Location, Location, Location and Correlation: a Gift of Nature*

Alcino Azevedo[a†], *Izidin El Kalak*[b], Michail Karoglou[c]

[a] *Centre for Business Prosperity, Aston Business School, Aston University, Birmingham, UK*
[b] *Cardiff Business School, Cardiff University, Cardiff, UK*
[c] *Centre for Business Prosperity, Aston Business School, Aston University, Birmingham, UK*

Abstract

We show that wind energy power developers should consider the correlation between the electricity market price (Price) and the energy produced (Quantity) of a wind farm when choosing the investment location. We estimate this correlation for 60 UK wind farms using a dataset that comprises 1.4 million half-hourly observations covering the period between 2006 and 2019, and find persistent and statistically significant differences. Then, we introduce a model that translates into a monetary value those correlation differences and we develop a real options model to evaluate wind energy investments based on Price and Quantity uncertainty as well as the correlation between these two. The two model approaches lead to similar quantitative results and attest that the value of a wind farm increases with the Price-Quantity correlation. Therefore, by investing in locations with higher correlations (*ceteris paribus*), energy developers benefit from an extra source of revenue, the *location Price-Quantity correlation premium* that is, indeed, a gift of nature.

Keywords: Price-Quantity Correlation; Electricity Price; Monopsony Hypothesis; Wind Energy Power; Wind Energy Production.

JEL Codes: Q42, Q56, L78, O13, R58.

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†Corresponding author's e-mail address: m.karoglou@aston.ac.uk

1 Introduction

The many natural disasters of the recent years have commonly been attributed to climate changes. Most importantly, however, the avid and often vocal interest of the public in actions that are friendly to the environment has drawn governments to set ambitious policies that have significantly enhanced renewable energy investments. Wind energy is currently the fastest growing form of electricity generation in the world (IEA, 2021); in the UK in 2019 it reached its largest market share with almost 8.5GW of operational capacity.[1] As of 2022, a capacity expansion program of nearly 30GW comprising about 4,900 planning applications has been granted.[2]

Nevertheless, this planned albeit substantial growth in wind energy capacity has led to a fierce competition for the best locations (see, for example, Fischetti & Fischetti, 2023). Unsurprisingly, this was actually predicted. Indeed, previous studies have warned about a location problem arising from the disparity between where the energy demand is and where the energy resources are (Staid & Guikema, 2015).

In this paper, we examine whether, and if so to what extent, there are economic and statistically significant differences in the correlation of individual wind farm production and energy prices. Then, we devise an empirical and a theoretical model to demonstrate how these differences can be translated into monetary gains/losses. This, in turn, enables us to establish the importance of accounting for the price-quantity co-movements when selecting the location of a wind farm.

Our main argument builds on the monopsony hypothesis which states that under a single homogeneous product, in our case electricity, the product prices are set by the demand, the monopsonist (see, for example, Manning, 2006, 2010). As the number of wind farms grows, the economic value differences among the available sites decreases.[3] Therefore, we should expect that the importance of factors that lead to marginal value differences will become more and more prominent in determining the preference for a site over another. Consequently, wind energy developers will demand more accurate investment evaluation techniques to optimally

[1] See Global Offshore Wind Report, 2019.

[2] According to the Global Energy Review, wind renewable generation of electricity grow by 275 TWh, or almost 17%, in 2021 compared to 2020 levels. https://www.iea.org/reports/global-energy-review-2021/renewables.

[3] In other words, after the best locations in terms of wind resources, initial investment, and maintenance costs have been occupied, the remaining locations are more similar.

decide when and where to build a wind farm beyond simply relying on the wind resource of and accessibility to the site.

And indeed, previous studies focused on reducing developers risk uncertainty in the pre-construction phase of wind farms (see, for example, Bier & Lin (2013) and Zitrou et al. (2022)). The motivation behind this research was that wind farm revenues vary significantly over time because of the nature of the wind and the volatility of energy prices that stem from abrupt changes in demand. The so-called energy price spikes, swift and dramatic price changes, are particularly notorious in this market. Peura & Bunn (2021) developed a theoretical market model to investigate how intermittently available wind generation affects electricity prices in the presence of forward markets, which are widely used by power companies to hedge against revenue variability. These fluctuations underlie the high uncertainty of wind farm investments and explain why wind energy developers "employ teams of meteorologists to scour the world for the best places to put turbines."[4] Consequently, the wind resource potential of the sites has been carefully assessed prior to the investment decision (Lackner, 2008). Our aim is to move this literature a step further by introducing an additional factor, what we denote as the price-quantity correlation, and establishing the importance.

In particular, we argue that locations with higher price-quantity correlations (ρ) are, *ceteris paribus*, more valuable. In other words, a wind farm located on a site which exhibits production above its average quantity (q) when the electricity price (p) is also above its average level (ρ^+) is more valuable than an equivalent wind farm located on a site which does not exhibit such a relationship. In contrast, a wind farm located on a site which exhibits production below its average q when p is above average (ρ^-), is less valuable.

To this aim, we make use of a notable feature of the renewable energy output, when compared to the non-renewable energy output, namely that it has priority to enter the national electricity grids. Hence, as long as there is wind and energy demand, wind farms sell all their production. Consequently, the level of output wind farms produce does not relate to the energy market price in the usual demand-supply fashion which, in turn, intrinsically favors the site locations with higher price-quantity correlations (ρ).

Building on this argument, we then proceed in three steps. First, we empirically test whether there are such statistically significant correlation differences. Using a unique high frequency

[4]See https://www.economist.com/special-report/2008/06/21/trade-winds.

(half-hour) dataset of 1.4 million observations, to address the fact that aggregation masks the actual effect of correlations, covering 60 UK wind farms that span 2006-2019, we estimate the (ρ) of each wind farm and differences among their ρs, and find that such differences do indeed exist; and they are statistically significant. Second, we develop the necessary framework to measure empirically the impact of ρ on firm revenues and profitability through a monetary value representation of the excess return that a wind farm will generate in comparison to an equivalent wind farm in a different location with lower price-quantity correlation. Finally, we develop a real option model that shows the theoretical effect of ρ on the ex-ante wind farm value, the parameters of which we calibrate with the real world values to examine how the value of the wind farm company changes with ρ. This is also particularly important for wind farm developers at the evaluation and pre-construction phases since it is a readily available tool for comparison of candidate sites.

Overall, our results show that there are indeed persistent and statistically significant ρ differences across wind farms; and selecting a site location with higher ρ yields on average a *location price-quantity correlation premium per MWh* of 65.75 pence which, based on our sample average production of a wind farm, corresponds to £589,510 extra revenues per year or £17,685,300 for a 30-year wind farm lifetime - a result that is confirmed also with the real option model.

The contribution of our paper is fourfold. First, we introduce ρ as a key factor that affects the value of wind farms which, to the best of our knowledge, has not been considered yet in the existing literature - probably due to the tacit assumption of both renewable energy developers and policy makers that the stochastic nature of wind fluctuations and energy prices implies that even at the individual wind farm level ρ is zero on average and therefore it does not matter. Second, we enrich the renewable energy empirical applications of the monopsony market, which is overwhelmingly dominated by labor market applications, and demonstrate its direct relevance when using high frequency data for determining the economic value of individual wind farms and how misleading can it be with the use of low frequency data. Third, we propose a new method to empirically demonstrate, using high frequency wind farm data, how differences in ρ can be translated to monetary gains/losses - which reveals a substantial location price-quantity correlation premium. Finally, we introduce a valuation method to complement existing ones for the selection of the optimal location to build a wind farm - which adds to the literature on the renewable energy market sustainability and operation management, a broad literature that covers areas such as supply chains (e.g., Cachon, 2014), production technology choices (e.g. Islegen and Reichelstein, 2011), and government regulations cite[see e.g.,][]Kim (2015).

The remainder of the paper is structured as follows. Section 2 sets the theoretical framework underlying this work. Section 3 describes the dataset. Section 4 provides the methodology used to empirically estimate the price-quantity correlation and the associated empirical findings. Section 5 presents the empirical methodology used to convert the correlation differences into monetary gains or losses. Section 6 develops a theoretical model to evaluate wind energy investments. Lastly, Section 7 contains our concluding remarks.

2 Theoretical Framework

There are different models that can be applied to describe the situation in UKs electricity market. However, for our purposes, it suffices to simply make some modifications to the partial equilibrium model of Robinson (1933) repurposed for the electricity market. Figure 1 presents the archetypical monopsony against perfect competition diagram to graphically depict the main underlying ideas.

[Figure 1 here]

It is worth noting that in the UKs electricity market, power is bought from generators on a competitive wholesale market at each half-hour trading period; and electricity generators bid to contribute to the power grid. However, prices are set by a merit order system, where low-cost sources like renewables are chosen first, and expensive, flexible sources like gas are chosen last. But the price is set at the higher cost of gas generation due to its role in balancing supply and demand. Consequently, from the perspective of individual wind farms, the existing market structure can indeed be considered a monopsony.

With the above in mind, we can now assume that the electricity market in the UK is comprised of just one buyer, the state, which pays the same price for electricity to all producers of electricity, be they may renewable energy producers or otherwise. The absence of alternative buyers means that a firm must accept the price that the state is offering. And the state, makes use of this privilege as a tool to implement its energy policies.

Given that the UK also trades electricity with its neighbors, the slope of the electricity supply curve, which relates the electricity price paid (P) to the level of electricity production generated and supplied (Q) and is denoted as an increasing function $c(Q)$, is upward - although relatively inelastic. Interestingly, its constituent for the domestic renewable energy producers, such as windfarms, in the short run is perfectly inelastic because they always sell whatever they produce to the state and the only way to increase production is by building new sites of electricity generation, which can take place in the long run.

Total costs of electricity production are given by $c(Q)\cdot Q$. The homogeneity of electricity suggests that the revenue (R) of an electricity producer increases with Q almost proportionally, although there have been various incentive schemes over the years especially for renewable energy producers. The firm wants to choose Q to maximize profit, $\pi(Q)$, which is given by the difference of total revenues and costs, namely:

$$\pi(Q) = R(Q) - c(Q)\cdot Q \tag{1}$$

which suggests that the first order conditions with respect to Q yield:

$$MR = R'(Q) = c'(Q)\cdot Q + c(Q) = MC \tag{2}$$

where $R(Q)$ and $c(Q)$ indicate the first order derivatives of the revenues and cost functions, and MP and MC are the marginal revenue and marginal cost respectively of electricity production.

Interestingly, we can safely assume that the marginal cost of electricity production is, in general, higher than the existing electricity production cost $c(Q)$ (specifically, in our setup, exactly by the amount $c(Q)\cdot Q$), primarily because, despite the continuous technological advancements in power generation and irrespective the large upfront investments that are demanded, electricity producers cannot easily change the amount of electricity they produce. In the case of renewable energy firms this restriction is even more stringent their production is fully depended upon the whims of nature. Consequently, we place the MC curve above the electricity supply curve.

Using Figure 1, the maximum profit in a monopsonistic market is obtained at point A, the intersection of the MR and MC curves, indicating P_A price and Q_A level of energy production. This, however, means that an electricity producer cannot reach point B, the competitive market equilibrium, suggesting an overall deadweight loss equal to the area of the triangle ABC. Nevertheless, this market efficiency loss is widely considered necessary to ensure that the state can offer a certain level of satisfaction from electricity to its citizens through energy providers that are regulated to sell electricity within certain price ranges which explains why the electricity market is commonly viewed as nominally efficient.

3 The Data Sample

Our data sample comprises synchronous half-hourly electricity market prices and wind energy production of 60 UK wind farm sites, covering the period between 12 September 2006 and 10 March 2019. The initial overall data sample contains about 1.4 million observations, although these vary significantly across wind farms, depending on their age. For instance, for the youngest wind farm (named "Beatrice 2") we have 11,322 observations, whereas for the oldest (named"Edinbane") we have 282,672.[5]

The electricity prices were collected from the Market Index Price Data (MID) which is used in the calculation of the Reverse price for each settlement period and reflects the price of wholesale electricity in the short-term market. The electricity output data was collected via an API connection to the Elexon portal. This data has physical notifications of half-hourly generation for wind farms that participate in the Balancing Mechanism (BM), which is a tool used by the national grid as the System Operator to balance supply and demand in real time. The BM data provides the national grid with a planned schedule of supply for each half-hourly settlement period. When demand is expected to deviate from the schedule, the national grid via the balancing mechanism accepts a bid or offer to either increase or decrease generation to ensure that the energy system remains in equilibrium.

Table 1 depicts the characteristics of our sample including the names of each wind farm and its developer, and the wind farm's code, location (county, country, and GPS coordinates), technology used (on-shore or off-shore), installed capacity, and number of turbines. Regarding the wind farm codes (column 2), they represent wind farms some of which developed in phases, so the numbers 1,2,3,..., after the code represent each of those phases. The half-hourly electricity output is reported separately for each wind farm site because our analysis is performed per site.[6]

Overall, our sample is a comprehensive representation of the existing UK wind farms since it

[5]We refer to our data as initial sample because of the data-cleaning issues we had to address before using it.

[6]The Renewable Energy Planning Database (REPD) is a governmental organization that provides the Department of Energy and Climate Change with the data used to track renewable energy projects as they move through the planning system.

comprises both on-shore and off-shore projects in England, Scotland and Wales developed over the last 13 years. The installed capacity of our sample ranges from 20.5 MWh (Cour) to 598 MWh (Beatrice).

[Table 1 here]

4 Price-Quantity Correlation Estimation

The relationship between the energy market price and wind farms' quantity production on aggregate is a standard example of having a single homogeneous product under monopsony, given that prices are uniform. Therefore, under the typical assumptions governing such a market, it would be natural to expect that the relationship between the two would be negative (see, e.g., Boal & Ransom, 1997; Manning, 2006, 2010). That is, higher energy prices would be observed when there is scarcity of energy quantity produced and lower energy prices would be observed when there is abundance of energy in the market. The profitability of the respective average or representative producer, here the wind farm, in such idealized conditions would simply follow the prescriptions of the standard literature of a monopsony market with many suppliers (Manning, 2010).

However, even in this setup the average producer is not very representative of the actual wind farms. There are several reasons for this being the case, two of which are particularly important for our discussion in this paper. First, the location of a wind farm affects the energy production since there are sites where the wind blows more frequently and possibly faster. Indeed, although meteorological conditions are often very unpredictable, especially in the long-run, there are locations that have proved to be more endowed in terms of wind resources. Second, the site location can also determine the price-quantity correlation which in turn affects profitability. This latter characteristic becomes more and more prominent as the wind resource characteristics of the available sites where to build wind farms become more homogeneous. Therefore, an exact procedure for the location selection demands at the outset to determine whether, and if so, to what extent, the energy market price and the energy production of each potential wind farm are correlated. And the impact of aggregation can be assessed by repeating the exercise at different frequencies.

To this aim, and using a comprehensive high frequency (intraday) dataset, we examine the realized correlations of energy prices and the quantities produced by each wind farm at different levels of temporal aggregation. However, in order to do so in a way that allows us to draw statistically robust inference, we need to bear several stylized facts about our data characteristics into account: i) there is an almost unanimous agreement in the literature that prices of goods and services have a unit root; ii) in the UK, it is not uncommon the phenomenon of negative power pricing and indeed, there have been several instances in our sample when prices were zero or negative;[7] iii) excluding periods of testing, maintenance, and adverse weather conditions, wind farms production over 30-minute intervals have effectively a unit root; iv) it is not uncommon for wind farms to generate for substantial period of time zero quantities of energy (see Barndorff-Nielsen & Shephard, 2004).

To account for the above data characteristics, we use the first differences of the inverse hyperbolic sine transformation of the price and quantity series:

$$\alpha_{i,t} = \Delta \log[p_{i,t} + (p_{i,t}^2 + 1)^{1/2} = \log[p_{i,t} + (p_{i,t}^2 + 1)^{1/2}] - \log[p_{i,t} + (p_{i,t-1}^2 + 1)^{1/2}] \tag{3}$$

$$y_{i,t} = \Delta \log[q_{i,t} + (q_{i,t}^2 + 1)^{1/2} = \log[q_{i,t} + (q_{i,t}^2 + 1)^{1/2}] - \log[q_{i,t} + (q_{i,t-1}^2 + 1)^{1/2}] \tag{4}$$

where log indicates the natural logarithmic function and p_t and q_t are the corresponding price and quantity values respectively at time t, where $t = 1, 2, ..., T$, being T the length of our sample time horizon. This enables us to work effectively with the standard interpretation of log-difference since it would require very small values (in absolute value) of p_t and q_t to make the inverse hyperbolic sine transformation deviate from being approximately equal to $log(2p_t)$ and $log(2q_t)$ respectively. In the difference specification, the $log(2)$ component is cancelled out. Therefore, the two transformed variables can be interpreted in exactly the same way as a standard (log-)returns and growth series.

Furthermore, the realized correlation values we calculate for wind farm i at aggregate time t are given by $\rho_{i,t}$ as:

$$\rho_{i,t} = h_{\alpha y,i,t}(h_{\alpha,i,t}.h_{y,i,t})^{-1/2} \tag{5}$$

where $h_{\alpha y,i,t}$ is the realized covariance for firm i based on n half-hourly returns at each time t, where $t = 1, 2, ..., \tau$, and τ is the number of observations at each temporal aggregation level, is

[7] Such cases occur typically when strong gusts result in excessive amounts of wind on the power network all while the demand for energy is low and so are the energy prices.

given by:

$$h^{(n)}_{\alpha y,i} = \sqrt{\frac{1}{n-1}\sum_{k=1}^{n}\left[\left(\alpha_{i,k} - \frac{1}{n}\sum_{l=1}^{n}\alpha_{i,l}\right)\left(y_{i,k} - \frac{1}{n}\sum_{l=1}^{n}y_{i,l}\right)\right]} \tag{6}$$

and $h_{\alpha,i,t}$ and $h_{y,i,t}$ are the realized variances based on n half-hourly returns at each time t, where $t = 1, 2, ..., \tau$, and τ is the number of observations at each temporal aggregation level obtained through the following expression:

$$h^{(n)}_{s,i} = \sqrt{\frac{1}{n-1}\sum_{k=1}^{n}\left(s_{i,k} - \frac{1}{n}\sum_{l=1}^{n}s_{i,l})^2\right)} \tag{7}$$

where s is either r or y. Finally, it is worth noting that the temporal aggregation levels we examine are half-daily ($max(n) = 24$), daily ($max(n) = 48$), weekly ($max(n) = 3, 36$), monthly ($max(n) = 1, 440$), quarterly ($max(n) = 4, 320$) and annual ($max(n) = 17, 088$), whenever our data permits us.

Once we measure the correlations of the growth of energy produced by each individual wind farm and the growth of energy prices (what we denote here as the price-quantity correlations), we can demonstrate the presence of substantial and statistically significant correlations across wind farms and determine the impact of data aggregation on the correlation values (Section 4). By doing so, we highlight how misleading the adoption of high data aggregation (low frequency) is for determining the effect of the price-quantity correlation on wind farms value.

Then, we can move on to determine the location price-quantity correlation premium, i.e., how much extra revenues a particular wind farm would have achieved due to the price-quantity correlation should it have been built-up in a different location both empirically (Section 5) and using a real options model (Section 6).

Figure 2 shows the variation of the half-hourly price-quantity correlation coefficient across wind farms. At the top are the wind farms with the highest (positive) correlations, whereas at the bottom are the wind farms with the lowest (negative) correlations. As we can see, the correlations across wind farm varies substantially, from a maximum of 2.94% to a minimum of -1.57%. As argued above, there is economic value for a wind farm from having a higher correlation - *ceteris paribus*.

[Figure 2 here]

Figure 3 shows the variation of the price-quantity correlations but now controlling for the wind farm's age (i.e., number of half-hourly observations). On average, the older the wind farm the closer to zero is its correlation coefficient. However, this does not apply universally. Indeed, there are older wind farms with correlation that are further away from zero than younger wind farms. For instance, the two highlighted wind farms in the middle of the figure (with approximately 70,000 half-hourly observations) have correlations that are among the highest (in absolute values) in the sample.

These findings contradict, therefore, the conventional assumption that the price-quantity correlation of wind farms is zero and, inherently, not an important factor determining the value of a wind farm. In fact, they provide support for the exact opposite view according to which there might be wind farm sites with more favorable price-quantity correlation that may well lead to further economic gains.

[Figure 3 here]

Figure 4 shows the price-quantity correlations at different levels of aggregation. As we can see, lower data frequencies (higher level of aggregation) correspond to much lower correlations; likewise, higher data frequencies (lower level of aggregation) correspond to much higher correlations. This could explain why energy developers have typically assumed that the correlation is zero. Indeed, if we look at the annual frequency correlations (panel f), we see that all correlations appear to be close to zero. However, for higher frequencies, the correlations deviate from zero strikingly more; at the daily frequency (panel a) the correlations span almost the whole spectrum of the correlation range (-1,+1). Therefore, the use of low frequency data for determining of the correlation effect on the economic value of wind farms may well be misleading, and the adoption of high frequency data is not only important for the robustness of the analysis but vital.

[Figure 4 here]

5 Determining the Location Price-Quantity Correlation Premium

So far, we have established that there are economically and statistically significant differences in the correlations of the growth of energy produced by each individual wind farm and the growth of energy prices. In this section, we develop a method to translate these correlation differences in monetary gains/losses. In other words, we introduce a method that tells us how much extra revenues a particular wind farm would have achieved due to the price-quantity correlation should it have been built-up in a different location. This ***location price-quantity correlation premium*** (effectively, excess revenues from selecting a different location on its price-quantity correlation) can then guide us into assigning, within our sites sample, a monetary value to capture the impact of the price-quantity co-movements. This, in turn, will enable us to establish the importance of accounting for the price-quantity co-movements when selecting the location of a wind farm.

A critical challenge of determining a location price-quantity correlation premium formula stems from the fact that not each wind farm has the same built-in capacity as the rest. Moreover, each wind farm might be exhibiting different special circumstances, some of which might be attributed to the specific location while others might be completely idiosyncratic - such as the quality of the wind turbines, the maintenance protocols and other requirements, and so on. A conclusive formula would demand that these two issues are addressed.

To this aim, we have looked at all the possible pairs of wind farms and for the common sample of each pair, of i and j wind farms, we have calculated at each period t the following measure of location price-quantity correlation premium (ΔR) for the wind farm i, the wind farm with the larger price-quantity correlation:

$$\Delta R_{i,j,t} = (U_{i,t} - U_{j,t})R_{i,t} \tag{8}$$

where $U_{i,t}$ and $U_{j,t}$ are the utilization of the turbines of the i and j wind farms and $R_{i,t}$ the revenues generated by the i wind farm at time t. This formula suggests that the premium is proportional to the level of revenues of the i wind farm, which accounts for the size of the wind farm - hence, addressing to a large extent the first issue we have raised above. It also suggests that the premium is proportional to the difference in the utilization of the wind turbines of the two wind farms, which is what is desired. And, also as desired, this difference is maximized when the i wind farm utilizes its turbines the most, all while the j wind farm utilizes its turbines the least. Therefore, we are left to specify how to measure each individual utilization.

A first answer could be to assume that the utilization is the quantity of electricity produced at time t divided by the installed capacity of the respective wind farm as documented in each firms technical specifications. Then, we could rewrite our formula as:

$$\Delta R_{i,j,t} = (U_{i,t} - U_{j,t})R_{i,t} = \left(\frac{Q_{i,t}}{C_i} - \frac{Q_{j,t}}{C_j}\right) R_{i,t} \tag{9}$$

where $Q_{i,t}$ and $Q_{j,t}$ are the quantities produced at time t for the i and j wind farms respectively and C_i and C_j are the corresponding installed capacities. Note that the latter two are by default time invariant given that the capacities of each wind farm are regulated.

A more pragmatic answer would be to substitute the installed capacities with the actual maximum quantities, or some other appropriate quantile, that are captured in our sample. This would also serve as a convenient way to address, to a large extent, the aforementioned idiosyncratic circumstances issue that each wind farm might exhibit. In such case, the formula for LP-QCP would be:

$$\Delta R_{i,j,t} = \left(\frac{Q_{i,t}}{q_i} - \frac{Q_{j,t}}{q_j}\right) R_{i,t} \tag{10}$$

where q_i and q_j are the observed maximum quantities of firms i and j respectively - for robustness, we have also tried the 99% and 95% quantiles but our inference remains unaffected.

At this point it is worth introducing the revenues variable as the product of quantities produced and prices:

$$\Delta R_{i,j,t} = \left(\frac{Q_{i,t}}{q_i} - \frac{Q_{j,t}}{q_j}\right) Q_{i,t}P_t \tag{11}$$

where P_t is the wind farm-independent energy prices at time t.

Therefore, we can now rewrite the formula in per megawatt hour (MWh) units:

$$\frac{\Delta R_{i,j,t}}{Q_{i,t}} = \left(\frac{Q_{i,t}}{q_i} - \frac{Q_{j,t}}{q_j}\right) P_t = \Delta\bar{Q}_{i,j,t}P_t \tag{12}$$

which enables us to aggregate across the different wind farms. The second equation is there to make the notation more compact.

Under the natural assumption that the generated quantities of wind farms i and j are independent of one another, and also under the assumption that each of these quantities is independent of the energy prices, we can derive the conditional mean of the variable (location price-quantity correlation premium per megawatt hour) as being given by:

$$E\left(\frac{\Delta R_{i,j,t}}{Q_{i,t}}|\Im_t\right) = E\left(\Delta\bar{Q}_{i,j,t}\right)E(P_t|\Im_t) = \left[\frac{1}{q_i}E(Q_{i,t}|\Im_t) - \frac{1}{q_j}E(Q_{j,t}|\Im_t)\right]E(P_t|\Im_t) \tag{13}$$

where $\Im_t$ is the information set at time t, excluding t. If quantities and prices were not independent then we would have to also take into account the covariance between the two; and the expectation would change to:

$$E\left(\frac{\Delta R_{i,j,t}}{Q_{i,t}}|\Im_t\right) = E\left(\Delta\bar{Q}_{i,j,t}P_t|\Im_t\right) = E\left(\Delta\bar{Q}_{i,j,t}|\Im_t\right)E(P_t|\Im_t) + Cov(\Delta\bar{Q}_{i,j,t}, P_t|\Im_t) \tag{14}$$

where $Cov(.)$ denotes the conditional covariance. Rewriting this, in terms of correlation, yields:

$$E\left(\frac{\Delta R_{i,j,t}}{Q_{i,t}}|\Im_t\right) = E\left(\Delta\bar{Q}_{i,j,t}P_t|\Im_t\right)E(P_t|\Im_t) + 2\left[V(\Delta\bar{Q}_{i,j,t}P_t|\Im_t)V(P_t|\Im_t)\right]^{0.5}\rho(\Delta\bar{Q}_{i,t,j}P_t|\Im_t) \tag{15}$$

where $V(.)$ indicates the conditional variances and $\rho(.)$ the conditional correlation.

Consequently, if prices and quantities are uncorrelated, as suggested by the existing conventional wisdom, this expression becomes unconditionally:

$$E\left(\frac{\Delta R_{i,j}}{Q_i}\right) = \left[\frac{1}{q_i}E(Q_i) - \frac{1}{q_j}E(Q_j)\right]E(P) \tag{16}$$

which suggests that the LP-QCP per MWh would effectively be a positive (when $E(Q_i) > E(Q_j)$) or a negative (when $E(Q_i) < E(Q_j)$) portion of the average price level. Therefore, for non-zero prices, this premium is expected to be zero:

$$E\left(\frac{\Delta R_{i,j,t}}{Q_i}\right) = 0 \forall P \in \Re \rightarrow \frac{1}{q_i}E(Q_i) = \frac{1}{q_j}E(Q_j) \tag{17}$$

which is exactly the view that we challenge in this paper. In other words, by arguing that this premium may well be non-zero, we are effectively establishing that a higher price-quantity correlation of a wind farm is associated *ceteris paribus* with higher revenues.

Following the above method to express the impact of the correlation differences in monetary values (gains/losses), we find that selecting a site location with higher ρ (average correlation difference 0.525%[8]) yields on average a *location price-quantity correlation premium per MWh*

[8]If we assume that the relationship between excess revenues and correlation difference is linear, the premium

of 65.75 pence (median 37.81 pence) which, based on our sample average production of a wind farm, corresponds to £589,510 (£391,677) extra revenues per year or £17,685,300 (£11,750,310) for a 30-year wind farm lifetime.

6 The impact of Price-Quantity correlation on wind farm value

In this section, we develop a theoretical model relying on the real options theory. This model enables us to study the effect of the Price-Quantity correlation on the value of a wind farm. We follow the notation used in the previous sections.

6.1 The real options model

The real options theory (ROT) advocates that, before investing, energy developers have the option to invest. Such an option has value in the presence of uncertainty. Consequently, energy developers should invest not when the net present value (NPV) of the investment is positive but when the NPV is greater than the value of the option to invest. This is because when the investment is made the expected NPV from the investment is gained but the value of the option is lost (see McDonald & Siegel, 1986; Dixit & Pindyck, 1994).

Let us, therefore, assume that the electricity market price (P) and the energy production of wind farm i (Q_i) are both uncertain and follow two independent and possibly correlated geometric Brownian motion (GBM) processes:

$$dP_t = \alpha_t P_t dt + \sigma_P P_t dW_1(t), \qquad P_0 = P \tag{18}$$

$$dQ_{i,t} = y_{i,t} Q_{i,t} dt + \sigma_{Q_i} Q_{i,t} dW_{2,i}(t), \qquad Q_{i,0} = Q_i \tag{19}$$

where the correlation between the two GBM processes equals $\mathrm{E}[dW_1(t)dW_{2,i}(t)] = \rho_i dt$, α and y_i are the drifts of P and Q_i under a risk-neutral measure, σ_P and σ_{Q_i} are the volatilities of P and Q_i, and dW_1 and dW_2 are the increments of the Wiener processes for P and Q_i respectively.

Using Ito's Lemma (see, for instance, Dixit & Pindyck, 1994, Chapter 3), we conclude that the evolution over time of the value of the option to invest in a wind farm, $f(P, Q_i)$, is defined

per MWh is 125.25 pence per 1 percentage point difference in the correlation by the following partial differential equation (PDE):

$$\frac{1}{2}\frac{\partial^2 f(P,Q_i)}{\partial P^2}\sigma_P^2 P^2 + \frac{1}{2}\frac{\partial^2 f(P,Q_i)}{\partial Q_i^2}\sigma_{Q_i}^2 Q_i^2 + \frac{\partial^2 f(P,Q_i)}{\partial P \partial Q_i} P Q_i \sigma_P \sigma_{Q_i}\rho_i + \frac{\partial f(P,Q_i)}{\partial P}\alpha P + \frac{\partial f(P,Q_i)}{\partial Q_i} y_i Q_i = r.f(P,Q_i) \tag{20}$$

where r is the risk-free rate.

This set-up allows us to model the option to invest as a two-factor American perpetual option that is linearly homogeneous in the underlying stochastic variables P and Q_i (that is, $f(\lambda P, \lambda Q_i) = \lambda f(P, Q_i)$). Therefore, we can reduce the dimensionality of this PDE (20) to a one-factor ordinary differential equation (ODE) using $R_i = PQ_i$, where R_i stands for revenue, for which we can now find a closed-form solution:[9]

$$\frac{1}{2}R_i^2\sigma_s^2\frac{\partial^2 f(R_i)}{\partial R_i^2} + R_i(\sigma_p\sigma_q\rho_i + \alpha + y_i)\frac{\partial f(R_i)}{\partial R_i} - \theta f(R_i) = 0 \tag{21}$$

The general solution for (21) is:

$$f(R_i) = A_{1,i}R_i^{\beta_{1,i}} + A_{2,i}R_i^{\beta_{2,i}} \tag{22}$$

where $A_{1,i}$ and $A_{2,i}$ are arbitrary constants to be determined and $\beta_{1,i}$ ($\beta_{2,i}$) is the positive (negative) root of the following characteristic quadratic equation function of the ODE (21):

$$0.5\sigma_{s_i}^2\beta_i(\beta_i - 1) + (\rho_i\sigma_p\sigma_{q_i} + \alpha + y_i)\beta_i - \theta = 0 \tag{23}$$

which are given by

$$\beta_{1,i} = \frac{0.5\sigma_{S_i}^2 - (\sigma_p\sigma_{q_i}\rho_i + \alpha + y_i) + \sqrt{(-0.5\sigma_{S_i}^2 + \sigma_p\sigma_{q_i}\rho_i + \alpha + y_i)^2 + 2\theta\sigma_{S_i}^2}}{\sigma_{S_i}^2} > 1 \tag{24}$$

and

$$\beta_{2,i} = \frac{0.5\sigma_{S_i}^2 - (\sigma_p\sigma_{q_i}\rho_i + \alpha + y_i) - \sqrt{(-0.5\sigma_{S_i}^2 + \sigma_p\sigma_{q_i}\rho_i + \alpha + y_i)^2 + 2\theta\sigma_{S_i}^2}}{\sigma_{S_i}^2} < 0 \tag{25}$$

[9] Examples of the usage of this dimension reduction technique can be seen in McDonald & Siegel (1986), Paxson & Pinto (2005), Malchow-Møller & Thorsen (2005), and Azevedo & Paxson (2018).

where

$$\sigma_{S_i}^2 = \sigma_P^2 + \sigma_{Q_i}^2 + 2\sigma_P \sigma_{Q_i} \rho_i \tag{26}$$

Since $f(R_i)$ increases with R_i, we have to set in (22) $A_2 = 0$ because $\beta_{2,i} < 0$. Therefore, the wind farm value function is given by:

$$F(R_i) = \begin{cases} A_{1,i} R_i^{\beta_{1,i}} & \text{if } R_i < R_i^* \\ \dfrac{R_i}{r - \alpha - y_i} - I & \text{if } R_i \geq R_i^* \end{cases} \tag{27}$$

where I is the investment cost, α and y_i are the drifts of price and quantity of the option's underlying variables, and R_i^* is the optimal revenue investment threshold. In other words, the first row represents the value of the wind farm before the investment is made (the real option value) and the second row represents the value of the wind farm after the investment has been made (the NPV).

There are two unknown variables in (27), namely the real option coefficient $A_{1,i}$ and the investment threshold R_i^*. To obtain the solutions for these unknown variableswe can make use of the so-called "value-matching" and the "smooth-pasting" conditions (see Dixit & Pindyck, 1994), which are given by:

$$A_{1,i} R_i^{*\beta_{1,i}} = \frac{R_i^*}{r - \alpha - y_i} - I \tag{28}$$

$$\beta_1 A_{1,i} R_i^{*\beta_{1,i}-1} = \frac{1}{r - \alpha - y_i} \tag{29}$$

The "value-matching" condition (28) ensures that the investment is made when the option value (the term on the left-hand side) equals the expected NPV (the terms on the right-hand side). The "smooth-pasting" condition (29) is simply the first derivative of (28) with respect to R_i^* and ensures that when the investment threshold is reached the wind farm's value is maximized. Solving the above equation system for $A_{1,i}$ and R_i^* yields:

$$A_{1,i} = \frac{R_i^{*1-\beta_{1,i}}}{(r - \alpha - y_i)\beta_{1,i}} \tag{30}$$

$$R_i^* = \frac{\beta_{1,i}(r - \alpha - y_i) I}{\beta_{1,i} - 1} \tag{31}$$

At this point the value function (27) is fully characterized and its value depends on the value of $\beta_{1,i}$ which in turns depends on ρ_i. Therefore, we can now calibrate the model parameters, based on our data, to measure the impact of ρ_i on the value of each wind farm.

It is worth noting that our work is based on the selection of the optimal location to build a wind farm. Therefore, our focus is on the option to wait ($A_{1,i} {R_i^*}^{\beta_{1,i}}$), which is held by energy developers before investing, and not on the optimal time to invest (R_i^*), which is useful only after choosing the wind farm location.

6.2 Calibrating the model parameters

Given the wind farm's value function we derived in (27), we can now undertake a sensitivity analysis on the effect on value $f(R_i)$ of the price-quantity correlation ρ_i (the correlation between the energy market price and the wind farm's energy production). Table 2 shows the model inputs for the base case, based on our data.

[Table 2 here]

We can see that for our data the base case refers to an average energy price of £44.62 per MW with energy production of £102.35 per MWh, which corresponds to about £40 million revenue per annum. This means that about £430 million average investment cost[10] are paid back in just above a decade.

Figure 5 shows the effect of ρ on the *ex-ante* wind farm value (i.e., the real option value to wait, ROV), for three different levels of uncertainty for price and quantity (σ_p and σ_q respectively). We can see that ROV increases with ρ, σ_p, and σ_q. In other words, the option to wait becomes more valuable when the price or quantity uncertainty increases; but the same is true for the price-quantity correlation. This means that locations with higher ρ make wind farms more valuable. In contrast, locations with lower ρ makes wind farms less valuable.

[Figure 5 here]

[10]The exact average investment cost for our sample is £432,554,484 which was computed as follows: according to 2020 data from the International Energy Arena Agency (IRENA), see https://www.irena.org/Energy-Transition/Technology/Wind-energy, the global weighted-average total installed cost is USD 3,185/kW for offshore and USD 1,355/kW for onshore; therefore, using the installed capacity of each wind farm (see Table 1), we can determine the average investment cost. To convert the investment cost to UK pounds, we used 1.2 as exchange rate. Other costs, such as maintenance and levelized cost of stored energy (LCOE), account for less than 1% of the overall cost of the project and, therefore, they can be safely ignored.

Table 3 Panel A shows the effect of ρ on the wind farm's value; it also attests that the value increases with ρ. Panel B shows the gain/loss a wind farm would face had it been located on site i instead of on site j - assuming that the wind farms are otherwise symmetric.[11] For instance, if location i has a ρ of 3% and location j has a ρ of -2%, the gain for the wind farm located on site i (instead of on site j) is about £49,058,919 (see value in bolt); likewise, if location i has a ρ of 1% and location j has a ρ of 0%, the gain for the wind farm located on site i, instead of on site j, is about £9,776,982 - see value in bolt.

[Table 3 here]

Figure 6 provides further details on the effect on the extra value that accrues to wind farm i due to a One, Two, or Three percentage points difference between the correlation of wind farm i and the correlation of wind farm j. It shows that the extra value that accrues to wind farm i (the wind farm with the higher correlation) increases with both the percentage point correlation difference between the two wind farms and with the correlations of the two wind farms. For instance, a two percentage points difference in the correlation leads to about £15.6 million extra value to wind farm i if it has a correlation of -4% and wind farm j has a correlation of -2%, but to almost £21.5 million extra value if wind farm i has a correlation of 3% and wind farm j has a correlation of 1%.

[Figure 6 here]

7 Conclusions

This study relies on a half-hourly data sample comprising over 1.4 million observations with information on 60 UK wind farms covering a period between 2006 and 2019. We show that there are statistically significant differences between the electricity market price (Price) and the energy produced (Quantity) by individual wind farms and that those differences favor the revenue of the wind farms located on sites with higher correlations. To the best of our knowledge, we are the first to highlight the importance of accounting for the above Price-Quantity correlation when

[11] Notice that, if the ρ of two locations, i and j, is the same, energy developers are indifferent between the two locations; this is the reason why the values in the diagonal of the matrix are all zeros - they represent cases where the ρ of the two competing locations (i and j) are the same .

choosing a location for a wind farm investment, which can be deemed as a unique contribution to the literature.

Furthermore, we present a method to empirically compute the extra revenue that accrues to the wind farms located on sites with higher correlations, which we name *location Price-Quantity correlation premium* (LP-QCP), and develop a theoretical model to evaluate wind energy investments considering both Price and Quantity uncertainty and the aforementioned correlation. This latter model enables us to determine the gain (loss) associated with the locations with higher (lower) correlations and the optimal revenue threshold which, if reached, triggers the investment.

Both our theoretical and empirical findings attest that the value of a wind farm increases with the Price-Quantity correlation; for our data sample, on average, the LP-QCP represents an increase in the return on investment of about 4%. Therefore, when choosing a wind farm location, energy developers should consider the so far neglected Price-Quantity correlation and select first the locations with higher correlations; this behavior is particularly relevant when the prospective locations under consideration are very similar in terms of wind resources, initial investment, and maintenance costs.

We expect that the LP-QCP factor will become even more relevant in the future, as a key determinant of a wind farm location, because as the wind energy capacity expands, the characteristics of the remaining available locations will be more similar in terms of the other characteristics that currently determine the choice of a location. We note that, as of March 2022, there are about 1,000 wind farm locations being studied in the UK, for which this work is directly applicable.

As a further research, it would be interesting to extend this study to a larger sample of UK wind farms; such a study may identify even more extreme Price-Quantity correlation differences across wind farms than those reported in this paper. The replication of this study in other countries is also a valuable study, since it could possibly show the existence of different patterns of correlation differences across countries that might be relate to the adoption of different investment incentives policies to promote renewable energy.

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Tables and Figures

Figure 1: The Monopsony Market for Electricity

This figure illustrates the archetypical monopsony against perfect competition. D and S indicate the demand and supply curves while MC and MR the marginal cost and revenue curves for electricity production.

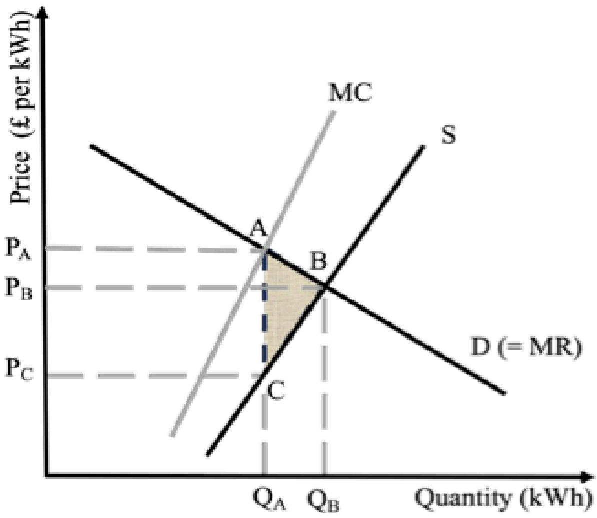


Figure 2: The Price-Quantity Correlation per Wind Farm

This figure presents the overall (aggregate) price-quantity correlation coefficient for each wind farm. Notably, the wind farm BEINW has the highest correlation (+2.94%) and the wind farm ABRBO the lowest (-1.57%). It is worth noting the quite substantial pair-wise differences.

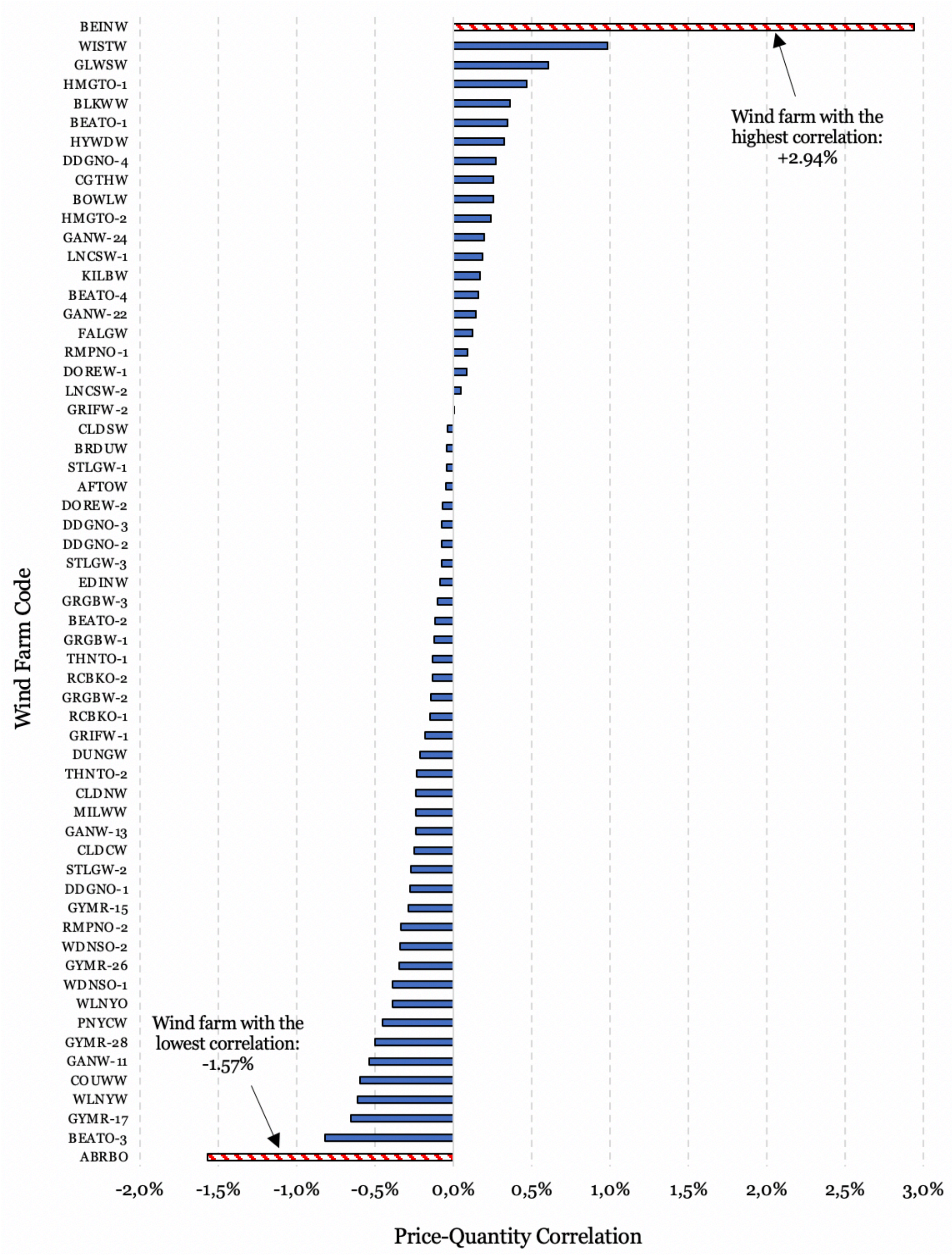


Figure 3: Effect of a Wind Farm's Age on the Price-Quantity Correlation

This figure depicts the relationship between the average correlation between the energy market price and each of the wind farm's energy production considering the age of the wind farm measured in half-hourly time period (one year is about 17,520 half-hourly periods). The red points at the bottom of the graph depict the wind farms with the highest (right-hand side) and the lowest (left-hand side) correlations, which are statistically significant at 10% level; the yellow points in the middle of the graph depict the correlation of two wind farms with similar ages and relatively old (above 70,000 half-hourly periods, i.e. about 8 years old).

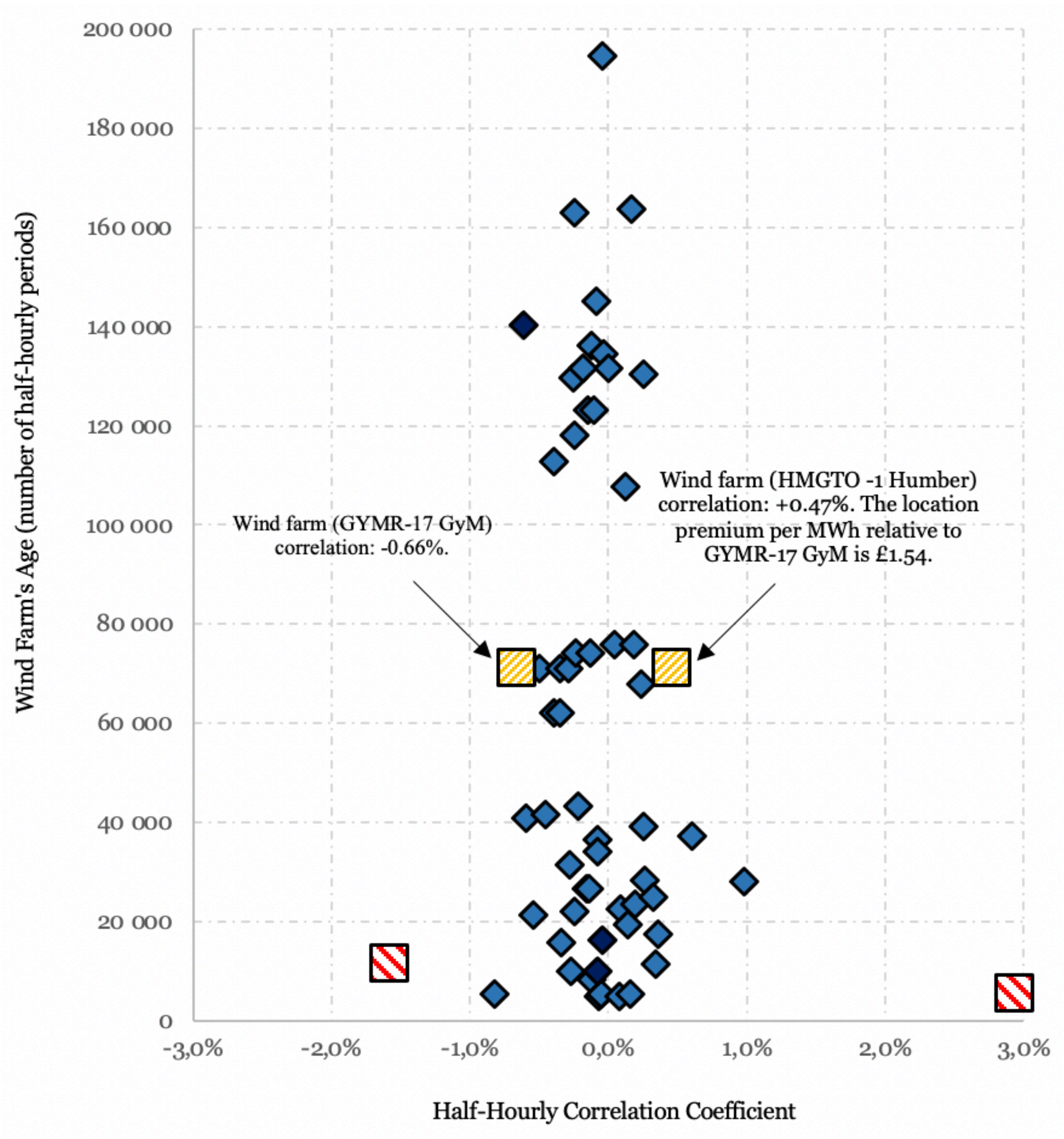


Figure 4: Evolution over Time of the Price-Quantity Correlation

This figure provides information about the evolution of the (half-daily, daily, weekly, monthly, quarterly, and annually) price-quantity correlation coefficient mean of our sample wind farms. Figures (a), (b), (c), (d), (e), and (f) refer to half-daily, daily, weekly, monthly, quarterly, and annually data, respectively.

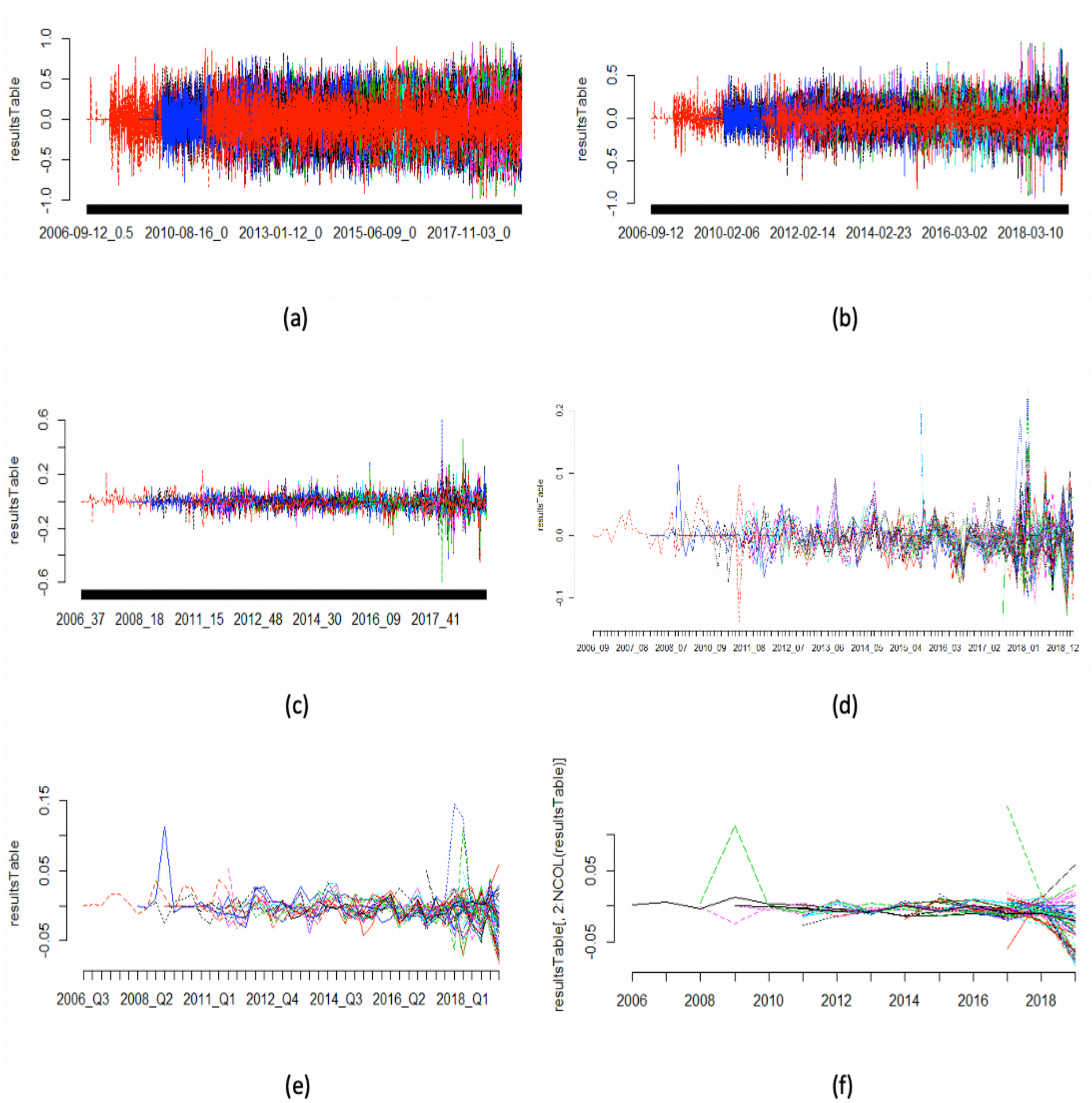
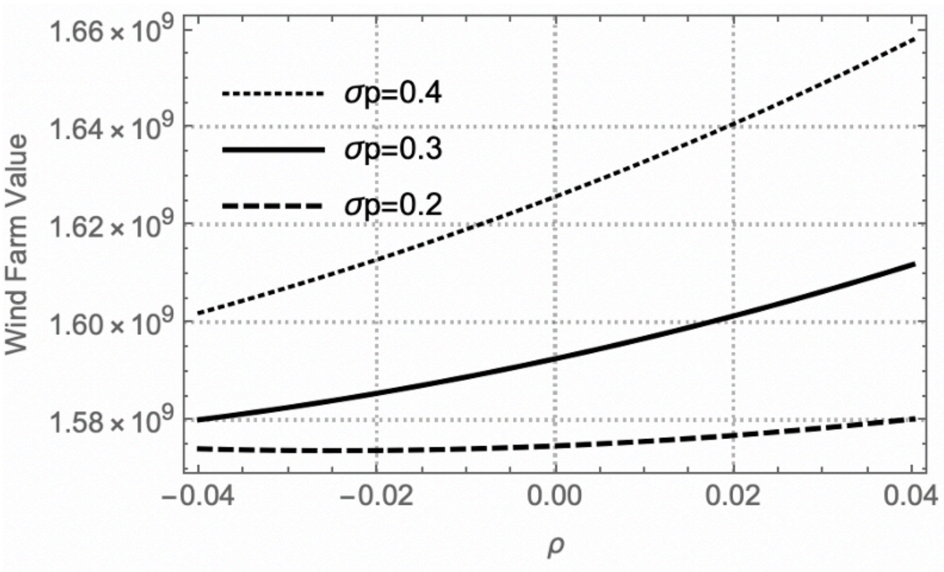
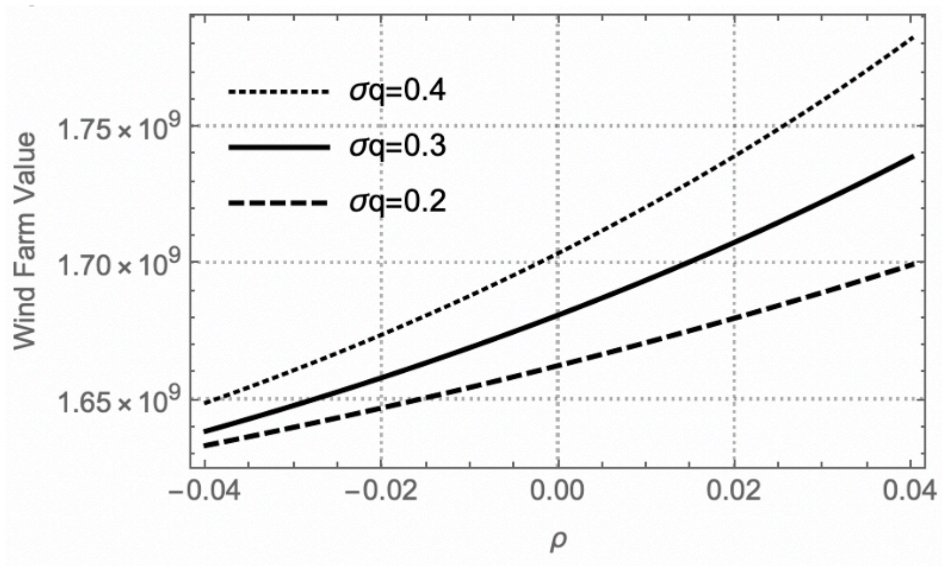


Figure 5: Effect of Uncertainty and Price-Quantity Correlation on a Wind Farm's Value

Figures (a) and (b) show the effect of Price-Quantity correlation (ρ) on a wind farm's value for different levels of Price and Quantity uncertainty (σ_p and σ_q respectively). In the Y-axis is the wind farm value, given in the British pound sterling (£), whereas in the X-axis is the Price-Quantity correlation (ρ).



(a)



(b)

Figure 6: The LP-QCP of Wind Farm i when compared to Wind Farm j

This figure shows that the effect of a One, Two, or Three percentages point correlation difference between wind farm i and wind farm j on the *location Price-Quantity correlation premium* (LP-QCP) of wind farm i, which has a higher correlation. On the X-axis is the correlation of wind farm j, which ranges from -4% to 3%, whereas in Y-axis is the extra value the wind farm i gets compared to wind farm j (*ceteris paribus*) if its correlation is One, Two, or Three percentage points higher. Specifically, the curve at the bottom shows the extra value of wind farm i compared to wind farm j for when the correlation of wind farm i is One percentage point higher than that of wind farm j (the first dot on the left-hand side represents the case where the correlation of wind farm j is -4% and the correlation of wind farm i is -3%, whereas the last dot on the right-hand side represent the case where the correlation of wind farm j is 3% and the correlation of wind farm i is 4%); the two curves above the one at the bottom of the graph obey to the same logic but represent scenarios where the correlation difference between the wind farms i and j are of Two and Three percentage points respectively.

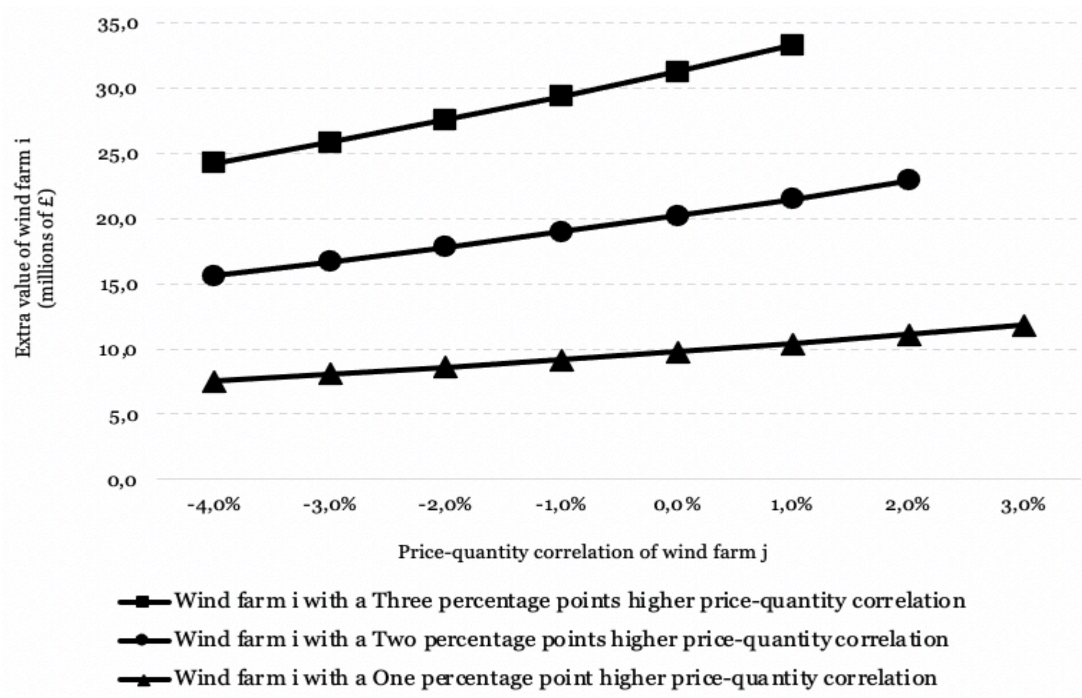


Table 1: Wind Farms' Characterization

This table presents the main characteristics of the wind farms in our sample. Specifically, column 1 shows the name of the wind farm; column 2, the code by which the wind farm is identified; columns 3, 4 and 5, the name of the developer, the county and country in which the wind farm was built, respectively; columns 6 and 7, the X and Y GpS co-ordinates; column 8, the type of wind turbine technology that is used; and columns 9 and 10, the MWh capacity and the number of turbines of each wind farm. Notice that there are wind farms that comprise of more than one site, for instance, Biatrice (row 5) has four sites (in column 2 we can see "1, 2, 3, and 4" to disclosure just this information), Clyde (row 10) has three sites (T CLDCW 1, T CLDNW, and T CLDSW), Dudgeon (row 12) has four sites (T DDGNO 1, 2, 3, and 4), Dorenell (row 13) has two sites (T DOREW 1, and 2), Galloper (row 17) has four sites (T GANW 11, 13, 22, and 24), GyM (row 21) has two sites (T GYMR 15, 17, 26, and 28), Humber (row 22) has two sites (T HMGTO 1, and 2), Lincs (row 24) has two sites (T LNCSW 1, and 2), Race Bank (row 27) has two sites (T LNCSW 1, and 2), Stronelairg (row 29) has three sites (T STLGW 1,2, and 3), Thanet (row 30) has two sites (T THNTO 1, and 2), and West of Duddon Sands (row 31) has two sites (T WDNSO 1, and 2). In total, this leads to 60 wind farms if we consider the wind farms development stages as an independent wind farm.

Wind Farm (1)	Code (2)	Developer (3)	County (4)	Country (5)	X-Cordi (6)	Y-Cordi (7)	Technology (8)	MWh (9)	Turbines (10)
Braes of Doune	E HYWDW 1	Braes of Doune Windfarm	Central	Scotland	272590	710500	Onshore	72	36
Hywind Generator	E HYWDW 1	Statoil	Offshore	Scotland	433500	846500	Offshore	30	5
Abrbo	T ABRBO 1	Peel Energy	Offshore	Scotland	395693	806148	Offshore	93.2	11
Afton	T AFTOW 1	InfraRed Capital partners/E.ON	Strathclyde	Scotland	262100	604100	Onshore	50	25
Beatrice	T BEATO 1,2,3,4	Fred Olsen Renewables	Offshore	Scotland	347955	929690	Offshore	598	86
Beinneun	T BEINW 1	Beinneun Wind Farm	Highland	Scotland	220442	804419	Onshore	85	25
Blackcraig	T BLKWW 1	Blackcraig Wind Farm	Dumfries & Galloway	Scotland	270500	582500	Onshore	53	23
Barrow	T BOWLW 1	Infinite Renewables	Offshore	England	314978	455827	Offshore	90	30
Corriegarth	T CGTHW 1	Corriegarth Wind Energy	Highland	Scotland	257500	813500	Onshore	69.5	23
Clyde	T CLDCW 1,CLDNW,CLDSW	SSE/Greencoat UK Wind	Strathclyde	Scotland	302500	617500	Onshore	522.2	206
Cour	T COUWW 1	Cour Wind farm (Scotland)	Strathclyde	Scotland	181005	648528	Onshore	20.5	10
Dudgeon	T DDGNO 1,2,3,4	Velocita/Forsa Energy	Offshore	England	575000	361000	Offshore	402	67
Dorenell	T DOREW 1,2	Dorenell Windfarm	Grampian	Scotland	332000	829500	Onshore	351.9	112
Dunmaglass	T DUNGW 1	Dunmaglass Wind Farm	Highland	Scotland	264000	820120	Onshore	94	33
Edinbane	T EDINW 1	Vattenfall Wind power	Highland	Scotland	134353	850769	Onshore	41.4	18
Fallago Rig	T FALGW 1	Fallago Rig Wind Farm	Borders	Scotland	357000	660000	Onshore	144	48
Galloper	T GANW 11,13,22,24	Cardinghill Renewables	Offshore	England	678139	227875	Offshore	353	56
Galawhistle	T GLWSW 1	Galawhistle Wind Farm	Strathclyde	Scotland	275440	629090	Onshore	66	22
Greater Gabbard	T GRGBW 1,2,3	Innogy	Offshore	England	670237	231640	Offshore	504	140
Griffin	T GRIFW 1,2	Griffin Wind Farm	Tayside	Scotland	293600	744600	Onshore	156	52
GyM	T GYMR 15,17,26,28	Cenin Renewables	Offshore	Wales	292082	396482	Offshore	576	160
Humber	T HMGTO 1,2	E.ON	Offshore	England	566400	390760	Offshore	219	73
Kilbw	T KILBW 1	Kilbraur Wind Energy	Highland	Scotland	278550	907550	Onshore	47.5	19
Lincs	T LNCSW 1,2	Mainstream Renewable power	Offshore	England	567020	368144	Offshore	270	75
Milww	T MILWW 1	Millennium Wind Energy	Highland	Scotland	225679	810840	Onshore	40	16
pen y Cymoedd Battery	T pNYCW 1	Vattenfall Wind power	Neath port Talbot	Wales	282793	196557	Onshore	228	76
Race Bank	T RCBKO 1,2	EnergieKontor	Offshore	England	528790	83836	Offshore	573	91
Rampion	T RMpNO 1	EnergieKontor	Offshore	England	528790	83836	Offshore	400	116
Stronelairg	T STLGW 1,2,3	Scottish & Southern Energy	Highland	Scotland	247166	806833	Onshore	228	66
Thanet	T THNTO 1,2	Thanet Offshore Wind	Offshore	England	649878	175192	Offshore	340	34
West of Duddon Sands	T WDNSO 1,2	EnergieKontor	Offshore	England	304230	455334	Offshore	389	108
Brockloch Rig	T WISTW 2	Brockloch Rig Wind Farm	Dumfries & Galloway	Scotland	257695	600320	Onshore	67.5	25
Walney	T WLNYW 1,2	Muirhall Energy	Offshore	England	300833	461449	Offshore	367.2	102

Table 2: Base Case Inputs

This table displays the estimated model parameters for the base case, relying on our data sample, where P is the energy market price per MW in £, Q is the energy production in MW per hour, R is the revenue in pounds per hour, α is the energy price growth rate, y is the growth rate of the energy production, σ_P is the price uncertainty, σ_y is the quantity uncertainty, and I is the investment cost. Unless explicitly stated, otherwise all model inputs are annualized.

Variable Description	Notation	Mean value
Energy price (£ per MWh)	P	44.62
Energy production (MW per hour)	Q	102.35
Revenue (£ per hour)	R	4,567.10
Revenue (£ per annum)	R	40,005,667.32
Price growth rate (drift of the GBM process for P)	α	0.0200
Quantity growth rate (drift of the GBM process for Q)	y	0.0000618
Price growth volatility	σ_P	0.50837
Quantity growth volatility	σ_Q	0.23019
Risk-free interest rate	r	0.04
Price-Quantity correlation	ρ	0.00
Investment cost (£)	I	432,554,484.65

Table 3: Effect of Price-Quantity Correlation on a Wind Farm's Value

All value are given in the British pound sterling (£). In Panel A, column 2 shows the wind farm's value (V) for different ρ, varying from -0.04 to 0.04. Panel B shows the wind farm's value difference (ΔV) considering different pairs of locations (i and j) each of which with a different ρ. Specifically, ΔV is defined as the V of location i minus the V of location j. For instance, if the ρ of location i is -0.03 and the ρ of location j is -0.04, ΔV is 7,545,991 in favor of wind farm i, *ceteris paribus* - see column 2, the value is in bolt; if the ρ of location i is 0.04 and the ρ of location j is -0.04, ΔV is 76,475,986 in favor wind farm i (see column 2, see value in bolt); if the two locations exhibit the same ρ, ΔV is nil (see the "zeros" in the diagonal of the matrix). The most extreme ρ difference considered is for when the ρ of location i is 0.04 and the ρ of location j is -0.04 and *vice-versa*, which lead to a ΔV of 76,475,986 and -76,475,986, respectively - see values in italic in columns 2 and 10. This matrix enables us to compute the wind farms' value differences due to the difference in the correlation of two sites that are under consideration - these two wind farms are assumed to be symmetric regarding all the other variables that affect the investment value. In this analysis, we use the inputs show in Table 2 as the base case.

Panel A: V as function of the correlation

ρ	V
-0.04	1,634,305,947
-0.03	1,641,851,938
-0.02	1,649,918,199
-0.01	1,658,527,370
0.00	1,667,705,465
0.01	1,677,482,447
0.02	1,687,892,934
0.03	1,698,977,118
0.04	1,710,781,933

Panel B: V difference (ΔV) for different pairs of (i and j) correlations

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\rho_{i/j}$	*-0.04*	*-0.03*	*-0.02*	*-0.01*	*0.00*	*0.01*	*0.02*	*0.03*	*0.04*
-0.04	0.00	-7,545,991	-15,612,252	-24,221,423	-33,399,518	-43,176,500	-53,586,987	-64,671,171	*-76,475,986*
-0.03	**7,545,991**	0.00	-8,066,261	-16,675,432	-25,853,527	-35,630,509	-46,040,996	-57,125,180	-68,929,995
-0.02	15,612,252	8,066,261	0.00	-8,609,171	-17,787,266	-27,564,248	-37,974,735	-49,449,748	-60,863,734
-0.01	24,221,423	16,675,432	8,609,171	0.00	-9,178,095	-18,955,077	-29,365,564	-40,449,748	-52,254,563
0.00	33,399,518	25,853,527	17,787,266	9,178,095	0.00	-9,776,982	-20,187,469	-31,271,653	-43,076,468
0.01	43,176,500	35,630,509	27,564,248	18,955,077	**9,776,982**	0.00	-10,410,487	-21,494,671	-33,299,486
0.02	53,586,987	46,040,996	37,974,735	29,365,564	20,187,469	10,410,487	0.00	-11,084,184	-22,888,999
0.03	64,671,171	57,125,180	**49,058,919**	40,449,748	31,271,653	21,494,671	11,084,184	0.00	-11,804,815
0.04	*76,475,986*	68,929,995	60,863,734	52,254,563	52,254,563	33,299,486	22,888,999	11,804,815	0.00