Online Supplementary Appendix

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A Project Costs and Benefits

Further detail on the estimation of project costs and benefits is provided here.

A.1 Electricity production

To estimate the capacity factors for solar projects I use estimates from Renewables Ninja (Pfenninger and Staffell, 2016; Staffell and Pfenninger, 2016) and the World Bank Solar Atlas (World Bank, 2022d,c). The former provides an hourly solar power production profile for a representative solar installation in the UK from 1985 to 2016. The latter provides monthly average solar power production estimates on a 1km spatial grid for a representative solar installation. I use the coordinates of each project to extract the nearest values from this grid. This provides a precise estimate of the seasonal variation in solar output for each project. I then combine these monthly averages with the national hourly profile to get a month-of-year by hour-of-day production profile that is specific to each project. The combination of both monthly and hourly variation captures the key seasonal and within-day variation in solar production.

For wind projects the capacity factor is much more heavily dictated by the kind of turbine installed. To account for this I use customized data downloaded from Renewables Ninja (Pfenninger and Staffell, 2016; Staffell and Pfenninger, 2016). Here a user can select a set of location coordinates, a wind turbine model and height, and then a wind power production profile is calculated over a set time period that accounts for both turbine characteristics and site wind conditions.

For each wind project I first assign a plausible turbine model. In principle I have data on the actual turbine make and model for most of the constructed project from The Wind Power Turbine Database (The Wind Power, 2019). However, these data do not cover all projects, and do not contain information on proposed projects that were ultimately not completed. As such, to assign a plausible turbine model to each project I first directly estimate both the turbine capacity (in MW) and the turbine power density (in MW per m^2 of blade swept area) using the data available in the planning database and for the projects with data from The Wind Power. For each project I then find the closest turbine model on these two metrics that is in the Renewables Ninja database and is consistent with the time period when a given project was being proposed. I sense check my assigned turbine model against actual models in The Wind Power dataset to ensure this approach is reasonable.[1]

[1]The mean absolute difference between the turbine capacity of the assigned turbine make/model and the actual turbine capacity is 2%, with the majority of projects getting the turbine capacity exactly right. The mean absolute difference between the turbine power density of the assigned turbine make/model is 4%.

Using the assumed turbine model and the location coordinates for each project, I query the Renewables Ninja database and extract an hourly power production profile for an entire year.[2] I then collapse the annual hourly profile to month-of-year by hour-of-day averages. As noted above, the combination of both monthly and hourly variation captures the key seasonal and within-day variation in wind production. This also ensures consistency with the approach taken to calculating solar capacity factors.

Finally, I check my estimated capacity factors by calculating average lifetime values for each completed wind and solar project, and then calculating annual averages based on the year in which projects were completed. I then compare these values to available data on observed performance (BEIS, 2022a; IRENA, 2022). For solar projects the estimated capacity factors generally have a very tight range around 10% and don't experience much of an increase over time. This matches observed trends well. For wind projects the estimated capacity factors show much greater dispersion and generally fall in the 30-50% range. The higher level of dispersion is consistent with the fact that wind conditions, project size and turbine type are highly heterogenous across projects. Offshore projects also have higher average capacity factors than onshore ones which is as expected. However, the estimated capacity factors don't exhibit the same level of growth over time that is clear from observed trends, with a consistent pattern of over-estimation for earlier projects. This is likely due to the Renewables Ninja platform used for estimation being better suited for predicting for current projects than for past ones.

To remedy this I adjust the wind capacity factors to better account for these annual trends. For onshore wind, I use annual average capacity factors for completed UK projects from IRENA (IRENA, 2022). I calculate the capacity-weighted average lifetime capacity factor for all completed projects in my sample in a given year. I then divide this by the observed average value from IRENA for that year to get a ratio. I use this ratio to rescale the estimated capacity factors for all proposed wind projects with an actual or expected opening data in that year.[3] For offshore wind I am able to take a more bespoke approach. I gather project specific observed capacity factors based on operational output data (Smith, 2023).[4] I then set the capacity factors for any offshore projects with observed data to these exact values. For projects without observed data (either completed or proposed) I replicate the approach used for onshore wind set out previously.[5]

[2]Given limitations on the frequency with which this database can be queried and the large number of projects, I am only able to extract power profiles for the year 2014. To the extent this year was not representative of wind conditions more generally, my findings may suffer from some bias. However, this annual profile is summarized in such a way as to limit the impact of having chosen this particular year.

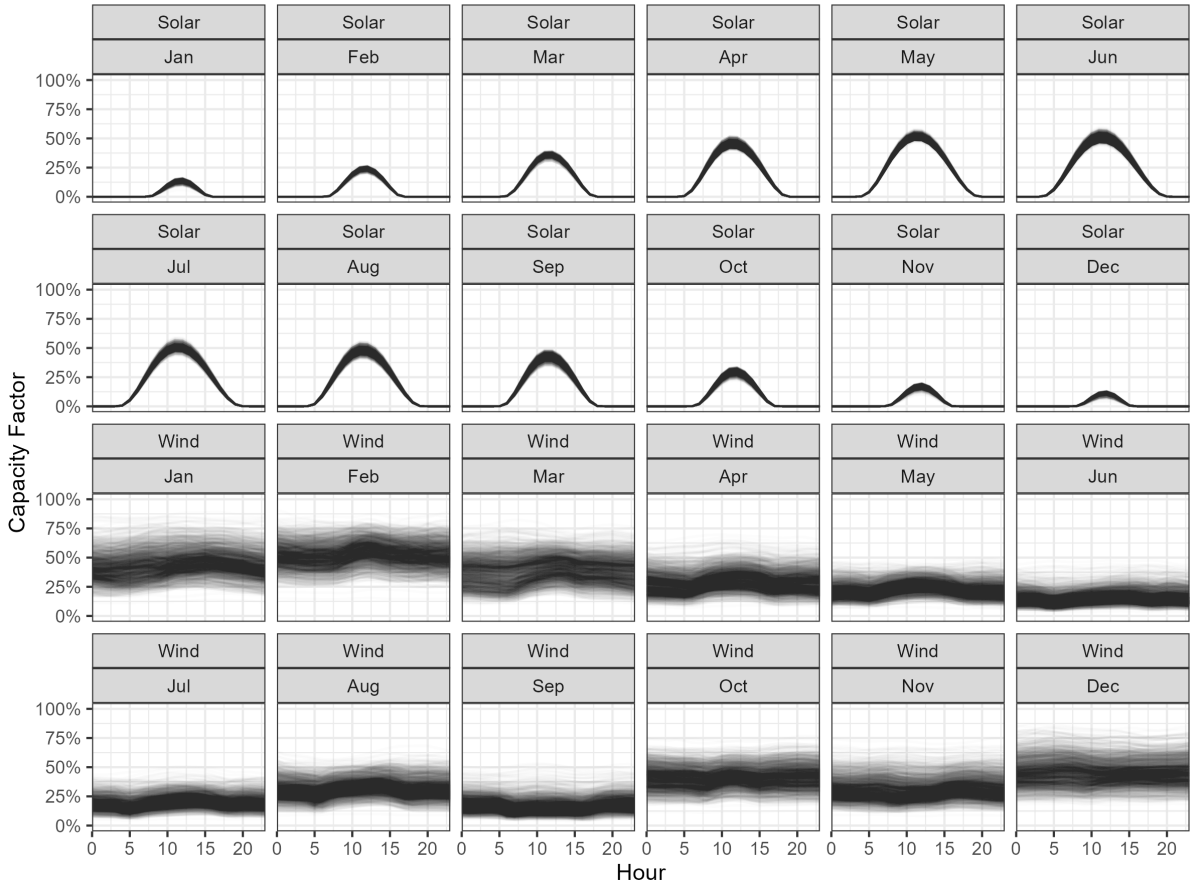
[3]To reduce the noise from year-to-year variation in this ratio value I use a five-year rolling average.

[4]I only collect values for projects with at least two years of operational data to avoid the capacity factors being biased by the initial months when the project is incrementally brought online.

[5]Here I average the observed project specific values to get annual averages comparable to those collected from IRENA. I then calculate ratios in the manner described, once again using the five-year rolling average.

The resulting month-of-year by hour-of-day capacity factors are shown in Figure A.1. As expected, solar capacity factors peak in the middle of the day, and are also higher in summer months than in winter. Wind capacity factors have a fairly flat profile over the hours of the day, but are generally higher in the winter months than in the summer. It is also clear from Figure A.1 that there is more heterogeneity in capacity factors across wind projects than is the case for solar projects. This makes sense given the greater variability in the turbines that can be installed and in wind conditions more generally.

Figure A.1: Estimated Hourly Capacity Factor Profiles

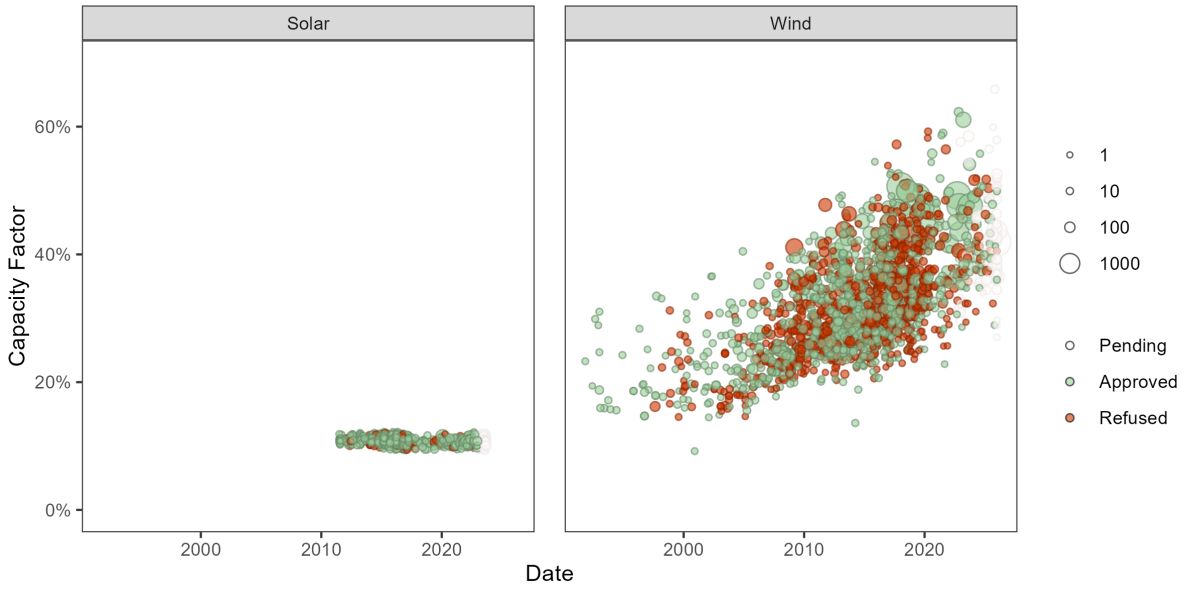


Notes: This figure shows the month-of-year by hour-of-day capacity factor profiles for all projects in my sample. Each line refers to a project. The top panels are for solar projects and the bottom panels are for wind projects.

Figure A.2 illustrates the variability in average capacity factors once aggregated up to a single project specific lifetime value. Once again there is much more heterogeneity in capacity factors across wind projects than solar projects. There is also a clear trend of increasing capacity factors over time for wind projects, while the trend for solar projects has been largely flat. There is also no clear pattern with regard to projects with higher capacity factor being more likely to approved, as illustrated by the overlap between approved (green) and refused (red) projects.

Importantly, the wind capacity factors in Figure A.1 and A.2 include both onshore and offshore wind projects, with capacity factors being seperately estimated for each project. Offshore wind projects tend to have higher capacity factors - the median offshore wind project in the sample has a capacity factor of 44% compared to 35% for onshore projects. Offshore projects are also generally much larger - the median offshore wind project in the sample has a capacity of 287MW compared to 11MW for onshore projects.

Figure A.2: Estimated Project Capacity Factors



Notes: This figure shows the estimated project capacity factors over time. Each point refers to a project. Point sizes are determined by the capacity (in MW) of a project. Projects are classified by their development status. "Pending" are projects that have submitted a planning application but have yet to receive a final decision. "Approved" are projects that have been approved and are either awaiting construction, under construction, operational or have been subsequently decommissioned. "Refused" are projects that were refused planning permission or were otherwise withdrawn or halted.

A.2 Market and Environmental Value of Electricity

The social value of the electricity produced by a new wind or solar project is a combination of both private and external factors. For the private value I rely on wholesale electricity prices. For the external value I incorporate estimates of the reduction in carbon emissions damages and local pollution damages. To do this I primarily rely on data from the UK government's guidance on cost benefit analysis and the valuation of climate change policies (BEIS, 2020b, 2021). I supplement this with a range of additional sources and analyses in order to value projects over my full sample window (1990 to 2050) and to capture within-year and even within-day variation in the value of renewable electricity production. For each project, hourly and seasonal variation in their output is matched up

with hourly and seasonal variation in the value of electricity production when computing their full net present value.

A.2.1 Wholesale Electricity Prices

For the private value of renewable electricity production I start with the available UK government guidance which includes annual values for wholesale electricity prices from 2001 to 2040 (BEIS, 2020b, 2021). The prices from 2001 to 2020 are based on historical average wholesale electricity prices. The values from 2020 to 2040 are based on the UK government's modeling of the future electricity grid.[6]

To extend the price data back to the start of my sample period I extrapolate using an index of industrial electricity fuel prices going back to 1970 from the Digest of UK Energy Statistics (BEIS, 2022a). I also directly collect hourly data on wholesale electricity prices from Elexon, which I average to the annual level to give up-to-date observed data from 2004-2022 (Elexon, 2022). To extend the price data out to the end of my sample period I use the forecast values from the guidance up until 2040. I then carry forward the 2040 values until 2050.

As well as varying from year-to-year, wholesale electricity prices also vary significantly from month-to-month, day-to-day and even hour-to-hour. To the extent that this variation is correlated with the variation in output from a given wind or solar project, the private value of the electricity being produced may differ from the annual average. There is no available dataset that can provide historical or forecast values for hourly wholesale prices from 1990 to 2050. To remedy this I use an econometric analysis to estimate plausible values for hourly electricity prices over my entire sample period. To do this I take the following steps.

First, I collect hourly data on wholesale electricity prices from Elexon from 2004 to 2022 (Elexon, 2022). I then calculate a price ratio variable that is the hourly electricity price divided by the annual average. This price ratio variable will serve as the dependent variable that I will aim to predict in all hours-of-sample from 1990 to 2050. It is unitless and captures the scale of within-year fluctuations in electricity prices. I can then multiply the annual average wholesale electricity prices (described above) by this estimated hourly price ratio to get hourly estimated values for wholesale electricity prices.

Second, I construct a series of covariates that can a) help explain hourly variation in price fluctuations, and b) be observed or estimated over the full sample period. The covariates include dummy variables for each hour-of-day, day-of-week, day-of-month and month-of-year. I then construct two further variables based on the level of electricity

[6]This modeling includes forecasting fuel prices, demand and investment in new capacity, and then running a dispatch model to solve for clearing market prices.

demand and composition of electricity production in a given hour. I seperately estimate both of these things, and the approach taken to do this is described in the next section on external values. The first variable I construct is the "peak load share". This is the hourly electricity demand in a given hour divided by the peak hourly demand for that year. The purpose is to produce a variable bounded 0 to 1 that reflects whether a given hour is a high demand period where prices tend to be higher, or low demand period where prices tend to be lower. The second variable I construct is the "baseload generation share". This is the hourly electricity production from baseload inflexible or intermittent sources in a given hour divided by hourly electricity demand in that hour. Again the resulting variable is bounded 0 to 1. Baseload inflexible or intermittent sources are taken to be wind, solar, hydro, tidal and nuclear. All of these have low marginal costs of production, so when they make up a large proportion of total generation the will tend to shift out the supply curve, reducing the amount of more expensive flexible generation that needs to operate, and thus reducing prices.

Third, I fit a model that can simulate wholesale electricity prices over the entire sample period. The dependent variable is the price ratio. The independent variables are the various time dummies, the "peak load share" and the "baseload generation share". This is simply a prediction exercise and one in which the functional form with which the various covariates enter is unclear. As such I use a random forest algorithm to fit the model. This achieves an out-of-sample R-squared of 0.41. Given the limitations on the covariates that can be included and the extent of underlying price variation this seems to be an acceptable level of model performance.

Fourth, I use the fitted model to make predictions for the price ratio in each hour of the full 1990 to 2050 sample. I then multiply these price ratios by the annual average electricity price to get simulated hourly values for wholesale electricity prices spanning my entire sample period. In my final analysis I use the observed historical prices for the 2004 to 2022 period and the simulated prices for pre-2004 and post-2022.

A final factor to account for is spatial variation in the private value of electricity. To date the UK has not had locational marginal pricing. Instead there is a single national price, and then congestion is resolved via a secondary redispatch market. To account for spatial variation in the private value of electricity output and approximate the effects of the redispatch market I use modelling results produced for the UK energy regulator, Ofgem, as part of their assessment of the impact of moving to nodal locational marginal pricing (Ofgem, 2022). I use the figures provided in their report to approximate how much average wholesale prices in each region differ from the national average in a given year.[7] I then adjust the private value of electricity production for each project by the

[7]Their report is forward looking so provides projected price levels nationally and by region in 2025, 2030, 2035 and 2040. I assume the 2025 spatial relationship holds back to 1990 and the 2040 spatial

relevant scaling factor depending on the region in which a project is located. Visually it is clear that the adjustments lead to projects further north earning lower wholesale prices than average while projects further south earn higher wholesale prices than average. For example, the average wholesale price in Scotland in 2025 is assumed to be around 63% of the national average while further south in England & Wales it is 106% of the national average.

A.2.2 Carbon Emissions and Local Pollution Damages

For the external value of renewable electricity production I start with the available UK government guidance on the value of avoided carbon emissions and local pollution (BEIS, 2020b, 2021). For marginal abated carbon emissions the guidance provides an annual series of carbon prices from 2010 to 2100.[8] I use the non-traded values which are £73/tCO2 in 2020 and increase steadily over time at approximately 2% per year.[9] I therefore extrapolate the values backwards from 2010 to 1990 assuming the same growth rate.

For local pollution the values of avoided local pollution damages are taken from UK government guidance (BEIS, 2020b, 2021). These are £8,152/ton for SO_2, £5,487/ton for $PM_{2.5}$, £3,616/ton for PM_{10}, and £2,272/ton for NO_X.[10]. The assumptions for the local pollutants are underpinned by UK government modelling of air pollution transport and damages. For all air pollutants I use the baseline national damage assumptions. These are calculated using an impact pathways modelling approach that accounts for the spatial distribution of pollutant emissions from existing sources, and how such a reduction affects exposed populations after accounting for pollution dispersion and population density.[11] For $PM_{2.5}$ and NO_X more detailed assumptions are available beyond a single national value in order to better reflect the pollution exposure of specific sectors and emission types. I use the damage values that are most approriate for large power plants with tall

relationship holds out to 2050.

[8]The guidance includes high, low and central values for carbon prices. I use the central values and then examine the high and low values in sensitivity analyses.

[9]Values here are in real 2021 prices. I do not use the traded values here as they are based on the EU Emissions Trading Scheme which had a number of idiosyncratic reasons why prices were very depressed in the early years existence. Furthermore, the traded values are assumed to converge to the non-traded ones by 2030 anyway. Because the goal here is to capture the true social value of reducing carbon emissions the non-traded ones are deemed to be more appropriate for this purpose.

[10]My analysis relies on the 2019 guidance and all the values cited are given in real 2021 prices for the year 2020. The guidance includes high, low and central values for carbon prices. I use the central values and then examine the high and low values in sensitivity analyses.

[11]The time period of projects studied spans over three decades while UK government modelling necessarily reflects the current distribution of emissions sources and population densities. I follow the government guidance in simply extrapolating current £/ton damage values forwards to 2050 when valuing new renewable energy projects, so does not seek to account for changing patterns of population exposure over time. This doesn't seem entirely unreasonable as existing emissions sources and populations are likely to highly correlated over time, even over many decades.

chimney stack heights.[12] So in this context, the damage assumptions should account for spatial variation in local pollution damages from the power grid in an aggregate sense, although this marginal damage is assumed to be the same for all wind and solar projects at a given point in time, irrespective of their own location.

To convert these damages in £/ton of pollutant into £/MWh of electricity requires data on the emissions intensity of electricity production in tons/MWh. The guidance does provide some values for carbon emissions intensity, although these do not include short-run marginal values or information pre-2010. Local pollution emissions intensities are not provided. As such I estimate emissions intensities directly.

To estimate marginal emissions intensities I gather annual data on historical emissions by pollutant and source type from the UK National Atmospheric Emissions Inventory (DEFRA, 2022) and historical electricity production by source type from the Digest of UK Energy Statistics (BEIS, 2022a). Dividing source-level emissions by source-level electricity production yields an annual emissions rate by source type. Averaging across all source types, weighted by their respective annual generation, yields an annual average emissions rate. Here I exclude baseload sources of electricity generation from this calculation (i.e. nuclear, wind, solar, hydro and tidal) and assume only flexible sources (i.e. coal, oil, gas, other thermal, storage and interconnectors) are "on-the-margin" such that they can be displaced by additional wind and solar output.[13] I find that the emissions intensity has fallen significantly over time across all pollutants, especially sulphur dioxide and particulate matter which are strongly tied to the presence of coal generation.

As well as varying from year-to-year, the emissions intensity of electricity also varies significantly from month-to-month, day-to-day and even hour-to-hour. To the extent that this variation is correlated with the variation in output from a given wind or solar project, the external value of the electricity being produced may differ from the annual average. Similar to the approach taken for wholesale electricity prices, I use an econometric approach to estimate plausible values for hourly electricity demand and electricity generation by source over my entire sample period, which I then use to calculate hourly emissions intensities. To do this I take the following steps.

First, I collect hourly data on electricity demand and electricity generation by source type from National Grid from 2009 to 2022 (NGESO, 2022, 2023).

[12]These are taken to fall under part A Category 9 in the guidance, which refers to large industrial emitters with chimney heights greater than 100m and a population density in the surrounding 31km radius in excess of 1000 people per square km. Most coal and natural gas plants in the UK are located in industrial regions relatively close to large urban centers which is consistent with this level of exposure.

[13]Storage and interconnector imports are assumed to have emissions factors of zero. Using the marginal emissions rate instead of the average described earlier does not substantively change the analysis. The marginal rate is consistently above the average rate but the two are generally quite close and tend to be highly correlated.

Second, I construct a series of covariates that can a) help explain hourly variation in demand or generation, and b) be observed or estimated over the full sample period. The covariates include dummy variables for each hour-of-day, day-of-week, day-of-month and month-of-year.

Third, I fit a simple regression model that can identify the key features of within-year variation in demand and generation. The dependent variable is electricity demand or electricity generation from each of the source types. The independent variables are the various time dummies. Given the absence of more complex covariates I determine the functional form for the model and estimate via ordinary least squares.[14]

Fourth, I use the fitted model to make predictions for electricity demand and electricity generation by source type in each hour of the full 1990 to 2050 sample. I rescale all values to ensure they match the annual totals for demand and generation already compiled by proportionally adjusting the generation totals in each hour to match the simulated demand in that hour.[15] I multiply each generation source by its annual emissions rate to calculate hourly estimates of emissions intensities.

Lastly, I now combine my estimates of the hourly emissions intensities with the marginal damage values to calculate hourly values for the avoided carbon and local pollution damages in £/MWh for my entire sample period. In my final analysis I use observed hourly data to calculate emissions intensities for the 2009 to 2022 period and the simulated hourly data to calculate emissions intensities for pre-2009 and post-2022.

A.2.3 Marginal Value Results

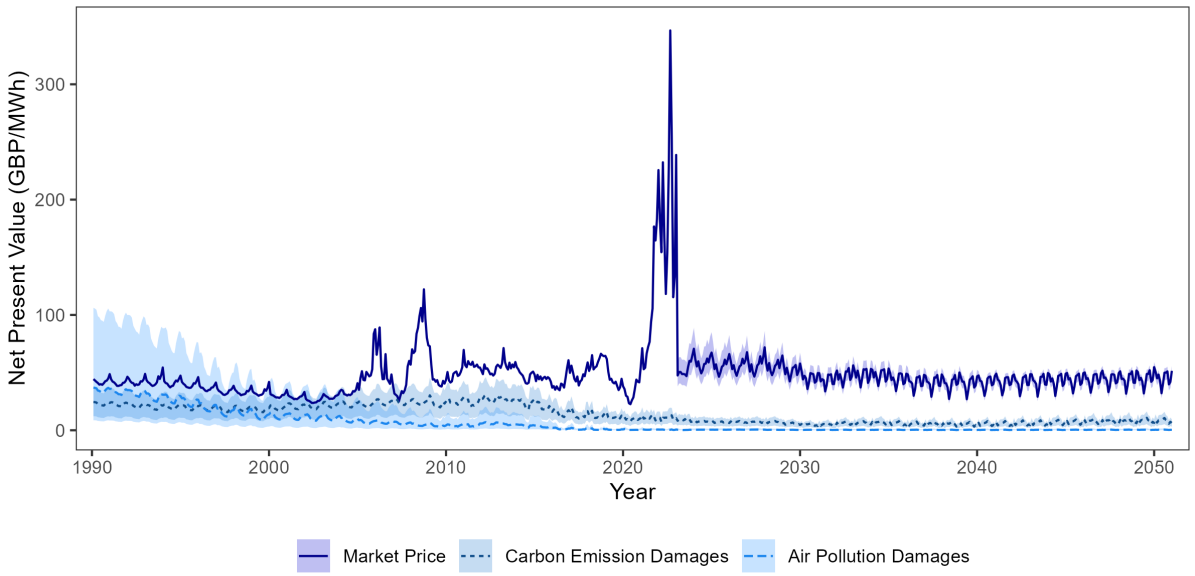
The resulting marginal values per MWh of electricity produced are shown in Figure A.3. These monthly averages convey both the long-term trends and the seasonal fluctuations in both private and external benefits from new wind and solar output. The shaded range also indicates the bounds created by the low and high sensitivities. These are the most pronounced for local pollution damages in the early years of the sample where coal generation played a larger role in UK electricity supply.

To better illustrate the underlying hourly variation, Figure A.4 shows the simulated hourly private and external value over the first week of April in 2005, 2025 and 2045. The corresponding simulated hourly generation mix is also shown below. The results highlight

[14]My regression includes month-of-year by day-of-month by hour-of-day effects to capture the core seasonal and within-day patterns, and then day-of-week by hour-of-day effects to capture the weekday/weekend variability.

[15]To do this I first proportionally adjust the flexible sources of generation. In the event that this is unable to reconcile aggregate generation and demand (e.g. where there is a surplus of baseload generation) I then proportionally adjust baseload sources of generation as well. In general these adjustments are fairly small. In 90% of hours the total simulated generation is between 82% and 106% of the total demand

Figure A.3: Marginal Market and Non-Market Values of Renewable Electricity Production



Notes: This figure shows the changing marginal value of renewable electricity production over time. "Market Price" refers to the private value of the electricity produced as captured by wholesale electricity prices. "Carbon Emission Damages" refers to the external value of the CO2 emissions abated by displacing generation from other sources. "Air Pollution Damages" refers to the external value of the local pollution emissions abated by displacing generation from other sources. The lines are based on historical data and the UK government's central scenario values, while the shaded areas are bounded by the low and high scenario values.

that a number of important trends are incorporated. First, the long-term decline in coal generation leads to the effective erosion of most air pollution damages in the second half of the sample period. Within-day fluctuations in demand from night to day are met with corresponding fluctuations in flexible generation. This increases both prices and external damages in certain hours. The growing penetration of renewable sources lowers emissions intensities over time and in certain hours. The relatively flat within-day profile of wind output also stands in contrast with the regular daytime peaks of solar output. Lastly, within-week variation is also present, with lower demand on weekends translating into lower prices.

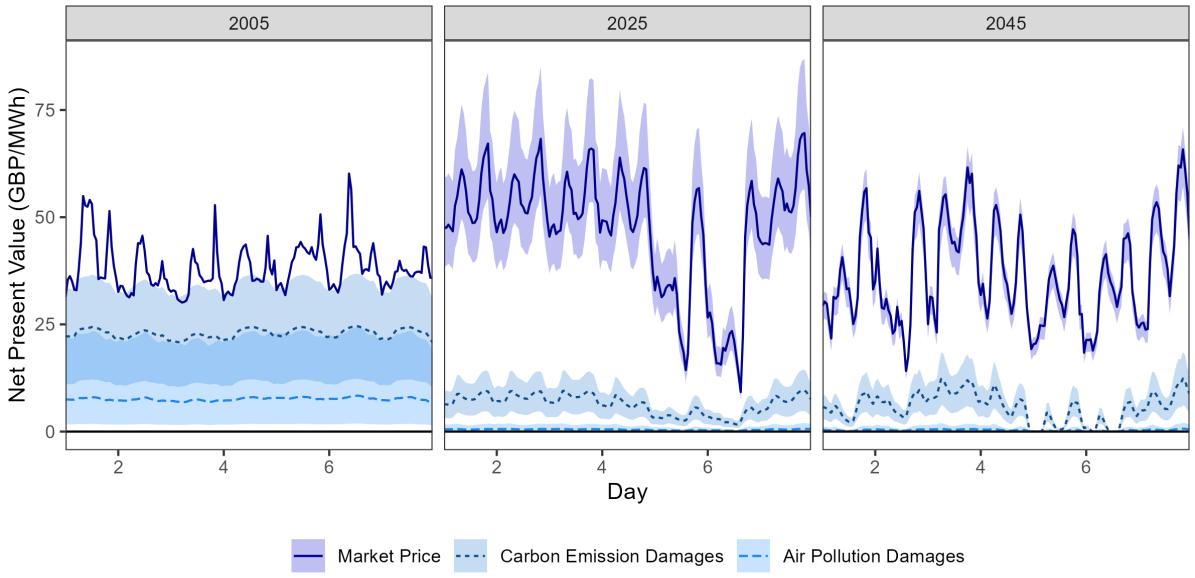
Of course, simulating hourly variability in demand, generation and prices over such a long time period still has some limitations. For instance, shifts in demand that were not observed pre-2022 will be challenging to capture, such as the uptake of electric vehicles and heat pumps. Similarly a growing prevelence of household solar and storage, or changes in the way existing generation assets operate, will also be missing. Nevertheless, the approach taken here is likely sufficient to ensure much of the hourly variability in the value of new wind and solar production is accounted for, particularly relative to the available alternatives and a baseline approach of using annual averages.

A.3 Capacity Value

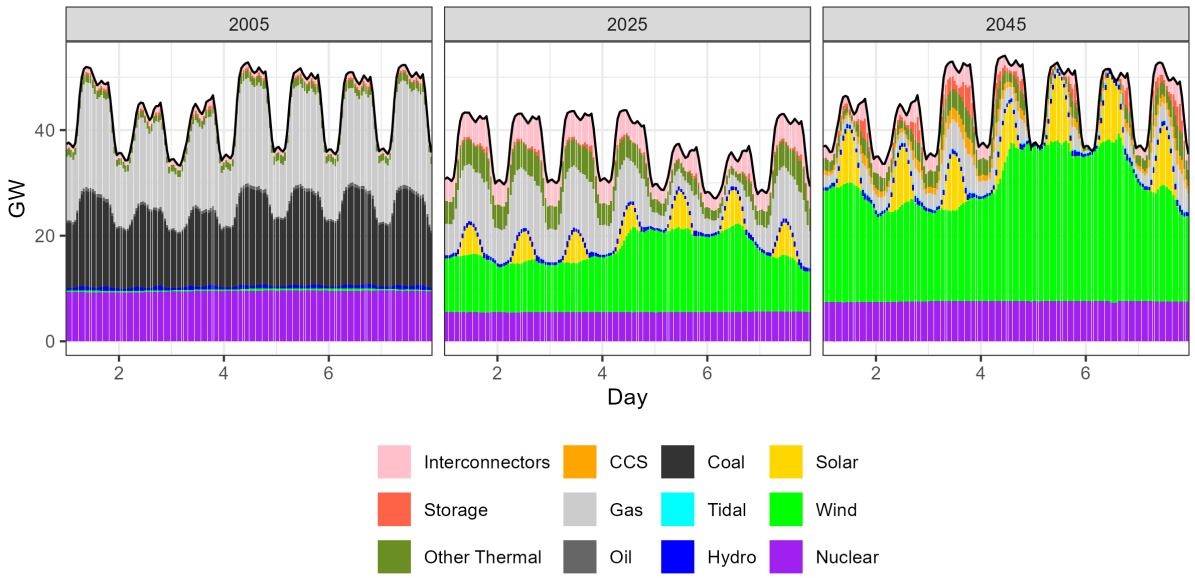
Further detail and figures on the estimation of capacity value is provided here. For intermittent power sources like wind or solar the capacity value is generally thought of in relative terms by starting with the capacity value of a conventional dispatchable generator (e.g. a gas-fired power plant) and then calculating "the proportion of installed renewable capacity that is able to 'displace' conventional generation or support extra demand while maintaining system reliability levels" (Harrison et al., 2015). Statistical modelling for the UK indicates that at present a wind project can expect around 10-20% of its capacity to provide this kind of reliable "firm" supply, while for solar the equivalent number is as low as 1%. These percentages are sometimes referred to as "equivalent firm capacity" de-rating factors. The values for the UK reflect the fact that peak demand periods in the UK occur on winter evenings, and so while there is a decent probability the wind will be blowing at this point, the sun will almost certainly have set.

My starting point for calculating capacity value is National Grid's guidance on the de-rating factors they use for the UK capacity market auctions. For the auctions in 2020 they settled on de-rating factors of roughly 8.5% for onshore wind, 13% for offshore wind, and 1.5% for solar. These values can and will change over time - they will fall as the generation share of wind or solar increases, and rise as demand shifts towards periods when the wind is usually blowing or the sun is shining. This is particularly important to

Figure A.4: Illustration of Simulated Hourly Electricity Production and Marginal Value



(a) Marginal Value of Electricity Output



(b) Generation by Source Type

Notes: The top panel of figure shows the simulated hourly private and external value of electricity production over the first week of April in 2005, 2025 and 2045. The solid line is the observed historical data or the central scenario value. The shaded band is bounded by the high and low sensitivities. The bottom panel shows the corresponding simulated hourly generation mix (colored bars) and total load (black line).

capture for wind power because this is expected to provide such a large portion of the UK's electricity supply by 2050.

To capture the change in de-rating factors for wind projects over time I therefore rely on estimates by (Harrison et al., 2015).[16] Their analysis examines how de-rating factors for onshore and offshore wind vary as the total wind power capacity in the UK increases. I converted this to points in time using information on the past and forecast growth of wind capacity from National Grid and BEIS (NGESO, 2022; BEIS, 2022a, 2020a). Based on this, onshore wind de-rating factors were around 20% in 1990, but have fallen to 9% today, and will likely reach 7% by 2050. Offshore wind de-rating factors were likely as high as 35% in 1990, but have fallen to 15% today, and will likely be as low as 9% by 2050. I assume solar de-rating factors remain at 1.5% across the entire period.

To get the capacity value of each wind or solar project I multiply the relevant "equivalent firm capacity" de-rating factor by the capacity of each project and then value the remaining "firm" capacity based on the UK government's capacity market guidance. The result is a capacity value for each project in £/MW/year. In practice the capacity value estimates are very small. Furthermore, because they only vary annually for each technology type they do not end up meaningfully driving any subsequent results which are conducted using variation that is within-technology and within-year.

A.4 Capital and Operating Costs

Further detail and figures on the estimation of capital and operating costs is provided here. Capital and operating costs are primarily taken from the International Renewable Energy Agency's report on Renewable Energy Costs (IRENA, 2022). These data provide annual average capital costs by technology type and country based on a sample of actual completed projects. The UK values therefore capture key trends in costs over time.

Additional data on capital costs by project size are taken from the Lawrence Berkeley National Laboratory (Wiser et al., 2022; Bolinger et al., 2022; Barbose et al., 2022).[17] These help capture economies-of-scale by reflecting the difference in unit capital costs between small and large projects at a given point in time. Unit capital costs differ within a given year according to different project size bands, where costs are normalised relative to the 50-100MW size band. Relative unit capital costs for wind projects are: 1-5MW = 1.46, 5-20MW = 1.09, 20-50MW = 1.03, 50-100MW = 1, 100-200MW = 0.99 and 200+MW = 0.92. For solar projects the size bands are: 1-2MW = 1.32, 2-3MW = 1.31,

[16] Namely those shown in Figure 11 in their paper.

[17] For any wind projects and for larger solar projects (>5MW) these values are taken from the utility-scale reports on each of these technologies. For smaller solar projects (<5MW) the equivalent cost changes by size are based on project-level data published as part of the seperate distributed solar report.

3-4MW = 1.15, 4-5MW = 1.12, 5-20MW = 1.16, 20-50MW = 1.11, 50-100MW = 1 and 100+MW = 1.13. This highlights the benefits of concentrating capacity at larger projects, especially for wind power.

Operating costs are also primarily taken from the International Renewable Energy Agency's report on Renewable Energy Costs (IRENA, 2022). Here again the data provide annual average operating costs by technology based on a sample of actual completed projects. UK specific data is not consistently available and so for onshore wind I use US values while for solar I use the values for projects in developed countries (IRENA, 2022).[18]

Additional data on operating costs by location are calculated using transmission system charging data from National Grid (NGET, 2022). Because the charging arrangements are complex and have changed over time, I focus on the largest component of the tariff paid by generators that also varies consistently geographically: the "wider tariff". I collect data on these tariffs going back to 2005 and forecast out to 2025.[19] To construct consistent estimates spanning the time period of my analysis I average the different location categories up to 11 regions. These match the UK Government Office Regions and can be easily merged with the project-level data.[20] Despite this aggregation, some of the key grid transmission constraints are still captured, especially the transfer of power from Scotland south into England. Where appropriate, all values were converted to real 2021 UK pounds using exchange rates and inflation index data from the World Bank (World Bank, 2022b,a).

The estimates for capital costs and operating costs are shown in Figure A.5. Key trends are clearly visible, with the long-term decline in costs most evident. The level shift in capital costs for some projects within a given technology type reflects the extent to which they fall into different size categories, and thus benefit from economies of scale. The level shift in operating costs for some projects within a given technology type reflects the extent to which they are located in areas with high grid transmission costs.

The initial increase in offshore wind costs, followed by a later decline, reflects the fact that early projects were relatively small and close to shore, but that later projects eventually reached a certain scale that cost declines also started to emerge. This mirrors trends in offshore costs seen globally, with additional outliers driven by experimental projects such as deep water and floating turbines. Offshore wind operating costs are assumed to be twice that of onshore projects. This is consistent with the higher costs of

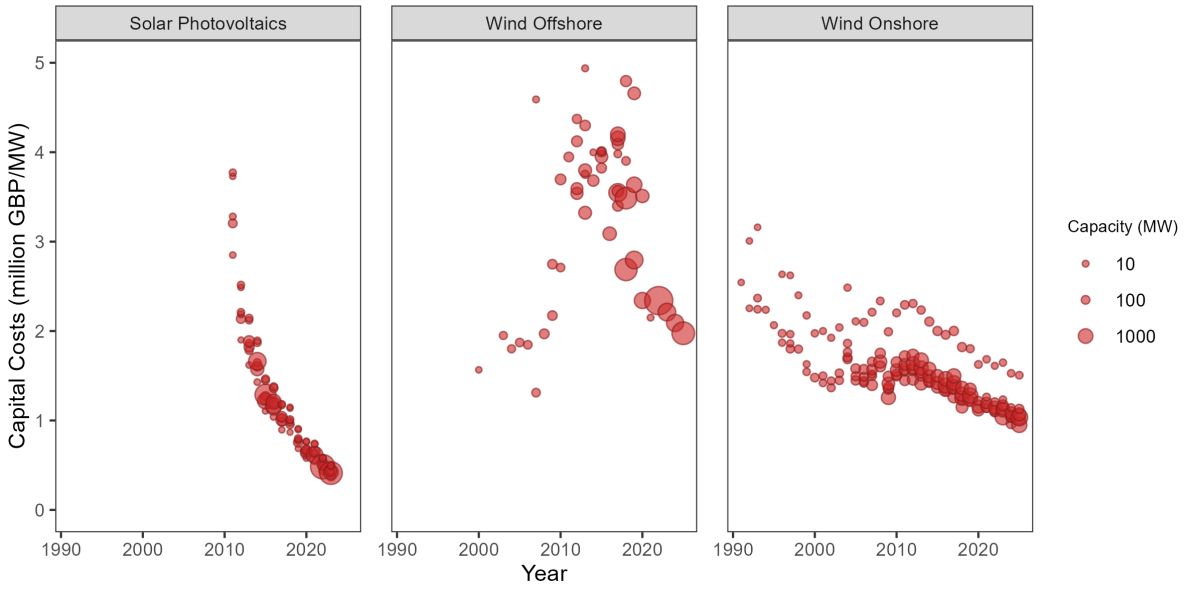
[18]Note that IRENA assumes onshore wind operating costs for the UK in 2021 of $37,000/MW/yr which is basically identical to the $38,000/MW/yr value they assume foir the US.

[19]Where the analysis requires values for years outside this range I simply extrapolate the nearest value forwards and backwards in time.

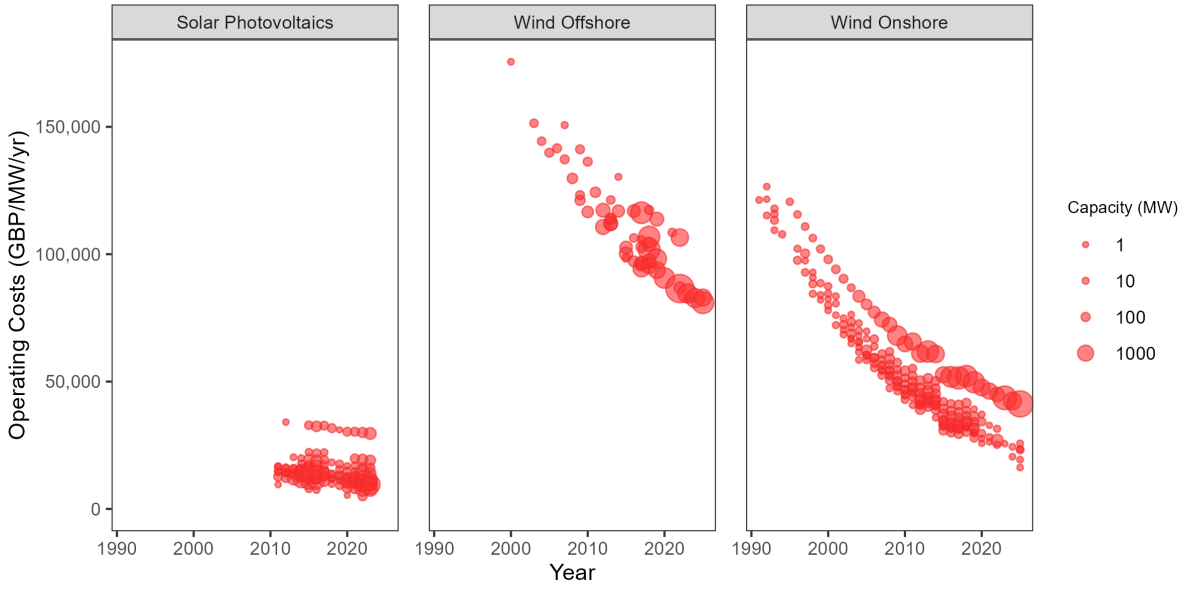
[20]In this instance the regions are South West, South East, London, East of England, East Midlands, West Midlands, Wales, North West, Yorkshire and The Humber, North East and Scotland.

servicing turbines at sea and is in keeping with UK government estimates of the relative costs of operating these projects.[21]

Figure A.5: Estimated Project Capital and Operating Costs by Year



(a) Capital costs



(b) Operating costs

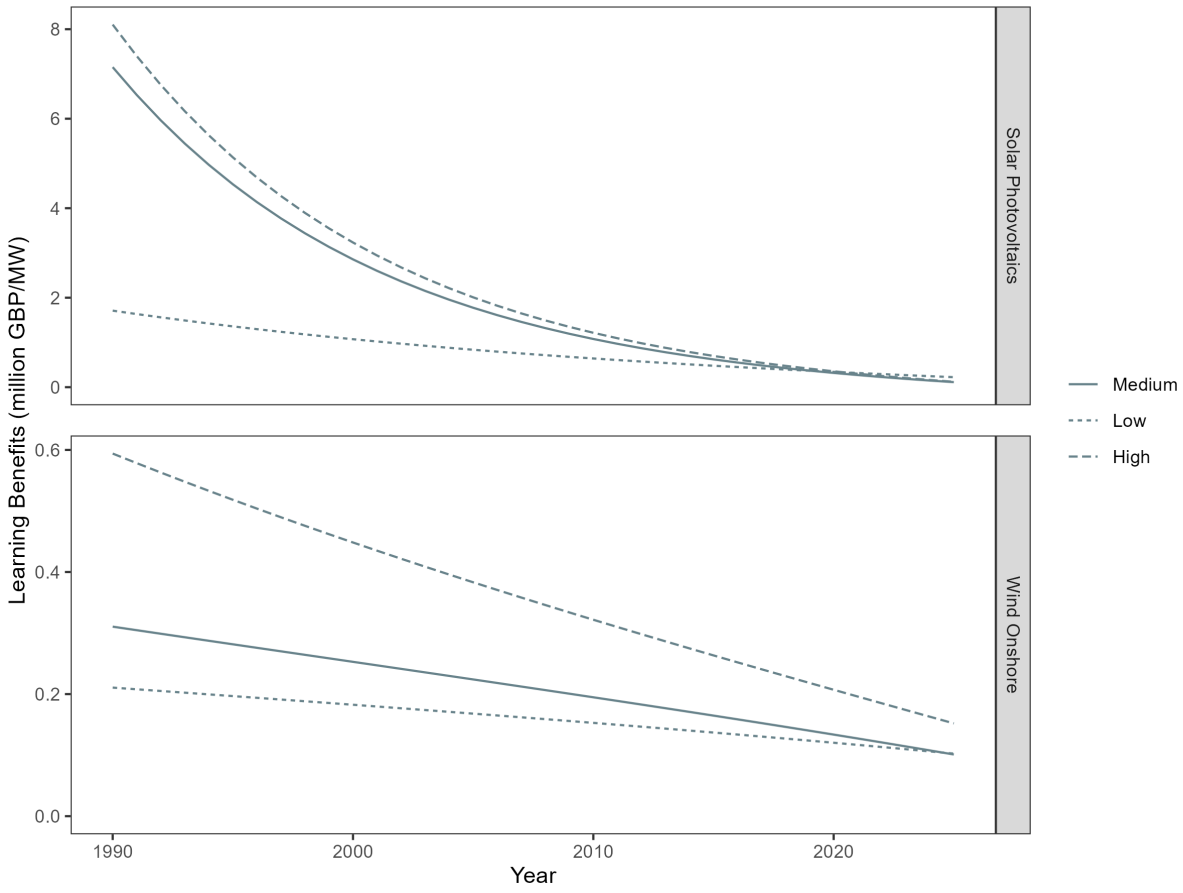
Notes: This figure shows the estimated costs over time. Each point represents the total amount of proposed capacity of a given technology type at a given cost level. Capital costs are at the top and operating costs are at the bottom. Panels refer to three different technology types: solar, onshore wind and offshore wind.

[21]UK government estimates of offshore wind operating costs for projects built between 2018 and 2025 are between 1.8 and 2.9 times those of onshore wind projects, with an average ratio of 2.2 times (BEIS, 2023).

A.5 Learning-by-doing

Further detail and figures on the estimation of learning-by-doing benefits is provided here. To try and capture some of the uncertainty in this particular impact I create "low", "medium" and "high" sensitivities. To do this I use the range of scenario assumptions set out by Newbery (2018) in Table 1. In particular, the "low", "medium" and "high" sensitivities for solar projects were taken from columns F, C and B respectively, and for wind projects from K, J, and I respectively. In all cases the optimal subsidy is scaled based on the average global installed capital cost for wind and solar projects in 2015, using data from IRENA. The resulting values can be seen in Figure A.6.

Figure A.6: Learning-by-doing Benefits from a New Wind or Solar Project by Year



Notes: This figure shows the changing learning-by-doing gains from installing a new wind or solar project in a given year over the sample period. These values were estimated based on the methodology developed by Newbery (2018). "Low", "medium" and "high" sensitivities are shown by the different dashed lines.

A.6 Costs to Local Residents

A.6.1 Project and property locations

The first step in the analysis of the impact of wind and solar projects on nearby residents is determining the location of each project and each property. For property locations I use data from the Office for National Statistics (ONS) on the centroid of each post code (Office for National Statistics, 2022d). Post codes are a very granular geographic measure in the UK context, with each post code representing around 15 properties.

For project locations I use the centroid of each project. This information is provided directly in the Renewable Energy Planning Database (BEIS, 2022b). Where possible I check these locations against more detailed spatial information available from Open Street Map (OpenStreetMap, 2022). In the limited number of cases where the coordinate was missing, or appeared erroneous, the project was dropped. All spatial data was converted to the Ordanance Survey National Grid reference system. The footprint of each project (e.g. the area covered by solar panels or the location of individual wind turbines) is taken directly from OSM where available. Where this information is not available solar projects are assumed to require 6 acres per MW (Ong et al., 2013) and wind projects are assumed to require the square of seven times the rotor diameter for each turbine installed.

A.6.2 Visibility analysis

To isolate the visual impacts of wind and solar projects I conduct a geospatial analysis to determine whether properties are likely to have direct line-of-sight to a project. In addition to specifying coordinates in the east-west and north-south directions, determining line-of-sight also requires specifying an elevation for each point. Elevation was calculated using a GB Digital Elevation Model (Blackwood, 2017). The default is to then use the ground-level elevation from the digital elevation model. No person standing by their property is realistically looking out at ground level, and so I assumed that the coordinate for each post code should be set at head height, around 1.6m off the ground.

For the wind and solar projects what matters is the visibility of the structures being installed (i.e., wind turbines or solar panels). For solar projects this is relatively trivial because panels are very homogenous and usually installed in very similar ways. As such I assume that the top of the solar panels are located at 3m off the ground.

For wind projects the height of the turbines is far more heterogenous, particularly as turbines have increased substantially in size over time. The planning dataset also does not include information on wind turbine tip heights. Fortunately it is possible to calculate the average capacity of the turbines installed by dividing the total capacity by the number

of turbines. Turbine capacity has a fairly stable relationship to turbine size. I use data on thousands of different turbine models in The Wind Power Turbine Database to fit a simple regression model that traces out the effectively quadratic relationship between turbine capacity and turbine height (The Wind Power, 2019). I then apply this to the information on turbine capacity in the project database. The resulting turbine tip heights range from around 50m to in excess of 200m. This is the height off the ground that I use for the project locations.

Finally, I conduct a direct line-of-sight analysis using the digital elevation model and each project-post code pair within a 10km radius. For this I use the "intervisibility" algorithm in QGIS (QGIS Development Team, 2022; Cuckovic, 2016). As well as calculating a binary indicator of whether there is direct line-of-sight between two points, it is also possible to use the "depth-below-horizon" algorithm to calculate what portion of the target structure is visible. So, if the top 40m of a 100m wind turbine is visible then I calculate a visibility metric of 0.4. Ultimately I convert this to a binary indicator which takes the value one if any of the project is visible. The results do not appear particularly sensitive to the use of alternative cutoffs.

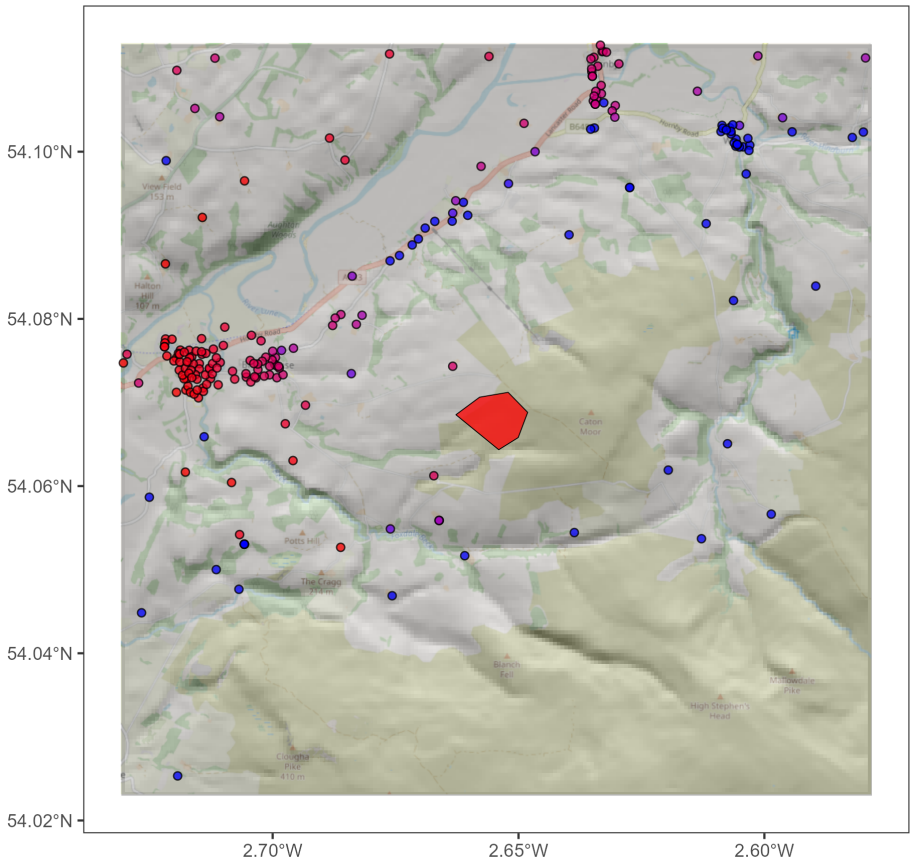
An illustration of this analysis can be seen in Figure A.7. This figure shows a map of the area surrounding the Caton Moor Wind Farm, denoted by the red polygon in the center. The red/blue points denote the post codes where properties are located. Postcodes in blue have no direct line-of-sight to the project. Postcodes in red have full direct line-of-sight to the project. Postcodes with colors in between have some partial line-of-sight (e.g. the tip of the turbine blades might be visible, while much of the base of the turbine is obscured).

A.6.3 Empirical strategy for hedonic analysis

Renewable energy projects create a number of local economic impacts. Of primary interest here are the various visual and noise disameneties associated with these projects. Credibly estimating these impacts is challenging. Here I employ a hedonic approach to look at changes to property values caused by wind and solar projects (Bishop et al., 2020).

I focus on capitalization into residential property values as this likely captures a large portion of the local impacts of interest. Wind and solar projects have been shown to have minimal persistent impacts on local employment (Costa and Veiga, 2021). Projects do generate rents for landowners, and prior research has found positive capitalization of wind energy subsidies into agricultural land values (Haan and Simmler, 2018). Unfortunately I lack the necessary data on land values to study this directly, although given the concentration of landholdings this is likely to only affect a very small number of local individuals. The impact of a project on local tax revenues is likely minimal in the UK

Figure A.7: Illustration of Postcode to Project Visibility



Notes: This figure shows the visibility of a wind project from different post codes within a 5km radius. The red polygon in the centre is the Caton Moor Wind Farm in north west England. The red and blue points are post codes. Blue points do not have direct line-of-sight. Red points do have direct line-of-sight. The background image is taken from Open Street Map and includes some shading to convey elevation.

because business rates and corporation tax have historically gone into the central government budget. Still, there may be other local impacts that my analysis fails to capture which should be kept in mind when considering the analysis set out here.

Residential property transactions data is from His Majesty's Land Registry and covers virtually all sales of residential properties in England & Wales since 1995 (His Majesty's Land Registry, 2022b). Each transaction includes a unique identifier for a given property, as well as the date of the sale and the post code location of the property. For the regression analysis I collapse the data to post code annual averages to facilitate the estimation method used later. In practice there is rarely more than one transaction in a given post code each year so the post-code-by-year dataset is very similar in structure to the original transaction data.

Throughout this analysis I employ a quasi-experimental difference-in-difference approach. This hinges on comparing changes in property values for locations that have a new renewable energy project constructed nearby to changes in property values for other similar locations that do not have a new renewable energy project constructed nearby. My preferred specification is an event study of the form:

$$log(P_{it}) = \sum_{s=S_{pre}}^{S_{post}} \sum_{d=1}^{D} \sum_{c=1}^{C} \beta_{d,c,s} T_{it} + \gamma X_{it} + \theta_t + \lambda_i + \epsilon_{it} \tag{1}$$

Here P is the transaction price of properties in post code location, i, in year, t. Treatment, T, is determined by the distance to a project, the project size in capacity, and whether a project has come online yet. For distances I use three bins ($D = 3$) of 0-2km, 2-4km and 4-6km. For capacity I use two bins ($C = 2$) of 1-10MW and 10+MW.

Prior studies in this area have generally conducted a simple difference-in-difference analysis with a single post-period dummy variable. Unfortunately this makes it challenging to see how the estimated effects evolve over time, or to provide any reassurance that the parallel trends assumption is likely to hold. Here I improve on prior work by estimating an event study with a set of dummy variables indicating whether a given observation is s years before (pre) or after (post) the year when a project became operational. I include ten years of pre-periods ($S_{pre} = -10$) and five years of post-periods ($S_{post} = 5$).[22] Unless otherwise specified the treatment effect coefficients, β, capture the percent change in property values from a new project of capacity c being completed in distance bin d.

In all regressions I limit the sample to properties in locations that are ever within 6km of a project by the end of the period. I focus on properties that are ever near to

[22]In the basic two-way fixed effects model the first pre-period dummy and the last post-period dummy capture any observations that are more than ten years before or more than five years after a project becomes operational.

a single project to avoid issues of properties being treated multiple times.[23] I also drop any projects from my sample that do not have observations at least ten years prior and five years after their start date. Given my property value data spans 1995 to 2022 this means my sample of projects includes those built between 2005 and 2017. This period is when the large majority of wind and solar capacity in the UK was completed.

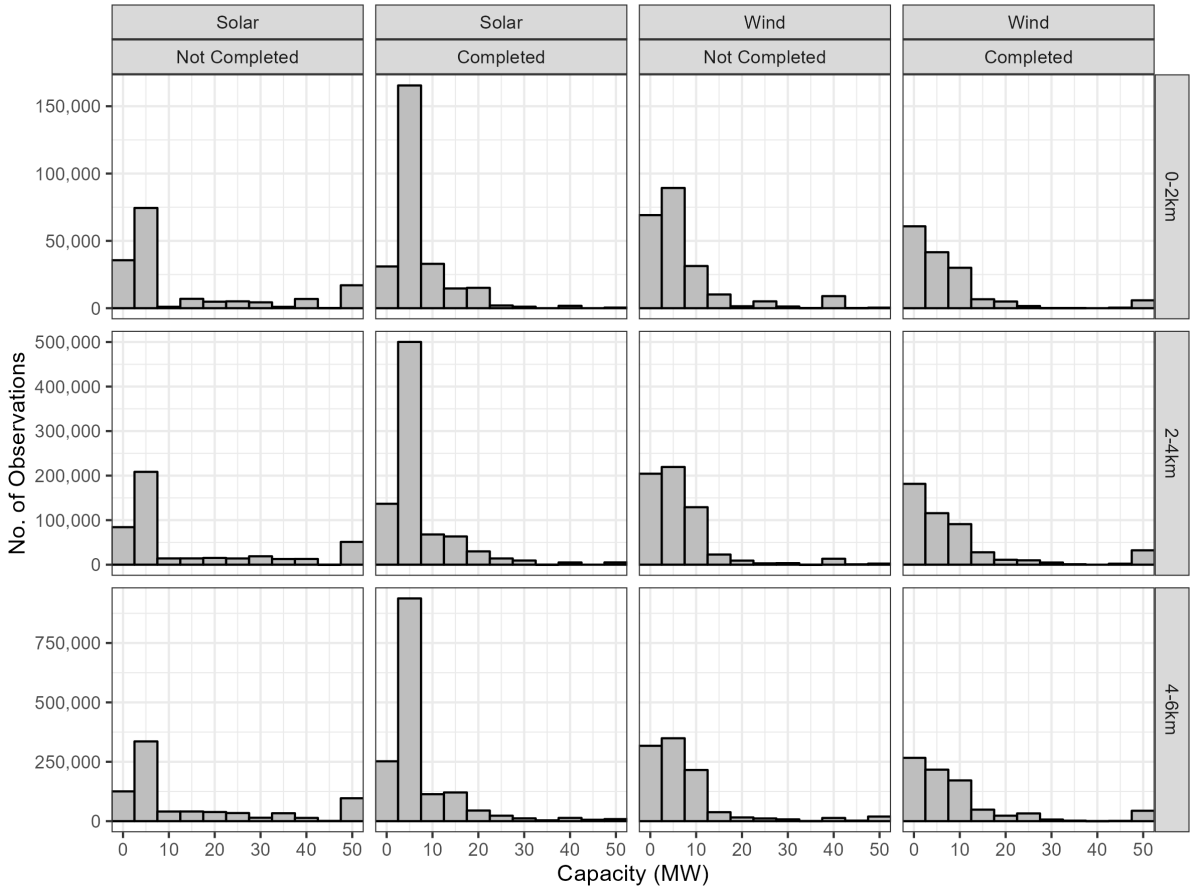
Figure A.8 shows histograms of the property transactions sample used for the hedonic analysis. There are roughly 2.6 million observations for the solar projects and 1.4 million observations for the wind projects. Observations tend to fall into the wider distance bins and the smaller capacity bin. As such the fewest property transaction observations can be found in the smallest distance bin (0-2km) for the larger projects (10+MW). It should be noted that not all combinations of distance and capacity bins will contain property transaction observations that are exposed to a consistent set of projects, and so there may be small differences in the composition of projects driving the effects in a given subsample. For example, there is a slight tendency for the further distance bins to have more property transaction observations where the project in question is relatively large. These differences are generally quite modest, as the histograms in Figure A.8 make clear, but this should be kept in mind when considering the results of the hedonic analysis. Ultimately the distance and capacity bins used here attempt to strike a balance between capturing the key sources of heterogeneity while still ensuring there is sufficient power to estimate effects in each combination of distance and capacity bins.

To account for unobservable determinants of property values I use a rich set of location fixed effects, λ_i, at the post code level, and time fixed effects, θ_t, at the year-of-sample level. To capture observable determinants of property values a limited set of additional controls, X, can be included, such as whether a sale is for a new home. These do not appear to affect the results and so the preferred results do not include these controls. Standard errors are clustered at the post code level.

The hedonic analysis conducted here improves on prior studies in important ways. Numerous studies have shown that difference-in-difference estimates can be biased when there is variation in treatment timing (Goodman-Bacon, 2018; Borusyak and Jaravel, 2017; Callaway and Sant'Anna, 2019). Here I estimate my effects using the approach developed by Callaway and Sant'Anna (2019) to tackle this problem. This paper is therefore the first paper using hedonic methods to quantify the local impacts of renewable

[23]Of the post codes that are within 6km of any proposed wind project, 68% are retained after dropping those near two or more wind projects. The modest impact on the sample here seems consistent with the fact that wind projects are often not placed closed together (e.g. due to wake effects from nearby turbines). Of the postcodes that are within 6km of any proposed solar project, 49% are retained after dropping those near two or more solar projects. In terms of the composition of the postcodes that are dropped, these tend to be similar to those that are retained in terms of how rural they are and their level of wealth. The main notable exception is for wind projects where the rural share of the retained sample is 22% while the dropped sample has a rural share of 32%.

Figure A.8: Histogram of Property Transaction Sample by Project Technology Type, Status and Capacity



Notes: This figure shows histograms of the property transaction sample used in the hedonic analysis. The panels from left to right are divided by technology type and project status. The panels from top to bottom are broken up by distance bin.

energy projects that has accounted for this potential source of bias. It appears from comparing the new estimates with those from a standard two-way fixed effects model that this source of bias is potentially substantial in this context. This makes sense given the extent to which treatment effects are heterogenous and that deployment of projects rolled out over many years.

One challenge created by this new approach is that currently it is only able to handle a simple binary treatment. As such it cannot use continuous treatments or interaction terms to capture important margins of heterogeneity that play a key role in the effects of interest, such as distance and project size. As such I split my sample and estimate seperate regressions by distance and capacity bin. In doing so I also take the novel step of using data on the projects that were proposed but not completed to construct the control group. The method developed by Callaway and Sant'Anna (2019) requires the definition of a "never treated" group. Here I am able to use proposed but unsuccessful projects in the same distance and capacity bin to form the "never treated" group.

Finally, I examine a number of key additional sources of heterogeneity in my analysis. The main one is the line-of-sight visibility of a project. The visual impact of wind and solar projects is consistently cited as a key reason that projects are refused planning permission. Prior work has also found that negative impacts on local property values are primarily due to visual disamenity (Gibbons, 2015; Sunak and Madlener, 2016). To examine this I conduct a geospatial analysis to determine whether a property has direct line-of-sight to a project, as set out earlier. I then conduct my analysis seperately for visible and non-visible projects.

A second source of heterogeneity I examine is whether effects differ based on how wealthy the area is where a property is located. It seems plausible that wealthier areas are likely to be disproportionately affected by a new renewable energy project, in part because property values in those areas are more likely to be driven by ameneties like beautiful views or low levels of noise pollution. I therefore include a version of the analysis of wind projects that further splits the sample into wealthy and non-wealthy areas using the deprivation index used elsewhere in the paper.

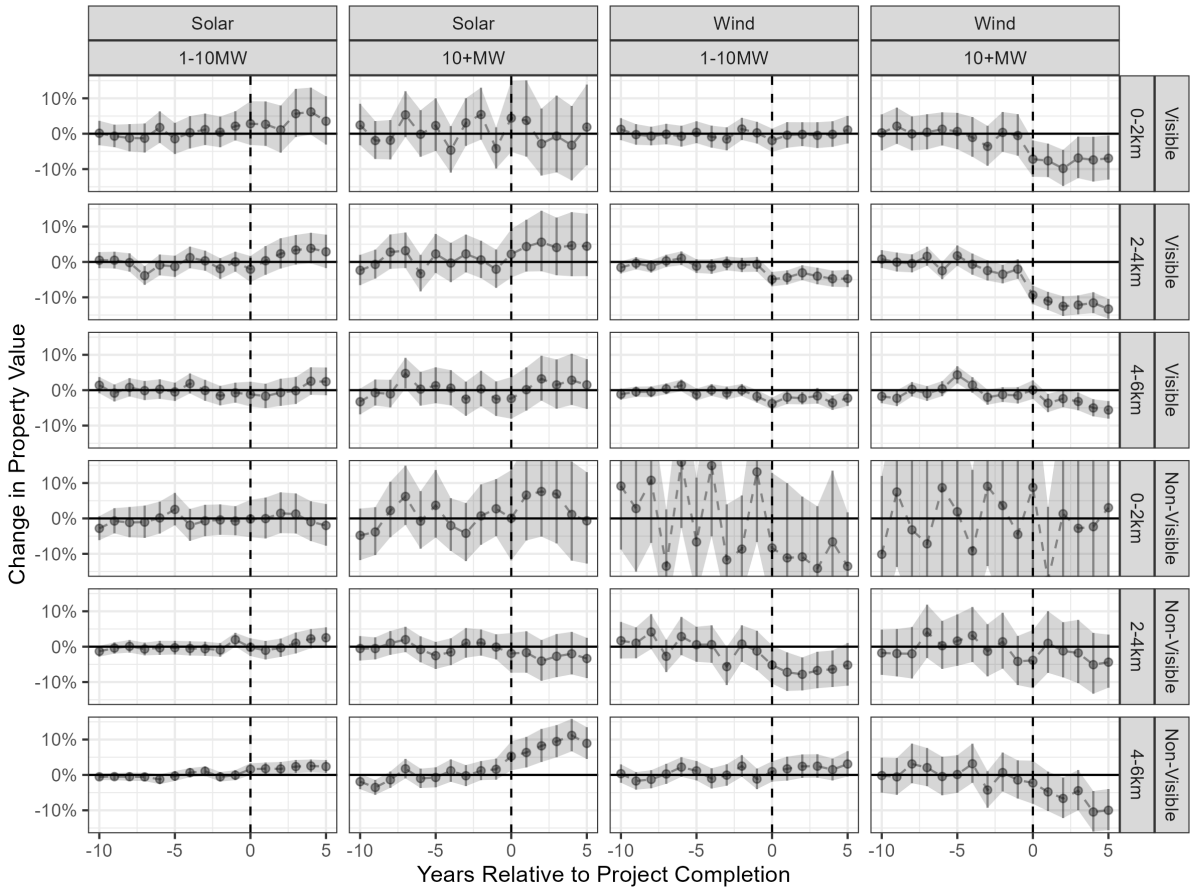
A.6.4 Detailed Hedonic Regression Results

Figure A.9 provides additional detail on the results presented in the main text. The clearest evidence of an impact on property values still arises for properties within 4km of a directly visible wind project, particularly a larger wind project of 10+MW. In these cases there is a sudden negative jump at the year of project completion that deviates from the prior flat pre-period trend, with an effect size on the order of 8-10%. There is also some potential evidence of a small effect in the 4-6km distance bin, and for smaller

projects in the 1-10MW capacity bin, although these are not quite as conclusive. There is no clear evidence of an effect for visible solar projects of any size in any distance bin.

The results for non-visible projects are also shown here. They are generally noisier, especially for wind projects where there are very few properties without direct line-of-sight at the closest distances. For both wind and solar projects there is consistently a lack of clear evidence of an effect, although given the size of confidence interval it is hard to rule out small effects. There are potential exceptions with statistically significant non-zero coefficients arising for larger wind and solar projects in the 4-6km distance bin. However, these effects don't really make intuitive sense given those observed at closer distances, and they do not feature the same jump at the treatment year seen in the effects for visible wind projects. As such these are more likely due to pre-existing trends or deficiencies in the estimation process.

Figure A.9: Estimated Capitalization of Wind and Solar Projects into Nearby Property Values

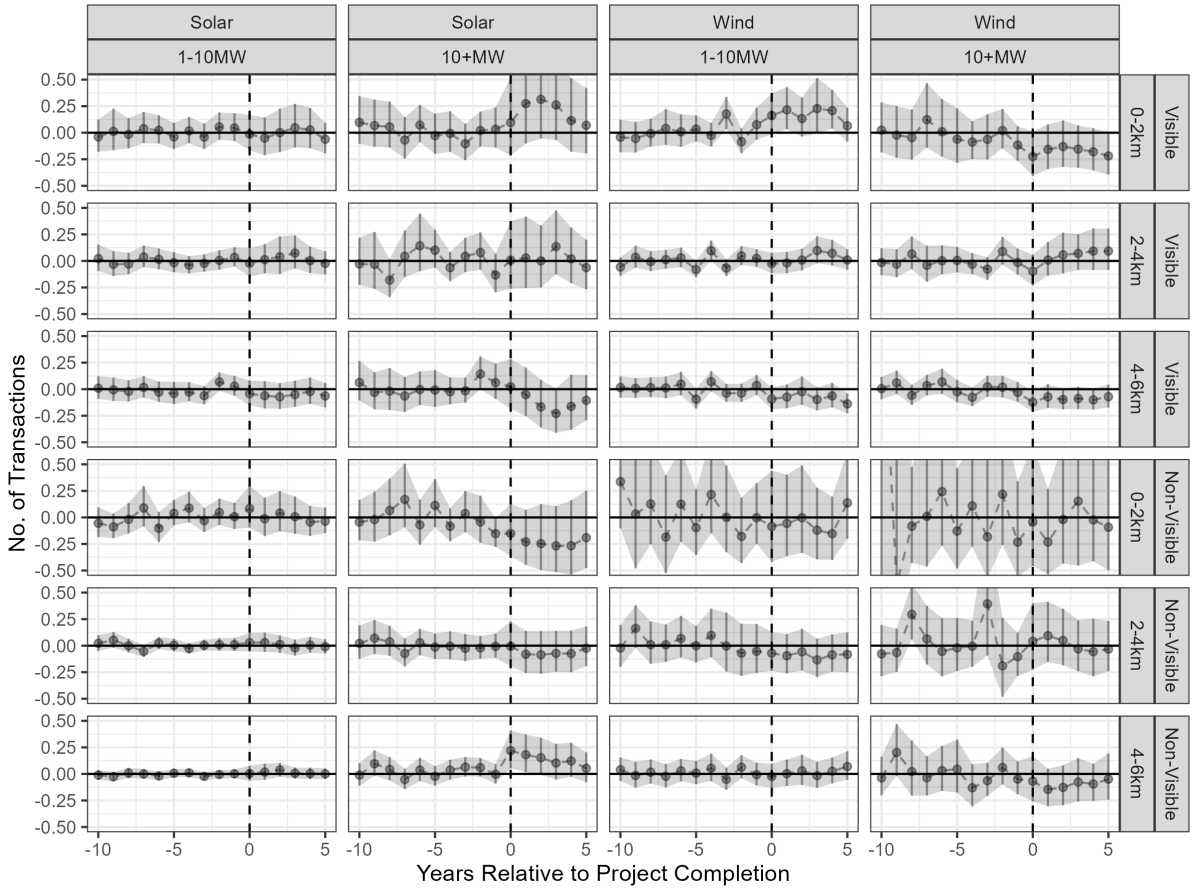


Notes: This figure shows the estimated capitalization effects of new wind and solar projects on nearby property values. The left panels are for solar projects and the right panels are for wind projects, with subpanels by capacity bin. The top panel shows visible projects and the bottom panel shows non-visible projects, with subpanels by distance bin.

To check for possible sorting I repeat my regression analysis but this time the depen-

dent variable is the number of sales per postcode-year. I make sure to expand the dataset to include zero values for postcode-years where there are no sales. Figure A.10 shows that across both wind and solar projects and various margins of heterogeneity I find no consistent evidence of a change in the frequency with which properties are sold.

Figure A.10: Estimated Effect of Wind and Solar Projects on Frequency of Property Transactions

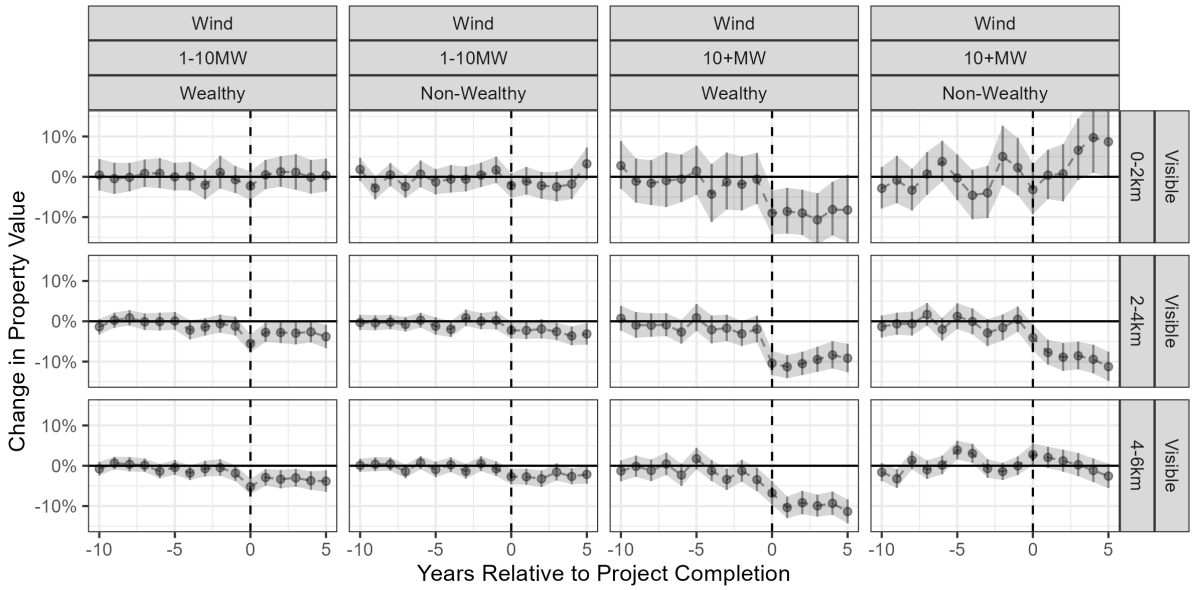


Notes: This figure shows the estimated effects of new wind and solar projects on the frequency of property transactions. The left panels are for solar projects and the right panels are for wind projects, with subpanels by capacity bin. The top panel shows visible projects and the bottom panel shows non-visible projects, with subpanels by distance bin.

To examine for differential effects by how wealthy an affected area is I repeat the main set of regressions for wind projects and include an additional split based on the wealth of properties in a given postcode. Figure A.11 shows that there is some potential evidence of the effects being concentrated amongst properties in wealthier post codes that are near to larger projects. There is still some evidence of effects for less wealthy postcodes in the 2-4 km distance bin. It seems likely the effects in these areas are not zero, although this may reflect imperfections in the depirvation measure used to divide postcodes into a binary split of wealthy and non-wealthy, and the smaller number of projects underpinning the results in each subsample being used to estimate the heterogenous effects. Even so,

the clear effects for larger projects near wealthy areas are consistent with the expectation that these areas are likely to be disproportionately affected by a new wind projects.

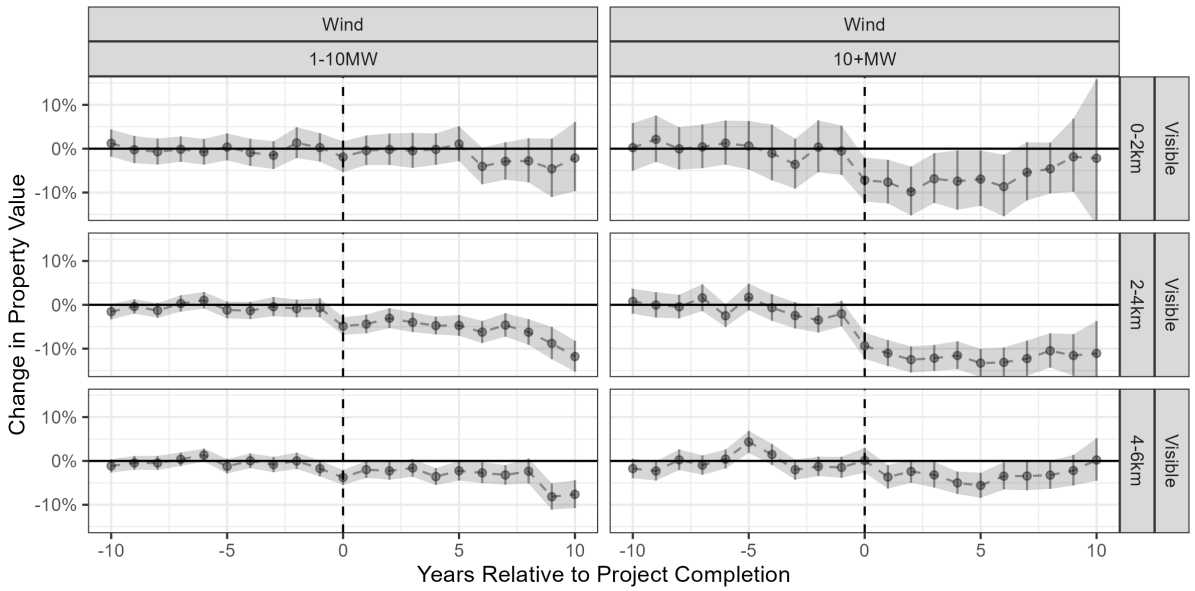
Figure A.11: Estimated Capitalization of Wind Projects into Nearby Property Values by Wealthy and Non-Wealthy Areas



Notes: This figure shows the estimated capitalization effects of new wind projects on nearby property values. The panels from left to right are divided by capacity bin and wealth. The figure shows results for visible projects with vertical panels broken up by distance bin.

To examine for the longer-term persistence of effects I plot the main set of regressions for wind projects and include additional post-periods out to 10 years following treatment. Figure A.12 shows that in general the observed effects do appear quite persistent. There may be some limited evidence of effects abating over time for the larger, visible projects where much of the impacts are concentrated, which is consistent with other studies (Dröes and Koster, 2016; Gaur and Lang, 2023). This kind of abatement of any observed effects is not present for the smaller projects, and if anything there are increasing effect sizes in later periods (i.e. close to a decade after projects come online). It is not clear why smaller projects exhibit these different trends in this particular sample. However, it is worth noting that these small projects are sometimes quite different from the standard view of large wind farms in more rural areas. For instance, small projects are sometimes located on industrial sites near urban centers and directly owned by a local industrial firm (e.g. a manufacturing plant or waste water treatment site). This point is noted later in the analysis on the planning approval process and misallocated investment, both of which include robustness checks that focus on larger projects only. Ultimately this issue of property value impacts abating over time remains an interesting area for further study, especially as more time passes that allows for empirical studies of these long-run effects.

Figure A.12: Estimated Capitalization of Wind Projects into Nearby Property Values with Longer Post-Period



Notes: This figure shows the estimated capitalization effects of new wind projects on nearby property values. The panels from left to right are divided by capacity bin. The figure shows results for visible projects with vertical panels broken up by distance bin.

A.6.5 Assumed capitalization effects

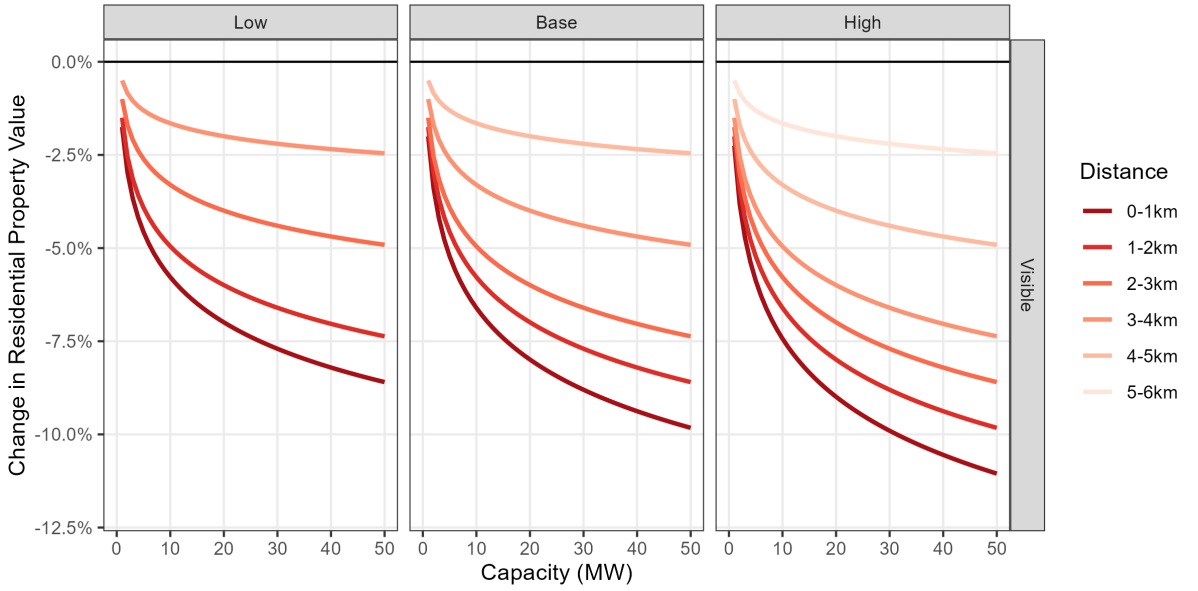
After conducting the hedonic analysis I use my estimated effects to inform the subsequent calculation of the local property value impacts of each project. The effects I estimate are informative of the general scale of the capitalization effects, but given the limitations of the econometric approach they remain fairly coarse in the way they capture heterogeneity. For instance, it doesn't seem plausible that at a threshold of 10MW there is a sudden change in these effects or that all projects greater than 10MW have the same impact at a given distance.

I therefore pick a set of capitalization effects, β, that produces a reasonable range of property value impacts that can approximate the hedonic estimates I find, and those found in the wider literature (Gibbons, 2015; Jensen et al., 2018; Dröes and Koster, 2021; Gaur and Lang, 2023; Parsons and Heintzelman, 2022). Here I assume a log relationship between project capacity and the effect size, consistent with prior work (Jensen et al., 2018). This conveniently produces a smooth increase that lends itself to the kind of extrapolation exercise envisaged here. It also captures the fact that the first few turbines installed are likely to be quite costly, but that there is a diminishing marginal impact as the extent of deployment increases. In using a log relationship I also make a slight adjustment to ensure the smallest projects have sensible effects. The resulting approach is set out below.

$$\Delta P = \beta \times (1 + log(capacity)) \tag{2}$$

In my central scenario, properties within 5km of a wind project with direct visibility have β values of -0.02, -0.0175, -0.015, -0.01 and -0.005 at distances of 0-1km, 1-2km, 2-3km, 3-4km and 4-5km respectively. See Figure A.13 for an illustration of how these assumptions translate into property value changes.

Figure A.13: Illustration of Assumed Capitalization Effects by Project Capacity



Notes: This figure plots the assumed property value impacts as a function of increasing project capacity. Colors represent different effects by distance of the property from the project. The left, middle and right panel refer to the "Low", "Central" and "High" scenarios.

A.6.6 Property values by post code

Calculating the local external costs requires understanding the value of any properties located near the various projects in the sample.

To estimate the number of properties in each post code I use data on property counts at the local authority level from the Valuation Office Agency and the National Registers of Scotland (Valuation Office Agency, 2021; National Registers of Scotland, 2021). I then use census data on population by post code to proportionally allocate the local authority totals to each post code (Office for National Statistics, 2011).

To estimate the average price of properties in each post code I start with data on annual average prices at the local authority level and downscale to each post code (His Majesty's Land Registry, 2022a). To do this I fit a predictive model and then use the

outputs to estimate post code level averages that are consistent with the known local authority averages.

First I take the property transaction data for England and Wales going back to 1995 that was used in the earlier hedonic analysis (His Majesty's Land Registry, 2022b). This includes the price, P, of property, i, in year, t and post code, p, of the property being sold for around 25 million property transactions. I can also match each post code to each local authority, a.

I then divide all post code-level transaction prices, P_{ipt}, by the local authority average in the year the transaction took place, P_{at}. This "post code price ratio", R_{ip}, effectively removes annual time series variation from the data and produces a measure of how much higher or lower a transaction price is for a given post code relative to the local authority average. This is the outcome variable used in the predictive model.

Next I download and merge a range of other variables, X_p, that are likely to be correlated with prices while also being consistently available at the post code level. This includes measures of whether a post code is rural or urban, index scores of social deprivation and census data on the socioeconomic status of residents (Consumer Data Research Centre, 2013; Office for National Statistics, 2011; Abel et al., 2016). Many of these measures are only available for a single year and so this means the relationships I fit will provide a static picture of how much more or less expensive properties are in a given post code relative to the local authority average. This means my predictions will not be able to capture spatial variation within-local-authority that changes over time. However, this approach is still likely to capture the bulk of the spatial variation of interest by distinguishing between typically rich and poor areas.

I then fit a machine learning model of my "post code price ratio" outcome variable, R_{ip}, on the range of post code-level covariates, X_p. For this I use the random forest algorithm.[24]

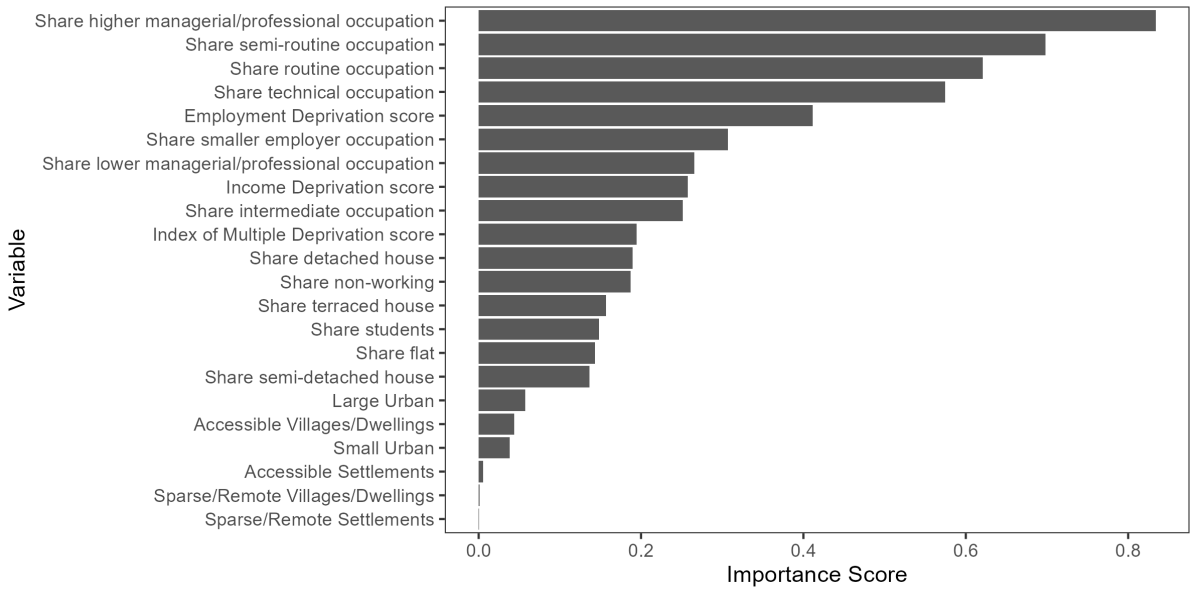
$$\frac{P_{ipt}}{P_{at}} = R_{ip} = f(X_p) \tag{3}$$

The model achieves an out-of-sample R-squared of 0.57. The relative importance of different covariates to the overall predictive power of the model can be seen in Figure A.14. The most important covariates are those associated with the prevelance of different types of occupation and aggregated scores of deprivation. The least important covariates are those capturing differences between urban and rural areas.

Lastly, I use the model to make predictions of the "post code price ratio" for every post code in my sample, including those in Scotland which were not in the original transaction

[24]Fit using the "ranger" package with $num.trees = 200$ and $mtry = 4$.

Figure A.14: Postcode Price Ratio Predictive Model Importance Scores



Notes: This figure shows the importance scores for the covariates included in the model used to predict the post code price ratio.

dataset. I then calculate the predicted post code-level price in a given year by rescaling the local authority average price using the predicted "post code price ratio".

$$P_{pt} = P_{at} \times \frac{\hat{R}_p}{\hat{R}_a} \tag{4}$$

The result is a consistent panel of average property prices for every post code in each year of the sample.

B Determinants of Planning Approvals

In the analysis examining the determinants of project approvals the primary dataset being directly studied is the Renewable Energy Planning Database (BEIS, 2022b). Where not already provided in the data, projects were assigned to a relevant local authority and local planning authority based on the closest relevant polygon (Office for National Statistics, 2022a,b). The distance from each project to the nearest National Park was calculated using polygons for national park boundaries (Office for National Statistics, 2022c). The local election data for each local authority was taken from Election Centre which provides results from 1995 to 2015 (Elections Centre, 2020). The data for elections post-2015 has not yet been integrated and so I simply extrapolate forward the vote shares from 2015 to 2022.

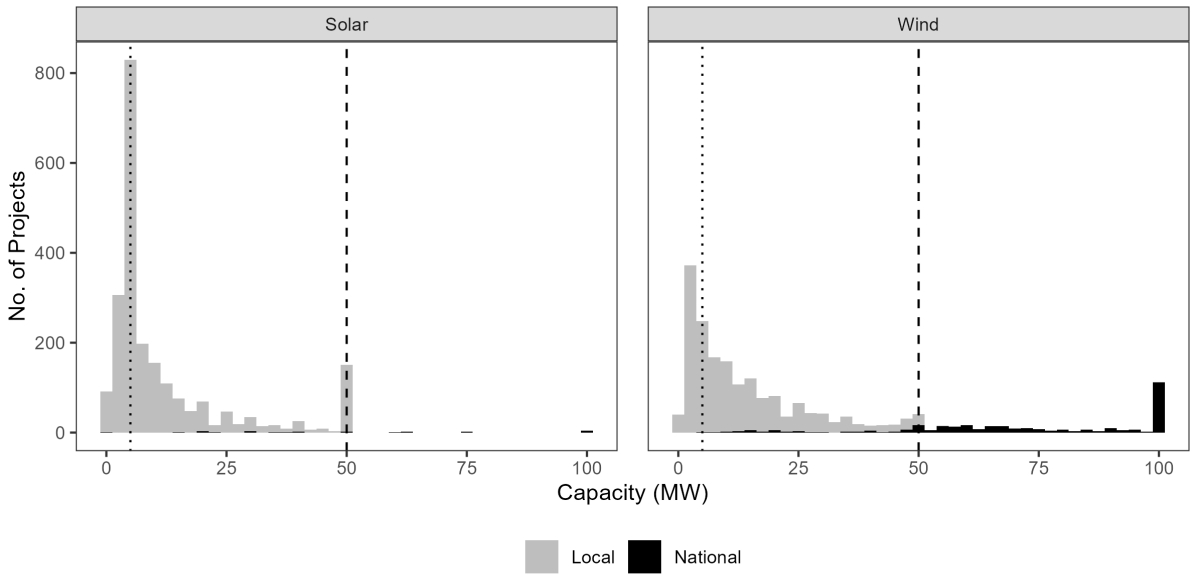
B.1 Threshold for National Significance

One important factor in considering the planning approval process is whether the decision was made at the national or local level. A key threshold to determine if a project is deemed of national significance is whether it is above a certain size, generally taken to be a size of 50MW or greater. Figure B.1 shows the distribution of project sizes for both wind and solar projects. The vast majority of projects larger than 50MW are decided nationally, while almost all of those smaller than 50MW are decided locally.

The bunching of projects in Figure B.1 may indicate developers strategically size their projects with certain cutoff points in mind. The clearest demonstration of this actually appears to be for solar projects. There is a large spike in projects at 5MW. This reflects the more generous feed-in-tariff subsidy regime that applies to projects up to 5MW in size, and this bunching has been used to show the extent to which these subsidies accelerated the deployment of solar in the UK (Srivastav, 2023). There is also a spike in solar projects just below the 50MW threshold, perhaps suggesting that solar developers view the national approval process as more onerous, not less. For wind projects there is not particularly pronounced bunching at either the 5MW or 50MW threshold.

The existence of the 50MW threshold does suggest a possible regression discontinuity design to exploit any change in approval likelihood as control moves from the local to the national level. Figure B.2 shows how the share of projects decided at the national level jumps discontinuously at 50MW. However, it does not appear there is any significant jump in approval probability at this threshold. Moreover, this threshold has long been well known to developers and given the sample size of projects there is insufficient mass of observations around the 50MW cutoff. The seemingly sharp nature of the transition from local to national control at this point also limits the scope for a matched analysis

Figure B.1: Wind and Solar Projects by Size



Notes: This figure shows the distribition of projects at different sizes. The scale is capped at 100MW, with all projects larger than 100MW aggregated into the right-most bin. Projects are grouped into 2.5MW bins. The 5MW threshold is marked with a dotted line as this is the maximum cutoff for the more generous feed-in-tariff subsidy regime aimed at smaller projects. Larger utility-scale projects are subject to less extensive and more competitive support schemes. The 50MW threshold is marked with a dashed line as this is a size that has historically been used to determine whether a project is of national significance, and therefore decided by the national Planning Inspectorate.

to compare similar projects that differ only in the extent of national vs local control.

B.2 Additional Regression Results

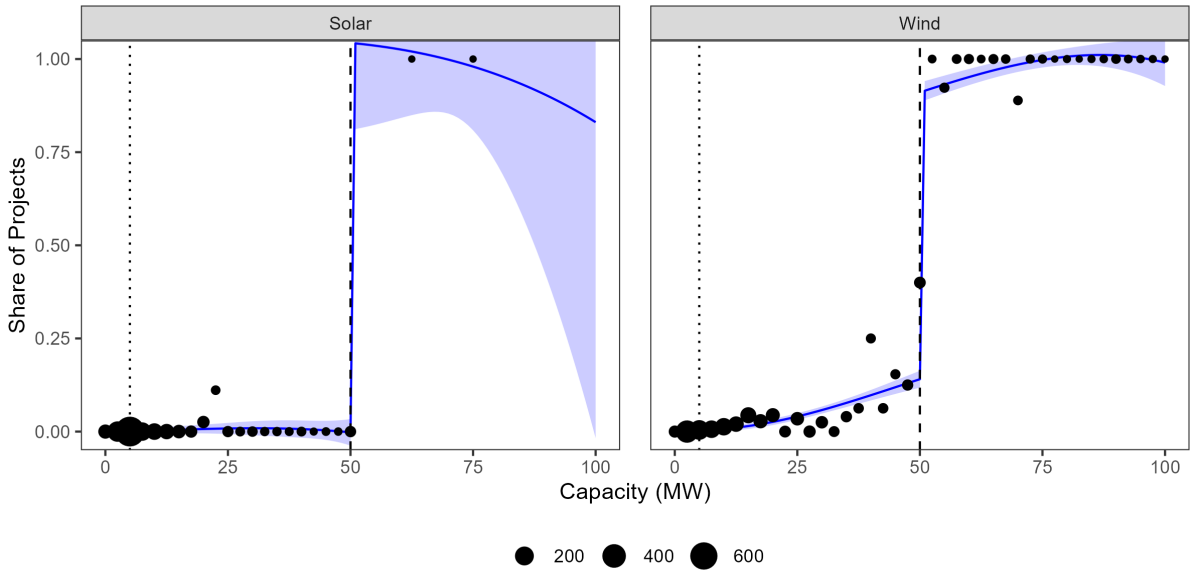
Table B.1 examines the robustness of the planning process results in the main text to alternative specifications. I examine the impact of using using a logit specification rather than a linear probability model and of using a log instead of linear functional form.

In general the direction and significance of the coefficients is fairly consistent across these various alternative specifications. As in the main text, specifications including fixed effects have less clear effects than those that use all the available variation.

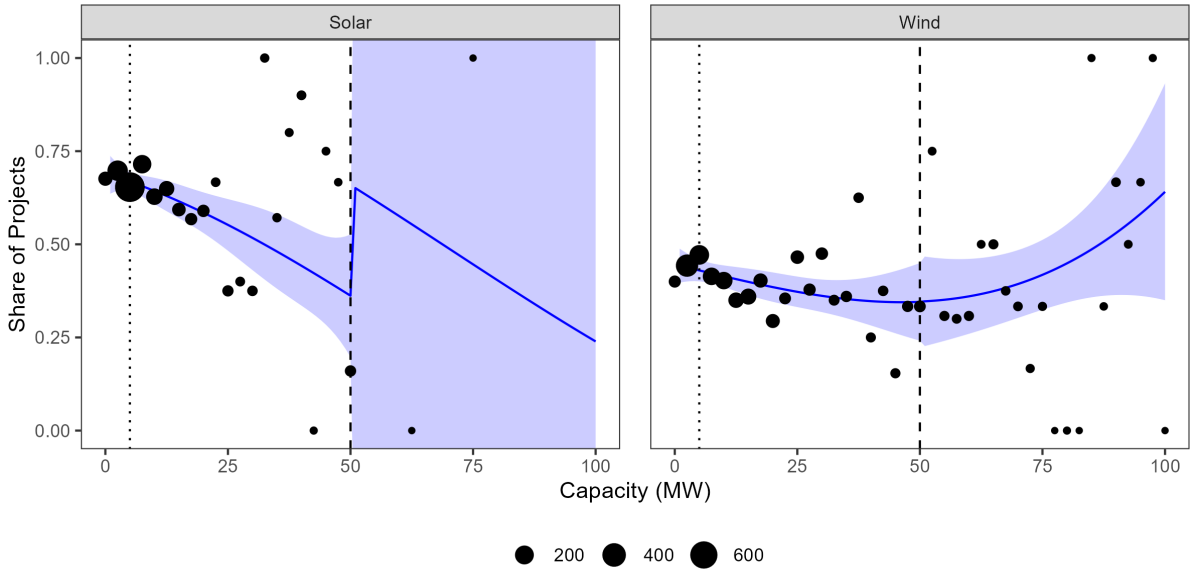
Unlike the linear functional form models, the log functional form does still have highly significant negative coefficients on the property value costs across all specifications. This is likely due to the high degree of dispersion in the estimates of property value costs. The tests of equality of the coefficients are less informative when using the log functional form as it is not clear that decisionmakers should be equilibrating their evaluation of changes in costs and benefits in percentage terms rather than absolute monetary values.

For the models with logit specifications, in each case they consistently identify coefficients with similar sign and significance level to the linear probability model. The tests

Figure B.2: Wind and Solar Projects by Size



(a) Share Decided Nationally by Size



(b) Share Approved by Size

Notes: This figure shows how project decisionmaking and approval varies by project size. The scale is capped at 100MW, with all projects larger than 100MW aggregated into the right-most bin. In the top panel the variable of interest is whether there was local or national control over the initial planning decision. In the bottom panel the variable of interest is whether a project was approved. Points indicate the average of the dependent variable for projects grouped into 2.5MW bins. The 5MW threshold is marked with a dotted line as this is the maximum cutoff for the more generous feed-in-tariff subsidy regime aimed at smaller projects. Larger utility-scale projects are subject to less extensive and more competitive support schemes. The 50MW threshold is marked with a dashed line as this is a size that has historically been used to determine whether a project is of national significance, and therefore decided by the national Planning Inspectorate. The blue fitted line is from a cubic regression with a break point at the 50MW threshold.

Table B.1: Planning Process Regressions for Project Costs and Benefits (Alternative Specifications)

Model:	(1) OLS	(2) OLS	(3) Logit	(4) Logit	(5) OLS	(6) OLS	(7) Logit	(8) Logit
Variables								
Cost Property (£10m)	-0.0071*	-0.0014	-0.0287*	-0.0069				
	(0.0038)	(0.0061)	(0.0169)	(0.0296)				
Cost Other (£10m)	0.0022***	0.0023***	0.0123**	0.0130**				
	(0.0007)	(0.0008)	(0.0061)	(0.0061)				
Benefits (£10m)	-0.0013**	-0.0015**	-0.0067	-0.0077				
	(0.0006)	(0.0007)	(0.0046)	(0.0051)				
log(Cost Property)					-0.0159***	-0.0177***	-0.0699***	-0.0868***
					(0.0029)	(0.0036)	(0.0139)	(0.0190)
log(Cost Other)					0.2367***	0.1885**	1.030***	1.124***
					(0.0478)	(0.0778)	(0.2168)	(0.4307)
log(Benefits)					-0.2282***	-0.1877**	-0.9854***	-1.095***
					(0.0444)	(0.0747)	(0.1990)	(0.4081)
Fixed-effects								
Local Authority		Yes		Yes		Yes		Yes
Year		Yes		Yes		Yes		Yes
Fit statistics								
Observations	1,942	1,942	1,942	1,718	1,942	1,942	1,942	1,718
Squared Correlation	0.01340	0.22330	0.01660	0.12804	0.05296	0.24240	0.05324	0.15005
Pseudo R^2	0.00929	0.17409	0.01177	0.10085	0.03749	0.19124	0.04000	0.11871
BIC	2,823.0	4,152.9	2,690.7	3,214.1	2,743.5	4,104.5	2,614.7	3,171.6
β_1=β_2 p-value	0.0178	0.5411	0.0255	0.5079	6.16×10^{-8}	0.0064	2.46×10^{-7}	0.0041
β_1=β_3 p-value	0.0302	0.6354	0.0483	0.6258	2×10^{-8}	0.0047	7.68×10^{-8}	0.0031

Clustered (Local Authority) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table shows the impact on approval probability from changes to local vs non-local project impacts. These specifications replicate the basic non-interacted results from the main text and therefore include specifications both with and without fixed effects included. Models 1-4 focus on a linear functional form and the 5-8 examine a log functional form. Models 3-4 and 7-8 are estimated using logit instead of OLS. For logit specifications each coefficient has been scaled to reflect the odds ratio of approval. For specifications using linear versions of the covariates the coefficients reflect the effect of a £10 million change in costs and benefits.

for equality of coefficients presented at the bottom of the table also lead to the same conclusions as those for specifications using a linear probability model.

I also examine the sensitivity of my findings to the inclusion of additional controls. For instance, the findings in Table 2 suggest we might expect that projects proposed by large firms are more likely to be approved and projects proposed in areas that already have a lot of capacity are less likely to be approved. When controlling for both these factors the results show much the same pattern as in the main analysis.

Table B.2: Planning Process Regressions for Project Costs and Benefits (Additional Controls)

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Cost Property (£10m)	-0.0087**	-0.0023	-0.0021	-0.0099**	0.0002	0.0076	0.0050	-0.0023
	(0.0043)	(0.0052)	(0.0054)	(0.0044)	(0.0058)	(0.0063)	(0.0059)	(0.0062)
Cost Other (£10m)	0.0020***	0.0018	0.0019***	0.0258**	0.0028***	0.0009	0.0029***	-0.0019
	(0.0006)	(0.0032)	(0.0006)	(0.0130)	(0.0007)	(0.0036)	(0.0008)	(0.0142)
Benefits (£10m)	-0.0015***	-0.0004	-0.0015***	-0.0250***	-0.0022***	-0.0003	-0.0024***	-0.0078
	(0.0005)	(0.0021)	(0.0005)	(0.0089)	(0.0006)	(0.0026)	(0.0007)	(0.0098)
Cost Property (£10m) x Interaction		-0.0191**	-0.0153*	0.0314***		-0.0257**	-0.0170	0.0263**
		(0.0092)	(0.0078)	(0.0117)		(0.0121)	(0.0108)	(0.0104)
Cost Other (£10m) x Interaction		0.0015	0.0006	-0.0240*		0.0058	-0.0002	0.0047
		(0.0079)	(0.0020)	(0.0130)		(0.0092)	(0.0019)	(0.0142)
Benefits (£10m) x Interaction		-0.0030	-0.0004	0.0237***		-0.0060	0.0004	0.0056
		(0.0048)	(0.0017)	(0.0089)		(0.0057)	(0.0016)	(0.0097)
Interaction: Wealthy	No	Yes	No	No	No	Yes	No	No
Interaction: Conservative	No	No	Yes	No	No	No	Yes	No
Interaction: National	No	No	No	Yes	No	No	No	Yes
Fixed-effects								
Local Authority					Yes	Yes	Yes	Yes
Year					Yes	Yes	Yes	Yes
Fit statistics								
Observations	1,942	1,889	1,936	1,942	1,942	1,889	1,936	1,942
R^2	0.09006	0.08095	0.09179	0.09978	0.28429	0.27828	0.28304	0.29040
Within R^2					0.08837	0.07987	0.08940	0.09615
$-\beta_1=-\beta_2$ p-value	0.0134	0.4943	0.4750	0.0060	0.6573	0.3358	0.7207	0.9805
$-\beta_1=\beta_3$ p-value	0.0180	0.6281	0.5219	0.0001	0.7307	0.2648	0.6589	0.3545
$-\beta_1=-\beta_2$ p-value (Interaction)		0.0274	0.0020	0.0905		0.0649	0.1096	0.0308
$-\beta_1=\beta_3$ p-value (Interaction)		0.0102	0.0025	0.0841		0.0301	0.1259	0.0270

Clustered (Local Authority) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table shows the impact on approval probability for changes to various project costs and benefits. Columns reflect the range of fixed effects included and differential effects studied. Columns 1 to 4 are the baseline model with no fixed effects. Columns 5 to 8 include year-of-sample and local authority fixed effects. Models including an interaction effect specify the name of the interaction variable in the rows below. "Wealthy" refers to interaction with a dummy for whether a local authority is wealthier than average. The "Conservative" refers to interaction with a dummy for whether a local authority is politically conservative. "National" refers to interaction with a dummy for whether a project's planning application was decided at the national level. Coefficients reflect the effect of a £10 million change in costs and benefits. I also include additional controls based on the firm that a project was proposed by and the log of the cumulative capacity already installed in a given local authority.

It may also be that the findings are driven by smaller projects that are assumed to impose large property costs because they are located on industrial sites near to urban areas. To test this and examine a set of projects more in line with larger utility-scale

wind projects I repeat the analysis using only projects that are larger than 10MW. Here again the results show much the same core findings as in the main analysis.

Table B.3: Planning Process Regressions for Project Costs and Benefits (Larger Projects)

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Cost Property (£10m)	-0.0101**	0.0016	-0.0129	-0.0152***	-0.0034	0.0079	-0.0088	-0.0128
	(0.0047)	(0.0074)	(0.0082)	(0.0054)	(0.0087)	(0.0083)	(0.0096)	(0.0105)
Cost Other (£10m)	0.0019***	0.0032	0.0019**	0.0168	0.0026***	0.0063**	0.0026***	0.0127
	(0.0007)	(0.0042)	(0.0008)	(0.0105)	(0.0006)	(0.0027)	(0.0007)	(0.0141)
Benefits (£10m)	-0.0010*	0.0002	-0.0010	-0.0185***	-0.0018***	-0.0021	-0.0018***	-0.0157
	(0.0006)	(0.0031)	(0.0006)	(0.0069)	(0.0005)	(0.0027)	(0.0006)	(0.0095)
Cost Property (£10m) x Interaction		-0.0222**	0.0058	0.0372***		-0.0455***	0.0543***	0.0334**
		(0.0105)	(0.0097)	(0.0132)		(0.0152)	(0.0192)	(0.0159)
Cost Other (£10m) x Interaction		0.0072	1.89×10^{-5}	-0.0149		0.0128	0.0005	-0.0100
		(0.0076)	(0.0020)	(0.0105)		(0.0088)	(0.0014)	(0.0141)
Benefits (£10m) x Interaction		-0.0057	-4.39×10^{-5}	0.0174**		-0.0098*	-0.0004	0.0137
		(0.0047)	(0.0017)	(0.0070)		(0.0056)	(0.0012)	(0.0094)
Interaction: Wealthy	No	Yes	No	No	No	Yes	No	No
Interaction: Conservative	No	No	Yes	No	No	No	Yes	No
Interaction: National	No	No	No	Yes	No	No	No	Yes
Fixed-effects								
Local Authority					Yes	Yes	Yes	Yes
Year					Yes	Yes	Yes	Yes
Fit statistics								
Observations	994	943	993	994	994	943	993	994
R^2	0.02759	0.01744	0.02787	0.04437	0.24635	0.23992	0.24965	0.25675
Within R^2					0.01774	0.02257	0.02307	0.03130
$-\beta_1=-\beta_2$ p-value	0.0111	0.8522	0.0708	0.0108	0.4826	0.8449	0.2295	0.1530
$-\beta_1=\beta_3$ p-value	0.0181	0.8149	0.0886	0.0002	0.5450	0.4908	0.2666	0.0332
$-\beta_1=-\beta_2$ p-value (Interaction)		0.0037	0.1023	0.0801		0.0016	0.0199	0.1341
$-\beta_1=\beta_3$ p-value (Interaction)		0.0045	0.1346	0.0695		0.0024	0.0176	0.1200

Clustered (Local Authority) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table shows the impact on approval probability for changes to various project costs and benefits. Columns reflect the range of fixed effects included and differential effects studied. Columns 1 to 4 are the baseline model with no fixed effects. Columns 5 to 8 include year-of-sample and local authority fixed effects. Models including an interaction effect specify the name of the interaction variable in the rows below. "Wealthy" refers to interaction with a dummy for whether a local authority is wealthier than average. The "Conservative" refers to interaction with a dummy for whether a local authority is politically conservative. "National" refers to interaction with a dummy for whether a project's planning application was decided at the national level. Coefficients reflect the effect of a £10 million change in costs and benefits. Here I conduct the analysis after limiting the projects in the sample to those that are larger than 10MW.

I also examine the role of measurement error in my estimates of the local property value costs. Classical measurement error may lead to attenuation bias in the coefficients. As a check I therefore instrument for local property costs using historic population density, which is a common instrument used in other studies. I use the log of population density in 1971 in the 6km radius surrounding a project (Lloyd et al., 2018). This time period is two decades before the first wind farm was ever built in the UK at a time when wind power was not envisaged as having any meaningful role in electricity supply. My instrument produces a strong first stage with F-statistics generally larger than twenty across specifications. The results show much the same pattern as in the main analysis

but with the coefficients on the local property value costs consistently larger in magnitude.

Table B.4: Planning Process Regressions for Project Costs and Benefits (Instrumenting for Measurement Error)

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Cost Property (£10m)	-0.0161	0.0046	-0.0096	-0.0243*	-0.0261	-0.0047	-0.0265	-0.0326
	(0.0129)	(0.0128)	(0.0148)	(0.0133)	(0.0320)	(0.0279)	(0.0345)	(0.0333)
Cost Other (£10m)	0.0021***	0.0040	0.0022***	0.0289***	0.0022***	0.0003	0.0024***	-0.0082
	(0.0007)	(0.0038)	(0.0008)	(0.0106)	(0.0008)	(0.0042)	(0.0008)	(0.0134)
Benefits (£10m)	-0.0013**	-0.0016	-0.0014**	-0.0269***	-0.0014**	0.0005	-0.0016**	-0.0027
	(0.0006)	(0.0024)	(0.0006)	(0.0072)	(0.0007)	(0.0032)	(0.0008)	(0.0091)
Cost Property (£10m) x Interaction		-0.0698***	-0.0249	0.0403		-0.1040**	-0.0022	0.0464
		(0.0216)	(0.0173)	(0.0274)		(0.0405)	(0.0284)	(0.0313)
Cost Other (£10m) x Interaction		0.0059	-0.0005	-0.0271**		0.0114	-0.0010	0.0104
		(0.0078)	(0.0020)	(0.0107)		(0.0082)	(0.0018)	(0.0134)
Benefits (£10m) x Interaction		-0.0043	0.0005	0.0258***		-0.0083	0.0010	0.0012
		(0.0049)	(0.0017)	(0.0073)		(0.0051)	(0.0016)	(0.0090)
Interaction: Wealthy	No	Yes	No	No	No	Yes	No	No
Interaction: Conservative	No	No	Yes	No	No	No	Yes	No
Interaction: National	No	No	No	Yes	No	No	No	Yes
Fixed-effects								
Local Authority					Yes	Yes	Yes	Yes
Year					Yes	Yes	Yes	Yes
Fit statistics								
Observations	1,942	1,889	1,936	1,942	1,942	1,889	1,936	1,942
R^2	0.01115	-0.01124	0.00778	0.02007	0.21640	0.18925	0.21382	0.22205
Within R^2					0.00190	-0.03363	0.00149	0.00909
Wald (1st stage), Cost Property (£10m)	77.849	36.577	40.517	37.109	36.553	18.166	26.977	18.101
Wald (1st stage), Cost Property (£10m) x Interaction		19.750	33.598	15.179		34.375	54.612	15.304
$-\beta_1=-\beta_2$ p-value	0.1615	0.9674	0.4254	0.0019	0.3759	0.8517	0.4008	0.5074
$-\beta_1=\beta_3$ p-value	0.1813	0.8181	0.4569	0.0003	0.3902	0.8765	0.4138	0.2796
$-\beta_1=-\beta_2$ p-value (Interaction)		0.0024	0.0199	0.6095		0.0387	0.3129	0.7332
$-\beta_1=\beta_3$ p-value (Interaction)		0.0033	0.0230	0.5915		0.0430	0.3262	0.7181

Clustered (Local Authority) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table shows the impact on approval probability for changes to various project costs and benefits. Columns reflect the range of fixed effects included and differential effects studied. Columns 1 to 4 are the baseline model with no fixed effects. Columns 5 to 8 include year-of-sample and local authority fixed effects. Models including an interaction effect specify the name of the interaction variable in the rows below. "Wealthy" refers to interaction with a dummy for whether a local authority is wealthier than average. The "Conservative" refers to interaction with a dummy for whether a local authority is politically conservative. "National" refers to interaction with a dummy for whether a project's planning application was decided at the national level. Coefficients reflect the effect of a £10 million change in costs and benefits. I also instrument for local property costs using the log of population density in 1971 within 6km of each project.

Lastly, I examine the robustness of my results to using an alternative approach to quantifying local property value costs. At present I generate the aggregate local property costs using a smooth set of capitalisation functions that are informed by the earlier hedonic analysis and the wider literature on this topic. An alternate approach would be to directly use the coefficients (i.e. by distance bin and capacity bin) as estimated in the earlier hedonic analysis. The results below do so using this approach and yield very similar findings regarding the impact of property value costs on approvals. This is somewhat to be expected given there is a very high correlation between the aggregate property value costs in the main analysis and the alternative ones calculated here (correlation coefficient of 0.93).

Table B.5: Planning Process Regressions for Project Costs and Benefits (Using Raw Hedonic Coefficients)

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Cost Property (£10m)	-0.0036*	0.0009	-0.0009	-0.0044**	-0.0016	0.0030	0.0010	-0.0020
	(0.0020)	(0.0028)	(0.0031)	(0.0021)	(0.0035)	(0.0039)	(0.0040)	(0.0036)
Cost Other (£10m)	0.0022***	0.0042	0.0022***	0.0297***	0.0023***	0.0010	0.0025***	-0.0086
	(0.0007)	(0.0040)	(0.0008)	(0.0105)	(0.0008)	(0.0039)	(0.0009)	(0.0133)
Benefits (£10m)	-0.0013**	-0.0012	-0.0013**	-0.0270***	-0.0015**	0.0003	-0.0017**	-0.0033
	(0.0006)	(0.0026)	(0.0007)	(0.0072)	(0.0007)	(0.0031)	(0.0008)	(0.0090)
Cost Property (£10m) x Interaction		-0.0097**	-0.0049	0.0251***		-0.0127**	-0.0061	0.0227***
		(0.0045)	(0.0040)	(0.0079)		(0.0055)	(0.0061)	(0.0083)
Cost Other (£10m) x Interaction		0.0041	-0.0001	-0.0279***		0.0087	-0.0010	0.0108
		(0.0082)	(0.0020)	(0.0105)		(0.0082)	(0.0018)	(0.0133)
Benefits (£10m) x Interaction		-0.0042	0.0001	0.0260***		-0.0074	0.0010	0.0018
		(0.0051)	(0.0017)	(0.0073)		(0.0051)	(0.0016)	(0.0090)
Interaction: Wealthy	No	Yes	No	No	No	Yes	No	No
Interaction: Conservative	No	No	Yes	No	No	No	Yes	No
Interaction: National	No	No	No	Yes	No	No	No	Yes
Fixed-effects								
Local Authority					Yes	Yes	Yes	Yes
Year					Yes	Yes	Yes	Yes
Fit statistics								
Observations	1,942	1,889	1,936	1,942	1,942	1,889	1,936	1,942
R^2	0.01334	0.00827	0.01409	0.02581	0.22337	0.22077	0.22168	0.23103
Within R^2					0.01077	0.00656	0.01147	0.02053
$-\beta_1=-\beta_2$ p-value	0.0075	0.5117	0.3451	0.0016	0.2682	0.6851	0.7079	0.6390
$-\beta_1=\beta_3$ p-value	0.0202	0.9547	0.4872	2.33×10^{-5}	0.3852	0.4630	0.8568	0.5778
$-\beta_1=-\beta_2$ p-value (Interaction)		0.0442	0.0128	0.0142		0.0314	0.1769	0.0252
$-\beta_1=\beta_3$ p-value (Interaction)		0.0214	0.0210	0.0106		0.0093	0.2328	0.0199

Clustered (Local Authority) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table shows the impact on approval probability for changes to various project costs and benefits. Columns reflect the range of fixed effects included and differential effects studied. Columns 1 to 4 are the baseline model with no fixed effects. Columns 5 to 8 include year-of-sample and local authority fixed effects. Models including an interaction effect specify the name of the interaction variable in the rows below. "Wealthy" refers to interaction with a dummy for whether a local authority is wealthier than average. The "Conservative" refers to interaction with a dummy for whether a local authority is politically conservative. "National" refers to interaction with a dummy for whether a project's planning application was decided at the national level. Coefficients reflect the effect of a £10 million change in costs and benefits.

B.3 Local Opposition and Public Comments

To further examine what might be driving the observed sensitivity to local impacts, and whether this can be linked to local opposition, I gathered information from local authority websites on the number of public comments for a subsample of onshore wind projects in Scotland. Specifically, the data was collected using the Improvement Service database that includes detailed information on every planning application submitted to local authorities in Scotland (Improvement Service, 2022). I use this dataset to identify possible wind project applications through a keyword search of the application details.[25] I then extract key information on each project from the relevant local authority website at the URLs provided in the dataset. One piece of information I can extract is the number of individual public comments that are recorded on the website. I then match the projects in the Improvement Service database to those in my sample using the planning reference code used for the local planning authority.

Over the 1990-2018 period I am able to collect data on public comments and find a match for 330 projects. Around 2015 this captures almost 50% of wind projects in Scotland in my sample, although in earlier and later years the share is closer to 25%. The lack of more comprehensive coverage is due to a range of factors. First, the database includes planning applications for smaller projects that are decided by local authorities, while larger wind projects that are decided nationally by the Scottish government are not included. Second, there is no guarentee that historical data or the formatting of local authority websites allows for public comment data to be consistently gathered. Third, the planning reference codes are not consistently provided in my sample dataset and so perfect matching for all relevant projects is not feasible. Despite these limitations, the subsample still includes several hundred projects of varying sizes across multiple local authorities. Some projects receive few public comments while some receive many, with the most contentious project receiving 1,721 comments. On average roughly three quarters of comments are classed as objecting, with only one quarter supportive. To be clear, these public comments are one way that public input for a planning application is recorded. In addition to allowing the submission of individual public comments, there are frequently consultation sessions and town hall events where public views are sought. As such this count of public comments provides one partial measure of local opposition, although it is a measure that is likely to be strongly correlated with the extent of public opposition more generally.

Table B.6 shows the results of regressing the number of comments a project received on the estimated local and non-local costs and benefits. Here I find evidence that projects with larger local costs, as measured by changes to property values, appear to receive

[25]For instance, using the phrase "wind turbine" I can identify roughly seven thousand applications submitted over my sample period.

higher numbers of public comments. A £10 million increase in local property value costs is associated with around 12 additional public comments. The association continues to be statistically significant after including local authority and year fixed effects. There is no significant relationship between the other non-local costs and benefits and the number of public comments. In fact the coefficients also have the wrong sign, mirroring the findings in the main planning process regressions that focus on the likelihood of approval.

Table B.6: Planning Process Regressions for Project Costs and Benefits (Comments)

Dependent Variables:	Total	Object	Support	Total	Object	Support
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Cost Property (£10m)	11.74**	8.683*	2.829*	6.611**	2.207	4.140*
	(5.662)	(4.447)	(1.661)	(2.735)	(2.313)	(2.101)
Cost Other (£10m)	-14.36	-11.31	-3.336	-7.829	-6.257	-2.040
	(8.944)	(7.025)	(2.623)	(14.37)	(8.462)	(6.450)
Benefits (£10m)	12.71**	10.38**	2.403	8.000	6.795	1.386
	(5.364)	(4.214)	(1.573)	(8.670)	(5.402)	(4.021)
Fixed-effects						
Local Authority				Yes	Yes	Yes
Year				Yes	Yes	Yes
Fit statistics						
Observations	330	330	330	330	330	330
R^2	0.03874	0.04165	0.01597	0.24874	0.27288	0.11483
Within R^2				0.01605	0.01764	0.01353

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table shows the impact on the number of public comments from changes to local vs non-local project impacts. These results include specifications both with and without fixed effects. Analysis is for a subsample of onshore wind projects in Scotland for which public comment information has been collected from local planning authority websites. "Total" refers to the count of all comments, "Object" refers to the count of objecting comments and "Support" refers to the count of supporting comments. The coefficients reflect the effect of a £10 million change in costs and benefits.

Table B.7 shows the results of regressing whether a project was approved on the number of comments a project received. I find clear evidence that projects with more public comments, and specifically more objecting public comments, are less likely to be approved. Ten additional objecting comments reduces approval probability by 1.2%. The effect for supporting comments is largely the inverse but is not statistically significant. These findings hold up even when including local authority and year fixed effects.

Taken together this additional analysis of local opposition as measured by public comments indicates that: 1) local opposition is higher for projects that have larger local impacts on nearby property values, and 2) more local opposition is associated with reductions in the chance of a wind project being approved.

Table B.7: Planning Process Regressions for Project Public Comments

Model:	(1)	(2)	(3)	(4)
Variables				
Total	-0.0006***		-0.0004	
	(0.0002)		(0.0003)	
Support		0.0011		0.0011
		(0.0007)		(0.0008)
Object		-0.0012***		-0.0009***
		(0.0003)		(0.0002)
Fixed-effects				
Local Authority			Yes	Yes
Year			Yes	Yes
Fit statistics				
Observations	330	330	330	330
R^2	0.04649	0.06393	0.25048	0.26374
Within R^2			0.02205	0.03936

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table shows the impact on approval probability from changes to the number of public comments. These results include specifications both with and without fixed effects. Analysis is for a subsample of onshore wind projects in Scotland for which public comment information has been collected from local planning authority websites. "Total" refers to the count of all comments, "Object" refers to the count of objecting comments and "Support" refers to the count of supporting comments. This provides valuable evidence that local opposition is associated with a project being less likely to be approved.

C Misallocated Investment

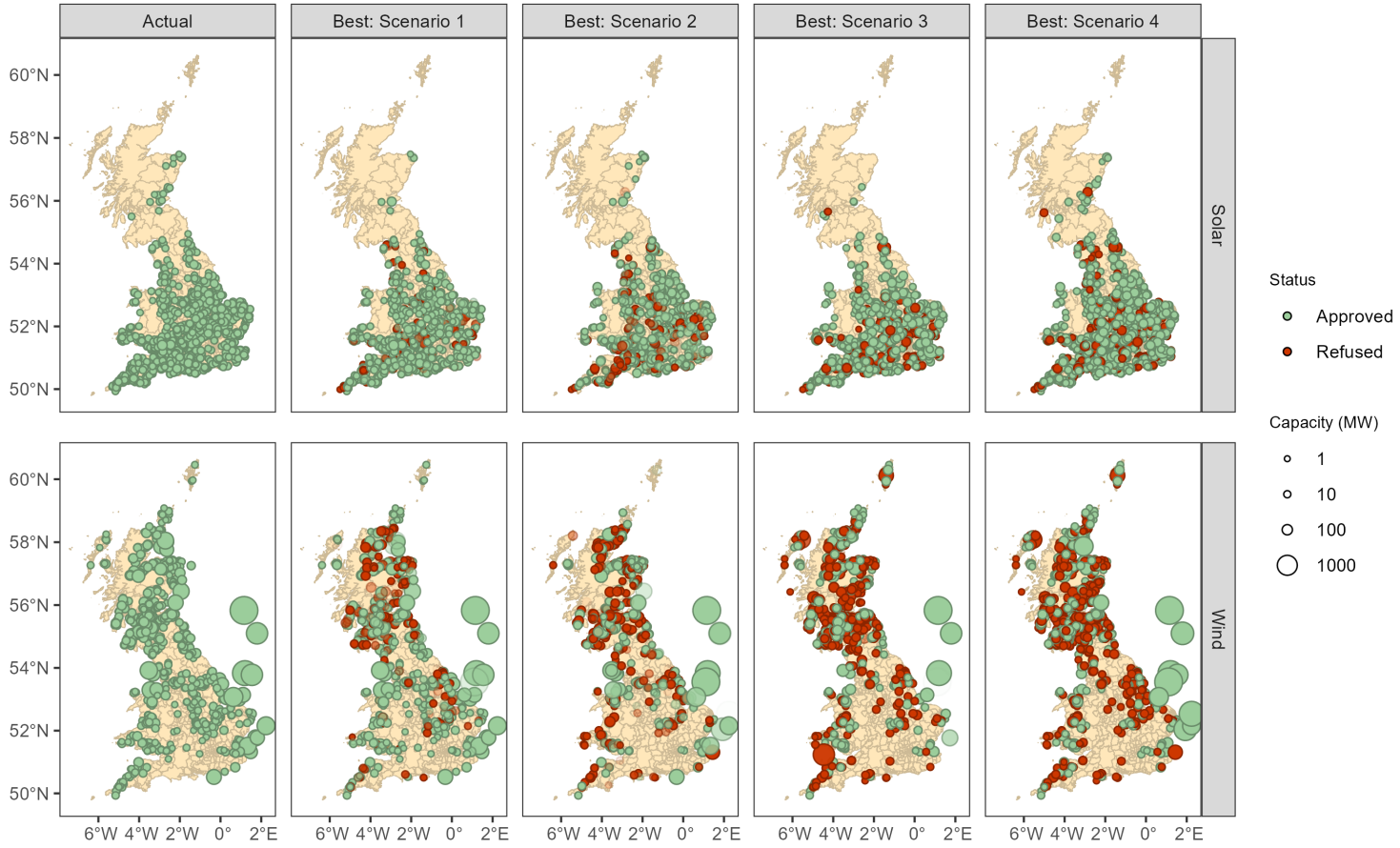
My primary approach to analyzing misallocated investment entails finding the set of projects that can produce the observed annual deployment of renewable energy at least cost. To further illustrate the findings in the main text, Figure C.1 plots the actual or best set of projects across the range of scenarios studied.

Naturally my analysis is potentially subject to uncertainties in the underlying estimates of costs and benefits.[26] As robustness checks, Tables C.1, C.2, C.3, C.4, C.5, C.6, C.7, C.8 and C.9 reproduce the findings from the main text for a range of sensitivities. The aim is to convey the extent to which the overall findings are affected by varying key assumptions. In the base case the central estimates for local property value costs and social market and environmental benefits are used, with a discount rate of 3.5%. The sensitivies are therefore as follows.

Table C.1 provides the results for the "Local Property Costs" sensitivity. Here the

[26]Despite the lengths this paper has gone to in estimating the impacts of these projects, it is impossible to fully account for the the idiosyncracies of each project and local area. For any given project, planning officials will have a better understanding of their specific circumstances, and so some humility about the ability of this kind of analysis to second guess individual decisions is probably in order. Still, the overall insights about systematic biases in the broader process remain.

Figure C.1: Misallocated Investment Results Detail



Notes: This figure shows the actual observed set of wind and solar projects, and then how these change across range scenarios identifying the least cost set of proposed projects. "Actual" refers to the observed set of projects that were actually built. The "Best" panels then refer to different scenarios for the optimal set of projects subject to a series of constraints on the extent to which deployment can be reallocated. "Scenario 1" allows reallocation subject to the total output remaining unchanged by year, technology, on/offshore and local authority. "Scenario 2" allows reallocation subject to the total output remaining unchanged by year, technology and on/offshore. "Scenario 3" allows reallocation subject to the total output remaining unchanged by year and technology. "Scenario 4" allows reallocation subject to the total output remaining unchanged by year. "Scenario 5" allows complete reallocation and so may lead to a different total output than was actually observed.

analysis is the same as the base case except alternative capitalization effects are assumed for the property value costs. These alternative assumptions are shown in the main text. The changes to the size of local property value costs have a relatively minimal impact on the calculated size of misallocation, in large part because these costs are small relative to the other social costs and benefits.

Table C.2 provides the results for the "Social Benefits" sensitivity. Here the analysis is the same as the base case except the benefits of wind and solar projects are assumed to be from the lower or higher range estimated. These alternative values can be seen in Figure A.3 and Figure A.6. The changes to the social benefits, and thus the resulting social net present value, can be quite substantial depending on the assumptions made. Notably though, the relative gains from reallocation as the scenarios become less constrained appear fairly stable, and even in the low case there is still potential evidence of underinvestment.

Table C.3 provides the results for the "Discount Rate" sensitivity. Here the analysis is the same as the base case except the discount rate is assumed to be a lower value of 1.5% or a higher value of 7%. Both are alternative values provided in UK government guidance (BEIS, 2021). The lower value is likely the more informative from a social perspective and the higher value is likely informative to the extent it better aligns with private rates of return. The findings generally mirror the prior sensitivity on social benefits. A low discount rate makes renewables look more favorable by increasing the benefits of electricity production (spread into the future) more than it does the capital and operating costs (mostly incurred at the start). Conversely a high discount rate creates the reverse situation, making renewables look less favorable. Even with a discount rate as high as 7%, it does seem there is still evidence of misallocation and underinvestment.

Table C.4 provides the results for the "Extrapolation Error" sensitivity. Here the analysis is the same as the base case except it is now assumed that the projects that were ultimately cancelled are in reality less cost-effective than the original estimation would suggest. In the low error case it is assumed that proposed projects that were cancelled actually have 10% higher costs and 10% lower benefits than originally estimated in the base case. In the high error case it is assumed that proposed projects that were cancelled actually have 25% higher costs and 25% lower benefits than originally estimated in the base case. The motivation is that the estimation of costs and benefits is heavily based on information gained from actual completed projects. Extrapolating this to make predictions for the costs and benefits of projects that were ultimately cancelled could be an issue if the cancelled projects failed precisely because they were more costly (e.g. were poorly conceived or managed and so would have had higher unit costs). In this sensitivity we can see that increasing the costs and decreasing the benefits for any cancelled projects does indeed reduce the potential efficiency gains from reallocation. This makes sense as

it makes the proposed projects that could substitute for existing completed projects look much less attractive. However, even with a large combined increase in costs and reduction in benefits for these cancelled projects, the same qualitative findings of misallocation and underinvestment still remain.

Table C.5 provides the results for the "Noise" sensitivity. Here the analysis is the same as the base case except now noise is added to the estimates of costs and benefits. Specifically, a percentage adjustment is made to each cost and benefit estimate for each project based on values drawn from a normal distribution with mean zero and some positive standard deviation. This leads the costs and benefits for different projects to be randomly increased or decreased proportionally relative to the baseline estimates. In the low noise case the standard deviation of the noise added is 10% relative to the base case. In the high noise case the standard deviation of the noise added is 25% relative to the base case. The motivation is that more general noise in the estimates of costs and benefits may itself bias the misallocation analysis upwards. To examine the extent to which this may be a problem let us assume that the existing estimates of costs and benefits are in fact completely accurate. If this is the case, how much larger do the gains from reallocation become as noise is added to the estimates? The sensitivity results do indeed show that adding noise does tend to increase the amount of misallocation identified. However, the change relative to the base case is fairly muted, even when a large amount of noise is added. This suggests the core findings are likely quite robust and not driven simply by noise in the underlying estimates of costs and benefits.

Table C.6 provides the results for the "Technology" sensitivity. Here the analysis is the same as the base case except now reallocation across technology types is limited in the various constrained scenarios. Specifically, I use the same four misallocation scenarios but first impose the constraint that reallocation cannot occur across wind and solar projects, and then impose the additional constraint that reallocation cannot occur across onshore wind, offshore wind and solar projects. As might be expected, adding additional constraints reduces the potential gains from reallocation. However, the change relative to the base case is fairly muted, with any notable divergence only appearing when limiting the scope for reallocating across local authorities away from offshore wind. Overall this suggests the core findings are not driven simply by large shifts away from one technology type (e.g. solar or offshore wind) and are instead driven to a significant degree by reallocation amongst comparable projects with equivalent technologies.

Table C.7 provides the results for the "Project Size" sensitivity. Here the analysis is the same as the base case except now the analysis is limited to larger projects. Specifically, I use the same four misallocation scenarios but first conduct the analysis only using projects larger than 10MW and then only using projects larger than 25MW. In general the potential gains to social net present value only decline modestly relative to the base

case. The big difference relates to local property value impacts which are frequently concentrated at a limited number of small projects. Focusing on larger wind farms with multiple turbines removes these outliers such that total local property costs fall from £8.5 billion in the base case to £3.2 billion and £0.9 billion in the sensitivities. Focusing on larger projects also results in total local property costs increasing in the full reallocation scenario when compared to current levels.

Table C.8 provides the results for the "Spatial" sensitivity. Here the analysis is the same as the base case except now the private value of the electricity produced by each project is assumed to have no spatial variation, which is in line with the historical lack of locational pricing in the UK. This inclusion of spatial variation does indeed cause a modest shift in the selected projects toward building less in the north and more in the south. Removing the spatial variation in this way reduces the available benefits from the existing set of projects (which presumably already capture some of these spatial differentials through redispatch revenues) and for the optimal set in the reallocation scenarios.

Table C.9 provides the results for the "Non-Marginal" sensitivity. Here the analysis is the same as the base case except now the private value of the electricity produced by each project is assumed to be lower to account for the way an expanded rollout of renewable energy should depress equilibrium wholesale prices over-and-above the observed levels. To approximate this, I first run the base case analysis and compare the share of electricity met by renewables in the full reallocation scenario (Scenario 4) with the share met by renewables in the actual scenario in each year. I find that the accelerated deployment of renewables starts to pick up in 2009, rising to a peak of a 20 percentage point differential in the share met by renewables in the mid-2020s, before gradually falling back to parity by the 2050s.

To approximate the impact of a higher share of renewables on wholesale prices I utilize my hourly values for wholesale prices and electricity generation by source type. If I simply regress the log of hourly wholesale prices on the hourly renewable share I find that a one percentage point increase in the renewable share leads to a roughly 0.2% decrease in prices. This response is fairly stable when including any of year-of-sample, date-of-sample, and hour-of-day fixed effects.

I take my measure of the sensitivity of wholesale prices to the share of renewables and combine this with the increase in the renewable share that is anticipated by the full reallocation scenario. So in the mid-2020s I calculate that the projected 20 percentage point increase in the share of renewables (relative to observed levels) should depress wholesale prices by around 4%. I then re-run the misallocation analysis, assuming each project earns a lower private value for their electricity in accordance with the annual

adjustments they would be exposed to over their lifetime. This means a project built in 2000 would see a 1.2% reduction in the private benefits of their output due to non-marginal price adjustments, while a project built in 2020 would see a 3.6% reduction.

Applying these adjustments and re-running the misallocation analysis does reduce the estimated costs of misallocation in Table C.9. However, the change is small such that instead of a 55% increase in renewables under full reallocation I find a 45% increase. The broader core findings of the misallocation analysis still hold, with significant gains available from both within-local-authority and across-local-authority reallocation.

Table C.1: Misallocated Investment Sensitivity Analysis (Local Property Costs)

No.	Scenario Constraints			Project Characteristics						Project Costs and Benefits			
		Year	Local Authority	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	2904	41	1883	0.78	0.30	0.26	-8.5	-142.4	160.1	9.3
1	Best	Fixed	Fixed	2904	40	1731	0.79	0.29	0.29	-6.8	-136.9	159.2	15.4
2	Best	-	Fixed	2904	40	1375	0.76	0.28	0.32	-3.8	-114.7	153.7	35.2
3	Best	Fixed	-	2904	43	1593	0.76	0.46	0.47	-2.9	-107.4	157.2	46.8
4	Best	-	-	4509	66	2566	0.74	0.40	0.39	-4.5	-170.7	239.3	64.1

(a) Base

No.	Scenario Constraints			Project Characteristics						Project Costs and Benefits			
		Year	Local Authority	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	2904	41	1883	0.78	0.30	0.25	-4.8	-142.4	160.1	13.0
1	Best	Fixed	Fixed	2904	40	1711	0.80	0.30	0.29	-3.9	-136.6	159.0	18.5
2	Best	-	Fixed	2904	39	1368	0.77	0.28	0.33	-2.6	-113.8	153.5	37.1
3	Best	Fixed	-	2904	42	1588	0.78	0.46	0.48	-2.4	-105.9	156.8	48.5
4	Best	-	-	4610	67	2704	0.74	0.39	0.39	-3.8	-174.5	244.8	66.5

(b) Low Local Property Cost

No.	Scenario Constraints			Project Characteristics						Project Costs and Benefits			
		Year	Local Authority	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	2904	41	1883	0.78	0.30	0.28	-13.3	-142.4	160.1	4.5
1	Best	Fixed	Fixed	2904	40	1737	0.79	0.29	0.31	-10.6	-137.2	159.3	11.5
2	Best	-	Fixed	2904	40	1359	0.75	0.28	0.32	-5.3	-115.3	153.7	33.1
3	Best	Fixed	-	2904	43	1623	0.75	0.45	0.47	-3.5	-108.9	157.7	45.3
4	Best	-	-	4397	64	2439	0.73	0.40	0.38	-4.7	-166.8	233.2	61.8

(c) High Local Property Costs

Notes: These tables show the aggregate costs and benefits of the actual observed set of wind and solar projects, as well as the same information for a range scenarios identifying the least cost set of proposed projects. Each table refers to a different sensitivity. All values are the cumulative lifetime totals for all wind and solar projects. The "Actual" row refers to the observed set of projects that were actually built. The "Best" rows then refer to different scenarios for the optimal set of projects subject to a series of constraints on the extent to which deployment can be reallocated. "Scenario 1" allows reallocation subject to the total output remaining unchanged by year and local authority. "Scenario 2" allows reallocation subject to the total output remaining unchanged by local authority. "Scenario 3" allows reallocation subject to the total output remaining unchanged by year. "Scenario 4" allows complete reallocation and so may lead to a different total output than was actually observed. Information on project characteristics includes total output, capacity and number of projects, as well as measures of the share of capacity in Scotland and the share of capacity that has any local property costs.

Table C.2: Misallocated Investment Sensitivity Analysis (Social Benefits)

No.	Scenario Constraints			Project Characteristics						Project Costs and Benefits			
		Year	Local Authority	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	2904	41	1883	0.78	0.30	0.26	-8.5	-142.4	160.1	9.3
1	Best	Fixed	Fixed	2904	40	1731	0.79	0.29	0.29	-6.8	-136.9	159.2	15.4
2	Best	-	Fixed	2904	40	1375	0.76	0.28	0.32	-3.8	-114.7	153.7	35.2
3	Best	Fixed	-	2904	43	1593	0.76	0.46	0.47	-2.9	-107.4	157.2	46.8
4	Best	-	-	4509	66	2566	0.74	0.40	0.39	-4.5	-170.7	239.3	64.1

(a) Base

No.	Scenario Constraints			Project Characteristics						Project Costs and Benefits			
		Year	Local Authority	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	2904	41	1883	0.78	0.30	0.26	-8.5	-142.4	136.4	-14.4
1	Best	Fixed	Fixed	2904	40	1719	0.79	0.30	0.29	-6.9	-136.7	135.5	-8.2
2	Best	-	Fixed	2904	39	1352	0.76	0.28	0.32	-3.9	-114.3	130.8	12.6
3	Best	Fixed	-	2904	42	1523	0.78	0.47	0.48	-3.3	-106.7	133.9	24.0
4	Best	-	-	3368	48	1577	0.77	0.46	0.46	-2.9	-115.6	151.9	33.3

(b) Low Social Benefits

No.	Scenario Constraints			Project Characteristics						Project Costs and Benefits			
		Year	Local Authority	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	2904	41	1883	0.78	0.30	0.26	-8.5	-142.4	189.5	38.6
1	Best	Fixed	Fixed	2904	40	1731	0.79	0.29	0.29	-6.8	-137.1	188.4	44.6
2	Best	-	Fixed	2904	40	1358	0.76	0.28	0.32	-3.7	-115.0	181.8	63.1
3	Best	Fixed	-	2904	43	1616	0.76	0.46	0.46	-2.9	-107.6	185.7	75.2
4	Best	-	-	5504	79	3169	0.74	0.35	0.35	-6.5	-228.3	349.2	114.3

(c) High Social Benefits

Notes: These tables show the aggregate costs and benefits of the actual observed set of wind and solar projects, as well as the same information for a range scenarios identifying the least cost set of proposed projects. Each table refers to a different sensitivity. All values are the cumulative lifetime totals for all wind and solar projects. The "Actual" row refers to the observed set of projects that were actually built. The "Best" rows then refer to different scenarios for the optimal set of projects subject to a series of constraints on the extent to which deployment can be reallocated. "Scenario 1" allows reallocation subject to the total output remaining unchanged by year and local authority. "Scenario 2" allows reallocation subject to the total output remaining unchanged by local authority. "Scenario 3" allows reallocation subject to the total output remaining unchanged by year. "Scenario 4" allows complete reallocation and so may lead to a different total output than was actually observed. Information on project characteristics includes total output, capacity and number of projects, as well as measures of the share of capacity in Scotland and the share of capacity that has any local property costs.

Table C.3: Misallocated Investment Sensitivity Analysis (Discount Rate)

No.	Scenario Constraints			Project Characteristics						Project Costs and Benefits			
		Year	Local Authority	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	2904	41	1883	0.78	0.30	0.26	-8.5	-142.4	160.1	9.3
1	Best	Fixed	Fixed	2904	40	1731	0.79	0.29	0.29	-6.8	-136.9	159.2	15.4
2	Best	-	Fixed	2904	40	1375	0.76	0.28	0.32	-3.8	-114.7	153.7	35.2
3	Best	Fixed	-	2904	43	1593	0.76	0.46	0.47	-2.9	-107.4	157.2	46.8
4	Best	-	-	4509	66	2566	0.74	0.40	0.39	-4.5	-170.7	239.3	64.1

(a) Base

No.	Scenario Constraints			Project Characteristics						Project Costs and Benefits			
		Year	Local Authority	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	2904	41	1883	0.78	0.30	0.26	-10.7	-154.8	192.7	27.3
1	Best	Fixed	Fixed	2904	40	1745	0.79	0.29	0.29	-8.5	-149.1	191.9	34.3
2	Best	-	Fixed	2904	40	1369	0.76	0.28	0.32	-4.6	-125.5	185.1	55.1
3	Best	Fixed	-	2904	43	1620	0.76	0.46	0.46	-3.3	-118.1	190.0	68.6
4	Best	-	-	5308	76	2983	0.74	0.35	0.34	-6.4	-236.6	342.4	99.5

(b) Low Discount Rate

No.	Scenario Constraints			Project Characteristics						Project Costs and Benefits			
		Year	Local Authority	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	2904	41	1883	0.78	0.30	0.26	-6.0	-127.9	120.6	-13.3
1	Best	Fixed	Fixed	2904	40	1718	0.79	0.29	0.29	-4.9	-123.2	120.0	-8.0
2	Best	-	Fixed	2904	40	1362	0.76	0.28	0.32	-2.9	-101.8	115.6	10.8
3	Best	Fixed	-	2904	42	1561	0.77	0.47	0.48	-2.5	-94.8	117.4	20.0
4	Best	-	-	3422	49	1722	0.75	0.45	0.45	-2.1	-105.5	136.2	28.6

(c) High Discount Rate

Notes: These tables show the aggregate costs and benefits of the actual observed set of wind and solar projects, as well as the same information for a range scenarios identifying the least cost set of proposed projects. Each table refers to a different sensitivity. All values are the cumulative lifetime totals for all wind and solar projects. The "Actual" row refers to the observed set of projects that were actually built. The "Best" rows then refer to different scenarios for the optimal set of projects subject to a series of constraints on the extent to which deployment can be reallocated. "Scenario 1" allows reallocation subject to the total output remaining unchanged by year and local authority. "Scenario 2" allows reallocation subject to the total output remaining unchanged by local authority. "Scenario 3" allows reallocation subject to the total output remaining unchanged by year. "Scenario 4" allows complete reallocation and so may lead to a different total output than was actually observed. Information on project characteristics includes total output, capacity and number of projects, as well as measures of the share of capacity in Scotland and the share of capacity that has any local property costs.

Table C.4: Misallocated Investment Sensitivity Analysis (Extrapolation Error)

No.	Scenario Constraints			Project Characteristics						Project Costs and Benefits			
		Year	Local Authority	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	2904	41	1883	0.78	0.30	0.26	-8.5	-142.4	160.1	9.3
1	Best	Fixed	Fixed	2904	40	1731	0.79	0.29	0.29	-6.8	-136.9	159.2	15.4
2	Best	-	Fixed	2904	40	1375	0.76	0.28	0.32	-3.8	-114.7	153.7	35.2
3	Best	Fixed	-	2904	43	1593	0.76	0.46	0.47	-2.9	-107.4	157.2	46.8
4	Best	-	-	4509	66	2566	0.74	0.40	0.39	-4.5	-170.7	239.3	64.1

(a) Base

No.	Scenario Constraints			Project Characteristics						Project Costs and Benefits			
		Year	Local Authority	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	2904	41	1883	0.78	0.30	0.26	-8.5	-142.4	160.1	9.3
1	Best	Fixed	Fixed	2904	40	1794	0.79	0.30	0.28	-6.9	-138.0	158.6	13.8
2	Best	-	Fixed	2904	40	1418	0.75	0.28	0.29	-3.7	-117.4	151.9	30.8
3	Best	Fixed	-	2904	43	1687	0.75	0.45	0.45	-3.0	-111.6	153.0	38.5
4	Best	-	-	4206	59	2069	0.76	0.41	0.39	-3.5	-159.1	215.6	53.0

(b) Low Extrapolation Error (10%)

No.	Scenario Constraints			Project Characteristics						Project Costs and Benefits			
		Year	Local Authority	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	2904	41	1883	0.78	0.30	0.26	-8.5	-142.4	160.1	9.3
1	Best	Fixed	Fixed	2904	40	1819	0.79	0.30	0.28	-7.1	-138.7	158.4	12.6
2	Best	-	Fixed	2904	40	1467	0.75	0.29	0.27	-3.8	-121.2	152.4	27.4
3	Best	Fixed	-	2904	43	1755	0.73	0.40	0.39	-2.5	-119.3	151.5	29.7
4	Best	-	-	3716	51	1709	0.74	0.37	0.33	-2.2	-142.3	186.6	42.1

(c) High Extrapolation Error (25%)

Notes: These tables show the aggregate costs and benefits of the actual observed set of wind and solar projects, as well as the same information for a range scenarios identifying the least cost set of proposed projects. Each table refers to a different sensitivity. All values are the cumulative lifetime totals for all wind and solar projects. The "Actual" row refers to the observed set of projects that were actually built. The "Best" rows then refer to different scenarios for the optimal set of projects subject to a series of constraints on the extent to which deployment can be reallocated. "Scenario 1" allows reallocation subject to the total output remaining unchanged by year and local authority. "Scenario 2" allows reallocation subject to the total output remaining unchanged by local authority. "Scenario 3" allows reallocation subject to the total output remaining unchanged by year. "Scenario 4" allows complete reallocation and so may lead to a different total output than was actually observed. Information on project characteristics includes total output, capacity and number of projects, as well as measures of the share of capacity in Scotland and the share of capacity that has any local property costs.

Table C.5: Misallocated Investment Sensitivity Analysis (Noise)

No.	Scenario Constraints			Project Characteristics						Project Costs and Benefits			
		Year	Local Authority	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	2904	41	1883	0.78	0.30	0.26	-8.5	-142.4	160.1	9.3
1	Best	Fixed	Fixed	2904	40	1731	0.79	0.29	0.29	-6.8	-136.9	159.2	15.4
2	Best	-	Fixed	2904	40	1375	0.76	0.28	0.32	-3.8	-114.7	153.7	35.2
3	Best	Fixed	-	2904	43	1593	0.76	0.46	0.47	-2.9	-107.4	157.2	46.8
4	Best	-	-	4509	66	2566	0.74	0.40	0.39	-4.5	-170.7	239.3	64.1

(a) Base

No.	Scenario Constraints			Project Characteristics						Project Costs and Benefits			
		Year	Local Authority	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	2904	41	1883	0.78	0.30	0.26	-8.5	-141.4	162.8	12.8
1	Best	Fixed	Fixed	2904	40	1761	0.79	0.30	0.29	-6.9	-139.6	161.6	15.0
2	Best	-	Fixed	2904	40	1436	0.76	0.28	0.33	-4.1	-116.6	160.3	39.6
3	Best	Fixed	-	2904	43	1703	0.76	0.47	0.46	-3.2	-109.4	160.2	47.6
4	Best	-	-	4553	66	2512	0.75	0.38	0.38	-4.7	-174.0	245.9	67.2

(b) Low Noise (10%)

No.	Scenario Constraints			Project Characteristics						Project Costs and Benefits			
		Year	Local Authority	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	2904	41	1883	0.78	0.30	0.26	-8.2	-135.7	150.4	6.5
1	Best	Fixed	Fixed	2904	40	1808	0.79	0.30	0.29	-7.0	-137.3	160.8	16.5
2	Best	-	Fixed	2904	40	1506	0.76	0.28	0.32	-4.4	-117.9	168.3	45.9
3	Best	Fixed	-	2904	43	1676	0.76	0.43	0.43	-3.5	-106.8	164.4	54.1
4	Best	-	-	4455	63	2315	0.76	0.38	0.37	-4.4	-167.1	252.6	81.1

(c) High Noise (25%)

Notes: These tables show the aggregate costs and benefits of the actual observed set of wind and solar projects, as well as the same information for a range scenarios identifying the least cost set of proposed projects. Each table refers to a different sensitivity. All values are the cumulative lifetime totals for all wind and solar projects. The "Actual" row refers to the observed set of projects that were actually built. The "Best" rows then refer to different scenarios for the optimal set of projects subject to a series of constraints on the extent to which deployment can be reallocated. "Scenario 1" allows reallocation subject to the total output remaining unchanged by year and local authority. "Scenario 2" allows reallocation subject to the total output remaining unchanged by local authority. "Scenario 3" allows reallocation subject to the total output remaining unchanged by year. "Scenario 4" allows complete reallocation and so may lead to a different total output than was actually observed. Information on project characteristics includes total output, capacity and number of projects, as well as measures of the share of capacity in Scotland and the share of capacity that has any local property costs.

Table C.6: Misallocated Investment Sensitivity Analysis (Technology)

No.	Scenario Constraints			Project Characteristics						Project Costs and Benefits			
		Year	Local Authority	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	2904	41	1883	0.78	0.30	0.26	-8.5	-142.4	160.1	9.3
1	Best	Fixed	Fixed	2904	40	1731	0.79	0.29	0.29	-6.8	-136.9	159.2	15.4
2	Best	-	Fixed	2904	40	1375	0.76	0.28	0.32	-3.8	-114.7	153.7	35.2
3	Best	Fixed	-	2904	43	1593	0.76	0.46	0.47	-2.9	-107.4	157.2	46.8
4	Best	-	-	4509	66	2566	0.74	0.40	0.39	-4.5	-170.7	239.3	64.1

(a) Base

No.	Scenario Constraints				Project Characteristics						Project Costs and Benefits			
		Wind/ Solar	Local Authority	Year	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	Fixed	2904	41	1883	0.78	0.30	0.26	-8.5	-142.4	160.1	9.3
1	Best	Fixed	Fixed	Fixed	2904	40	1799	0.78	0.29	0.29	-7.0	-137.5	159.4	14.9
2	Best	Fixed	Fixed	-	2904	39	1407	0.77	0.28	0.33	-5.1	-115.2	153.7	33.4
3	Best	Fixed	-	Fixed	2904	41	1720	0.79	0.45	0.47	-2.9	-110.4	157.8	44.5
4	Best	-	-	-	4509	66	2566	0.74	0.40	0.39	-4.5	-170.7	239.3	64.1

(b) Wind / Solar

No.	Scenario Constraints					Project Characteristics						Project Costs and Benefits			
		Off/ Onshore	Wind/ Solar	Local Authority	Year	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	Fixed	Fixed	2904	41	1883	0.78	0.30	0.26	-8.5	-142.4	160.1	9.3
1	Best	Fixed	Fixed	Fixed	Fixed	2904	40	1738	0.78	0.29	0.27	-6.9	-140.6	159.6	12.0
2	Best	Fixed	Fixed	Fixed	-	2904	38	1237	0.77	0.27	0.27	-4.4	-121.0	153.0	27.6
3	Best	Fixed	Fixed	-	Fixed	2904	38	1293	0.77	0.27	0.25	-0.8	-133.1	158.9	25.0
4	Best	-	-	-	-	4509	66	2566	0.74	0.40	0.39	-4.5	-170.7	239.3	64.1

(c) Onshore Wind / Offshore Wind / Solar

Notes: These tables show the aggregate costs and benefits of the actual observed set of wind and solar projects, as well as the same information for a range scenarios identifying the least cost set of proposed projects. Each table refers to a different sensitivity. All values are the cumulative lifetime totals for all wind and solar projects. The "Actual" row refers to the observed set of projects that were actually built. The "Best" rows then refer to different scenarios for the optimal set of projects subject to a series of constraints on the extent to which deployment can be reallocated. "Scenario 1" allows reallocation subject to the total output remaining unchanged by year and local authority. "Scenario 2" allows reallocation subject to the total output remaining unchanged by local authority. "Scenario 3" allows reallocation subject to the total output remaining unchanged by year. "Scenario 4" allows complete reallocation and so may lead to a different total output than was actually observed. Information on project characteristics includes total output, capacity and number of projects, as well as measures of the share of capacity in Scotland and the share of capacity that has any local property costs.

Table C.7: Misallocated Investment Sensitivity Analysis (Project Size)

No.	Scenario Constraints			Project Characteristics						Project Costs and Benefits			
		Year	Local Authority	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	2904	41	1883	0.78	0.30	0.26	-8.5	-142.4	160.1	9.3
1	Best	Fixed	Fixed	2904	40	1731	0.79	0.29	0.29	-6.8	-136.9	159.2	15.4
2	Best	-	Fixed	2904	40	1375	0.76	0.28	0.32	-3.8	-114.7	153.7	35.2
3	Best	Fixed	-	2904	43	1593	0.76	0.46	0.47	-2.9	-107.4	157.2	46.8
4	Best	-	-	4509	66	2566	0.74	0.40	0.39	-4.5	-170.7	239.3	64.1

(a) Base

No.	Scenario Constraints			Project Characteristics						Project Costs and Benefits			
		Year	Local Authority	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	2680	34	587	0.87	0.33	0.26	-3.2	-129.9	136.0	3.0
1	Best	Fixed	Fixed	2680	34	584	0.87	0.32	0.29	-3.0	-125.6	135.3	6.7
2	Best	-	Fixed	2680	34	547	0.84	0.31	0.32	-2.1	-106.2	130.9	22.5
3	Best	Fixed	-	2680	38	813	0.81	0.48	0.48	-2.3	-97.8	134.1	34.0
4	Best	-	-	3804	53	1094	0.79	0.44	0.43	-3.0	-136.8	186.6	46.7

(b) Projects > 10MW

No.	Scenario Constraints			Project Characteristics						Project Costs and Benefits			
		Year	Local Authority	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	2438	29	237	0.94	0.35	0.22	-0.9	-118.6	122.2	2.8
1	Best	Fixed	Fixed	2438	29	242	0.94	0.34	0.25	-1.0	-115.5	121.7	5.2
2	Best	-	Fixed	2438	28	250	0.92	0.33	0.30	-1.0	-99.0	118.1	18.1
3	Best	Fixed	-	2438	32	390	0.86	0.47	0.43	-1.2	-91.6	120.7	27.8
4	Best	-	-	3313	44	540	0.83	0.45	0.41	-1.7	-119.0	160.8	40.1

(c) Projects > 25MW

Notes: These tables show the aggregate costs and benefits of the actual observed set of wind and solar projects, as well as the same information for a range scenarios identifying the least cost set of proposed projects. Each table refers to a different sensitivity. All values are the cumulative lifetime totals for all wind and solar projects. The "Actual" row refers to the observed set of projects that were actually built. The "Best" rows then refer to different scenarios for the optimal set of projects subject to a series of constraints on the extent to which deployment can be reallocated. "Scenario 1" allows reallocation subject to the total output remaining unchanged by year and local authority. "Scenario 2" allows reallocation subject to the total output remaining unchanged by local authority. "Scenario 3" allows reallocation subject to the total output remaining unchanged by year. "Scenario 4" allows complete reallocation and so may lead to a different total output than was actually observed. Information on project characteristics includes total output, capacity and number of projects, as well as measures of the share of capacity in Scotland and the share of capacity that has any local property costs.

Table C.8: Misallocated Investment Sensitivity Analysis (Spatial)

No.	Scenario Constraints			Project Characteristics						Project Costs and Benefits			
		Year	Local Authority	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	2904	41	1883	0.78	0.30	0.26	-8.5	-142.4	160.1	9.3
1	Best	Fixed	Fixed	2904	40	1731	0.79	0.29	0.29	-6.8	-136.9	159.2	15.4
2	Best	-	Fixed	2904	40	1375	0.76	0.28	0.32	-3.8	-114.7	153.7	35.2
3	Best	Fixed	-	2904	43	1593	0.76	0.46	0.47	-2.9	-107.4	157.2	46.8
4	Best	-	-	4509	66	2566	0.74	0.40	0.39	-4.5	-170.7	239.3	64.1

(a) Base

No.	Scenario Constraints			Project Characteristics						Project Costs and Benefits			
		Year	Local Authority	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	2904	41	1883	0.78	0.30	0.26	-8.5	-142.4	149.5	-1.4
1	Best	Fixed	Fixed	2904	40	1732	0.79	0.29	0.29	-6.8	-137.0	148.5	4.8
2	Best	-	Fixed	2904	40	1377	0.76	0.28	0.32	-3.8	-114.7	143.1	24.7
3	Best	Fixed	-	2904	43	1596	0.76	0.46	0.47	-2.9	-107.5	146.6	36.2
4	Best	-	-	4043	59	2309	0.73	0.41	0.41	-3.8	-147.5	200.2	48.9

(b) No Spatial Variation

Notes: These tables show the aggregate costs and benefits of the actual observed set of wind and solar projects, as well as the same information for a range scenarios identifying the least cost set of proposed projects. Each table refers to a different sensitivity. All values are the cumulative lifetime totals for all wind and solar projects. The "Actual" row refers to the observed set of projects that were actually built. The "Best" rows then refer to different scenarios for the optimal set of projects subject to a series of constraints on the extent to which deployment can be reallocated. "Scenario 1" allows reallocation subject to the total output remaining unchanged by year and local authority. "Scenario 2" allows reallocation subject to the total output remaining unchanged by local authority. "Scenario 3" allows reallocation subject to the total output remaining unchanged by year. "Scenario 4" allows complete reallocation and so may lead to a different total output than was actually observed. Information on project characteristics includes total output, capacity and number of projects, as well as measures of the share of capacity in Scotland and the share of capacity that has any local property costs.

Table C.9: Misallocated Investment Sensitivity Analysis (Non-Marginal)

No.	Scenario Constraints			Project Characteristics						Project Costs and Benefits			
		Year	Local Authority	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	2904	41	1883	0.78	0.30	0.26	-8.5	-142.4	160.1	9.3
1	Best	Fixed	Fixed	2904	40	1731	0.79	0.29	0.29	-6.8	-136.9	159.2	15.4
2	Best	-	Fixed	2904	40	1375	0.76	0.28	0.32	-3.8	-114.7	153.7	35.2
3	Best	Fixed	-	2904	43	1593	0.76	0.46	0.47	-2.9	-107.4	157.2	46.8
4	Best	-	-	4509	66	2566	0.74	0.40	0.39	-4.5	-170.7	239.3	64.1

(a) Base

No.	Scenario Constraints			Project Characteristics						Project Costs and Benefits			
		Year	Local Authority	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	2904	41	1883	0.78	0.30	0.26	-8.5	-142.4	156.0	5.2
1	Best	Fixed	Fixed	2904	40	1732	0.79	0.29	0.29	-6.8	-137.0	155.1	11.3
2	Best	-	Fixed	2904	40	1373	0.76	0.28	0.32	-3.8	-114.7	149.5	31.1
3	Best	Fixed	-	2904	43	1594	0.76	0.46	0.47	-2.9	-107.4	153.1	42.7
4	Best	-	-	4218	62	2459	0.73	0.39	0.40	-4.2	-156.3	218.5	58.0

(b) Non-Marginal Adjustment

Notes: These tables show the aggregate costs and benefits of the actual observed set of wind and solar projects, as well as the same information for a range scenarios identifying the least cost set of proposed projects. Each table refers to a different sensitivity. All values are the cumulative lifetime totals for all wind and solar projects. The "Actual" row refers to the observed set of projects that were actually built. The "Best" rows then refer to different scenarios for the optimal set of projects subject to a series of constraints on the extent to which deployment can be reallocated. "Scenario 1" allows reallocation subject to the total output remaining unchanged by year and local authority. "Scenario 2" allows reallocation subject to the total output remaining unchanged by local authority. "Scenario 3" allows reallocation subject to the total output remaining unchanged by year. "Scenario 4" allows complete reallocation and so may lead to a different total output than was actually observed. Information on project characteristics includes total output, capacity and number of projects, as well as measures of the share of capacity in Scotland and the share of capacity that has any local property costs.

D Transfer Payments to Local Residents

To study the feasibility of different local compensation schemes I look at a four transfer schemes. These were illustrated in the main text and range from simple flat payments based on distance, to payments that account for project size and are made proportional to the average local authority property value.

In principle it is possible to more exactly match the payments made to the precise local external costs calculated here. However, fully compensating those with the largest negative impacts would require conditioning payments on individual property values and this does not seem desirable from an administrative, political or equity standpoint.

The size of the payments made to different affected households is estimated using the data on the property value impacts from each project at each post code location. I fit a regression model with the aim of best approximating the heterogeneity in local property value impacts using a parsimonious set of explanatory variables that could plausibly be used to target payments. The estimation is weighted based on the number of properties at each post code. The sample is restricted to paired observations for each post code location, i, and project, j, where there are non-zero impacts, I, on nearby properties, which effectively means any properties within 5km of a project in my sample.

The regression specifications I estimate for each transfer scheme are as follows:

$$I_{ij} = \sum_{d=1}^{5} \beta_d D_i + \epsilon_{ij} \tag{5}$$

$$I_{ij} = \sum_{d=1}^{5} \beta_d D_i + \sum_{d=1}^{5} \beta_d^C D_i C_j + \epsilon_{ij} \tag{6}$$

$$I_{ij} = (\sum_{d=1}^{5} \beta_d D_i + \sum_{d=1}^{5} \beta_d^C D_i C_j) \times P_a + \epsilon_{ij} \tag{7}$$

Here I start by estimating a set of flat payments for each 1km distance bin, D. I then add an interaction for project capacity, C, to provide both a flat fee and an additional per MW payment. Finally, I interact the entire set of covariates with the average property value, P, in the relevant local authority, a, to convert all payments from absolute amounts to fractions of local authority property values. The results of these regressions can be seen in Table D.1.

The total costs to developers can then be calculated by summing up the value of all payments relevant to each project. I compare these to observed voluntary payments from community benefits funds as listed in Scotland's Community Benefits Register (Local Energy Scotland, 2022). The latest government guidance for Scotland calls on developers

to adopt funds with a value of £5,000/MW/year, and this increasingly appears to be followed for the most recent projects (Scottish Government, 2019).

Table D.1: Local Compensation Scheme Regression Results

Model:	(1)	(2)	(3)
Variables			
£(0-1km)	7,702.98***	7,168.38***	
	(384.42)	(397.21)	
£(1-2km)	5,832.67***	4,894.14***	
	(203.16)	(248.94)	
£(2-3km)	4,971.62***	4,092.08***	
	(143.43)	(260.37)	
£(3-4km)	3,533.31***	2,832.54***	
	(98.19)	(135.25)	
£(4-5km)	1,881.32***	1,610.62***	
	(50.92)	(68.29)	
£per MW (0-1km)		24.11**	
		(11.61)	
£per MW (1-2km)		97.40***	
		(20.04)	
£per MW (2-3km)		91.44***	
		(24.77)	
£per MW (3-4km)		67.06***	
		(10.73)	
£per MW (4-5km)		22.45***	
		(4.66)	
% of Avg LA Prop. Value (0-1km)			4.49***
			(0.23)
% of Avg LA Prop. Value (1-2km)			3.34***
			(0.13)
% of Avg LA Prop. Value (2-3km)			2.72***
			(0.12)
% of Avg LA Prop. Value (3-4km)			1.92***
			(0.10)
% of Avg LA Prop. Value (4-5km)			1.04***
			(0.04)
% of Avg LA Prop. Value per MW (0-1km)			0.03***
			(0.01)
% of Avg LA Prop. Value per MW (1-2km)			0.07***
			(0.01)
% of Avg LA Prop. Value per MW (2-3km)			0.07***
			(0.01)
% of Avg LA Prop. Value per MW (3-4km)			0.05***
			(0.01)
% of Avg LA Prop. Value per MW (4-5km)			0.02***
			(0.00)
Fit statistics			
Observations	485,301	485,301	485,301
R^2	0.21457	0.31663	0.52847
Adjusted R^2	0.21457	0.31661	0.52846

Clustered (Project) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table shows the regression results for three different transfer schemes. The dependent variable for these regressions is the impact per property. The unit of observation is a project-post code pair. The regression is weighted according to the number of properties at each post code.

E Programming

All analysis was conducted using the R statistical programming language (R Core Team, 2022). The one exception was the visibility analysis which was conducted using QGIS (QGIS Development Team, 2022).

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