The Effect of Price-Quantity Correlation Coefficient on Wind Farm

Investments: A "Gift" of Nature

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Abstract

From previous two-factor real options models (e.g., Paxson and Pinto, 2005; Armada et al., 2013), we acknowledge that the output price-quantity correlation coefficient affects significantly the value and timing of the investment (firms invest earlier the lower is the correlation coefficient). We highlight that the opposite result holds for wind energy investments. We study the price-quantity correlation mean of 14 UK wind farms over the time period between January 2003 and December 2014, and conclude that it varies significantly across wind farms (from -0.35 to 0.28). We test the correlation mean differences among the wind farms and find that some are high and statistically significant; thus, we conclude that there are wind farms located on sites which persistently exhibit higher price-quantity correlations and, therefore, *ceteris paribus*, are more valuable.

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1. Introduction

Firms assess the wind resource potential of a site before investing because it is directly related to the amount of energy that can be extracted. A major inconvenience of wind energy is the variability of production due to the unpredictability nature of the wind. Despite the technological progress, estimations of the energy production from wind farms are still inaccurate (Kwon, 2010; and Mirhosseini et al., 2011). For instance, Tindal et al. (2007) use a dataset which comprises information on 156 wind farms from the US and Europe and concludes that, on average, actual energy production is 92.1% of what was estimated. On the other hand, energy market prices are also volatile because of, among other aspects, changes in energy demand and the so-called spikes which can increase prices significantly in a matter of hours. Consequently, wind farms revenue over time is very uncertain.

Different technologies and methodologies have been developed to assess the wind resource potential of sites, and map the wind resource of various geographic locations (see, e.g., Ramos and Iglesias, 2014; Landry et al., 2017; Gualtieri and Zappitelli, 2014; and Hassanzadeh, 2016). There is also empirical evidence showing that the wind blows irregularly and its (monthly and hourly) speed pattern is site-specific. For instance, Ramos and Iglesias (2014) study the viability of wind power in Arousa, a natural reserve small island of Spain, and reveal that "the [wind] resource is characterised by its narrow range of direction (southwest and northeast in winter and summer, respectively) and marked monthly and hourly variability." Specifically, they show that the windiest months are July and August and February and March, and the periods of higher wind speed are from 1 to 5 pm and from 8 pm to midnight (p. 750).

To our best knowledge, currently, while selecting a wind farm site, wind power developers do not consider the expected correlation between the energy market price and the energy production. However, we advocate that it affects significantly the value and timing of the investment, and show that it is site-specific and, therefore, *ceteris paribus*, wind power developers should select the sites

which exhibit a higher expected energy output price-quantity correlation.[2] We support this assertion on both the available two-factor real options literature and our empirical results.

The real options literature shows that when the value of a project is contingent on the future evolution of two (possibly correlated) stochastic variables (e.g., price-quantity, or price-investment cost), the correlation coefficient between the two variables affects significantly the value and timing of the investment (see Dixit and Pindyck, 1994, chapter 6; Paxson and Pinto, 2005; Adkins and Paxson, 2011; and Armada et al., 2013, among others). The two-factor model of Dixit and Pindyck (1994) uses revenue and investment cost, whereas that of Adkins and Paxson (2011) uses revenue and operating costs, and those of Paxson and Pinto (2005) and Armada et al. (2013) both use output price and quantity. From the latter two models, we conclude that firms invest earlier the lower is the output price-quantity correlation (see, e.g., Paxson and Pinto (2005, p. 219).

However, the theoretical findings of Paxson and Pinto (2005) and Armada et al. (2013), regarding the effect on the investment value of the price-quantity correlation, does not apply to the evaluation of wind farm investments. This is because the above literature was developed for the evaluation of projects where the output market price and the output quantity are both uncertain but guided by the market forces (i.e., their evolution and relationship over time obey to the so-called law of demand and supply). Therefore, the output price-quantity correlation is negative and the output production is not affected by the geographic location of the production facility – for further details see Section 2.

However, in the wind energy market, all the output produced is sold, due to regulation, and depends significantly on the wind conditions, and not, as usual, on the market demand. Notice that, the wind energy has usually priority to enter the electricity national grids, due to regulation, which turns the demand and supply relationship very atypical. Therefore, the price-quantity correlation is less predictable and, possibly, site-specific. We show that there are significant differences in the output

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[2] Notice that a higher output price-quantity correlation means that in periods when the energy price is higher the (wind farm's) energy production tends to be higher as well. Thus, a higher output price-quantity correlation implies a higher revenue.

price-quantity correlation amongst wind firms, and the higher the correlation the more valuable is the investment.

We provide empirical evidence on the daily energy production irregularity of 14 UK wind farms, over the time period between January 2003 and December 2014, and conclude that the energy output price-quantity correlation varies across firms (it is site-specific). More specifically, we find that there are wind farms which persistently exhibit a higher output price-quantity correlation coefficients and, therefore, *ceteris paribus*, are more valuable.[3]

Our work has some relation with those of Olauson and Bergkvist (2016), who study the correlation coefficient between wind power generation in different countries, emphasizing that this aspect is important for quantifying the reduction in power generation variability when countries are electrically interconnected, Figueiredo et al. (2016a), who investigate the effect of price arbitrage and weather dynamics on the renewable energy output variations across several integrated power markets, and Masurowski et al. (2016), who propose a new approach to assess the impact of "varying minimum distances" between the wind turbines on the wind energy potential of a given geographic place.

It also intersects with the works of Figueiredo et al. (2016b), who use a dataset from Denmark to illustrate the effects of the renewable energy output variation across multiple interconnected markets, and advocate that cross-border flows can play a role in the market splitting behaviour, Hoogwijk et al. (2004), who provide a global onshore wind energy potential analysis, taking into account the current technologies available and the main uncertainties underlying their methodological assumptions, and Eurek et al. (2016), who use mesoscale reanalysis data to estimate wind quality for both onshore and offshore wind sites across the globe.

The next section discusses both the effect of the price-quantity correlation on the timing of the investment, relying on Paxson and Pinto (2005) and Armada et al. (2013), and justifies why the result

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[3] To better illustrate our argument, let us consider the results of Ramos and Iglesias (2014) for the patterns of wind speed over time, according to which the windiest months are July and August and February and March, and the periods of higher wind speed during the day are from 1 to 5 pm and from 8 pm to midnight. Because the wind farms' revenue is given by the market price times the quantity produced (sold), so the higher the correlation between price and quantity, the more valuable is the wind farm. This is because a higher correlation would mean that, in Arousa, the periods when energy market price is higher would tend to coincide with the periods when the wind speed (i.e., energy production) is stronger.

we obtain from these two models, regarding the effect of the correlation on the timing of the investment, does not hold for a wind farm investment. Section 3 restates the key steps of the analytical derivation of a two-factor (price-quantity) model, following Adkins and Paxson (2011) and Armada et al. (2013). Section 4 describes our data sample and the methodology used for testing the correlation mean differences among the wind farms. Section 5 describes the main results. Section 6 concludes.

2. The price-quantity relationship

In the current investment literature, the price-quantity relationship is normally modelled using a demand function with constant parameters (e.g., Dixit and Pindyck, 1994; and Caballero and Pindyck, 1996). The assumption that both price and quantity follow independent stochastic processes means that the two variables are driven by exogenous factors. Yet, it does not mean that they are independent. For instance, when the law of demand and supply holds, the price-quantity correlation is negative. For this economic context, Paxson and Pinto (2005) and Armada et al. (2013) show that firms invest earlier (i.e., the investment is more valuable) the lower is the output price-quantity correlation. This result holds because when the law of demand and supply holds, the negative correlation works as a hedging factor in models which consider price and quantity uncertainty.

However, we highlight that if we apply the above two-factor models to the evaluation of a wind farm investment, the above result regarding the effect of the correlation on the value/timing of the investment does not hold. Wind firms are more valuable (i.e., invest earlier) the higher is the price-quantity correlation. This is because of regulation. For instance, the EU's Renewable Energy Directive 2009/28/EC [4] ensures that priority access or guaranteed access to the grid-system of electricity produced from renewable energy sources is safeguarded for renewable energy, which turns the relationship between demand and supply very atypical, because all the energy produced is sold at a given price.

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[4] See: http://eur-lex.europa.eu/legal-content/en/ALL/?uri=CELEX%3A32009L0028.

3. A two-factor real option model

In this section, we restate the key steps of the derivation of a two-factor real options model for a wind farm investment, following Adkins and Paxson (2011) and Armada et al. (2013).

Let us assume that the energy market price (P) and the energy production (Q) both follow independent (but possibly correlated) geometric Brownian motion (GBM) processes given by:

$$dP = \alpha_P P dt + \sigma_P P dz_P \qquad (1)$$

$$dQ = \alpha_Q Q dt + \sigma_Q Q dz_Q \qquad (2)$$

$$E[dZ_P dZ_Q] = \rho dt \qquad (3)$$

where α_P and α_Q are the instantaneous drift rates of the energy price and energy production (quantity sold), respectively; σ_P and σ_Q are the instantaneous volatility of P and Q, respectively; and z_P and z_Q are the increment of a standard Wiener process for P and Q, respectively. For convergence of the solution, we assume that the condition $r - \alpha_P - \alpha_P > 0$ holds, where r is the risk-free interest rate.

Thus, while inactive, the firm holds the option to invest in a wind farm, which has valued under uncertainty. The value of the option to invest ($F(P,Q)$) is represented by the following partial differential equation (PDE):

$$\frac{1}{2}\frac{\partial^2 F}{\partial P^2}\sigma_P^2 P^2 + \frac{1}{2}\frac{\partial^2 F}{\partial Q^2}\sigma_Q^2 Q^2 + \frac{\partial^2 F}{\partial Q \partial P}QP\sigma_Q\sigma_P\rho_{QP} + \frac{\partial F}{\partial P}(r - \delta_P)P + \frac{\partial F}{\partial Q}(r - \delta_Q)Q - rF = 0 \qquad (4)$$

where $\delta_P = \mu_P - \alpha_P$, $\delta_Q = \mu_Q - \alpha_Q$ and μ_j, with $j = \{P, Q\}$, is the market equilibrium required rate of return, given by:

$$\mu_j = r + \lambda\rho_{jm}\sigma_j \qquad (5)$$

where $\lambda_j = \frac{r_m - r}{\sigma_m}$ is the market price for risk, ρ_{jm} is the correlation between the asset j and the market, and σ_m is the market volatility.

The homogeneous part of Equation (4) has the following general solution:

$$F(P,Q) = AP^\beta Q^\eta \tag{6}$$

where β and η are the roots of an elliptical characteristic equation.

Following Adkins and Paxson (2011) we obtain:

$$\delta_R = \delta_P + \delta_Q - \rho\sigma_P\sigma_Q - r > 0 \tag{7}$$

Using Ito´s Lemma we can show that the project revenue, $R(P,Q) = PQ$, is represented by the following GBM process:

$$dR = \alpha_R R dt + \left(\sigma_P dz_P + \sigma_Q dz_Q\right)R \tag{8}$$

where $\alpha_R = \alpha_P + \alpha_Q + \rho\sigma_P\sigma_Q$.

The required rate of return for the investment is given by the sum of the expected drift and the shortfall rate of return:

$$\mu_R = \alpha_R + \delta_R = r + \lambda(\rho_{Pm}\sigma_P + \rho_{Qm}\sigma_Q) \tag{9}$$

Armada et al. (2013) show that the optimal investment threshold is reached when there is a pair (P^*,Q^*) for which Equation (10) holds:

$$P^*Q^* = R^* = \frac{\beta}{\beta-1}\delta_R K \tag{10}$$

where $\delta_R = \delta_P + \delta_Q - \rho\sigma_P\sigma_Q$ and β is the positive root of a quadratic equation given by:

$$\beta = \frac{1}{2} - \frac{r-\delta_R}{\sigma_R^2} + \sqrt{\left(-\frac{1}{2} + \frac{r-\delta_R}{\sigma_R^2}\right)^2 + \frac{2r}{\sigma_R^2}} \tag{11}$$

For the same modelling setting, Paxson and Pinto (2005) obtain the following solution for the optimal investment threshold:

$$R^* = \frac{\beta}{\beta-1} \delta_R^{'} K \qquad (12)$$

where $\delta_R^{'} = r - \alpha_P + \alpha_Q$.

As highlighted in Armada et al. (2013), the difference between Paxson and Pinto (2005) and Armada et al. (2013) models is that the latter obtains a solution for the investment threshold without invoking homogeneity of degree one. Nevertheless, from both models, we conclude that firms invest earlier the lower is the correlation coefficient.

4. Data Sample and methodology

4.1 Data sample

We collect monthly data on the energy market prices and the energy production of 14 UK wind farms, over the time period between 2003 and 2014. The data on energy prices and energy production was collected from the DataStream (APX UK spot power market) and the Renewable Energy Foundation (www.ref.org.uk), respectively.

Table 1 provides further information on our data sample, namely, the time period, location, number of turbines and production capacity of each wind farm, the name of the project developer, and whether the wind farms are located on-shore or off-shore.

Table 1: this table provides information about the wind farms of our data sample. Specifically, it provides shows our data sample the time period, the location, number of turbines and production capacity of each wind farm, and name of the wind farm project developer and whether the wind farms are located on-shore or off-shore.

Wind Farm	Location	Technology	Nº Turbines	Capacity (kW)	Developer	Sample Time Period
B. A. Tuire (1)	Scotland	On-shore	23	660	Scottish Power	2003-2014
Hare Hill (2)	Scotland	On-shore	20	660	Scottish Power	2003-2014
Rothes (2)	Scotland	On-shore	22	2,300	Fred Olsen Renewables	2005-2014
Cefn. Croes (3)	Wales	On-shore	30	1,500	Falck Reneables	2006-2014
Crystal Rig (4)	Scotland	On-shore	20	2,500	Fred Olsen Renewables	2004-2014
Casyemire (5)	Scotland	On-shore	21	2,300	Scottish Power	2005-2014
Scroby Sand (6)	England	Off-shore	30	2,000	E. ON UK Renewables	2005-2014
Braes D. (7)	Stotland	On-shore	36	2,000	SSE Renewables	2007-2014
Pauls Hill (8)	Scotland	On-shore	28	2,300	Fred Olsen Renewables	2006-2014
Black Law (10)	Scotland	On-shore	54	2,300	Scottish Power	2006-2014
Haydard (11)	Scotland	On-shore	52	2,300	Scottish & Southern	2007-2014
Kentish (12)	England	Off-shore	30	3,000	Vattenfall	2006-2014
Barrow (13)	England	Off-shore	30	3,000	Dong/Centrica Energy	2007-2014
Whitelee (14)	Scotland	On-shore	140	2,300	Scottish Power	2009-2014

4.2 Methodology

Our aim is to study the correlation between the energy market price and the energy production of 14 wind farms, using monthly data, and examine the correlation mean difference among the wind farms and their respective statistical significance. We start by computing the monthly correlation mean for each wind farm and the correlation mean differences among the wind farms. Then, we examine the statistical significance of the correlation mean differences, using a one-tailed test.

4.2.1 Mean difference hypothesis test

Let us define $\bar{\rho}_{PQ}^{i,j} = \left|\bar{\rho}_{PQ}^i - \bar{\rho}_{PQ}^j\right|$ as the mean difference of the monthly correlation between the energy price and the energy production of wind farm i, and the monthly correlation between the energy price and the energy production of wind farm j, with $i = \{1,2,\dots,14\}$ and $j = \{1,2,\dots,14\}$ where $\neq j$, where $\bar{\rho}_{PQ}^i$ is the correlation between the monthly energy price and the monthly energy production of wind farm i, and $\bar{\rho}_{PQ}^j$ is the correlation between the monthly energy price and the monthly energy production of wind farm j. in our analysis we use mean values for energy price and production, and a one-tailed mean difference test, formalized as follows:

$$H_0 = \bar{\rho}_{PQ}^{i,j} > 0 \tag{13}$$

$$H_1 = \bar{\rho}_{PQ}^{i,j} = 0 \tag{14}$$

where H_0 is the null hypothesis and H_1 is the alternative hypothesis.

We consider the following significance level: 0.01, 0.05 and 0.10. Thus, if the p-value is below 0.01, 0.05 or 0.10 we accept the null hypothesis with 1%, 5% or 10% significance level, respectively. Otherwise, we reject the null hypothesis.

5. Results

In this section, we present our results for price-quantity correlation mean of each wind farm and the correlation mean difference among the wind farms.

Tables 2, 2a and 2b provide information on the monthly correlation mean, maximum and minimum per wind farm and the correlation mean, maximum and minimum for the full sample. For instance, in the last three columns on the right hand-side, we show that the correlation mean, maximum and minimum for the Pauls Hill wind farm are 0.025, 0.896 and -0.634, respectively. At the bottom, Table 2a shows, for instance, that the correlation mean, maximum and minimum for January, considering all the wind farms together, are -0.33, 0.479 and -0.50, respectively, and Table 2b shows that the correlation mean, maximum and minimum for the full sample are 0.072, 0.275 and -0.350, respectively.

From these results, we conclude that the correlation mean varies significantly over time and across wind farms.

Table 2: this table provides information on the correlation coefficient mean, maximum and minimum per month for each wind farm. The last three columns on the right hand-side, show the monthly correlation coefficient mean, maximum and minimum per wind farm. At the bottom, Table 2a shows the mean, maximum and minimum of the correlation coefficient mean per month, considering the 14 wind farms. Table 2b shows the correlation coefficient mean, maximum, and minimum for the full sample.

Wind Farm	Time Period	Correlation Mean per Month (per wind farm, for the sample time period)												Monthly Correlation (per wind farm)		
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Mean	Max	Min
B. A Tuirc (1)	2003-14	-0.353	0.108	-0.025	-0.419	-0.073	0.323	-0.205	0.324	0.020	-0.028	0.091	-0.151	- 0.032	0.324	- 0.419
Hare Hill (2)	2003-14	-0.500	-0.378	-0.499	-0.082	-0.211	-0.075	-0.036	-0.082	0.017	0.010	0.266	-0.244	- 0.151	0.266	-0.050
Rhodes (3)	2005-14	0.301	-0.644	0.392	0.045	-0.262	-0.019	0.770	0.301	-0.444	0.052	0.549	-0.523	0.043	0.770	- 0.644
Cefn. Croes (4)	2006-14	-0.054	-0.102	0.146	0.211	0.361	0.292	-0.094	0.073	0.518	0.021	0.455	-0.625	0.100	0.519	- 0.625
Crystal Rig (5)	2004-14	0.211	0.516	0.339	0.422	0.145	0.368	0.255	-0.281	-0.445	-0.092	0.520	-0.160	0.150	0.520	- 0.445
Casuamire (6)	2005-14	-0.067	-0.071	0.206	0.099	-0.187	-0.096	0.734	0.554	-0.285	0.004	0.292	-0.496	0.057	0.734	- 0.495
Scroby S. (7)	2005-14	-0.261	0.200	0.355	0.061	-0.017	0.221	-0.548	-0.523	0.141	0.072	-0.306	0.235	- 0.031	0.355	- 0.548
Braes D. (8)	2007-14	0.332	0.597	0.580	0.067	0.346	0.150	0.409	0.253	-0.063	-0.033	0.387	-0.165	0.238	0.597	- 0.165
Pauls Hill (9)	2006-14	-0.205	-0.543	0.224	0.262	-0.251	-0.049	0.895	0.382	-0.267	0.171	0.311	-0.634	0.025	0.896	- 0.634
Black Law (10)	2006-14	-0.158	-0.430	0.212	0.166	0.084	0.102	0.617	0.173	-0.127	0.125	0.348	-0.739	0.031	0.617	- 0.739
Haydard (11)	2007-14	-0.101	-0.098	0.155	0.328	-0.002	0.239	0.468	0.228	-0.332	0.220	0.289	-0.461	0.078	0.468	- 0.461
Kentish (12)	2006-14	0.037	0.342	0.312	0.312	0.384	0.310	0.051	0.013	0.497	0.132	0.136	0.076	0.217	0.497	0.013
Barrow (13)	2007-14	0.479	0.766	0.185	0.453	0.618	0.471	0.613	0.463	0.145	0.078	0.105	-0.481	0.325	0.766	- 0.481
Whitelee (14)	2009-14	-0.117	0.706	0.035	0.082	0.242	0.586	-0.080	-0.544	-0.848	0.010	0.002	-0.527	- 0.038	0.706	- 0.848

Table 2a

	Correlation Mean per Month (considering the 14 wind farms)											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Mean	-0.033	0.069	0.187	0.143	0.084	0.202	0.275	0.095	-0.105	0.053	0.246	-0.350
Max.	0.479	0.766	0.580	0.453	0.618	0.586	0.895	0.554	0.518	0.220	0.549	0.235
Min.	-0.500	-0.644	-0.499	-0.419	-0.262	-0.096	-0.548	-0.544	-0.848	-0.092	-0.306	-0.739

Table 2b

Correlation (full sample)		
Mean	Max	Min
0.072	0.275	- 0.350

Table 3 shows the mean difference among the wind farms and (in between brackets) the respective p-values, from which we can see that most of the results are statistically significant at least at 10% level. For instance, we find that the mean difference between the Barrow wind farm and the Braes wind farm is of 8.6 percentage points and statistically significant at 1% level. From Table 2 we acknowledge that the former wind farm has a correlation mean of 0.325, whereas the latter has a correlation mean of 0.238. Therefore, based on the reasoning discussed in Sections 2 and 3, we conclude that the Barrow wind farm is located on a site with a higher price-quantity correlation and, therefore, *ceteris paribus*, is more valuable.

Similarly, we find that the correlation mean difference between the Kentish wind farm and the Braes wind farm is 2.1 percentage points and statistically significant at 5% level. From Table 2 we acknowledge that the former wind farm has a correlation mean of 0.217, whereas the latter has a correlation mean of 0.238. Therefore, following the same arguments as above we conclude that, *ceteris paribus*, the Braes wind farm is slightly more valuable.

Finally, we find that the correlation coefficient mean difference between the Whitelee wind farm and the Crystal wind farm is 18.8 percentage points and statistically significant at 5% level. From Table 2 we acknowledge that the correlation mean of the former wind farm is -0.038, whereas the correlation coefficient mean of the latter is 0.15. Hence, we conclude that, *ceteris paribus*, the Crystal wind farm is significantly more valuable. This result represents a very extreme case, in terms of correlation coefficient mean difference, and shows that high correlation mean differences among wind farms are possible.

Paxson and Pinto (2005, p. 219) show a sensitivity analysis which illustrates the impact on firms' investment threshold of changes in the price-quantity correlation from which we can infer that the Crystal wind farm, when compared with the Whitelee wind farm, is significantly more valuable because it is benefiting from a very generous "gift" of nature.

Table 3: this table provides information on the correlation coefficient mean differences among the wind farms. In between brackets are the p-values, where "***", "**" and "*" mean that the result is significant at 1%, 5% and 10% significant level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
					Correlation Mean Differences								
Hare Hill (2)	0.119*												
	(0.0874)												
Rhodes (3)	0.076*	0.194											
	(0.0623)	(0.1179)											
Cefn. Croes (4)	0.133*	0.251*	0.057										
	(0.0677)	(0.0582)	(0.1124)										
Crystal Rig (5)	0.182*	0.301*	0.107	0.050									
	(0.0740)	(0.0631)	(0.1475)	(0.1087)									
Casuamire (6)	0.090*	0.208	0.014	0.043	0.093*								
	(0.0938)	(0.1374)	(0.1443)	(0.1633)	(0.0536)								
Scroby S. (7)	0.001	0.120*	0.074	0.131*	0.181*	0.088							
	(0.1178)	(0.0634)	(0.1069)	(0.0841)	(0.0791)	(0.1375)							
Braes D. (8)	0.271	0.389	0.195	0.138*	0.088*	0.181*	0.269*						
	(0.1005)	(0.1363)	(0.1874)	(0.0978)	(0.0913)	(0.0660)	(0.0966)						
Pauls Hill (9)	0.057*	0.176*	0.019*	0.075	0.125*	0.033*	0.056	0.214					
	(0.0774)	(0.0905)	(0.0374)	(0.1514)	(0.0789)	(0.0813)	(0.1429)	(0.1167)					
Black Law (10)	0.063*	0.182*	0.012*	0.069	0.119*	0.026*	0.062	0.207	0.006*				
	(0.0774)	(0.0905)	(0.0374)	(0.1514)	(0.0789)	(0.0813)	(0.1429)	(0.1167)	(0.0990)				
Haydard (11)	0.110*	0.229*	0.034*	0.022	0.072*	0.020	0.109	0.160*	0.053	0.047*			
	(0.0989)	(0.0299)	(0.0433)	(0.1876)	(0.0571)	(0.1249)	(0.1153)	(0.0843)	(0.1167)	(0.0709)			
Kentish (12)	0.249*	0.368*	0.173*	0.117	0.067	0.160*	0.248*	*0.021***	0.192*	0.186	0.139		
	(0.0689)	(0.0651)	(0.0703)	(0.1870)	(0.1426)	(0.0605)	(0.0735)	(0.0272)	(0.0946)	(0.1110)	(0.1176)		
Barrow (13)	0.357	0.476*	0.281	0.224*	0.175*	0.267	0.355*	*0.086****	0.300	0.293	0.247	0.108*	
	(0.1111)	(0.0639)	(0.1506)	(0.0913)	(0.0661)	(0.1310)	(0.0900)	(0.0076)	(0.1483)	(0.1463)	(0.1290)	(0.0690)	
Whitelee (14)	0.005	0.113*	0.081	0.138	*0.188***	0.095	0.007	0.276*	0.063	0.069	0.116*	0.255	0.362
	(0.1118)	(0.0936)	(0.1056)	(0.2029)	(0.0159)	(0.1372)	(0.1206)	(0.0842)	(0.1073)	(0.1205)	(0.0944)	(0.1520)	(0.1458)

6. Conclusion

Previous two-factor real options models show that the price-quantity correlation affects significantly the timing/value of investments (i.e., firms invest earlier the lower is the correlation). We highlight that because of the wind irregularity over time and the regulation (e.g., the EU's Renewable Energy Directive 2009/28/EC), the above theoretical result does not hold for wind farm investments which are more valuable the higher the correlation.

Our results for the price-quantity correlation mean show that it varies significantly across wind farms (from -0.35 to 0.28) and there are (high) correlation mean differences among the wind farms which are statistically significant. For instance, the correlation mean difference between the Whitelee wind farm and the Crystal wind farm is 18.8 percentage points and statistically significant at 5% level. Relying on Paxson and Pinto (2005) and Armada et al. (2013) real option models, we conclude that such an extreme correlation mean difference means that the latter wind farm is benefiting from a very generous (price-quantity correlation) gift of the nature. We find other less extreme correlation mean differences between the wind farms. Overall, our results show that while inspecting sites where to install wind farms, developers should estimate the expected correlation between the energy price and the energy production of each site and, *ceteris paribus*, select that which exhibit a higher energy price-quantity correlation.

The wind energy capacity has grown significantly in the last decades, and it is expected to continue to growth significantly in the next years. This could press wind energy developers to improve their evaluation methods in order to select the wind farm sites. Our work suggests that they should also study the expected correlation between the energy market price and the energy production of the sites.

This paper is devoted to wind energy investments, but our conclusions also apply to other types of renewable energy investments whose production is under regulation, such as that of the EU (EU's Renewable Energy Directive 2009/28/EC). Our findings can lead to improvements in the wind farm site selection methods currently used by wind energy developers.

This research can be extended in several ways. For instance, it would be interesting to do a similar study using a larger sample with intraday data, if available, or to replicate our study for other EU countries. It would also be interesting to test whether the wind farms we identify here as "more valuable", because they have a higher energy output price-quantity correlation, are indeed more valuable (profitable), if there is data is available.

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