REALIZED CAPACITY FACTOR ANALYSIS OF OFFSHORE WIND FARMS IN THE UK

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Overview

Offshore wind has been pursued with great effort to increase the proportion of renewables in the energy mix and to meet increasing consumption demands. A substantial amount of research has been conducted to improve operational performance and to reduce cost. Net present value (NPV) and levelized cost of energy (LCoE) are frequently used to assess profitability. In both approaches, lifetime electricity production and production time profile are important drivers of profitability (Osmundsen et al., 2021.; Aldersey-Williams, et al., 2019). Production (MWh) is a product of three factors: capacity (MW), timespan (hours) and capacity factor. Capacity factor is defined as the ratio of between actual electricity output and the maximum possible output. There is scant analytical research on the realized capacity factor of offshore wind farms.

The aim of this paper is to augment the literature by applying econometric methods to analyse data from 36 offshore wind farms in UK commissioned between 2004 and 2020. There are two key objectives of our paper. First, we examine how capacity factors are affected by wind farm characteristics. Second, we assess how capacity factors evolve throughout the wind farms' lifespan. A wind farm's capacity factor depends chiefly on two variables: wind resources and the wind turbine's ability to capture the kinetic energy of the wind. For wind resources, we use the monthly average wind speed of UK as proxy for wind power in each region. The local wind conditions can be proxied by the location of the wind farm. We create dummy variable of the location of the 36 wind farms and divide them into six groups according to their clustered location. For the turbine's ability to capture wind power, it depends on the technology development and the state and the condition of the wind turbines. Turbine capacity captures improvements in turbine technology. Wear and tear accumulate as the wind turbines age. Consequently, age is expected to have a negative impact on capacity factor. To address the possibility of nonlinearity, we include both age and age squared as independent variables.

Methods

Our econometric approach involves running random effect panel data regression with the logarithm of monthly, realized capacity factor and the proposed explanatory variables. Production data was extracted from the UK Office of Gas and Electricity Markets (OFGEM) Renewables and CHP register database. Monthly capacity factor is defined in Equation (1).

$$\begin{matrix} Monthly \\ capacity \\ factor \end{matrix} = \frac{Realized\ generation\ of\ MWh}{Nominal\ capacity \times \left(24\ hours \times \begin{matrix} Days\ in \\ month \end{matrix}\right)} \tag{1}$$

Based on our ex-ante expectations and the extant literature (Hughes, G., 2012; Aldersey-Williams, et al., 2020), our regression equation is specified as follows:

$$\begin{aligned} \ln CF_{it} \quad = {} & \beta_0 + \beta_1 Age_{it} + \beta_2 Age_{it}^2 + \beta_3 WindSpeed_t + \beta_4 UnitTurbineCapacity_i + \\ & \sum_{j=1}^{5} \beta_{j+4} DLocation_j + \beta_{10} DWinter_{it} + \beta_{11} DSummer_{it} + \beta_{12} DAutumn_{it} \ + \varepsilon_{it} \end{aligned} \tag{2}$$

where CF_{it} is the capacity factor of wind farm i at month t into its lifespan and we use the logarithm term in the model, Age_{it} is the number of months of wind farm i at month t into its lifespan, Age_{it}^2 is the squared term of age, $WindSpeed_t$ is the average wind speed at month t of twelve regional weather stations in UK, $UnitTurbineCapacity_i$ is nominal capacity of the unit turbine used by wind farm i (for wind farms having turbines with different nominal capacity, the average number is used). We divide 36 wind farms into six groups according to their location $DLocation_j$ and create five dummy location variables. The remaining three dummy variables $DWinter_{it}$, $DSummer_{it}$, and $DAutumn_{it}$ represent different seasons, with the Spring season serving as the base group.

Results

The regression result shows that the model is overall significant, with R-square 0.55. Conforming to ex ante expectations, average UK wind speed and the unit turbine capacity (proxy for technology) have positive and significant coefficients. Location dummy variables suggests variation in capacity factor due local geographical differences in wind condition. Capacity factor of Autumn and Winter are on average significantly higher than Spring, while Summer is significantly lower.

Table 1. Regression result

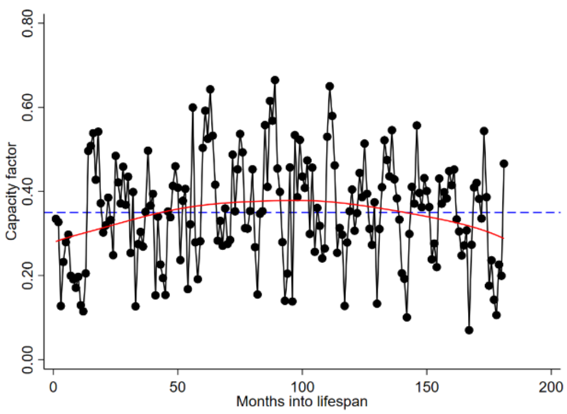
Age	Age2	Windspeed	UnitTurbineCapacity	North	North East	South	South East	West
0.00137**	-0.00000653*	0.147***	0.0536***	-0.0724	-0.112***	0.0296	-0.0734	-0.108**
-0.000605	-0.00000376	-0.00673	-0.0122	-0.136	-0.0428	-0.0415	-0.0506	-0.0454

DSummer	DAutumn	DWinter	_cons	N	R squared	Wald Chi2	Prob > chi2
-0.123***	0.172***	0.171***	-2.519***	3419	0.5507	4914.41	0
-0.00939	-0.0126	-0.0128	-0.0821				

Standard errors in parentheses * p<0.1 ** p<0.05 *** p<0.01

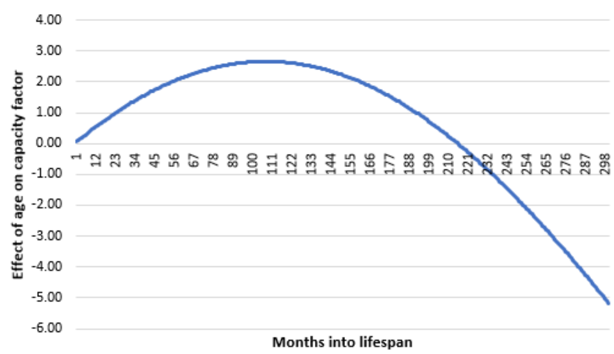
Description statistics suggests a nonlinear relationship between the capacity factor and the progress into lifespan. For illustrative purpose, we showcase the temporal development of Barrow offshore wind farm in Figure 1. As observed, there is an inverted U-chape between capacity factor and age. Regression results support the notion of a reverse U-shaped relationship. Age squared has a negative estimated beta coefficient, significant at 10% level, and age is positive and significant at 5% level. This results in an asymmetric inverted U-shape. Capacity factor will initially increase, reach a top, and then begin to decay until the end of the wind farm's lifespan. The turning point occurs at 104.9 months (about 8.7 years). It means that holding other factors constant, the capacity factor would increase with age until 8.7 years, and then the additional year of operating would decrease the capacity factor. We use mean value of the wind speed and unit turbine capacity of the dataset and calculate the predicted capacity factor according to our estimation model. As shown in Figure 2, the capacity factor is expected to decrease by 5.68 percentage points from beginning to the end of the wind farm's lifetime (25 years). From the peak to the end, the decrease is 8.22 percentage points.

Figure 1. Capacity factor of Barrow offshore wind farm



In Figure 1, the black, solid line with dots represents the actual, realized capacity factor of Barrow offshore wind farm. The horizontal blue and dashed line denotes the wind farm's average capacity factor based on currently available data. The red, solid line represents the smoothed, moving average of the capacity factor.

Figure 2. Age-related change in capacity factor throughout lifespan



In Figure 2, the blue line is an example of the percentage point changes in capacity factor as the age of wind farm increases.

Conclusions

Using the realized electricity production data in UK, our analysis elucidates important aspects of capacity factor development for offshore wind farms. Based on our analysis, we find that the performance of offshore wind farms is significantly correlated with technology development and local wind conditions. We also find a non-linear relationship between capacity factor and age, providing important information for investors and analysts. Declining capacity factors obviously impact optimal project duration and possibly project profitability calculations.

References

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