minus the wind curtailed under each installed wind capacity respectively. Both are expressed as capacity factors, i.e. as proportions of the total installed wind capacity. There is little difference between the wind available for generation under each scenario. At low levels of wind the level of curtailment appears to be similar. However there is significant curtailment

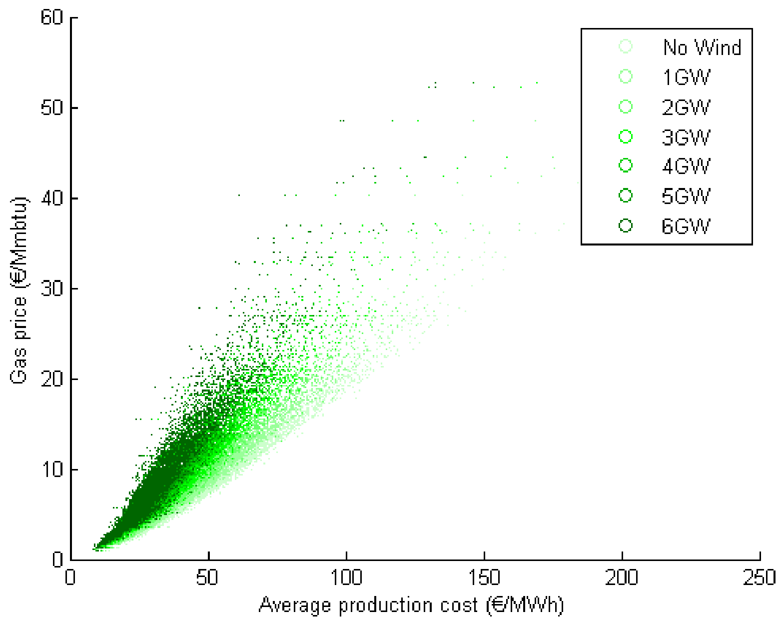

Figure 5: Scatter plot of average production costs against gas price

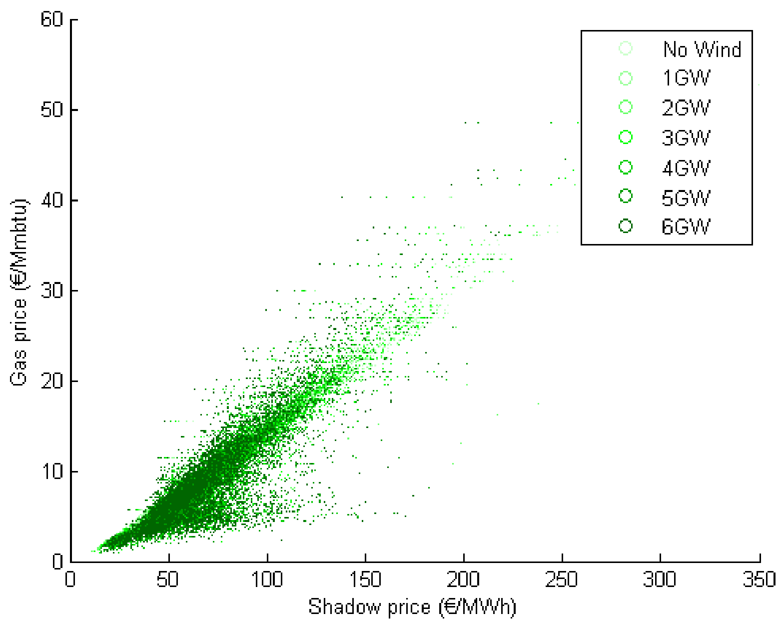

Figure 6: Scatter plot of average shadow price against gas price

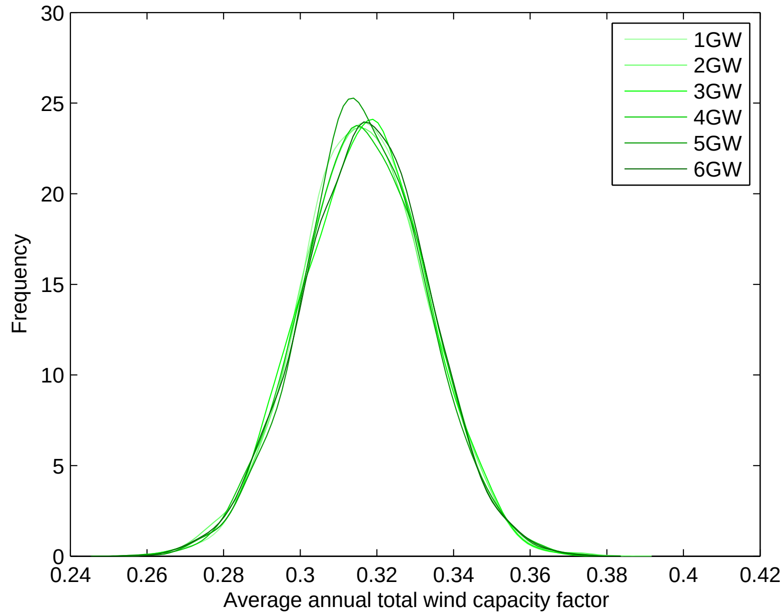

Figure 7: Distribution of average annual capacity factors of available wind generation

at higher levels of installed wind capacity. It may be that storage or interconnection, which we do not model here, would mitigate this result somewhat.

5.2 Utility considerations

Section 2 outlined the framework in which we examine the welfare implications of increasing wind generation on the electricity system. We start in the next section with the special case of no aversion to risk, i.e., $\beta_i = 0$, and subsequently consider the more general cases of risk aversion for both producers and consumers.

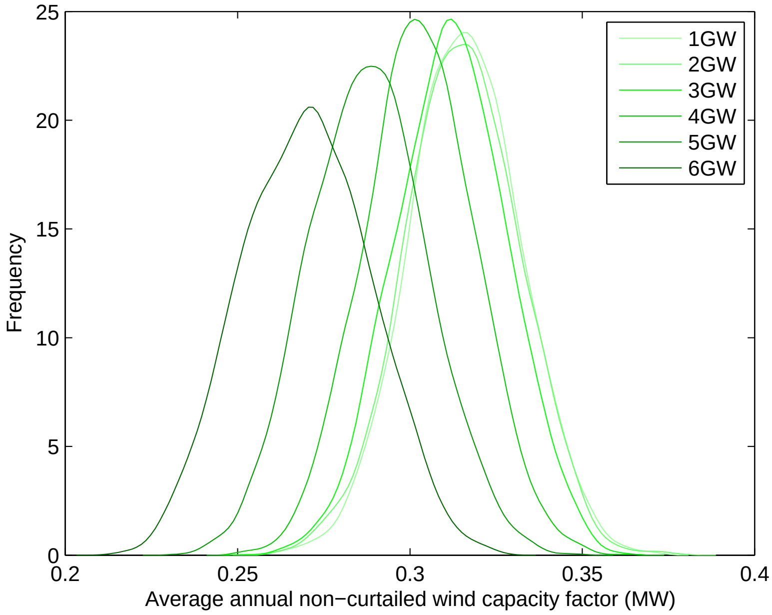

Figure 8: Distribution of average annual non-curtailed wind capacity factor

5.2.1 No risk aversion, $\beta_i = 0$

Figures 9 and 10 show the percentage change in producer surplus and consumer energy payments respectively,[4] relative to a scenario in which there is no wind. In the majority of instances the percentage change in producer surplus is moderate and clustered around zero but under specific circumstances there is the potential for large reductions in producer surplus compared to the 'no wind' scenario. In the case of consumers the risk is predominately downside, though the proportionate changes are relatively modest. With increasing amounts of installed wind capacity, the variance in consumer payments compared to a 'no wind' scenario increases and much of the variance results in higher rather than lower consumer payments.

[4] As defined in equations 2 and 3.

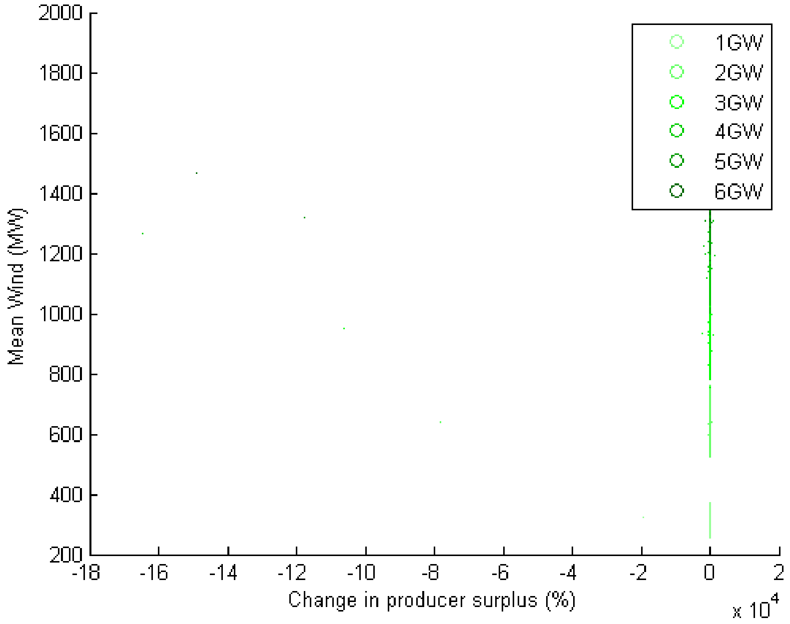

Figure 9: Change in producer surplus against mean wind output

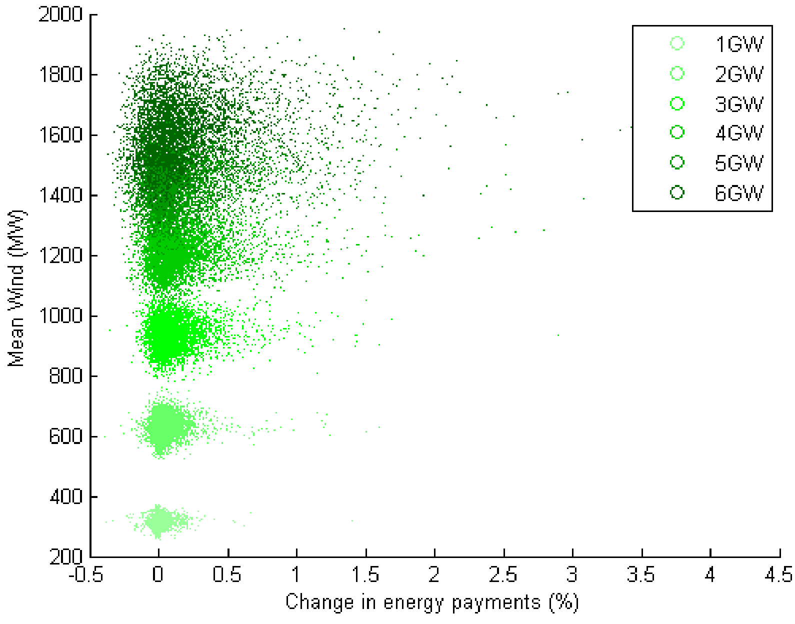

Figure 10: Change in consumer payments against mean wind output

Figure 11 gives the average of the total energy payments made by consumers and the average of annual producer surplus for each wind level. Each demand, wind, and fuel price simulation was repeated for each level of installed wind capacity, so we can directly compare across wind scenarios. As noted earlier, average electricity prices increased, thus as demand is consistent across wind scenarios total consumer payments increase as wind capacity increases. Electricity consumers often directly fund subsidies to wind generators. Such subsidisation is typically justified on the grounds that wind generation results in reduced prices for consumers. However according to our analysis this does not hold; on average consumers actually pay more (excluding consumer subsidy payments). The offsetting benefit to consumers is that wind hedges against very high electricity prices.

The change in producers' welfare due to higher installed wind capacity is more vivid. Producer surplus, both in absolute terms and as a share of consumers' energy payments, increases with higher wind. At 6 GW installed wind capacity producers' surplus levels are almost three times those observed under the 'no wind' scenario, though the growth in surplus declines as wind capacity increases. At higher wind penetration levels revenues marginally increase but producer surplus grows substantially. Producers as a whole are therefore the primary direct beneficiary of an expansion in wind generation capacity.

Given that production costs are borne by fossil fuel generators only, while electricity payments accrue to all producers, we separate out that portion of producer surplus accruing to fossil fuel generators, calculated as energy market revenues minus production costs. Figure 12 shows the change in surplus against a zero wind scenario for fossil fuel generators. As in the case of all producers, the change in surplus is clustered around

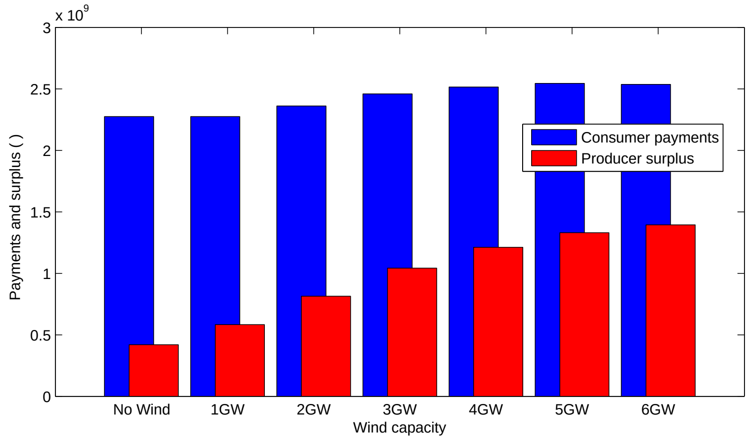

Figure 11: Average annual energy payments and surplus for each level of wind

zero.

Figure 13 shows energy profits per megawatt of installed generation capacity in aggregate, for fossil capacity and wind capacity. The profit per megawatt of fossil-fuelled generation exhibits the same pattern as total surplus because the installed capacity of fossil generation remains fixed for each level of installed wind capacity. However the profits per megawatt of wind capacity are much higher than those of fossil generation, and decline as installed wind capacity increases. This is to be expected as curtailment increases at higher levels of installed wind.

The conclusion we can draw from this analysis is that consumers' electricity payments and conventional generators' surpluses will not decline with additional wind capacity on the system. As noted earlier, high levels of wind do not reduce prices (and payments) but can reduce upside risk in electricity payments in very high fuel price scenarios. This result does not accord with what has been observed in most electricity markets to date, but as discussed above the small number of technologies considered may go

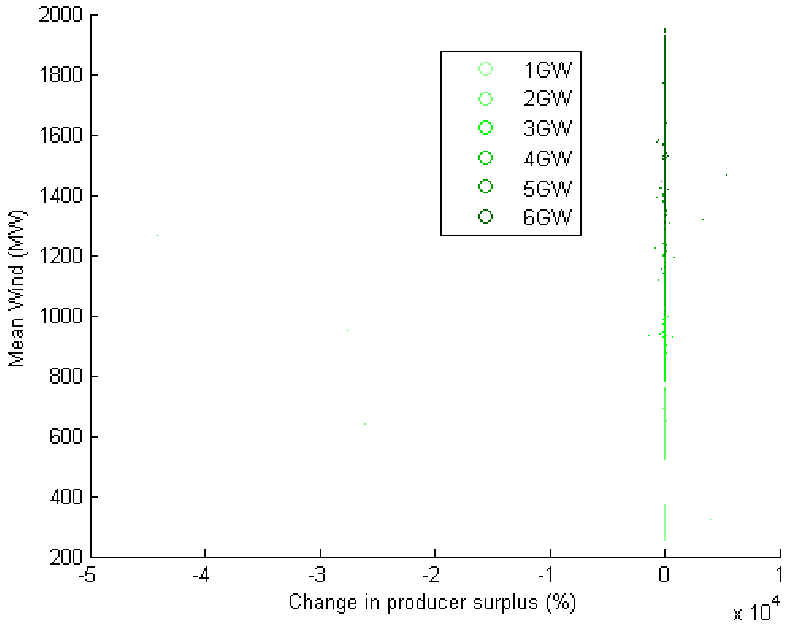

Figure 12: Change in fossil fuel surplus against wind capacity

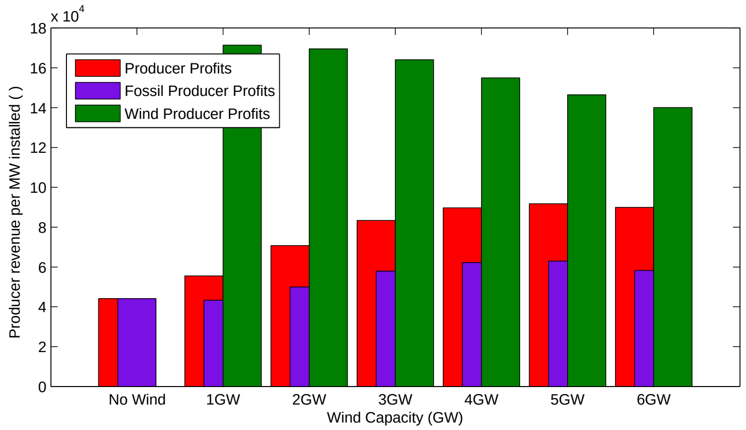

Figure 13: Decomposed producer profits per MW for each level of wind generation

some way to explaining this result. This suggests that wind may bring about the most significant reductions in prices when there is a high level of diversity in the marginal costs of the conventional generation on the system. In addition, our pricing algorithm gives the shadow price that arises when reserve targets and wind curtailment is taken into account, while prices on the Irish system do not take these constraints into account, and side-payments are made to those units which were employed to provide ancillary services and reserve.

5.2.2 With risk aversion, $0 \leq \beta_i \leq 1$

In this section we assume that the optimal level of wind generation depends not only on electricity costs and prices, but also on the level of risk aversion as specified in equation 4. Figure 14 displays the CVaRs of both producers and consumers at each level of wind installed. As wind increases, producers' CVaR increases while consumers' decreases. This is in keeping with the observation that wind has a large impact in reducing electricity prices at very high fuel price levels, which benefits consumers but not producers. Figures 15 and 16 display the utility for producers and consumers respectively, at different levels of risk aversion. The data points where the plots intersect with the primary y-axis are the same data points plotted in Figure 11, which is the point where risk is not included in utility (i.e. $\beta_i = 0$).

At low rates of risk aversion higher levels of wind capacity increase producer welfare. Therefore, if electricity generators as a group are not very risk averse their preference will be towards higher levels of wind capacity. As producers' risk aversion increases the level of optimal wind declines, with the risk of large losses offsetting the utility of higher producer surplus. The small amount by which producer surplus increases at high wind

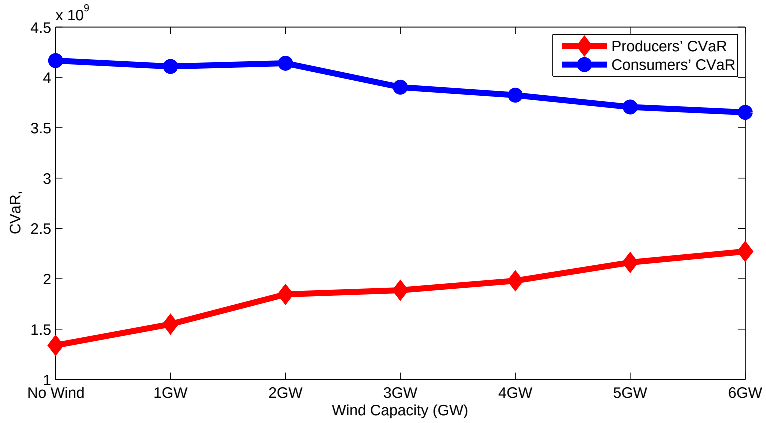

Figure 14: CVaR of producers and consumers for each level of wind

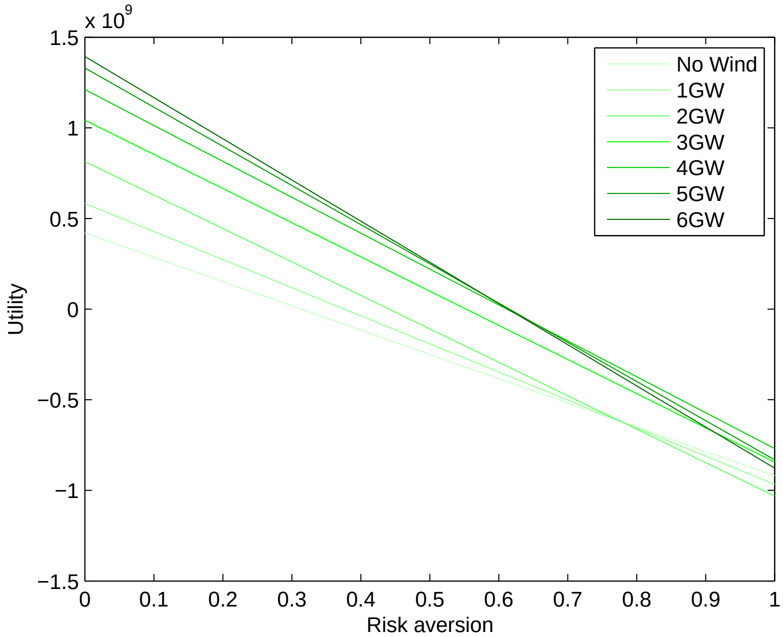

Figure 15: Producer utility for each level of wind against risk aversion.

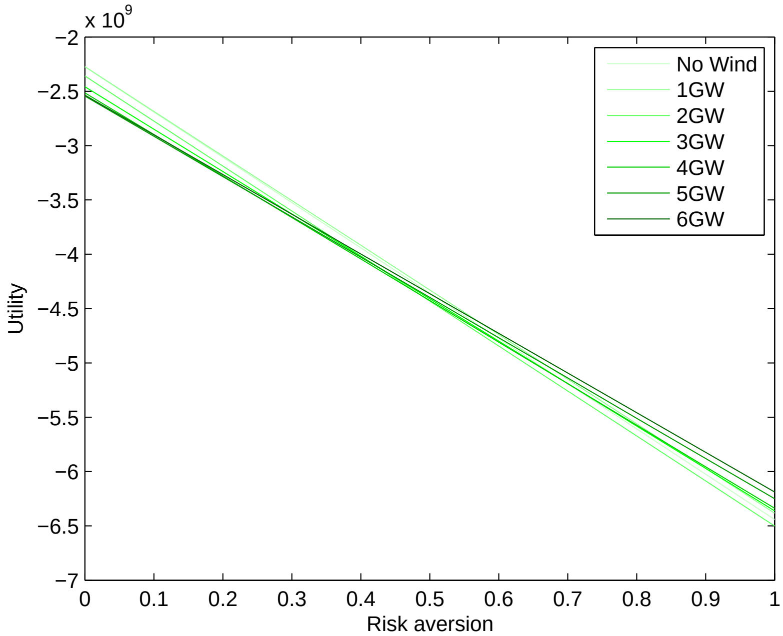

Figure 16: Consumer utility for each level of wind against risk aversion

capacity (i.e. 5–6GW) coupled with the increased CVaR, mean that at higher levels of risk aversion lower levels of wind capacity is optimal (i.e. 4GW). What this suggests is that while generators benefit from higher levels of wind they are unlikely to have an insatiable appetite for investment in wind generation capacity.

In the case of consumers the result is more dramatic[5]. At low levels of risk aversion consumers' utility is optimised at low levels of installed wind capacity (i.e. 0–1GW) but as risk aversion increases, welfare is optimised with high levels of wind capacity (i.e. up to 6GW). High levels of wind hedge against high electricity prices and payments and if consumers are highly risk averse they prefer high levels of installed wind capacity to offset that risk. It should be noted, however, that the difference in utility between

[5]The negative sign on consumer utility is a consequence of modelling consumer welfare as the negative of energy payments.

different wind levels is lower for consumers than producers.

There are other costs and benefits regarding renewable generation which are not considered here but which could have a significant impact on distributional effects. One is renewable subsidies. Most renewable generation is subsidised in electrity markets worldwide, with the form of the subsidy varying according to the regulatory regime. Subsidies which provide generators with a fixed or a floor price transfers risk to consumers, while subsidies which take the form of a top-up payment or a tax credit do not (Devine et al., 2014). In addition, if carbon permits are auctioned, or if carbon emissions are taxed, consumers and producers can gain from the revenue raised through decreased taxation in other areas. Finally for European electricity consumers, failure to meet EU targets for renewable generation may result in financial penalties being imposed, the cost of which we do not consider.

6 Conclusions

Increased renewable energy on an electricity system can bring about economic benefits both by reducing expenditure on fossil fuels and their associated carbon emissions and also by acting as a hedge against fuel price volatility, thus reducing the volatility of electricity prices. However, quantifying these effects with accuracy is a non-trivial exercise due to the complexities of power system operation and the need to allow for volatility in inputs. For this reason studies to date tend to relax many of the technical constraints or to run only a few fuel-price scenarios.

This paper proposes a new methodology for incorporating volatile fuel prices while respecting technical constraints by using a novel unit commitment and economic dispatch algorithm. In this way start costs and no load costs can be incorporated and true cost-minimising schedules can be determined. Electricity demand, renewable generation, fuel and carbon prices are generated according to a Monte Carlo methodology and a corresponding range of outputs is generated. Risk aversion is studied using Conditional Value-at-Risk, which is calculated by means of linear programming. The methodology is applied to a test case based on the single electricity market on the island of Ireland with increasing levels of installed wind capacity.

The results indicate that increased levels of wind reduce average electricity production costs but not average shadow prices. This effect increases producer surplus without bringing about a similar reduction in costs to consumers. However, wind is seen to bring about a reduction in prices during high fuel cost scenarios, which benefits consumers over producers. These two effects mean that at low levels of risk aversion, the optimal level of wind generation for consumers is relatively low while producers gain from higher levels of wind. As risk aversion increases, this effect reverses.

In determining the societally-optimal level of wind generation, the effect should be decomposed between different producers, for example between flexible and inflexible generators as well as wind generators. The effect of subsidisation of wind energy producers by consumers should also be examined. We leave these considerations for further work.

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