

Market behaviour with large amounts of intermittent generation

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Abstract

This paper evaluates the impact of intermittent wind generation on hourly equilibrium prices and output, using data on expected wind generation capacity and demand for 2020. Hourly wind data for the period 1994-2005 are used to obtain wind output generation profiles for thirty regions (onshore and offshore) across Great Britain. Matching the wind profiles for each month to the actual hourly demand (scaled to possible 2020 values), we find that the volatility of prices will increase, and that there is significant year-to-year variation in generators' profits. In the presence of significant market power (the equivalent of two symmetric firms owning fossil-fuelled capacity, rather than six), the level of prices more than doubled, and their volatility increased. Our results lend support to the theoretical findings of Twomey and Neuhoff (2005), showing that the impact of market power should be expected to raise revenues less for wind than for thermal generators.

JEL Codes: D43, L13, L94, Q41, Q42

Keywords: Electricity markets, Intermittent Output, Imperfect Competition, Wind generation, Generation Mix.

1. Introduction

If the UK is to meet its targets for renewable electricity generation, a very large amount of wind power capacity (onshore and offshore) will have to be installed. It is well known that wind generation can be intermittent and unpredictable, and that this can pose problems for the industry. Put simply, if there is little wind when the demand for power is high, there is a significant risk that a system with a high penetration of wind capacity will have a shortage of power, unless that system carries a large amount of reserve plant, and accepts the costs entailed in doing so. The recent

* This research is funded by the Engineering and Physical Sciences Research Council and our industrial partners, via the Supergen Flexnet Consortium, Grant Number EP/E04011X/1. We would like to thank participants at the workshop on wind power and market design, held at Univesité Paris Sud in June 2008, and at the Toulouse Conference on the Economics of Energy Markets, June 2008, for helpful comments. The views expressed are ours alone.

assessment by the UK Energy Research Centre (Gross et al, 2006) studies these costs, and shows that they should be acceptable for the UK, at least up to penetration levels of around 20% of intermittent generation. This assessment was made from a technical point of view, however, and while it looked at the impact on the costs of the electricity system, it did not study the impact on market prices. That is the purpose of this paper.

Our aim is to predict the amount of price and revenue volatility that could arise from variable wind speeds in 2020. This is the year by which the EU's 20% renewable energy target is to be met. In the UK's case, the target is likely to require around a third of electricity to come from renewable sources, and the majority of this would be from wind power. We will present frequency distributions for short-term hourly energy prices in each month, of the kind that a standard real-time electricity market would produce.¹ We will also present distributions of the annual revenues received by wind stations in different locations, to see whether the volatility of wind speeds is a significant risk to the generators.

We use hourly data from the Meteorological Office, covering 1994 to 2005, which give wind speeds at a variety of locations around Great Britain. We transform this wind data to give the level of output from a typical turbine at each location, using standard relationships between wind speed and power. We have used data from the British Wind Energy Association, giving the locations of existing stations and those at various stages of the planning and construction process, to guide our estimates of where to site wind capacity.

We have used the Supergen Futurenet scenarios for 2020 (Elders et al, 2008) for predictions of the amount of thermal plant in Great Britain, and the overall level of demand. These scenarios were constructed to show how the system might evolve over the next few years, and are themselves intermediate stages towards a set of scenarios for 2050. The focus of the scenarios is on the impact on electricity networks, and in future work, we will be considering the network implications of our output patterns. We take the costs of each type of generator from the DTI Energy Review of 2006, using fuel prices from their Central Case favouring coal (which implies medium-high gas prices).

While the overall level of demand is taken from the Supergen Futurenet scenarios, the demand patterns within the year need consideration, since the weather (and hence wind speeds) is intimately linked with demand on a day-to-day basis. Our approach is to match wind patterns and demand patterns from individual days, while scaling demand from its original year to match that predicted in 2020. We are conscious that this does not allow for the impact of climate change on demand, and hope that this will be limited in the period to 2020.

We use a numerical supply function equilibrium model to calculate the market outcomes on an hourly basis. The model allows for imperfect competition between generating firms, and is a better representation of this than the Cournot models that are the most common alternative. In particular, if there are a reasonable number of firms, off-peak prices will be very close to the companies' marginal costs, while peak prices can still rise above marginal fuel and O&M costs, as seen in real electricity markets. The particular version of the model used is based upon that of Green (2008a).

¹ Great Britain does not actually have such a market at present, relying on bilateral trading between generators and the system operator, but creating one would be an appropriate response to the challenges of integrating large amounts of renewable generation (Green, 2008b)

We calculate the equilibrium market price patterns on the basis of the actual wind profiles and the historic demand levels, scaled up to 2020 levels, for each day between 1994 and 2005. This gives us between 339 and 372 price profiles per month (depending on the number of days in the month), which is sufficient to show a significant amount of volatility. We also consider annual revenue risks, which are based on the actual annual wind profiles. Using random combinations of 12 months or 365 days could have generated more observations (some of which would have been extreme) but ran the risk of (implicitly) creating a time series of wind speeds that could not occur in nature.

Finally, we will consider the sensitivity of our results to the level of market power among thermal generators. Twomey and Neuhoff (2005) have shown how market power can amplify the revenue volatility faced by renewable generators, because the margins between price and marginal cost are likely to be at their highest when thermal demand is high (and hence wind output is low), and lower when high wind outputs depress the demand for thermal plant. Their model is a largely theoretical one, and our simulations offer a chance to explore the importance of this issue in practice.

In the next section, we consider previous work on the interaction between wind generation and electricity wholesale markets. We then outline our simulation model in more detail, and discuss the steps needed to obtain a set of hourly wind outputs at locations around Great Britain. Section 5 presents our results for the volatility of prices and generators' revenues in a workably competitive wholesale market. In section 6, we consider the impact of a duopoly – which in the context of electricity is far from a workably competitive market – on these results. Finally, section 7 offers conclusions and suggestions for further work.

2. Previous Work

Given the dramatic increase in the amount of wind generation, it is hardly surprising that it has attracted academic attention. Much of this work is in the engineering literature, studying the technical challenges of integrating a potentially large amount of variable and intermittent generation into the electricity system. Studies relevant to the UK are surveyed and summarised by Gross et al (2006). They find that with about 20% of intermittent generation, the costs of additional balancing capacity (for short-term fluctuations) and reserve (for periods without wind) would be around £5-8/MWh of wind generation.

The interaction between wind generation and the wholesale market can be considered on a variety of scales. At the micro scale, some studies consider trading strategies for individual generators. For example, Bathurst *et al* (2002) showed how the NETA imbalance pricing regime (since amended) might mean that a wind generator in England and Wales would obtain a negative average revenue. In the Nordic market, in which a generator normally has to trade between 12 and 36 hours before delivery, Holttinen (2005) shows trading between 6 and 12 hours in advance would increase its net income by 4%, and trading just one hour before delivery would increase net income by 8% (in total). This would also reduce the cost of thermal power, according to Müsgens and Neuhoff (2006), since there would be fewer times when a thermal station would be started up on the basis of trading in the day-ahead markets, only to find that wind power that had not been expected at that point would substitute for their output.

At a macro scale, Sensfuss *et al* (2007) and Sáenz de Miera *et al* (2008) have shown that wind generators can depress wholesale prices by reducing the average demand for thermal generation. Sensfuss *et al* study Germany while Sáenz de Miera *et al* study Spain, but in both cases, the estimated impact on wholesale market prices is roughly equal to the cost of supporting renewable generators. This implies that in the short term, the support for renewable generators has come from thermal generators rather than electricity consumers. In the longer term, as Sáenz de Miera *et al* point out, electricity wholesale prices should return to the level needed to remunerate the appropriate mix of capacity for the expected pattern of demand. The long-run time-weighted average price should hardly react to the amount of wind generation.² The amount and pattern of price volatility should still affect the demand-weighted average price, however.

The amount of volatility depends on the characteristics of the national wind resource, of course. In the UK context, Sinden (2007) used wind speed data from the British Atmospheric Data Centre (which we also use) to show that wind speeds and likely wind outputs were higher, on average, at the times of higher electricity demand, and that the correlation between the output of wind generators would decrease as they were placed further apart. This would reduce the impact of wind variability on the market. Sinden did not, however, choose to present any distributions of wind output, to show the minimum contribution that might be reasonably anticipated, and hence the need for back-up plant. Oswald *et al* (2008) remedy this omission and also show that conditions of low wind speeds over the UK would often be correlated with low wind speeds on the Continent, reducing the benefits of interconnection. They present data on the variable demand that thermal stations in the UK would have to meet, but do not translate this into price impacts.

At a theoretical level, Twomey and Neuhoff (2005) consider how the relationship between wind output and market prices is affected by market power. First, they show that wind generators are likely to receive less than the time-weighted average price of power, since high levels of output from wind generators (assuming a sufficiently high share of capacity) will tend to depress the spot price. Second, they show that since generators with market power are likely to exercise it to a greater extent when their residual demand is high, this will tend to strengthen the inverse relationship between prices and wind generation, and hence exacerbate this effect. (The exercise of market power does increase the profits of price-taking renewable generators, but by less than those of the conventional generators.) Third, they find that long-term contracts (forward contracts or, particularly, option contracts) reduce the second effect – renewable generators now share a higher proportion of the gains of market power achieved by conventional stations. They work with a small-scale model, using plausible numbers, but not a full representation of the electricity system. This paper considers the impact of wind generators on market prices within a full-scale simulation of the British wholesale market.

² Sáenz de Miera *et al* point out that since the rise in wind generation will reduce fossil generation and hence the demand for permits in the EU (carbon) Emissions Trading Scheme, this would reduce their price, causing additional indirect effects on the marginal cost of electricity – that is, assuming that policy-makers do not reduce the number of permits available, using the expansion of renewable generation to accept a tougher target for carbon emissions.

3. The Model

The model is based on that used in Green (2008a) and Yago et al (2008), but with additional detail in the wind sector. We assume that generators compete in supply functions, offering a schedule of prices and quantities to the market. The original paper on supply function equilibria (Klemperer and Meyer, 1989) assumed that this was because the firms faced an uncertain demand function. Green and Newbery (1992) applied this concept to the British electricity market, pointing out that variation in demand due to uncertainty was mathematically equivalent to variation due to changing conditions over time. In the British electricity market of the early 1990s, in which generators had to submit offers that would last for an entire day, the latter source of demand variation was far more important than the former. In the future, when generators trade in separate markets for every half-hour, and the output from wind power is hard to predict, uncertainty may be the more important source of demand variation.

For a mathematical description of the supply function model, see Green (2008a). The model calculates the industry supply function, rather than individual firm functions, “as if” the industry contained a number of symmetric firms. That number is given by the inverse of the industry’s Herfindahl index. This allows us to work with an industry-wide cost function, and ignore the difficulties of numerically deriving asymmetric supply functions – Evans and Green (2005) show that for the linear case in which exact solutions exist, this approximation is a good one. In our base case, we assume the equivalent of six symmetric firms, which implies little change in concentration from current levels.

We have taken the capacity of the main types of thermal plant from the Supergen “supportive regulation” scenario (Elders *et al*, 2008). This is a scenario in which there is some expansion of renewable generation, over and above the wind power that we are modelling here, and a modest increase in nuclear capacity. Most of the additional and replacement capacity that will be needed, however, comes from combined cycle gas turbine stations. These are shown in table 1.

The industry cost function used is based on data from the UK government’s 2006 Energy Review (DTI, 2006). For each type of plant, the review gives data on capital cost, operating and maintenance cost, and the efficiency with which it converts its fuel to electricity (if applicable). We do not consider the costs of starting a plant, or changing its output levels – this is an important extension for future work. However, the margin between price and marginal cost is highest at high output levels, and it is only at peak times of day that start-up costs make a significant contribution to marginal cost. At other times, plants which were started to meet the rising load in one period would have been needed in the subsequent period in any case, and so their start-up cost contributes little or nothing to the marginal cost of meeting demand at those times. We use the DTI Central Case favouring Coal (i.e., a medium-high gas price) for our fuel prices. Our supply function for thermal plant is shown in figure 1.

Our model is calibrated to 2020, and we assumed that the nuclear power stations currently owned by British Energy would still be independent of the industry’s other large firms at that date. This means that we subtract the available nuclear capacity from demand when we calculate the supply that needs to come from the industry’s “strategic” firms, rather than adding it to those firms’ supply functions.³

³ A recently-announced agreement between British Energy and EdF makes this assumption incorrect, but its consequences are quantitative rather than qualitative differences in the results we report.

Similarly, we subtract the output of wind stations from demand, rather than adjusting the supply functions. In practice, most wind farms are owned by the large electricity companies, which might support the alternative approach of including their output (at zero marginal cost) in the marginal cost function from which the industry supply function is calculated. This would potentially imply a different supply function for each hour, depending on the level of wind output. A study of the best way to incorporate this (remembering that much trading takes place in well in advance of real time, before accurate wind forecasts are available) is another area for further research. For the time being, subtracting the level of wind output from demand is broadly equivalent to assuming that fossil-fuelled power stations base their bids on an assumed level of wind output, rather than adjusting their bids to the latest wind forecast.

As described in the next section, we use hourly wind data, and so calculate hourly, rather than half-hourly prices and outputs. The demand curves are based on actual hourly demands from our period, scaled up to reflect assumed demand growth of 1.1% a year to 2020. The scaling is based on the annual weather-adjusted energy requirements, rather than peak demand figures, and thus preserves the variation in year-to-year demand due to weather conditions. We use a linear demand slope of –80MW per £/MWh, which gives an elasticity at the mean values of price and quantity of approximately –0.2 (based on the wholesale price). The demand elasticity based on the retail price (which is higher) is around –0.3, the level used in the Office of Gas and Electricity Market’s regulatory impact assessments.

4. Wind Data and Outputs

We predict hourly outputs from wind generators located in nineteen onshore and eleven offshore regions. They reflect the distribution of existing and proposed wind stations around Great Britain, using information available from the British Wind Energy Association (2008). We have assumed that capacity equivalent to that existing, under construction or in the planning process is built in each onshore region, scaled up (but only by a small amount) to give 11 GW of onshore wind. We also distributed 19 GW of offshore wind over our offshore regions, largely in the English part of the North Sea. These headline figures are those which the transmission system operators are currently considering in their investment planning process (National Grid, 2008). The regions and their capacities are shown in table 2. Some weather stations are used for both coastal and offshore wind generators – we describe the adjustment we made to their wind speeds below.

We have obtained hourly wind speed data from 1994 to 2005 for selected weather stations from the UK Meteorological Office (available at badc.nerc.ac.uk/data/ukmo-midas). Our choice of stations was based on two criteria: first, the station had to be in an area with a significant amount of wind generation (existing or planned); second, the data series needed to be reasonably complete. Rather than dropping days for which we did not have a complete set of observations across all of our 25 stations, we created synthetic data for the (relatively small) number of missing observations. When a single hour at a time was missing from the series, we interpolated the missing values. When more than one hour was missing, we

imputed values from a regression of that station's wind speed on the speeds observed at nearby stations which had a high correlation with it in that year.⁴

We used a standard power curve for the relationship between wind speed, measured at a 10 metre mast, and the output from a 1.75 MW turbine with a 65 metre hub height. In practice, some turbines will be higher and some lower than this – the higher turbines will have greater outputs, as the wind is faster away from the ground. This gave us a provisional set of outputs for 19 areas onshore and 11 offshore. These outputs were provisional because we knew our weather stations could well have a lower (or higher) average wind speed than the sites preferred by wind generators. For example, a number were at Royal Air Force bases which required large areas flat enough for runways, while wind farms are often built on hills. We have assumed that when it is relatively windy at our weather station, it would also be relatively windy at wind farms in the region, but recognise that the absolute speeds will differ.

Our procedure to deal with this is based on that used by Oswald et al (2008). For onshore regions, we converted our provisional output patterns for 2005 into load factors and compared them with the load factors achieved by actual wind generators in the same region in that year. (These were obtained from the Renewable Energy Foundation, at www.ref.org.uk.) We then scaled the wind speed up or down so that the resulting load factor was close to that achieved in practice.⁵ We also checked that the average across all our regions was close to the 27% load factor achieved UK-wide in 2007. For offshore wind stations, where experience to date has been limited and disappointing, we chose scaling factors that gave load factors averaging 38%, in line with predictions for “settled operation”.

If we have over-predicted our load factors, then we will get more output from a given set of wind generators than would occur in practice. Since the EU is adopting a target for renewable output, and not renewable capacity, this implies that a greater amount of capacity would be required to meet the target. Assuming that this target binds, and that wind generation remains the favoured way of meeting it, then a larger amount of wind capacity would be built, and the total output would be similar to that assumed in our simulations. Any impact on the pattern of that output over time, and hence on our price predictions, would be second order.

Given the relatively limited number of wind stations, we slightly over-estimate the variation in wind output – we would expect the load factor of a range of turbines within a region to be less variable than that of a single turbine. However, we do not take account of wind variation within an hour, and this would tend to reduce the amount of variation in our results.

5. Results – Competitive Market

The amount of price volatility due to wind power in an electricity market depends on two factors. The first is the amount of variation in wind output. The second is the relationship between prices and the net demand for thermal generation. If there are many hours with similar levels of wind output, we will not see much price volatility in

⁴ We used annual estimates to minimise the impact of any clustered missing values in the proxy stations wind speed series.

⁵ Oswald et al used a different correction factor for each month within a three-year dataset. We had a much longer dataset, and no reference against which to correct early years, so used a single annual figure throughout.

those hours – unless the relationship between price and net demand is extremely sensitive. Alternatively, if part of the supply curve has a very flat slope, so that large changes in the net thermal demand have little impact on the market price, we will see little price volatility during hours in which the wind output places us on that part of the supply curve. Significant price volatility requires first, sufficiently changing levels of wind output, and second, a strong relationship between net demand and price. We start to explore these relationships in a case with the equivalent of six competitive generators – a workably competitive wholesale market.

Figure 2 shows the distribution of output from our 30 GW of wind stations for each hour of the day during January, based on 403 daily wind profiles. We show the maximum level of output we obtained, the minimum, the median, and four intermediate percentiles. The maximum outputs imply that almost all our stations were simultaneously very close to full capacity, whereas the minima imply that there were some hours in which the wind was nowhere strong enough to generate more than a trivial amount of power. The median output is around 40% of capacity, with slightly more wind in the afternoon than in the early hours of the morning. The lower quartile is at around 20% of capacity, and the upper quartile at around 60%. We are therefore likely to have more hours with a wind output of between 4 GW and 5 GW than with a wind output of between 24 GW and 25 GW, but we will find that the distribution is more even than in the summer months. With volatile wind outputs, our first precondition for volatile prices is fulfilled.

Figure 3 shows the resulting price simulations, giving the distribution of prices for each hour of the day. For much of the day, we obtain a wide range of prices – at the early evening peak, the maximum price we observe is more than double the minimum. This reflects the variability in wind speed, and its significant impact on total production (and hence the net demand for thermal plant, on which the price depends) once the amount of wind capacity has grown. The variation in prices is greatest in the peak demand hours, because the supply function is convex, and so a given variation in wind output (and thermal demand) produces a greater variation in prices when they are already high.

In most hours, the minimum price recorded is close to zero. If the wind output is high enough, relative to demand, to displace all the gas and coal-fired plant, this implies prices would have to fall to the level at which either wind or nuclear generators would have to be constrained off. In our simulations, we set this to be a small positive price – in practice, however, both nuclear and wind generators might perceive a high negative cost of spilling output. Some nuclear plants are inflexible and would not be able to reduce output (except by the very costly process of shutting down), while wind generators in receipt of output-linked subsidies would need compensation for the subsidy foregone if they reduce output. In the early hours of the morning, exceptionally high winds are enough to cause this to happen, even with average levels of demand, whereas at other times, high wind and unusually low demand are both required for prices to fall this low.

In the early hours of the morning, the distance between the 10th and 90th percentiles of prices is relatively small – within this range, the different levels of wind output have relatively little impact on wholesale market prices at these times. The industry supply function is relatively flat when little fossil-fuelled plant is running, and so the price is insensitive to the exact amount of thermal generation required. In other words, the second condition for volatile prices, introduced at the start of this section, does not hold.

This flat section of the supply function is also responsible for the relative insensitivity of the market price to the level of wind generation in daytime hours when the wind is above average and prices are low. The gap between the median and the minimum price in daytime hours is far smaller than that between the maximum and the median. This implies that the marginal impact of a moving a set number of places through the distribution of wind outputs is lower when the wind is strong than when it is weak. Although moving from the 75th to the 90th percentile of wind outputs implies a greater change in output than a move from the 10th to the 25th percentile, the supply curve is so much flatter over the range that is relevant when the wind output is high than when it is low that this effect dominates. We thus find prices that are relatively insensitive to wind conditions when winds are high, and more sensitive when they are low.

Figure 4 shows the pattern of wind outputs for July. While the maximum output is between 70% and 90% of the industry's capacity, the median output is generally between 10% and 20%, with only a few hours in the afternoon where it approaches 30%. For fourteen hours of the twenty-four, the lower quartile output is less than 10% of capacity. In other words, the distribution of outputs is heavily skewed towards the lower end of the range.

Figure 5 shows how this pattern of wind outputs feeds through to prices. Once again, high winds can send prices to the minimum level allowed in the simulation. If this does not happen, however, the level of price variation is much lower than in January, whatever the time of day. The demand for thermal generation is much lower, even after adjusting for the lower levels of availability during the summer maintenance period, and taking the generally lower wind speeds into account. This means that the industry stays on a flatter part of its supply function than in January, and prices vary less with the wind output. Furthermore, the variation in wind output between the highest and the lowest profiles is smaller than in January, and the asymmetry between the marginal effects of higher and lower levels of wind output has disappeared. The other key difference is that prices are highest around lunchtime, which is when demand is highest.

The price distributions for the other months, which we do not report here, are somewhere between those for January and July. The "winter" profiles between November and March have their highest prices in the early evening, whereas "summer" profiles between April and October see prices peaking around lunchtime. Prices are most dispersed in the winter months, and the dispersion falls as we move towards mid-summer.

These price distributions imply that anyone trading – on either side of the market – on the basis of spot prices is likely to see wide variations in their daily profitability, depending on the wind. Thermal generators that are only required on a few occasions (but are then vital to prevent power cuts) could see a significant part of their earning potential disappear if they are not in fact available to generate at those times. This provides a strong incentive to be ready to run when needed, but also makes the task of designing adequate systems to remunerate these plants particularly challenging.

We are not convinced that daily variability in prices matters for wind generators, however. It would be completely inappropriate to measure their financial performance over such a short timescale. Instead, figure 6 shows the range of annual profits received by our onshore wind stations, giving the maximum, minimum and median among our 12 simulated years. The variation between years is clearly visible, with an average range between the highest and lowest revenues of £25/kW-year. This

is equal to one-third of the median revenues (note that our graph has a false zero). It is obviously something that should concern a generator (100% debt finance would seem inadvisable), but this level of risk, on its own, would not make them uneconomic.

Figure 7 shows all 12 annual revenue figures for each station, with lines that link the figures for each year. While the detail is hard to read (and we do not advise readers to try), one clear message is that the lines frequently cross each other – that is, when one wind station is receiving relatively low revenues, another one is benefitting from relatively high earnings. This implies that a portfolio of stations will be less risky than a single station.

6. Results – Duopoly

We repeated our analysis for a case in which the industry's thermal capacity was split between the equivalent of just two symmetric firms. This is an extreme case, unlikely to be seen again in the UK, although it was representative of the situation shortly after privatisation in 1990. In some countries on the Continent, however, there is a single dominant firm, and a highly concentrated market remains a real possibility, although (enough) cross-border transmission can provide effective competition.

Figure 8 shows the distribution of prices we obtained for our January demand profile. It should be noted that this is on a very different scale to figure 3, and that prices are much higher in every hour of the day. The mean price over the day is twice as great with two firms as with six. There is also far more variation in prices. The range between the 10th and 90th percentiles averages £62.59/MWh, or around 80% of the median price. With six strategic firms, the range had an average of £10.38/MWh, just over 30% of the median price.

As before, we find that particularly large amounts of wind output can drive prices to the minimum level allowed in the simulation. Apart from this, the distribution is much more nearly symmetric with regard to the wind. In other words, the impact on prices of moving from the 25th to the 10th percentile of wind outputs will be similar to that of moving from the 90th to the 75th. The more competitive supply function had a long section that was nearly flat, over which changes in wind output would have had little impact on the market price. This was the section which was relevant for high wind speeds, and had outweighed the fact that a one-percentile change in wind output implied a greater change in GW when the wind was strong than when it was weak. With only two firms, the industry supply function is steeper than with six firms. For a given number of firms, the supply function will still be steeper when the wind output is low than when it is high, but the difference is now less pronounced, and is balanced by the greater absolute changes in wind output seen at high wind speeds.

Figure 9 shows the distribution of prices in July. The average level of prices and their variability are lower than in January, but much higher than in the simulation for July with six strategic firms. The marginal impact of moving a given number of places through the distribution of wind outputs has now been reversed – it is greater when the wind is high than when the wind is low. This is because the wind outputs in July are clustered around low values. When the wind speed is low, an increase of one percentile in the rank order will imply a lower gain in wind output than an increase of one percentile when the wind is blowing strongly. With a small change in output, the change in prices is also small, even though an equal change in output would have

given a greater change in prices, given the greater slope of the supply function. In the more competitive case, the supply function is so flat for low levels of thermal output that this outweighs the impact of having a greater change in wind output for a given move through the ranking.

Figure 10 shows the annual variability in revenues, for the duopoly case and also for the equivalent of six competitive firms. The wind generators' revenues are quite clearly both higher and more variable in the less competitive case. However, the variability is no greater, in proportion to the average revenues, than in the six-firm simulation. This implies that the presence of market power would not increase the relative level of risk faced by wind generators, and it would certainly raise their profitability.

Twomey and Neuhoff (2005), however, have pointed out that wind generators will not gain as much from market power as thermal generators do. Our simulations allow us to calculate the significance of this point, and we present the relevant figures in table 3. In the competitive (6-firm) case, the time-weighted annual average price that would be received by a base-load generator (ignoring the need for maintenance) averages £32.13/MWh, with a range from maximum to minimum of just 3% of this mean value. On average, our onshore wind generators earn £31.50/MWh, two percent less than the base-load price. This difference is quite small, because two factors have opposite effects on the wind generators' revenues. First, within each month, the price is lower when the wind generators' output is higher, which tends to depress the wind generators' average earnings. Second, in the UK, there is more wind in the winter months when prices are (on average) higher, and this tends to raise the wind generators' average earnings.

We find that offshore wind generators earn £30.97/MWh, four per cent less than the time-weighted average price. There are more offshore than onshore generators, and so their outputs will have a greater impact on the market price. This will tend to increase the gap between their output-weighted price and the time-weighted price for a given day. Furthermore, their outputs are slightly less skewed towards the winter months of higher prices, reducing the impact of a factor that raised the average revenues of onshore stations.

When we consider the case with market power, the annual time-weighted price that a conventional base-load generator would receive (ignoring maintenance) has a mean of £73.94/MWh, more than double the previous case. The variability of prices has also increased, both absolutely and relatively, with a range equal to 8% of the mean. Wind generators do not fare as well in this scenario, relative to their conventional cousins. Onshore generators receive only £65.66/MWh, eleven per cent below the time-weighted average price. As Twomey and Neuhoff predicted, there is a stronger negative correlation between the output of wind stations and the market price in the presence of market power, and this reduces the wind generators' earnings – albeit only in a relative sense. Furthermore, in the supply function model, we find that average prices in the summer increase by relatively more than in the winter. While winter prices remain higher than summer prices, their lower (relative) increase reduces the benefit that wind stations gained from producing more in the winter than in the summer.

Our offshore wind generators earn £64.81/MWh on average, twelve per cent below the time-weighted average – once again, they tend to fare worse than the onshore generators because their greater outputs have a bigger impact on the market price. However, because their outputs are slightly more evenly spread across the year than those of the onshore stations, the relative increase in summer prices (compared to

winter prices) helps the offshore stations. This means that the gap between their revenues and the time-weighted annual average price is only slightly greater than that for the onshore stations.

7. Conclusions

We have found that electricity wholesale spot prices in Great Britain would be significantly affected by the amount of wind generation in each hour, if the UK relies on wind generation to meet a large share of its targets for renewable energy. This short-term volatility would be exacerbated in the presence of market power.

For many generators and electricity consumers, however, short-run volatility of this kind should not be a major problem, even without the use of hedging instruments, as much of the volatility will cancel itself out over a longer period. In the absence of market power, the range of annual time-weighted prices between the year with the least wind and the year with the most⁶ was just three per cent. Individual wind generators face more uncertainty, combining their own volatile output with the variable market price. The range between the highest and lowest annual revenues for a typical onshore station was £25/kW-year, just under one-third of their mean income (from the wholesale market) of £74/kW-year. We do not believe that this level of variation would cause serious difficulties, particularly remembering that wind generators also receive support from the Renewables Obligation, a system of tradable green certificates.

Finally, we were able to assess the impact of market power (amongst conventional generators) in a market with a significant amount of variable generation. We found that prices were higher and more volatile, but that the volatility in wind generators' incomes rose only in proportion to those incomes. We did find that wind generators gained less than base-load generators from the increase in prices due to market power, as predicted by Twomey and Neuhoff (2005). While the base load price rose by 130 per cent when we replaced a workably competitive six-firm structure with a duopoly, onshore wind generators' revenues rose by "only" 108 per cent, and offshore generators' revenues by 109 per cent. While the wind generators clearly gain less from others' exercise of market power than conventional generators do, they are hardly disadvantaged by it!

While we believe that the volatility of generators' revenues due to wind variation is unlikely to be a serious obstacle to them, an obvious extension is to consider the benefits of combining a number of wind generators in different parts of the country in a single portfolio, or to combine wind and thermal generators – a solution considered by Awerbuch (2000). If the windiest sites still available for development are close together, there will be a trade-off between building most of the new capacity at these sites to obtain the highest possible output and dispersing generators to obtain the diversity benefits of a less correlated resource. Our model will allow us to quantify this trade-off.

We have simulated market prices for an assumed level of wind and thermal capacity, and not sought to find a long-term equilibrium. For that reason, our results should not be seen as predicting the average level of electricity prices, even if out-turn fuel prices are close to those we assume. The next stage is to calculate the full static

⁶ We mean "most" in the sense of producing the greatest output at times when it has an impact in reducing prices, rather than in terms of the physical amount of wind.

equilibrium of the wholesale market, as described by Sáenz de Miera et al (2008), in which the amount of each kind of capacity is such that it just breaks even from the resulting market prices. Such a model would neglect the dynamics of investment, however, as it would not show whether generators would find it optimal to own this capacity mix in a world of volatile fuel prices. Our long-term aim is to use the short-term model of wholesale pricing described in this paper as an input into a study of investment behaviour in an uncertain world. If the volatile prices revealed in this paper prove too much of a disincentive for investment, the UK could face significant problems in its transition towards a lower-carbon electricity system.

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Table 1: Generation Capacity by type of plant

Generation technology	Installed Capacity (MW)
Onshore wind	11,018
Offshore wind	19,016
Marine generation	2,000
Biomass	1,453
Hydro	2,000
Micro-generation	250
Nuclear	13,000
CCGT	38,000
Coal	12,000
Total	98,737

Table 2: Wind Generation Capacities by Region

Wind region	Installed Capacity (MW)	Representative Weather Station	
		Name	SRC ID
Onshore:			
Aberdeen	236	Dyce	161
Argyll	709	Machrihanish	908
Cornwall	129	St Mawgan	1405
Cumbria	328	Warcop Range	1076
Devon	147	Chivenor	1346
E Anglia	560	Wittering	583
Fife	686	Leuchars	235
Galloway	697	West Freugh	1039
Mid Wales	575	Aberporth	1198
Moray	734	Kinloss	132
N East	475	Boulmer	315
N Wales	173	Valley	1145
Orkney	41	Kirkwall	23
S Wales	300	Pembrey Sands	1226
SE Scotland	2526	Charterhall	268
SW Scotland	1295	Eskdalemuir	1023
Thames	105	Manston	775
W Isles	726	Stornway Airport	54
Yorkshire	575	Waddington	384
Offshore:			
Aberdeen Offshore	500	Inverbervie No 2	177
Moray Offshore	510	Kinloss	132
N East Offshore	2094	Boulmer	315
N Wales Offshore	990	Valley	1145
Norfolk Offshore	1560	Weybourne	421
S Wales Offshore	108	Pembrey Sands	1226
SW Scotland Offshore	180	Carlisle	1070
Thames Offshore	1562	Manston	775
Walney Offshore	1460	Walney Island No 2	1078
Wash Offshore	6752	Holbeach	421
Yorkshire Offshore	3300	Donna Nook No 2	405

Table 3: Annual average prices and revenues

	Price: time-weighted average (£/MWh)	Revenues for an onshore station (£/MWh)	Revenues for an offshore station (£/MWh)
6 firms			
Max	32.75	32.66	31.38
Mean	32.13	31.50	30.97
Min	31.65	30.30	30.16
Range	1.09	2.36	1.22
(relative to mean)	0.03	0.07	0.04
2 firms			
Max	76.71	70.11	66.65
Mean	73.94	65.66	64.81
Min	71.04	61.64	62.97
Range	5.66	8.47	3.68
(relative to mean)	0.08	0.13	0.06

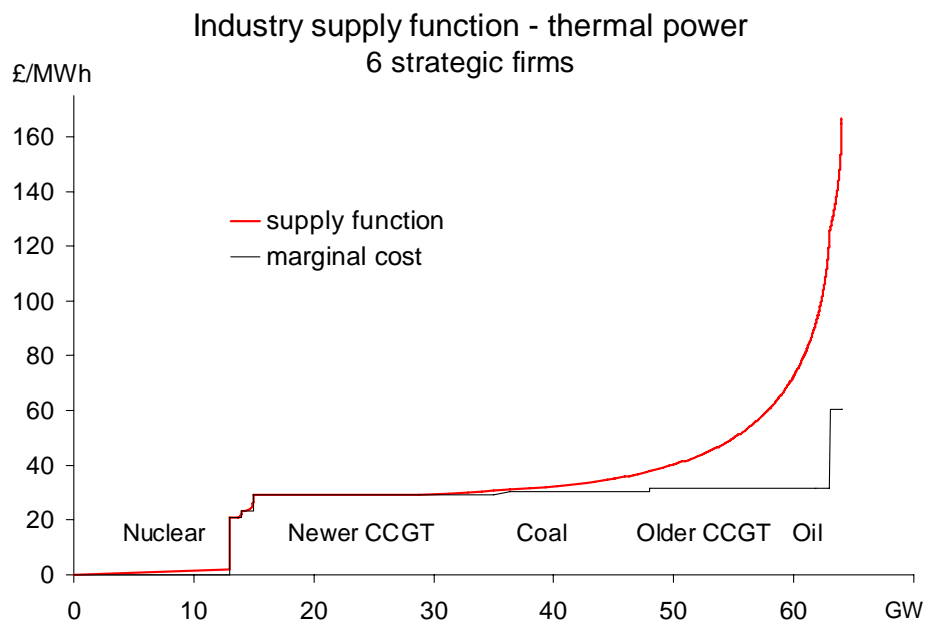


Figure 1

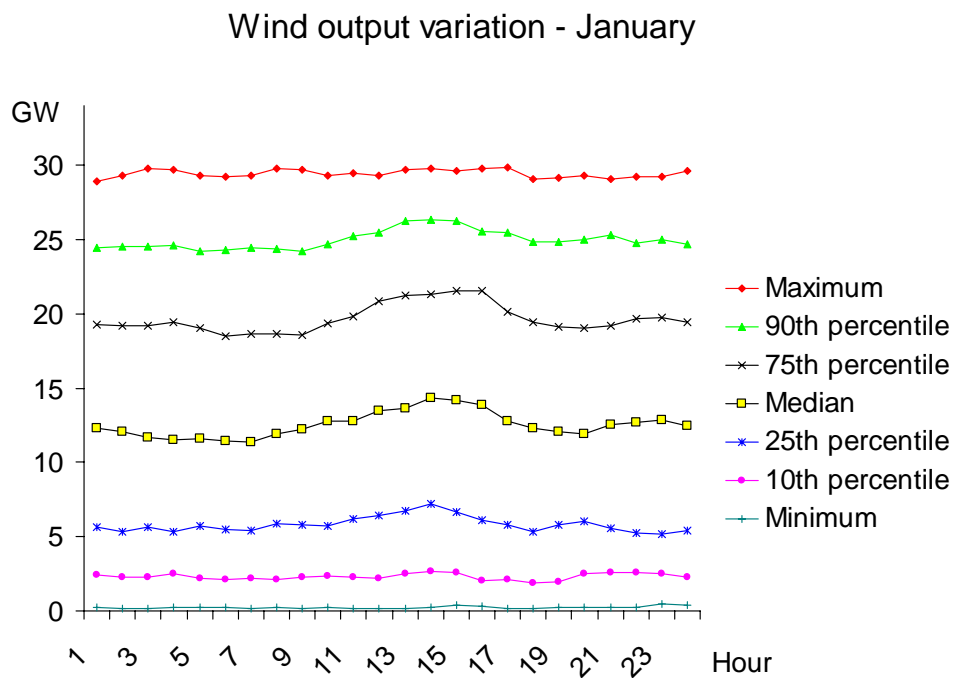


Figure 2

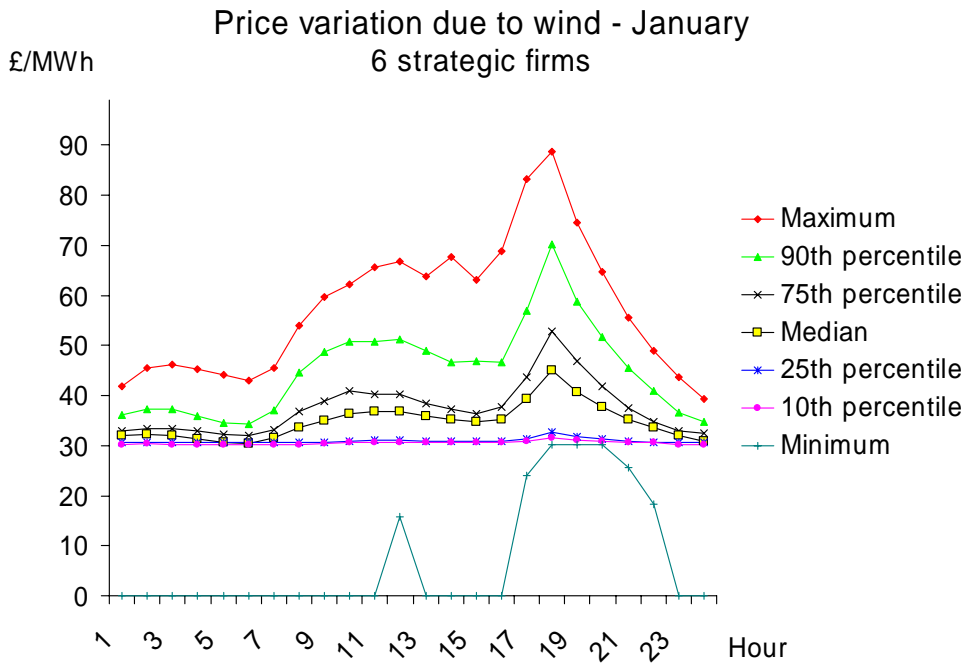


Figure 3

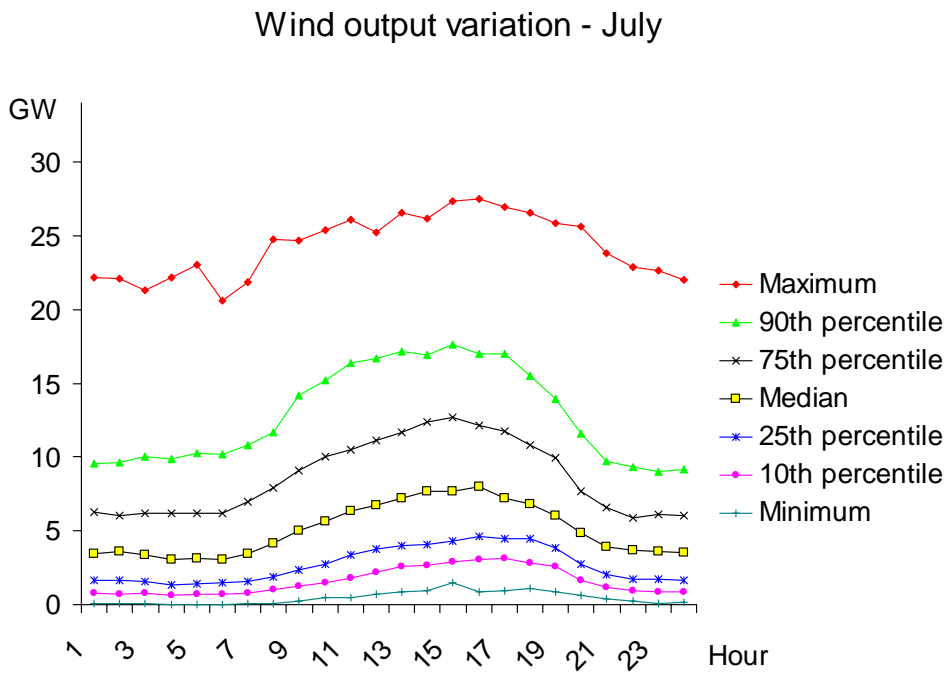


Figure 4

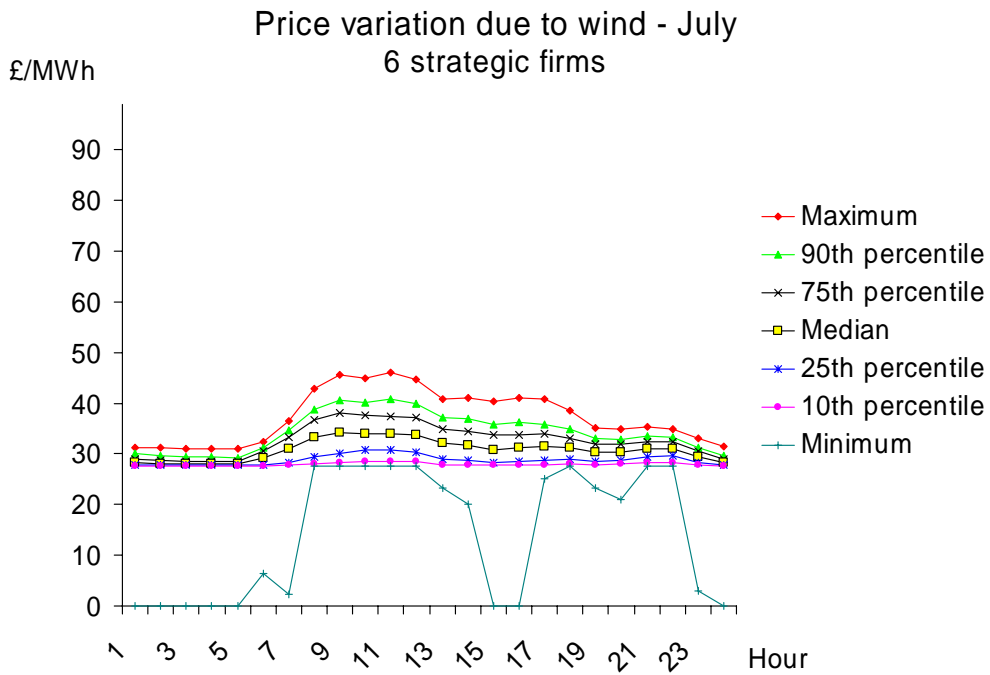


Figure 5

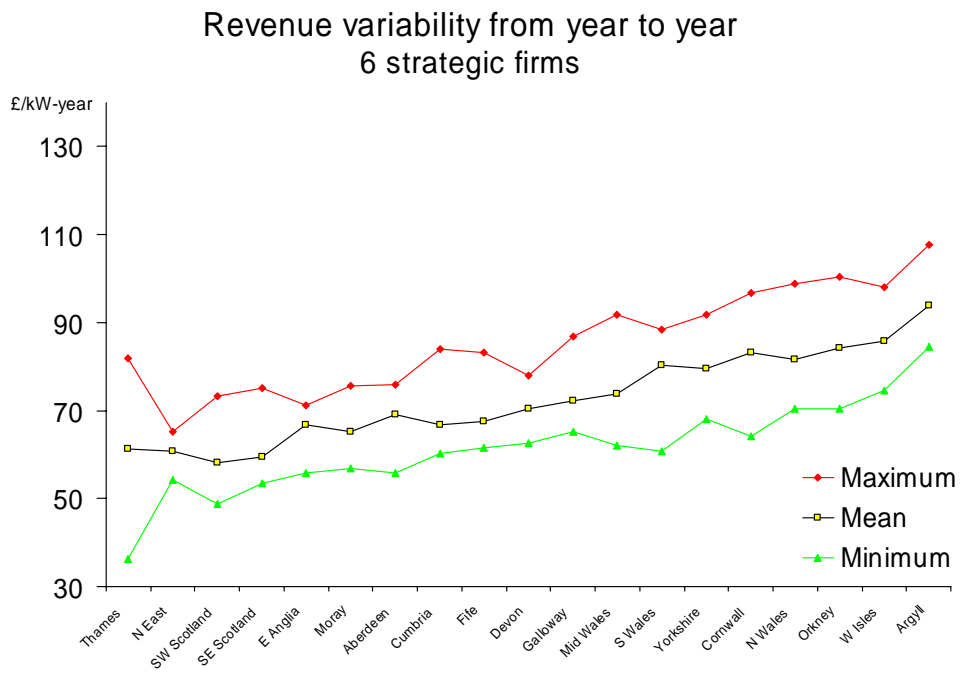


Figure 6

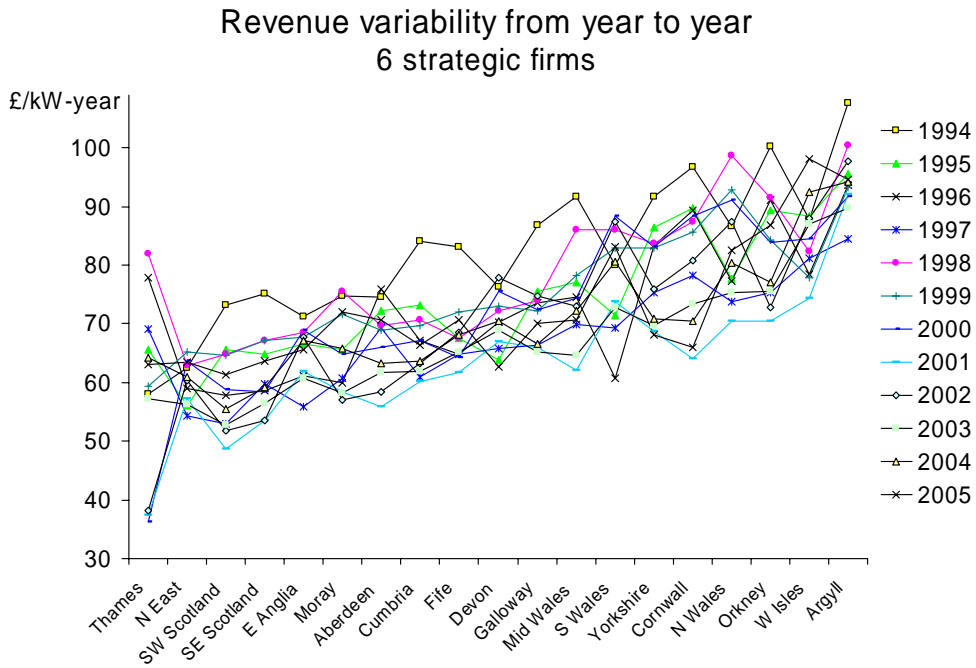


Figure 7

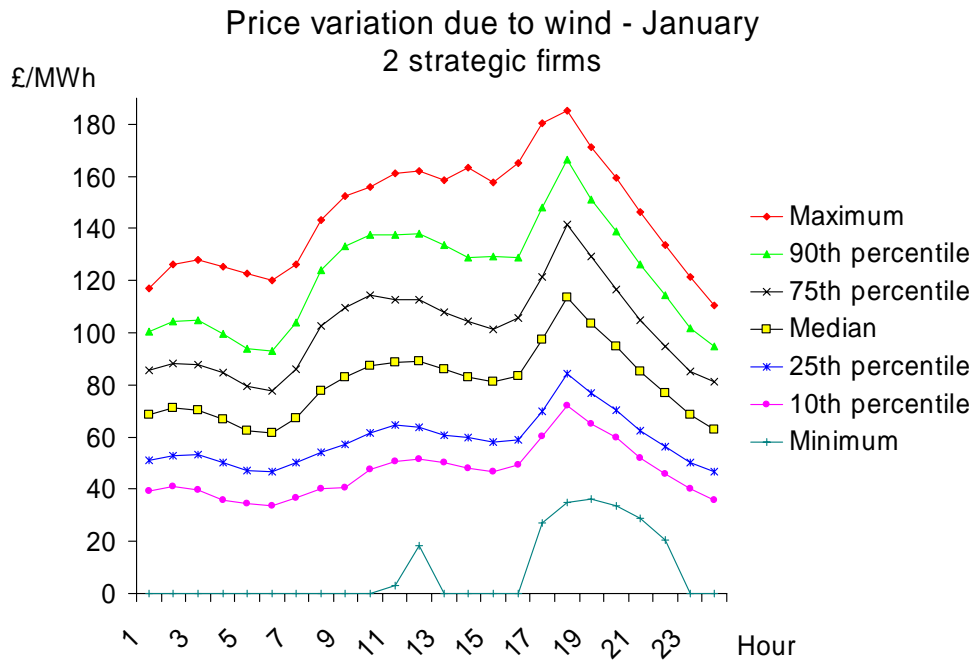


Figure 8

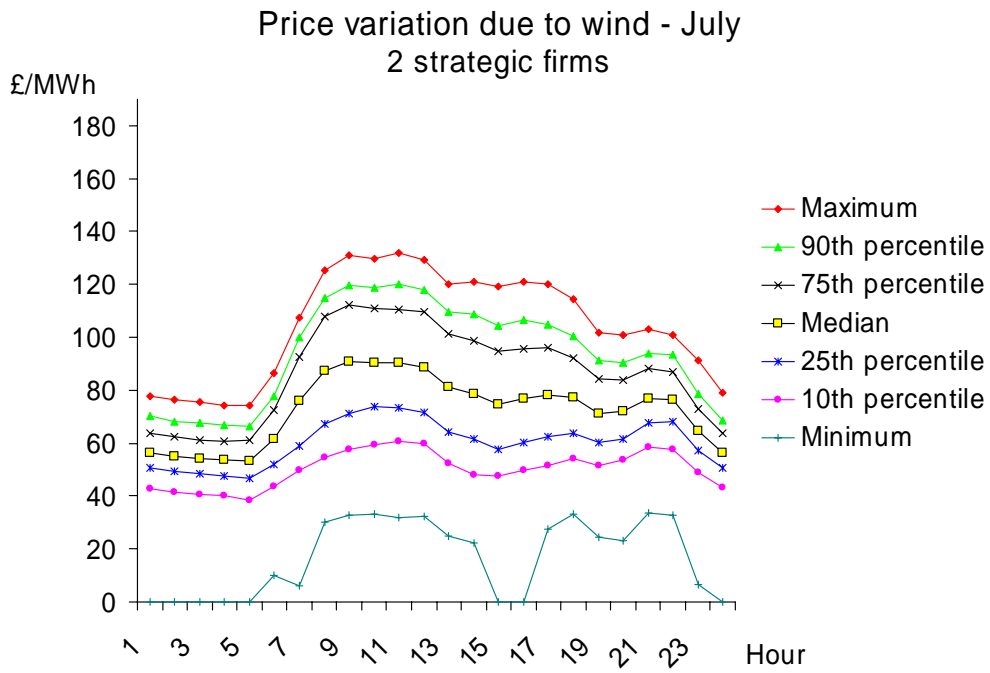


Figure 9

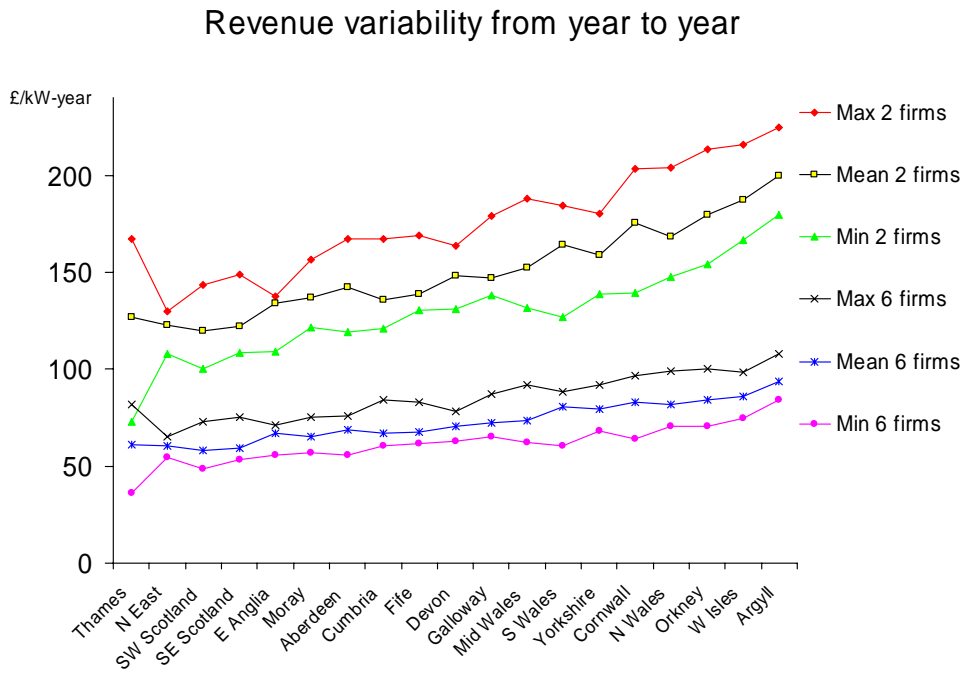


Figure 10