Gone with the wind: valuing the local impacts of wind turbines through house prices [1]

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1 Introduction

Renewable energy technology provides potential global environmental benefits in terms of reduced CO_2 emissions and slower depletion of natural energy resources. However, like most power generation and transmission infrastructure, the plant, access services and transmission equipment associated with renewable electricity generation may involve environmental costs. This is particularly so in the case of wind turbine developments, where the sites that are optimal in terms of energy efficiency are typically in rural, coastal and wilderness locations that offer many natural environmental amenities. These natural amenities include the aesthetic appeal of landscape, outdoor recreational opportunities and the existence values of wilderness habitats. In addition, residents local to operational wind turbines have reported health effects related to visual disturbance and noise (e.g. Bakker et al 2012, Farbouda et al 2013).

The UK, like other areas in Europe and parts of the US has seen a rapid expansion in the number of these wind turbine developments since the mid-1990s. Although these 'wind farms' can offer various local community benefits, including shared ownership schemes and the rents to land owners, in the UK, and elsewhere in Europe, wind farm developments have faced significant opposition from local residents and other stakeholders with interests in environmental preservation. This opposition suggests that the environmental costs may be important. This is a controversial issue, given that opinion polls and other surveys generally indicate majority support of around 70% for green energy, including windfarms, (e.g. results from the Eurobarometer survey in European Commission 2006). This contradiction has led to accusations of 'nimbyism' (not in my backyard-ism), on the assumption that it is the same people opposing windfarm developments in practice as supporting them in principle. There is a perhaps less of a contradiction when it is considered that the development of windfarms in rural locations potentially represents a transfer from residents in these communities and users of natural amenities (in the form of loss of amenities) to the majority of the population who are urban residents (in the form of energy). Other possible explanations for the tension between public support and private opposition to wind energy developments are discussed at length in Bell et al (2007).

This paper provides quantitative evidence on the local benefits and costs of wind farm developments. In the tradition of studies in environmental, public and urban economics, housing costs are used to reveal local preferences for wind farm development in England and Wales. This is feasible in England and Wales because wind farms are increasingly encroaching on rural, semi-rural and even urban residential areas in terms of their proximity and visibility, so the context provides a large sample of housing sales that potentially affected (at the time of writing, around 2.5% of residential postcodes are within 4 km of operational or proposed wind farm developments). Estimation is based on quasi experimental, difference-in-difference based research designs that compare price changes in postcodes close to wind farms when wind farms become operational with postcodes various comparator groups. These comparator groups include: places close to wind farms that became operational in the past, or where they will become operational in the future; places close to wind farms sites that are in the planning process but are not yet operational; places close to where wind farms became operational but where the turbines are hidden by the terrain; and places where wind farm proposals have been withdrawn or refused planning permission. The postcode fixed effects design implies that the analysis is based on repeat sales of the same, or similar housing units within postcode groups (typically 17 houses grouped together).

All these comparisons suggest that operational wind farm developments reduce prices in locations where the turbines are visible, and that the effects are causal. This price reduction is around 5-6% for housing with a visible wind farm of average size (11 turbines) within 2km, falling to 3% within

4km, and to 1% or less by 14km which is at the limit of likely visibility. Evidence from comparisons with places close to wind farms, but where wind farms are less visible suggests that most if not all of these price reductions are directly attributable to turbine visibility.

The remainder of the paper is structured as follows. Section 2 discusses background policy issues and the existing literature on wind farm effects. Section 3 outlines the data used for the analysis. Section 4 describes the empirical strategy and Section 5 the results. Finally, Section 6 concludes.

2 Wind farm policy and the literature on their local effects

In England and Wales, many wind farms are developed, operated and owned by one of a number of major energy generation companies, such as RES, Scottish Power, EDF and E.ON, Ecotricity, Peel Energy, though some are developed as one-off enterprises or agricultural farms. Currently, wind farms are potentially attractive businesses for developers and landowners because the electricity they generate is eligible for Renewables Obligation Certificates, which are issued by the sector regulator (Ofgem) and guarantee a price at premium above the market rate. This premium price is subsidised by a tariff on consumer energy bills. The owners of the land on which a wind farms is constructed and operational will charge a rent to the wind farm operator. Media reports suggest that this rent could amount to about £40,000 per annum per 3 MW turbine (Vidal 2012).

The details of the procedures for on-shore wind farm developments in England and Wales have evolved over time, but the general arrangement is that applications – in common with applications for most other types of development - have to pass through local planning procedures. These procedures are administered by a Local Planning Authority, which is generally the administrative Local Authority, or a National Park Authority. Very small single wind turbines (below the scale covered by the current analysis) can sometimes be constructed at a home, farm or industrial sites within the scope of 'permitted development' that does not require planning permission. The planning process can take several years from the initial environmental scoping stage to operation, and involves several stages of planning application, environmental impact assessment, community consultation and appeals. [2] Once approved, construction typically takes 6 to 18 months. Large wind farms (over 50 Mw) need approval by central government. Offshore wind farms are also subject to a different process and require approval by a central government body.

Wind farms have potential local economic benefits of various types. Interesting qualitative and descriptive quantitative evidence on the community and local economic development benefits of wind farms in Wales is provided by Mundlay et al (2011). Potential benefits include the use of locally manufactured inputs and local labour, discounted electricity supplies, payments into community funds, sponsorship of local events, environmental enhancement projects, and tourism facilities. They argue that the local economic development effects have been relatively limited, although in many of the communities surveyed (around 21 out of 29 wind farms) payments were made to community trusts and organisations, and these contributions can be quite substantial – at around 500-£5000 per megawatt per annum. Based on these figures, a mid-range estimate of the community funds paid out to affected communities in Wales would be about £21,000 per wind farm per year.

There is an extensive literature on attitudes to wind farm developments, the social and health aspects, and findings from impact assessments and planning appeals. Most existing evidence on preferences is based on surveys of residents' views, stated preference methods and contingent valuation studies and is mixed in its findings. There have been some previous attempts to quantify impacts on house prices in the US. Hoen et al (2011) apply cross-sectional hedonic analysis, based

[2] E.g. Peel Energy http://www.peelenergy.co.uk/ provide indicative project planning timelines for their proposed wind farm developments

on 24 wind farms across US states. Their study is interesting in that it makes the comparison between price effects at places where turbines are visible compared to places where nearby trurbines are non-visible (a technique which is applied later in the current paper) but finds no impacts. For the UK: Sims et al (2007) also conduct a cross-sectional hedonic analysis of 900 property sales, which all postdate construction, near three windfarms in Cornwall. Again this study finds no effects.

Few studies have carried out an analysis using difference-in-difference methods to try to establish the causal impacts of wind farm development. However, such methods have been applied to the valuation of other types of power infrastructure, for example Davis (2011, Restats) who finds negative impacts from US power plants. One study to attempt this, and probably the most comprehensive previous work on the impacts of wind farms on housing prices, is recent work by Hoen at al (2013). Hoen et al look at the effect of 61 wind farms across nine states the US using difference in difference style comparisons and some spatial econometric methods, on a sample of 51276 transactions. There are, however, very few transactions in the areas near the wind farms: only 1198 transactions reported within 1 mile of current or future turbines (p20). Their regressions do not, as far as can be deduced, exploit repeat sales within localised groups below county level and rely on county fixed effects and sets of housing and geographical control variables. The conclusions of the paper are that there is 'no statistical evidence that home values near turbines were affected' by wind turbines, which is true in a literal sense. However, the point estimates indicate quite sizeable negative impacts; it is the fact that the point estimates are imprecise and have big standard errors that makes them statistically insignificant.

In contrast, the current study has 28,951 quarterly, postcode-specific housing price observations over 12 years, each representing one or more housing transactions within 2km of wind farms (about 1.25 miles). Turbines are potentially visible in 27,854 of these. There is therefore a much greater chance than in previous work of detecting price effects if these are indeed present.

3 Data

Information on wind-farm location (latitude and longitude), characteristics and dates of events was provided by RenewableUK, a not for profit renewable energy trade association (formerly BWEA). This dataset records dates of operation and other events related to their planning history, number of turbines, MW capacity, height of turbines (to tip). The dates in these data relate to the current status of the wind farm development, namely application for planning, approval, withdrawal or refusal, construction and operation. Unfortunately these data do not provide a complete record of the history for a given site, because the dates of events are updated as the planning and construction process progresses. Therefore, for operational sites, the dates of commencement of operation are known, but not the date when planning applications were submitted, approved or construction began. Dates are also given in the data in relation to withdrawal or refusal of planning applications. For the remaining cases of sites which are not as yet either operational, withdrawn or refused planning permission, the date refers to the latest development event – either application, approval, or the start of construction. This limits the scope of investigation of the impact of different events in the planning and operation process, other than for cases where there is a final event recorded i.e. that the wind farm is operational, or a planning has been withdrawn or refused.

A GIS digital elevation model (DEM)[3] based was combined with this wind-farm site and height data to generate 'viewsheds' on 200m grid. These viewsheds were used to differentiate residential

[3] GB SRTM Digital Elevation Model 90m, based on the NASA Shuttle Radar Digital Topography Mission and available from the EDNIA ShareGeo service http://www.sharegeo.ac.uk/handle/10672/5

postcodes (geographical units with approximately 17 houses) into those from which the wind farm is visible, and those from which it is less likely they are visible, using information on the underlying topography of the landscape. These viewsheds provide approximate visibility indicators, both in terms of the 200m geographical resolution of the view sheds (necessary for manageable computation times), and because they are based on wind-farm centroids, not individual turbines. This means that in the case of large wind farms, a turbines may be visible from locations which the procedure classifies as non-visible, given a large wind turbine array can extend over 1km or more. However, the median wind farm development in the data contains only 6 turbines, in which case the errors introduced by basing visibility on site centroids is likely to small. Note the error will in general result in mis-classification of sites from which the turbines are deemed non-visible, given that if the tip of a turbine at the centroid of the site is visible, it is almost certain that at least one turbine is visible. The viewsheds also take no account of intervening buildings, trees and other structures, because Digital Surface Models which take account of such features are not yet available for the whole of England and Wales. As a further refinement, to eliminate cases where visibility was highly ambiguous, I calculated the rate of change of visibility from one 200m grid cell to the next, and dropped postcodes in cells in the top decile of this visibility gradient.

Given the focus of this study on the visual impacts of wind farms in rural areas, a number of single-turbine wind farms in urban areas and industrial zones were excluded from the analysis (around 21 operational turbines are dropped). Land cover estimates were used first to restrict the analysis to wind farms outside zones with continuous urban land cover. Some additional turbines were eliminated on a case-by-basis where the information available in the wind farm data, and reference to web-based maps and information sources, suggested that turbines were on industrial sites within or close to major urban areas. The land cover at the wind farm centroid was obtained by overlaying the wind farm site data with 25m grid based land cover data (LandCoverMap 2000 from the Centre for Ecology and Hydrology). Land cover was estimated from the modal land cover type in a 250m grid cell enclosing the wind farm centroid. In cases where no mode exists (due to ties), the land cover in the 25 m grid cell enclosing the centroid was used.

Housing transactions data comes from the England and Wales Land Registry 'pricepaid' housing transactions data, from January 2000 to the first quarter of 2012. These data include information on sales price, basic property types – detached, semi-detached, terraced or flat/maisonette – whether the property is new or second-hand, and whether it is sold on freehold or leasehold basis. The housing transactions were geocoded using the address postcode and aggregated to mean values in postcode-by-quarter cells to create an unbalanced panel of postcodes observed at quarterly intervals (with gaps in the series for a postcode when there are no transactions in a given quarter). For a small subset of the data, floor area and other attributes of property sales can be merged from the Nationwide building society transactions data. Demographic characteristics at Output Area (OA) level from the 2001 Census were merged in based on housing transaction postcodes. These additional characteristics are used in some robustness checks which appear later in the empirical results.

Postcode and wind farm visibility data were linked by first forming a panel of postcodes at running quarterly (3 month) intervals over the period January 2000-March 2012. The cumulative number of turbines in the different planning categories, within distance bands of 0-1km, 1-2km, 2-4km, 4-8km and 8-14km of each postcode was then imputed at quarterly intervals by GIS analysis of the information on site and postcode centroids. The 14km limit is set in part to keep the dataset at a manageable size, but also because as the distance to the wind farm increases, the number of other potential coincident and confounding factors increases, making any attempt to identify wind farm impacts less credible. Existing literature based on field work suggests that large turbines are potentially perceptible up to 20km or more in good visibility conditions, but 10-15km is more typical for casual observer and details of individual turbines are lost by 8km (University of Newcastle 2002). In the next step, the site viewsheds were used to determine whether wind-farm sites are visible or not visible from each postcode in each quarter, again using GIS overlay techniques. Additional GIS analysis with the Digital Elevation Model provided estimates of the elevation, slope and aspect (North, East, South and West in 90 degree intervals) of the terrain at each postcode. These are potentially important control variables, because places with good views of wind farms may have good views generally, be more exposed to wind, or have more favourable aspects, and these factors may have direct effects on housing prices.

Finally, the housing transactions and wind farm visibility data was linked by postcode and quarter to create an end product which is an unbalanced panel of postcode-quarter cells, with information on mean housing prices and characteristics, the cumulative number of visible and non-visible turbines within the distance bands and in each planning category, plus additional variables on terrain and demographics. Note, prices in quarter t are linked to the turbine data at t-1, so although the price data extends to the first quarter of 2012, only wind farm developments up to the last quarter of 2011 are utilised. The next section describes the methods that are applied using these data to estimate the house price effects of wind farm developments.

4 Estimation strategies

The research design involves a number of alternative regression-based 'difference-in-difference' strategies. These strategies all compare the average change in housing prices in areas where wind farms become operational and visible, with the average change in housing prices in some comparator group. The starting point for these different approaches is the following basic difference-in-difference/fixed effects regression specification:

$$\ln price_{it} = \sum_k \beta_k (visible, j_k < dist < k, operational)_{it-1} + x'_{it}\gamma + f(i,t) + \varepsilon_{it} \qquad (1)$$

Here $price_{it}$ is the mean housing transaction price in postcode i in quarter t. The variable capturing exposure to wind-farm developments is $(visible, j_k < dist < k, operational)_{it-1}$. This is a dummy (1-0) treatment variable, indicating that postcode i has at least one visible-operational turbine between j_k and k km distance in the previous quarter. This indicator is essentially an interaction between an indicator that turbines are potentially visible from a postcode (*visible*), an indicator that these turbines are within a given distance band ($j_k < dist < k$), and a 'post-policy' indicator which indicates that the turbines have been built and become operational (*operational*). The date of operation is taken as the date around which the price effects are expected to bite, because there is no information in the wind farm data on the date when construction started or finished. Since the estimation method exploits differences in average prices between the post-operation and pre-operation periods, the exact timing is not critical, although errors are likely to attenuate estimated price effects. Note, it is not necessary to explicitly control for the separate components (*visible*, $j_k < dist < k$ and *operational*) because these are going to be subsumed through the specification of geographical and time fixed effects $f(i,t)$ described below.

The coefficient of interest β_k is the average effect of wind farm turbines visible within distance band j_k-k on housing prices. The sign of β_k is ambiguous a priori, since it depends on the net effects of preferences for views of wind farms, the impact of noise or visual disturbance – at least for properties very close to the turbines – and other potential local gains or losses such as shares in profits, community grants, or employment related to turbine maintenance and services.

Two versions of the distance specifications in (1) are used in the empirical work. In the first case, separate regressions are estimated for different values of k (1km, 2km, 4km, 8km, 14km) and $j_k = 0$, i.e β_k estimates the effects of visible wind farms within a radius k. The estimation sample is restricted to postcodes within distance k. In the second case, a series of distance bands is used (0 < distance ≤ 1km, 1km < distance ≤ 2km, 2km < distance ≤ 4km, 4km < distance ≤ 8km and 8km < distance ≤ 14km) in a single regression, and the sample is restricted to postcodes within the maximum 14km. These distance thresholds are chosen somewhat arbitrarily in order to give reasonable detailed delineation of the distance decay close to wind farm sites, while allowing for potential impacts up towards the limits of visibility.

Crucially, specification (1) allows for unobserved components which vary over time and space $f(i,t)$, and these are inevitably correlated with the wind farm visibility indicator. This correlation with the geographical effects occurs because wind farms are not randomly assigned across space and postcodes close to wind farms and where turbines are visible may not be comparable to postcodes further away in terms of the other amenities that affect housing process. The correlation with the time effects occurs because the number of wind farms is growing over time, so there is obviously a spurious correlation between any general trends in prices over time and the indicator of wind farm visibility. It is therefore essential to control in a very general way for geographical fixed effects and time trends.

This is done in part by restricting the sample to groups of postcodes that are likely to be comparable to each other in terms of their propensity to have visible wind farm developments close by, and in addition by controlling for postcode fixed effects. Postcode fixed effects are eliminated in (1) using the within-groups estimator (i.e. differences in the variables from postcode-specific means) and common time effects eliminated within the estimation sample using quarter-specific dummies (i.e. for the 48 quarters spanned by the data). Where applicable, separate sets of year dummies for each distance band, $j_k < dist < k$, control for differences in the price trends in these different distance bands. Additional time varying geographical effects are captured by interactions between year dummies, and dummies for categories of postcode elevation (0-25m, 26-50m, 51-100, >100m), slope (0-0.5%, 0.51-1%, 1.01-1.5%, 1.51-2.5%, >2.5%), and aspect (315-45 degrees, 46-135 degrees, 136-225 degrees, 226-316 degrees). These terrain variables are potentially important, because wind farm visibility may depend on the elevation, slope and direction of the land at the postcode location. Vector x'_{it} also includes optional, time varying observable characteristics of the postcode mean property transactions (proportion of each property type, proportion new, proportion freehold) to control for changes in sample composition.

Comparisons can be made with placebo interventions, or other events, using difference-in-difference-in-difference methods, in which the effect visible operational turbines (β_k) is compared with counterfactual effects estimated from treatment indicators corresponding to other wind farm planning and visibility categories. These categories are: turbines that might eventually be visible but are still in the planning process, wind farms that are operational but hidden from the postcode location by the terrain, and turbines that were refused planning permission. These exact details are described in Sections 4.1 to 4.3 below and in the results section.

4.1 *Strategy A: Existing and future wind farms as comparator groups*

The first and simplest approach applies (1) in a setting which focusses only on postcodes with potentially visible-operational turbines within a given radius, that is postcodes which had visible turbines within a given distance radius at the beginning of the study period, or will have visible turbines within these radii or bands by the end of it. More precisely, a postcode is included in the sample for estimating (1) if it has a visible wind turbine development within the specified radius before January 2000 or if turbines become visible over the course of the study period from 2000 to 2011. The aim of this sample restriction to postcodes with potentially visible-operational wind farms is to create a group of postcodes, which are similar in respect of: a) being close to sites which are suitable for wind farm developments, and where the planning and construction process has been completed; and b) in terms of the likelihood of turbines being visible from the postcode's geographical location. In this sample of postcodes the treatment indicator equals 1 for at least one quarter over the sample period. A postcode that has, for example, a visible, operational wind farm within 4km opening in the last quarter of 2004 will be included in the sample, but will have $(visible, 0 < dist < k, operational)_{it-1} = 0$ in all quarters up to t corresponding to the first quarter of 2005, and $(visible, 0 < dist < k, operational)_{it-1} = 1$ in all quarters thereafter. Postcodes with at least one visible, operational turbine from the beginning of the study period are included in the sample, but have the indicator $(visible, 0 < dist < k, operational)_{it-1} = 1$ throughout.

Identification of the price effects β_k therefore comes from the difference between the average price change in postcodes associated with the zero-one changes in the treatment indicator at the times wind farms becomes operational, and the average price change in the control postcodes that already have visible wind farms or do not yet have visible wind farms but will do so in the future. Since the estimates control for postcode fixed effects, identification of β_k comes only from postcodes that have transaction observations before and after a wind farm becomes operational, although postcodes that had wind farms visible at the start of the study period in 2000 also form part of the control group. Note that a within-groups estimator, which compares the post-operation average price with the pre-operation average price over the whole sample period, is preferable in this setting to a specification using differences between two time periods, because: a) there is unlikely to be a step-change in prices coincident with wind farm operation, both because price changes evolve slowly, and because buyers may be aware of the turbines before operation; and b) the panel is unbalanced, with missing quarters (and even years) where there are no price transactions in a given postcode, so working with differences over specific time intervals within postcodes would result in a large reduction in sample size (e.g. a 4 quarter difference can only be observed in postcodes where there happen to be sales observed 4 quarters apart).

Estimation of the distance-band specification version of (1) proceeds in a similar way, but is based on the sample of postcodes which have a visible operational turbine within the maximum 14km radius. Separate treatment indicators $(visible, j_k < dist < k, operational)_{it-1}$ are included in the same regression for each distance band. To control for different time trends in the different distance band groups, these distance band regressions include interactions between year dummies, and dummies indicating that a postcode has a wind farm visible and operational, within a given distance band, in at least one quarter over the study period.

4.2 *Strategy B: placebo tests using wind farm developments in the planning process*

It is well known that difference-in-difference based research designs suffer from the problem of pre-existing differences in trends between the 'treatment' and 'control' groups. In Strategy A this problem is mitigated by using the same postcodes as both treatment and control groups. Postcodes with existing visible-operational turbines, and postcodes with potentially visible turbines that become visible-operational in the future, provide information on the counterfactual price changes for postcodes in which turbines have just become visible-operational. In principle, this approach should not be sensitive to differences in trends between areas targeted for wind farm developments and those that are not. However, this method may not completely take care of more subtle differential trends in the affected postcodes, e.g. if areas receiving wind farms in earlier years are on different trends from the areas receiving wind farms in later years, and where the distribution of the start of wind farm operations is not equally distributed over the sample (which it is not, as evident from Figure 1. These differential trends may be picked up by the estimates of the average price changes between the before-operation and after-operation periods. It is infeasible to control directly for these different trends at the postcode level. However, as a general robustness check, I use a difference-in-difference-in-difference approach which compares the effects of visible-operational turbines with 'placebo' price effects from wind farms developments where we would not necessarily expect to find them.

To implement this test I re-estimate specifications of type (1) using additional treatment indicators, based on wind-farms which were or are planned, but have not yet been developed. Similar ideas have been used elsewhere in the assessment of the impacts of various spatial policies (Busso, Gregory and Kline 2013). These specifications are of the form

$$\begin{aligned} \ln price_{it} &= \sum_k \beta_k (visible, j_k < dist < k, operational)_{it-1} \\ &+ \sum_k \lambda_k (visible, j_k < dist < k, planning)_{it-1} \\ &+ x_{it}'\gamma + f\left(i,t\right) + \varepsilon_{it} \end{aligned} \tag{2}$$

Here, $(visible, j_k < dist < k, planning)_{it-1}$ is an indicator taking the value 1 if a postcode has potentially visible wind turbines within distance k, but the wind farm is in the planning process, and zero otherwise. The estimation sample is restricted to postcodes in which there is a potentially visible-operational wind farm (i.e. a visible-operational turbine in at least one quarter) within distance band *k*, plus postcodes in which there is a potentially visible-planned wind farm in at least one quarter (i.e. a visible-planned turbine in at least one quarter) within distance band *k*. As before, the regressions control for postcode fixed effects, quarterly dummies and (optionally) slope-by-year dummies, elevation-by-year dummies, aspect-by-year dummies and property characteristics. In addition, specification (2) controls for different trends (year dummies) for the groups of postcodes with current or future visible-operational turbines and/or postcodes with current or future visible-planned turbines in each distance category. The price changes in postcodes with current or future visible-operational turbines, and the postcodes with current or future visible but non-operational turbines thus form the counterfactual for the changes occurring as turbines are built and become operational, as in Strategy A. The price changes in postcodes from which planned wind farms are potentially visible provide an additional counterfactual control group, with which the price changes in postcodes with visible operational turbines can be compared in a difference-in-difference-in-difference estimate. [4]

As before, the multiple distance band specification is estimated on all the postcodes with potentially visible-operational and potentially visible-planned wind farms within 14km, with additional controls for differential trends (separate sets of year dummies) for groups of postcodes with potentially visible-operational and potentially visible-planned wind farms in each distance band.

The purpose of these exercises is to test for the threat from potential pre-existing trends in wind farm-targeted areas, rather than for price effects from wind farms that have entered the planning process. In fact, estimation of the price effects from planning would not be very easy, since operational sites in the data would have been in planning at an earlier stage in the study period, and yet the timing of this is not recorded. The dates recorded in the data are predominantly towards the end of the series. Therefore, given that the date assigned to the start of the wind farm planning stage is not critical for current purposes, I randomly re-allocate the timing of the onset of

[4] The only difference between this set up, and running separate regressions for the group of potentially visible-operational turbines and the group of potentially visible-planned turbines is that the quarterly time trend and the coefficients on property characteristics are constrained to be the same in both groups. The combined regression makes it easier to test for differences in between β_k and λ_k

planning status to quarters over the whole study period, within their original postcodes. This helps put the pattern of planning applications more closely in line with the pattern of the timing of operational turbines, and minimises the risks of detecting causal price effects from entry into the planning process in the estimates of λ_k.[5]

Tests of $\lambda_k = 0$ in equations (3) and (4) provide a placebo test, in that the event of entering planning will not trigger large price effects given that the events have been randomly assigned to quarters. Estimates of $\beta_k - \lambda_k$ also provide difference-in-difference-in-difference estimates which net out any spurious effects associated with non-random targeting of planned wind farm developments.

4.3 Strategy C: effects of visibility from comparison of effects of visible and invisible turbines

A drawback of Strategy B is that the places where wind farms are planned are not usually the same places as those with operational wind farms, so the comparison of β_k and λ_k is based on only partially overlapping geographical areas. A much better alternative is to compare the effects of visible operational wind farms with the effects from wind farm operation on postcodes where the wind farms are hidden from view. The postcodes with non-visible-operational turbines within a given radius of the turbines are likely to be much better comparators to the postcodes within the same radius with visible-operational turbines.

The structure of the regression specifications for these visible-non-visible comparisons is identical to (1) and (2), but the sample now includes the sample of postcodes with potentially visible-operational turbines plus the sample of postcodes which are close to the same set of turbines, but where these are non-visible. Accordingly, specification (3) uses a treatment indicator that is an

[5] There are, in any case, unlikely to be big price impacts from the instigation of a planning application, because the planning process can be lengthy, and the extent of visibility and impact of turbines is unlikely to be fully evident, either to residents or potential home buyers for some time.

interaction of an indicator that there are no visible wind farms (*non-visible*) at the postcode, that the postcode is within a given radius or distance band ($j_k < dist < k$) and the indicator that the turbines are operational (*operational*):

$$\begin{aligned}\ln price_{it} = &\sum_k \beta_k (visible,\ j_k < dist < k, operational)_{it-1} \\ &+\sum_k \delta_k (non-visible,\ j_k < dist < k, operational)_{it-1} \\ &+x'_{it}\gamma + f\left(i,t\right) + \varepsilon_{it}\end{aligned} \qquad (3)$$

In this setup, the postcodes with non-visible neighbouring operational turbines are potentially exposed to direct effects from the turbine developments. These sign of these effects is theoretically ambiguous, for the same reasons discussed in Section 4.1 for visible operational turbines. However, the difference-in-difference-in-difference estimate of $\beta_k - \delta_k$ can be interpreted as the specific impact of wind farm visibility and thus provides an explicit estimate of the amenity or dis-amenity value of turbine visibility.

4.4 Additional specifications including wind farm size, further robustness tests and other planning events

The set up described above is based around a treatment effect design with a simple 1-0 indicator of turbine visibility and operation, and thus implicitly estimates the effect of wind farms of average size. Clearly, the impacts are likely to differ by wind farm size (number of turbines) and there are likely to be interactions of size with distance, especially if visibility turns out to be an important influence on prices. I therefore estimate additional specifications that look at the interactions between wind farm size and distance, using a similar set up to (1), but with separate indicators for the number of turbines visible and operational at each distance and the number of turbines.

Other planning events in the data such as the refusal and withdrawal of planning applications, approval or the start of construction could be interesting and useful. However, estimation of their direct effects is limited by the fact there are few such events and/or that 80-100% of these events are stacked in the last 4 years of the data set. More importantly, the full history of planning process is never recorded, so interpretation of the effects of intermediate stages of development would not be straightforward. Estimation of the effects of refusal of planning permission is feasible, given that there is a reasonable spread of these events over the study period, and the potential effects are interesting in their own right. This analysis uses the same set up as equations (3) and (4), but with planning refusal as the key event rather, than the entry into the planning process, and with treatment assigned to the actual date of approval rather than a randomly assigned date.

A number of other robustness checks are carried out to assess sensitivity to local price trends, changing composition of housing sales, and assumptions about the clustering of standard errors. These are described where they arise in the Results section below.

5 Results

Figure 1 shows the historical development of non-urban wind turbines in England and Wales from the mid 1990s to 2011. By the end of 2011, these turbines could provide up to 3200mw of generating capacity, which amounts to sufficient power for about 1.8 million homes (or around 7.7% of the 23.4 million households in England and Wales)[6]. Figure 2 illustrates the evolution of the spatial distribution of these turbine sites between 2000 and 2011. These sites are predominantly in coastal and upland areas in the north, west and east, although are increasingly seen in inland

[6] This figure is estimated from DECC 2013a and DECC 2013b as follows. Total UK electricity output from onshore and offshore wind was 15.5TWh in 2011 (DECC 2013a Table 6.4) from 6500MW total capacity. Scaling down to the capacity of 3200MW in England and Wales, suggests an output of 7.6 TWh from wind farms in England and Wales. Average UK domestic household electricity consumption is $4.2\text{x}10^{-6}$TWh, based on total domestic electricity consumption of 111.6TWh (DECC2013b, Table 5.1.2), and a figure of 26.4 million households in the UK (2011 Census). Therefore, wind farms in England and Wales could power approximately $7.6/4.2\text{x}10^{-6}$ = 1.8 million households.

areas in the midland areas of central England. There are very few sites in the south and east of England.

Some basic summary statistics for the operational, non-urban wind farms in the dataset are shown in Table 1. There are 148 wind farms recorded in operation in England and Wales over this period. The mean operational wind farm has 11 turbines (6 median) with a capacity of 18.6 MW, but the distribution is highly skewed, with a maximum number of turbines of 103 and capacity of 150MW. These largest wind farms are off-shore. The average height to the tip of the turbine blades of just over 90m, though the tallest turbines (mainly offshore) reach to 150m. The distribution of wind farms across land cover types shows that most wind farms are in farmland locations, followed by mountain and moorland locations (wild). Offshore sites are also included in the analysis, where these are potentially visible from residential areas on shore. Urban and most industrial locations (except where these impact on rural areas) are excluded from the analysis. The table also shows the numbers of wind farms in the planning process and in other stages of development. Only the operational, planning and refused categories are used in the empirical analysis described below.

Table 2 summarises the main postcode-by-quarter aggregated panel data set, with information on property prices and characteristics, and the distribution of visible and non-visible operational turbines. This sample is the sample of postcodes with visible-operational turbines within 14km in 2000, or appearing within 14km at some time over the sample period up to the end of 2011. Price data is merged to the windfarm data with a one-quarter lag, so the price data runs from the first quarter of 2000 to the first quarter of 2012.

5.1 Strategy A results

Table 3 reports the results from the postcode fixed effects approach of Strategy A, described in Section 4.1. This restricts the sample to postcodes which have or will have an operational wind farm within the specified distance band. Identification comes purely from comparing the change in postcode prices between the periods before and after the site, with the changes occurring in postcodes that have already got visible-operational wind farms or which will do so in the future. Results are reported for 6 radiuses from 1km-14km. The table reports coefficients and standard errors from the regressions. Standard errors are clustered at Census Output Area level (10 or so postcodes) to allow for serial correlation in the errors over time and some degree of spatial correlation in the price changes across neighbouring postcodes. Alternative clustering assumptions are explored in Table 10 in the Appendix, where the conclusion is that OA level clustering gives similar results to more general double clustering that allows for serial correlation within postcodes and cross sectional correlation within quarters. All specifications include a full set of quarterly dummy variables. There are two columns for each distance category, one in which the specification includes no other control variables, and the second controlling for the array of property characteristics and trends described in the methods section. Evidently, controlling for these property and terrain characteristics makes little difference to the results.

The key finding from this table is that prices in places where wind farms are close and visible are reduced substantially after a wind farm becomes operational. The price impact is around 7% within 1km, falling to 6% within 2km, 3% within 4km. Within the 8km or 14km radius, the effect is less than 1%. These results do not inform us specifically about the visibility impacts of wind farms, as distinct from other costs and benefits associated with their visibility and operation. These estimates should be interpreted as the net impact on prices resulting from all channels, including the potential costs linked to visual impact and noise, and potential benefits of wind farm proximity. Disentangling visibility from other impacts is left until Section 5.3.

Clearly, interpretation of the estimates in Table 3 as estimates of the causal impact of wind farms assumes that there are no changes in unobserved housing characteristics coinciding with wind farms. The results may also be sensitive to pre-existing area specific price trends, that are not controlled using the various groups of time dummies. Table 4 and Table 5 present some assessment of these identifying assumptions, based on the sample with the 4km distance threshold – this being the maximal distance at which there appear to be substantial price effects in Table 3. Table 4 presents a series of 'balancing' tests in which the dependent variable in the regressions of Table 3, column 6, is replaced by housing characteristics, and the housing characteristics are excluded from the set of regressors. The aim here is to see if there are within-postcode changes in the composition of the sample, in terms of housing characteristics, that coincide with the start of wind farm operations. Columns (1)-(6) use the few characteristics that are available in the Land Registry data set. In the remaining columns, mean postcode-by-year characteristics taken from an auxiliary dataset of transactions from the Nationwide building society are merged to the dataset. This dataset has far more information on housing characteristics, but is only a sub-set of transactions, and hence postcodes, in the Land Registry data, therefore the sample size is much reduced. Looking across Table 4 it is evident that there are no statistically significant changes in the composition of housing transactions associated with wind farm operation, and there is no systematic pattern in the point estimates that would suggest that the price changes in Table 3 could be related to the sale of lower quality houses. The floor area of the property, a potentially important omitted variable in the land Registry data is in fact positively associated with the wind farm treatment, though the point estimate (in metres squared) is not large.

Table 5 carries out further robustness tests on the 4km sample, firstly adding in the Nationwide data set characteristics as control variables (column 2), and replacing the Land Registry prices with prices from the Nationwide data (column 3) The coefficient estimates from the Nationwide sample are slightly larger than those from the Land Registry data, although not by much relative to the standard errors, and changing the source of the price information does not make any difference. Column (4) adds in additional demographic characteristics from the 2001 Census (proportion not qualified, proportion tertiary qualified, proportion born in UK, proportion white ethnicity, proportion employed, proportion in social rented accommodation) interacted with linear time trend, but again this has no bearing on the results.

Columns (5) shows a specification which controls for region-specific quarterly changes. It is not feasible to do this simply by including region-by-quarter dummies in the regressions, because there are too few wind farms becoming operational in any region-quarter period. Instead, the region-quarter price effects are recovered from a first stage postcode-fixed effects regression of log prices on region-quarter dummies in the Land Registry dataset, using postcodes beyond the 14km wind-farm distance limit. The estimated region-quarter effects are then used as controls in the second stage estimation. Again this has no impact on the key result, even though the region-quarter effects are strongly correlated with the prices close to the wind farms (the coefficient on the region-quarter effects is 0.456, with a coefficient of 0.021).

Column (6) does something similar, but controlling for predicted pre-operational linear price trends in the area defined by the set of postcodes that share the same nearest operational wind farm within 4km. Again it is not practical to simply include nearest-wind-farm specific trend variables, since the price changes in response to wind-farm operation are not sharp enough to successfully identify separately from wind-farm specific price trends over the whole period. Instead, similarly to the region-quarter trends, the pre-operation wind farm price trends are estimated in a first stage regression of prices wind farm-specific time trends using observations for the pre-operation period only. The first stage regression predictions of the wind farms specific price trends from the pre-operation period are then extrapolated over the whole sample period and included as controls in the second stage regression. Nothing much changes as a result of this exercise, although the point estimate is reduced slightly (by around 1 standard error).

Overall, there is no evidence from Table 4 and Table 5 that the finding of negative impacts from wind farms on prices arises from omitted variables or unobserved price trends.

More detail on distance-decay of the wind farm price effects within the 14km limit is provided in Table 6. Here the sample is postcodes with transactions within 14km of a site, and the treatment indicators for the different distance bands are included in the same regression. The coefficients indicate the effects at each distance band within this 14km radius. As before Column (1) includes just quarterly dummies, whereas Column (2) includes the full set of control variables, including distance-band-by-year dummies. The results are broadly in line with the alternative presentation in Table 3. The price effect within 1km, and at 1-2km is around 5.5-6%. This falls quite sharply in the 2-4km distance band, to 1.9%. Beyond this there are price effects right out as far as 14km, although these are small at around 1%.

5.2 Strategy B placebo results

Section 4.2 described extensions to the analysis that compares the price effects of operational turbines with the price effects of planned, but undeveloped wind farms that are not yet constructed. The distribution of these planned wind farms is shown in Figure 3. The regression results relating to planned and refused wind farm developments are shown in Table 7. The sample includes postcodes within the specified distance of sites that are operational by the end of the study period (same samples as Table 3) plus postcodes within the specified distance of sites that are in planning by the end of the study period. The purpose of these results is to assess whether the patterns in Table 3 could arise from endogenous spatial targeting of wind farms.

Looking across Table 7, the same pattern of results for visible-operational wind farms emerges as in Table 3 (which is the case by construction – the coefficients are basically identified from the same variation as in Table 3). By contrast the coefficients on the placebo 'planning 'treatment are statistically insignificant and small in magnitude relative to the operational effects, in the distance bands close to the wind farm sites. There are, however, small positive, significant effects in the larger samples corresponding to the bigger distances. There is no clear causal explanation for these patterns, given that the planning events are randomly allocated across time within postcodes. A potential explanation is that the before-after planning treatment indicator is picking up interactions between non-linear postcode-specific unobserved price trends and the postcode fixed effects, which may not successfully be controlled for by postcode fixed effects and the time trend dummies included in the regressions. Whatever the explanation, the effects are opposite in sign to those for operational turbines, so do not appear to be a cause of the patterns seen for the effects of operational turbines.

The distance decay of the price effects for operational, as compared to planned wind farms is illustrated in Figure 4. The figure plots the coefficients from regressions of the type shown in Table 6 for visible operational wind farms, but with the addition of the 'placebo' treatment effects for the planned wind farms. The sample includes postcodes which have visible-operational wind farms or visible-planned wind farms within 14km by the end of the period. In this distance-band set up there is no evidence of statistically significant effects of any magnitude from the placebo treatments. The final row presents a difference-in-difference-in-difference comparison between the visible-operational and visible-planned treatment effects, which are virtually identical to the results in Table 6.

5.3 Strategy C results

The methods described in 4.3 proposed comparing the price effects in postcodes with visible-operational turbines to the price effects in postcodes with non-visible operational turbines. To illustrate the basis for Strategy C, Figure 5 shows the viewshed for a wind farm in north east England. This is the Haswell Moor wind farm in County Durham, which has 5 turbines, a total capacity of 10MW and the height to the tip of the turbines is 110m. This is a fairly typical wind farm development in the sample. The dark shaded areas are residential postcodes and the light grey shading indicates the land where at least the tips of the turbine blades are visible (technically, these are computed as the land surface that is visible to an observer at the tip of the turbine). Strategy C is compares prices changes occurring with the start of wind farm operation in postcodes where the turbines are visible, with those occurring where they are not-visible.

The results for different distance radii are shown in Table 8. This is presented in the same way as Table 7, but allowing for effects from non-visible operational wind farms rather than planned wind farms. The sample includes postcodes with visible-operational turbines and non-visible operational turbines within each distance band by the end of the period. All regressions include the usual controls for trends and differences in topography, and allow for differences in general time patterns between postcodes where operational turbines will become visible and postcodes where they do not. Note that it is infeasible to compare visible and non-visible wind-farms within the 1km distance band as there almost no cases where turbines are not visible at this distance, so the 1km results are missing. Otherwise, the usual pattern is seen in the coefficients for visible-operational turbines, but the effects in areas close to operational turbines where these are not visible is quite different. The point estimates within the 2km band are similar to those for visible-operational turbines, but statistically insignificant. Again, an issue here is that there are relatively few cases where turbines are not visible at a postcode if they are this close, and the classification into visible and non-visible cases is potentially very noisy, given the 200m resolution of the viewshed (and the fact that a person probably does not have to move far from there house to observe turbines at this distance, even if they are obscured from view at the house itself). Further out, a more interesting pattern emerges: within 4km there is no effect on prices from operational turbines that are not visible, which begins to suggest that the effects from visible-operational turbines are largely attributable to visibility. Within 8km, and at bigger radii around the wind farm site, small significant positive price effects start to emerge, whilst the effects in postcodes with wind turbine visibility remain negative. Again, the results for distance bands are presented graphically in Figure 6, to show the distance decay pattern, and the offsetting effects of visibility and non-visibility are clearly evident (except within the 1km band where the estimates for non-visibility are too imprecise).

One potential explanation for these contrasting effects is that wind farms provide some general benefits in the local area, due to community donations, shares in profits, other local area enhancement schemes and rents to land owners. There may also be wage and employment benefits. In this case, the basic price effects estimated from the visible-operational treatment dummies under-estimate the marginal willingness to pay to avoid the visual dis-amenity, because these are in part already compensated by higher wages or other benefits (as in the classic wage-price-amenity trade off in the Roback model of compensating wage and land price disparities, (Roback 1982). An alternative interpretation is that housing market frictions create very localised housing markets, and construction of turbines therefore restricts the availability of housing without views of the turbines, thus raising the price of postcodes without visibility relative to those where the turbines are visible. Unfortunately, it is not possible to distinguish between these two hypotheses in the current set up. Either way, the willingness to pay to avoid visibility should be estimated by the difference between the coefficients on the visible-operational treatment dummies and the non-visible operational treatment dummies. These difference-in-difference-in-difference estimates are shown at the bottom of Figure 6, and indicate a visibility impact of around 2.6% from 2km out to 8km. Beyond 8km there is no effect from the average wind farm, and below 2km no effect is detectable due the lack of clear distinction in visibility at this distance.

5.4 *Further results on numbers of turbines.*

The results so far have looked simply at turbine development as a binary treatment effect, and have ignored the scale of the wind farm. Table 9 investigates the whether there is a greater cost associated with larger developments with more turbines, and over what distance. The setup is basically the same as in Table 6, but with interactions between dummies for wind farm size and distance. The results are in line with what would be expected if the price impacts are related to the dis-amenity of wind farm visibility. Bigger wind farms have a bigger impact on prices at all distances. A wind farm with 20+ turbines within 2km reduces prices by some 11% on average. Note though that a postcode within 2km of the centroid of a 20+ turbine windfarm could be almost at the turbine field, so this price effect could relate to noise and visual flicker problems, and is quite clearly an extreme case. However, even at 8-14km there is a 3.7% reduction in prices associated with large visible operational wind farms. Medium size wind farms above average size also have strong effects throughout the distance range, falling from 5.7% within 2km to just over 1% by 14km. The effect of smaller wind farms with less than 1-10 turbines is, as might be expected, concentrated in the first 2km where there is a 5% reduction in prices, falling to just over 1% at 4km and becoming smaller and/or insignificant beyond that.

The possibility of using other planning events was discussed in Section 4.4. Figure 7 shows findings related to the impacts of wind farm planning refusal, using the same distance band set up of Figure 4 , but with postcodes with potentially visible wind farms that were refused planning permission, alongside the usual visible-operational cases. The results are quite surprising. Refusal events seem to be associated with positive price effects, and these are very large close to the proposed wind farm locations. One potential explanation for these positive impacts is that refusal of planning permission may trigger price effects, if it signals to home owners and buyers that the local planning authority will be unwilling to proceed with future wind farm developments in the local area.

It is also possible that places where wind farms were refused permission were the subject of vigorous local campaigning, and these campaigns may have lowered prices prior to refusal – e.g. because local residents tried to sell quickly, or because the campaigns raised awareness amongst potential buyers. The positive effects from refusal of permission may therefore represent some bounce back of prices to pre-planning levels. Of course if similar effects were observed during the planning and pre- approval periods for operational wind farms, the results presented so far could underestimate of the impact of visible operational wind farms, because there is a pre-operation dip in prices in response to the planning process, and this will reduce the estimated pre-post operation price differential. In this case the refusal effects are, in effect, the mirror image of the effect of wind farm planning on local prices (which it is not possible to estimate directly, for reasons discussed in 4.2).

Under either of these assumptions, the difference-in-difference-in-difference estimates implicit in the graph in Figure 7 might provide better estimates of the effects of wind farm operation relative to the re-planning stage. These estimates are shown at the bottom of the figure, and are substantially bigger than the baseline estimates of visible operational turbines in Table 6 and elsewhere in this paper. Given the uncertainties in interpretation, these estimates are best treated as an upper bound to the potential impacts.

6 Conclusions

The paper has estimated the effects of visible wind farm turbines on housing prices in England and Wales. The study used a micro-aggregated postcode-by-quarter panel of housing transactions spanning 12 years, and estimated difference-in-difference effects using a postcode fixed effects based methodology. Comparisons were made between postcodes in which turbines became operational and visible with various control groups. All the results point in the same direction, regardless of the specific research design. Wind farms reduce house prices in postcodes where the turbines are visible. This price reduction is around 5-6% for housing with a visible wind farm of average size (11 turbines) within 2km, falling to 3% within 4km, and to 1% or less by 14km which is at the limit of likely visibility.

Evidence from comparisons with places close to wind farms, but where wind farms are less visible suggests that most if not all of these price reductions are directly attributable to turbine visibility. The effects of wind farms on the prices of locations with limited visibility are statistically insignificant or even positive – providing some indication that wind farms generate some local benefits, though these are more than offset by the dis-amenity associated with visibility. This may be why previous studies that have failed to distinguish between places where nearby turbines are visible and places where they are not, have failed to find effects. As might be expected, the effects are bigger and have greater geographical spread for larger wind farms. Wind farms with 20 or more turbines reduce prices by 3% at distances between 8-14km, and by up to 12% within 2km.

The paper presents a number of robustness tests, but even so the findings should be interpreted with some 'health warnings'. The information on wind farm location and visibility is limited by lack of data on the precise location of individual turbines, so the classification of postcodes in terms of visibility is subject to measurement error. This is most likely to result in some attenuation of the estimated effects. Steps were taken to minimise this problem by eliminating postcodes where visibility is ambiguous. More importantly, the data lacks historical information on the timing of events leading up to wind farm operation (announcement, approval, construction etc.) so the price effects reported here relate to the difference between the post-operation and pre-operation periods, for the periods spanned by the data. However, the wind farm development cycle can last a number of years, and price changes evolve fairly slowly over time in response to events. Again the most likely consequence of this is that the results underestimate the full impact between the pre-announcement and post-construction phase. Results based on comparison of operational sites and those refused planning permission suggest that these full impacts could be much bigger – the upper-bound estimate is about 15% within 2km of the average wind farm. Further data collection effort is required to fully address these issues.

Well established theories (Rosen 1974) suggest that these price effects can be interpreted as marginal willingness to pay to avoid the dis-amenity associated with wind farm proximity and visibility, net of any benefits provided by the wind farms in terms of economic opportunities, community payments or other financial compensation. If we take the figures in the current paper seriously as estimates of the mean willingness to pay to avoid wind farms in communities exposed to their development, the implied costs are quite substantial. For example, a household would be willing to pay around £600 per year to avoid having a wind farm of average size visible within 2km, or would be willing to pay around £200 per year to avoid having a large wind farm visible within 8-14km.[7] The implied amounts required per wind farm to compensate households for their loss of visual amenities is therefore fairly large: about £12 million for a typical 11 turbine wind

[7] This is based on an average house price of £140,000, a 3% price reduction and a 5% interest rate

farm, based on the average numbers of households with turbines currently visible within 4km.[8] The corresponding values for large wind farms will be much higher than this, as their impact is larger and spreads out over much greater distances.

These per-household figures are comparable to the highest estimates from the stated preference literature. The figures cited in Bassi, Bowen and Fankhauser (2012) are typically much less than £100 per year, though this is per individual, so household willingness to pay could be higher. It is worth noting, however, that the revealed preference method based on housing markets elicits the preferences of marginal home owners in the areas close to wind farms, which may differ from the mean willingness to pay amongst all households in the population.

[8] Based on: around 1.8% of postcodes within 4km of a visible turbine; the number of households in England and Wales is 23.4 million; the capitalised effect of visibility within 4km is 3%; the average house price is £140000; and the number of operational turbines is 148.

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Table 1: Windfarm summary data, 1992-2011 England and Wales

	Mean	s.d.	Min	Max
Operational				
Turbines mean	11.2	15.4	1	103
Turbines median	6			
MW capacity	18.6	39.2	.22	300
Height to tip	90.9	29.2	42	150
Offshore	14			
Forest	8			
Farm	82			
Wild	39			
Coast	5			
Status				
Operational	148			
Approved	61			
Construction	10			
Planning	160			
Refused	57			
Withdrawn	34			

Table 2: Main estimation sample summary data, 2000-2011 England and Wales

	Visible-operational turbines within 14km	
	Mean	s.d.
Log price	11.542	0.654
New build	0.043	0.197
Detached house	0.261	0.428
Semi-detached house	0.065	0.24
Terraced house	0.332	0.455
Flat/Maisonette	0.342	0.462
Freehold	0.859	0.34
Proportion with visible turbines within 1km	0.004	0.062
Proportion with visible turbines within 1-2km	0.014	0.119
Proportion with visible turbines within 2-4km	0.046	0.210
Proportion with visible turbines within 4-8km	0.158	0.365
Proportion with visible turbines within 8-14km	0.306	0.461
Obs	797470	

Table 3: Fixed effects estimates; sample with operational windfarm within k km, during 2000-2011

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Radius	1km	1km	2km	2km	4km	4km	8km	8km	14km	14km
Control vars.	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Postcode fixed fx										
Visible and	-0.0539**	-0.0713**	-0.0601***	-0.0596***	-0.0308***	-0.0289***	-0.0184***	-0.0081**	-0.0097***	-0.0053**
operational:	(0.0185)	(0.0239)	(0.0097)	(0.0099)	(0.0059)	(0.0056)	(0.0033)	(0.0031)	(0.0020)	(0.0018)
Obs	6,164	6,164	27,854	27,854	99,114	99,114	339,991	339,991	797,470	797,470
R-squared	0.8098	0.8421	0.8140	0.8471	0.8292	0.8562	0.8460	0.8699	0.8423	0.8674

Robust standard errors in parentheses, clustered at Census OA *** p<0.001, ** p<0.01, * p<0.05
Data in postcode-quarter cells, 2000-2011. Dependent variable is postcode-quarter-mean log prices.
Visible and operational is the treatment indicator (visible, 0<distance<k, operational) described in Section 4, indicating that a postcode has an operational windfarm visible within the specified radius k.
Sample restricted to postcodes with visible-operational turbines within distance k at some time over the study period.
All regressions control for quarter dummies.
Control variables are postcode slope-by-year, elevation-by-year, aspect by-year dummies, proportions of sales of detached, semi-detached, terraced, flat/maisonette.

Table 4: Balancing tests for various housing characteristics. 4km radius

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
New	Detached	Semi	Terraced	Flat	Leasehold	Age	Area	Beds
-0.0051	0.0011	-0.0001	-0.0059	0.0049	0.0034	-0.6389	0.3803	-0.0383
(0.0062)	(0.0040)	(0.0017)	(0.0046)	(0.0039)	(0.0022)	(1.7063)	(2.0852)	(0.0457)
99,114	99,114	99,114	99,114	99,114	99,114	13,256	13,256	13,256
0.4968	0.6412	0.6462	0.5200	0.6461	0.7595	0.9248	0.8133	0.7936

(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Baths	No CH	No Gar	Detached	Semi	Terraced	PB Flat	Conv Fl	Other
0.0587	-0.0051	-0.0018	-0.0214	0.0099	-0.0072	0.0194	0.0040	-0.0048
(0.0451)	(0.0152)	(0.0307)	(0.0229)	(0.0284)	(0.0244)	(0.0150)	(0.0097)	(0.0053)
13,256	12,678	13,256	13,256	13,256	13,256	13,256	13,256	13,256
0.7709	0.6874	0.7601	0.7898	0.7620	0.8224	0.8087	0.7796	0.7805

Specifications as in Table 3, column 6, but with property type control variables excluded.

Table 5: Robustness to additional control variables and trends. 4km radius

		(1)	(2)	(3)	(4)	(5)
	Baseline estimate from Table 3	Sub-sample with additional Nationwide property Xs	Nationwide prices and Xs	Census output area Xs x trends	Control for regional trends from from full dataset	Control for pre-operational nearest wind farm trends
Visible operational turine within 4km	-0.0289***	-0.0463**	-0.0405***	-0.0275***	-0.0272***	-0.0219***
	(0.0056)	(0.0145)	(0.0120)	(0.0057)	(0.0052)	(0.006)
Observations	99,114	12,678	12,678	93,510	99,114	99114
R-squared	0.8562	0.8913	0.9768	0.8383	0.8582	0.857

Robust standard errors in parentheses, clustered at Census OA *** p<0.001, ** p<0.01, * p<0.05
Column 2 controls for floor size, number of bedrooms, bathrooms, central heating type, garage type, and detailed property type for postcodes represented in Nationwide data. Column 3 similar, using price reported in Nationwide data. Column 3 adds linear trends interacted with census 2001 variables at output area (OA) level (OA land area, proportion with no qualifications, proportion with tertiary qualifications, proportion born UK, proportion white ethnicity, proportion employed, proportion in social rented housing).
Column 5 controls for piecewise constant quarterly price trends predicted from transactions beyond 14km from any windfarm, operational, planned or refused (coefficient on predicted prices 0.456 (0.021).
Column 6 controls for nearest operational windfarm linear time trends estimated from pre-operational period (coefficient on predicted prices 0.103 (0.014).
Specifications otherwise as Table 3, column 6,

Table 6: Postcode fixed effects estimates; distance bands; sample with operational windfarm within 14km, during 2000-2011

	(1)	(2)
Control Xs	No	Yes
Visible, operational <1km	-0.0332*	-0.0580**
	(0.0131)	(0.0180)
Visible, operational 1-2km	-0.0294***	-0.0556***
	(0.0085)	(0.0099)
Visible, operational 2-4km	-0.0011	-0.0189**
	(0.0046)	(0.0060)
Visible, operational 4-8km	-0.0094**	-0.0116***
	(0.0029)	(0.0033)
Visible, operational 8-14km	-0.0171***	-0.0104***
	(0.0020)	(0.0020)
Observations	797,470	797,470
R-squared	0.8424	0.8675

Robust standard errors in parentheses, clustered at Census OA *** p<0.001, ** p<0.01, * p<0.05

Table 7: Postcode fixed effects estimates; comparisons of operational windfarms with planned windfarms within k km, during 2000-2011

	(1)	(2)	(3)	(4)	(5)
Radius	1km	2km	4km	8km	14km
Control Xs	Yes	Yes	Yes	Yes	Yes
Operational	-0.0770***	-0.0595***	-0.0183**	-0.0095**	-0.0054**
	(0.0218)	(0.0103)	(0.0060)	(0.0032)	(0.0020)
Planned	-0.0153	0.0042	0.0049	0.0117***	0.0109***
	(0.0165)	(0.0078)	(0.0043)	(0.0028)	(0.0018)
Obs.	11,117	50,754	169,237	506,208	1,085,839
R-squared	0.8480	0.8585	0.8656	0.8706	0.8684

Robust standard errors in parentheses, clustered at Census OA *** p<0.001, ** p<0.01, * p<0.05

Table 8: Postcode fixed effects estimates; comparisons of visible operational windfarms with non-visible operational windfarms within k km, during 2000-2011

	(1)	(2)	(3)	(4)	(5)
Radius	1km	2km	4km	8km	14km
Control Xs		Yes	Yes	Yes	Yes
Operational visible	-	-0.0596***	-0.0274***	-0.0074*	-0.0059***
		(0.0099)	(0.0056)	(0.0030)	(0.0018)
Operational	-	-0.0688	0.0059	0.0162***	-0.0117***
not visible		(0.0630)	(0.0133)	(0.0042)	(0.0021)
Obs.	-	28,951	116,595	508,147	1,391,879
R-squared	-	0.8498	0.8578	0.8712	0.8685

Robust standard errors in parentheses, clustered at Census OA *** p<0.001, ** p<0.01, * p<0.05

Table 9: Effects by windfarm size and distance bands

	(1) <2km	(2) 2-4km	(3) 4-8km	(4) 8-14km
1-10 turbines	-0.0531***	-0.0153*	-0.0031	-0.0057**
	(0.0091)	(0.0061)	(0.0035)	(0.0022)
11-20 turbines	-0.0565**	-0.0321***	-0.0483***	-0.0117***
	(0.0189)	(0.0097)	(0.0059)	(0.0035)
20+ turbines	-0.1163***	-0.0568***	-0.0593***	-0.0276***
	(0.0284)	(0.0171)	(0.0063)	(0.0030)

Obs. 797469. R-squared 0.8676

Figure 1: Development of wind turbines in England and Wales, 1993-2011

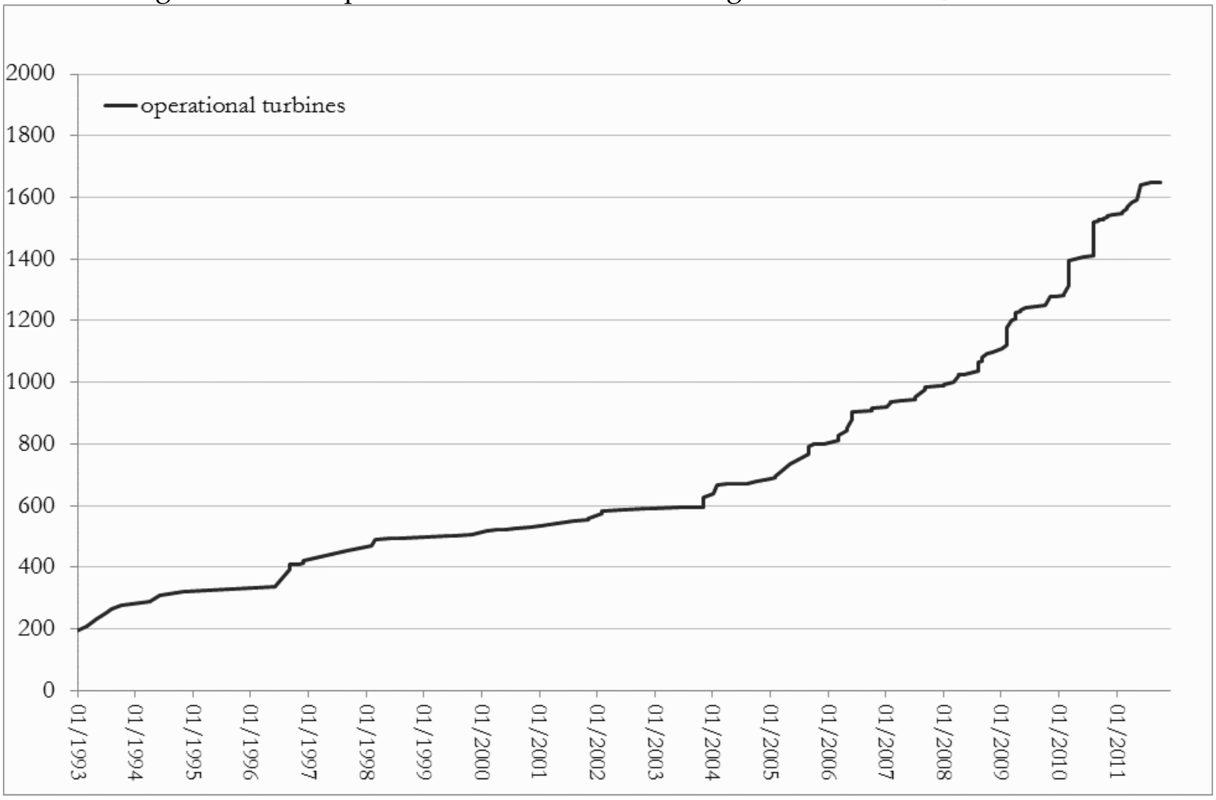
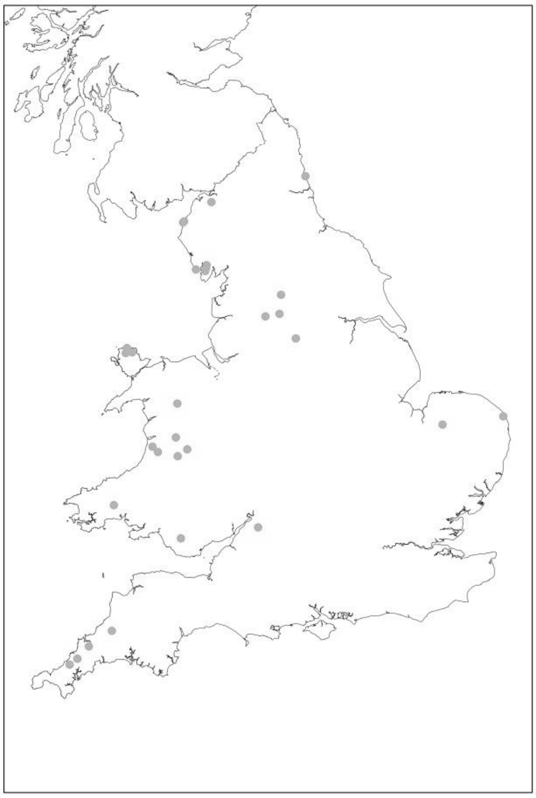
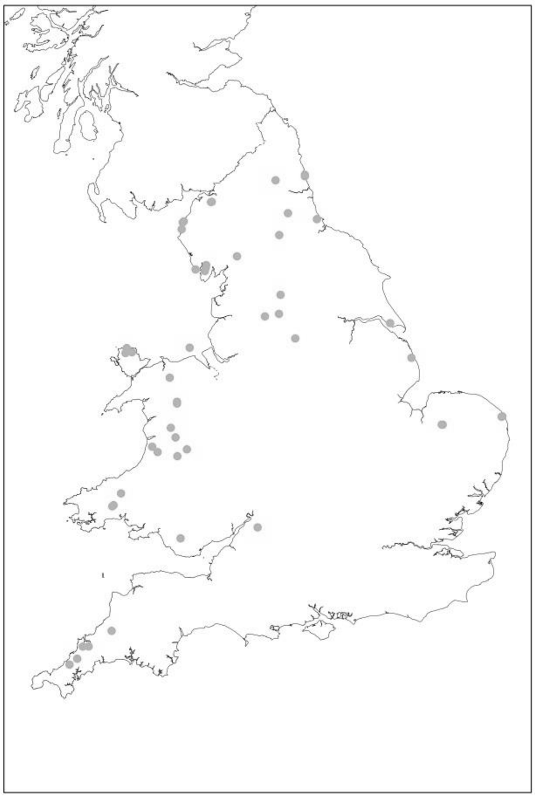


Figure 2: Development of wind turbine sites in England and Wales

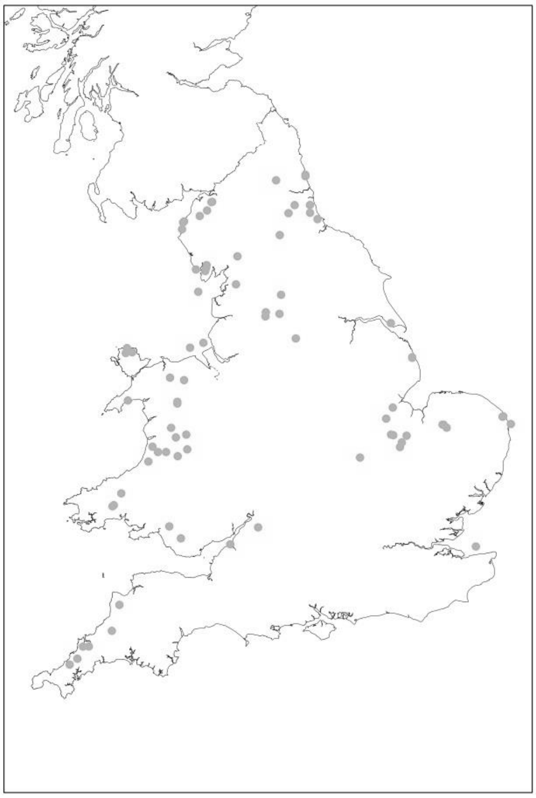
2000: 30 sites



2003: +20 sites



2007: +33 sites



2011: +65 sites

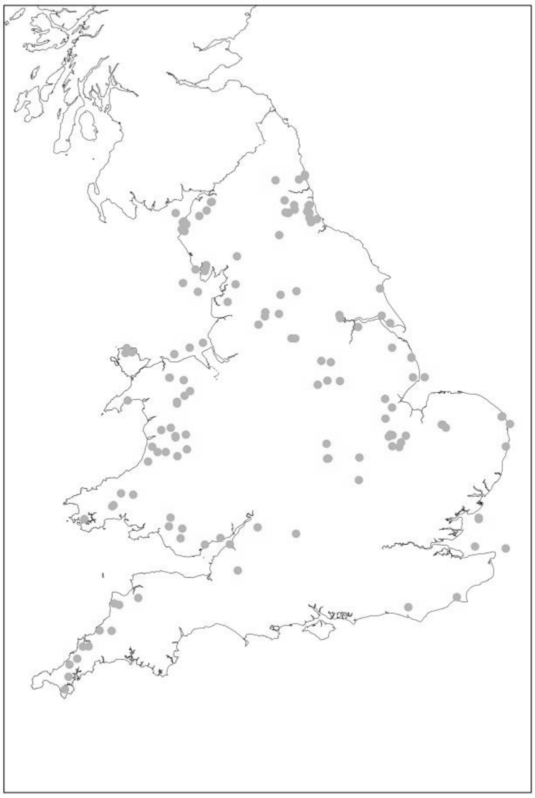


Figure 3: Spatial distribution of planned windfarm sites in 2011

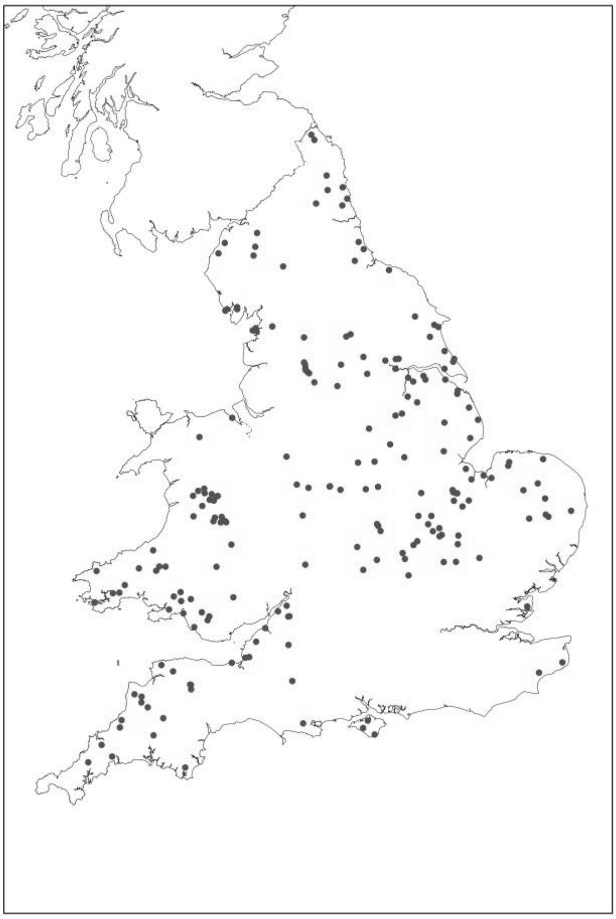
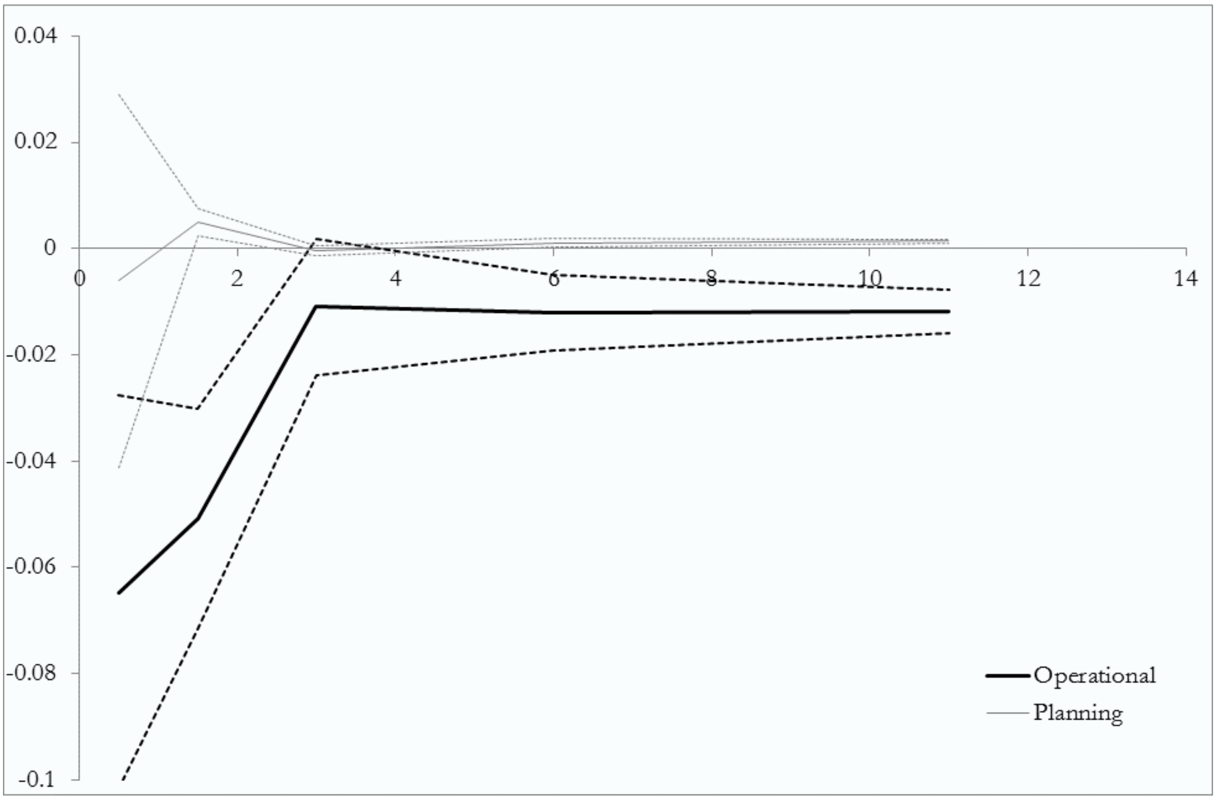


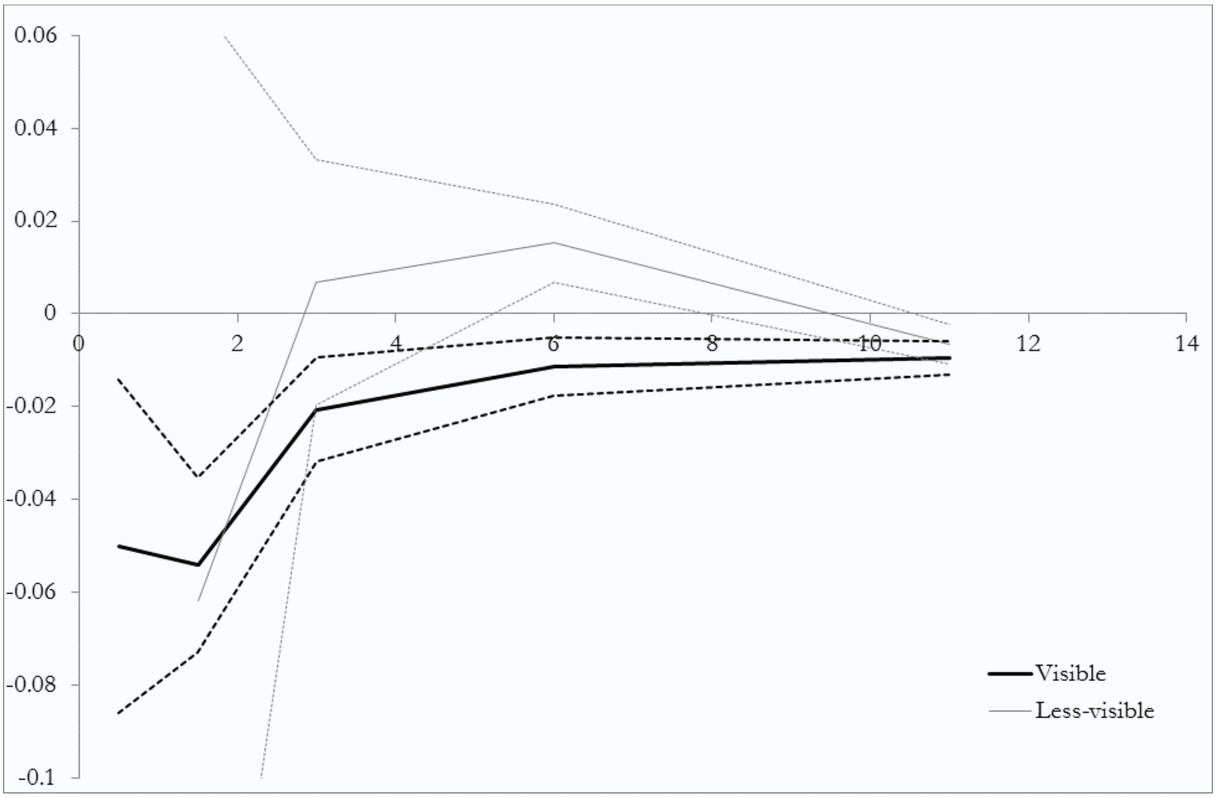
Figure 4: Comparisons by planning status: Postcode fixed effects estimates; distance bands; controls include distance-band-by-status-by-year effects



Difference-in-difference-in-difference comparisons at each distance band					
	<1km	1-2km	2-4km	4-8km	8-14km
Operational v	-0.0586*	-0.0558***	-0.0106***	-0.0132***	-0.0133**
Planning	(0.0260)	(0.0107)	(0.0065)	(0.0036)	(0.0021)

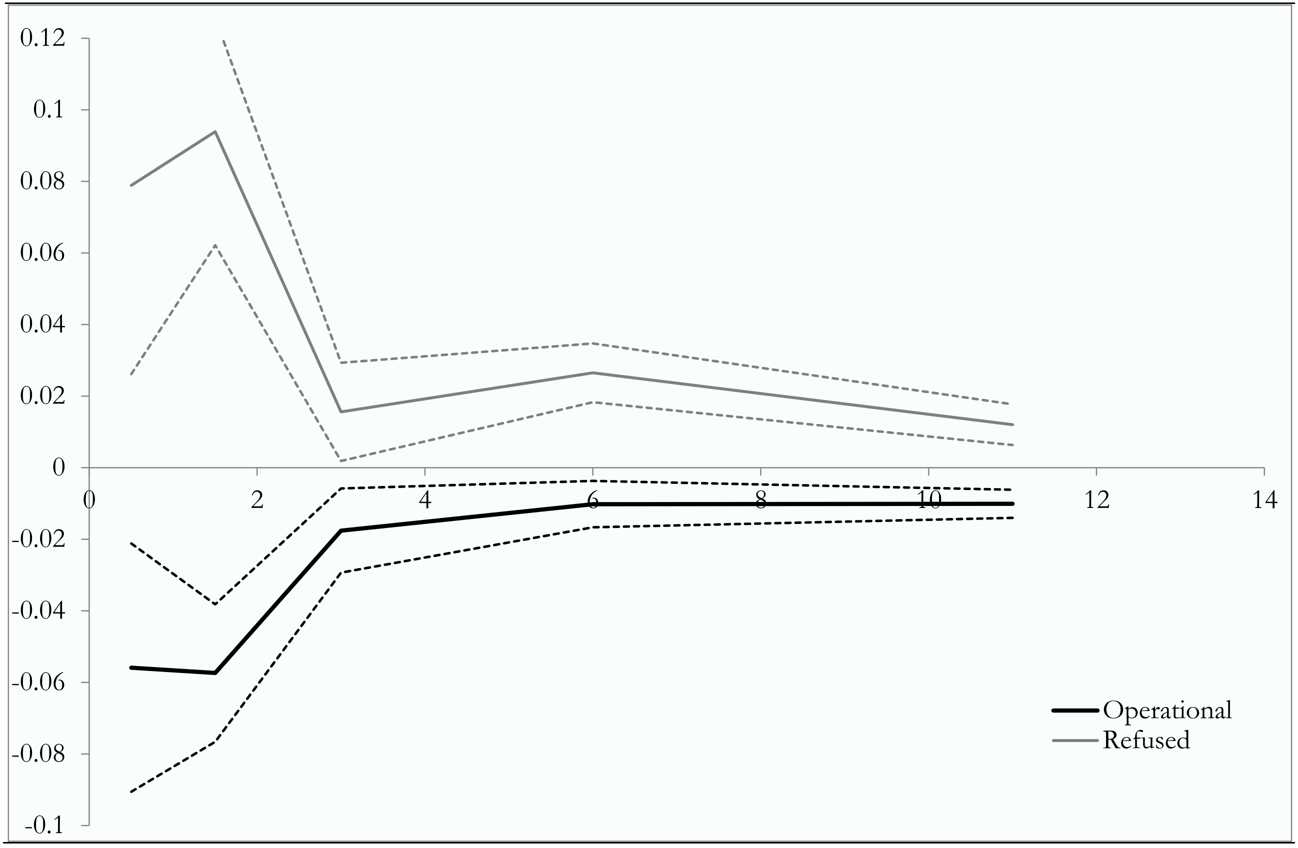
Figure 5: Example viewshed. Haswell Moor wind farm in north east England

Figure 6: Comparison by visibility: Postcode fixed effects estimates; distance bands; controls include distance-band-by-visibility-by-year effects



Difference-in-difference-in-difference comparisons at each distance band					
	<1km	1-2km	2-4km	4-8km	8-14km
Visible v	-	0.0079	-0.0275†	-0.0267**	-0.0029
less-visible	-	(0.0670)	(0.0146)	(0.0054)	(0.0029)

Figure 7: Comparisons by planning status: Postcode fixed effects estimates; distance bands; controls include distance-band-by-status-by-year effects



Difference-in-difference-in-difference estimates

	0-1km	1-2km	2-4km	4-8km	8-14km
Operational v Refused	-0.1349***	-0.1514***	-0.0332***	-0.0367***	-0.0220***
	(0.0322)	(0.0189)	(0.0092)	(0.0054)	(0.0035)

7 Appendix

There are potential concerns over the standard errors of the estimates presented in the main results, because the regression unobservables are potentially correlated over space in unknown ways, and are undoubtedly serially correlated within postcodes. As is well known (Moulton 1990), the standard errors on aggregated treatment variables can be downward biased when there is serial and/or spatial correlation in the regression error terms, although in the current application the treatment is by its nature aggregated. In the current analysis the treatment is constructed at postcode level, although the effect is aggregated across postcodes within the distance bands in Table 6 for each wind farm, since when a windfarm is built it affects visibility in all postcodes within that distance band. Of course this is a genuine effect due to the geographical level of the treatment, not an arbitrary geographical aggregation of micro level interventions, so the Moulton example does not necessarily apply exactly.

The usual adjustment for this kind of problem is to use 'clustered' standard errors at the level of the treatment - i.e. distance band-by-windfarm clusters in the current example - though in this case this would be an extremely conservative assumption, since it assumes, in effect that the errors are perfectly correlated both within a distance band, both in the cross section and over time. An equivalent evaluation of a national policy would dictate a single cluster, which is clearly a silly assumption. On the other hand, when researchers use fixed effect estimators, they generally cluster at the level of the fixed effects – i.e. postcodes in this case - to allow for serial correlation within the erros within panel units. The standard errors reported in the main results cluster at Census output area (OA) level, but given the uncertainty over the appropriate level, Table 10 in the Appendix explores a range of clustering options, using the specification of Table 6.

The first column reports the standard errors with OA level clusters. The second column clusters at groups define by the distance-band, the identifier of the nearest windfarm and the time period (quarter) allowing for cross sectional spatial error autocorrelation or heteroscedasticity across these groups. The standard errors are smaller in this case. The next column allows for clusters both at postcode level (to allow for serial correlation within panel units) and for each quarter (allowing for correlation across all panel units within each period).[9] These standard errors are close to those estimated using OA clusters, and seem likely to account for most plausible sources of bias in the standard errors.

The remaining columns adopt other more conservative assumptions. Column 4 expands to Census ward clusters, allowing for cross sectional and serial correlation within census wards, which doubles the standard errors, although the coefficients remain significant witn the 0-1 and 1-2 km bands. Finally, the last column adopts the most conservative clustering assumption and allows for arbitrary correlation over time and in the cross section within wind-farm-by-distance-band-groups. The estimates in the 0-1km and 1-2km bands are still significant, if only at the 10% level.

[9] Using the method of Thompson (2011).

Table 10: Postcode fixed effects estimates; distance bands; sample with operational windfarm within 14km, during 2000-2011. Alternative clustering assumptions.

Fixed effects	Postcode	Postcode	Postcode	Postcode	Postcode
Clusters	OA	Nearest windfarm x distance-band x quarter	Postcode and quarter (Thompson 2011)	Ward	Nearest windfarm x distance-band
Number of clusters	21278	22526	87517 + 48	1942	614
Control Xs	Yes	Yes	Yes	Yes	Yes
Visible, operational <1km	-0.0580**	-0.0580***	-0.0580**	-0.0580*	-0.0580†
	(0.0180)	(0.0150)	(0.0188)	(0.0256)	(0.0313)
Visible, operational 1-2km	-0.0556***	-0.0556***	-0.0556***	-0.0556**	-0.0556*
	(0.0099)	(0.0089)	(0.0082)	(0.0195)	(0.0268)
Visible, operational 2-4km	-0.0189**	-0.0189***	-0.0189**	-0.0189	-0.0189
	(0.0060)	(0.0056)	(0.0059)	(0.0124)	(0.0206)
Visible, operational 4-8km	-0.0116***	-0.0116*	-0.0116*	-0.0116	-0.0116
	(0.0033)	(0.0051)	(0.0053)	(0.0080)	(0.0180)
Visible, operational 8-14km	-0.0104***	-0.0104***	-0.0104**	-0.0104*	-0.0104
	(0.0020)	(0.0031)	(0.0034)	(0.0049)	(0.0097)
Observations	797,470	797,470	797,470	796,829	797,470

*** p<0.001, ** p<0.01, * p<0.05, †p<0.10