Renewable Energy 75 (2015) 468–473

Contents lists available at ScienceDirect

Renewable Energy

journal homepage: www.elsevier.com/locate/renene

Estimating the impact of wind generation and wind forecast errors on energy prices and costs in Ireland

Gregory P. Swinand [a], Amy O'Mahoney [b,*]

[a] London Economics, United Kingdom
[b] IPA Energy + Water Economics, United Kingdom

ARTICLE INFO

Article history:
Received 29 July 2014
Accepted 11 September 2014
Available online 29 October 2014

Keywords:
Cost function
Econometrics
Power generation economics
Power system economics
Wind power generation

ABSTRACT

This paper studies the impact of wind generation on system costs and prices in Ireland. The importance of wind power and potential impacts on system costs is of interest to power system planners and policy makers globally. However, the impact of wind generation on system costs has been only studied with limited actual data from power systems with increased wind penetration. The paper uses a unique dataset of half-hourly system demand, generation, forecast and actual wind generation, along with Irish system marginal price (SMP) data from 2008 to autumn 2012. An econometric time-series model of SMP as a function of forecast and realized demand and wind generation yields results which suggest that each 1% increase in wind generation reduces SMP in Ireland by about 0.06%, while each 1% wind forecast error increases SMP about 0.02%. In absolute terms, though, at the mean the impact of wind forecast errors is small, or about 0.4€cent/MWh-wind generated.

© 2014 Elsevier Ltd. All rights reserved.

1. Introduction

While climate change continues to be one of the most important policy issues facing the developed world, the continuing pressure on the national budgets and expenditures from the economic downturn means that the costs of meeting climate change targets are increasingly at the center of policy debates. This paper contributes estimates of the added system costs of wind penetration and thus might prove valuable in the context of such debates.

Wind power has been seen as perhaps the best way towards meeting climate change and emissions targets by many countries, both small[1] and large.[2] Wind power external costs exist in total transmission system losses, system balancing costs, the cost of required reserves (both spinning and non-spinning), other ancillary services and the total cost of power generation. The cost of using wind power to meet renewables targets is of course uncertain and must be estimated. The costs to the system may exhibit scale and scope economies. The impact of increasing levels of wind power on smaller systems may be different than for larger systems and thus it is important to estimate the impacts of wind generation on system costs for a variety of systems. Finally, the external costs of wind on power systems may interact with fuel prices, market design elements, levels of competition, and other factors. Thus it is important to estimate wind system costs for a variety of systems and at different points in time.

This study investigates the impact of wind power on electricity costs in Ireland. Ireland is a particularly interesting case in which to study wind power system costs for a variety of reasons. The Irish electricity market has a number of characteristics which makes it an ideal case study for electricity market research. It is somewhat unique in that it operates in two different jurisdictions and operates with dual currencies. It is a small island system, with an installed capacity of 9 GW of conventional capacity of which approximately 2 GW is excess capacity and planning reserve, and limited interconnection to the Great Britain (GB) system through two interconnectors. Because of the system's small capacity and low interconnection (the interconnectors with GB are capable of importing 500 MW[3] each and exporting slightly less), the percentage increase and expected overall proportion of wind power in Ireland will be large, with targets of 40% of electricity to be generated by wind in 2020 [15].

* Corresponding author. Tel.: +44 (0)207 659 9895.
E-mail addresses: gswinand@londecon.co.uk (G.P. Swinand), omahonea@tcd.ie (A. O'Mahoney).

[1] Ireland is planning about 5.5–6 GW wind capacity by 2020, or about 40% of generation. See Ref. [17].

[2] See the UK Renewables Energy Roadmap Update 2013 [16]. This indicates between 25 and 30 GW wind capacity potential development as policy target to meet 2020 climate change goals.

[3] The East–West interconnector was commissioned in Autumn 2013 and the interconnection will increase to 1000 MW by 2023.

http://dx.doi.org/10.1016/j.renene.2014.09.060
0960-1481/© 2014 Elsevier Ltd. All rights reserved.

The All-Island system has a high proportion of installed wind capacity equivalent to roughly 18% of total installed capacity. This has been used to generate up to 49.9% of the island's electricity demand; wind (non-synchronous generation) is curtailed if it exceeds 50% of total system generation at any given time due to power system reliability issues [18].

A second element perhaps unique to Ireland relates to its market design. While the generation market is fully open to competition, due to regulators' concerns about market power the prices bid by generators into the power pool are for practical purposes regulated; generators must bid their marginal cost (or average variable cost) of generation, with fuel prices and thermal efficiency of generation units checked by the regulator. A straightforward merit order and the day-ahead forecasts of demand and wind generation forms a day-ahead dispatch schedule and a daily set of half-hourly system marginal prices (*ex ante* SMP). In addition, the cost of constraints and other factors, and balancing, are included in the *ex post* SMP paid to generators, which adjusts the day-ahead SMP. This means that the final price paid to generators for the power they generate is not finalized until four days *ex post*. A more detailed description of the Single Electricity Market (SEM) design in operation in Ireland can be found in Ref. [7]. The market data are also all available online from SEMO (the market operator). Further, wind forecast and actual generation outturn data are available from Eirgrid (the Republic of Ireland (ROI) TSO). Thus the possibility of studying the total cost of wind power on the system, and including the impacts of wind forecast errors is made possible by the Irish data and market design. This is different from a previous study of the GB wind system balancing costs [10], which a) focused only on balancing and b) did not include the difference between forecast and actual outturn wind generation.

2. Review of literature

The overall system cost and price impacts as a result of wind are likely ambiguous, as different characteristics of wind affect cost both positively and negatively. For example, baseload units, such as coal, may be cycled more frequently with the introduction of variable generation sources such as wind [8]. This in turn could result in significant increases in a variety of costs, including impacting the merit order (flexible plant may run ahead of inflexible plant), and operation and maintenance (O&M) and start costs. Di Cosmo and Valeri [9] find that this may be dependent on market rules, however. Their results indicate that as wind increases, this may benefit baseload units such as coal relative to more flexible plants like gas and create an incentive to invest in less flexible units as their profit levels are less affected by variable wind generation given technical constraints. On the other hand, thermal units displaced by wind will lead to a fuel cost saving as wind has zero fuel costs.[4] The cost of providing reserve may also increase as wind penetration rises; as wind output is not as constant relative to traditional thermal units [3,4].

A number of previous studies have estimated the cost of wind generation on the system (Fig. 1). The results from the studies reviewed by Gross et al. [13] and Holttinen et al. [14] are neatly summarized by a figure they present. They conclude that system balancing costs increase by about €1–4/MWh of wind power produced, for system wind penetration levels up to 20% of power generated. They also demonstrate that the methodologies used so far to examine the issue of balancing cost implications of wind power have mostly relied on simulation approaches. Historically in many countries, wind generation has contributed to a negligible degree to the overall generation mix, so that empirical studies have been of limited value. Moreover, the seasonal and annual variation in energy consumption means that meaningful analysis likely requires time series of several years, which are only now becoming available. Ketterer [6] examines the impact of wind on electricity prices in Germany using a Garch model. This finds that prices decrease while overall price volatility increases. In one of the specifications considered, as wind increases by 1 percentage point the electricity price fell by 1.45 per cent. Wurzburg et al. [12] looked at the effect of wind and solar on electricity prices in Germany and Austria using an empirical approach. They found that prices in both countries fell by approximately €1/MWh for each additional GWh of renewables on the system expected in the day-ahead market.

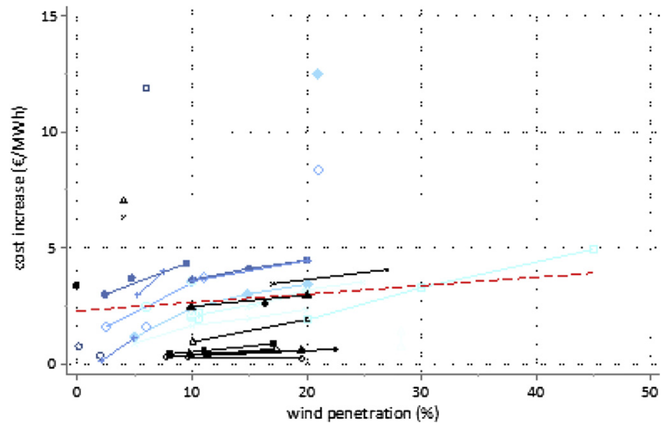

Fig. 1. The figure presents the range of cost estimates from previous studies on the increase in balancing costs due to intermittent generation (% wind penetration). (Note: the figure summarizes 36 estimates from 22 studies from Europe and the USA. It is based on Fig. 5 in Ref. [14] and Fig. 3.2 in Ref. [13]. £ values from Ref. [1] have been recalculated using exchange rates at the date of publication and adjusted by the Eurostat industry producer price index for "electricity, gas, steam and air conditioning supply". The dashed red line is a regression line through all observations.) (figure found in Ref. [10]). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Felder [4] notes that some of the savings associated with the fuel saving in the marginal price may simply be transferred to the uplift and capacity payment mechanisms. This would occur if units are switched on and off more frequently, or if generators require additional payments in order to recover their lost-energy operating margin. Brouwer [2] found that variable generation requires additional flexibility, while thermal generation is typically inflexible. This mismatch in needs may create operational issues with this combination. Tashpulatov [11] found that large fluctuations can introduce uncertainties about revenues for producers and costs for retail suppliers, which could result in higher costs paid by consumers.

3. Data

The dataset for the study comes from publically available data on the SEMO and Eirgrid websites [19,20]. SEMO is a joint venture between Eirgrid plc, the Transmission System Operator (TSO) in the Republic of Ireland, and System Operator of Northern Ireland (SONI) Limited, the TSO in Northern Ireland. All data are actual historic output from the system, recorded on a half-hourly[5] basis from January 2008 to December 2012. Demand and price data are from SEMO and thus are All-Island system outputs. Wind generation data is only available for ROI from public sources. ROI represents 72% of the total All-Island market, and 79% of installed wind capacity. We use ROI data due to a lack of available data for Northern Ireland over a similar time period, however as both

[4] For a more detailed investigation, see Denny & O'Malley, 2007.

[5] Wind and demand from EirGrid are actually available for each quarter hour, but we aggregate these data to half-hourly.

Table 1
Summary statistics key variables.

Variable	Obs[a]	Mean (levels)	Std. Dev.	Min	Max
lnep2_smp	88,237	54.33	0.436	0.068	6.866
lndem	70,293	2916	0.222	7.359	8.534
lnwindgen	70,297	255.19	1.061	0.000	7.313
lnwindfc_e	50,218	0.88	0.442	−3.952	2.032
lngas_e_co2	87,299	2.02E + 05	0.329	10.865	12.973
lnoil_e_co2	87,299	76.94	0.276	3.536	4.840
lndem_wind	70,293	2.436	1.070	0.588	7.638
lndem_wind2	70,293	7.078	6.246	0.345	58.338

lnep2_smp represents the logged *ex post* system marginal price (SMP) in €/MWh on the All-Island electricity system on a half-hourly basis—this will be the dependent variable.
lndem represents the logged electricity demand in MW/h[b] on the system. We expect that demand should have a positive effect on the SMP, because as more units are dispatched, the associated fuel costs will increase accordingly.
lndem represents the logged electricity demand in MW/h on the system. We expect that demand should have a positive effect on the SMP, because as more units are dispatched, the associated fuel costs will increase accordingly.
lnwindgen is the logged wind output in MW/h from the Republic of Ireland. We expect that wind will reduce the SMP as it offsets more expensive units and their fuel inputs from being dispatched.
lnwindfc_e is the logged wind forecast error in MW/h, which is calculated as the difference between the day-ahead forecast and actual wind observed. We expect that this should have a positive impact on the SMP, as errors in forecasting must be met by added flexible generation.
[a] The number of observations varies in general due to small variations across the data collected. For one variable, wind forecast error, the log of this variable when the underlying variable equals zero will show as missing. Excluding these results we do not think would have a large impact on the outcomes as the impact of the coefficient estimate times zero would indeed be still zero.
[b] MW power data are half and quarter hourly MW averaged over each daily hour.

systems are operated as a whole we anticipate that the results of our study would also be applicable in Northern Ireland. Such high-frequency micro-data enabled us to test whether short-term changes in the wind generation in the Republic of Ireland had any impact on system costs.

Table 1 provides summary statistics for each of the variables included in our model specification.

We also included as regressors the log of natural gas prices, inclusive of CO_2 cost, in Euro/MWh, as *lngas_e_co2* and the price of oil in €/MWh, as *lnoil_e_co2*. For the gas price, the GB NBP day-ahead daily price was used for each hour in the delivery day and for CO_2, the EU ETS daily price was used (these data sourced from the Bloomberg Professional data terminal-London Economics). We expect that the value of both of these variables to have a positive, significant effect on the SMP, as intuitively the final price of electricity should be highly dependent on the fuel inputs associated with generating said electricity. Finally, our Model 3 includes the variables *lndem_wind*, and *lndem_wind2*, which is the log difference between demand and wind generation (and its square). We expect demand less wind to impact marginal cost similarly to demand itself (i.e., positive) but the expectation on the squared term is perhaps weakly negative given the expected convex nature of the cost structure, as this allows a non-linear impact on marginal cost the higher is wind generation as a portion of demand.

4. Methods

We start with the assumption of a cost function for the Irish electricity system. The cost function is a standard assumption for cost-minimizing behavior and/or perfect competition,[6] and the since bidding above marginal cost is not allowed, the market design

[6] More technically, a utility that minimizes cost subject to a demand constraint with competitive input markets yields the same outcome as perfect competition.

Table 2
Model results.

Variables	M1	M2	M3
lndem	1.004***	1.111***	
	(0.014)	(0.014)	
lnwindgen	−0.0626***	−0.0509***	
	(0.003)	(0.003)	
lnwindfc_e	0.0159**	0.00976	0.0311***
	(0.007)	(0.006)	(0.008)
Mar		0.0553***	
		(0.018)	
Apr		0.199***	
		(0.019)	
May	0.131***	0.268***	0.0777***
	(0.012)	(0.018)	(0.017)
Jun		0.220***	
		(0.018)	
Jul		0.257***	
		(0.017)	
Aug		0.278***	
		(0.018)	
Sep	0.135***	0.2682***	0.0899***
	(0.013)	(0.018)	(0.017)
Oct		0.1433***	
		(0.017)	
Nov		0.0433**	
		(0.018)	
Jan_Feb		−0.0120	
		(0.016)	
lngas_e_co2	0.486***	0.551***	0.581***
	(0.026)	(0.029)	(0.033)
lnoil_e_co2	0.129***	0.158***	0.190***
	(0.036)	(0.034)	(0.044)
year	0.0195***		−0.0259***
	(0.006)		(0.008)
lndem_wind			0.222***
			(0.013)
lndem_wind2			−0.0227***
			(0.002)
Constant	−49.414***	−12.208***	47.593***
	(12.790)	(0.268)	(15.666)
Observations	48,285	48,285	48,285
Adj. *R*-squared	0.353	0.369	0.283

Standard errors in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

in Ireland probably assures this is a reasonable approximation. Nonetheless more analysis might be considered in order to relax this assumption.

Under the competitive bidding requirements, the SMP is then equal to the derivative of the cost function with respect to demand. Input prices are considered exogenous, along with demand, and factors such as wind generation and forecast errors are considered as added explanatory variables to the system.

To operationalize the model, we assume the cost function takes the transcendental logarithmic, or translog, form. The translog is a second order Taylor series approximation to an arbitrary cost function[7]:

[7] A number of papers introduced the translog cost function, from Christensen, L, D.W. Jorgensen, and L. Lau (1971), “Conjugate Duality and Transcendental Logarithmic Production Functions, *Econometrica*, 39:4, July, 255–256 [5]. The translog cost function has been studied extensively in the literature. The translog function is by assumption a smooth or twice differentiable function. While the notion of a ‘step function’, which might have points of non-differentiability might be attractive in common representations of an electricity supply curve, it should be noted that the step-wise linear representation is, like the translog, a simplified representation; it is well-known that heat rate curves are quadratic/non-linear, some generation can exceed nameplate capacity if called, while others will fall short of expected capacity, balancing requires data on actual running, etc. Even ambient temperatures and conditions will alter somewhat generation system performance. Thus, we consider that a smooth function with appropriate random error is likely to be a reasonable assumption.

$$lnC = \alpha + \sum_{i=1}^{N} \alpha_i lnp_i + \sum_{k=1}^{M} \alpha_k lnY_k + \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \beta_{ij} lnp_i lnp_j + \frac{1}{2} \sum_{k=1}^{M} \sum_{l=1}^{M} \gamma_{kl} lnY_k lnY_l + \sum_{i=1}^{N} \sum_{l=1}^{M} \delta_{il} lnp_i lnY_l \quad (1)$$

where, C, is total variable cost, the p_i are fuel input prices: i = gas (g) (*lngas_e_co2*), and oil (o) (*lnoil_e_co2*),[8] the Y_k are outputs: k = demand (D) (*lndem*), wind generation (W) (*lnwindgen*), and wind forecast error (F) (*lnwindfc_e*). The total variable cost function is the cost-minimizing function from neoclassical microeconomic producer theory.[9] Taking the derivative of the cost function with respect to demand gives the marginal cost function. Since we will work in logs, we take the logarithmic derivative, to give:

$$\frac{\mathrm{d}lnC}{\mathrm{d}lnY_D} = \alpha_D + \gamma_{DD} lnY_D + \gamma_{DW} lnY_W + \gamma_{DF} lnY_F + \delta_{gD} lnp_g + \delta_{oD} lnp_o \quad (2)$$

We posit that the SMP is the marginal cost based on the competitive bidding requirements of the SEM (*lnep2_smp* in Table 1).

$$\frac{\mathrm{d}lnC}{\mathrm{d}lnY_D} = lnSMP \quad (3)$$

We present estimation results from three models in Table 2 below. The estimation methods are Prais-Winsten regressions corrected for first-order serial correlation of the errors (AR1).[10] The rationale for presenting three models is mainly for specification sensitivity. Models M1 and M2 are the same estimates of equation (2) with different sets of seasonal dummies: M1 contains selected months for seasons, M2 and 12 (minus one) monthly dummies.[11] M3, rather than including demand and wind generation separately, contains the difference between demand and wind generation, and its square (*lndem_wind*, *lndem_wind2*). M3 is thus a specification sensitivity which restricts the coefficients on wind and demand to be equal, but allows for differences to be non-linear. This has some intuitive appeal, as wind generation is 'must-run' in the SEM, and in essence, dispatchable thermal generation is demand net of wind.

The modeling results show reasonably good fits and most of the variables included are significant. Inclusion of seasonal versus monthly dummies (M1 vs. M2) seems to have a very small impact on the overall size and significance of the regression coefficients of interest, although the wind forecast error coefficient becomes insignificant in M2. Standard statistical tests of the constraint that the coefficient on the wind generation variable was equal and opposite to the demand variable coefficient rejected the restricted model (we do not report these statistics), but the lower Adj. R-squared of the constrained model (28% vs. 37%, 35%) is an indication of this.

Table 3
Correlation matrix of the main explanatory variables.

	lndem	*lnwindgen*	*lnwindfc_e*	*lngas_e_co2*	*lnoil_e_co2*
lndem	1				
lnwindgen	0.0789	1			
lnwindfc_e	0.0018	0.509	1		
lngas_e_co2	0.0328	0.164	0.144	1	
lnoil_e_co2	−0.020	0.172	0.151	0.771	1

Table 3 shows the correlations between the main explanatory variables. Some evidence of collinearity of oil and gas prices is evident, although given that oil and gas prices are statistically significant in all the equations estimated, collinearity does not appear to be a problem.

We calculate the main results from Model 1. Model 2 demonstrates some small sensitivity to the inclusion of a larger set of dummy variables by month. The main coefficients do not differ much, but importantly M2's estimate of the impact of wind forecast errors is not statistically significant. Therefore we interpret most of our main results from Model 1.

Of key importance is the interpretation of the coefficients. From Model 1, a 1% increase in demand increases SMP by about 1%. Conversely, a 1% increase in wind generation decreases SMP by about 0.06%. A 1% forecast error in wind increases SMP by about 0.016%. The results are not largely sensitive to inclusion of a variety of other variables, whereas the model appears sensitive to the assumption about how to model the demand net of wind and the form of this impact (e.g., quadratic or linear). Overall, by comparing the coefficient estimates on wind generation and wind forecast errors, the size of the cost of wind forecast errors is estimated to be approximately 1/5th of the % marginal cost savings (price) benefit from wind. In absolute money terms, though, at the means of the data, the impact of wind forecast errors is small. From model 1, the impact on SMP per MWh forecast error is about €1 at the means, (taking 0.0159 × 54.33 × 0.88). However, taking this increase and dividing by the average wind generation of 255 MW per hour gives about a 0.4€cent/MWh-of-wind-generated. The absolute cost savings from wind are more in-line with the demand impact, as average demand is roughly ten times average wind generation.

Ireland added significant amounts of wind capacity over the study period in question. The effective capacity of wind – measured as the maximum wind output per annum – increased by an average of 14.2% annually over the time period under investigation, from 888 MW in 2008 to 1500 MW in 2012. Thus, to consider the impacts of both wind and its forecast error for increasing wind capacity levels, and allow for the model parameters to further change as wind penetration changes, we rerun our Model 3[12] specification on an annual basis. Years 2008 and 2009 do not have complete data, therefore we present results from 2010 onwards in Table 4. Model 3 was used for the annual regressions as this constrained the impact of demand and wind generation on price to be the same at a particular point on the supply curve, within any one year.

The effect of wind forecast error, given by the coefficient on *lnwindfc_e*, in our annual specifications is greater than in our previous versions. In 2010, a 1% increase in wind forecast error increases SMP by about 0.06% and in 2011 by 0.08%, as compared to 0.0159% in M1 across all years. In 2012, wind forecast error is not a statistically significant driver of the SMP, however.

[8] In a previous study by O'Mahoney & Denny, the coal price was found to be insignificant. We estimate that the coal price infrequently is 'on the margin' and that fuel prices for more flexible generation technologies drive the SMP [7].

[9] The total variable cost function is a function of output levels and input prices. The minimum cost tangency point reflects total variable cost fuel mix which is also a function of all fuel prices and outputs.

[10] The Durbin–Watson statistics from M1 were: (original) 0.513, (transformed) 2.007.

[11] We do not interpret the seasonal or monthly dummies *per se*. It is most common to model only three or four seasons (e.g., Winter, Spring/Fall, Summer) in electricity markets in moderate climates such as Ireland. The dummy indicates a shift in the mean price during that time period relative to the average 'not that time period'. The expected net impact of the dummies is perhaps ambiguous as shifts in the supply curve due to maintenance, outage, as well as seasonal components of electricity prices not otherwise captured by the independent variables could be present.

[12] Allowing the coefficient's to change by year M3 gave the best fits.

Table 4
Annual results.

Variables	2010	2011	2012
lndem_wind	0.245***	0.316***	0.303***
	(0.031)	(0.024)	(0.025)
lndem_wind2	−0.0180***	−0.0318***	−0.0330***
	(0.005)	(0.004)	(0.004)
lnwindfc_e	0.0629***	0.0820***	0.0202
	(0.018)	(0.015)	(0.014)
lngas_e_co2	0.126	0.284*	0.281*
	(0.121)	(0.158)	(0.165)
lnoil_e_co2	0.632**	−0.339	0.317
	(0.263)	(0.281)	(0.364)
Jan	−0.313*	−0.125***	−0.0726
	(0.164)	(0.048)	(0.066)
Feb	−0.248***	−0.0503	−0.0821
	(0.096)	(0.040)	(0.069)
Mar	−0.287***	−0.0394	−0.112
	(0.097)	(0.043)	(0.080)
Apr	−0.281***	0.0219	−0.0026
	(0.090)	(0.053)	(0.072)
May	−0.0661	0.123***	−0.0359
	(0.084)	(0.040)	(0.063)
Jun	−0.0920	−0.0818**	−0.0942
	(0.080)	(0.041)	(0.078)
Jul	0.0309	−0.123***	−0.0661
	(0.074)	(0.045)	(0.067)
Aug	−0.0799	−0.0634	−0.0300
	(0.077)	(0.039)	(0.067)
Sep	−0.0166	0.0575	0.0229
	(0.077)	(0.038)	(0.063)
Oct	−0.0811	−0.0465	−0.0678
	(0.059)	(0.037)	(0.060)
Nov	−0.0934*	−0.00083	
	(0.049)	(0.038)	
Constant	−0.7168	1.5739	−1.3228
	(1.989)	(2.026)	(2.743)
Observations	15,714	17,493	15,078
R-squared	0.478	0.510	0.573

Standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Demand net of wind and its square are statistically significant in all three annual model specifications. We find that net demand has a positive effect on SMP, and that the effect is increasing at a decreasing rate in each year (similar to what was found in Ref. [10]). Fig. 2 presents the non-linear effect of net demand on the SMP for each year separately.

In comparing these annual effects, we find that as the effective capacity of wind on the system increases, the effect of net demand (demand net of wind output) is reduced. The effect of wind forecast errors as wind capacity increases over time on the system is less clear from our analysis. When accounting for variations in effective wind capacity, we find errors to have a greater impact than in the unconstrained version, yet this effect is not always found to be statistically significant.

5. Conclusions and future directions

This paper has estimated a model of the marginal impact of wind generation on system costs in Ireland. Overall, the results are good in the sense of good fits, significant variables, and grounding in theory; the paper advances on previous work [10] in that the derivation of the cost function is explicit from the SMP definition and the translog form. The estimates of the size of the coefficients are credible and we believe that they should be useful to policy makers when considering what external system costs various levels of wind generation might have on systems sharing similar characteristics with Ireland. An advantage of our approach is that updates with respect to fuel price changes and added data on wind,

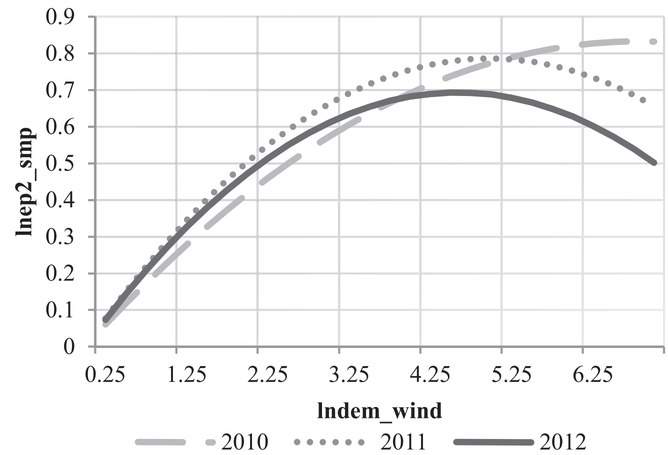

Fig. 2. Effect of logged net demand on logged SMP as per annual Model 3 specifications for full range of net demand values in our dataset, *ceteris paribus*.

generation and capacity are straightforward and can be made from the model, without recourse to extensive model revision. The cost of wind generation and impacts on system costs could be predicted by prediction of the exogenous variables in the system, such as using forward curves for gas and oil; a similar model could be estimated and implemented for other systems.

We thus conclude that the econometric approach to estimating the cost of wind external system costs should be considered in future studies and system planning and across a wide range of applications.

While the paper, we believe, advances the state of knowledge of the external costs of wind generation, many caveats should be kept in mind, such as the impacts of other factors such as interconnection, generation capacity mix, other flexibility parameters, market rules, etc., in addition to the need to update models across time and jurisdiction.

The comparison with previous studies is interesting, and qualitatively our results are somewhat similar to [10] with the impact of wind net of demand on cost increasing at a decreasing rate, but comparison of like-with-like is difficult because of the different market designs and available data, so comparisons should be made with due caution.

With this in mind, the paper suggests some particular areas for future research. First, studies across other jurisdictions would be interesting. Second, and perhaps more curiously, the sensitivity of the model and rejection of the constraint that wind generation should have an equal and opposite impact to demand on SMP is surprising and suggests more testing of different functional forms. We are not aware of other studies which tested this hypothesis and thus this likely warrants further research. The need to track impacts as wind penetration grows is also suggested by our results.

References

[1] Black M, Strbac G. Value of storage in providing balancing services for electricity generation systems with high wind penetration. J Power Sources 2006;162:949–53.
[2] Brouwer AS, van den Broek M, Seebregts A, Faaij A. Impacts of large-scale intermittent renewable energy sources on electricity systems, and how these can be modeled. Renew Sustain Energy Rev May 2014;33:443–66.
[3] Denny E, O'Malley M. Quantifying the total net benefits of grid integrated wind. Power Syst IEEE Trans 2007;22(2):605–15.
[4] Felder FA. Examining electricity price suppression due to renewable resources and other grid investments. Electr J 2011;24(4):34–46.
[5] Christensen L, Jorgensen DW, Lau L. Conjugate duality and transcendental logarithmic production functions. Econometrica 1971 July;39(4):255–6.
[6] Ketterer JC. The impact of wind power generation on the electricity price in Germany. Energy Econ July 2014;44:270–80.

[7] O'Mahoney A, Denny E. Electricity prices and generator behaviour in gross pool electricity markets. Energy Policy December 2013;63:628–37.
[8] Troy N, Denny E, O'Malley M. Base-load cycling on a system with significant wind penetration. Power Syst IEEE Trans 2010;25(2):1088–97.
[9] Di Cosmo V, Malaguzzi Valeri L. The incentive to invest in thermal plants in the presence of wind generation. Energy Econ 2014;43:306–15.
[10] Swinand GP, Godel M. Estimating the impact of wind generation on balancing costs in the GB electricity markets. 10–12 May 2012. European energy market (EEM), 2012 9th international conference on the, vol., no., pp.1–8.
[11] Tashpulatov SN. Estimating the volatility of electricity prices: the case of the England and Wales wholesale electricity market. Energy Policy September 2013;60:81–90.
[12] Würzburg K, Labandeira Xavier, Linares Pedro. Renewable generation and electricity prices: taking stock and new evidence for Germany and Austria. Energy Econ December 2013;40(Suppl. 1):S159–71.
[13] Gross R, Heptonstall P, Anderson D, Green T, Leach M, Skea J. The costs and impacts of intermittency: an assessment of the evidence on the costs and impacts of intermittent generation on the British electricity network. 2006 [A report of the Technology and Policy Assessment Function of the UK Energy Research Centre].
[14] Holttinen H, Meimborn P, Orths A, Lange B, O'Malley M, Tande JO, et al. "Impacts of large amounts of wind power on design and operation of power systems: results of IEA collaboration," IEA task 25 homepage. 2009. Available from: www.IEAwind.org.
[15] DCENR. Strategy for renewable energy: 2012–2020. 2012. Available from: http://www.dcenr.gov.ie.
[16] UK renewables energy roadmap update. 2013. Available from: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/255182/UK_Renewable_Energy_Roadmap_-_5_November_-_FINAL_DOCUMENT_FOR_PUBLICATIO___.pdf.
[17] SEAI. Wind farms in Ireland. 2013. Available from: http://www.seai.ie/Renewables/Wind_Energy/Wind_Farms/Wind_Farms_in_Ireland/.
[18] Eirgrid. 2012 curtailment report. 2012. Available from: http://www.eirgrid.com/media/2012_Curtailment_Report.pdf.
[19] Market schedules of the Irish single electricity market. Available from: http://www.sem-o.com/Pages/default.aspx.
[20] System demand and wind generation data for the Irish single electricity market. Available from: http://www.eirgrid.com/.