The Economic Costs of NIMBYism: Evidence from Renewable Energy Projects

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Abstract

Large infrastructure projects can have important social benefits, but also prompt strong local opposition. This is often attributed to NIMBY (Not In My Backyard) attitudes. I study the economic costs of NIMBYism and local planning restrictions by looking at renewable energy projects. Using hedonic methods I find that wind projects can impose significant external local costs, while solar projects do not. I then show that planning officials are particularly sensitive to local costs in their area. The resulting misallocation of investment may have increased wind power deployment costs by 10-29%. I conclude by examining compensation payments as a policy solution.

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1 Introduction

Large infrastructure projects can create widespread social benefits and are often critical to tackling major national or global challenges. However, large infrastructure projects also create concentrated local impacts that can lead to fierce lobbying by affected residents. This kind of local opposition is sometimes pejoratively labeled NIMBY (Not In My Backyard) behavior. It is most commonly associated with projects that combine public goods with private bads and spans issues as diverse as housing to landfills (Frey, Oberholzer-Gee and Eichenberger, 1996; Feinerman, Finkelshtain and Kan, 2004).

One area where the topic of NIMBYism has been extensively debated in recent years is renewable energy deployment (Carley et al., 2020). Here a wealth of survey-based studies have examined community acceptance for wind projects, with many challenging the NIMBY characterization (Wolsink, 2000; Bell, Gray and Haggett, 2005; Rand and Hoen, 2017; Hoen et al., 2019). But revealed preference evidence strongly suggests that wind farms prompt real local pushback, including lowering local residents' interest in clean energy tariffs, reducing voting for "green" politicians, and prompting the emergence of new restrictive zoning regulations (Stokes, 2016; Winikoff, 2019; Germeshausen, Heim and Wagner, 2021). Importantly though, whether this kind of local opposition is imposing real social costs due to insufficient or misallocated investment has not yet been studied.

In this paper I estimate the economic costs of NIMBYism and local planning restrictions by examining their role in determining the siting of renewable energy projects. To do this I focus on the United Kingdom, where I am able to draw on detailed planning data for all proposed projects, including those that were not approved. The planning data allows me to credibly estimate the scale and distribution of impacts on local residents in the form of changes to nearby property values. I then link these local costs to the likelihood of projects gaining approval. The vast majority of wind and solar projects in the UK must be approved at the local level by county planning officials. This allows me to show how local officials weigh local impacts during the approval process, including how this compares to the weight they place on the other wider social benefits of these projects. I conclude by estimating the scale of the spatial misallocation of investment caused by the planning process, and look at whether providing compensation to affected households could offer a viable solution.

This paper fits into a rich literature on the location of undesirable industrial facilities, which has linked siting decisions to both the size of the local external costs imposed and to the political power of nearby residents (Mitchell and Carson, 1986; Hamilton, 1993; Currie et al., 2015).[1] That local officials often pay attention to local factors is unsurprising - arguably they are just trying to make optimal private decisions for their respective jurisdictions. Whether those decisions actually end up raising local welfare is often unclear, with evidence for both successes (Greenstone and Moretti, 2003) and failures (Sadun, 2015). But what is clear is that what may seem optimal for a given local area can in aggregate create harmful outcomes for society as a whole. For instance, much of the evidence on local development zones points to underwhelming returns and significant risks of spatial misallocation (Glaeser and Gottlieb, 2008; Chen et al., 2019). Research on housing development has also shown that local planning restrictions have led to chronic underinvestment in important locations, creating a substantial drag on the economy (Glaeser and Gyourko, 2018; Hsieh and Moretti, 2019). Given the scale of planned investments to mitigate climate change, it seems plausible that local planning processes for renewable energy deployment could also impose large costs on society.

The first step in answering this question requires understanding the size of the external costs imposed by a wind or solar power project on nearby residents and businesses. To do this I focus on estimating how the construction of a project is capitalized into local property values. A number of studies have already looked at power projects, such as fossil or nuclear power plants (Davis, 2011; Tanaka and Zabel, 2018). Increasingly research has

[1]Early studies on landfills and harzardous waste sites also formed the basis for the broader literature on environmental justice (Banzhaf, Ma and Timmins, 2019). The transition to renewable energy has often been held up as a panacea to many unequal distributions of environmental burdens. But wind and solar projects create their own winners and losers too, and existing political processes will be key to determining whether they perpetuate past inequities (Carley and Konisky, 2020).

turned to looking at renewable power projects; primarily the visual and noise disamenities of wind farms. On balance these studies find negative effects on property values, although the magnitudes can range from finding no effect (Lang, Opaluch and Sfinarolakis, 2014; Hoen and Atkinson-Palombo, 2016), to finding modest or even large reductions (Gibbons, 2015; Sunak and Madlener, 2016; Dröes and Koster, 2016; Jensen et al., 2018; Dröes and Koster, 2020).

Here I find that the median wind project causes a roughly 4-5% reduction in residential property values at distances of around 2km. Using the largest dataset of projects and properties studied thus far I go further than previous studies in using an event study framework to show how there are important anticipation effects in advance of a project being completed. In looking at important margins of heterogeneity I find that effects are larger at closer distances. Effects also increase with the size of a project, although at an attenuating rate. I use a geospatial analysis to show that effects are larger when a property is likely to have direct line-of-sight to the wind farm, indicating the bulk of the adverse impact is due to visual intrusion. I also show for the first time how the observed negative effects are driven by properties located in wealthier, less deprived areas. Lastly, in a novel addition I use information on planned but unsuccessful projects to uncover evidence of an appreciation in property values in areas where projects are refused planning permission.

In addition to looking at wind farms I also provide one of the first estimates of the impact of solar projects on nearby residential property values (Dröes and Koster, 2020; Gaur and Lang, 2020). Interestingly, I do not find any statistically significant effects, even at relatively small distances of 1km. This seems consistent with the lower levels of visual intrusion created by solar panels when compared to wind turbines. I also expand the scope of my analysis beyond the prior literature and look at impacts on commercial property values. I do not find statistically significant effects from either wind or solar projects, although these results are less precisely estimated.

Understanding the local external costs created by large infrastructure projects is important in and of itself. However, the main gap that this paper fills is to study whether planning officials actually do a good job of incorporating these local impacts into their decisions. To examine this issue I leverage the detailed data I have on the planning outcomes for the roughly 3,500 wind and solar projects proposed in the UK over the past three decades. For each project I estimate both the local impacts (e.g., on residential property values) and the wider social impacts (e.g., the market value of the electricity produced or the external value of any emissions abated and the costs of constructing and operating the project). I then estimate which factors have a stronger effect on the likelihood of projects receiving planning approval. I find evidence that local planning officials are indeed particularly responsive to local property value impacts. This is consistent with the fact that wind projects are much less likely to be appoved than solar projects.

Refusing a proposed project to avoid adverse local impacts may indeed benefit local residents. However, the resulting underprovision of renewable energy, or the shift in development to more remote, more expensive projects, raises the costs of climate change mitigation for society as a whole. To quantify the scale of the problem and the scope for Pareto-improving trades, I identify the set of projects that would have produced the observed annual deployment of renewable energy at least cost to society. I find that inefficiencies in the planning process have contributed to a significant misallocation of investment, increasing the cost of the UK's deployment of wind power by between £8 billion and £23 billion as of 2019. These costs are substantial, amounting to between 10% and 29% of the lifetime capital and operating costs of all the wind projects built over this period. The range in costs is driven by the degree of substitutability between onshore and offshore wind. The equivalent misallocation in solar power has been just £0.3 billion, or less than 2%. This analysis is the first in the literature to quantify the costs of inefficient planning decisions for this kind of large scale infrastructure investment.

Of the potential gains from reallocating wind power investment, a substantial portion can be achieved by switching to wind projects that are cheaper to build and less remotely located, even though many create larger local impacts. A systematic bias against projects with high local costs is consistent with the finding that local planning officials are particularly responsive to costs imposed on their local area. This suggests there are legitimate concerns around the impact of NIMBYism on planning outcomes. However, in many cases the observed misallocation is actually driven by projects with high local costs that have still gone ahead. The likely explanation lies in the fact that while local planning officials are responsive to variations in local costs *within* their jurisdictions, they appear to do a poor job of accounting for variation in local costs *across* jurisdictions. Because most of the variation in local costs in this case is actually across jurisdictions, failing to coordinate at the regional or national level is potentially even more costly than concerns about NIMBYism.

Policymakers have tried a range of policies that could address the misaligned incentives identified here. I examine the feasibility of developers making direct payments to nearby residents. I show that a simple transfer scheme can be designed that compensates the large majority of affected households, often at a manageable cost to developers.

A further $20 trillion in new power plant investment is expected by 2040, mostly in renewable sources (IEA, 2018). The findings in this paper suggest that this expansion could be achieved at much lower cost and with less political opposition if changes are made to the planning and development process. The local opposition to renewable energy studied here also shares many similarities with challenges faced by other large infrastructure projects in areas like transportation, water and waste. There is every reason to think that similar planning inefficiencies may be present in those sectors too.

2 Context

The first commercial wind farms in the UK were constructed in the early 1990s. Rapid adoption of wind power took off in the 2000s such that capacity has now grown to 24GW as of 2019, producing 20% of the UK's electricity (BEIS, 2020). This expansion is set to continue, with wind power forecast to provide 40-55% of the UK's electricity by 2030 (NGET, 2019). Projects are mostly located in the windier and more remote regions of the north and west of the country. Many projects have also been sited in coastal areas with roughly half of the total capacity now located offshore.

The emergence of solar power in the UK has been more recent with capacity only really starting to grow in 2010 following the adoption of a more generous subsidy regime. By 2019 the UK's solar capacity stood at 13GW and produced 4% of the UK's electricity (BEIS, 2020). Future growth is expected to be modest with solar power forecast to provide 6-7% of the UK's electricity by 2030 (NGET, 2019). Most of this capacity has been located in the flatter agricultural areas in the south of the country where solar potential is highest. Unlike wind power, small-scale residential and commercial solar installations are widespread making up roughly a third of total solar capacity.

[Figure 1 about here.]

Despite a relatively broad political consensus in the UK on the importance of tackling climate change, the expansion of renewable energy has still been uneven and contentious. Both wind and solar projects have historically been dependent on carbon taxes and production subsidies, both of which are set at the national level. In the 1990s and 2000s onshore wind was the most widespread technology, but from 2009 a range of more generous subsidies spurred the expansion of solar power and offshore wind. In 2015 several reforms were introducted that led to a decline in new investment for both solar power and onshore wind, including freezing the UK carbon tax and cutting renewable subsidies. Some of these changes were driven in part by the vocal opposition of rural voters to onshore wind turbines, with then-prime minister David Cameron vowing to "rid" the countryside of these "unsightly" structures. Notably offshore wind was not subjected to the same withdrawl of policy support. In 2020 some of these cutbacks began to be reversed, including for onshore wind.

Besides shifting national politics, arguably the most important determinant of the deployment of renewable energy is the planning approval process. In the UK the overwhelming majority of applications for planning permission are managed by local planning authorities. Local authorities are the primary unit of local government in the UK and are broadly analogous to US counties. Project developers submit a planning application to the relevant local authority. Planning officials then consider the merits of the proposal in line with national and local planning guidelines. A public consultation period is required where affected stakeholders have the opportunity to provide comments. The local authority then decides to either approve or refuse the planning application.

In making their determinations local planning authorities must weigh a range of competing factors. Planning authorities have a legal duty under the 2008 Planning Act to mitigate and adapt to climate change. However, the national guidelines are relatively open-ended, stating that "all communities have a responsibility to help increase the use and supply of green energy, but this does not mean that the need for renewable energy automatically overrides environmental protections and the planning concerns of local communities". Important local concerns often center on changes to the character of the surrounding landscape, particularly for culturally and environmentally important sites (e.g., castles, monuments, national parks etc). For wind projects a noise assessment must be conducted, and there are several safety standards to ensure the turbines do not interfere with flight paths or radar installations. In making their final decision, planning officials in the UK generally avoid following strict zoning criteria (e.g., setbacks, buffers or quotas). However, sometimes planning authorities will seek amendments to planning applications, or approve them with conditions aimed at mitigating certain concerns.

There are two main exceptions to local control of the planning process. The first arises when projects are sufficiently large that they are deemed to have substantial national or regional importance (e.g., motorways, airports, rail networks, ports etc.). In the case of renewable energy, projects with a capacity greater than 50MW have historically been deemed to be of national significance. In these situations the planning decision is made by the national Planning Inspectorate, and any directly affected local authority is included as a statutory consultee. The second exception arises when a developer appeals the decision of a local planning authority. Once an appeal is lodged the national Planning Inspectorate conducts a review and decides to either uphold or overturn the initial decision. In both cases the split between local and national control provides an opportunity to examine the decisionmaking of officials at different levels of government.

To help document the impact of the planning process on the deployment of renewable energy, the UK government compiles a database on the planning applications for all large renewable energy projects that have been proposed since 1990. Figure 1 shows where these projects have been located and when they were submitted for planning approval. Table 1 provides a range of additional summary statistics on outcomes from the planning process as documented in the database.

[Table 1 about here.]

The projects in the planning database comprise the overwhelming majority of wind and solar capacity in the UK. There is a roughly even split across the two technology types, although wind projects are larger and so account for the vast majority of total capacity. Despite this, it is noticeable from Table 1 just how much tougher the planning process is for wind projects. Recieving a planning decision takes three to four times longer for wind projects. The approval rate is much lower as well, with 39% of wind projects being approved compared to 72% for solar projects.

Interestingly, Table 1 provides suggestive evidence that national planning decision-makers are more positively predisposed to renewable energy projects. This is reflected in the higher approval probability for projects decided at the national level. This is also further demonstrated by the impact of the appeals process. In total just under 600 projects were subject to an appeal, representing roughly 10GW of capacity. A larger proportion of these are wind projects, consistent with their higher likelihood of refusal. The appeal success rate is 46%, giving a roughly even split between projects that were upheld on appeal and projects that were overturned on appeal. Accounting for appeals means the final planning approval rates increase to 49% for wind projects and 78% for solar projects.

To provide further information on some of the key reasons why projects are refused I collected the decision letters for 120 wind and solar projects. By far the most cited reason for refusal is the visual impact of a project, which was mentioned in 60% of solar refusals and 75% of wind refusals. By comparison, noise concerns do not feature particularly heavily, This is unsurprising for solar projects. For wind projects though, the noise from rotating turbine blades is a common complaint so it is interesting that noise is mentioned in only 25% of wind refusals. It may simply be that, while important, noise impacts are still small relative to visual disamenities. Another explanation is that there are already clear objective regulations for noise limits, and so developers are likely to ensure these are met for all proposed projects. Visual impacts, on the other hand, are harder to explicitly include in planning procedures and so provide far greater latitude for subjective interpretation by planning officials.

The planning outcome data described here makes clear that a big challenge for the deployment of renewable energy is gaining the backing of local residents and firms. In many ways this makes renewable energy projects similar to most other large-scale infrastructure projects, and so the findings here may be instructive for other sectors. However, the particular importance of national and global factors (e.g., climate change) makes wind and solar projects a particularly challenging case when planning processes are so dominated by local decisionmakers. Unlike more traditional local infrastructure like transport or housing, most of the benefits of wind and solar projects are spread diffusely throughout wider society while many key costs remain concentrated locally. This misalignment between local and wider social incentives is the focus of the paper.

3 Empirical Strategy

To examine the economic impacts of NIMBYism on the planning process I conduct five pieces of analysis. First, I use a hedonic analysis to identify the local impact of wind and solar projects as measured by their capitalization into nearby property values. Second, I quantify the aggregate costs and benefits of each project. The goal is to understand how large the local impacts are relative to various non-local factors that are the reason for pursuing renewable energy in the first place. Third, I conduct a regression analysis to understand how sensitive planning officials are to local versus non-local impacts. Fourth, I estimate the potential costs created by the planning process in the form of misallocated investment. Fifth, I conclude by examining the feasibility of a key policy solution: making transfers to affected local residents. This section provides an abbreviated summary of the empirical strategy, with additional detail provided in the appendix.

3.1 Capitalization into local property values

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 no persistent impacts on local employment (Costa and Veiga, 2019). Furthermore, I find no statistically significant capitalization effect when I look at commercial property rents, details of which can be found in the appendix. Projects do generate rents for landowner, 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. The impact of a project on local tax revenues is likely minimal in the UK 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 Her Majesty's Land Registry and covers virtually all sales of residential properties in England & Wales since 1995. Each transaction includes a unique identifier for a given property, as well as the date of the sale and the postcode location of the property. Summary statistics can be found in Table 2.

[Table 2 about here.]

Treatment in this context is determined by: 1) whether projects are nearby (*distance*), 2) whether projects have come online yet (*post*), and 3) the intensity of exposure as measured by the project capacity (*capacity*).

$$T_{lt} = (distance_{lt} \in k) \cdot post_{lt} \cdot f(capacity_{lt}) \quad (1)$$

For residential properties their location, l, is based on the centroid of their postcode. I use five distance bins ($K = 5$). For wind projects these are: 0-2km, 2-4km, 4-6km, 6-8km and 8-10km. For solar projects the distance bins are: 0-1km, 1-2km, 2-3km, 3-4km and 4-5km. The nature of the treatment effect estimated is then determined by a measure of project size, which I capture as a function of the cumulative wind or solar capacity from all nearby projects. Following Jensen et al. (2018) I estimate capitalization as being related to the log of installed capacity to capture the attenuation of the treatment effect as exposure increases.

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:

$$log(P_{it}) = \sum_{s=S_{pre}}^{S_{post}} \sum_{k=1}^{K} \beta^C_{k,s} T^C_{lt} + \sum_{s=S_{pre}}^{S_{post}} \sum_{k=1}^{K} \beta^F_{k,s} T^F_{lt} + \gamma X_{it} + \theta_{rt} + \lambda_l + \epsilon_{it} \quad (2)$$

Here P is the transaction price of a property, i, at postcode location, l, within region, r, in year, t. I estimate treatment effects for the completed projects T^C as described earlier. In a novel addition I also estimate treatment effects for failed projects, T^F, that were proposed but did not go ahead (e.g. because they were refused planning permission). The failed projects can act as a placebo test and help look at issues like sorting. The treatment variables are interacted with a set of event dummies indicating whether a given observation is s years before (pre) or after (post) the date when a project became operational. I include ten years of pre-periods ($S_{pre} = -10$) and five years of post-periods ($S_{post} = 5$), the last of which also captures any observations that are more than five years after a project becomes operational. Unless otherwise specified the treatment effect coefficients, β_k, capture the % change in property values from a 1% increase in wind or solar capacity in distance bin k. For ease of presentation many of the results shown later will convert this into an estimate of the absolute impact for the median project, which is around 10MW in size.

Regressions are estimated separately for wind and solar projects. In addition to estimating the regressions jointly for all k distance bins, I also repeat the analysis in a sequential manner for a set of distance circles (i.e. individual regressions for 0-2km, 0-4km, and so on). This facilitates making comparisons to other studies. Standard errors are clustered based on location to account for correlation between nearby observations.

In all regressions I limit the sample to properties in locations that are ever within 10km of a wind or 5km of a solar project by the end of the period.[2] To account for unobservable determinants of property values I use a rich set of location fixed effects, λ_l, at the postcode-by-housing-type level, and time fixed effects, θ_{rt}, at the year-of-sample-by-region level. To capture observable determinants of property values a limited set of additional controls, X, are included, such as whether a sale is for a new home.

The event study approach is key to providing visual evidence that the parallel trends assumption holds and also helps mitigate two potential sources of bias: the presence of anticipation effects and the staggered nature of treatment. On anticipation effects, it is plausible these may arise because planning and construction can last several years before a project becomes operational. A standard difference-in-difference model would not capture this. Similarly, a number of recent papers have shown that difference-in-difference estimates can be biased when there is variation in treatment timing (Goodman-Bacon, 2018). One partial solution is to employ some form of event study as it can more consistently pin down the source of identifying variation and how it is affected by variation in treatment timing (Borusyak and Jaravel, 2017; Callaway and Sant'Anna, 2019).

I look at three key sources of heterogeneity. First, the visual impact of wind and

[2] 34% of the residential sales sample are within 5km of a solar project and 34% of the residential sales sample are within 10km of a wind project.

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 use a GIS analysis to determine whether a property has direct line-of-sight to a project. Second, we might expect the impact of a nearby wind or solar project on property values to be larger in wealthier neighborhoods that tend to already enjoy more of the environmental amenities that a renewable energy project would adversely impact, like historic landscapes and beautiful views (Gibbons, Mourato and Resende, 2014). To explore this I allow for differential effects based on whether a property is in a deprived area. Third and finally, I look at whether effects differ for projects that were subject to an appeal. This offers a potential way to mitigate concerns about selection bias by focusing on a subset of more "marginal" projects (i.e. projects that only just got built or only just failed). It seems plausible that this subset of projects is more credibly comparable than simply using the entire sample of projects. Full details on the differential effects I look at can be found in the appendix.

3.2 Estimating project-level costs and benefits

3.2.1 Local costs and benefits

I calculate the total local impacts of wind and solar projects by taking capitalization treatment effects and multiplying by the total value of all affected properties near each project. The coefficients I use are based on the capitalization analysis set out in the previous section. This includes accounting for heteregenous effects at different distances, for visible vs non-visible properties, and for local levels of deprivation. Because of the inherent uncertainty in this analysis I examine a central scenario, as well as a low and high sensitivity case. These scenarios are informed by the confidence intervals around the effects estimated in the hedonic analysis, as well as by any effects estimated in comparable hedonic studies.

To construct a panel dataset of the total value of all properties in the UK I start with more aggregated data on average property values and counts at the local authority level. I then downscale these to the postcode level. This downscaling is based on a range of data, including the residential property transactions data used in the prior hedonics analysis. Full details can be found in the appendix.

3.2.2 Non-local costs and benefits

The next step requires estimating the various non-local costs and benefits associated with each renewable energy project over their twenty-five year operating lifetime. To start I construct project-specific estimates of electricity production, accounting for improvements in technology over time, the available wind or solar resource, and even the detailed characteristics of the turbine installed for wind projects.[3] I then estimate five main benefits and two main costs. Extensive details on the sources and methods used in estimation can be found in the appendix.

For benefits, first I calculate the market value of the electricity produced using wholesale electricity prices. Second I calculate the value of any carbon emissions abated using the carbon emissions intensity of any fossil fuel power production that is displaced. Third I calculate the value of any local pollution emissions abated in much the same way, but using local pollution intensity instead. Fourth I calculate the capacity value provided by a project through its contribution to reliably meeting peak demand, accounting for how this varies over time. Fifth I attempt to calculate the learning-by-doing benefits, accounting for how these fall over time.[4]

[3] In calculating and valuing the electricity produced by a project I do so in terms of annual averages. In reality there is significant temporal variation in the output from wind and solar resources and the value of renewable energy production (Borenstein and Bushnell, 2018; Callaway, Fowlie and McCormick, 2018). Fully simulating these dynamics at an hourly level is beyond the scope of this paper. To a first order though, annual averages should be sufficient for the purpose envisaged here, especially given the focus on the value of projects over their entire lifetime.

[4] The early adoption of wind and solar power can create learning spillovers that provide an external benefit to future projects (Borenstein, 2012). Quantifying the value of this kind of learning is very challenging. Here I rely on a paper by Newbery (2018).

For costs, first I calculate the capital construction costs of installing each project, accounting for reductions in cost over time, economies-of-scale for larger projects, and even project-specific estimates for offshore wind projects. Second I calculate the operation and maintainence (O&M) costs incurred each year, accounting for reductions in cost over time and variation in transmission costs by location.

There may be other secondary costs and benefits created by these projects, and this should be kept in mind when interpreting the results presented later. Even so, the ones included are quite extensive, covering all aspects that would be required by UK government guidance for evaluating these projects.

Each of the costs and benefits I do estimate are still subject to significant uncertainty, particularly those that are more challenging to quantify like the benefits of learning-by-doing. To deal with this I examine additional low and high sensitivities for some of the most uncertain categories. A final source of uncertainty is the discount rate used when converting everything to present value levelized quantities. Here I examine a baseline real discount rate of 3.5% in line with UK Treasury guidance, as well as low and high sensitivities of 1.5% and 7% respectively.

To keep the analysis tractable I treat each project as if it is "on-the-margin" and being considered in isolation. The alternative would be to consider many projects in aggregate or treat larger projects as non-marginal. Doing so would require making complex alternative assumptions about equilibrium electricity prices or project costs, which is beyond the scope of this study. Treating each project as a marginal project also has the added benefit of mirroring the governmental guidance that planning officials should be following when valuing these projects.

An important limitation to the valuation undertaken here is that the data and approaches used are necessarily based on our current understanding, which may be quite different from the state of knowledge available to decisionmakers at the time they were considering a project. Moreover, the use of a mixture of observed historical data pre-2020 and forecasted data post-2020 is also slightly incongruous. In reality, any decisionmaker appraising a project would be relying on forecasts made at the time. Fully tackling these issues is beyond the scope of this paper. As such I continue to use values based on current knowledge and methods, but this should be kept in mind when considering the results.

3.3 Determinants of planning approvals

To evaluate the planning process I employ a relatively straightforward regression model that links variation in project costs and benefits with the likelihood of a project being approved.[5]

$$approve_{ict} = \beta_1 local_i + \beta_2 nonlocal_i + \theta_t + \lambda_c + \epsilon_{ict} \tag{3}$$

The observations here are the roughly 3,500 wind and solar projects in my sample. The dependent variable is a binary approval decision indicator, *approve*, for each project, i, in county, c, in year, t and it is regressed on both the local net benefits, *local*, and the non-local net benefits, *nonlocal*. The resulting coefficients capture the percentage change in approval probability for a £10 million improvement in net present value.[6] This improvement could be realized through higher benefits (e.g. earning higher electricity prices or displacing a more emissions) or through lower costs (e.g. cutting construction costs or reducing impacts on nearby property values).

To control for general national trends in the likelihood of projects being approved I include a set of year-of-sample fixed effects, θ. I then examine the impact of including location fixed effects, λ, for each local authority to capture differences in planning approvals across jurisdictions. This allows me to show how the results change when they

[5] The regression setup here is similar to the approach taken by Roddis et al. (2018). However, instead of looking for general features that may be associated with projects being approved (e.g. nearby national parks or population density), my focus is on measures of costs and benefits that have a clear economic interpretation.

[6] This is estimated using a linear probability model. Estimation using a logit model gives qualitatively similar results and can be found in the appendix.

are identified using only within-authority variation from the range of projects that each local authority is in charge of reviewing.

In this context we might expect an idealized global social planner to find that any increase in net present value to have the same impact on approval likelihood, irrespective of where it occurs (i.e. $\beta_{local} = \beta_{nonlocal} > 0$). A national planner is likely to get pretty close to this, although most of the carbon emission reduction benefits do accrue to other countries. However, for a local planner we might reasonably expect them to only pay attention to the local net benefits as these are the ones that directly affect actors in their jurisdiction (i.e. $\beta_{local} > \beta_{nonlocal}$=0).[7]

Lastly, I extend the analysis to look at differential effects. First I see if the planning process differs in conservative areas relative to more liberal areas. Using data on local elections I classify a local authority is politically conservative based on whether it has a majority of Conservative party councillors.[8] Second, I use information in the planning data to see whether decisionmaking by the national planning agency differs from the local level.[9]

3.4 Quantifying misallocated investment

If particular emphasis is placed on avoiding certain costs arising from renewable energy projects, such as adverse impacts on local property values, the result may be that socially beneficial projects are consistently refused, leading to under-investment. Even if aggregate deployment of renewable energy is unaffected, a systematic bias towards approving more expensive projects could still emerge, again on the basis that they have smaller impacts on local property values. This could take the form of building solar power instead

[7] Altruistic motivations are an obvious exception to this though.

[8] The local elections data is from Election Centre. In the UK, councillors for each local authority are elected at least every four years and the vast majority of councillors are affiliated with one of the main UK political parties.

[9] I classify projects as having national planning agency involvement if the initial planning authority was at the national level (e.g. for large projects) or if the project's initial local decision was reviewed at the national level (e.g. during an appeal).

of wind; building more remote wind projects or even moving projects offshore.

To try and quantify the potential for insufficient or misallocated investment, I use my estimates of project specific costs and benefits to find the set of proposed projects that can produce the observed annual deployment of renewable energy at least cost. To do this I group projects by their actual or expected start year and then rank them in order of their social net present value. I sum up the least cost set of projects necessary to reproduce the actual observed capacity additions for each year. I then compare the cumulative total social net present value between this "least cost" set of projects and the actual set of projects that were built.

3.5 Compensation for local residents

If local impacts on residents are a significant impediment to the deployment of renewable energy, a natural solution may be some form of direct compensation. This practice does already happen for some projects, with payments being made by wind and solar developers to local communities in the form of grants to fund public services or discounts on electricity bills.

To understand how feasible it is to target payments to affected households, and how cost effective transfers might be for developers, I examine two simple transfer schemes. The first "Basic" scheme makes lump sum payments to all affected households within 4km, with payments varying in size based on the capacity of the project, how close a resident is to the project, and whether a household has direct line-of-sight. The second "Detailed" scheme is similar except payments are also proportional to average county-level property values, resulting in larger costs to developers in areas with high house prices. Full details on how the payment amounts are derived can be found in the appendix.

4 Results

4.1 Capitalization into local property values

The capitalization results for residential property values are presented here, with additional detail available in the appendix. For wind projects the event study in Figure 2 shows a reduction in property values of around 4-5% for properties located within 2km of a newly built 10MW project. The effect is smaller at distances of 2-4km and decays to virtually zero beyond 4km. The log specification also means the effect attenuates as the size of a project increases, with the first wind turbine being the most costly. The effects observed here are of a similar magnitude to those found in previous studies. The event study plots make clear the presence of important anticipation effects one to two years before projects ultimately come online, as well as adjustment effects over the following two years. This is consistent with the planning and construction process for wind projects generally taking around two to three years.

[Figure 2 about here.]

In a novel addition to the existing literature, I am also able to check the observed effects for the treated locations where projects were built against the changes in the control locations where projects failed. The dotted lines in Figure 2 indicate that in locations where projects were proposed but ultimately failed there is no significant negative impacts on property values. If anything those locations see an appreciation in property values once the fate of the proposed project becomes clear. This may be in part due to sorting behavior and the increasing value placed on any remaining locations yet to be "spoiled" by the construction of a wind farm.

The event study results provide strong supportive evidence that prior to any anticipation in the pre-period there are parallel trends for both completed and failed projects. This validation of the difference-in-difference empirical strategy has been lacking in prior studies on this particular topic, in large part due to studies relying on smaller datasets or failing to examine pre- and post-treatment trends over a long time period.

One concern with the distance bins approach is that the time fixed effects will be overwhelmingly determined by properties in the outermost distance bins as these have the most observations. To check that this is not driving the results I also estimate five separate regressions for a series of expanding distance circles. The effects using this approach are broadly comparable to those using distance bins throughout the analysis and so are presented in the appendix. I also conduct a number of robustness checks using alternative fixed effects, as well as making comparisons between the event study approach and the coefficients from a regular difference-in-difference specification. Again, all of these results can be found in the appendix.

Lastly, I look at differential effects. These results can be seen in the lower half of Figure 2. Note that these results also use the approach of estimating five separate regressions for a series of expanding distance circles. As expected, I find that the property value impacts of wind projects appear to be more pronounced for properties that have direct line-of-sight to a project, and for properties in less deprived areas.

For solar projects I find no consistent evidence of an impact on residential property values. Figure 3 makes clear there is no noticeable change in property values when a solar project is built nearby. This is the case even though the distance bins being used are smaller, with the smallest capturing properties that are within 1km of a project. There is also no appreciation effect for properties near failed projects either.

[Figure 3 about here.]

Figure 3 also shows the results of the analysis of differential effects for solar projects. Here again there is no consistent evidence of a statistically significant effect, even for the properties with direct line-of-sight to a project that are also located in a wealthier, less deprived area. Of course, the effects in the smallest 0-1km distance bin are noisy due to a lack of power at this level of disaggregation. Nevertheless, even at distances of 0-2km there is no clear evidence of an effect.

4.2 Project-level costs and benefits

Figure 4 summarizes the estimated costs and benefits for all the wind and solar projects studied here. The top panel shows how annual averages of these costs and benefits have changed over time. The large declines in project capital costs over time are clearly visible and reflect the substantial technological progress that has taken place over this period. The declining environmental benefits over time are also striking and reflect the fact that the marginal electricity production being displaced by a project built in 1990 was much dirtier than for a project built in 2020. The bottom panel shows the full ranking of projects in order of their total net present value. This makes clear the significant heterogeneity across projects, particularly with regard to the local property value impacts.

[Figure 4 about here.]

4.3 Determinants of planning approvals

Table 3 presents the results of the planning process analysis. When only controlling for year fixed effects (column 1) I do not find any significant evidence of sensitivity to local impacts. However, when I add county fixed effects to look at within-county variation (column 2) the local impacts have a large, positive and statistically significant effect on the likelihood of receiving planning approval. Here I find that if a wind project imposes £1 million in losses to nearby residential property values, it will be 0.3% less likely to be approved. The results is that local authorities are responsive to local factors for the range of projects in their jurisdictions.

The same magnitude of responsiveness is not apparent for non-local impacts. For instance, a similar £1 million increase in capital costs or a £1 million decrease in electricity revenues has a negligible effect on the chance of approval. This fits with the hypothesis set out earlier that local decisionmakers are incentivized to focus on impacts on local actors while ignoring other impacts that are largely externalized to non-local actors. Interestingly, the coefficient on non-local impacts is actually negative and statistically significant, although the coefficient is an order of magnitude smaller than the coefficient for local impacts. This small size of the coefficient highlights the relative lack of attention paid to non-local factors.

[Table 3 about here.]

Table 3 also examines whether these effects are heterogeneous by political leaning (columns 3-4) or the extent of local control (columns (5-6). When looking at the signs of the interaction terms the results are as expected. Conservative areas are more sensitive to local impacts, consistent with their history of opposition toward wind farms. Similarly, national planning officials are less sensitive to local impacts and more responsive to non-local impacts. In both cases though it should be noted that the observed differences are not statistically significant.

4.4 Misallocated investment

Table 4 shows that the potential gains from more efficiently reallocating investment to the set of proposed projects that can reproduce the observed annual deployment of renewable output at least cost. Further details on this analysis can be found in the appendix, including a version of this analysis that focuses more on the issue of insufficient investment.

An important caveat to note with this misallocation analysis is that many of the findings are subject to the significant uncertainties in the underlying estimates of costs and benefits, particularly the local impacts from the capitalization analysis. Despite going further than any previous study to estimate the local and non-local impacts of these projects, my approach may simply lack sufficient detail to fully account for the the idiosyncracies of each local area and the projects being proposed. 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 those decisions is probably in order. That being said, the findings set out here are hopefully instructive of the nature of the challenges in this area and potential scale of the problem at hand.

[Table 4 about here.]

Table 4 shows that the potential gains of reallocation for solar projects amount to £0.5 billion, £0.3 billion of which can be achieved by reversing planning decisions. This is equivalent to roughly 2% of the aggregate lifetime capital and operating costs for all the solar projects built over this period. For wind projects, the potential gains of reallocation amount to £26.6 billion, £22.4 billion of which can be achieved by reversing planning decisions. This is equivalent to roughly 29% of the aggregate lifetime capital and operating costs for all the wind projects built over this period.

A big driver of the potential gains for wind power is an apparent overinvestment in offshore wind, with the hypothetical least cost scenario consistently reallocating towards cheaper onshore wind projects. However, there is significant uncertainty in one of the key determinants of the tradeoff between onshore and offshore wind: the learning-by-doing benefits experienced by these two technologies. To explore this I examined the impact of preventing any substitution between onshore and offshore wind.

In the constrained version of the least cost analysis, the total potential gains from reallocation fall significantly to £8.3 billion. £7.4 billion these gains can be realized by reversing planning decisions, and are equivalent to roughly 10% of the aggregate lifetime capital and operating costs for all the wind projects built over this period. The gains are also overwhelmingly concentrated in reallocation amongst onshore wind projects. This leads to an interesting conclusion: if the UK's investments in offshore wind have indeed resulted in substantial learning-by-doing, opposition to onshore wind may have had the unintended consequence of spurring beneficial innovation. However, if offshore wind learning has been relatively muted, opposition to onshore wind may have cost the UK dearly.

One possible explanation for the misallocated wind power investment is the influence of local costs on planning decisions. If I subset the potential gains further, it is consistently the case that around half can be achieved by reallocating toward projects with higher local costs. This suggests that the kind of NIMBYism concerns raised by the earlier regression analysis in Table 3 do appear to manifest in real economic costs.

Interestingly though, this means the rest of the potential gains come from reallocating toward projects with lower local costs. Given the earlier findings that planning officials are particularly sensitive to local impacts, it may seem odd that high local cost wind projects would ever be systematically approved. However, the responsiveness to local impacts identified in Table 3 was only found using the within-county variation. Approval decisions did not appear responsive to variations in local impacts across jurisdictions. Two thirds of the variation in the local costs imposed by projects can be explained by differences across jurisdictions. This suggests that the failure to coordinate decisions across jurisdictions has the potential to be just as important as the issue of NIMBYism within each jurisdiction.

4.5 Compensation for local residents

Figure 5 shows the impacts on all local households affected by the wind projects in my sample. For most residents the impacts are less than £1000 although there is a long tail of larger impacts, primarily for those in particularly expensive properties. Figure 5 also illustrates how two relatively simple schemes for targeting compensation to local residents can offset much of the impacts on affected households. I find that both the transfer schemes studied target payments such that three quarters of affected households end up better off. Fully compensating those with the largest negative impacts is more challenging and would require conditioning payments on individual property values. However this does not seem desirable from an administrative, political or equity standpoint.

Historically community benefits funds for onshore wind projects in the UK have amounted to total payments of around £2,000-3,000/MW/year. The latest government guidance calls for developers to adopt funds with a value of £5,000/MW/year. Figure 5 illustrates that in most instances the total costs of these payment schemes to project developers is similar to historical levels. There are still many projects where implementing the compensation schemes set out above would be very expensive, although that may be an indicator that those projects are not worth pursuing once developers internalize the costs they impose on local residents.

[Figure 5 about here.]

5 Conclusion

In this paper I estimate the economic costs of misallocated investment arising from the planning process for renewable energy projects. I find that wind projects can have significant negative external local costs, primarily in the form of visual disamenity. This is captured by reductions in nearby residential property values. Based on my analysis of the planning process I find that planning officials place particular weight on these local factors when making their decisions. This has important implications when the vast majority of the planning decisions for wind and solar projects are made at the local level. I estimate that this has resulted in socially beneficial projects being systematically refused, substantially increasing the cost of the UK's deployment of wind power. A significant portion of this misallocation arises due to tendency to avoid projects that create signficant local impacts, suggesting NIMBYism is a real concern. The remainder appears to come from a misallocation in capacity across jurisdictions, pointing to a coordination problem. Solar projects, on the other hand, do not appear to have significant adverse local impacts. As such they are approved at much higher rates and are subject to negligible risks of misallocated investment.

There are a range of policy solutions that could remedy this misalignment between local and wider social incentives. The approach of providing direct compensation to affected local residents and businesses was mentioned above. Providing these kinds of community benefits is voluntary in the UK so they can vary significantly in prevalence, size and structure. In many instances the current process of Coasian bargaining does appear to be resulting in payments that of a similar scale to the local costs estimated here. However, where negotiation frictions are a concern, mandating a level of local compensation could be desirable. My analysis indicates that payments could be better targeted if they also accounted for important margins of heterogeneity, such as proximity or direct line-of-sight.

Concerns have been raised in the past about the effectiveness of direct payments to combat NIMBYism (Frey, Oberholzer-Gee and Eichenberger, 1996). Another way to keep more of the benefits of renewable energy in local communities is greater local ownership. This has been growing in the UK, but a key challenge is scalability. Community owned capacity represents about 1% of total renewable electricity generation in the UK (Braunholtz-Speight et al., 2018). It seems unlikely that local communities can deploy the kind of financial and technical resources that larger private companies can to roll out renewable energy at the scale and pace required.

The other major issue identified with the localized nature of the planning process was a lack of coordination leading to misallocation across jurisdictions. It is possible that national planning guidelines are currently exacerbating this problem. Existing guidelines emphasizes the need for all localities to do their part to support renewable energy, but also contain explicit provisions to take into account cumulative effects whenever multiple projects have been proposed in the same area. This desire to share the burden of renewable deployment is understandable, but it potentially puts pressure on all local authorities to approve at least a few projects, even in areas where local costs are high, while discouraging the concentrated deployment of capacity in areas where local costs are low.

One solution to the coordination problem could be to set stricter rules for local authorities by reforming national planning guidelines. Alternatively national planning officials could take a larger direct role by lowering the threshold for projects to be moved to national jurisdiction or streamlining the appeal process. The main risk with these solution is that shifting too much control out of local hands could backfire if it results in local residents believing their concerns are not being heeded.

Managing the tension between local and national decisionmaking is a significant challenge, and one that is not unique to renewable energy projects. For many other forms of infrastructure there is a tension between meeting the needs of local residents and considering the merits of a project for society as a whole, particularly in relation to the available alternatives. Finding policies to resolve those tensions will require further research and experimentation. The findings in this paper on the shortfalls of existing processes suggest this work is sorely needed.

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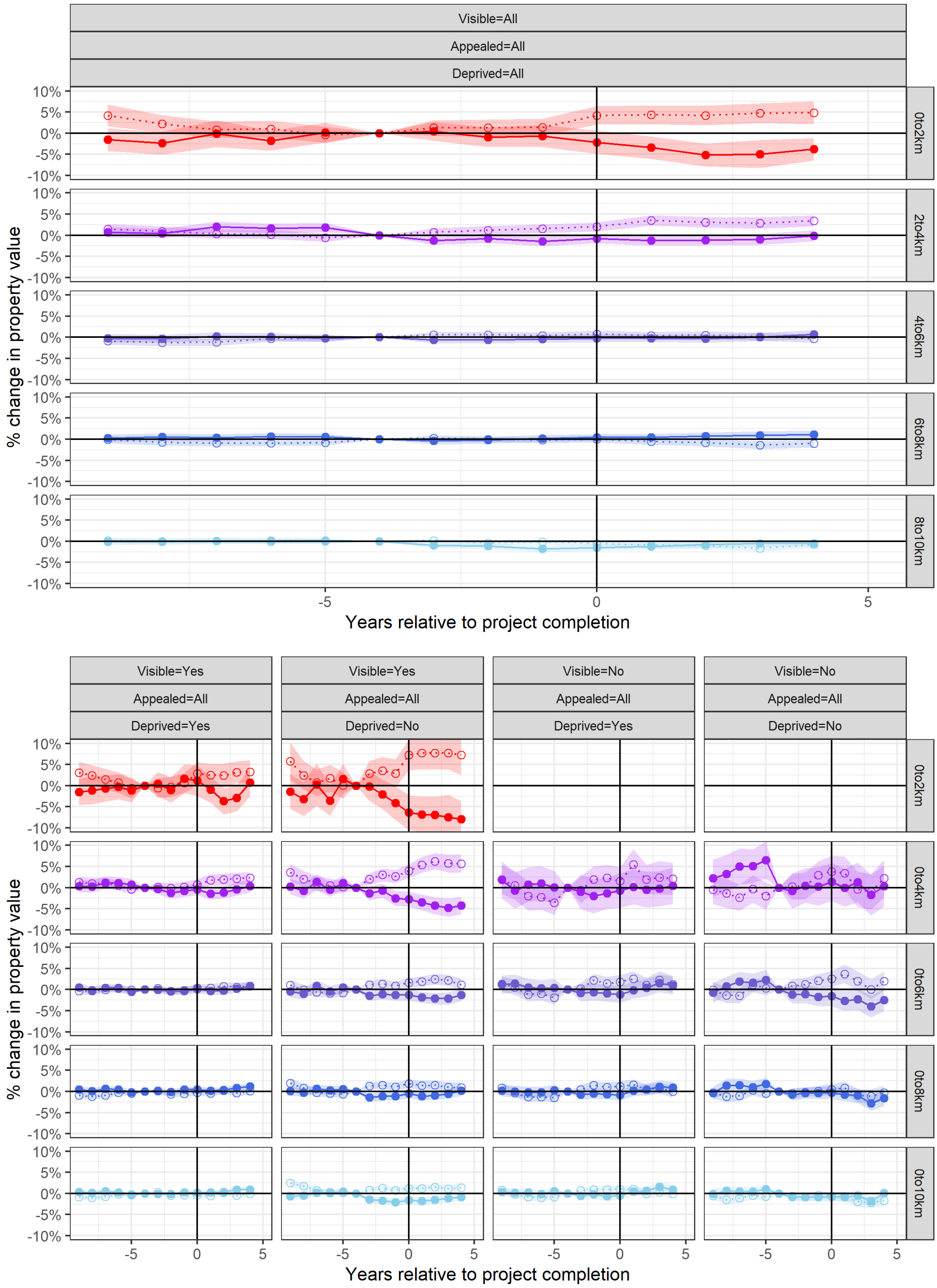
Figure 1: Renewable Energy Projects in the UK

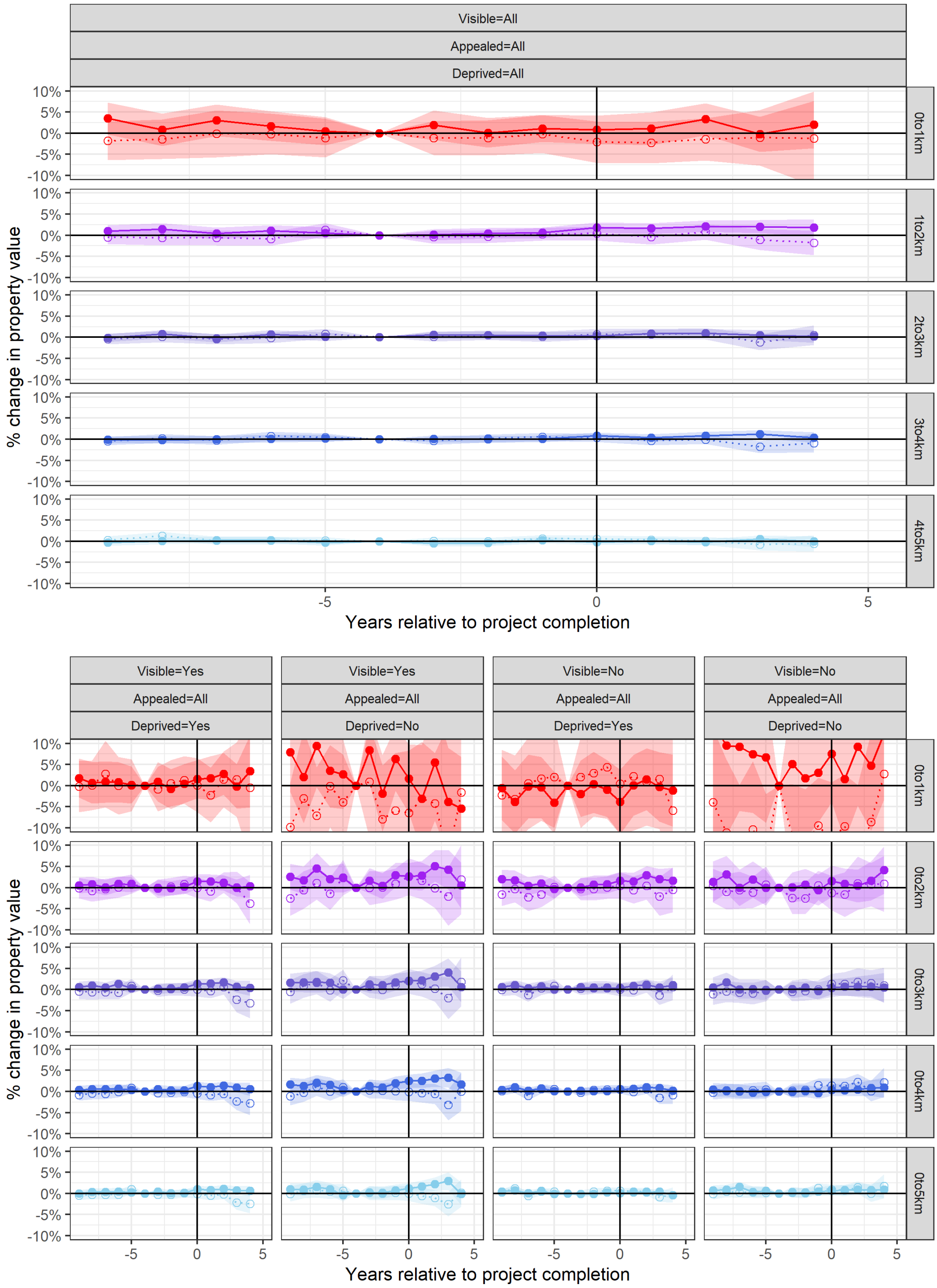
Notes: These figures show the location of projects and the timing of when they were submitted for planning permission. Project sizes are determined by their capacity (in MW). Projects are classified by their development status. “Pending” are projects that have submitted a planning application but have 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. The administrative boundaries depicted are the local planning authorities responsible for processing planning applications.

Figure 2: Residential Property Values Event Study Results for Wind Projects



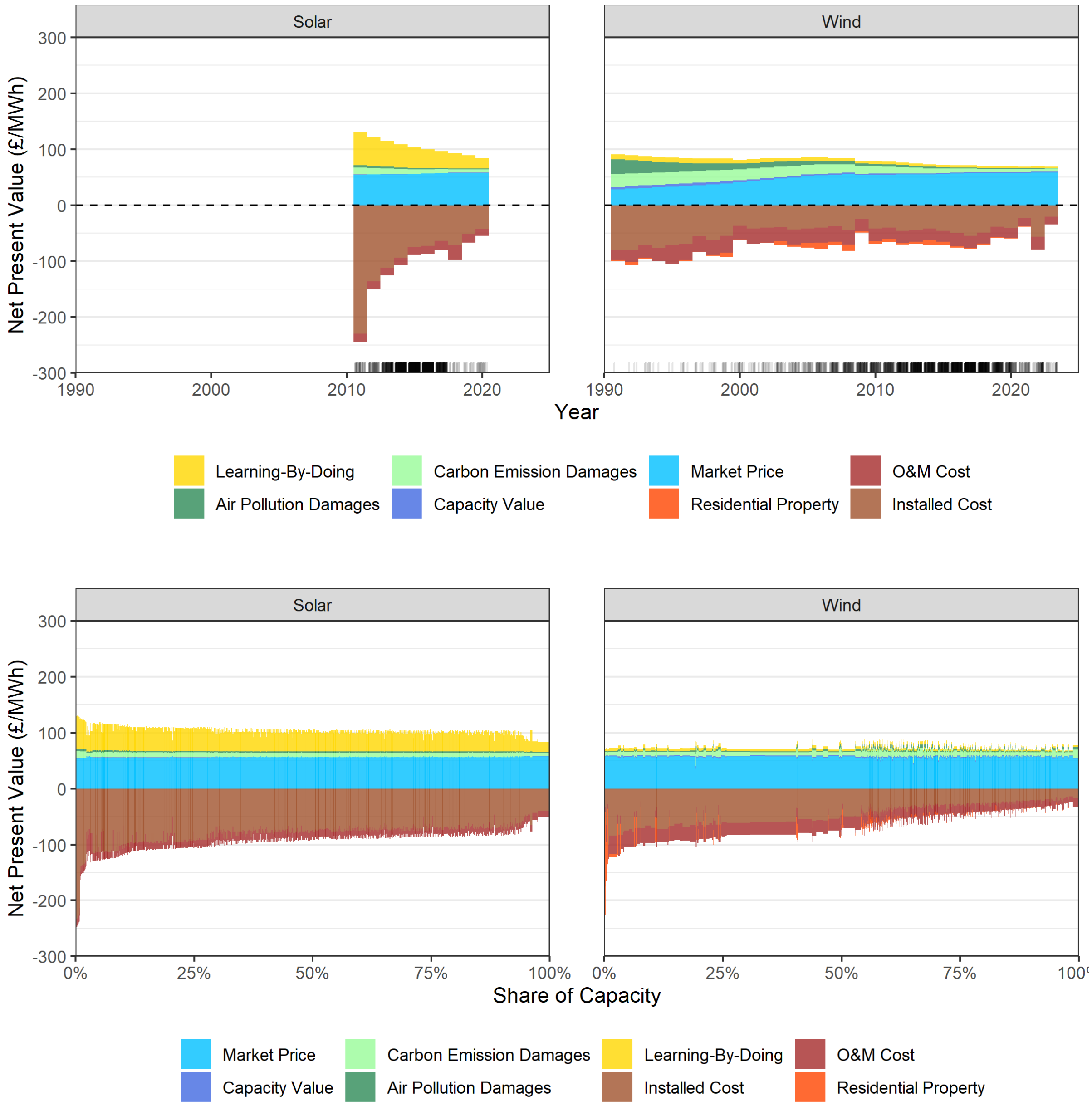
Notes: This figure shows the event study results for residential properties and wind projects. The top figure shows the pooled results estimated using distance bins. The bottom figure shows the heterogenous effects results estimated using distance circles. All event bin coefficients for a given distance bin are normalized relative to the fourth pre-period event bin ($s = -4$). All coefficients should be interpreted as the % change in property values resulting from a location going from having no nearby project to having a 10 MW project at the relevant distance away. The original coefficient can be recovered by dividing by ln(10). Panel rows capture distances, which are also denoted with colors. Panel columns capture the different heterogenous effects estimated. Solid lines and points indicate the effects derived from the treatment variables based on completed projects. Dotted lines and hollow points indicate the effects derived from the treatment variables based on failed projects. Shaded areas represent the 99% confidence intervals.

Figure 3: Residential Capitalization Event Study for Solar Projects



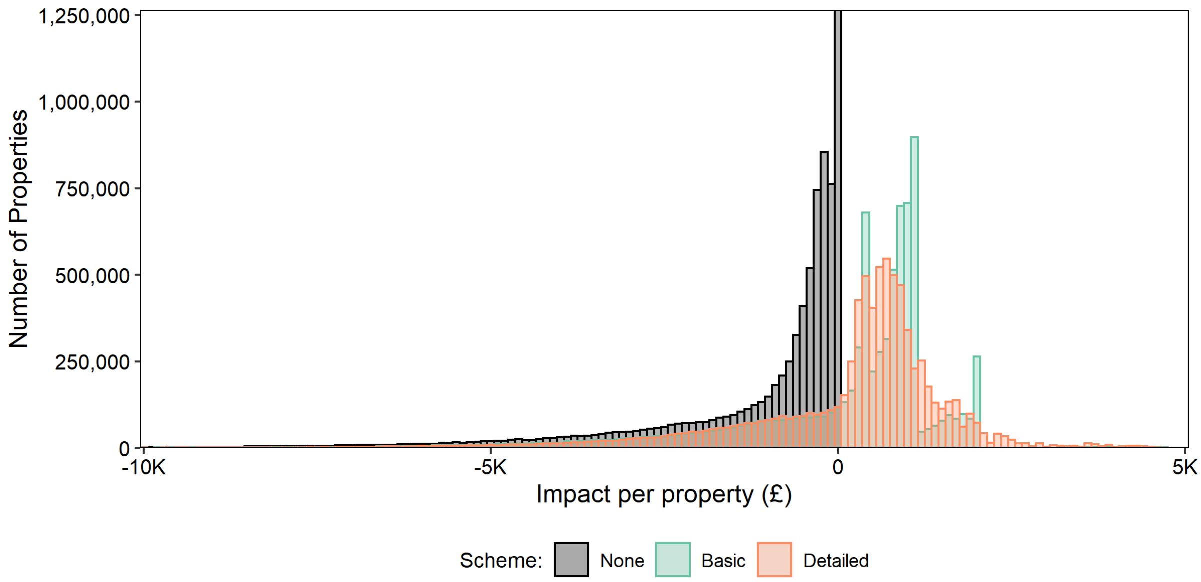
Notes: This figure shows the event study results for residential properties and solar projects. The top figure shows the pooled results estimated using distance bins. The bottom figure shows the heterogenous effects results estimated using distance circles. All event bin coefficients for a given distance bin are normalized relative to the fourth pre-period event bin ($s = -4$). All coefficients should be interpreted as the % change in property values resulting from a location going from having no nearby project to having a 10 MW project at the relevant distance away. The original coefficient can be recovered by dividing by ln(10). Panel rows capture distances, which are also denoted with colors. Panel columns capture the different heterogenous effects estimated. Solid lines and points indicate the effects derived from the treatment variables based on completed projects. Dotted lines and hollow points indicate the effects derived from the treatment variables based on failed projects. Shaded areas represent the 99% confidence intervals.

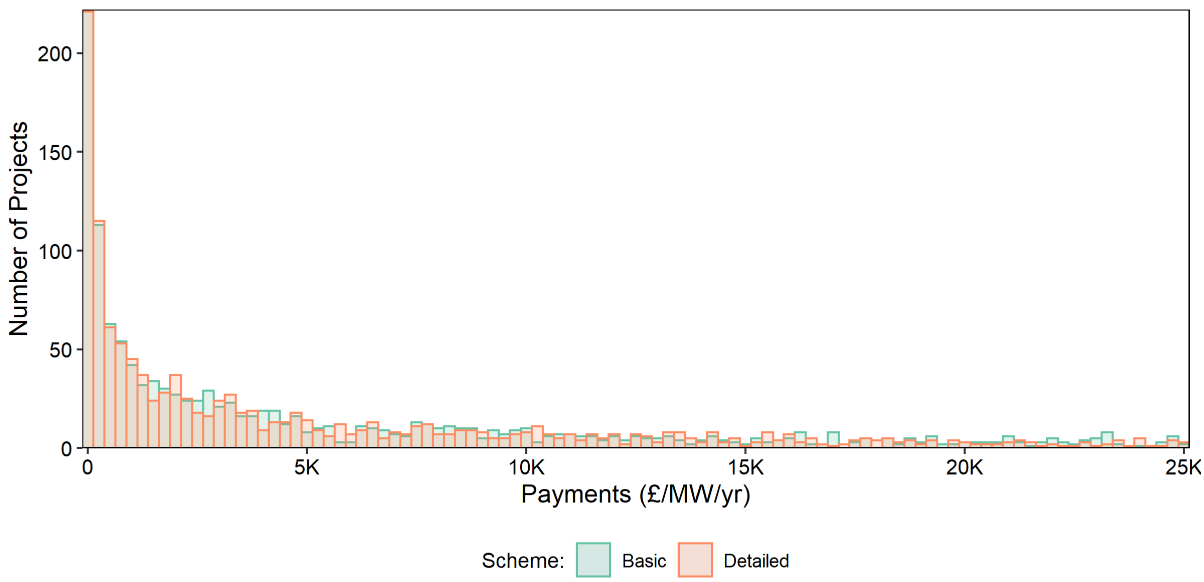
Figure 4: Estimated Project Costs and Benefits



Notes: This figure shows the estimated project-level costs and benefits for all the projects submitted for planning approval since 1990. The left panel is for solar projects and the right panel is for wind projects. All value categories have been converted to consistent levelized net present value terms in £/MWh. These values use a 3.5% real discount rate in line with UK Treasury guidance. Assuming a higher 7% real discount rate produces estimates more in line with industry figures on private developer levelized costs. The top figure shows how average costs and benefits over time. In each year the median was calculated for each value category across all projects that were or would have been commissioned in that year. The black dashes at the bottom of the plot indicate the number of projects in a given year to convey when the bulk of projects were being proposed and commissioned. The bottom figure shows the full ranking of projects in order of their total net present value. The width of each bar is determined by the capacity of each project.

Figure 5: Local Compensation Schemes for Wind Projects





Notes: This figure shows the scope for direct compensation to offset the property value losses incurred by local residents that live near the wind projects. The top figure shows a histogram of the distribution of impacts on local residents from the wind projects, in grey. The net impact on local residents after accounting for two different compensation schemes is then shown by the green and orange histograms. The "Basic" scheme makes payments to households within 4km of a project, with additional payments for larger projects, for those within 2km and for those with direct line-of-sight. The "Detailed" scheme is the same, but makes the payments proportional to the average property value of the relevant local authority. The bottom figure aggregates these potential compensation payments up to the project level to examine how expensive they would be for project developers. Values have been converted to £/MW/year for comparability. Note that for both figures the axes are trimmed. There are residents that experience property value reductions of more than £10,000, as well as project developers that would incur compensation scheme costs of more than £25,000/MW/year.

Table 1: Summary Statistics on Project Planning Outcomes

	Solar	**Wind**
Number of Projects	1675	1775
Total Capacity (MW)	13737	58618
Average Capacity (MW)	8.2	33.0
Length of Planning Process to Initial Decision (days)	143	545
Length of Planning Process to Final Decision (days)	184	643
Initial Decision Approval Rate	0.724	0.391
Share of Projects subject to National Authority Decision	0.001	0.128
National Authority Initial Decision Approval Rate	1.000	0.648
Local Authority Initial Decision Approval Rate	0.723	0.353
Share of Projects Appealed	0.123	0.230
Appeal Success Rate	0.461	0.460
Final Decision Approval Rate	0.779	0.490

Notes: This table contains summary statistics for all wind and solar energy projects in the UK with a capacity of 1MW or greater that were submitted for planning approval since 1990. This excludes projects that are under review at the time of writing. Projects can be subject to approval by either a local or national planning authority. The planning authority makes an initial decision to either approve or refuse the project. Projects may then be appealed in which case the final decision may differ from the initial decision.

Table 2: Residential Property Transactions Summary Statistics

	Total	Detached	Semi-Detached	Terraced	Flat
Sale price (thousands)	185.1	278.1	165.9	149.3	169.0
	(223.4)	(261.2)	(160.8)	(224.6)	(225.3)
New property	0.0909	0.134	0.0608	0.0563	0.155
	(0.287)	(0.341)	(0.239)	(0.230)	(0.362)
Leasehold tenure	0.222	0.0388	0.0731	0.0924	0.974
	(0.416)	(0.193)	(0.260)	(0.290)	(0.160)
Floor area	90.48	127.9	89.05	82.84	59.70
	(58.06)	(85.30)	(48.95)	(38.97)	(28.01)
Energy efficiency rating	61.32	60.55	60.02	60.30	66.55
	(12.98)	(13.52)	(12.13)	(12.61)	(13.11)
Rural	0.177	0.339	0.175	0.129	0.0645
	(0.381)	(0.473)	(0.380)	(0.336)	(0.246)
Index of Multiple Deprivation	19.48	12.84	18.21	23.96	21.17
	(13.95)	(9.207)	(13.10)	(15.65)	(13.05)
N (millions)	23.90	5.55	6.64	7.34	4.37

Notes: This table shows summary statistics for residential property transactions data covering all residential property sales in England & Wales since 1995. Means and standard deviations (in parentheses) are shown for the entire dataset and then for each of four broad housing types. Floor areas and energy efficieny ratings are taken from Energy Performance Certificates and are available for a subset of properties. The rural control is based on whether the output area (OA) that a property's postcode belongs to was classed as rural in 2011. The Index of Multiple Deprivation is a composite measure of regional living standards where higher numbers refer to more deprived areas. The unit of observation is a sale of a residential property on a given date.

Table 3: Planning Process Regressions for Wind Projects

	(1)	(2)	(3)	(4)	(5)	(6)
Local	0.014	0.296*	−0.055	0.235	0.028	0.305*
	(0.063)	(0.130)	(0.069)	(0.156)	(0.082)	(0.150)
Local (Conservative)			0.285	0.174		
			(0.173)	(0.277)		
Local (National Planner)					−0.054	−0.061
					(0.129)	(0.230)
Non-Local	−0.029***	−0.028**	−0.022*	−0.026*	−0.106	−0.096
	(0.008)	(0.009)	(0.010)	(0.010)	(0.084)	(0.088)
Non-Local (Conservative)			−0.037†	−0.011		
			(0.021)	(0.023)		
Non-Local (National Planner)					0.079	0.069
					(0.084)	(0.088)
R-Squared	0.060	0.236	0.066	0.235	0.068	0.243
AIC	2582.681	2613.108	2567.130	2613.560	2573.731	2604.004
N	1810	1810	1804	1804	1810	1810
Wind	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Solar	-	-	-	-	-	-
Year FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
County FE	-	*Y*	-	*Y*	-	*Y*

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; †$p < 0.1$

Notes: This table shows the impact on approval probability from changes to local vs non-local project impacts. Each coefficient has been scaled to reflect the % change in approval probability for a £1 million improvement in its respective value category. The "Local" coefficients refer to changes in local net present value (e.g. nearby property values). The "Non-Local" coefficients refer to changes in non-local net present value (e.g. the value of the electricity produced or the costs of constructing and operating the project). Columns reflect different regression specifications, with specifications varying based on their inclusion of different fixed effects and heterogenous treatment effects. The "Conservative" coefficients are where a variable has been interacted with a dummy for whether a local authority is politically conservative. The "National Planner" coefficients are where a variable has been interacted with a dummy for whether a project's planning application has recevied national input to the decision.

Table 4: Misallocated Investment Analysis

Δ Total NPV (£bn)	**Wind**	**Wind***	**Solar**
All projects	26.6 (1.7)	8.3 (0.6)	0.5 (0.1)
Projects with planning decision change	22.4 (1.0)	7.4 (1.2)	0.3 (0.2)
Projects with planning decision change and local costs increase	10.9 (3.8)	4.7 (2.1)	0.1 (0.1)

Notes: This table shows the costs of misallocated investment calculated under a range of scenarios. All values are cumulative totals to the end of 2018 and are averages across many estimation runs, with standard deviations in parantheses. The different estimation runs are formed from the grid of cost estimates created by the "Low", "Medium" and "High" variants of key inputs, full details of which can be found in the appendix. Values give the results of finding the set of projects that can reproduce the observed annual deployment of renewable output at least cost. Values in columns denoted * have the added constraint that there can be no substitution between onshore and offshore wind. Row 1 covers potential gains from all projects. Row 2 covers potential gains from projects were a different planning decision would have been preferable. Row 3 is a further subset of row 2 that focuses in on changes to planning decisions that would be beneficial and increase average local costs.

Online Supplementary Appendix

Contents

A Capitalization Analysis Detail

A.1 Geospatial Visibility

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. An illustration of this analysis can be seen in Figure S1. This figure shows a map of the area surrounding the Caton Moor Wind Farm, denoted by the red diamond in the center. The top panel shows the surrounding 6km and the bottom panel shows the surrounding 12km. The black/grey/white points denote the postcodes where properties are located. Postcodes in black have no direct line-of-sight to the project. Postcodes in white have full direct line-of-sight to the project. Postcodes in grey 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).

[Figure S1 about here.]

This visibility metric was calculated using the GB SRTM Digital Elevation Model compiled by Pope (2017). Project coordinates were taken from the Renewable Energy Planning Database. In the limited number of cases where the coordinate was missing, or appeared erroneous, the postcode centroid from the address listed in the planning database was used. Postcode coordinates were taken from the ONS postcode lookup file. All spatial data was converted to the Ordanance Survey National Grid reference system.

In addition to specifying coordinates in the east-west and north-south directions, determine line-of-sight also requires specifying an elevation for each point. The default is to simply 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 1.5m 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 (Pierrot, 2019) to fit a simple regression model that traces out the effectively quadratic relationship between turbine capacity and turbine height. 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-postcode pair within a 20km radius. For this I use the intervisibility algorithm developed by Cuckovic (2016) in QGIS. As well as calculating a binary indicator of whether there is direct line-of-sight between two points, it is also possible to use this 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. I did consider looking at the impact of partial visibility, but this is likely not possible for this particular dataset given the measurement error in the coordinate locations and the lack of information on the area covered by each project.

A.2 Appealed Projects

Table S1 provides details on the number of wind and solar projects that have been subject to an appeal. I use appealed projects as a source of potential heterogeneity in my capitalization analysis, which is explained further below.

[Table S1 about here.]

A.3 Residential Capitalization Analysis Detail

A.3.1 Defining treatment

The capitalization analysis throughout this paper consistently uses a difference-in-differences framework. Treatment is determined by the combination of 1) whether projects are nearby (*distance*), 2) whether projects have come online yet (*post*), and 3) the intensity of exposure as measured by the size of a project (*capacity*).

$$T_{lt} = (distance_{lt} \in k) \cdot post_{lt} \cdot f(capacity_{lt}) \tag{4}$$

The proximity of a property to a nearby renewable energy project (*distance*) is determined by whether the distance between that property's location and the centroid of the project falls into a given distance bin, k. For residential properties their location, l, is based on the centroid of their postcode. I use five distance bins ($K = 5$). For wind projects these are: 0-2km, 2-4km, 4-6km, 6-8km and 8-10km. This is informed by prior studies which found the primary effects for wind projects are concentrated within distances of less than 3km (Dröes and Koster, 2016; Jensen et al., 2018; Dröes and Koster, 2020) and have completely decayed by around 10km (Gibbons, 2015). For solar projects the distance bins are: 0-1km, 1-2km, 2-3km, 3-4km and 4-5km. The smaller bins are consistent with the likely smaller distance over which these projects are visible.

The temporal specificity of treatment (*post*) is based on the year when a project becomes operational. Though the project data do include exact dates, fully specifying treatment at the postcode-day level is not necessary. This is because there is unlikely to be a sharp change in property values on the date when projects become operational because of the presence of significant anticipation and adjustment effects that persist over several years. This is substantiated by the event study regressions discussed later.

[Figure S2 about here.]

The nature of the treatment effect estimated is then determined by a measure of project size, which I capture as a function of the cumulative wind or solar capacity from all nearby projects (*capacity*). I focus on the cumulative capacity across all projects because this accounts for the fact that many locations have multiple wind or solar projects nearby, and so only focusing on the nearest or the first project will understate the true nature of exposure. Similarly, limiting the analysis to locations that are only near to a single project also risks undermining the external validity of the analysis. I use project capacity as my measure of the intensity of treatment because it is a straightforward measure of the size of a project. Larger capacity solar projects have more solar panels spread across a greater area. Larger capacity wind projects have more wind turbines and/or taller wind turbines. As a robustness check, I also estimate additional specifications using alternative measures of project size (e.g., the number of wind turbines) and find broadly comparable results.

Prior studies generally use a simple binary indicator for the presence of any project. In a limited number of cases this is extended by looking at differential effects based on the intensity of exposure (e.g., using different bins for small vs large projects). One of the most recent studies on this topic demonstrates that a log specification does a good job of capturing the general response of the treatment effect to increasing exposure (Jensen et al., 2018). In particular, a log specification captures the attenuation of the treatment effect as project size increases. As we might expect, the first wind turbine or acre of solar panels should probably have a larger incremental effect than the tenth or the hundreth. I also found a log specification to perform well, and so my preferred functional form is the log of cumulative wind or solar capacity.[10] The resulting treatment effects show how a 1% increase in wind or solar capacity nearby leads to a x% change in property values. For ease of presentation many of the results shown later will convert this into an estimate of the absolute impact for the median project, which is generally around 10MW in size.

Lastly, prior studies have only ever used locations near completed projects to define both the treated and control groups. However, I also have access to information on proposed but unsuccessful projects. It seems reasonable to think that locations near to proposed projects that ultimately were not built could still act as plausible controls, whilst also offering the opportunity to look at issues like sorting. I therefore construct a full secondary set of treatment variables derived from projects that were proposed but ultimately failed. For failed projects treatment happens based on the date when a project would have become operational if it had been approved and completed.[11] I include these additional treatment variables for the failed projects, T^F, alongside the treatment variables for the completed projects, T^C.

A.3.2 Estimation approach

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:

$$log(P_{it}) = \sum_{s=S_{pre}}^{S_{post}} \sum_{k=1}^{K} \beta_{k,s}^{C} T_{lt}^{C} + \sum_{s=S_{pre}}^{S_{post}} \sum_{k=1}^{K} \beta_{k,s}^{F} T_{lt}^{F} + \gamma X_{it} + \theta_{rt} + \lambda_l + \epsilon_{it} \qquad (5)$$

Here P is a measure of the value of a property, i, at location, l, within region, r,

[10]When taking logs of variables that contain zeroes I use the approach set out in (Bellego and Pape, 2019).

[11]Note that this is based on the final planning decision and so is after accounting for any delays created by the appeal process.

in year, t. For the residential property sales this is the transaction price of a property. The treatment variables are interacted with a set of event dummies indicating whether a given observation is s years before (pre) or after (post) the date when a project became operational. I include ten years of pre-periods ($S_{pre} = -10$) and five years of post-periods ($S_{post} = 5$), the last of which also captures any observations that are more than five years after a project becomes operational. Unless otherwise specified the treatment effect coefficients, β_k, capture the % change in property values from a 1% increase in wind or solar capacity in distance bin k.

Regressions are estimated separately for wind and solar projects and jointly for all k distance bins. In addition to estimating the regressions jointly for all k distance bins, I also repeat the analysis in a sequential manner for a set of distance circles (i.e. individual regressions for 0-2km, 0-4km, 0-6km, and so on). This alternative approach helps make comparisons to other studies, as well as facilitating the examination of possible sources of heterogeneity (discussed later).[12] Standard errors are clustered based on location to account for correlation between nearby observations.[13]

Identification of a credible causal effect faces a number of challenges in this context. Key to this is the parallel trends assumption; namely that in the absence of treatment the treated and control locations would have experienced similar changes in property values. If the location and timing of wind and solar projects was randomly assigned we could be confident that this assumption holds. However, here the treatment is obviously not randomly assigned. Some of the major factors driving selection into treatment may be seemingly unrelated to property values (e.g., wind speed). However, other factors almost certainly are (e.g., visual or historical appeal of local landscape, local political preferences, presence of important ecological habitats and wildlife). To tackle these challenges I take a

[12] The primary benefit here is computational. For the regressions with all k distance bins estimated jointly, the memory requirements when estimating these in an event study setup with multiple interactions for heterogeneous treatment effects quickly becomes prohibitive. The distance circles approach that estimates treatment effects based on one distance at a time mitigates this while still producing coefficients that are similar.

[13] For the residential property regressions I cluster at the output area (OA) level.

number of steps. None of these will perfectly deal with the problem, but the combination of all of them should produce a proponderence of evidence that can provide a reasonable degree of confidence in the estimated effects.

First, in all regressions I limit the sample to properties in locations that ever fall into one of the included distance bins. For the joint regressions this means the analysis is limited to locations within 10km of a wind or 5km of a solar project by the end of the period.[14] Properties are treated in a given time period when a project is completed nearby (i.e. within a relevant nearby distance bin). The resulting control group is formed by properties that do not experience a change in their treatment status during that period. This includes locations that have yet to have a project completed and locations or where a project was completed in previous time periods. This ensures that the control observations are broadly comparable to those undergoing treatment.[15]

To account for unobservable time-invariant determinants of property values I use a rich set of location fixed effects, λ_l. For the residential property regressions these are at the postcode-by-housing-type level. Properties in a given postcode of a given housing type are likely to be highly comparable, particularly because postcodes only include around fifteen properties each.[16] To explore purely within-property variation I also estimate

[14] 34% of the residential sales sample are within 5km of a solar project and 34% of the residential sales sample are within 10km of a wind project.

[15] To further ensure the focus is on the rural and suburban areas where these visual and noise disamenities are likely to be most relevant I also dropped any remaining properties located in the core of major urban areas. In most cases these locations had already been dropped due to wind and solar projects not being sited in built up areas. However, there were a small number of exceptions where a few small wind or solar projects were sited in industrial areas (e.g., along the River Thames in London). Dropping these manually ensured the analysis was not unduly influenced by the very large number of observations in these dense urban areas.

[16] As can be seen in Table 2 there are clearly substantial differences between property types and so controlling for these is important. Where this isn't the case though, a postcode fixed effect can be averaging across very different property types. Increasing the granularity of the fixed effects to the postcode-by-housing-type level resolves this in a far more robust manner than including a simple aggregate control for housing type.

versions with address-level unit fixed effects.[17]

To account for unobservable time-variant determinants of property values all regressions include time fixed effects, θ_{rt}, at the year-of-sample-by-region level. The regions used are the roughly four hundred local authorities in the UK.[18] I also explore the sensitivity of my results to using less granular regions to reduce the richness of these fixed effects.[19] Of course, allowing the time fixed effects to vary by region does risk absorbing a portion of the treatment effect of interest and so this should be kept in mind when interpreting the results.[20]

To capture observable time-variant determinants of property values a limited set of additional controls, X, are included. For residential properties the available controls include whether a sale is for a new home and the type of tenure (e.g., freehold vs leasehold).[21] For a subset of the residential proporties there is also information on house floor areas and energy efficiency ratings.

[17] This has the benefit of capturing property-specific factors that can't be captured by the post code fixed effect. The drawback here is that the estimation can only use the subset of addresses with multiple sales, which reduces statistical power and raises the issue that these repeatedly sold properties are not representative.

[18] My preferred specifications absorb this region-by-year variation by controling for annual average property values that are calculated for each local authority by the ONS. Broadly similar results are achieveable by directly including the relevant fixed effects during the estimation and allowing these to be based on the prices available in the transactions dataset itself.

[19] I use the eleven regions that were formerly known as Government Office Regions. These comprise nine English regions and then Wales and Scotland and range in size from roughly 1 to 4 million households so are fairly analogous to small US states.

[20] I did explore just using a single set of year-of-sample effects for the whole of the UK. However, different parts of the UK have clearly experienced differential rates of economic growth and property value appreciation over this period, and these divergences are probably at least partially correlated with treatment. For instance, the more prosperous south is also where the majority of solar projects are located, while the north where economic growth has lagged behind has also seen a larger portion of wind projects.

[21] Someone with a freehold property owns the property and the land it stands on. A leaseholder owns the property but not the land is built on. The latter is more commonly used for flats and apartments where the property owner is only purchasing a part of an entire building.

The event study approach is key to providing visual evidence that the parallel trends assumption holds. The event study approach also helps mitigate two potential sources of bias: the presence of anticipation effects and the staggered nature of treatment. On anticipation effects, it is plausible these may arise because planning and construction can last several years before a project becomes operational. A standard difference-in-difference model would not capture this leading to a biased estimate of the treatment effect. Similarly, a number of recent papers have shown that standard difference-in-difference estimates can be biased when there is variation in treatment timing (Goodman-Bacon, 2018). One partial solution is to employ some form of event study as it can more consistently pin down the source of identifying variation and how it is affected by variation in treatment timing (Borusyak and Jaravel, 2017; Callaway and Sant'Anna, 2019).

The first source of heterogeneity I examine is visibility. 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 use a GIS analysis to determine whether a property has direct line-of-sight to a project, or if a project is obscured by the landscape (e.g., behind a hill). I then include this as an interaction with treatment to see if properties experience different effects by visibility.

The second key source of heterogeneity I examine is neighborhood quality. In general we might expect the impact of a nearby wind or solar project on property values to be larger in both absolute and proportional terms for properties in wealthier, less deprived neighborhoods. This is because wealthier neighborhoods will tend to already enjoy greater value from the kinds of environmental amenities that a new renewable energy project would adversely impact, like unspoiled green space, historic landscapes and beautiful views (Gibbons, Mourato and Resende, 2014). To explore this I use the UK's Index of Multiple Deprivation to classify areas as more deprived or less deprived.[22] I then include

[22]This is a measure of relative level of deprivation that draws on a range of indicators covering income, employment, education, health, crime, housing quality and environmental quality. I define more deprived

this as an interaction with treatment to see if properties experience different effects by neighborhood deprivation.

Finally, I conduct an additional set of regressions that only use projects that were subject to an appeal. This offers a potential way to mitigate concerns about selection bias by focusing on the effects for a subset of more "marginal" projects (i.e. projects that only just got built or only just failed). Marginal completed projects are those where the appeal overturns the initial refusal and marginal failed projects are those where the appeal upholds the initial refusal. Limiting the analysis to properties treated by this subset of projects rules out locations with projects that a) were almost certain to be approved and likely imposed smaller local disamenities, and b) were almost certain to be refused and likely imposed larger local disamenities. As such it seems plausible that this subset of projects is more credibly comparable than simply using the entire sample of projects.

A.3.3 Further Results

Table S2 illustrates how these effect sizes vary across a range of specifications. Columns 1 to 3 are results from a standard difference-in-difference estimation. Columns 4 to 6 are results from the equivalent event studies, with the treatment effects calculated as the difference between the earliest five pre-period coefficients and the five post-period coefficients. It is immediately clear that the treatment effects using the event study approach are larger. This is likely due to the event study better capturing anticipation and adjustment effects, as well as mitigating potential biases due to the staggered nature of treatment in this setting. The other source of variation across columns is the choice of location fixed effects. The effects are stable across specifications, even when limiting the data to repeat sales properties and using address-level fixed effects.

[Table S2 about here.]

In Table S3 each column is based on a different distance circle, with an increasing

areas as those above the median on the index, and less deprived areas as those below the median.

number of observations as the circle gets larger. The effects using this approach are broadly comparable to those using distance bins.

[Table S3 about here.]

Lastly, Table S4 shows the results of the differential effects analysis. Note that these results also use the approach of estimating five separate regressions for a series of expanding distance circles.

[Table S4 about here.]

The main approach taken in the capitalization analysis measures wind project size as being a function of the capacity of a project in MW. However, there are other ways to capture the relative size of a project. In the case of solar projects, a natural alternative is the land area covered by the panels. Fortunately the relationship between solar capacity and the land area covered has been broadly stable at roughly 5-6 acres per MW (Ong et al., 2013). For wind projects though, the relationship between total capacity and the number of turbines has been changing as turbines have gotten larger. To explore the possible implications of this for the findings on wind projects, I re-run the capitalization analysis with number of turbines as the measure of project size, rather than total capacity. Table S5 shows that the results are largely unchanged. In fact the coefficient sizes are broadly similar because the average size of wind turbines over this period has tended to be on the order of around 1MW.

[Table S5 about here.]

Table S6 largely confirms the findings in the event study plot, with again no consistent effect emerging across a range of specifications.

[Table S6 about here.]

Table S7 shows the results of the analysis using the alternative distance circles approach for solar projects. As with the wind projects the same broad correspondence with the distance bins approach is still apparent.

[Table S7 about here.]

Table S8 and shows the results of the analysis of differential effects for solar projects. Here again there is no consistent evidence of a statistically significant effect, even for the properties with direct line-of-sight to appealed projects.

[Table S8 about here.]

A.4 Commercial Capitalization Analysis

A.4.1 Property value data

Commercial property rents data is from the Valuation Office Agency (VOA) and provides average annual assessed rental values for commercial properties in England and Wales since 2000. The underlying source of this data is property-level information that VOA collects as part of its role in setting taxes levied on commercial properties, known as business rates. Unfortunately the raw property-level data is not yet available for use in academic research. However, the VOA does still publish detailed data on annual average rents at the Lower Layer Super Output Area (LSOA) level. Fortunately LSOAs are sufficiently granular geographic units (approximately equivalent to census tracts in the US) to ensure there is meaningful variation in exposure to renewable energy projects. Summary statistics can be found in Table S9.

[Table S9 about here.]

A.4.2 Treatment and estimation approach

The nature of treatment and the estimation approach used are the same as was set out for residential properties, with the following exceptions. First, the dependent variable is the average rental value per square meter. Second, because the commercial rents data is LSOA averages, treatment is determined at the LSOA level. As such promixity to a project is taken to be the average of the proximity values for the postcodes within each LSOA. Third, for the commercial property regressions standard errors are clustered at the middle layer super output area (MSOA) level. Fourth, the sample is limited to LSOAs that contain any postcodes that are ever within 10km of a proposed wind project and 5km of a proposed solar project.[23] Fifth, the location fixed effects are at the LSOA level. This presents a challenge in that any LSOA may have a range of different commercial activities contributing to the average. However, this is mitigated somewhat by estimating these regressions both for the average of all commercial properties, and for four sectors within each LSOA: retail, office, industrial and other. Moreover, while an LSOA is a more aggregated unit than a postcode it is still relatively small, corresponding to roughly one thousand households. As such, commercial activities within a given LSOA are still likely to be relatively homogenous, particularly at the sector level. Finally, the available controls for the commercial rents analysis include average floor areas.

A.4.3 Results

Table S10 suggests there may be a negative effect of around 4% in the 0-2km distance bin, but it is not statistically significant. To see what might be driving this I repeat the analysis for four sub-sectors of commercial property types. The specifications using the "other" sub-sector are indeed the ones with the largest effect sizes in the 0-2km distance bin. Even so, the sub-sector analysis still fails to find statistically significant effects. Additional regressions looking at differential effects do not reveal clear effects either. However, the more aggregated nature of the data on commercial rents means the analysis has less statisical power than was the case when looking at residential property values. This is reflected in the much wider confidence intervals.

[23] 32% of the commercial rents sample are within 5km of a solar project and 30% of the commercial rents sample are within 10km of a wind project.

[Table S10 about here.]

Table S11 does not reveal any discernible effects for solar projects. Once again though this analysis of commercial rents lacks statistical power as reflected in the wide confidence intervals. There is no consistent pattern in the direction and magnitude of the coefficients, and the standard errors are consistently large when compared to the results for wind projects. Looking at the four sub-sectors of commercial property types also does not reveal any discernible trends.

[Table S11 about here.]

B Project Costs and Benefits Analysis

B.1 Capitalization effect assumptions

To estimate the local impacts of wind and solar projects I use the capitalization into local property values. The rates of capitalization I examine are primarily based on the treatment effects estimated earlier, combined with other comparable estimates in the literature. The assumed effects for residential property values are shown in Table S12. Impacts on commercial rents are not explored given the inconclusive nature of my earlier findings and the lack of any alternative studies.

For wind projects my analysis found that at 10MW wind project leads to a roughly 4-5% reduction in residential property values at distances of 0-2km. Effects are smaller at 2-4km, roughly around 1.5% depending on the specification. Beyond 4km it seems plausible that the effects have largely decayed to zero. These numbers seem broadly consistent with other studies. For instance, estimates from Jensen et al. (2018) imply that a similar 10MW project should also lead to a roughly 2% decrease in residential property values within 3km. Similarly, Dröes and Koster (2020) find that turbines lead to a 2.5% reduction for properties less than 2km away, rising to 5% for larger turbines. Table S12 shows that the central case mirrors these broad effect sizes.

My analysis also finds some limited evidence that effects are larger for properties with direct line-of-sight. This seems consistent with the findings from Dröes and Koster (2020) regarding the increased impact of larger - and presumably more visible - turbines. Similarly, (Gibbons, 2015) finds more pronounced effects for directly visible properties, with those located within 2km experiencing reductions of 5-6%. To capture these more pronounced effects due to direct visibility, Table S12 shows that the assumed effects for visible properties are twice as large as those for non-visible properties.

My analysis also found that effects are larger in less deprived areas. This margin of heterogeneity is potentially even more important than direct visibility and has not been examined in prior studies. To capture these more pronounced effects due to levels of deprivation, Table S12 shows that the assumed effects for less deprived properties are four times as large as those for more deprived properties.

Lastly, my earlier capitalization analysis also extended on any prior research in examining the impacts on property values for comparable areas where projects were proposed, but ultimately did not go ahead. Beyond finding a null effect in these areas, I actually found some evidence of an appreciation in property values. The exact drivers of this are unclear, but it might plausibly be the result of some kind of sorting behavior. Conventionally any treatment effects from a new wind project are taken as the estimated effect on properties near completed projects. However, there is a possible argument for calculating the overall treatment effects by taking the difference between the reductions in areas near completed projects and the increases in areas near abandoned projects. This would have the effect of almost doubling the final treatment effects from wind projects. I do not explore this approach directly, but instead try to allow for the possibility of these larger effects with the "high" sensitivity case shown in Table S12.

For solar projects I do not find any clear evidence of an effect on residential property values. At best I can rule out the possibility of either large positive or large negative effects. There is a lack of other studies that have examined this question. Dröes and Koster (2020) do suggest there is evidence of a 3% reduction in property values within 1km of a solar project. However, the sample size for their analysis is very small and so they acknowledge the evidence for this is weak. (Gaur and Lang, 2020) find a 1.7% reduction in property values within 1 mile of a solar project, although their analysis lacks an event study so it is difficult to evaluate whether their results are suffering from some of the estimation issues mentioned earlier. Given the lack of a clear effect in my earlier analysis, my central case assumes the impact is indeed zero. However, to explore the possibility of both positive and negative effects the "low" and "high" sensitivity cases shown in Table S12 allow for impacts on the order of 1% either way within 1km.

[Table S12 about here.]

B.2 Value of local property

To estimate of the total value of all residential properties near each project, the transactions data used earlier is not quite suitable for this task. This is because it does not include all properties, and for the properties it does include it only has values at the time of sale, rather than in each year. To remedy this and construct a panel of total residential property values at each post code I start with a range of more aggregated data and then downscale these to the post code level.

For residential property prices I start with annual average prices published by the UK Office for National Statistics (ONS) at the local authority level. The averages themselves are constructed based on the same transaction data from HMLR used earlier. The main difference is that they correct for the overall composition of the housing stock, as well as extending the coverage to include equivalent values for Scotland based on separate property-level data held by the National Registers of Scotland (NRS). To downscale the average property prices to the post code level I fit a predictive model that allows me to estimate how house prices in a given post code vary relative to the local authority average.

To be more explicit, when conducting this downscaling exercise I fit a predictive model based on other data that is 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, census data on the socioeconomic status of residents and geospatial data on terrain and landcover. I then use the transaction-level data for England & Wales from HMLR to fit a predictive model that maps these covariates into residential property values. I then construct a house price index for all postcodes using the predictions from this model. Finally I downscale the local authority annual average prices using this predictive index to get an equivalent set of annual average residential property prices at the postcode-level that also remain consistent with the original local authority values.

In order to get total residential property values I then combine these average prices with data on the number of residential properties. Here I use data on counts of properties at the local authority level from the Valuation Office Agency (VOA) for England & Wales and from the NRS for Scotland. To downscale the property counts I proportionally allocate the total number of properties in each local authority based on census data of the number of households in each post code. The result is a panel of average prices and property counts for each post code over the entire period of interest.

B.3 Electricity production

To estimate the main benefits of the electricity produced by a wind or solar project requires estimating the amount of electricity a project will produce over its lifetime. Electricity production for wind and solar projects is almost entirely determined by three factors: the available wind or solar resource, the capacity of the project and the characteristics of the turbines or panels installed. A key statistic for summarizing the output from any renewable energy project is the capacity factor: the average amount of power the project produces normalized by the maximum power output capacity. In the UK this is generally around 30% for wind projects and 10% for solar projects.

To estimate the capacity factors at each project I start with estimated capacity factors based on geospatial data. For solar projects I use the photovoltaic power potential estimates from the World Bank Solar Atlas. This provides estimated solar power productions profiles on a 1km grid for a representative solar installation. I use the coordinates of each project to extract the nearest solar production profile from this grid.

For wind projects the capacity factor is much more heavily dictated by the kind of turbine installed. To account for this I use data 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 a hub height, and then Renewables Ninja will calculate a wind power production profile that accounts for the characteristics of the turbine and the wind conditions in the specified location. For each wind project I first assign a likely turbine model from the list of possible turbine models in the Renewables

Ninja database.[24] I then use the location coordinates of each project to extract an hourly power production profile from Renewables Ninja, which I then collapse to a single average capacity factor value.

Lastly, I collect data on country-level annual average capacity factors from the International Renewable Energy Agency (IRENA). I then use the IRENA data to normalize my initial project specific estimates. This allows me to ensure the original IRENA annual averages are maintained. The results are shown in Figure S3.

[Figure S3 about here.]

B.4 Market value of renewable electricity

To value the electricity produced by each project I rely on data from the UK government's guidance on cost benefit analysis and the valuation of climate change policies. This primarily draws on data published by the Department for Business, Energy & Industrial Strategy (BEIS) and the Department for Environment, Food & Rural Affairs (DEFRA). The relevant data includes historical values for key inputs like electricity prices, the social cost of carbon and monetary damages from local pollution emissions. Projections of these inputs out to 2050 are made based on the UK government's modeling of the future electricity grid. Where data is missing or projections are not available I interpolate and extrapolate based on a range of additional industry sources.

I measure the market value of the electricity produced by each project using the prevailing wholesale price of electricity. The values for annual average wholesale electricity prices are taken from the UK government's guidance on cost benefit analysis and the val-

[24] To do this I start with the data on turbine manufacturers and models in The Wind Power Database (Pierrot, 2019). I match these to the turbine models available in the Renewables Ninja database. For each project in the planning database I calculate both the turbine capacity (in MW) and the turbine power density (in MW per m^2 of blade swept area). For each project I then find the closest turbine model on these two metrics that is also in the Renewables Ninja database. Where possible I prioritize selecting turbine models that have been more commonly installed in the UK.

uation of climate change policies. Pre-2020 the electricity prices are based on observed traded wholesale market prices. Post-2020 the electricity prices are based on projections out to 2050 that were made based on the UK government's modeling of the future electricity grid. This modeling includes forecasting fuel prices, demand and investment in new capacity, and then running a dispatch model to solve for clearing market prices. The guidance includes a set of "low", "medium" and "high" scenarios which I use to form my own "low", "medium" and "high" sensitivities for this particular impact.

Wind and solar projects do also receive production subsidies in addition to any wholesale market revenues.[25] I do not include subsidy revenues in my estimates of the market value of the electricity produced because from the perspective of a social planner they are simply transfers. However, these subsidies may be of interest from a developer perspective, or even for county officials in the event that local royalties and taxes are based on the total revenues a project receives. As such I do separately estimate the value of the subsidies each project using data from BEIS and Ofgem.

B.5 External environmental benefits

The electricity produced by renewable projects has added non-market benefits when it displaces other forms of environmentally harmful power production. In particular, where increased production of renewable electricity displaces coal or gas-fired power plants it will reduce both carbon emissions and local pollutant emissions.

To calculate the amount of emissions abated I start with historical data on annual total electricity generation by source from BEIS and annual emissions by source from DEFRA. I use this to calculate annual average marginal emissions factors for CO_2, SO_2, $PM_{2.5}$, PM_{10} and NO_X assuming that either coal or natural gas has been the marginal source of generation. I then project these marginal emissions factors forward to 2050 assuming they decline in line with the forecast average carbon emission intensity of the

[25]The main renewable subsidy programs over this time period are the Non-Fossil Fuel Obligation, the Renewables Obligation, Feed-In-Tariffs and Contracts for Difference.

total generation mix. These forecasts are again taken from the UK government's modeling of the future electricity grid.

Marginal abated carbon emissions are then valued using the UK values for the social cost of carbon and local pollution damages. In the 2019 guidance the central values are £68/ton for CO_2, £7,612/ton for SO_2, £128,415/ton for $PM_{2.5}$, £82,442/ton for PM_{10}, and £7,521/ton for NO_X. The resulting marginal values per MWh of electricity produced are shown in Figure S4 alongside the wholesale price of electricity. Once again the guidance includes a set of "low", "medium" and "high" scenarios which I use to form my own "low", "medium" and "high" sensitivities for these two impacts.

[Figure S4 about here.]

B.6 Capacity value

The capacity value of a power project reflects the contribution it makes to reliably matching demand, particularly during peak demand periods when supply is tight. For intermittent power sources like wind or solar this is generally thought of in relative terms by starting with the capacity value of a conventional dispatchable generator (e.g. a natural 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 recently published 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. Importantly though, these values can and will change over time. In particular they will tend to fall as the generation share of wind or solar increases, and tend to rise as demand shifts towards periods when the wind is blowing or the sun is shining. This is particularly important to 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 temporal variation in de-rating factors for wind projects I therefore rely on estimates by (Harrison et al., 2015) - namely those shown in Figure 11 in their paper. 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. 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.

B.7 Capital and operating costs

To calculate project specific estimates of installed capital costs I rely primarily on data from IRENA. Unfortunately it is particularly challenging to get detailed project-level data on costs as this is usually treated as commercially confidential. The data provided by IRENA are country-level annual average installed capital costs for onshore wind and solar projects and so for these projects I use the UK values. For offshore wind IRENA only publishes global average values, although given the UK makes up such a large portion of offshore wind projects these values are a decent approximation of costs for the UK.

Moreover, given the relatively small number of offshore wind projects I supplement this part of the analysis with direct project specific estimates of offshore wind costs taken from various industry sources. In all cases I convert these to consistent £/MW capital costs.

I then make an additional adjustment to account for variation in costs due to economies-of-scale. There is evidence that large projects have consistently lower per MW capital costs than small ones. To capture this I use additional US data from Lawrence Berkeley National Laboratory (LBNL) on relative costs by project size. For example, they show that the per MW capital costs for a 50MW solar project are 10% lower than those for a 5MW solar project. The difference is even more pronounced for wind projects where the equivalent cost reduction is 35%. As such I use the LBNL data to ensure large projects have appropriately lower per MW capital costs than small ones. After making this adjustment I once again normalize the estimated per MW capital costs to ensure the original IRENA annual averages are maintained. Lastly I multiply by the capacity of each project to get project-level values for total installed capital costs.

To calculate project specific estimates of ongoing O&M costs I also rely primarily on data from IRENA to capture general trends over time. Here no UK specific data is available and so for onshore wind I use US values while for solar I use the global values that IRENA applies to projects in OECD countries. In both cases I convert these annual averages to consistent £/MW/year values and compare to UK government estimates to ensure they seem reasonable. For offshore wind I assume the O&M costs are twice those of onshore wind to capture the increased costs of servicing turbines out at sea, again checking against UK government estimates.

An important additional contributor to O&M costs are grid connection and transmission use charges. These costs can vary substantially depending on the location that a wind or solar project is connected to the grid. To capture this I modify the average O&M costs based on transmission system charging data from National Grid. This ensures that projects connecting to the grid in remote regions have appropriately higher costs than projects located close to demand centers.[26] This includes accounting for the additional grid infrastructure costs associated with the offshore wind.[27] Finally I once again multiply by the capacity of each project to get annual project specific estimates of O&M costs.

[Figure S5 about here.]

B.8 Learning-by-doing

To measure the learning-by-doing benefits created by constructing a wind or solar project I rely on a paper by Newbery (2018). The paper sets out a methodology for calculating the maximum justifiable learning-by-doing subsidy for wind and solar power. Based on this I estimate learning benefits in 2015 of £600,000/MW for solar and £250,000/MW for onshore wind. These values decline steadily over time as each technology matures, and so can be substantially higher for some of the earliest projects. Unfortunately it is not straightforward to adapt this method for offshore wind. Recent cost declines could point to significant learning occurring, so here I assume that the learning benefits for offshore wind are twice the level for onshore wind.

To try and capture some of the uncertainty in this particular impact I also create "low", "medium" and "high" sensitivities. To do this I use the range of scenario assumptions set out in the paper 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. The optimal subsidy is scaled based on the average global installed capital cost for wind and solar projects in 2015, based on data from IRENA. The resulting values can be seen in Figure S6.

[Figure S6 about here.]

[26]For example, the locational portion of National Grid's transmission charge can vary from more than £20,000/MW/year in Scotland to less than -£10,000/MW/year near London.

[27]These add an average of roughly £45,000/MW/year to the costs for offshore wind projects.

C Determinants of Planning Approvals Analysis

Table S13 is the same as Table 3 but estimated using a logit model rather than a linear probability model. The findings are broadly consistent with those discussed in the main text.

[Table S13 about here.]

D Misallocated Investment Analysis

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 do this I group projects by their actual or expected start year and then rank them in order of their social net present value. I sum up the least cost set of projects necessary to reproduce the actual observed capacity additions for each year. I then compare the cumulative total social net present value between this "least cost" set of projects and the actual set of projects that were built.

I also include here a secondary approach where I simply identify the set of proposed projects that have positive net present values, and thus maximize social net benefits. I then compare the cumulative total social net present value of this "maximum net benefits" set of projects with the the actual set of projects that were built. This approach has the benefit of examining the issue of insufficient investment by allowing the total amount of deployed renewable capacity to differ from what was actually built. However, this is also a potential drawback because non-marginal deviations from the existing scale of deployment will undermine the plausibility of the estimated project level costs and benefits which are based on observed prices.

Table S14 shows that the potential gains from more efficiently reallocating investment across all the proposed projects. Values in columns titled (1) are based on finding the set of projects that have positive net present values. This is reflected in the new totals for renewable output differing from the current totals. Values in columns titled (2) give the results of finding the set of projects that can reproduce the observed annual deployment of renewable output (in lifetime discounted TWh) at least cost. Values in column (2*) employ the same approach as column (2) with the added constraint that there can be no substitution between onshore and offshore wind.

[Table S14 about here.]

For solar projects, Table S14 shows that the total net present value of the existing projects is £0.7 billion. However, this masks potential for significant positive or negative net present values, depending on key input assumptions such as the discount rate. The existing set of projects impose minimal local impacts on nearby residents, consistent with the earlier analysis on the capitalization of solar projects into property values.

In a scenario where all positive net present value projects are completed, there is a 20% increase in solar deployment over this period. This is actually achieved with fewer projects indicating a shift towards larger projects. Total net present value rises by £2 billion. £1.5 billion of this is attributable to actually reversing planning decisions (i.e. approving some projects that were refused and refusing some projects that were approved), suggesting the planning process is a key barrier to realizing these gains. This is equivalent to roughly 13% of the aggregate lifetime capital and operating costs for all the solar projects built over this period.

In the second scenario I explore how the existing solar deployment could be achieved at least cost. The changes to the set of completed projects are less extensive, although there is still a shift toward larger projects with fewer projects needed to achieve the same output. The potential gains of reallocation amount to £0.5 billion, £0.3 billion of which can be achieved by reversing planning decisions. This is equivalent to roughly 2% of the aggregate lifetime capital and operating costs for all the solar projects built over this period.

For wind projects, Table S14 shows that the total net present value of the existing projects is £1.7 billion. However, this once again masks potential for significant positive or negative total net present values depending on assumptions regarding discounting. The existing set of projects impose significant local impacts on nearby residents, with an average total of £2.3 billion.

In a scenario where all positive net present value projects are completed, there is a 26% increase in wind deployment over this period. Total net present value rises by £35.5 billion. £30.3 billion of this is attributable to actually reversing planning decisions (i.e. approving some projects that were refused and refusing some projects that were approved), suggesting the planning process is a key barrier to realizing these gains. This is equivalent to roughly 40% of the aggregate lifetime capital and operating costs for all the wind projects built over this period.

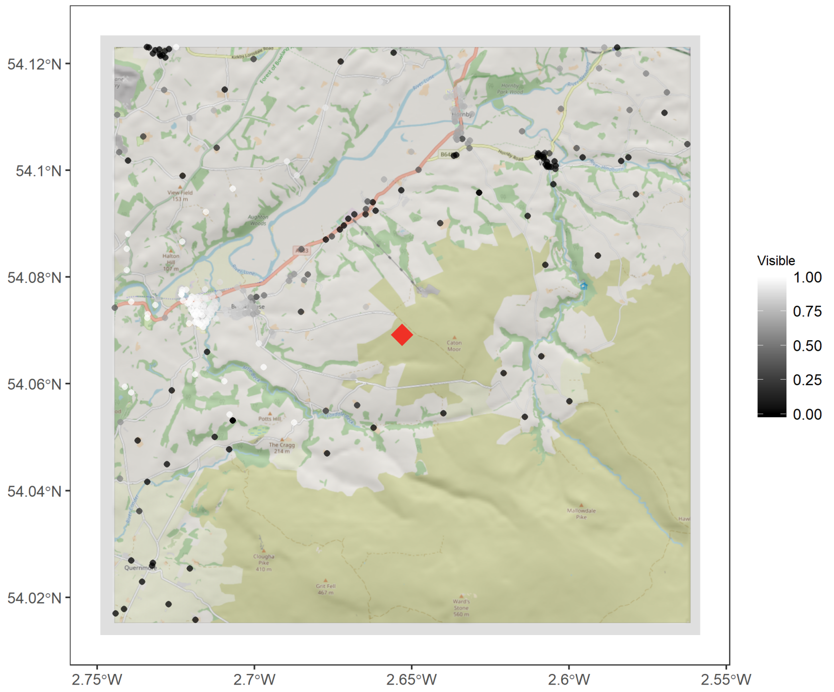
In the second scenario I explore how the existing wind deployment could be achieved at least cost. The potential gains of reallocation amount to £26.6 billion, £22.4 billion of which can be achieved by reversing planning decisions. This is equivalent to roughly 29% of the aggregate lifetime capital and operating costs for all the wind projects built over this period. Constraining this to prevent any substitution between onshore and offshore wind causes the total potential gains from reallocation fall significantly to £8.3 billion. £7.4 billion these gains can be realized by reversing planning decisions, and are equivalent to roughly 10% of the aggregate lifetime capital and operating costs for all the wind projects built over this period.

E Local Compensation Analysis

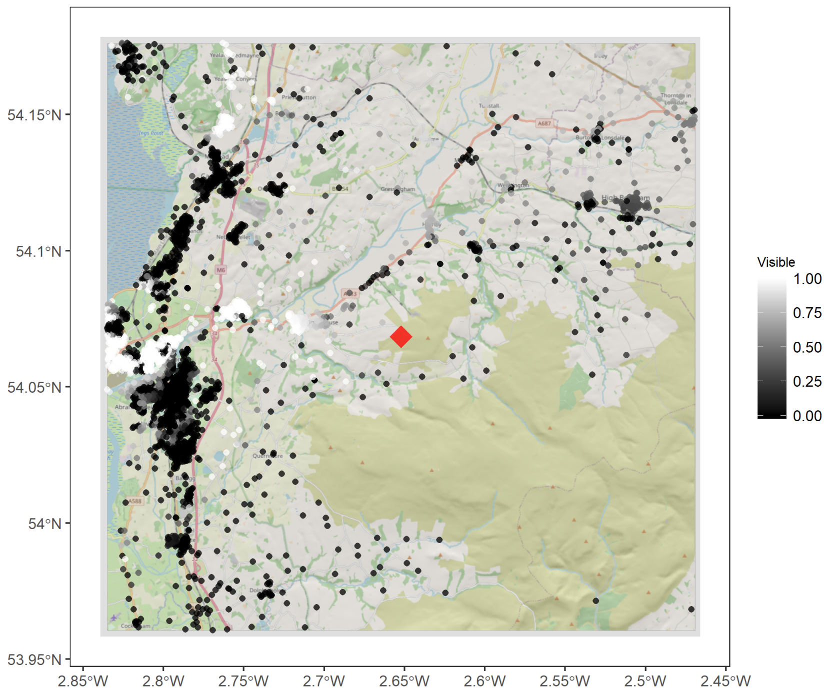
To study the feasibility of different local compensation schemes I look at a "Basic" and a "Detailed" scheme. These are estimated using the data on the property value impacts from each project, i, at each post code location, l. The estimation is weighted based on the number of properties at each postcode. The sample is restricted to project-location pairs with non-zero impacts on nearby properties, which effectively means any properties within 4km of a project in my sample. Results of these two regressions can be found in Table S15 below.

[Table S15 about here.]

Figure S1: Illustration of Postcode to Project Visibility



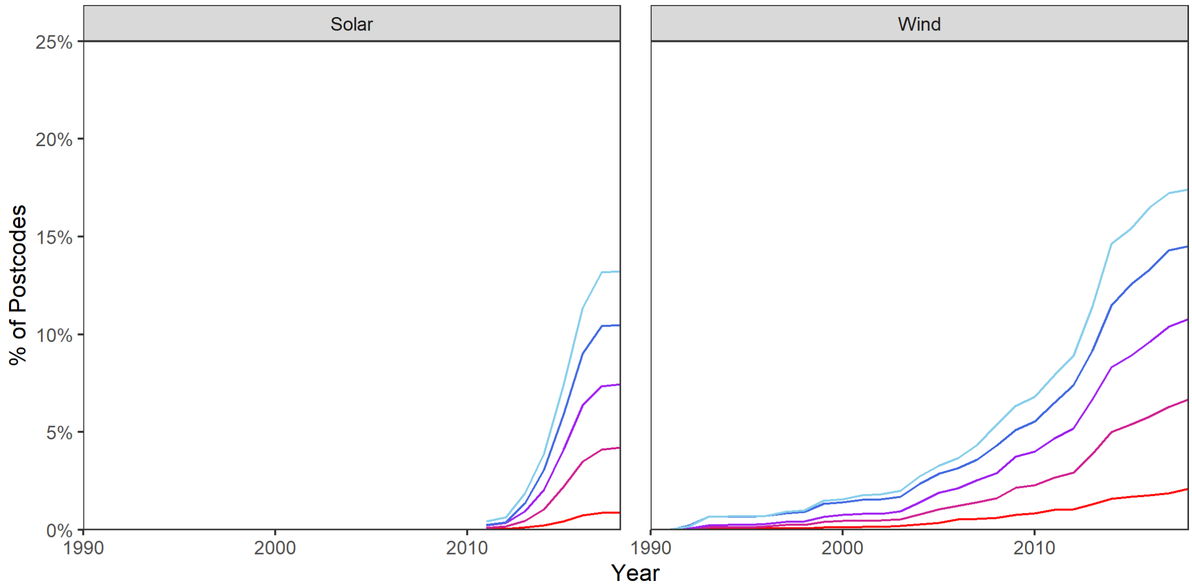
(a) 6km radius



(b) 12km radius

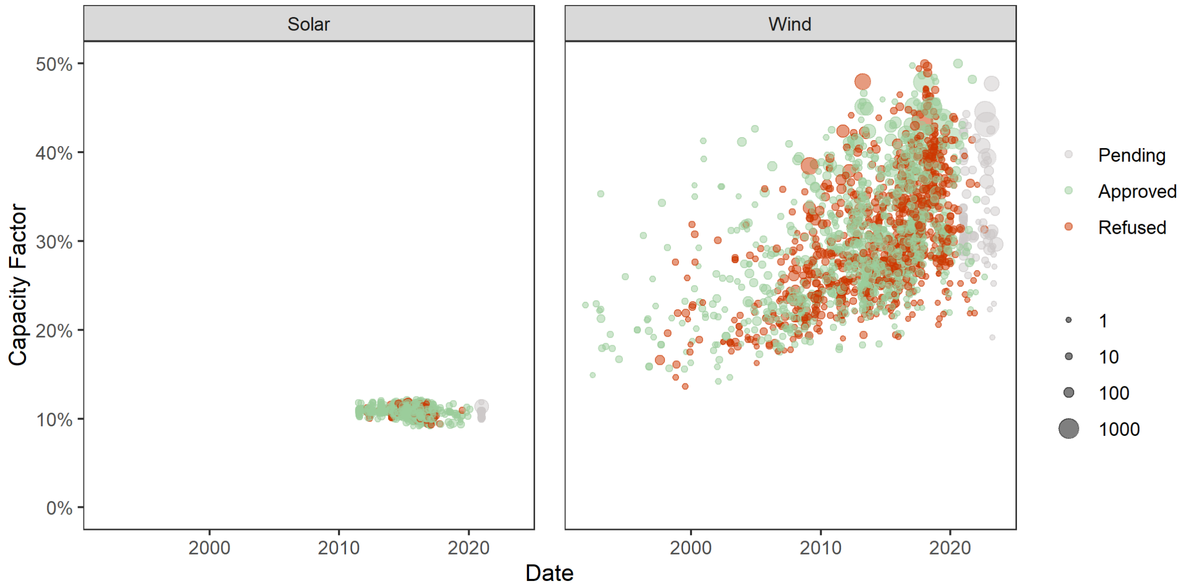
Notes: This figures shows the visibility of a wind project from different postcodes. The red diamond is the Caton Moor Wind Farm in north west England. The black and white points are postcodes. Black points do not have direct line-of-sight. White points do have direct line-of-sight. The top figure shows a zoomed in view of the 6km surrounding the wind farm. The bottom figure shows a zoomed out view of the 12km surrounding the wind farm. The background image is taken from Open Street Map and includes some shading to convey elevation.

Figure S2: Treatment Exposure



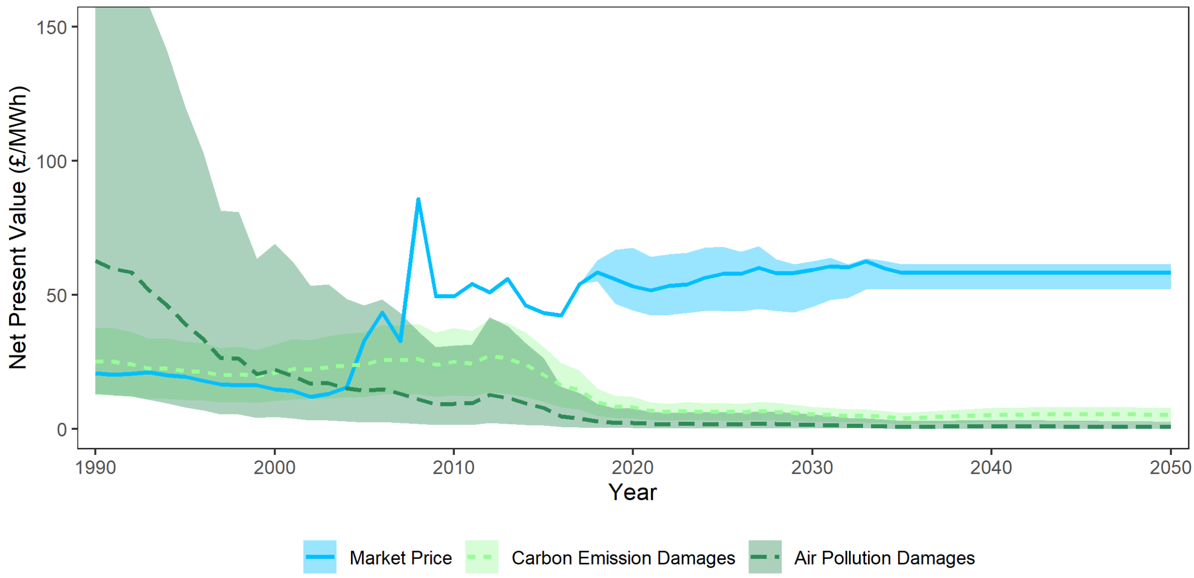
Notes: This figure shows the proportion of postcodes over time that are exposed to at least one renewable energy project at a given distance range. The closest distance bin is in red and the furthest is in light blue. Treatment is clearly increasing over time as more projects come online. Treatment begins earlier in the period for wind projects whereas solar projects only began meaningful development after a change in the subsidy regime in 2010. In all regressions I drop any properties at locations that do not fall into one of these distance bins by the end of the analysis period.

Figure S3: Estimated Project Capacity Factors



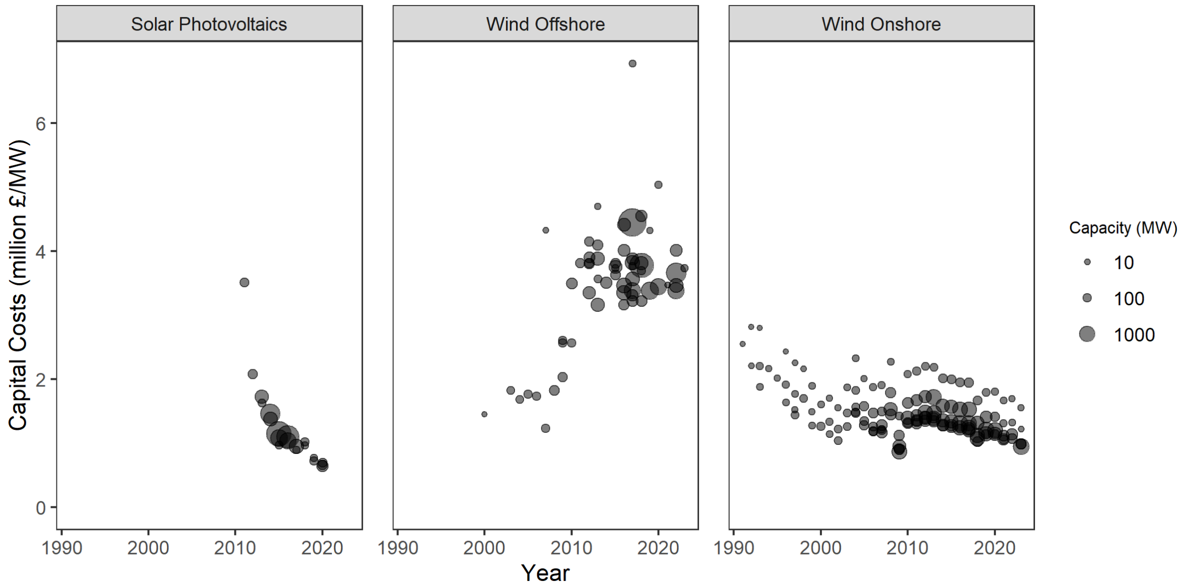
Notes: This figure shows the estimated project capacity factors over time. Each point refers to a project. Point sizes are determined by the capacity (in MW) of a project. Projects are classified by their development status. "Pending" are projects that have submitted a planning application but have yet 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.

Figure S4: Marginal Market and Non-Market Values of Renewable Electricity Production

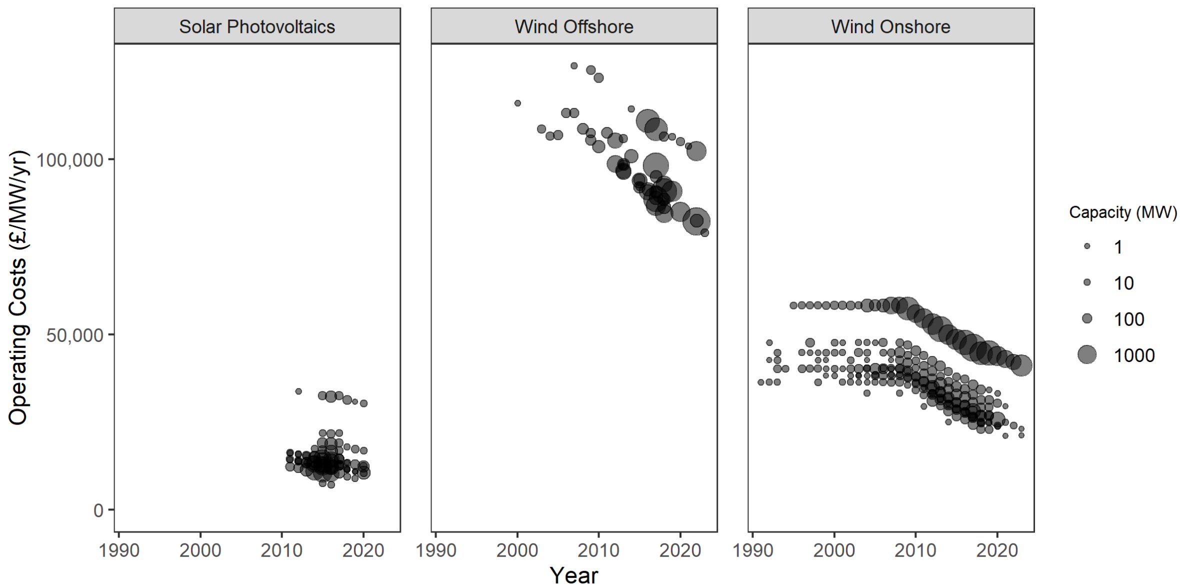


Notes: This figure shows the changing marginal value of renewable electricity production over time. "Market Price" refers to the private value of the electricity produced as captured by wholesale electricity prices. "Carbon Emission Damages" refers to the external value of the CO2 emissions abated by 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 the UK government's central scenario values and the shaded areas are bounded by the low and high scenario values.

Figure S5: Estimated Project Capital and Operating Costs by Year



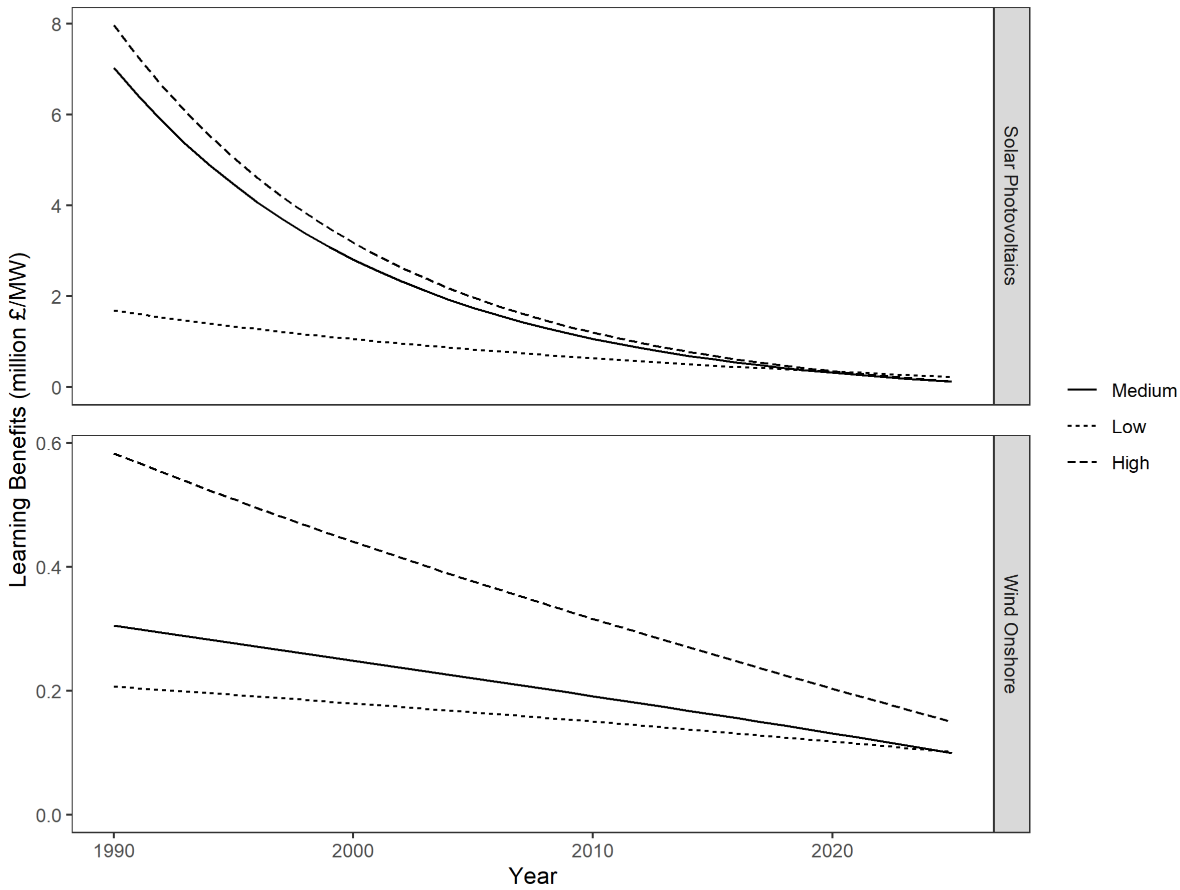
(a) Capital costs



(b) Operating costs

Notes: This figures 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.

Figure S6: 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.

Table S1: Summary Statistics on Appealed Projects

Technology	**Initial Decision**	**Final Decision**	**Total Capacity (MW)**	**Number of Projects**
Solar	Refused	Approved	786	95
Solar	Refused	Refused	1027	101
Wind	Refused	Approved	4249	188
Wind	Refused	Refused	3931	203

Notes: This table contains summary statistics for all wind and solar energy projects that have been subject to appeal. The sample is taken from the planning database which covers all projects with a capacity greater than 1MW that were proposed in the UK since 1990. This excludes projects that are under review at the time of writing.

Table S2: Residential Capitalization for Wind Projects

	(1)	(2)	(3)	(4)	(5)	(6)
Completed						
0to2km	-2.38^{***}	-2.01^{***}	-1.76	-3.28^{***}	-2.77^{***}	-3.37^{***}
	(0.55)	(0.49)	(0.78)	(0.64)	(0.65)	(0.87)
2to4km	0.26	-0.22	0.04	-1.97^{***}	-2.20^{***}	-1.69^{***}
	(0.29)	(0.24)	(0.32)	(0.33)	(0.30)	(0.37)
4to6km	0.86^{***}	0.41	0.03	0.04	0.09	0.30
	(0.21)	(0.19)	(0.25)	(0.22)	(0.21)	(0.26)
6to8km	0.62^{**}	0.33	1.05^{***}	0.25	0.27	0.37
	(0.20)	(0.17)	(0.24)	(0.20)	(0.18)	(0.24)
8to10km	-0.47^{*}	-0.74^{***}	-0.50^{*}	-0.84^{***}	-0.93^{***}	-0.56^{*}
	(0.18)	(0.16)	(0.21)	(0.19)	(0.17)	(0.21)
Failed						
0to2km	2.52^{***}	3.07^{***}	3.51^{***}	2.22^{***}	2.89^{***}	2.64^{***}
	(0.53)	(0.50)	(0.63)	(0.56)	(0.55)	(0.68)
2to4km	2.80^{***}	2.29^{***}	1.52^{***}	2.57^{***}	2.51^{***}	1.71^{***}
	(0.30)	(0.26)	(0.35)	(0.32)	(0.29)	(0.35)
4to6km	0.09	0.04	-0.10	0.86^{***}	1.10^{***}	0.75^{**}
	(0.21)	(0.19)	(0.26)	(0.23)	(0.21)	(0.26)
6to8km	-0.29	-0.50^{**}	-0.59^{*}	-0.16	-0.03	0.14
	(0.19)	(0.17)	(0.24)	(0.20)	(0.18)	(0.24)
8to10km	-0.84^{***}	-1.10^{***}	-0.81^{***}	-0.92^{***}	-1.01^{***}	-0.87^{***}
	(0.17)	(0.15)	(0.20)	(0.18)	(0.16)	(0.20)
R-Squared	0.96	0.90	0.82	0.96	0.90	0.82
N (millions)	5.71	8.07	8.21	5.71	8.07	8.21
Log Functional Form	Y	Y	Y	Y	Y	Y
Event Study	–	–	–	Y	Y	Y
Address Fixed Effects	Y	–	–	Y	–	–
Postcode Fixed Effects	–	Y	–	–	Y	–
LSOA Fixed Effects	–	–	Y	–	–	Y
County-Year Fixed Effects	Y	Y	Y	Y	Y	Y

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: This table shows the results of the capitalization regressions for residential property values and wind projects. All specifications are estimated as pooled regressions using distance bins. Specifications vary based on the inclusion of different location fixed effects. Point estimates for the first three columns are coefficients from a standard difference in difference regression. Point estimates in the last three columns are based on the event study regressions and are calculated by taking the difference between the earliest five pre-period coefficients and the latest five post-period coefficients. All coefficients should be interpreted as the % change in property values resulting from adding 10 MW of capacity at a given distance away. The original coefficient can be recovered by dividing by ln(10).

Table S3: Residential Capitalization for Wind Projects by Distance Circles

	(0-2km)	(0-4km)	(0-6km)	(0-8km)	(0-10km)
Completed					
, ,	-3.27^{***}	-3.06^{***}	-1.25^{***}	-0.56^{***}	-0.57^{***}
	(0.64)	(0.27)	(0.16)	(0.12)	(0.10)
Failed					
, ,	3.29^{***}	2.70^{***}	1.79^{***}	1.00^{***}	0.41^{***}
	(0.55)	(0.26)	(0.16)	(0.12)	(0.10)
R-Squared	0.90	0.90	0.90	0.90	0.90
N (millions)	0.68	2.69	4.82	6.61	8.07

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: This table shows the results of the capitalization regressions for residential property values and wind projects. Specifications are estimated as separate regressions using distance circles. All specifications use the same postcode-by-housing-type and county-by-year fixed effects. Point estimates are based on the event study regressions and are calculated by taking the difference between the earliest five pre-period coefficients and the latest five post-period coefficients. All coefficients should be interpreted as the % change in property values resulting from adding 10 MW of capacity at a given distance away. The original coefficient can be recovered by dividing by ln(10).

Table S4: Residential Capitalization for Wind Projects with Differential Effects

	(0-2km)	(0-4km)	(0-6km)	(0-8km)	(0-10km)
Completed					
Not Appealed, Not Visible, Deprived		-2.09	-1.00	0.01	0.14
		(1.03)	(0.50)	(0.33)	(0.23)
Not Appealed, Not Visible, Not Deprived		-2.59^{*}	-1.62^{*}	-1.04^{*}	-0.27
		(0.95)	(0.58)	(0.41)	(0.33)
Not Appealed, Visible, Deprived	-0.25	-2.04^{***}	-0.75^{**}	-0.16	0.05
	(0.85)	(0.38)	(0.25)	(0.20)	(0.16)
Not Appealed, Visible, Not Deprived	-5.04^{***}	-2.93^{***}	-0.19	-0.17	-1.39^{***}
	(1.04)	(0.53)	(0.35)	(0.27)	(0.22)
Appealed, Not Visible, Deprived		6.66^{*}	4.62^{***}	3.45^{***}	2.04^{***}
		(2.60)	(1.22)	(0.73)	(0.54)
Appealed, Not Visible, Not Deprived		-2.48	-7.88^{***}	-4.68^{***}	-3.18^{***}
		(2.67)	(1.74)	(1.04)	(0.75)
Appealed, Visible, Deprived	-0.45	-0.30	1.01^{**}	1.01^{***}	1.03^{***}
	(1.55)	(0.65)	(0.35)	(0.28)	(0.24)
Appealed, Visible, Not Deprived	-8.05^{***}	-7.72^{***}	-6.67^{***}	-3.24^{***}	-0.53
	(2.12)	(1.20)	(0.82)	(0.65)	(0.50)
Failed					
Not Appealed, Not Visible, Deprived		4.15^{***}	2.43^{***}	1.92^{***}	1.13^{***}
		(0.86)	(0.45)	(0.30)	(0.21)
Not Appealed, Not Visible, Not Deprived		1.76	2.39^{***}	0.91^{*}	0.13
		(0.92)	(0.59)	(0.38)	(0.31)
Not Appealed, Visible, Deprived	2.26^{***}	2.09^{***}	1.17^{***}	0.90^{***}	0.57^{***}
	(0.61)	(0.33)	(0.23)	(0.18)	(0.14)
Not Appealed, Visible, Not Deprived	5.78^{***}	4.09^{***}	2.46^{***}	1.02^{***}	0.09
	(1.01)	(0.48)	(0.30)	(0.26)	(0.21)
Appealed, Not Visible, Deprived		-2.81	0.16	-1.79	-0.47
		(2.39)	(1.24)	(0.86)	(0.64)
Appealed, Not Visible, Not Deprived		12.52^{***}	3.14^{*}	0.32	-1.84^{*}
		(2.52)	(1.26)	(0.92)	(0.77)
Appealed, Visible, Deprived	-3.78	-5.32^{***}	-3.06^{***}	-2.34^{***}	-0.60
	(2.04)	(1.20)	(0.79)	(0.59)	(0.45)
Appealed, Visible, Not Deprived	3.46	0.76	0.49	2.97^{**}	2.94^{***}
	(4.30)	(1.46)	(0.97)	(0.91)	(0.77)
R-Squared	0.90	0.90	0.90	0.90	0.90
N (millions)	0.68	2.69	4.82	6.61	8.07

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: This table shows the results of the capitalization regressions for residential property values and wind projects with differential effects. As well as coefficients being shown for both completed and failed projects, these coefficients are broken out by three margins of heterogeneity. "Appealed" refers to properties near to appealed projects. "Visible" refers to properties with direct line-of-sight to a project. "Deprived" refers to properties in less wealthy, deprived areas. Specifications are estimated as separate regressions using distance circles. All specifications use the same postcode-by-housing-type and county-by-year fixed effects. Point estimates are based on the event study regressions and are calculated by taking the difference between the earliest five pre-period coefficients and the latest five post-period coefficients. All coefficients should be interpreted as the % change in property values resulting from adding 10 MW of capacity at a given distance away. The original coefficient can be recovered by dividing by ln(10).

Table S5: Residential Property Values Results for Wind Projects with Number of Turbines

	(0-2km)	(0-4km)	(0-6km)	(0-8km)	(0-10km)
Completed					
	-3.40^{***}	-2.43^{***}	-0.65^{**}	-0.20	-0.46^{***}
	(0.72)	(0.31)	(0.18)	(0.14)	(0.11)
Failed					
	3.86^{***}	3.64^{***}	2.61^{***}	1.52^{***}	0.81^{***}
	(0.68)	(0.31)	(0.19)	(0.15)	(0.12)
R-Squared	0.90	0.90	0.90	0.90	0.90
N (millions)	0.68	2.69	4.82	6.61	8.07

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: This table shows the results of the capitalization regressions for residential property values and wind projects using number of turbines as the measure of project size, instead of MW of capacity. Specifications are estimated as separate regressions using distance circles. All specifications use the same postcode-by-housing-type and county-by-year fixed effects. Point estimates are based on the event study regressions and are calculated by taking the difference between the earliest five pre-period coefficients and the latest five post-period coefficients. All coefficients should be interpreted as the % change in property values resulting from adding 10 additional turbines at a given distance away. The original coefficient can be recovered by dividing by ln(10).

Table S6: Residential Capitalization for Solar Projects

	(1)	(2)	(3)	(4)	(5)	(6)
Completed						
0to1km	−0.17	0.46	−0.54	−1.31	−0.51	−1.49
	(0.69)	(0.72)	(1.43)	(0.77)	(0.86)	(1.45)
1to2km	1.26***	1.33***	1.21*	1.08**	0.98**	0.96
	(0.34)	(0.30)	(0.48)	(0.35)	(0.32)	(0.47)
2to3km	0.46	0.56*	0.55	0.19	0.34	0.31
	(0.28)	(0.24)	(0.32)	(0.29)	(0.25)	(0.33)
3to4km	0.84***	0.98***	0.73	0.57*	0.73***	0.66
	(0.21)	(0.19)	(0.32)	(0.23)	(0.21)	(0.33)
4to5km	−0.09	0.15	−0.04	−0.34	0.00	−0.32
	(0.20)	(0.17)	(0.26)	(0.21)	(0.19)	(0.26)
Failed						
0to1km	−0.96	−1.63	−0.12	0.10	−0.70	0.20
	(1.10)	(1.07)	(1.28)	(1.33)	(1.37)	(1.56)
1to2km	−0.02	−0.14	−0.30	0.30	−0.18	0.07
	(0.43)	(0.37)	(0.58)	(0.50)	(0.46)	(0.60)
2to3km	−0.62	0.05	0.73	0.03	0.32	0.54
	(0.39)	(0.31)	(0.43)	(0.48)	(0.39)	(0.51)
3to4km	−0.70*	−0.19	0.04	−1.08**	−0.67	−1.05
	(0.27)	(0.24)	(0.45)	(0.34)	(0.31)	(0.71)
4to5km	−0.21	−0.16	−0.17	−0.28	−0.51	−0.38
	(0.26)	(0.22)	(0.37)	(0.32)	(0.28)	(0.44)
R-Squared	0.96	0.91	0.83	0.96	0.91	0.83
N (millions)	5.82	8.18	8.31	5.82	8.18	8.31
Log Functional Form	Y	Y	Y	Y	Y	Y
Event Study	–	–	–	Y	Y	Y
Address Fixed Effects	Y	–	–	Y	–	–
Postcode Fixed Effects	–	Y	–	–	Y	–
LSOA Fixed Effects	–	–	Y	–	–	Y
County-Year Fixed Effects	Y	Y	Y	Y	Y	Y

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Notes: This table shows the results of the capitalization regressions for residential property values and solar projects. All specifications are estimated as pooled regressions using distance bins. Specifications vary based on the inclusion of different location fixed effects. Point estimates for the first three columns are coefficients from a standard difference in difference regression. Point estimates in the last three columns are based on the event study regressions and are calculated by taking the difference between the earliest five pre-period coefficients and the latest five post-period coefficients. All coefficients should be interpreted as the % change in property values resulting from adding 10 MW of capacity at a given distance away. The original coefficient can be recovered by dividing by ln(10).

Table S7: Residential Capitalization for Solar Projects by Distance Circles

	(0-1km)	(0-2km)	(0-3km)	(0-4km)	(0-5km)
Completed					
, ,	−0.02	0.82*	0.57**	0.55***	0.32**
	(0.85)	(0.30)	(0.20)	(0.14)	(0.11)
Failed					
, ,	−0.26	0.39	0.40	−0.08	−0.25
	(1.37)	(0.45)	(0.30)	(0.22)	(0.17)
R-Squared	0.91	0.91	0.91	0.91	0.91
N (millions)	0.33	1.83	3.93	6.13	8.18

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Notes: This table shows the results of the capitalization regressions for residential property values and solar projects. Specifications are estimated as separate regressions using distance circles. All specifications use the same postcode-by-housing-type and county-by-year fixed effects. Point estimates are based on the event study regressions and are calculated by taking the difference between the earliest five pre-period coefficients and the latest five post-period coefficients. All coefficients should be interpreted as the % change in property values resulting from adding 10 MW of capacity at a given distance away. The original coefficient can be recovered by dividing by ln(10).

Table S8: Residential Capitalization for Solar Projects with Differential Effects

	(0-1km)	(0-2km)	(0-3km)	(0-4km)	(0-5km)
Completed					
Not Appealed, Not Visible, Deprived	1.25	0.99	0.21	0.08	-0.22
	(1.24)	(0.50)	(0.33)	(0.21)	(0.16)
Not Appealed, Not Visible, Not Deprived	-2.51	0.43	-0.01	0.38	-0.08
	(3.06)	(1.07)	(0.57)	(0.39)	(0.31)
Not Appealed, Visible, Deprived	1.19	0.25	0.30	0.51	0.62^{**}
	(1.09)	(0.41)	(0.29)	(0.24)	(0.19)
Not Appealed, Visible, Not Deprived	-6.42	0.44	1.20	1.39^{**}	0.91^{*}
	(2.95)	(0.86)	(0.56)	(0.43)	(0.36)
Appealed, Not Visible, Deprived	3.63	1.93	-1.20	0.46	0.67
	(8.14)	(2.12)	(1.54)	(1.26)	(1.06)
Appealed, Not Visible, Not Deprived	-29.76	5.80	3.85	1.91	0.38
	(67.70)	(5.15)	(4.31)	(3.50)	(2.65)
Appealed, Visible, Deprived	-53.11^{***}	2.68	1.18	-0.13	0.49
	(6.23)	(2.61)	(1.46)	(1.33)	(1.44)
Appealed, Visible, Not Deprived	-130.90	3.93	2.77	1.37	-1.48
	(67.99)	(2.98)	(2.02)	(1.94)	(1.69)
Failed					
Not Appealed, Not Visible, Deprived	0.61	0.42	-0.09	-0.19	-0.06
	(2.59)	(0.88)	(0.46)	(0.32)	(0.27)
Not Appealed, Not Visible, Not Deprived	8.76	1.37	2.77^{***}	1.73^{**}	1.47^{**}
	(4.81)	(1.10)	(0.74)	(0.53)	(0.43)
Not Appealed, Visible, Deprived	-1.25	-0.89	-1.18	-1.25^{*}	-1.02^{*}
	(2.03)	(0.75)	(0.61)	(0.47)	(0.36)
Not Appealed, Visible, Not Deprived	-2.57	1.20	-0.01	-0.63	-0.89
	(5.65)	(1.29)	(0.90)	(0.70)	(0.55)
Appealed, Not Visible, Deprived	-4.83	3.15	1.58	0.06	-0.15
	(7.38)	(2.34)	(1.44)	(0.95)	(0.77)
Appealed, Not Visible, Not Deprived	9.27	-4.80	3.32	4.85^{*}	0.91
	(6.18)	(6.67)	(2.63)	(1.74)	(1.17)
Appealed, Visible, Deprived	5.36	4.03	4.05	1.17	0.52
	(4.57)	(3.16)	(2.09)	(1.60)	(1.39)
Appealed, Visible, Not Deprived	-55.72^{***}	-7.55	-6.00	-7.56	-5.28
	(13.94)	(3.46)	(2.92)	(3.42)	(2.93)
R-Squared	0.91	0.91	0.91	0.91	0.91
N (millions)	0.33	1.83	3.93	6.13	8.18

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: This table shows the results of the capitalization regressions for residential property values and solar projects with differential effects. As well as coefficients being shown for both completed and failed projects, these coefficients are broken out by three margins of heterogeneity. "Appealed" refers to properties near to appealed projects. "Visible" refers to properties with direct line-of-sight to a project. "Deprived" refers to properties in less wealthy, deprived areas. Specifications are estimated as separate regressions using distance circles. All specifications use the same postcode-by-housing-type and county-by-year fixed effects. Point estimates are based on the event study regressions and are calculated by taking the difference between the earliest five pre-period coefficients and the latest five post-period coefficients. All coefficients should be interpreted as the % change in property values resulting from adding 10 MW of capacity at a given distance away. The original coefficient can be recovered by dividing by ln(10).

Table S9: Commmercial Property Rents Summary Statistics

	Total	Industrial	Retail	Office	Other
Average rental value (thousands)	16.85	19.64	21.60	24.20	9.122
	(29.38)	(37.58)	(48.33)	(49.65)	(13.27)
Average floorspace	303.3	612.8	189.8	240.0	147.6
	(524.7)	(1078.5)	(280.4)	(355.8)	(185.8)
Rental value per m2	61.78	34.93	89.64	89.67	63.43
	(47.17)	(19.14)	(59.70)	(49.76)	(58.80)
Number of properties	64.37	31.34	33.47	34.43	24.54
	(130.4)	(39.46)	(51.70)	(101.3)	(45.58)
Rural	0.217	0.310	0.142	0.199	0.274
	(0.402)	(0.450)	(0.344)	(0.387)	(0.434)
Index of Multiple Deprivation	22.44	23.02	25.35	22.82	22.45
	(15.59)	(15.33)	(16.24)	(15.90)	(15.54)
N (millions)	0.57	0.41	0.33	0.31	0.43

Notes: This table shows summary statistics for the commercial rents data for England and Wales since 2000. Means and standard deviations (in parentheses) are shown for the entire dataset and then for each of four broad sector categories. The rural control is based on the population-weighted share of output areas (OA) classed as rural in 2011. The Index of Multiple Deprivation is a composite measure of regional living standards where higher numbers refer to more deprived areas. The unit of observation is at the lower layer super output area (LSOA) by year level.

Table S10: Commercial Capitalization for Wind Projects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Completed										
0to2km	−4.00	−0.90	1.33	−3.73	−6.00	−4.31	−3.91	2.43	−0.23	−5.57
	(2.59)	(3.17)	(4.08)	(4.94)	(3.30)	(2.90)	(3.36)	(4.14)	(6.27)	(4.14)
2to4km	0.43	1.23	0.68	7.84^{*}	2.60	−0.52	−0.80	−0.14	−1.29	1.46
	(1.77)	(2.20)	(1.93)	(3.28)	(2.09)	(1.73)	(2.37)	(1.99)	(3.55)	(2.20)
4to6km	−0.43	-5.28^{**}	0.65	−0.74	−3.13	−0.12	-4.12^{*}	1.09	0.48	−3.49
	(1.36)	(1.68)	(1.66)	(2.52)	(1.55)	(1.32)	(1.57)	(1.75)	(2.50)	(1.57)
6to8km	−0.52	1.81	2.10	−2.23	1.34	−0.54	2.71	1.12	−4.36	1.83
	(1.13)	(1.56)	(1.53)	(2.21)	(1.39)	(1.15)	(1.51)	(1.41)	(2.27)	(1.43)
8to10km	−0.50	−1.49	−1.98	3.01	−1.89	−1.65	-3.99^{**}	−1.94	−1.37	−2.18
	(0.92)	(1.33)	(1.16)	(1.77)	(1.15)	(0.93)	(1.26)	(1.24)	(1.79)	(1.22)
Failed										
0to2km	1.14	3.33	−1.94	3.23	3.19	1.69	1.18	−2.50	1.22	6.31
	(2.06)	(3.18)	(3.47)	(3.99)	(2.89)	(2.12)	(3.14)	(3.58)	(4.61)	(3.25)
2to4km	2.08	−1.42	2.20	1.06	0.94	1.05	−2.82	1.52	−0.59	−1.39
	(1.68)	(2.20)	(2.30)	(3.15)	(2.02)	(1.58)	(2.34)	(1.98)	(3.16)	(2.22)
4to6km	−1.37	−0.02	2.46	1.04	−1.40	−0.39	−1.53	1.92	1.17	0.91
	(1.33)	(1.86)	(1.79)	(2.59)	(1.53)	(1.19)	(1.67)	(1.74)	(2.35)	(1.45)
6to8km	−2.10	−0.63	0.94	−0.14	−0.75	-2.99^{*}	−0.33	−1.30	−1.93	-3.63^{*}
	(1.23)	(1.52)	(1.50)	(2.03)	(1.32)	(1.15)	(1.31)	(1.35)	(2.02)	(1.33)
8to10km	1.94	2.26	−0.46	−0.36	0.03	1.51	0.36	0.65	1.84	1.47
	(0.93)	(1.16)	(1.16)	(1.75)	(1.11)	(0.83)	(1.13)	(1.14)	(1.65)	(1.04)
R-Squared	0.94	0.94	0.96	0.92	0.90	0.94	0.94	0.96	0.92	0.90
N (millions)	0.20	0.12	0.09	0.06	0.13	0.20	0.12	0.09	0.06	0.13
Log Functional Form	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Event Study	–	–	–	–	–	Y	Y	Y	Y	Y
LSOA Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Region-Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Total Sector	Y	–	–	–	–	Y	–	–	–	–
Industrial Sector	–	Y	–	–	–	–	Y	–	–	–
Retail Sector	–	–	Y	–	–	–	–	Y	–	–
Office Sector	–	–	–	Y	–	–	–	–	Y	–
Other Sector	–	–	–	–	Y	–	–	–	–	Y

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: This table shows the results of the capitalization regressions for commercial property values and wind projects. All specifications are estimated as pooled regressions using distance bins. Specifications vary based on the commercial sector being studied. Point estimates for the first five columns are coefficients from a standard difference in difference regression. Point estimates in the last five columns are based on the event study regressions and are calculated by taking the difference between the earliest five pre-period coefficients and the latest five post-period coefficients. All coefficients should be interpreted as the % change in property values resulting from adding 10 MW of capacity at a given distance away. The original coefficient can be recovered by dividing by ln(10).

Table S11: Commercial Capitalization for Solar Projects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Completed										
0to1km	−3.44	−4.01	2.77	5.47	1.65	−2.80	−4.26	2.95	1.98	3.40
	(2.60)	(3.12)	(4.18)	(5.41)	(3.55)	(2.62)	(3.27)	(4.71)	(6.08)	(4.05)
1to2km	0.68	−0.29	−0.07	−3.57	−3.57	0.21	−2.29	2.66	−0.61	−2.37
	(2.17)	(2.98)	(3.69)	(4.41)	(2.76)	(2.11)	(2.82)	(3.73)	(4.50)	(2.82)
2to3km	−2.64	1.17	−1.07	−3.77	2.44	−1.26	1.35	−4.16	−1.85	0.83
	(1.78)	(2.48)	(2.56)	(3.66)	(2.11)	(1.48)	(2.23)	(2.37)	(3.62)	(2.15)
3to4km	2.40	−1.37	−0.13	2.87	−2.75	2.30	0.54	0.64	−1.01	−3.25
	(1.50)	(1.90)	(2.08)	(3.01)	(1.83)	(1.43)	(1.81)	(2.22)	(3.03)	(1.76)
4to5km	−1.46	−0.78	−0.81	−1.41	2.73	−1.82	−1.74	−2.21	−1.84	1.16
	(1.39)	(1.70)	(1.63)	(2.55)	(1.40)	(1.31)	(1.64)	(1.60)	(2.40)	(1.32)
Failed										
0to1km	2.40	6.22	−9.40	−5.01	−5.09	3.67	9.03	−14.51	−7.07	−4.25
	(2.77)	(3.68)	(6.37)	(5.44)	(4.19)	(3.16)	(4.03)	(7.19)	(6.12)	(4.93)
1to2km	−0.66	1.03	0.25	−6.94	−1.13	0.83	−0.89	−0.22	−2.52	−3.63
	(2.55)	(3.19)	(4.69)	(4.67)	(3.53)	(2.96)	(3.74)	(5.08)	(5.23)	(4.04)
2to3km	−3.13	−2.94	3.08	3.71	8.28^{**}	−4.00	−4.97	1.89	6.51	11.49^{**}
	(2.14)	(2.76)	(3.18)	(3.77)	(2.67)	(2.36)	(2.91)	(3.41)	(4.55)	(3.29)
3to4km	−1.26	−3.24	−2.57	−2.66	−3.53	−2.10	−0.75	−0.89	−5.48	−5.77
	(1.96)	(2.37)	(2.57)	(3.24)	(2.37)	(2.29)	(2.49)	(2.86)	(3.79)	(2.69)
4to5km	1.79	0.82	1.72	4.87	0.62	2.27	0.47	1.16	5.59	1.17
	(1.38)	(1.90)	(1.94)	(2.75)	(1.78)	(1.52)	(1.87)	(2.07)	(3.05)	(1.85)
R-Squared	0.94	0.94	0.96	0.92	0.90	0.94	0.94	0.97	0.92	0.90
N (millions)	0.21	0.13	0.09	0.06	0.14	0.21	0.13	0.09	0.06	0.14
Log Functional Form	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Event Study	–	–	–	–	–	Y	Y	Y	Y	Y
LSOA Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Region-Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Total Sector	Y	–	–	–	–	Y	–	–	–	–
Industrial Sector	–	Y	–	–	–	–	Y	–	–	–
Retail Sector	–	–	Y	–	–	–	–	Y	–	–
Office Sector	–	–	–	Y	–	–	–	–	Y	–
Other Sector	–	–	–	–	Y	–	–	–	–	Y

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Notes: This table shows the results of the capitalization regressions for commercial property values and solar projects. All specifications are estimated as pooled regressions using distance bins. Specifications vary based on the commercial sector being studied. Point estimates for the first five columns are coefficients from a standard difference in difference regression. Point estimates in the last five columns are based on the event study regressions and are calculated by taking the difference between the earliest five pre-period coefficients and the latest five post-period coefficients. All coefficients should be interpreted as the % change in property values resulting from adding 10 MW of capacity at a given distance away. The original coefficient can be recovered by dividing by ln(10).

Table S12: Assumptions on Residential Property Capitalization Effects

Technology	Distance	Visible	Deprived	Effect (Low)	Effect (Central)	Effect (High)
Wind	0-2km	Yes	Yes	-0.5%	-1%	-2%
Wind	0-2km	Yes	No	-2%	-4%	-8%
Wind	0-2km	No	Yes	-0.25%	-0.5%	-1%
Wind	0-2km	No	No	-1%	-2%	-4%
Wind	2-4km	Yes	Yes	-0.25%	-0.5%	-1%
Wind	2-4km	Yes	No	-1%	-2%	-4%
Wind	2-4km	No	Yes	-0.125%	-0.25%	-0.5%
Wind	2-4km	No	No	-0.5%	-1%	-2%
Solar	0-1km	Yes	Yes	0.25%	0%	-0.25%
Solar	0-1km	Yes	No	1%	0%	-1%
Solar	0-1km	No	Yes	0.125%	0%	-0.125%
Solar	0-1km	No	No	0.5%	0%	-0.5%
Solar	1-2km	Yes	Yes	0.125%	0%	-0.125%
Solar	1-2km	Yes	No	0.5%	0%	-0.5%
Solar	1-2km	No	Yes	0.0625%	0%	-0.0625%
Solar	1-2km	No	No	0.25%	0%	-0.25%

Notes: This table contains the assumed values for the capitalization effect of a wind or solar project into the value of a nearby residential property. Effect coefficients shown are logarithmic, but are scaled to show the equivalent % change in property values for a 10MW project. The actual logarithmic coefficients can be calculated by dividing these values by ln(10).

Table S13: Planning Process Regressions (Logit)

	(1)	(2)	(3)	(4)	(5)	(6)
Local	0.001	0.016*	−0.002	0.013	0.001	0.018*
	(0.003)	(0.007)	(0.003)	(0.008)	(0.003)	(0.009)
Local (Conservative)			0.015	0.013		
			(0.010)	(0.018)		
Local (National Planner)					−0.002	−0.008
					(0.006)	(0.013)
Non-Local	−0.001**	−0.002**	−0.001*	−0.001*	−0.005	−0.005
	(0.000)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)
Non-Local (Conservative)			−0.002	−0.000		
			(0.001)	(0.001)		
Non-Local (National Planner)					0.003	0.003
					(0.004)	(0.004)
R-Squared						
AIC	2438.654	2243.467	2427.719	2247.514	2429.892	2234.593
N	1779	1581	1779	1581	1779	1581
Wind	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Solar	-	-	-	-	-	-
Year FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
County FE	-	*Y*	-	*Y*	-	*Y*

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\dagger}p < 0.1$

Notes: This table shows the impact on approval probability from changes to local vs non-local project impacts. These specifications were estimated as logit regressions rather than as a linear probability model. Each coefficient has been scaled to reflect the odds ratio of approval for a £1 million improvement in its respective value category. The "Local" coefficients refer to changes in local net present value (e.g. nearby property values). The "Non-Local" coefficients refer to changes in non-local net present value (e.g. the value of the electricity produced or the costs of constructing and operating the project). Columns reflect different regression specifications, with specifications varying based on their inclusion of different fixed effects and heterogenous treatment effects. The "Conservative" coefficients are where a variable has been interacted with a dummy for whether a local authority is politically conservative. The "National Planner" coefficients are where a variable has been interacted with a dummy for whether a project's planning application has recevied national input to the decision.

Table S14: Misallocated Investment Analysis

	Wind			Solar	
Category	**(1)**	**(2)**	**(2*)**	**(1)**	**(2)**
No. of Projects [Current]	709 (0)	709 (0)	709 (0)	1,042 (0)	1,042 (0)
No. of Projects [Final]	1,063 (316)	843 (25)	335 (17)	989 (507)	875 (37)
Capacity (GW) [Current]	24 (0)	24 (0)	24 (0)	8 (0)	8 (0)
Capacity (GW) [Final]	30 (8)	24 (0)	22 (0)	9 (4)	8 (0)
Output (TWh) [Current]	1,227 (281)	1,227 (281)	1,227 (281)	128 (29)	128 (29)
Output (TWh) [New]	1,563 (742)	1,227 (281)	1,227 (281)	152 (89)	128 (29)
Total NPV (£bn) [Current]	1.7 (16.1)	1.7 (16.1)	1.7 (16.1)	0.7 (2.0)	0.7 (2.0)
Total NPV (£bn) [Added]	17.8 (9.4)	13.3 (7.1)	7.6 (3.9)	0.7 (0.6)	0.4 (0.5)
Total NPV (£bn) [Removed]	-12.5 (7.1)	-9.1 (7.1)	-0.8 (6.4)	-0.9 (0.7)	0.1 (0.7)
Total NPV (£bn) [Final]	37.2 (21.7)	28.3 (17.3)	10.0 (16.4)	2.6 (2.4)	1.2 (2.0)
Local NPV (£bn) [Current]	-2.3 (0.7)	-2.3 (0.7)	-2.3 (0.7)	0.0 (0.5)	0.0 (0.5)
Local NPV (£bn) [Added]	-1.7 (0.9)	-1.2 (0.4)	-0.2 (0.1)	0.0 (0.2)	0.1 (0.1)
Local NPV (£bn) [Removed]	-1.4 (0.7)	-1.5 (0.4)	-2.2 (0.7)	-0.1 (0.2)	-0.2 (0.3)
Local NPV (£bn) [Final]	-2.8 (1.6)	-2.2 (0.7)	-0.4 (0.1)	0.2 (0.6)	0.2 (0.5)
Δ Total NPV (£bn)	35.5 (6.2)	26.6 (1.7)	8.3 (0.6)	2.0 (0.7)	0.5 (0.1)
Δ Total NPV (£bn) [Subset I]	30.3 (3.4)	22.4 (1.0)	7.4 (1.2)	1.5 (0.5)	0.3 (0.2)
Δ Total NPV (£bn) [Subset II]	14.5 (4.2)	10.9 (3.8)	4.7 (2.1)	0.7 (0.5)	0.1 (0.1)

Notes: The costs of misallocated investment are shown under a range of scenarios. All values are cumulative totals to the end of 2018 and are averages across 729 estimation runs, with standard deviations in parantheses. These estimation runs are formed from the grid of parameters created by the "Low", "Medium" and "High" variants of key inputs. Values in column (1) give the results of finding the set of projects that have positive net present values. Values in column (2) give the results of finding the set of projects that can reproduce the observed annual deployment of renewable output (in lifetime discounted TWh) at least cost. Values in column (2*) employ the same approach as column (2) with the added constraint that there can be no substitution between onshore and offshore wind. A range of relevant data is then presented in the row categories. "Output" shows the lifetime discounted electricity output of the installed projects in TWh. "Capacity" shows the installed capacity in GW. "NPV" is the Net Present Value in £billions. "Current" refers to the actual observed values. "Final" refers to the new hypothetical best or least cost values. "Added" refers any previously refused or uncompleted projects that are now added. "Removed" refers any currently completed projects that are now removed. "Local" gives the portion of the total NPV comprised of local impacts. To prevent the analysis being driven by outliers, projects have their local costs capped at 100% of their total lifetime capital and operating costs. This affects a very small portion of wind projects. "ΔNPV" indicates the difference in NPV between the current set of projects and the final hypothetical best or least cost set projects. "Subset I" indicates the portion of any change in NPV that is due to projects that were refused planning permission (or approved when it would have been preferable not to). "Subset II" is a further subset of this that focuses in on changes to planning decisions that would be beneficial while also increasing average local costs.

Table S15: Local Compensation Scheme Regressions

Dependent Variable:	-IMPACTPERPROP_MID	
Model:	(1)	(2)
Variables		
MW of Capacity	7.385***	7.744***
	(0.0577)	(0.0546)
0-2km	625.5***	
	(30.22)	
2-4km	434.5***	
	(8.488)	
0-2km and Visible	1,414.6***	
	(31.09)	
2-4km and Visible	681.4***	
	(9.298)	
Shr of Avg. Property Value (0-2km)		0.0050***
		(0.0002)
Shr of Avg. Property Value (2-4km)		0.0035***
		(5.76×10^{-5})
Shr of Avg. Property Value (0-2km and Visible)		0.0097***
		(0.0002)
Shr of Avg. Property Value (2-4km and Visible)		0.0041***
		(6.19×10^{-5})
Fit statistics		
Observations	413,232	413,232
R^2	0.08891	0.16883
Adjusted R^2	0.08890	0.16882

Normal standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table shows the regression results for the two compensation schemes: "Basic" in column one and "Detailed" in column two. The dependent variable for these regressions is the impact per property. The unit of observation is a project-postcode pair. The regression is weighted according to the number of properties at each postcode.