The Economic Costs of NIMBYism

Evidence from Renewable Energy Projects

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Abstract

Large infrastructure projects can create widespread societal benefits, but also frequently prompt strong local opposition. This is sometimes pejoratively labeled NIMBY (Not In My Backyard) behavior. In this paper I estimate the economic costs of NIMBYism and its role in local planning decisions. To do this I use detailed data on all major renewable energy projects proposed in the United Kingdom spanning three decades. First, I use hedonic methods to show that wind projects impose significant negative local costs, whilst solar projects do not. I then show that planning officials are particularly responsive to the local costs imposed within their jurisdictions, but fail to account for variation in these costs across jurisdictions. The result has been a systematic misallocation of investment, which may have increased the cost of deploying wind power by 14-32%. Much of this can be attributed to the fragmented and localized nature of the planning process.

JEL Codes: Q4, Q5, R1

Keywords: Infrastructure, Electricity, Renewables, NIMBY, Local, Planning

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1 Introduction

Large infrastructure projects can create widespread societal benefits and are often critical to tackling major national or global challenges. A prime example is climate change mitigation and adaption, which will require large investments over the coming decades in areas such as renewable energy production, power grid infrastructure and public transit (IEA, 2018). However, large infrastructure projects such as these also create concentrated local impacts that can in turn lead to fierce lobbying during the planning approval process. This lobbying by local residents and businesses is sometimes pejoratively labeled NIMBY (Not In My Backyard) behavior and is thought to be common in a range of settings.

One area where the topic of NIMBYism has been debated extensively is renewable energy deployment.[1] Here a wealth of survey-based studies have examined the factors that determine community acceptance for wind and solar projects (Wolsink, 2000; Bell et al., 2013; Burningham, Barnett and Walker, 2015; Rand and Hoen, 2017; Hoen et al., 2019). Importantly though, the actual economic consequences of local opposition and its influence on the planning process remains poorly understood. There is some empirical evidence that local residents that oppose wind farms respond by voting the politicians responsible out of office (Stokes, 2016), or by pushing for new zoning regulations constraining development (Winikoff, 2019). There is also some limited evidence that certain features of wind or solar projects may be associated with projects being more likely to be approved (Roddis et al., 2018), but whether this is resulting in insufficient or misallocated investment has yet to be studied. Research on housing development has shown that local planning restrictions can indeed result in chronic underinvestment that acts as a substantial drag on the economy (Glaeser and Gyourko, 2018; Hsieh and Moretti, 2019). Given the growing urgency of combating climate change, it seems plausible that similar impediments to the deployment of renewable energy could also impose large costs on society.

In this paper I estimate the economic costs created by frictions in the planning process for renewable energy projects. For this I focus on the United Kingdom where I am able to draw on detailed planning data for all renewable energy projects, including information on projects 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

[1] NIMBYism can be more precisely defined as "the combined preference for the public good and a refusal to contribute to this public good" (Wolsink, 2000). The public good of interest here is the provision of renewable energy, with the aim of mitigating climate change and ensuring secure energy supplies, and the refusal to contribute is most clearly expressed by a locality's decision to deny planning permission for a proposed project.

projects in the UK must be approved at the local level by county planning officials. This allows me to estimate how local officials weigh local impacts during the approval process, including how this compares to the weight they place on the other wider societal benefits of these projects (e.g., carbon emissions reductions).

To approximate the impacts of a new wind or solar power project on nearby residents and businesses I focus on estimating how the construction of a project is capitalized into local property values and rents. There is a burgeoning literature that uses hedonic methods to estimate the value of various environmental amenities, including those affected by large infrastructure projects (Bishop et al., 2020). One area of focus has been power projects, such as fossil or nuclear power plants (Davis, 2011; Tanaka and Zabel, 2018). Increasingly research has turned to looking at the local impacts of renewable power projects; primarily the visual and noise disamenities caused by wind farms. On balance these studies find negative effects on property values, although the magnitudes can range significantly 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). I find that the median wind project causes a roughly 3-4% reduction in residential property values at distances of around 2km. Effects are larger at closer distances and also increase with the size of a project, although at an attenuating rate. Effects are larger when a property is likely to have direct line-of-sight to the wind farm, and when properties are located in wealthier, less deprived areas. This suggests the bulk of the adverse impact is due to visual intrusion. I also find new evidence of an appreciation in property values in areas where projects are refused planning permission. In reaching these estimates this paper makes a number of important methodological improvements; the most important of which is that I use information on planned but unsuccessful projects to more credibly construct a plausible comparison group and increase confidence in the observed effects.

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. In addition to looking at solar projects I also expand the scope of my analysis beyond the prior literature and look at impacts on commercial property values. Existing research has focused exclusively on residential property values, with the exception of Haan and Simmler (2018) who look at agricultural land values. The impact on commercial property values is as yet unstudied and seems potentially important if these projects have adverse effects on tourism or displace existing agricultural activity. I do not find statistically significant effects from either wind or solar projects on commercial property values, although these results are less precisely estimated.

Using my estimates of the local impacts of wind and solar projects I then examine how they influence the planning approval process. To do this I use data on the planning outcomes of roughly 3,500 wind and solar projects spanning almost three decades. For each project I estimate both the local impacts (e.g., on residential property values) and the wider societal impacts (e.g., the market value of the electricity produced, 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. Here I find evidence that by far the most significant factor guiding local planning officials is indeed local property value impacts. This is consistent with the fact that wind projects are much less likely to be appoved than solar projects. Interestingly these effects are more pronounced in politically conservative areas.

That local officials pay attention to local factors is unsurprising. In fact, there is a compelling argument to be made that local policymakers are in fact making optimal private decisions for their respective jurisdictions. For instance, Greenstone and Moretti (2003) show how local government policies to attract new large manufacturing plants do actually increase the welfare of local residents in the form of increased employment and local tax revenues. The key here is that what may be optimal for a given local area may in aggregate create harmful outcomes for society as a whole. In the context of renewable energy, I find that refusing a renewable energy 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. This problem is particularly acute for wind projects as they are most clearly subject to misaligned planning incentives.

To quantify the potential 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 failure to allocate investment in a more societally efficient manner has increased the cost of the UK's deployment of wind power by as much as £29 billion by 2019. Moreover, £25 billion of these foregone gains are from projects that were refused planning permission, indicating that the main driver of misallocated investment is the planning process. These frictions in the planning process are substantial, amounting to 32% of the lifetime capital and operating costs of all the wind projects built over this period. The equivalent misallocation in solar power has been just £0.3 billion, or less than 2%.

Interestingly, the scale of the increased costs in wind deployment depend heavily on the tradeoff between onshore and offshore wind. The UK's early investments in offshore wind power have been expensive, with large potential cost savings available from simply substituting toward onshore wind, even where this incurs larger local costs. Studying onshore and offshore wind separately causes the misallocated investment costs from the planning process fall to £11 billion, or around 14%. The merits of any substitution between onshore and offshore wind to date are largely driven by the extent of any learning and technological progress that has been created by the growing shift toward offshore wind. Where offshore wind learning has been substantial, local opposition to onshore wind may even have had the beneficial unintended consequence of pushing development offshore, driving down future costs for this nascent technology. Where offshore wind learning has been minimal, local opposition to onshore wind will likely have cost the UK dearly.

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 these create larger local impacts. A systematic bias against projects with higher local costs is entirely consistent with the fact that local planning officials are particularly responsive to variations in local costs within their jurisdictions. This suggests that there are potentialy legitimate concerns around the impact of NIMBYism on planning outcomes.

Importantly though, an even larger portion of the observed misallocation appears to be driven by the opposite problem; namely that many projects with high local costs have actually still gone ahead. The likely explanation lies in another dynamic created by the fragmented and localized nature of the planning process: a lack of coordination. Whilst 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 is in fact across jurisdictions, failing to coordinate at the regional or national level is potentially even more costly than concerns about NIMBYism. Furthermore, current planning guidance exacerbates the problem by trying to share the burden of renewable deployment across all jurisdictions, discouraging the concentration of capacity at larger projects in fewer areas, especially those with lower local costs in general. Reversing these tendencies could produce large gains for society as a whole, including for many local communities if the right policy structures are put in place.

Policymakers have already tried a range of policies that would appear to address some of the undesirable planning outcomes identified here. These policies include direct payments to local residents in the form of community benefits funds, changes to tax regulations to allow more revenues from renewable energy projects to be kept locally, and efforts to encourage local ownership of renewable energy projects. My findings suggest the scale of these sorts of transfer mechanisms may have to increase significantly in some instances to remedy concerns about NIMBYism. Having a more explicit process for providing compensation payments to affected local communities could also yield real benefits. This includes finding ways to make transfers across jurisdictions to incentivize some areas to host more concentrated deployment of renewable energy projects.

The findings in this paper have important policy implications both in the energy sector and beyond. Rapidly growing global demand for electricity and concerns about climate change mean that 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 if more care is taken when incorporating the impacts on local communities into the process. Finally, energy infrastructure projects such as those studied here share many similarities with other major infrastructure projects, such as roads, railways, airports, landfill sites, water and waste treatment works, and so on. There is every reason to think that NIMBYism presents a similar problem in those sectors as well, and so exploring the gains elsewhere remains a fruitful area for further research.

This paper is structured as follows. Section 2 provides context on the development of renewable energy in the United Kingdom. Section 3 covers the analysis on the capitalization into property values. Section 4 covers the analysis on the planning process. Section 5 concludes.

2 Background on Renewable Energy in the UK

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*a*). This expansion is set to continue, with wind power forecast to provide 40-55% of the UK's electricity by 2030 (NGET, 2019). Projects have tended to be 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 wind 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*a*). 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.

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 the vast majority of support went to onshore wind, in part because this was the most well-established technology at the time. In 2009 and 2010 a number of reforms were introduced that supported the rapid expansion of both solar power and offshore wind. In 2015 a new Conservative government made a number of major changes that led to a significant decline in new investment for both solar power and onshore wind. These changes included freezing the UK carbon tax, cutting the funds available to solar power and blocking future onshore wind farms from receiving any subsidies. In the case of onshore wind these policy changes were driven in part by the vocal opposition of rural voters to wind turbines. Their views were echoed by the then-prime minister David Cameron who vowed to "rid" the countryside of these "unsightly" structures. Interestingly offshore wind was not subjected to the same hostile policy environment, perhaps because these projects tend to be located a long way out at sea. In 2020 the moratorium on subsidies for onshore wind was lifted, in part due to waning opposition from Conservative voters.

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. These local authorities are the primary unit of local government in the UK and on average cover around sixty thousand households.[2] Project developers submit a planning application to the relevant local planning authority. The local planning authority considers the merits of the proposal in line with national and local planning guidelines. A public consultation period

[2]This means UK local authorities are broadly analogous to US counties.

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. "In Review" are projects that have submitted a planning application but have yet to receive a final decision. "Completed" are projects that have been approved and are either awaiting construction, under construction, operational or have been subsequently decommissioned. "Abandoned" 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.

is required where affected stakeholders have the opportunity to provide comments. The local planning 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”. In considering any issues raised by local stakeholders, planning guidelines emphasize the importance of promoting renewable energy, the suitability of the local area for the technology being proposed, and the impact (both individually and cumulatively) on the character of the surrounding landscape, especially where this affects nearby heritage assets of cultural significance (e.g., churches, castles and monuments), national park designations, or sites of environmental significance. In many cases EU law requires that applicants conduct an environmental impact assessment. For wind projects there is also a requirement to conduct a noise assessment, as well as a number of safety standards to ensure the proposed turbines do not interfere with flight paths or radar installations. Beyond these requirements there is a general preference against strict criteria or zoning (e.g., setbacks, buffer zones or quotas). However, there is scope for planning authorities to seek amendments to planning applications, or approve them with certain conditions aimed at mitigating potential concerns that may have been raised.

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 these situations the planning decision is made by the national Planning Inspectorate, and any directly affected local authority is included as a statutory consultee to the process. In the case of renewable energy, projects with a capacity greater than 50MW have historically been deemed to be of national significance. However, as part of the reforms introduced by the Conservative government of 2015 this threshold was removed for onshore wind projects such that all subsequent projects would be considered at the local level irrespective of size. The second exception to local control 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 interesting opportunity to examine how decisionmakers at these different scales weigh planning applications.

To help document the impact of the planning process on the deployment of renewable energy, the UK government maintains and publishes a database on the planning applications for all major 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 for wind and solar projects as documented in the planning database.

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. 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.

The projects covered in the planning database comprise the overwhelming majority of wind and solar capacity in the UK, and so many of the trends described earlier are evident in Figure 1. There is a roughly even split of projects across the two technology types, although wind projects are larger on average and so account for the vast majority of total renewable 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 decisionmakers are more positively predisposed to renewable energy projects and perhaps less influenced by local political considerations. 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.

I provide further information on some of the key reasons why projects are refused by collecting the planning decision letters for a sample of projects. Based on the refusal decisions of 120 wind and solar projects I find that by far the most cited reason is the visual impact of a project on nearby residents and the overall character of the surrounding landscape. Visual impact reasons were mentioned in 60% of solar refusals and 75% of wind refusals. The next most common are a related set of concerns about the proximity of a project to culturally important heritage sites. Heritage concerns were mentioned in 30% of solar refusals and 50% of wind refusals. Unsuprisingly, noise concerns do not appear in any of the solar refusals. Interestingly though, noise concerns do not feature particularly heavily for wind projects either, with only 25% mentioning noise as a reason for refusal. This may seem puzzling at first given the noise from rotating turbine blades is widely considered to be a major local impact of any wind project. It may simply be that, whilst important, noise impacts are still small relative to visual disamenities. However, the lack of refusals due to noise concerns might also be driven by the fact 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 are harder to explicitly include in planning procedures and so provide far greater latitude for subjective interpretation by local decisionmakers.

The planning outcome data described here makes clear that a major 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 projects, and so the findings here may be instructive for other kinds of infrastructure. 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 projects like transport or housing, most of the benefits of wind and solar projects are spread diffusely throughout wider society whilst many key costs remain concentrated locally. The risk here is that, in the absence of some kind of direct payments, local decisionmakers are unlikely to put much weight on benefits accruing to non-local actors. This paper will assess the extent of the costs posed by these misaligned incentives.

3 Capitalization analysis

Renewable energy projects create a number of local economic impacts. Of primary interest here are the various visual and noise disameneties generally associated with these projects. Credibly estimating the scale of any of these impacts is challenging. Hedonic property value models have become the primary empirical tool for estimating willingness to pay for environmental quality (Bishop et al., 2020). Studies using this approach have shown capitalization into property values of numerous environmental disamenities, such as hazardous waste (Currie et al., 2015), road noise (von Graevenitz, 2018) and water pollution (Keiser and Shapiro, 2018). The primary measure of local impacts utilized here is therefore based on estimating capitalization into property values. In general, the hedonic analysis undertaken here does not seek to differentiate between the various local impacts associated with wind and solar projects, but rather considers them in aggregate through their effects on property values.

3.1 Empirical Strategy

3.1.1 Property value data

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. Postcodes in the UK are a very granular geographic unit with around 15 households per postcode (approximately equivalent to census blocks in the US). Summary statistics can be found in Table 2.

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 3.

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 means and standard deviations 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 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: 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 means and standard deviations 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.

3.1.2 Defining treatment

The capitalization analysis throughout this paper consistently uses some variation on a difference-in-differences framework. Treatment is therefore 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*).

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

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. For commercial properties promixity is taken to be the average of the proximity values for the postcodes within each LSOA. 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.

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 the size of projects (e.g., the number of wind turbines).[3] For reference the results for these alternative measures of project size can be found in the appendix.

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.[4] 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. For reference the results using alternative functional forms (e.g., linear in capacity) can be found in the appendix.

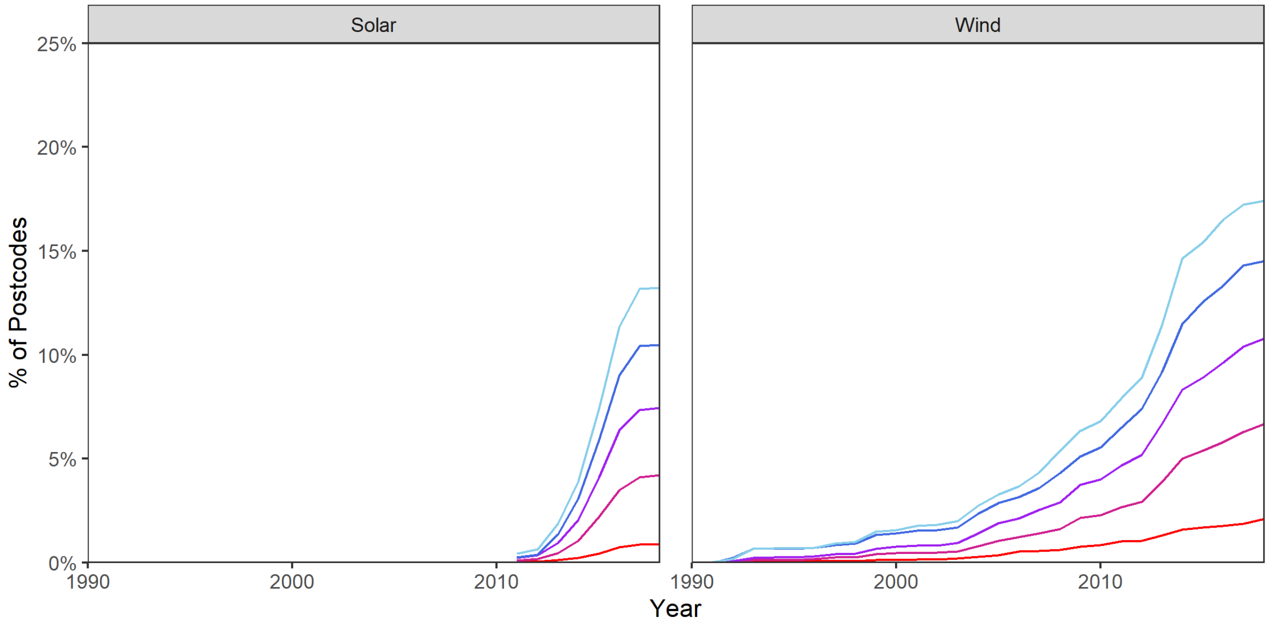
3.1.3 Difference-in-difference specification

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. The basic difference-in-difference specification used here is of the general form:

[3]For wind projects an obvious choice is the number of turbines, in line with prior work. This seems particularly important because the relationship between MW of capacity and the number of turbines has been changing over time as turbines become larger. Examining the capitalization effects of both measures can offer valuable insights into whether the move to projects with fewer, larger turbines is mitigating or exacerbating local impacts. For solar projects I considered the land area covered by solar panels to be the most appropriate choice. Unlike wind turbines though, the relationship between solar panel capacity and surface area has remained relatively constant at roughly 5-6 acres per MW (Ong et al., 2013). As such, the results estimated using solar capacity can be simply rescaled where an effect in terms of area covered is desired.

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

Figure 2: 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.

$$log(P_{ilrt}) = \sum_{k=1}^{K} \beta_k T_{lt} + \gamma X_{it} + \theta_{rt} + \lambda_l + \epsilon_{ilrt} \tag{2}$$

Here P is a measure of the value of a property (or group of properties), i, at location, l, within region, r, in year, t. For the residential property sales this is the transaction price of a property and for the commercial property rents this is the annual average rental value per square meter. 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. In this case separate regressions are estimated with treatment determined by distances of 0-2km, 0-4km, 0-6km, 0-8km and 0-10km for wind projects, and 0-1km, 0-2km, 0-3km, 0-4km and 0-5km for solar projects. This alternative approach helps make comparisons to other studies, as well as facilitating the examination of possible sources of heterogeneity (discussed later).[5] Standard errors are

[5]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

clustered based on location to account for correlation between nearby observations.[6]

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.[7] 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 where a project was already completed in previous time periods. This ensures that the control observations are broadly comparable to those undergoing treatment.[8]

I account for unobservable time-invariant determinants of property values using 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.[9] To explore purely within-property variation I also estimate versions with address-level unit fixed effects.[10] For the commercial property regressions the data are already aggregated to regional annual totals by LSOA. As such 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, whilst an LSOA is a more aggregated unit than a postcode it is still relatively small, corresponding to roughly one thousand households. As such, commercial

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effects based on one distance at a time mitigates this somewhat, whilst still producing coefficients that are broadly similar.

[6]For the residential property regressions I cluster at the output area (OA) level and for the commercial property regressions I cluster at the middle layer super output area (MSOA) level

[7]For solar projects this is 34% of the residential sales sample and 32% of the commercial rents sample. For wind projects this is 34% of the residential sales sample and 30% of the commercial rents sample.

[8]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.

[9]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.

[10]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 of properties more generally.

activities within a given LSOA are still likely to be relatively homogenous, particularly at the sector level.

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. I also explore the sensitivity of my results to using more granular regions to increase the richness of these fixed effects.[11] 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.[12]

Finally, 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).[13] For a subset of the residential proporties there is also information on house floor areas and energy efficiency ratings. For commercial properties the available controls include average floor areas.

Identification of a credible causal effect using a difference-in-difference approach 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. Instead there is selection of locations into treatment in terms of where projects are actually approved and built. Moreover, conditional on ever being treated there is also selection in terms of when treatment happens (earlier vs more recent projects). Some of the major factors driving selection into treatment may be seemingly unrelated to residential or commercial property values (e.g., wind speed). However, other factors almost certainly are related to selection into treatment during the planning process and directly or indirectly related to local property values (e.g., visual or historical appeal of local landscape, local political preferences, presence of important ecological habitats and wildlife). The primary solutions to this challenge that I have set out thus far are the decision to a) limit the controls

[11]First 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. Second I use the roughly four hundred local authorities in the UK which are more analoguous to US counties.

[12]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, whilst the north where economic growth has lagged behind has also seen a larger portion of wind projects.

[13]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.

to locations that are near to a completed project by the end of the period, and b) make the parallel trends assumption conditional on a rich set of fixed effects and controls. This ensures that the control properties forming the counterfactual are very similar to treated properties and that the variation being used for identification is not confounded by other factors.

I augment the difference-in-difference setup using a series of event studies. Here the treatment variable is now interacted with a series 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. This should allow for sufficient time for the any effects to materialize. The resulting specification is of the form:

$$log(P_{ilrt}) = \sum_{s=S_{pre}}^{S_{post}} \sum_{k=1}^{K} \beta_{k,s} T_{lt} + \gamma X_{ilt} + \theta_{rt} + \lambda_l + \epsilon_{ilrt} \tag{3}$$

The event study approach has a number of benefits in this setting which is why it is my preferred specification. First, it helps identify potential anticipation and adjustment effects. Because planning and construction can last several years we might expect anticipatory effects well before a project becomes operational. It also seems plausible that it could take time for the housing market to adjust before the true scale of the local effects from a new project become clear. Both of these factors mean that the standard difference-in-difference treatment coefficients estimated using Equation 2 may underestimate or overestimate the true effect. Properly accounting for these anticipation and adjustment effects is therefore important for understanding the true capitalization effect and the manner in which it manifests. Second, the event study can help provide some supporting evidence that parallel trends hold in the pre-period. Third, 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). Of course, the main drawback to the event study approach is that it requires estimating a far larger number of coefficients which reduces statistical power.

3.1.4 Comparing approved and refused projects

At present the analysis follows prior studies by using locations near completed projects to define both the treated and control groups. However, it seems reasonable to think that locations near to completed projects are not the only areas with properties that could act as plausible controls. For example, there are many remote windy areas in the UK that have properties that are comparable to treated ones, but that have not yet themselves had a wind farm completed nearby. I take advantage of the unique information available in the UK's renewable energy planning database to construct an alternative comparison group based on properties near to proposed projects that ultimately were not built.

To do this, I first construct a full secondary set of treatment variables in the exact same manner set out previously, but this time 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.[14] These additional treatment variables for the failed projects, T^F, are included in the regression alongside the original treatment variables for the completed projects, T^C. This can be seen in the modified version of Equation 2 below, and the intution is the same for modifying Equation 3.

$$log(P_{ilrt}) = \sum_{k=1}^{K} \beta_k^C T_{lt}^C + \sum_{k=1}^{K} \beta_k^F T_{lt}^F + \gamma X_{ilt} + \theta_{rt} + \lambda_l + \epsilon_{ilrt} \tag{4}$$

Coefficients are estimated as before but now a direct comparison can be made between the coefficents for the completed projects and the coefficients for the failed projects. This change has a number of possible benefits. First, the sample size of properties available for use in the estimation is larger which improves statistical power. This is because I still include any properties at locations that ever fall into one of the included distances bins, but the distance bins now refer to both completed and failed projects. Second, the control groups for each distance bin are now more targeted because I can more explicitly compare areas that were or could have been a certain distance from a project. Third, there is the possibility of looking more explicitly at sorting behavior. However, this expansion of the control group has some clear drawbacks, not least the fact that comparing locations with completed projects to those with failed projects puts concerns about selection bias into even sharper relief.

To tackle possible concerns about selection, I exploit information about the planning pro-

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

cesses for projects. I repeat the estimation for all specifications set out thus far but now interact treatment with whether a project was 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. The remaining projects were clearly thought to be sufficiently undesirable by the local planning authority to warrant refusal and thought to be sufficiently valuable by the developer to warrant appealing. As such it seems plausible that this subset of projects is more credibly comparable than simply using the entire sample of projects.

3.1.5 Differential impacts

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). I examine whether properties that are likely to have direct line-of-sight to a project experience different effects than properties where projects are obscured by the landscape (e.g., behind a hill). To do this I start with the location of each project and the heights of the turbines or panels installed. I then combine this with a digital elevation model of the UK to determine if the straight line that connects each pair of points is intersected by the terrain. Where it is, the project is assumed to be obscured and where it is not the project is assumed to be visible. It is worth noting that this approach is certainly not without its flaws. For instance, it only uses the central point of a project rather than the area covered, and it can't account for other features that may act to block line-of-sight such as trees or buildings. Nevertheless, it should still be sufficient to isolate clear differences in visibility. Full details on the visibility analysis can be found in the appendix.

The second key source of differential impacts that I study is whether effects are different in wealthy neigborhoods relative to poorer neighborhoods. 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 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). Properties located in more deprived areas, on the other hand, are already more likely to be characterized by unsightly and noisy industrial development. To explore this possible distinction I examine whether properties that are in more deprived areas experience different effects than properties in less deprived areas. To do this I use the UK's Index of Multiple Deprivation. This measure classifies neighborhoods based on their relative level of deprivation by weighting across a range of indicators covering income, employment, education, health, crime, housing quality and environmental quality. I define more deprived areas as those above the median on the index, and less deprived areas as those below the median.

3.2 Results

The capitalization results are primarily summarized by the event study plots. Further detailed tables can be found in the appendix.

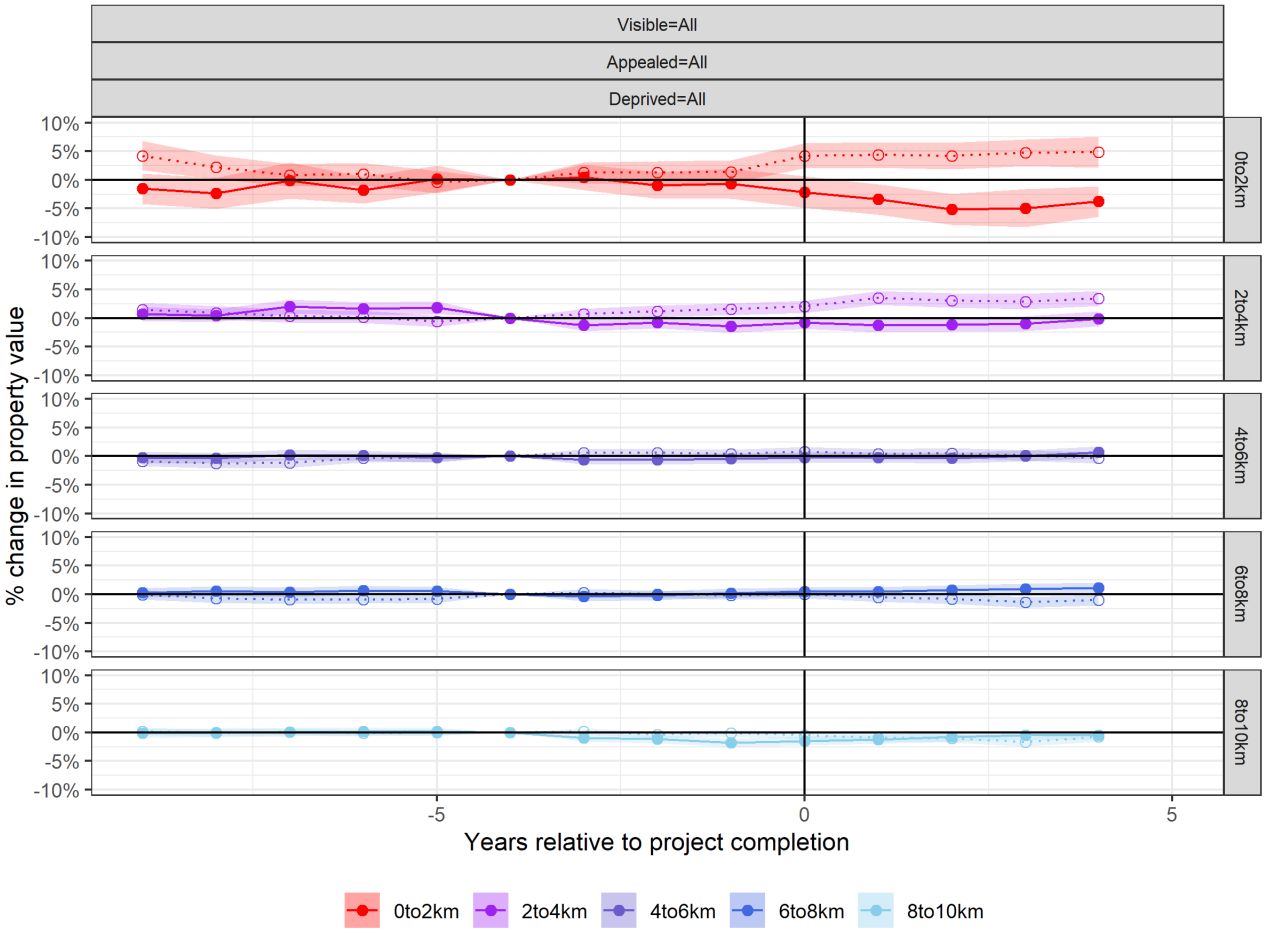
3.2.1 Impacts on residential property values

Wind projects

For wind projects the event study in Figure 3 shows a reduction in property values of around 3-4% for properties located within 2km of a newly built 10MW project. This effect is minimal 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.

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 3 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

Figure 3: Residential Property Values Event Study Results for Wind Projects



Notes: 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. Distances are denoted throughout using colors, with red being the closest and light blue the furthest. 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.

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. In Table 4 each column is based on a different distance circle, with an increasing number of observations as the circle gets larger. The effects using this approach are broadly comparable to those using distance bins. Beyond this I also conduct a number of robustness checks of the analysis using alternative fixed effects and by comparing the event study approach to the findings from directly estimating a single coefficient. All of these results can be found in the appendix.

Table 4: Residential Capitalization for Wind Projects by Distance Circles

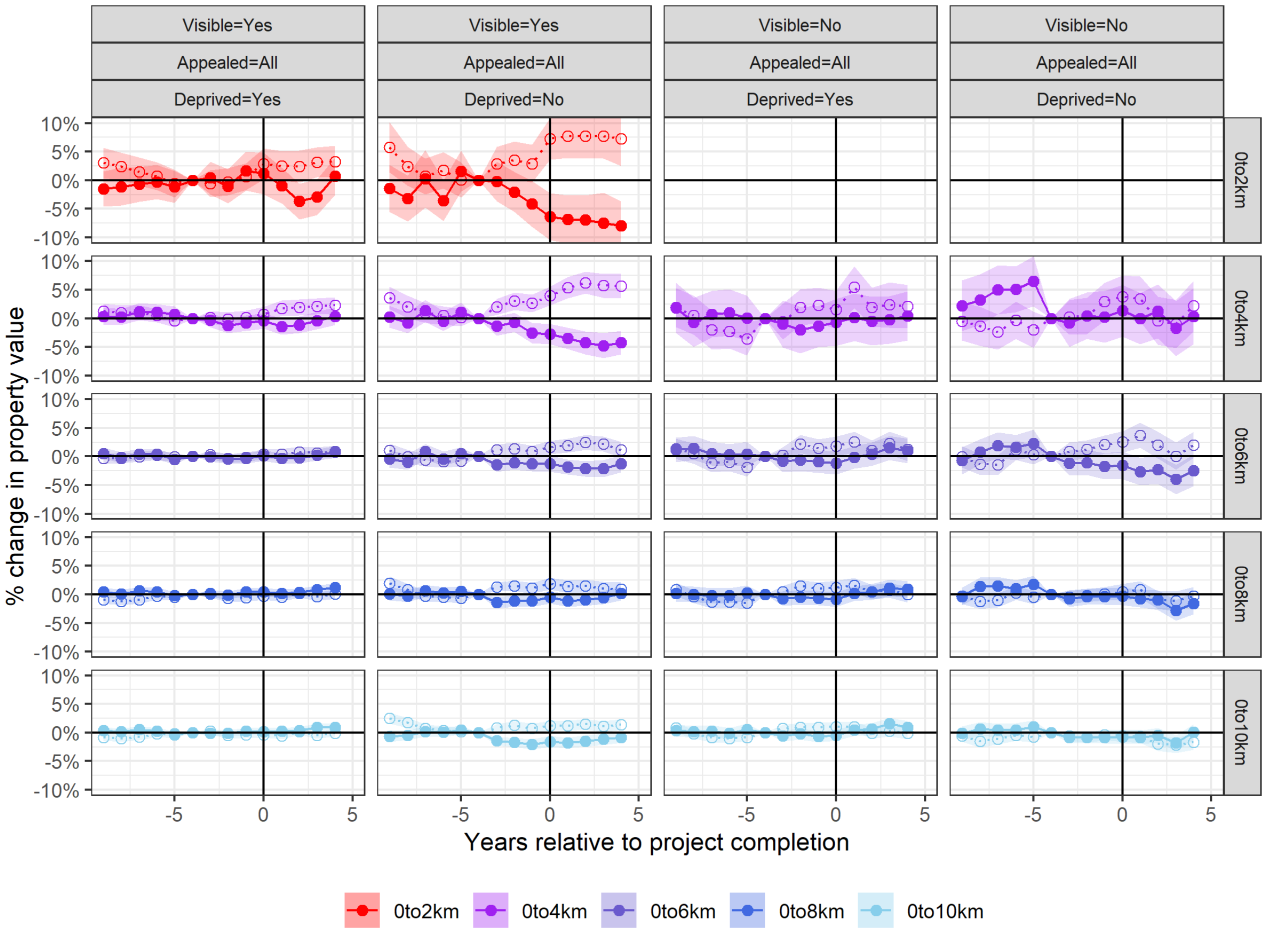
	(0-2km)	(0-4km)	(0-6km)	(0-8km)	(0-10km)
Completed					
, ,	-3.27^{***}	-3.06^{***}	-1.25^{***}	-0.56^{***}	-0.57^{***}
	(0.64)	(0.27)	(0.16)	(0.12)	(0.10)
Failed					
, ,	3.29^{***}	2.70^{***}	1.79^{***}	1.00^{***}	0.41^{***}
	(0.55)	(0.26)	(0.16)	(0.12)	(0.10)
R-Squared	0.90	0.90	0.90	0.90	0.90
N (millions)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

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

Notes: Point estimates based on the event study specifications 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.

Lastly, I look at differential effects. These results can be seen in Figure 4. 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 in locations near a project that was appealed, for properties that have direct line-of-sight to a project, and for properties in less deprived areas.

Figure 4: Residential Capitalization Event Study for Wind Projects with Differential Effects



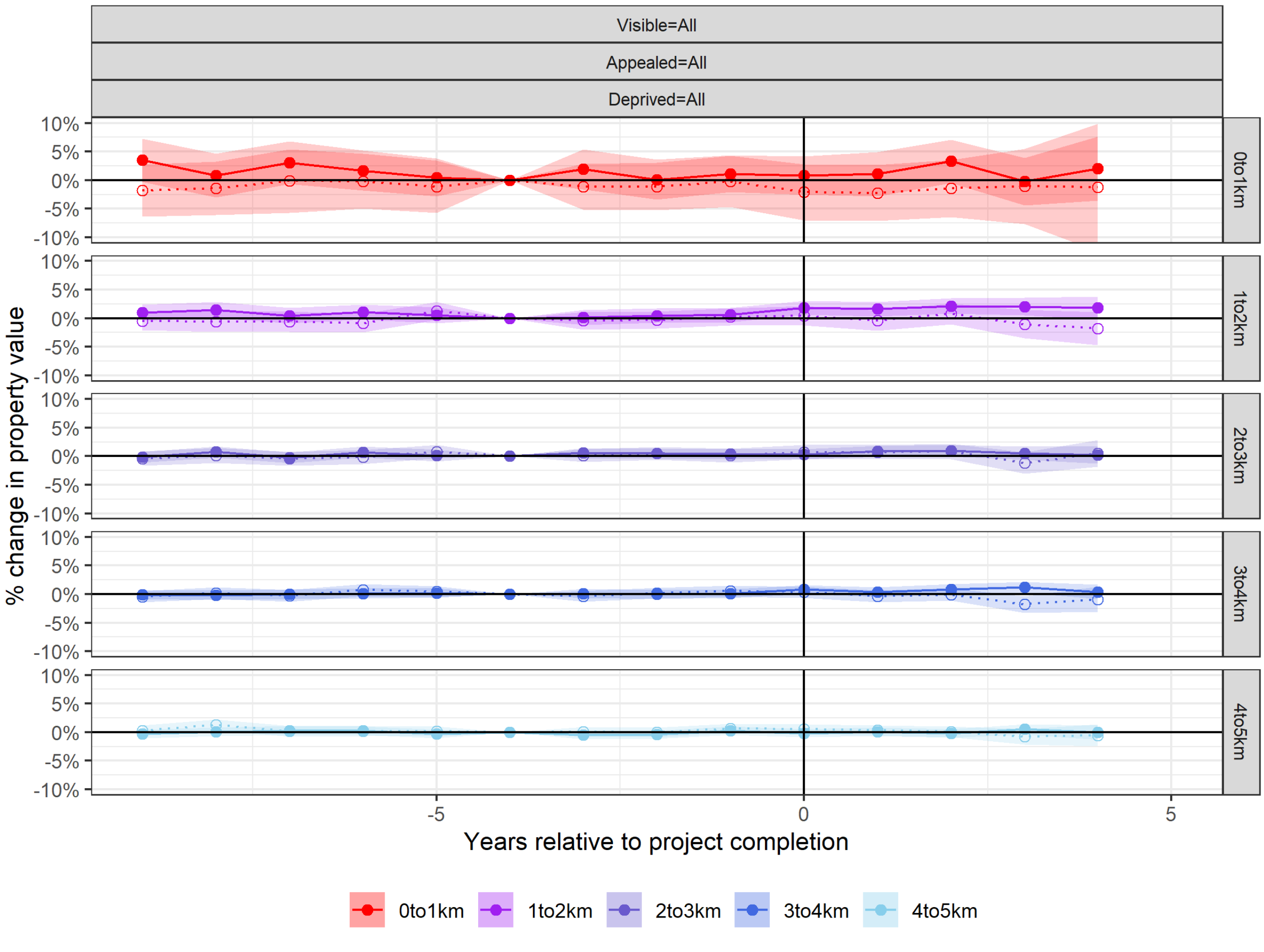
Notes: All event bin coefficients for a given distance bin are normalized relative to the fourth pre-period event bin ($s = -4$). All coefficients should be interpreted as the % change in property values resulting from a location going from having no nearby project to having a 10 MW project at the relevant distance away. Distances are denoted throughout using colors, with red being the closest and light blue the furthest. 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. Panel columns capture the different heterogenous effects estimated.

Solar projects

For solar projects I find no consistent evidence of an impact on residential property values. Figure 5 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.

Table 5 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. Lastly, I check the robustness of my findings using a range of alternative specifications, all of which can be found in the appendix.

Figure 5: Residential Capitalization Event Study for Solar Projects



Notes: 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. Distances are denoted throughout using colors, with red being the closest and light blue the furthest. 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.

Table 5: 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: Point estimates based on the event study specifications 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.

Figure 6 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.

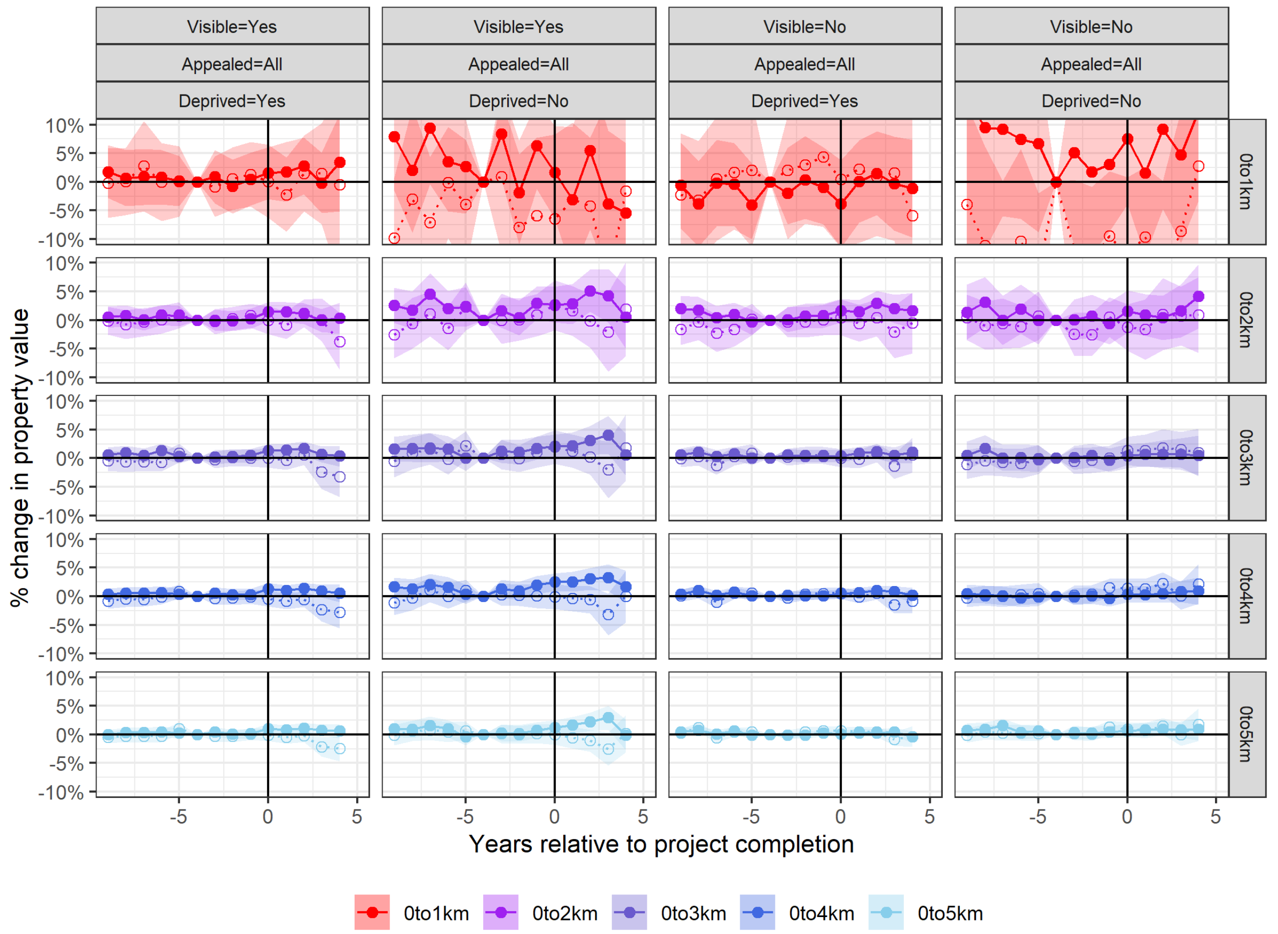
3.2.2 Impacts on commercial property values

Wind projects

For wind projects the event study in Figure 7 provides some weak evidence of a possible impact on commercial property values in the closest 0-2km distance bin. This appears to be supported by the fact that the divergence with the effects for the failed projects is clearest for this closest distance bin. However, the more aggregated nature of the data on commercial rents means this analysis has less statisical power than was the case when looking at residential property values. This is reflected in the much wider confidence intervals. As such any negative effect is not consistently statistically different from zero.

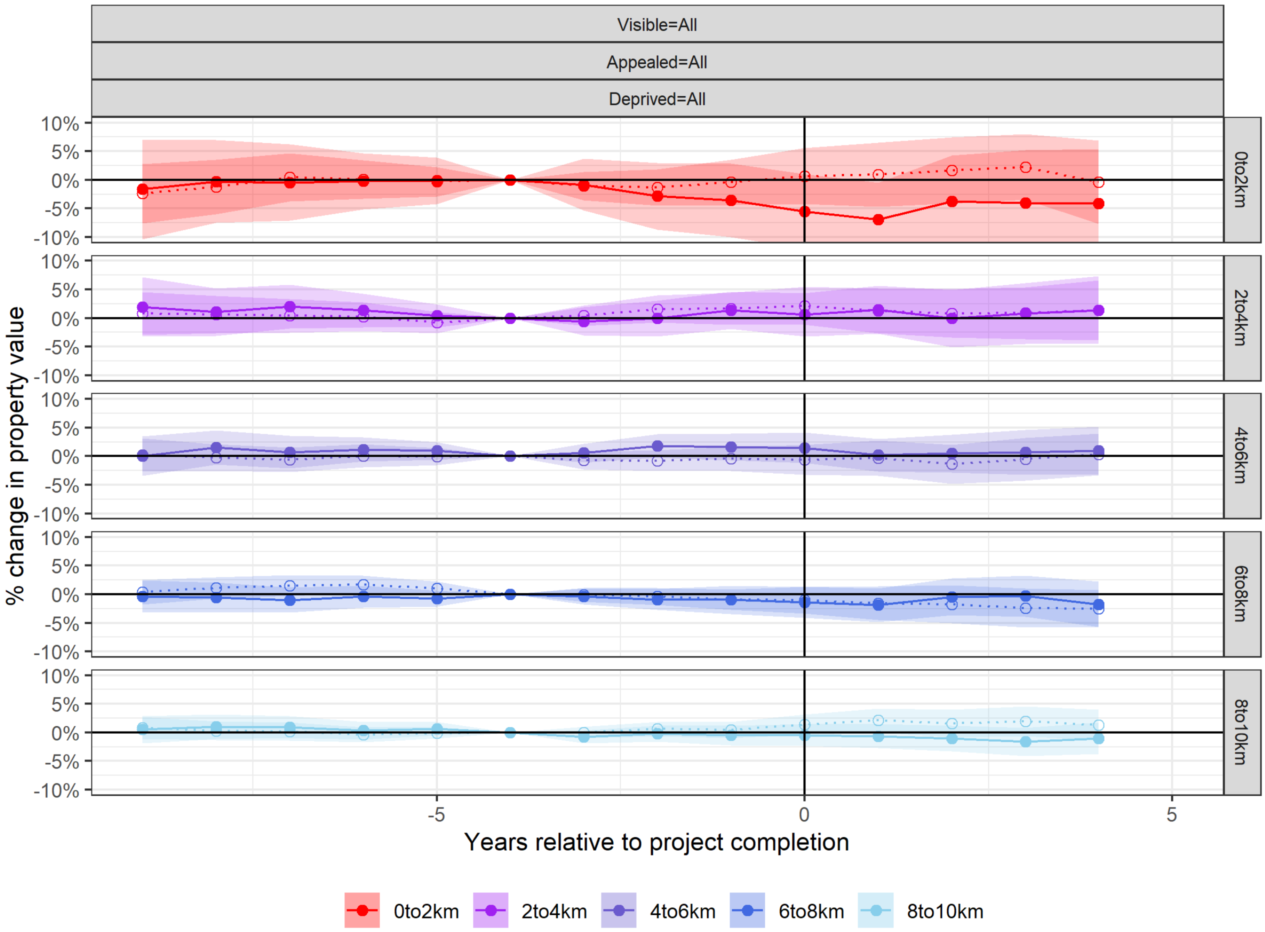
Importantly, these results aggregate across all commercial property types. As such I repeat the analysis for four sub-sectors of commercial property types. The available categories are industrial, retail, office and other. Of these "other" is probably the one that contains the commercial uses that would be the most likely to be affected by a nearby wind or solar project, such as accomodation (hotels, guest houses, campgrounds), food and dining (cafes, restaurants) and leisure (museums, tourist attractions). This sub-sector analysis also fails to find statistically significant effects. The full results, including the analysis of differential effects, can be found

Figure 6: Residential Capitalization Event Study for Solar Projects with Differential Effects



Notes: 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. Distances are denoted throughout using colors, with red being the closest and light blue the furthest. 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. Panel columns capture the different heterogenous effects estimated.

Figure 7: Commercial Capitalization Event Study for Wind Projects



Notes: 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. Distances are denoted throughout using colors, with red being the closest and light blue the furthest. 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.

in the appendix.

Table 6 shows the results of the analysis using distance circles. The same general findings as with the pooled distance bins approach are evident.

Table 6: Commercial Capitalization for Wind Projects by Distance Circles

	(0-2km)	(0-4km)	(0-6km)	(0-8km)	(0-10km)
Completed					
, ,	−4.22	−2.19	−1.96	−1.54	−1.59*
	(2.73)	(1.46)	(1.00)	(0.73)	(0.62)
Failed					
, ,	2.08	0.53	−0.48	−0.99	−0.11
	(1.67)	(1.11)	(0.78)	(0.64)	(0.52)
R-Squared	0.95	0.94	0.94	0.94	0.94
N (millions)	0.04	0.09	0.13	0.17	0.20

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

Notes: Point estimates based on the event study specifications 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.

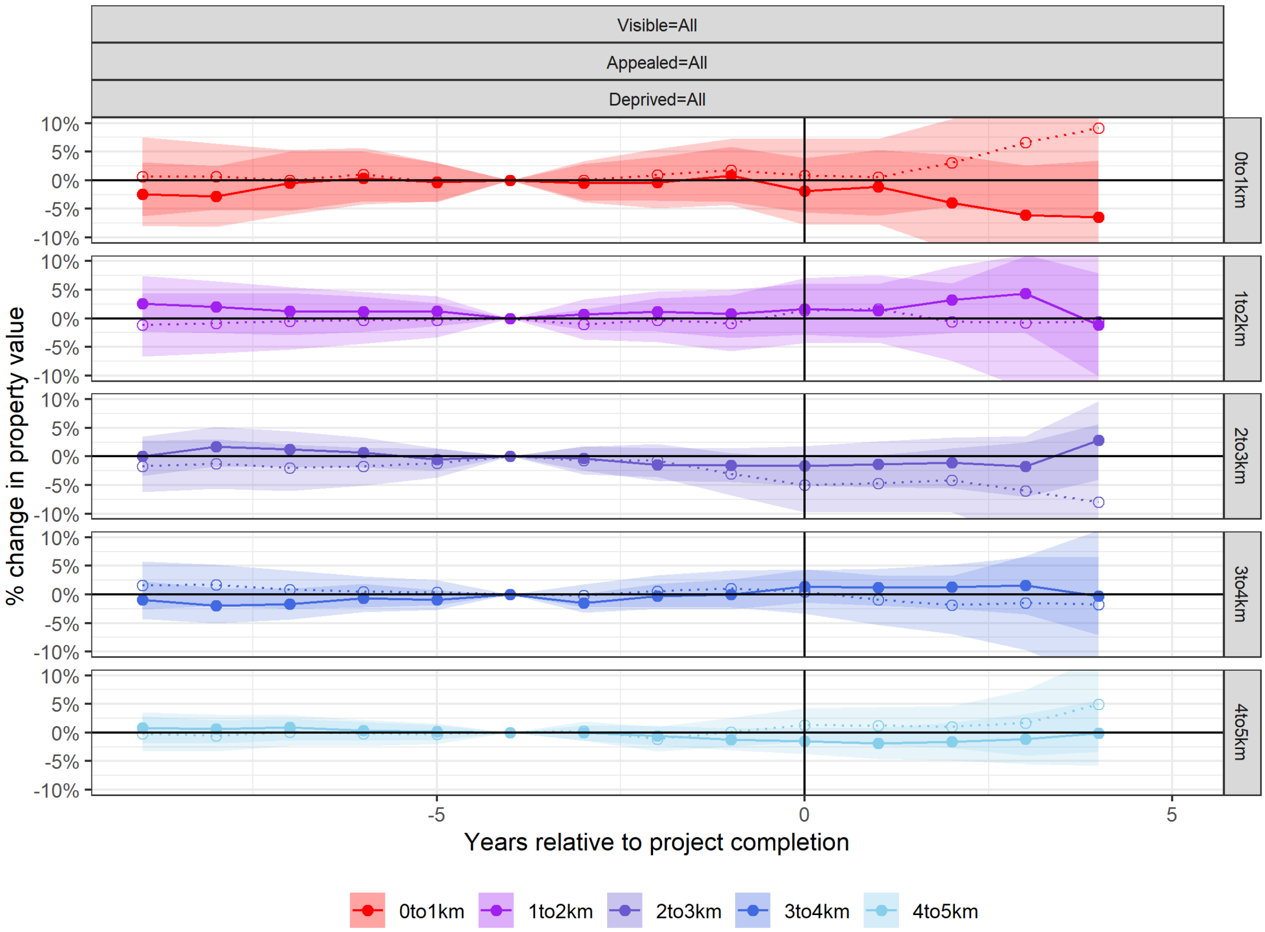
Solar projects

For solar projects, Figure 8 shows the results of the event study, and it is clear that there is no noticeable change in property values when a nearby solar project is built.

When I repeat this analysis for four sub-sectors of commercial property types I also do not any discernible effects. Once again though this analysis of commercial rents lacks statistical power as reflected in the wide confidence intervals. This is also the case with the differential effects analysis which can be found in the appendix.

Lastly, table 7 shows the results of the analysis using the distance circles approach. As before the same general results are evident as those found using the distance bins approach.

Figure 8: Commercial Capitalization Event Study for Solar Projects



Notes: 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. Distances are denoted throughout using colors, with red being the closest and light blue the furthest. 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.

Table 7: Commercial Capitalization for Solar Projects by Distance Circles

	(0-1km)	(0-2km)	(0-3km)	(0-4km)	(0-5km)
Completed					
, ,	−3.26	−1.91	−1.29	−0.87	−0.98
	(2.10)	(1.34)	(0.89)	(0.74)	(0.66)
Failed					
, ,	1.47	−0.27	−1.83	−1.35	−0.46
	(2.35)	(1.68)	(1.16)	(0.97)	(0.88)
R-Squared	0.95	0.94	0.94	0.94	0.94
N (millions)	0.04	0.08	0.13	0.17	0.21

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

Notes: Point estimates based on the event study specifications 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.

4 Planning process analysis

Now that I have estimates of the local impacts of wind and solar projects in terms of capitalization into property values, a number of questions follow. How large are these impacts in aggregate when applied to the properties located near a given project? Are they small relative to the other costs and benefits associated with these projects, and is there significant heterogeneity across projects? How does variation in these local impacts affect the planning approval process? Do local officials place particular emphasis on these local costs relative to other potential benefits, such as carbon emissions reductions? Lastly, have the resulting planning decisions led to insufficient or misallocated investment during the deployment of renewable energy? If so, what are the potential costs for society and could some form of transfer policy help remedy this?

In thinking about the role of NIMBYism and local interests in the planning process, it is worth being clear about what is actually meant by NIMBYism. NIMBYism can be more precisely defined as "the combined preference for the public good and a refusal to contribute to this public good" (Wolsink, 2000). The public good of interest here is the provision of renewable energy, with the aim of mitigating climate change, reducing local pollution, and ensuring secure energy supplies. The refusal to contribute arises when there is local opposition to having a project sited nearby. Much of the literature on community acceptance of renewable energy has challenged the NIMBY characterization as oversimplistic (Wolsink, 2000; Bell et al., 2013; Burningham, Barnett and Walker, 2015; Rand and Hoen, 2017; Hoen et al., 2019). For instance, whilst NIMBYism is usually characterized by a narrow emphasis on individual self-interest, actual stated opposition is frequently expressed in terms of concerns about the impact on the community, or the fairness of the political process. Moreover, even classic narrowly self-interested NIMBYism need not be widespread in a given locality for it to have an effect if the NIMBYs are a particularly vocal minority that can exert outsize influence. Conflicts over proposed projects can also be exacerbated by pre-conceived notions of local residents as parochial obstacles and project developers as extractive corporate outsiders.

In this study, I primarily think about local interests and NIMBYism in terms of the community-level decisions made during the planning process. Part of the motivation is that a decision to refuse a project in this way is probably the most straightforward and impactful way that a "refusal to contribute to [the] public good" could be expressed. These community-level decisions are still determined by the complex interaction of individual attitudes, political power and the idiosyncracies of local circumstances that prior studies have highlighted. Rather than examining these underlying drivers of each planning decision, my main focus is on whether local communities in general make decisions that systematically reflect their own economic self-interest, and whether this imposes economic costs on wider society through the underprovision of public goods that are otherwise broadly supported.

To examine the planning process I conduct three pieces of analysis. First, I quantify the various 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. Second, I conduct a regression analysis to understand how sensitive planning officials are to local versus non-local impacts. Third, I conclude by estimating the potential costs created by the planning process in the form of misallocated investment.

4.1 Empirical Strategy

4.1.1 Estimating local project costs and benefits

I calculate the total local impacts of wind and solar projects using estimates of the capitalization into local property values. To calculate this I start with hedonic estimates of how the construction of a nearby project translates into a percentage change in the value of a given property. I then multiply these treatment effects by the total value of all properties near each project.

The treatment effect 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 the scale of 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 property values, rents and counts at the local authority level. I then downscale these to the postcode level for residential properties and the LSOA level for commercial properties. This downscaling is based on a range of data, including the residential property transactions and average commercial rents data used in the prior hedonics analysis. Full details can be found in the appendix.

4.1.2 Estimating non-local project costs and benefits

The next step requires estimating the various non-local costs and benefits associated with each renewable energy project. The primary costs and benefits estimated here are: 1) the market value of the electricity produced, 2) the value of any carbon emissions abated, 3) the value of any local pollution emissions abated, 4) the capacity value from contributing to supply security, 5) the capital construction costs of installing the project, 6) the operation and maintainence (O&M) costs incurred over its lifetime, and 7) the benefits of learning-by-doing.

There are undoubtedly other secondary costs and benefits created by these projects not included here. For instance, the employment benefits from building and maintaining the project are not included here. In general though these should be minimal for wind and solar projects. For instance, Costa and Veiga (2019) find evidence of a small temporary boost to employment from wind projects during the construction phase, but no lasting impact on employment beyond that. I confirm this using employment data and the results can be found in the appendix. Even so, the included costs and benefits are not exhaustive and this should be kept in mind when interpreting the results presented later.

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 again 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 government’s general approach to valuation, which in turn should be consistent with the valuation guidance that planning officials should be following when considering these projects.

To estimate the main benefits of the electricity produced by a wind or solar project (items 1 to 3) requires estimating the amount of electricity a project will produce over its lifetime. Here I use data from the International Renewable Energy Agency (IRENA), which I then adjust to account for project specific information on wind speeds and solar insolation from Renewables Ninja and the World Bank. Full details can be found in the appendix.

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. Full details can be found in the appendix.

In valuing the electricity produced by a project I almost exclusively do so in terms of annual average marginal values. In reality there is significant temporal variation in the output from wind and solar resources, the price of electricity, the emissions intensity of marginal generation, and even line losses; all of which can affect the overall 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. I do still capture some of this variability through the calculation of capacity value (item 4), which reflects the contribution a project makes to reliably matching demand, particularly during peak demand periods when supply is tight. Beyond this it seems reasonable to assume that, to a first order, annual averages should be sufficient for the purpose envisaged here, especially given the focus on the value of projects over their entire lifetime.

To calculate project specific estimates of installed capital costs (item 5) I rely primarily on data from IRENA. For offshore wind I supplement this part of the analysis with direct project specific estimates of offshore wind costs taken from various industry sources. I then make an additional adjustment to account for variation in costs due to economies-of-scale using additional US data from Lawrence Berkeley National Laboratory (LBNL) on relative costs by project size. For ongoing O&M costs (item 6) I also rely primarily on data from IRENA to capture general trends over time. I then supplement this with transmission system charging data from National Grid in order to capture how transmission connection and usage costs vary by location. This ensures that projects connecting to the grid in remote regions have appropriately higher costs than projects located close to demand centers. Full details can be found in the appendix.

Finally, a potentially critical wider benefit of the wind and solar projects under consideration here is learning-by-doing (item 7). The early adoption of these technologies can create learning spillovers that drive down costs, providing an external benefit to future projects and lowering the costs of climate change mitigation (Borenstein, 2012). The rapid decline in the costs of wind and solar power over the past few decades suggests these learning effects could be substantial. However, actually quantifying the value of this kind of learning is very challenging. Here I rely on a paper by Newbery (2018) which sets out a methodology for calculating the maximum justifiable learning-by-doing subsidy for onshore wind and solar power. 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. Given the important role the UK has played in supporting this nascent technology the learning effects could be particularly important. I return to this issue when considering aspects of the results that involve comparing onshore and offshore wind. Full details on my implementation of this method can be found in the appendix.

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 exclusively on forecasts made at the time, or even sometime in the past. Fully tackling these issues would involve assembling a dataset of the same set of key inputs for all past years going back to 1990. This kind of exercise is potentially a paper in its own right, and it is not clear that it would even be feasible to locate the necessary data at this point. As such I continue to use values based on current knowledge and methods, but the limitations of this should be kept in mind when considering the results presented later.

4.1.3 Estimating the determinants of planning approvals

To evaluate the planning process I employ a relatively straightforward regression model that aims to identify which categories of costs and benefits drive project approvals. The observations here are the roughly 3500 wind and solar projects in my sample. The dependent variable is a binary indicator for whether or not a project was approved. The independent variables of interest are the various key costs and benefits associated with each project. All these costs and benefits were calculated as described above and discounted to consistent present value terms. The resulting regression is as follows:

$$approve_{ict} = \beta_1 local_i + \beta_2 nonlocal_i + \theta_t + \lambda_c + \epsilon_{ict} \tag{5}$$

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 impact of a positive change in their respective value categories. I also scale each coefficient such that it reflects the percentage change in approval probability for a £10 million improvement in net benefits. This improvement could be realized through higher benefits (e.g. earning a higher electricity price or displacing a larger amount of emissions) or through lower costs (e.g. cutting the costs of constructing the project or reducing the impacts on nearby property values).

To control for unobservable determinants of planning approvals I also include a set of time, θ, and location, λ, fixed effects. The time fixed effects are year-of-sample and capture general national trends in the likelihood of projects being approved. The location fixed effects are for each local authority and capture general differences in planning processes across jurisdictions. Because local authorities are the administrative units responsible for reviewing planning applications this means the results are identified using within-authority variation from the range of projects that each local authority receives. I estimate these regressions first by pooling across all projects and then separately for wind and solar projects.

This model allows me to test a number of interesting hypotheses. First, for an idealized global social planner we might expect to find that all improvements in new benefits have the same impact on approval likelihood, irrespective of where they occur (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 likely accrue to other countries. However, a local planner might deviate significantly from this. In fact we might reasonably expect them to primarily 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).[15]

To further explore some of the dynamics at work, I extend the analysis to see if there are differential effects based on local political preferences. Survey data consistently shows that strong majorities in the UK express concern about climate change and support for renewable energy, including when asked whether they would be happy to have a large scale renewable energy development in their area (BEIS, 2020*b*). Despite this broad support, it is still the case that concern about climate change and support for renewable energy has tended to be weaker amongst conservative voters (NatCen, 2018). As such political voting behavior could plausibly act as a proxy for variation in local attitudes towards nearby wind and solar projects. To explore this I collect data on local elections 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. Using this data I construct an indicator for whether a local authority is politically conservative based on whether it has a majority of Conservative party councillors. I then interact this with the local and non-local variables to see if the planning process differs in conservative areas relative to more liberal areas.

A second possible source of differential effects that I examine is the impact of a project being decided by the national planning agency rather than at the local level. To do this I now interact the variables of interest with an indicator for whether the planning authority in charge was national or local. It was noted earlier that the decision to review a project at the national level is based on whether the project is larger than 50MW. As such the projects considered by national planners are systematically larger.[16] This is mitigated slightly by the fact that I

[15]Altruistic motivations that extend beyond narrow self-interest are an obvious exception to this though.

[16]I did consider using a Regression Discountinuity design for this part of the analysis. However, the data is simply not rich enough to have enough observations around the threshold. This approach is also undercut by the fact the 50MW threshold is public information and so it can be gamed if developers think having a national

also included the appealed projects in the national planner category. This is because the final decision for these projects was in fact made by the national Planning Inspectorate. Given that the vast majority of projects are below the 50MW threshold, the inclusion of appealed projects has the added benefit of making the split between the numbers of local and national projects more balanced.

4.1.4 Quantifying misallocated investment

The final analysis I conduct is to quantify the extent of insufficient or misallocated investment. A key issue the regression analysis examines is the prospect that not all costs and benefits may be weighed equally during the planning approval process. For example, if particular emphasis were to be placed on avoiding adverse impacts on local property values, the result may be that socially beneficial projects are consistently refused, slowing the deployment of renewable energy. Even if the aggregate deployment of renewable energy is unaffected the planning process could still create a systematic bias towards approving more expensive projects, again on the basis that they have smaller impacts on local property values. This could take the form of building solar power instead of wind, even though the UK has far better wind resources than it does solar potential. Alternatively this misallocation could take the form of building more remote wind projects, or moving projects offshore, even if they are ultimately more socially expensive due to higher construction costs or requirements to transmit power over longer distances.

To try and quantify the potential for insufficient or misallocated investment, I conduct two counterfactual pieces of analysis using my estimates of project specific costs and benefits. For the first approach, I simply examine 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.

As an alternative, I also implement a second approach that produces the observed annual deployment of renewable energy at least cost. To do this I group projects by their actual or

planning decisionmaker is desirable.

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 once again compare the cumulative total social net present value between this "least cost" set of projects and the actual set of projects that were built. This latter approach may still lead to projects with negative net present values being built, but it has the benefit of ensuring it mirrors the pace and scale of renewables deployment seen to date.

4.2 Results

4.2.1 Project costs and benefits

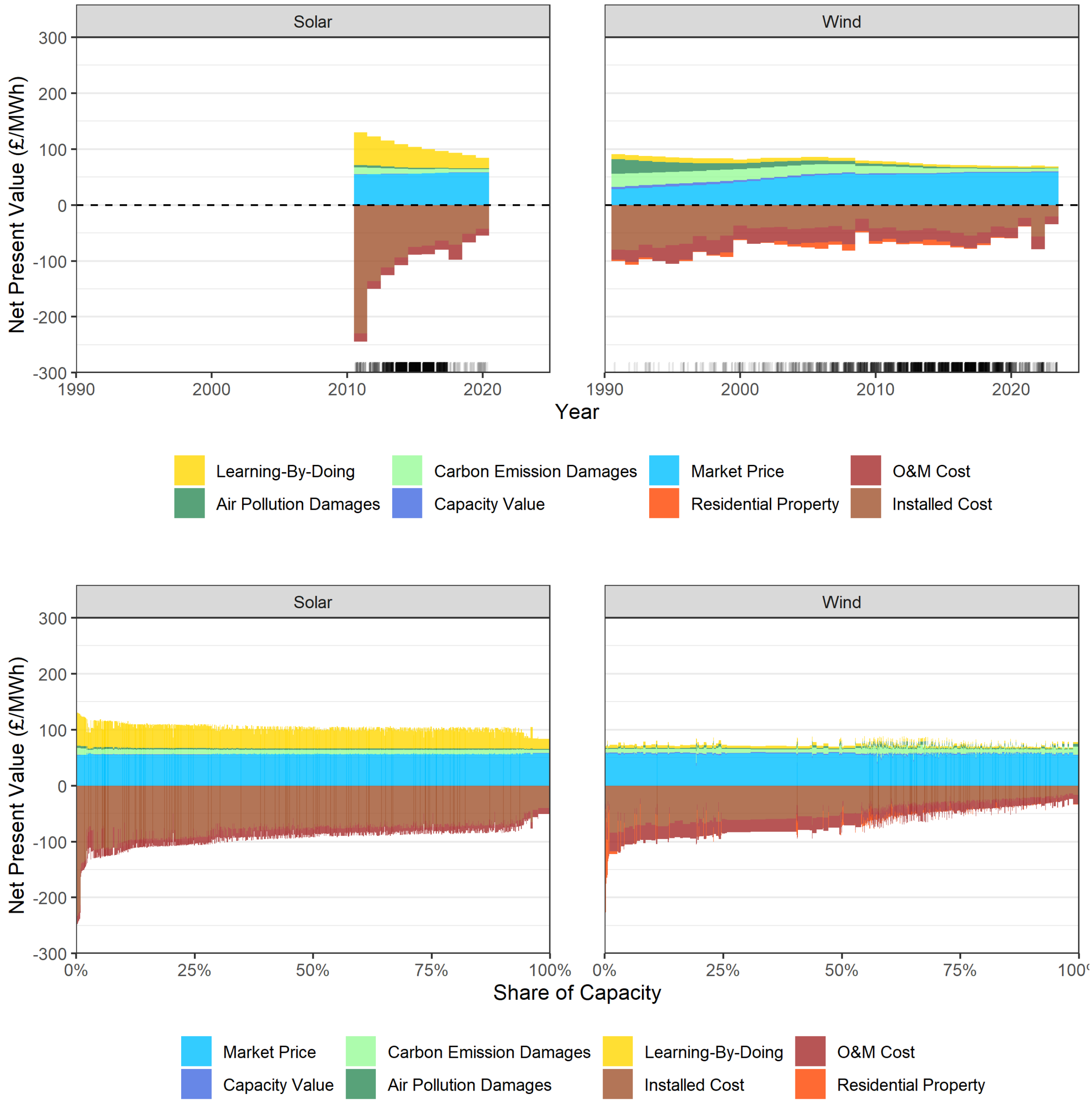
Figure 9 summarizes the estimated costs and benefits for all the wind and solar projects studied here. The top panel shows how annual averages of these costs and benefits have changed over time. The large declines in project capital costs are clearly visible and reflect the substantial technological 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. Plots including the subsidies can be found in the appendix.

4.2.2 Determinants of planning approvals

Table 8 presents the results of the planning process analysis. When only controlling for year fixed effects (columns 1-3) 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 (columns 4-6) the local impacts that have a large, positive and statistically significant effect on the likelihood of receiving planning approval. Here I find that if a wind project imposes £10 million in losses to nearby residential property values, it will be 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 £10 million increase in capital costs or a £10 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 whilst ignoring

Figure 9: Estimated Project Costs and Benefits



Notes: This figures shows the estimated project-level costs and benefits for all the projects submitted for planning approval since 1990. All value categories are consistent with those described earlier and 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 panel 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 panel 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.

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 these non-local factors.

Table 8 also examines whether these effects are heterogeneous by political leaning or the extent of local control of the decision. When looking at the signs of the interaction terms the results are as expected. More conservative areas are more sensitive to local impacts, consistent with a pattern of conservative 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.

Table 8: Planning Process Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Local	0.137	−0.550	0.277	2.956*	2.354	3.049*
	(0.634)	(0.694)	(0.816)	(1.300)	(1.563)	(1.502)
Local (Conservative)		2.854			1.739	
		(1.735)			(2.770)	
Local (National Planner)			−0.542			−0.612
			(1.287)			(2.295)
Non-Local	−0.285***	−0.218*	−1.058	−0.282**	−0.260*	−0.962
	(0.084)	(0.095)	(0.836)	(0.091)	(0.101)	(0.879)
Non-Local (Conservative)		−0.365†			−0.110	
		(0.208)			(0.229)	
Non-Local (National Planner)			0.792			0.686
			(0.841)			(0.881)
R-Squared	0.060	0.066	0.068	0.236	0.235	0.243
N	1810	1804	1810	1810	1804	1810
Wind	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Solar	-	-	-	-	-	-
Year FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
County FE	-	-	-	*Y*	*Y*	*Y*

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

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 £10 million improvement in its respective value category. Wind and solar projects are considered separately.

4.2.3 Misallocated investment

Table 9 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. Consistent with this, the new totals for renewable output match the current totals by construction. 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 9: Misallocated Investment Analysis

	Wind			**Solar**	
Category	**(1)**	**(2)**	**(2*)**	**(1)**	**(2)**
Output (TWh) [Current]	1,226 (284)	1,227 (285)	1,229 (284)	128 (30)	128 (30)
Output (TWh) [New]	1,541 (729)	1,227 (281)	1,226 (282)	153 (89)	128 (29)
Capacity (GW) [Current]	24 (0)	24 (0)	24 (0)	8 (0)	8 (0)
Capacity (GW) [Final]	29 (8)	24 (0)	22 (0)	9 (4)	8 (0)
Total NPV (£bn) [Current]	-0.5 (16.3)	-0.5 (16.3)	-0.5 (16.3)	0.7 (2.0)	0.7 (2.0)
Total NPV (£bn) [Added]	17.6 (9.3)	13.3 (7.0)	7.6 (3.9)	0.7 (0.6)	0.4 (0.5)
Total NPV (£bn) [Removed]	-14.6 (7.5)	-11.2 (7.4)	-3.0 (6.8)	-0.9 (0.8)	0.1 (0.8)
Total NPV (£bn) [Final]	36.9 (21.4)	28.1 (17.3)	10.0 (16.4)	2.7 (2.4)	1.3 (2.0)
Local NPV (£bn) [Current]	-4.5 (2.4)	-4.5 (2.4)	-4.5 (2.4)	0.0 (0.6)	0.0 (0.6)
Local NPV (£bn) [Added]	-1.4 (0.7)	-1.0 (0.2)	-0.2 (0.1)	0.1 (0.2)	0.1 (0.1)
Local NPV (£bn) [Removed]	-3.7 (2.3)	-3.8 (2.2)	-4.3 (2.4)	-0.1 (0.3)	-0.2 (0.3)
Local NPV (£bn) [Final]	-2.4 (1.3)	-1.8 (0.5)	-0.4 (0.1)	0.2 (0.7)	0.3 (0.6)
Δ Total NPV (£bn) [Current $\rightarrow$ Final]	37.4 (6.0)	28.6 (2.1)	10.5 (2.2)	2.0 (0.7)	0.5 (0.2)
Δ Total NPV (£bn) [Current $\rightarrow$ Final (Subset I)]	32.2 (3.3)	24.5 (1.8)	10.7 (3.1)	1.6 (0.5)	0.3 (0.2)
Δ Total NPV (£bn) [Current $\rightarrow$ Final (Subset II)]	13.1 (5.1)	9.9 (4.4)	4.8 (2.3)	0.7 (0.5)	0.2 (0.2)

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, full details of which can be found in the appendix. The relevant inputs are: the discount rate, the market value of electricity, the local property value impacts, the external costs of air pollution, the external costs of climate damages and the learning-by-doing benefits. Values in columns titled (1) give the results of finding the set of projects that have positive net present values. 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 columns titled (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 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. "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 whilst also increasing average local costs.

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.

For solar projects, Table 9 shows that the total net present value of the existing projects is on average quite close to zero (£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. As well as removing costly projects, an even larger number of beneficial projects are added, suggesting there may be reasonable concerns about underinvestment. Total net present value rises to £2 billion. £1.6 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, with some high net benefit projects replacing less valuable ones. 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 9 shows that the total net present value of the existing projects is on average quite close to zero (-£0.5 billion). However, this once again masks potential for significant positive or negative total net present values, with the 95% confidence interval spanning ±£30 billion. As before this is driven by key input assumptions such as the discount rate. The existing set of projects impose significant local impacts on nearby residents, with an average total of £4.5 billion.

In a scenario where all positive net present value projects are completed, there is a 26% increase in wind deployment over this period. As well as removing costly projects, an even larger number of beneficial projects are added, suggesting there may be reasonable concerns about underinvestment. Total net present value rises to £37 billion. £32 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 41% 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 changes to the set of completed projects are less extensive, with some high net benefit projects replacing lower net benefit ones. The potential gains of reallocation amount to £29 billion, £25 billion of which can be achieved by reversing planning decisions. This is equivalent to roughly 32% of the aggregate lifetime capital and operating costs for all the wind projects built over this period.

A major factor in the scale 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 this 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 £11 billion. All these gains can be realized by reversing planning decisions, and are equivalent to roughly 14% 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 prime explanation for the scale of the misallocated investment shown by this analysis is the strong influence of local impacts on planning decisions. If I subset the potential gains further, it is consistently the case that between one third and one half can be achieved by either removing previously approved projects with below average local costs, or adding previously refused projects with above average local costs. This suggests that the kind of NIMBYism concerns raised by the earlier regression analysis in Table 8 do appear to manifest in real economic costs. These costs arise because of an apparent bias toward approving projects with lower local costs, even when these are more costly for society as a whole.

Interestingly though, this leaves the remaining majority of the potential gains as coming from changes in the opposite direction. Given the earlier finding that planning decisionmakers are particularly sensitive to local impacts, it may seem odd that high local cost projects would ever be systematically approved, or that low local cost projects would ever be systematically refused. In fact, it seems that a number of very high cost projects have been approved, often resulting in large relative costs both for the local community and for society as a whole. As evidence for this, Table 9 clearly shows that in all the reallocation scenarios, moving to a more optimal set of projects results in a large fall in local costs from the initial total of £4.5 billion.

The earlier findings on the determinants of planning approvals provide valuable insights into why the planning process may be allowing projects with large local costs to go ahead in many instances. The results in Table 8 showed that any responsiveness to local impacts was only found using the within-county variation. Approval decisions did not appear responsive to variations in local impacts across jurisdictions. This makes sense given that planning decisions are generally made at the local level, and so each decisionmaker has limited exposure to the the range of local costs at projects proposed in other jurisdictions.

Furthermore, the variation in local costs is larger across jurisdictions than it is within jurisdictions. 66% of the variation in the local costs imposed by projects can be explained by differences between counties.[17] This suggests that the failure to coordinate decisions across jurisdictions has the potential to be a larger concern than any particular sensitivity to local costs within jurisdictions.

It is also noteworthy that the national planning guidance emphasizes the need for all localities to do their part in combating climate change through supporting renewable energy. The desire to share the burden of renewable deployment widely may seem understandable on its face. However, the resulting pressure on local authorities to install at least some renewable capacity may be resulting in projects with high local costs being approved, particularly in areas where local costs are high in general. It is likely that in some cases significant gains could be realized by shifting development to areas where local costs are lower in general.

Lastly, the national planning guidance also allows for explicit consideration of cumulative effects in cases where multiple projects have been proposed in the same area. Again, this seems

[17] 66% is the R-squared from regressing project-level local costs on a set of local authority fixed effects.

entirely reasonable and is consistent with a desire not to overburden certain areas. However, this does appear to run contrary to the attenuating nature of the local impacts identified earlier in this study. The intuition that the first wind turbine has a much larger incremental impact than adding a tenth or a hundreth is compelling. The result is that substantial gains could be realized by concentrating capacity at larger projects in fewer areas, especially in areas where local costs are lower in general.[18] Even from an incremental standpoint, siting projects in areas with existing turbines is likely to create less additional local costs than siting projects in completely new areas.

5 Conclusion

In this paper I estimate the economic costs from misallocated investment arising from the planning process for renewable energy projects. I find that wind projects can have significant negative impacts on the surrounding area, 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 is consistent with the fact that 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 societally 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. Interestingly another large share of these misallocation costs also arise from a few smaller projects with relatively large local impacts, pointing to a wider set of issues with the planning process. Solar projects, on the other hand, do not appear to have significant adverse local impacts. This has meant solar projects 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 societal incentives. The most straightforward solution involves making direct transfer payments to affected local residents and businesses. Probably the clearest example of these kind of payments are community benefits funds. These provide payments from the project owner to the local community, usually in the form of grants, awards, stipends for community organiza-

[18] This is especially true in the context of renewable energy where the good being produced is perfectly homogenous and is provided over a national network that largely removes the need for siting supply locally.

tions or even discounts on electricity bills. The decision to provide these community benefits is currently voluntary so they can vary significantly in prevalence, size and structure. Public registers where developers provide information on their community engagement suggest that funds for onshore wind projects have often amounted to around £2,000-3,000/MW/yr. The latest government guidance calls for developers to adopt funds with a value of £5,000/MW/yr. Whether this guidance is being followed is hard to gauge, but the most recent register information for Scotland indicates that for many projects it is.

My analysis suggests the local impacts of wind projects on local property values have a median of around £3,500/MW/yr, which may suggest that the current scale of support being negotiated is appropriate. However, this masks significant heterogeneity in local impacts: the top 25% of projects have local impacts greater than £21,000/MW/yr and the top 10% have local impacts greater than £75,000/MW/yr. As such there may be an argument for significantly increasing the value of community payments in certain instances to more adequately compensate local residents. This should help prevent societally beneficial projects being refused planning permission purely on the grounds that they create local impacts that are not being adequately offset by an equivalent level of local compensation.

The heterogeneity in local impacts also points to another way in which transfer payments could be beneficial that has yet to be tested. My analysis indicates that several projects with large local costs have gone ahead. It is possible that this could be because planning officials and local residents sometimes misperceive the true local impacts, or there is a lack of political power amongst the affected communities to resist development. However, my analysis suggests that this may also be due to a coordination problem across jurisdictions. If building wind and solar capacity does indeed impose a declining incremental cost on local communities, there is a compelling argument for avoiding the tendency to "share the burden" by installing at least some capacity in most jurisdictions. Instead there could be large gains from concentrating more capacity at larger projects in a smaller number of designated areas.

This has clear distributional consequences for the communities that are exposed to this kind of concentrated deployment of renewable energy. However, making transfer payments between jurisdictions could provide the necessary compensation to facilitate a more societally beneficial reallocation of investment. In this case communities that do not want to be exposed to new renewable energy deployment would make payments that compensate other communities that are willing to host a more concentrated deployment of renewable energy nearby. Ensuring both communities get appropriate credit for investing in renewable deployment could go a long way to ensuring all jurisdictions share the financial burden, even if they are not all physically hosting capacity.

An alternative to providing compensation payments is outright local ownership. This has certainly been growing and there is some evidence in the UK that the direct local benefits provided by these projects are in fact much larger than for privately owned projects. A key challenge here is scalability. There is currently roughly 250MW of community owned capacity in the UK (Braunholtz-Speight et al., 2018). This represents about 1% of total renewable electricity generation. Whilst it might be possible for this to be increased, it seems unlikely that local communities can deploy the kind of financial and technical resources that larger private companies can in order to roll out renewable energy at the scale and pace required.

A final option raised by the findings in this paper could be to give national planning officials a larger role in the approval process. My analysis suggests that national decisionmakers have a more balanced approach to weighing the local and non-local costs and benefits of these projects. This may be because national planning officials are less beholden to local political considerations, or perhaps they are just more likely to have the necessary institutional capacity to effectively consider projects at this scale. In either case more national oversight and support might be beneficial, especially if it can facilitate better coordination across local jurisdictions. This could be achieved by setting stricter national planning guidelines, lowering the threshold for projects to be moved from local to national jurisdiction, or by streamlining the appeal process. One potential downside of this 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.

Ultimately finding the best policy solution will require further research and experimentation. The findings in this paper on the costs imposed by the existing planning process suggest this work is sorely needed.

References

BEIS. 2020*a*. "Energy Trends 2020." Department for Business, Energy & Industrial Strategy Technical Report.

BEIS. 2020*b*. "Public Attitudes Tracker." Department for Business, Energy & Industrial Strategy Technical Report.

Bell, Derek, Tim Gray, Claire Haggett, and Joanne Swaffield. 2013. "Re-visiting the 'social gap': public opinion and relations of power in the local politics of wind energy." *Environmental Politics*, 22(1): 115–135.

Bellego, Christophe, and Louis-Daniel Pape. 2019. "Dealing with the log of zero in regression models." Center for Research in Economics and Statistics Working Papers 13.

Bishop, Kelly C, Nicolai V Kuminoff, H Spencer Banzhaf, Kevin J Boyle, Kathrine von Gravenitz, Jaren C Pope, V Kerry Smith, and Christopher D Timmins. 2020. "Best Practices for Using Hedonic Property Value Models to Measure Willingness to Pay for Environmental Quality." *Review of Environmental Economics and Policy*, 14(2): 260–281.

Borenstein, Severin. 2012. "The Private and Public Economics of Renewable Electricity Generation." *Journal of Economic Perspectives*, 26(1): 67–92.

Borenstein, Severin, and James B Bushnell. 2018. "Do Two Electricity Pricing Wrongs Make a Right? Cost Recovery, Externalities, and Efficiency." National Bureau of Economic Research Working Paper 24756.

Borusyak, Kirill, and Xavier Jaravel. 2017. "Revisiting Event Study Designs." *Available at SSRN 2826228.*

Braunholtz-Speight, Tim, Sarah Mander, Matthew Hannon, Jeff Hardy, Carly McLachlan, Ed Manderson, and Maria Sharmina. 2018. "The Evolution of Community Energy in the UK." Working paper, London:UKERC.

Burningham, Kate, Julie Barnett, and Gordon Walker. 2015. "An Array of Deficits: Unpacking NIMBY Discourses in Wind Energy Developers' Conceptualizations of Their Local Opponents." *Society & Natural Resources*, 28(3): 246–260.

Callaway, Brantly, and Pedro H. C. Sant'Anna. 2019. "Difference-in-Differences with Multiple Time Periods." *SSRN Working Paper.*

Callaway, Duncan S., Meredith Fowlie, and Gavin McCormick. 2018. "Location, Location, Location: The Variable Value of Renewable Energy and Demand-Side Efficiency Resources." *Journal of the Association of Environmental and Resource Economists*, 5(1): 39 – 75.

Costa, Hélia, and Linda Veiga. 2019. "Local labor impact of wind energy investment: an analysis of Portuguese municipalities." *TSE Working Paper*.

Cuckovic, Zoran. 2016. "Advanced viewshed analysis: a Quantum GIS plug-in for the analysis of visual landscapes." *Journal of Open Source Software*, 1(4): 32.

Currie, Janet, Lucas Davis, Michael Greenstone, and Reed Walker. 2015. "Environmental Health Risks and Housing Values: Evidence from 1,600 Toxic Plant Openings and Closings." *American Economic Review*, 105(2): 678–709.

Davis, Lucas W. 2011. "The Effect of Power Plants on Local Housing Values and Rents." *The Review of Economics and Statistics*, 93(4): 1391–1402.

Dröes, Martijn, and Hans R.A. Koster. 2020. "Wind turbines, solar farms, and house prices." C.E.P.R. Discussion Papers CEPR Discussion Papers 15023.

Dröes, Martijn I., and Hans R.A. Koster. 2016. "Renewable energy and negative externalities: The effect of wind turbines on house prices." *Journal of Urban Economics*, 96: 121 – 141.

Gaur, Vasundhara, and Corey Lang. 2020. "Property Value Impacts of Commercial-Scale Solar Energy in Massachusetts and Rhode Island." *Working Paper*.

Gibbons, Stephen. 2015. "Gone with the wind: Valuing the visual impacts of wind turbines through house prices." *Journal of Environmental Economics and Management*, 72: 177 – 196.

Gibbons, Stephen, Susana Mourato, and Guilherme M. Resende. 2014. "The Amenity Value of English Nature: A Hedonic Price Approach." *Environmental and Resource Economics*, 57.

Glaeser, Edward, and Joseph Gyourko. 2018. "The Economic Implications of Housing Supply." *Journal of Economic Perspectives*, 32(1): 3–30.

Goodman-Bacon, Andrew. 2018. "Difference-in-Differences with Variation in Treatment Timing." National Bureau of Economic Research Working Paper 25018.

Greenstone, Michael, and Enrico Moretti. 2003. "Bidding for Industrial Plants: Does Winning a 'Million Dollar Plant' Increase Welfare?" National Bureau of Economic Research Working Paper 9844.

Haan, Peter, and Martin Simmler. 2018. "Wind electricity subsidies — A windfall for landowners? Evidence from a feed-in tariff in Germany." *Journal of Public Economics*, 159(C): 16–32.

Harrison, Gareth P, Samuel L Hawkins, Dan Eager, and Lucy C Cradden. 2015. "Capacity value of offshore wind in Great Britain." *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 229(5): 360–372.

Hoen, Ben, and Carol Atkinson-Palombo. 2016. "Wind Turbines, Amenities and Disamenities: A Study of Home Value Impacts in Densely Populated Massachusetts." *Journal of Real Estate Research*, 38: 473–504.

Hoen, Ben, Jeremy Firestone, Joseph Rand, Debi Elliott, Gundula Hübner, Johannes Pohl, Ryan H. Wiser, Eric Lantz, Ryan Haac, and Ken Kaliski. 2019. "Attitudes of U.S. Wind Turbine Neighbors: Analysis of a Nationwide Survey." *Energy Policy*, 134.

Hsieh, Chang-Tai, and Enrico Moretti. 2019. "Housing Constraints and Spatial Misallocation." *American Economic Journal: Macroeconomics*, 11(2): 1–39.

IEA. 2018. "World Energy Outlook 2018." International Energy Agency Technical Report.

Jensen, Cathrine Ulla, Toke Emil Panduro, Thomas Hedemark Lundhede, Anne Sofie Elberg Nielsen, Mette Dalsgaard, and Bo Jellesmark Thorsen. 2018. "The impact of on-shore and off-shore wind turbine farms on property prices." *Energy Policy*, 116: 50 – 59.

Keiser, David A, and Joseph S Shapiro. 2018. "Consequences of the Clean Water Act and the Demand for Water Quality*." *The Quarterly Journal of Economics*, 134(1): 349–396.

Lang, Corey, James J. Opaluch, and George Sfinarolakis. 2014. "The windy city: Property value impacts of wind turbines in an urban setting." *Energy Economics*, 44: 413 – 421.

NatCen. 2018. "British Social Attitudes: The 35th Report." The National Centre for Social Research Technical Report.

Newbery, David. 2018. "Evaluating the case for supporting renewable electricity." *Energy Policy*, 120: 684 – 696.

NGET. 2019. "Future Energy Scenarios 2019." National Grid Electricity Transmission Technical Report.

Ong, Sean, Clinton Campbell, Paul Denholm, Robert Margolis, and Garvin Heath. 2013. "Land-Use Requirements for Solar Power Plants in the United States." *NREL Technical Report*, TP-6A20-56290.

Rand, Joseph, and Ben Hoen. 2017. "Thirty years of North American wind energy acceptance research: What have we learned?" *Energy Research & Social Science*, 29: 135 – 148.

Roddis, Philippa, Stephen Carver, Martin Dallimer, Paul Norman, and Guy Ziv. 2018. "The role of community acceptance in planning outcomes for onshore wind and solar farms: An energy justice analysis." *Applied Energy*, 226: 353 – 364.

Stokes, Leah C. 2016. "Electoral Backlash against Climate Policy: A Natural Experiment on Retrospective Voting and Local Resistance to Public Policy." *American Journal of Political Science*, 60(4): 958–974.

Sunak, Yasin, and Reinhard Madlener. 2016. "The impact of wind farm visibility on property values: A spatial difference-in-differences analysis." *Energy Economics*, 55: 79 – 91.

Tanaka, Shinsuke, and Jeffrey Zabel. 2018. "Valuing nuclear energy risk: Evidence from the impact of the Fukushima crisis on U.S. house prices." *Journal of Environmental Economics and Management*, 88(C): 411–426.

von Graevenitz, Kathrine. 2018. "The amenity cost of road noise." *Journal of Environmental Economics and Management*, 90: 1 – 22.

Winikoff, Justin. 2019. "Learning by Regulating: The Evolution of Wind Energy Zoning Laws." *Job Market Paper*.

Wolsink, Maarten. 2000. "Wind power and the NIMBY-myth: institutional capacity and the limited significance of public support." *Renewable Energy*, 21(1): 49 – 64.

A Appendix

Contents

A.1 Capitalization Analysis Detail

A.1.1 Geospatial analysis of project 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 A.1. 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, whilst much of the base of the turbine is obscured).

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.1.2 Additional Residential Capitalization Results

Wind projects

Table A.1 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.

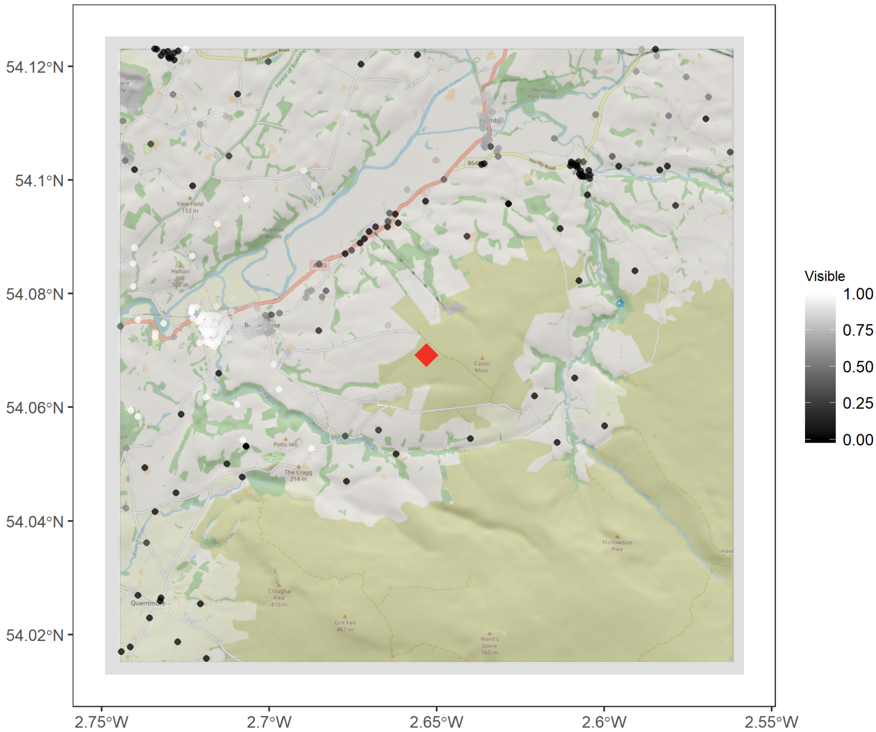
Lastly, Table A.2 shows the results of the differential effects analysis. Note that these results also use the approach of estimating five separate regressions for a series of expanding distance circles.

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, such as the land area covered by the solar panels, or the number of wind turbines. In the case of solar projects, the relationship between total capacity and the land area covered has been broadly stable. For wind projects though, the relationship between total capacity and the number of turbines has been changing as turbines have gotten larger.

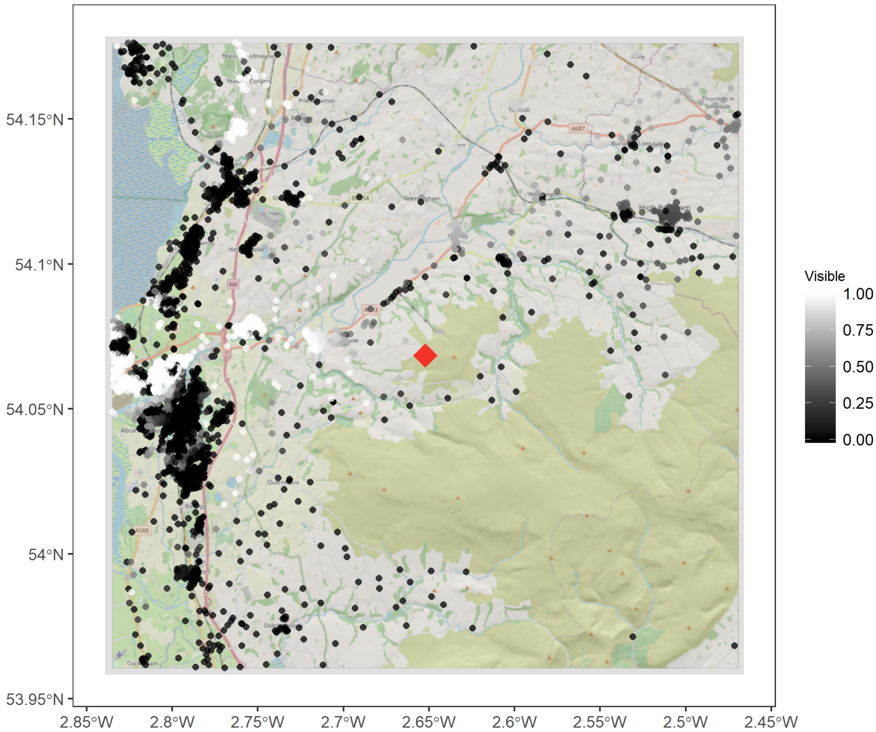
To explore the possible implications of this for the findings on wind projects, I re-run the capitalization analysis with number of turbines as the measure of project size, rather than total capacity. Table A.3 shows that the results are largely unchanged. In fact the coefficient sizes are broadly similar because the average size of wind turbines over this period has tended to be on the order of around 1MW.

Solar projects

Figure A.1: 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. The black and white points are postcodes. Black points do not have direct line-of-sight. White points do have direct line-of-sight.

Table A.1: 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: Point estimates based on the event study specifications 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.

Table A.2: *Residential Capitalization for Wind Projects with Differential Effects*

	(0-2km)	(0-4km)	(0-6km)	(0-8km)	(0-10km)
Completed					
, Not Visible, Deprived		-0.76	-0.44	0.34	0.34
		(0.95)	(0.47)	(0.30)	(0.21)
, Not Visible, Not Deprived		-4.20^{***}	-3.77^{***}	-2.33^{***}	-1.24^{***}
		(0.90)	(0.53)	(0.36)	(0.28)
, Visible, Deprived	-0.18	-1.33^{***}	-0.03	0.31	0.32^{*}
	(0.77)	(0.33)	(0.20)	(0.16)	(0.13)
, Visible, Not Deprived	-5.86^{***}	-4.17^{***}	-1.62^{***}	-0.83^{**}	-1.29^{***}
	(0.96)	(0.49)	(0.31)	(0.25)	(0.20)
Failed					
, Not Visible, Deprived		3.75^{***}	2.24^{***}	1.51^{***}	0.85^{***}
		(0.80)	(0.42)	(0.28)	(0.20)
, Not Visible, Not Deprived		2.92^{**}	2.36^{***}	0.35	-0.50
		(0.93)	(0.55)	(0.36)	(0.29)
, Visible, Deprived	1.43^{*}	1.08^{**}	0.75^{**}	0.57^{**}	0.39^{**}
	(0.58)	(0.31)	(0.22)	(0.17)	(0.13)
, Visible, Not Deprived	5.39^{***}	3.94^{***}	2.11^{***}	1.08^{***}	0.19
	(0.99)	(0.46)	(0.29)	(0.24)	(0.20)
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: Point estimates based on the event study specifications 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.

Table A.3: *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: Point estimates based on the event study specifications 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.

Table A.4 largely confirms the findings in the event study plot, with again no consistent effect emerging across a range of specifications.

Table A.4: 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: Point estimates based on the event study specifications 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.

Table A.5 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 A.5: Residential Capitalization for Solar Projects with Differential Effects

	(0-1km)	(0-2km)	(0-3km)	(0-4km)	(0-5km)
Completed					
, Not Visible, Deprived	1.09	1.00	0.24	0.16	−0.22
	(1.23)	(0.49)	(0.32)	(0.21)	(0.16)
, Not Visible, Not Deprived	−2.42	0.45	0.11	0.48	0.00
	(3.03)	(1.05)	(0.56)	(0.39)	(0.30)
, Visible, Deprived	1.01	0.28	0.34	0.51	0.59**
	(1.09)	(0.41)	(0.28)	(0.23)	(0.19)
, Visible, Not Deprived	−6.15	0.46	1.03	1.20*	0.76
	(2.93)	(0.85)	(0.55)	(0.42)	(0.36)
Failed					
, Not Visible, Deprived	0.08	0.70	−0.04	−0.47	−0.28
	(2.47)	(0.82)	(0.43)	(0.30)	(0.25)
, Not Visible, Not Deprived	2.64	0.23	2.08**	1.31*	0.74
	(4.45)	(1.08)	(0.70)	(0.50)	(0.40)
, Visible, Deprived	−0.47	−0.63	−0.77	−1.15*	−1.01**
	(1.93)	(0.72)	(0.59)	(0.45)	(0.35)
, Visible, Not Deprived	−1.67	1.02	−0.15	−1.02	−1.29*
	(5.05)	(1.23)	(0.86)	(0.67)	(0.53)
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: Point estimates based on the event study specifications 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.

A.1.3 Additional Commercial Capitalization Results

Wind projects

Table A.6 largely confirms the findings in the event study plot. There is a pronounced 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.

Table A.6: 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: Point estimates based on the event study specifications 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.

Table A.7 shows the results of the analysis of differential effects for wind projects. Here again there is no consistent evidence of a statisically significant effect. Interestingly the properties with direct line-of-sight to appealed projects do have the largest reductions, and this is precisely the category we would expect to have the most pronounced effects.

Table A.7: Commercial Capitalization for Wind Projects with Differential Effects

	(0-2km)	(0-4km)	(0-6km)	(0-8km)	(0-10km)
Completed					
, Not Visible, Deprived		2.75	−2.43	−1.86	−1.72
		(4.89)	(2.51)	(1.62)	(1.16)
, Not Visible, Not Deprived		−0.47	−1.62	−0.90	−2.24*
		(2.40)	(1.36)	(1.05)	(0.84)
, Visible, Deprived	−3.79	−3.43	−2.22	−0.68	−1.26
	(4.26)	(2.15)	(1.51)	(1.10)	(0.95)
, Visible, Not Deprived	−4.99	−1.92	−0.52	−1.64	−1.45
	(3.24)	(1.82)	(1.38)	(1.03)	(0.87)
Failed					
, Not Visible, Deprived		0.24	1.57	0.75	0.87
		(2.56)	(1.48)	(1.12)	(0.82)
, Not Visible, Not Deprived		−4.06	−2.01	−0.99	−0.31
		(3.02)	(1.52)	(1.16)	(0.90)
, Visible, Deprived	0.27	0.51	−0.84	−1.94	−0.15
	(2.20)	(1.53)	(1.20)	(0.94)	(0.79)
, Visible, Not Deprived	4.60	0.80	0.28	−0.10	0.35
	(2.46)	(1.76)	(1.18)	(0.92)	(0.80)
R-Squared	0.95	0.94	0.94	0.94	0.94
N (millions)	0.04	0.09	0.13	0.17	0.20

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

Notes: Point estimates based on the event study specifications 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.

Solar projects

Table A.8 largely confirms the findings in the event study plot. 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 A.9 shows the results of the analysis of differential effects for wind projects. Here again there is no consistent evidence of a statisically significant effect.

Table A.8: 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: Point estimates based on the event study specifications 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.

Table A.9: Commercial Capitalization for Solar Projects with Differential Effects

	(0-1km)	(0-2km)	(0-3km)	(0-4km)	(0-5km)
Completed					
, Not Visible, Deprived	−1.35	−1.46	−0.48	−0.20	−0.62
	(3.05)	(1.92)	(1.21)	(0.96)	(0.92)
, Not Visible, Not Deprived	−7.52	−4.38	−5.57**	−1.93	−0.71
	(5.64)	(2.92)	(1.83)	(1.40)	(1.05)
, Visible, Deprived	−3.82	−1.42	−2.08	−0.44	−0.31
	(2.48)	(1.51)	(1.13)	(0.95)	(0.85)
, Visible, Not Deprived	−0.23	−2.70	−1.00	−1.25	−1.82
	(4.21)	(2.36)	(1.62)	(1.57)	(1.36)
Failed					
, Not Visible, Deprived	−1.85	1.66	−1.97	−0.50	−0.88
	(3.69)	(2.05)	(1.53)	(1.24)	(1.08)
, Not Visible, Not Deprived	0.83	−1.94	−0.62	−1.00	−1.53
	(6.12)	(3.61)	(2.07)	(1.57)	(1.48)
, Visible, Deprived	1.54	0.58	1.04	−0.15	−0.11
	(2.53)	(1.96)	(1.74)	(1.43)	(1.23)
, Visible, Not Deprived	0.67	−2.84	−0.56	0.82	2.85
	(4.66)	(2.98)	(2.13)	(2.22)	(2.10)
R-Squared	0.95	0.94	0.94	0.94	0.94
N (millions)	0.04	0.08	0.13	0.17	0.21

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

Notes: Point estimates based on the event study specifications 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.

A.1.4 Employment Impacts

To provide some additional supporting evidence for the analysis on commercial property values I also examine impacts on employment. In principle we might expect that any impacts on employment would in turn be capitalized into the value of commercial properties that support that employment, and vice versa. For example, if a wind project adversely affects nearby tourism, this might lower the rental value of hotels whilst also leading to a reducting in employment at those same hotels, especially if they close. Similarly, if a wind project boosts local employment through the provision of new jobs during construction or maintainence, this may lead to an appreciation in property values and rents.

To do this I collect data on employment by sector from the ONS Business Register and Employment Surveys for the period 2003 to 2017. The data is available at the LSOA level, so the level of spatial granularity is the same as for the commercial rents data. However, the data is available for a much more detailed set of subsectors - eighty five instead of the four in the commercial rents data. I select from these the eight sectors that are most likely to be affected by a nearby wind or solar project: Agriculture, Accomodation, Tourism, Restaurants, Retail, Leisure, Real Estate, Construction, Civil Engineering and Utilities. Summary statistics can be seen in Table A.10.

Table A.10: Employment Summary Statistics

	Total	Agriculture	Accommodation	Tourism	Restaurants	Retail	Leisure	RealEstate	Construction	CivilEng	Utilities
Employees	535.3	3.633	8.546	5.576	30.66	52.99	9.017	13.09	8.167	4.721	26.47
	(1810.8)	(14.70)	(39.93)	(35.85)	(119.5)	(231.4)	(44.98)	(83.33)	(33.43)	(28.72)	(143.6)
Sector Employee Share	100	1.219	1.680	0.478	6.366	7.755	2.049	2.984	2.227	1.349	1.863
	(0)	(4.664)	(4.425)	(1.938)	(10.97)	(13.68)	(5.675)	(7.119)	(4.142)	(3.176)	(7.589)
Rural	0.212	0.518	0.235	0.232	0.226	0.221	0.234	0.236	0.219	0.227	0.297
	(0.400)	(0.483)	(0.415)	(0.411)	(0.409)	(0.406)	(0.414)	(0.415)	(0.405)	(0.410)	(0.443)
Index of Multiple Deprivation	21.46	17.23	21.34	21.18	21.37	21.31	20.61	19.34	20.64	20.18	22.05
	(15.42)	(11.82)	(15.14)	(14.95)	(15.22)	(15.28)	(15.04)	(14.64)	(14.86)	(14.48)	(14.56)
N (millions)	0.67	0.12	0.54	0.21	0.58	0.61	0.50	0.47	0.62	0.59	0.04

Notes: This table shows means and standard deviations 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.

To estimate the impacts on employment I employ exactly the same regression approach set out for the hedonic capitalization analysis. The only difference is that this time the dependent variable is the log of employment, rather than the log of property prices or rents. The results are summarized in Table A.11 for wind projects and Table A.12 for solar projects. In both cases I fail to find any statistically significant effects, even for the eight more detailed sub-sectors I examine. This is consistent with the results for commercial rents, and is again likely indicative of a lack of statistical power.

Table A.11: Employment Results for Wind Projects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Completed											
0to2km	11.14	22.86	26.14	67.05	14.01	−9.92	−45.11*	−10.95	−29.46	−34.03	0.51
	(8.93)	(27.14)	(15.57)	(29.89)	(17.43)	(16.22)	(19.01)	(16.85)	(15.55)	(44.97)	(21.55)
2to4km	0.35	−2.91	11.03	−28.67	−0.85	7.39	16.97	−12.69	14.48	−54.88	−35.80*
	(5.71)	(17.21)	(9.12)	(19.44)	(9.90)	(9.76)	(11.36)	(9.59)	(8.53)	(37.58)	(13.39)
4to6km	−1.87	−14.30	0.99	16.71	3.78	−7.05	5.27	5.46	1.07	50.52	7.03
	(3.72)	(13.93)	(6.43)	(12.80)	(7.30)	(6.83)	(7.75)	(6.75)	(6.28)	(33.11)	(9.00)
6to8km	−0.07	8.99	−1.18	4.85	−5.62	2.88	−6.26	0.25	13.36*	19.35	0.88
	(3.08)	(11.27)	(5.68)	(10.96)	(5.85)	(5.54)	(7.08)	(6.04)	(5.43)	(29.79)	(6.89)
8to10km	0.37	5.70	−1.42	−1.46	8.57	3.68	1.66	1.39	−2.65	−10.02	4.71
	(2.64)	(9.37)	(4.65)	(9.84)	(4.68)	(4.67)	(5.44)	(4.25)	(4.29)	(17.46)	(6.13)
Failed											
0to2km	4.10	−30.13	15.49	32.49	2.90	−13.70	6.47	−7.87	13.77	−30.94	−15.84
	(6.16)	(20.31)	(14.95)	(21.32)	(16.51)	(12.18)	(13.17)	(11.97)	(11.91)	(46.27)	(16.23)
2to4km	1.97	35.43	−12.00	−13.53	−6.90	−1.20	−5.63	−10.23	−15.58	14.03	7.74
	(4.81)	(16.69)	(8.20)	(14.66)	(9.41)	(8.11)	(9.14)	(7.54)	(7.74)	(33.30)	(11.30)
4to6km	0.15	−7.08	4.89	9.80	−0.93	−8.76	−0.80	−1.90	6.90	13.42	−2.73
	(3.90)	(10.79)	(6.05)	(11.22)	(6.83)	(6.15)	(6.76)	(5.51)	(6.01)	(24.76)	(7.92)
6to8km	0.57	−2.09	−0.01	8.63	−15.39*	−3.74	0.41	−0.59	2.05	26.96	−15.19
	(3.60)	(9.26)	(4.66)	(9.20)	(5.63)	(5.27)	(5.65)	(4.83)	(4.68)	(23.09)	(6.67)
8to10km	0.71	−1.89	5.15	−3.88	12.63*	0.45	6.01	−2.34	4.06	−12.34	1.54
	(2.47)	(7.51)	(3.97)	(7.48)	(4.57)	(4.26)	(4.65)	(3.94)	(3.91)	(16.16)	(5.50)
R-Squared	0.73	0.36	0.71	0.46	0.65	0.67	0.58	0.54	0.56	0.43	0.45
N (millions)	0.42	0.08	0.34	0.13	0.37	0.38	0.31	0.39	0.37	0.03	0.29
Log Functional Form	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Event Study	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
LSOA Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Region-Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Total Sector	Y	–	–	–	–	–	–	–	–	–	–
Agriculture Sector	–	Y	–	–	–	–	–	–	–	–	–
Accommodation Sector	–	–	Y	–	–	–	–	–	–	–	–
Tourism Sector	–	–	–	Y	–	–	–	–	–	–	–
Restaurants Sector	–	–	–	–	Y	–	–	–	–	–	–
Retail Sector	–	–	–	–	–	Y	–	–	–	–	–
Leisure Sector	–	–	–	–	–	–	Y	–	–	–	–
Construction Sector	–	–	–	–	–	–	–	Y	–	–	–
CivilEng Sector	–	–	–	–	–	–	–	–	Y	–	–
Utilities Sector	–	–	–	–	–	–	–	–	–	Y	–
RealEstate Sector	–	–	–	–	–	–	–	–	–	–	Y

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

Notes: Point estimates based on the event study specifications 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 employment resulting from adding 10 MW of capacity at a given distance away.

Table A.12: Employment Results for Solar Projects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Completed											
0to1km	−2.43	−43.25	2.47	48.44	−9.13	−7.57	9.24	17.86	41.91	−95.06	−40.33
	(5.42)	(30.64)	(24.10)	(34.68)	(20.82)	(20.10)	(25.05)	(19.31)	(22.22)	(70.10)	(23.97)
1to2km	−11.06	−2.23	−37.13	7.48	5.97	−1.08	−9.41	6.40	2.75	−43.75	15.00
	(5.32)	(27.11)	(17.89)	(29.52)	(18.53)	(15.94)	(19.79)	(17.28)	(16.35)	(63.19)	(20.35)
2to3km	5.19	−14.42	−9.71	12.10	−8.50	14.00	−8.90	5.41	−16.28	25.01	−2.71
	(4.80)	(21.14)	(12.10)	(21.57)	(13.50)	(11.13)	(15.24)	(12.90)	(11.68)	(62.27)	(15.04)
3to4km	1.25	19.91	9.23	−30.77	3.18	−12.77	18.97	−17.69	1.35	−28.93	−0.60
	(3.81)	(17.54)	(10.67)	(17.56)	(10.87)	(9.58)	(13.04)	(10.56)	(9.70)	(58.77)	(12.81)
4to5km	−2.70	6.15	−11.56	−3.95	0.14	−4.98	−3.82	2.55	−0.92	−8.54	16.88
	(2.61)	(13.44)	(8.30)	(13.20)	(8.35)	(7.44)	(10.10)	(8.44)	(7.65)	(37.84)	(9.35)
Failed											
0to1km	4.44	−53.80	14.15	55.47	35.31	17.80	−42.24	2.81	−12.24	197.14	47.15
	(7.66)	(37.79)	(34.39)	(41.86)	(28.28)	(26.16)	(31.85)	(30.37)	(30.65)	(116.53)	(36.54)
1to2km	5.02	13.30	−34.91	−25.17	−34.25	29.98	60.19^{*}	−15.57	−6.46	−27.90	−40.38
	(7.48)	(31.77)	(25.17)	(33.68)	(23.22)	(21.12)	(25.08)	(23.28)	(22.05)	(130.81)	(28.98)
2to3km	−6.30	−36.96	11.29	38.91	23.85	−29.17	−39.69	18.67	4.63	84.95	−6.63
	(5.92)	(26.29)	(19.36)	(27.85)	(18.63)	(16.30)	(20.53)	(20.17)	(17.82)	(98.09)	(22.28)
3to4km	5.25	31.52	−14.63	−24.64	−12.18	5.41	23.81	−26.15	14.56	−87.08	14.36
	(6.07)	(25.52)	(14.13)	(22.97)	(16.04)	(15.15)	(18.33)	(16.83)	(15.14)	(74.73)	(18.82)
4to5km	−2.65	27.51	0.24	13.46	18.48	−0.42	−3.99	4.86	1.70	−10.07	1.65
	(4.22)	(18.75)	(10.85)	(17.20)	(11.61)	(11.25)	(12.80)	(12.35)	(10.97)	(56.89)	(13.14)
R-Squared	0.73	0.38	0.72	0.44	0.66	0.68	0.59	0.55	0.58	0.45	0.46
N (millions)	0.26	0.06	0.22	0.09	0.23	0.24	0.20	0.25	0.24	0.02	0.19
Log Functional Form	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Event Study	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
LSOA Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Region-Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Total Sector	Y	–	–	–	–	–	–	–	–	–	–
Agriculture Sector	–	Y	–	–	–	–	–	–	–	–	–
Accommodation Sector	–	–	Y	–	–	–	–	–	–	–	–
Tourism Sector	–	–	–	Y	–	–	–	–	–	–	–
Restaurants Sector	–	–	–	–	Y	–	–	–	–	–	–
Retail Sector	–	–	–	–	–	Y	–	–	–	–	–
Leisure Sector	–	–	–	–	–	–	Y	–	–	–	–
Construction Sector	–	–	–	–	–	–	–	Y	–	–	–
CivilEng Sector	–	–	–	–	–	–	–	–	Y	–	–
Utilities Sector	–	–	–	–	–	–	–	–	–	Y	–
RealEstate Sector	–	–	–	–	–	–	–	–	–	–	Y

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

Notes: Point estimates based on the event study specifications 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 employment resulting from adding 10 MW of capacity at a given distance away.

A.2 Evaluating the Planning Process Detail

A.2.1 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 A.13. 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 3% 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 A.13 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, although this evidence is mixed and only emerges clearly when looking at appealed projects. In this case the effect on a visible property at 0-2km rises to 6%. 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 A.13 shows that the assumed effects for visible properties are twice as large as those for non-visible 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 A.13.

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 also 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. To reflect this 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 A.13 allow for impacts on the order of 1.5% either way within 1km.

Table A.13: 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 of a wind or solar project into the value of a nearby residential property. Values shown are the equivalent % change in property values for a 10MW project. The actual logarithmic coefficients can be calculated by dividing these values by ln(10).

A.2.2 Value of local property

Too 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 whilst 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 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.

The process of estimating the value of all commercial properties near each project is more straightforward. The same LSOA data from the VOA that was used in the capitalization analysis is sufficient for England & Wales in that it provides both average values and numbers of commercial properties for each LSOA. I supplement this with comparable data for Scotland from the Scottish Government's Local Government Financial Statistics. These are at the more aggregated local authority level but are otherwise equivalent in that they include both average values and numbers of commercial properties. As with the residential property values I once again conduct a downscaling exercise using the same approach set out above.

A.2.3 Capacity factors

To estimate the main benefits of the electricity produced by a wind or solar project (items 1 to 3) 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.

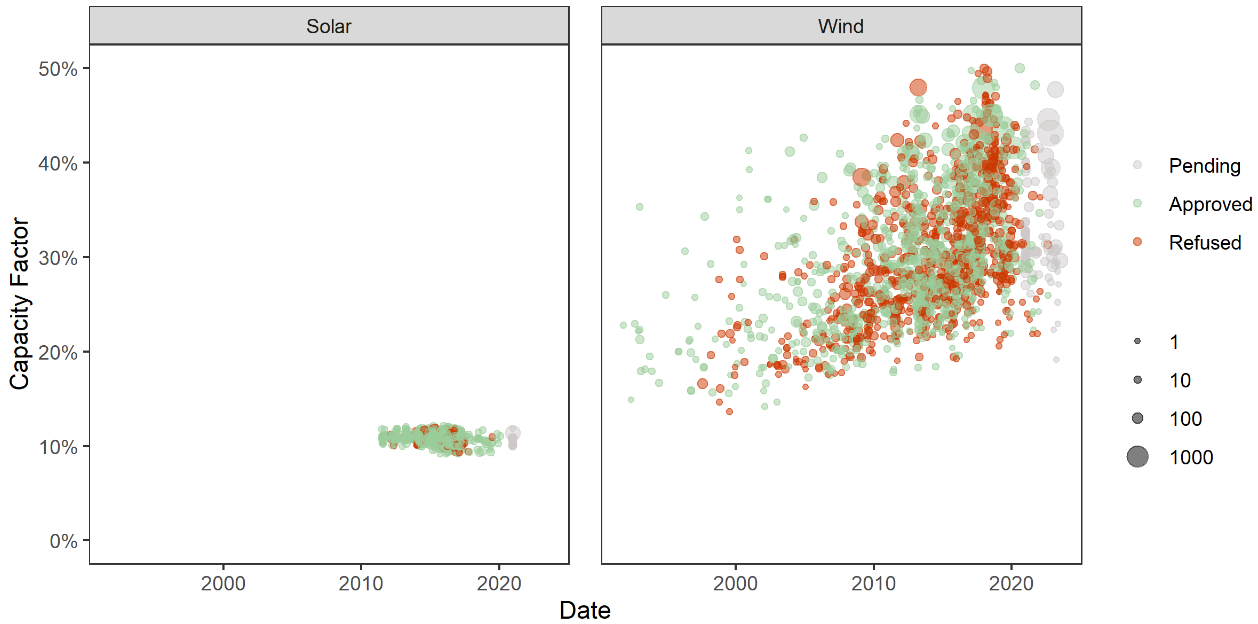
To estimate the capacity factors at each project I start with estimated capacity factors based on geospatial data. For solar projects I use the photovoltaic power potential estimates from the World Bank Solar Atlas. This provides estimated solar power productions profiles on a 1km grid for a representative 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. 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.[19] 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.

[19]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.

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 A.2.

Figure A.2: Estimated Project Capacity Factors



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

A.2.4 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 (item 1) 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 valuation 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.[20] 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.

A.2.5 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 (item 2) and local pollutant emissions (item 3).

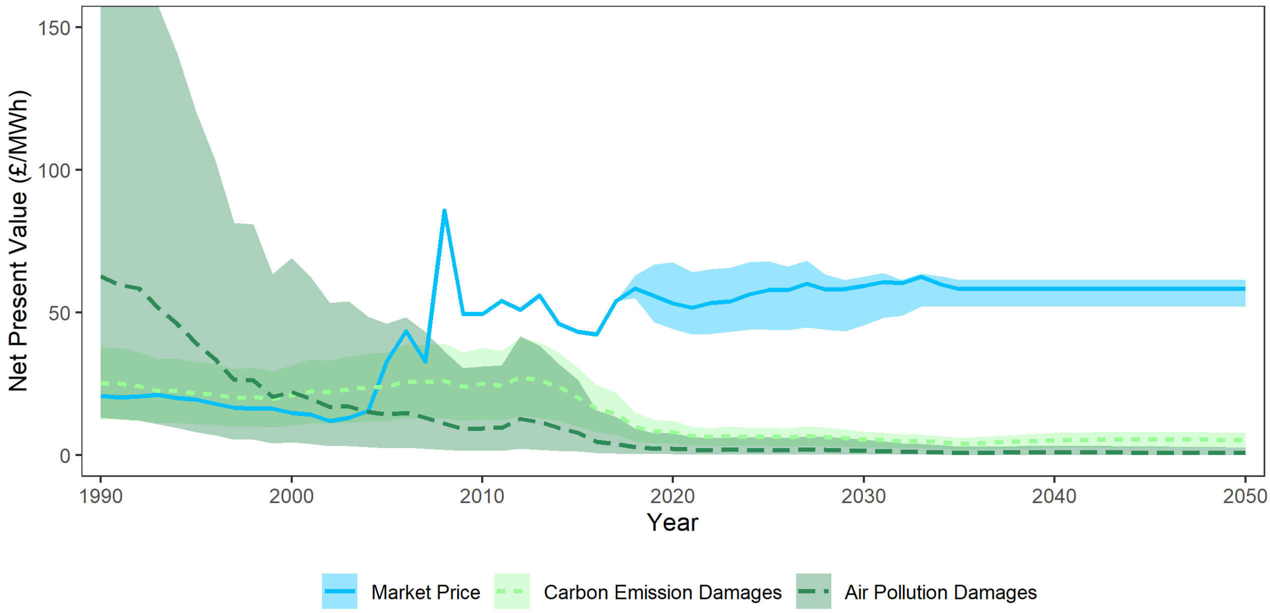
To calculate the amount of emissions abated I start with historical data on annual total electricity generation by source from BEIS and annual emissions by source from DEFRA. I use this to calculate annual average marginal emissions factors for CO_2, SO_2, $PM_{2.5}$, PM_{10} and NO_X assuming that either 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 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

[20]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.

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



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

A.2.6 Capacity value

The capacity value of a power project (item 4) 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, whilst 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 whilst there is a decent probability the wind will be blowing at this point, the sun will almost certainly have set.

My starting point for is National Grid's recently published guidance on the de-rating factors they will use for the upcoming UK capacity market auctions. For the upcoming auctions in 2020 they have 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.

A.2.7 Capital and operating costs

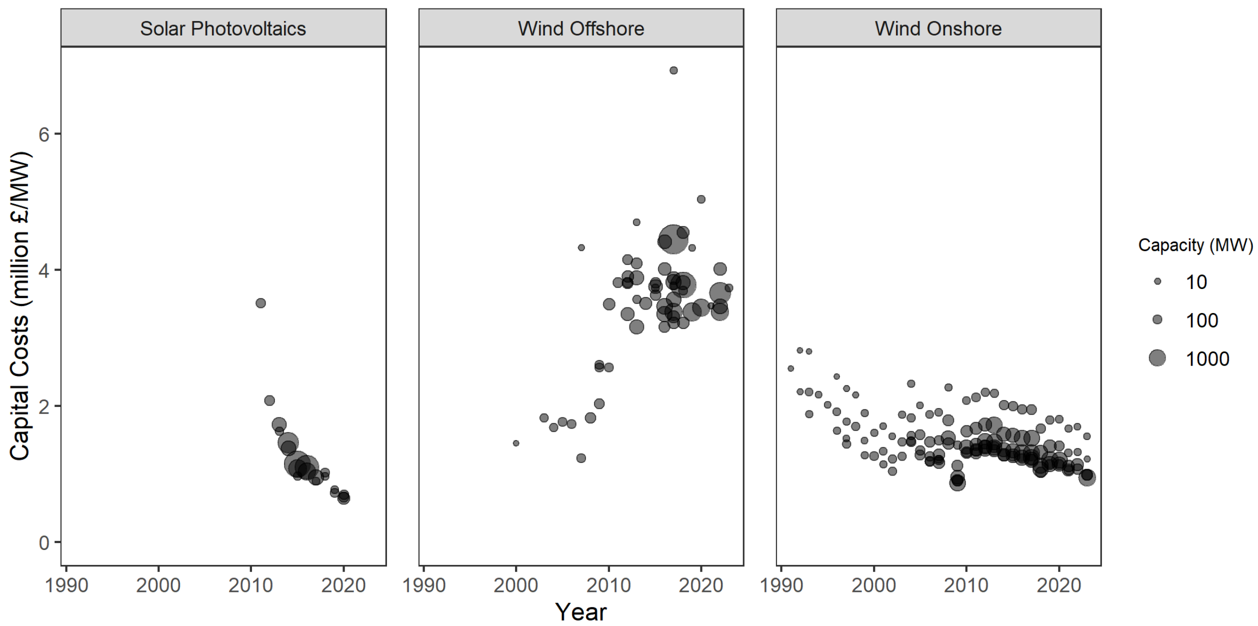
To calculate project specific estimates of installed capital costs (item 5) I rely primarily on data from IRENA. Unfortunately it is particularly challenging to get detailed project-level data on costs as this is usually treated as commercially confidential. The data provided by IRENA are country-level 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 (item 6) 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 whilst 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 consistent with 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.[21] This includes accounting for the additional grid infrastructure costs associated with the offshore wind.[22] See the appendix for full details. Finally I once again multiply by the capacity of each project to get annual project specific estimates of O&M costs.

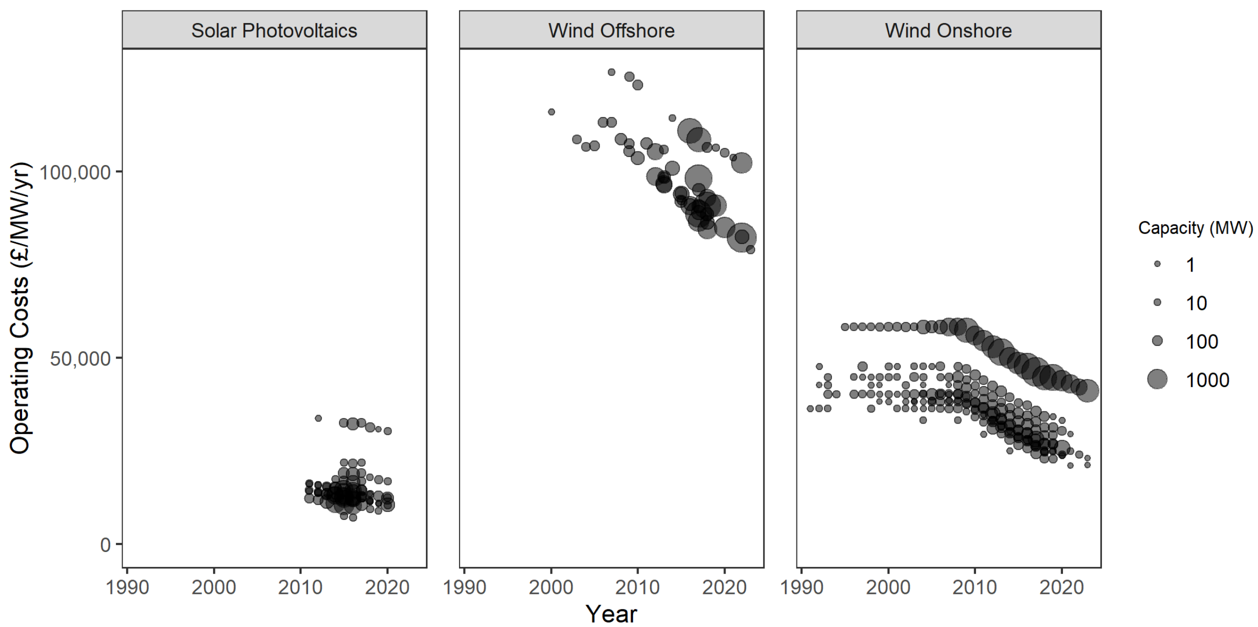
[21]For example, the locational portion of National Grid's transmission charge can vary from more than £20,000/MW/year in Scotland to less than -£10,000/MW/year near London.

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

Figure A.4: Estimated Project Capital and Operating Costs by Year



(a) Capital costs



(b) Operating costs

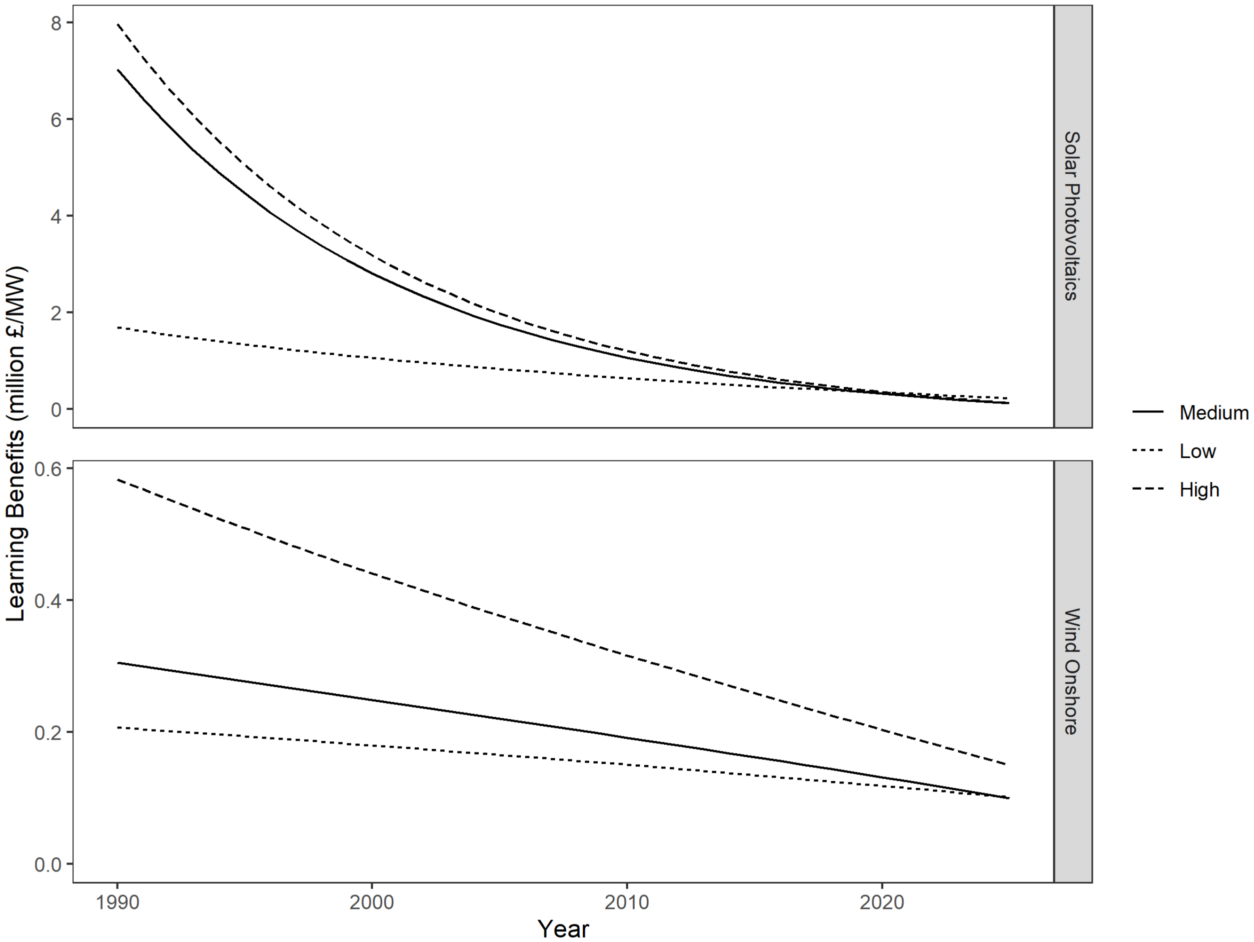
Notes: This figures shows the estimated costs over time. Each point represents the total amount of proposed capacity of a given technology type at a given cost level. Capital costs are at the top and operating costs are at the bottom.

A.2.8 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 A.5.

Figure A.5: 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. "Low", "medium" and "high" sensitivities are shown by the different dashed lines.