The Economic Costs of NIMBYism: Evidence from Renewable Energy Projects

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Abstract

Large infrastructure projects have important social benefits, but can also prompt strong local opposition. I estimate the economic costs of NIMBY (Not In My Backyard) attitudes and local planning restrictions by studying renewable energy projects. Using data on thousands of permitting applications, I show that wind and solar projects can have highly heterogeneous impacts depending on their characteristics and location. In some cases this includes significant external local costs, and I conduct a hedonic analysis to quantify the impact on nearby property values. I then show that planning officials are particularly sensitive to these local costs, especially when wealthy residents are affected. This often comes at the expense of considering the wider social benefits of these projects. These biases in the permitting process create inefficiencies that increased costs and led to substantial underinvestment in renewable energy.

JEL Codes: Q42, R11, Q58, R52

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1 Introduction

Large infrastructure projects can create widespread economic benefits and are often critical to tackling major national or global problems. In most countries new buildings and infrastructure require some form of local permitting. Getting planning approval can often be challenging, especially where there are concentrated local impacts that prompt strong pushback from affected residents.

This kind of local opposition is sometimes pejoratively labeled NIMBY (Not In My Backyard) behavior. It is most commonly associated with projects that combine public goods with private bads and spans issues as diverse as highways to landfills (Frey, Oberholzer-Gee and Eichenberger, 1996; Feinerman, Finkelshtain and Kan, 2004). Available evidence on housing construction suggests that the economic costs of distortions created by local planning restrictions can be substantial (Glaeser and Gyourko, 2018; Hsieh and Moretti, 2019).

In this paper I estimate the economic costs of NIMBYism and local planning restrictions by examining the case of renewable energy projects. Renewable energy is of particular interest because many countries have committed to policies that require a dramatic rollout of new energy infrastructure. Based on existing policies and pledges, global electricity production from wind and solar is expected to increase four-fold by 2030, and twelve-fold by 2050 (IEA, 2022). Currently wind and solar account for 10% of global electricity output, but this could rise to 30% by 2030 and 60% by 2050 (IEA, 2022). NIMBYism and permitting challenges have increasingly been raised as significant barriers to this rollout (Carley et al., 2020).

My analysis focuses on the United Kingdom, where I am able to draw on detailed planning data for all proposed projects, including those that were denied planning permission and did not go ahead. The data covers roughly four thousand large wind and solar projects proposed in the UK over the past three decades. I start by describing some of the key trends observed in the data. I find that wind projects have a tougher time getting approved than solar projects. I find evidence that local county decisonmakers are more hostile to these projects than national ones. I also provide evidence on some of the key drivers of local opposition, which appears to be heavily motivated by the visual and noise disamenitites that residents have historically associated with these projects, particularly wind power.

It is possible that observed planning outcomes, and the low approval rates for wind power, are simply the efficient result of the planning process accounting for local external costs. Alternatively, local permitting decisions may be placing outsize weight on local factors, while dismissing the wider social merits for expanding renewable energy. To test this I move to more explicitly evaluating the effectiveness of the planning process.

First I estimate the full range of costs and benefits for each project. Here I incorporate a wide range of information to estimate the electricity production for each project; the market value of that electricity production and the external value of any emissions or pollution abated. This includes accounting for hourly variability in both renewable production and the marginal value of that production. I also bring together numerous sources to estimate the costs of constructing and operating each project.

A critical further addition I make is to estimate the local external costs on nearby residents and businesses. To fill this gap I focus on the capitalization into local property values. A number of studies have used hedonic methods to quantify the visual and noise disamenities from wind farms, generally finding negative effects on property values (Parsons and Heintzelman, 2022). There are also important margins of heterogeneity, such as visibility or the size and number of turbines installed (Gibbons, 2015; Sunak and Madlener, 2016; Dröes and Koster, 2016; Jensen et al., 2018; Dröes and Koster, 2020). The evidence for solar projects is less extensive, but mostly points to smaller effects limited to distances within 1km (Dröes and Koster, 2020; Gaur and Lang, 2020).

Here I provide new estimates of these capitalization effects, incorporating new methods that tackle challenges with the staggered deployment of these projects (Callaway and Sant'Anna, 2019). I find wind projects can reduce property values by 8-10% at distances of up to 4km and where the project is directly visible. I find no significant effects for solar projects. I use these estimates to calculate the change in nearby property values for each project in my sample. In doing so I account for both the proximity and line-of-sight visibility between each property and project. Changes to property values are unlikely to capture all the local impacts (e.g. employment or wildlife). Nevertheless, there are good reasons to think these capture a substantial portion of the impacts of interest in this setting, particularly when thinking about sources of local opposition.

Taken together my estimates of project-level costs and benefits reveal significant heterogeneity and important tradeoffs. For instance, productivity is mainly a function of location - namely how windy or sunny a site is. Productive locations near population centers create higher local external costs, but similar locations in remote areas incur higher operational costs of transmitting power over long distances. Larger projects have lower capital costs due to economies-of-scale, but also impose higher local external costs.

Using my complete set of estimates for project-level costs and benefits, I proceed to examine whether the planning and permitting process actually does a good job of accounting for these different tradeoffs. Using a fixed effects regression analysis I find evidence that permitting decisions are indeed particularly responsive to local factors. This is especially true in wealthier areas where a £10 million increase in local property value costs leads to a 2.4% reduction in the likelihood of approval. This effect is significantly different from the impact of wider social costs and benefits (e.g. electricity production benefits or capital and operating costs) on the likelihood of approval. Local opposition likely plays a role here. I find projects with higher local property value costs receive more public comments, and that more objecting public comments are associated with a lower likelihood of approval. These findings are also consistent with the localized nature of the process, with decisions for most projects being made by local planning authorities.

Refusing a proposed project to avoid adverse local impacts may benefit local residents. But what appears optimal for a given local area can in aggregate create harmful outcomes for society as a whole. To quantify the scale of the problem and the scope for Pareto-improving trades, I calculate the potential gains from approving and constructing an alternative set of projects drawn from all of those that were proposed. I look at the gains from approving all projects with a positive social net present value, and a more constrained analysis that reproduces the observed deployment of renewable energy at least cost.

I find that inefficiencies in planning and permitting decisions have contributed to a significant misallocation of investment. The wind and solar projects actually built as of 2022 have lifetime capital and operating costs of £142 billion. My analysis indicates that the same deployment of renewable energy could have been achieved with costs savings of 18% if reallocating within local authorities and across years, and 26% if reallocating across local authorities within years.

Furthermore, the existing rate of deployment has likely been much too slow. Approving all socially beneficial projects would entail increasing the amount of wind and solar power by a further 55%, pointing to significant underinvestment. The majority of socially beneficial projects that failed to be built were refused planning permission, indicating that much of the blame can be attributed to the planning and permitting process.

Policymakers have tried a range of policies that could address the misaligned incentives identified here. I examine the feasibility of developers making direct payments to nearby residents. I show that a simple transfer scheme can be designed that compensates the large majority of affected households, often at a manageable cost to developers. Understanding the effectiveness of these transfer payments, and possible changes that could improve the permitting process, remains a key area for further research.

Clean energy investment is expected to reach $2 trillion per year by 2030, mostly to build new wind and solar power (IEA, 2022). The findings in this paper suggest that this expansion could be achieved at much lower cost and with less political opposition if changes are made to the planning and development process. The local opposition to renewable energy studied here also shares many similarities with challenges faced by other large infrastructure projects in areas like transportation, water and waste. There is every reason to think that similar planning inefficiencies may be present in those sectors too.

Prior Literature and Contributions

This work contributes to several important literatures. First there is a range of research on the economic impacts of place-based policies. In some cases these policies can be aimed at encouraging desirable local development, often with mixed results (Greenstone and Moretti, 2003; Glaeser and Gottlieb, 2008; Sadun, 2015; Chen et al., 2019). In other cases the goal is to restrict local development viewed as disruptive. Much of this work has been limited to studying housing development, where local planning restrictions have been shown to cause chronic underinvestment in important locations, creating a substantial drag on the economy (Glaeser and Gyourko, 2018; Hsieh and Moretti, 2019; Anagol, Ferreira and Rexer, 2021).

The findings in this paper provide new evidence of significant costs in the context of large-scale infrastructure deployment. Research of this kind for infrastructure projects is particularly challenging due to small sample sizes and the idiosyncratic nature of large projects. This paper leverages the fact that renewable energy projects are numerous and fairly homoegenous, making consistent valuation more tractable. The planning database used here also contains both completed and failed projects which is key to providing new insights into the effectiveness of the permitting process.

Second there is a rich literature focused on the location of undesirable industrial facilities. Studies in this area have linked siting decisions to both the size of the local external costs imposed and to the political power of nearby residents (Mitchell and Carson, 1986; Hamilton, 1993; Currie et al., 2015). Linkages are often made to concerns about NIMBY-ism, and possible ways to mitigate this kind of local opposition (Frey, Oberholzer-Gee and Eichenberger, 1996; Feinerman, Finkelshtain and Kan, 2004). This paper explores many of the same issues in a new context, and is able to conduct a more detailed assessment of the feasibility of a common policy solution: transfer payments to affected residents.

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

Lastly, there is the extensive literature on climate change and the deployment of renewable energy. Much of this has considered the optimal policy mix to solve emissions and pollution market failures, with the accelerated uptake of renewable energy a consistent focus (Callaway, Fowlie and McCormick, 2018; Fell, Kaffine and Novan, 2021; Holland, Mansur and Yates, 2022; Borenstein and Kellogg, 2022).

Beyond getting price incentives right, a key challenge is overcoming regulatory and political barriers (Carley et al., 2020). A wealth of survey-based studies have examined community acceptance for renewable energy projects, with several questioning the validity of the NIMBY characterisation (Wolsink, 2000; Rand and Hoen, 2017; Hoen et al., 2019). But a growing body of revealed preference evidence does suggest that wind farms can prompt political and regulatory pushback at the local level. This can come through the emergence of new restrictive zoning regulations (Winikoff, 2019) or efforts to punish "green" politicians at the ballot box (Stokes, 2016; Germeshausen, Heim and Wagner, 2021).

This paper builds on prior revealed preference studies by studying the observed decisions made by local planning officials. The findings provide new evidence quantifying the scale of the inefficiencies being created, and the potential benefits from policy changes that can improve infrastructure permitting more broadly.

2 Data and Context

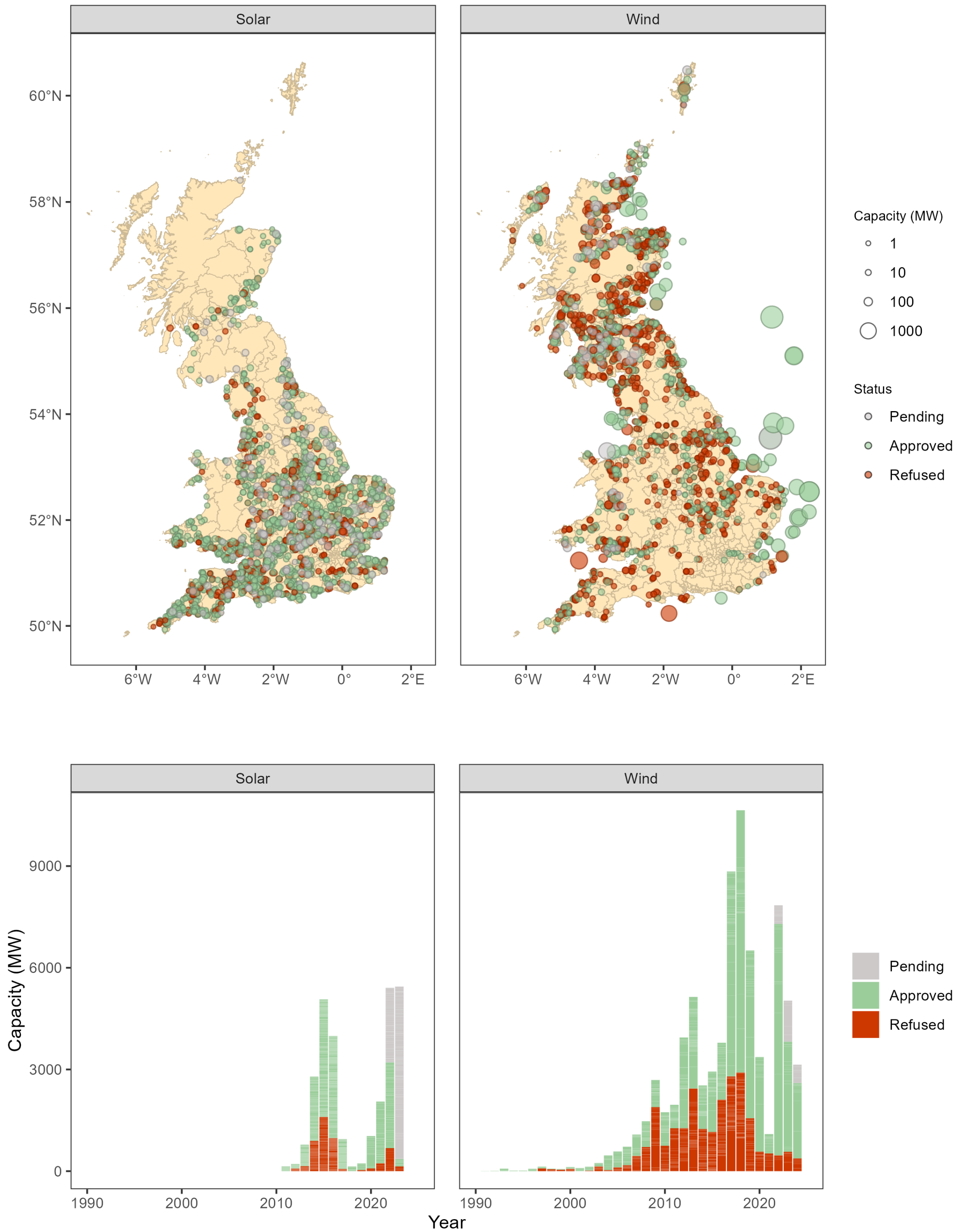
2.1 Renewable Energy Policy in the UK

The first commercial wind farms in the UK were constructed in the early 1990s. Capacity has since grown to 26GW as of 2021. These wind farms produce 33% of Great Britain's electricity, and this is expected to rise to 61-69% by 2030 (NGET, 2022). Projects are mostly located in the windier and more remote regions of the north and west of the country. Many projects have also been sited in coastal areas with roughly half of the total capacity now located offshore.

The emergence of solar power in the UK has been more recent, starting in the 2010s. By 2021 total solar capacity stood at 13GW. Solar power currently produces 5% of Great Britain's electricity, and this is expected to rise modestly to 5-10% by 2030 (NGET, 2022). 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 onshore wind was the most widespread technology, but from 2009 a range of more

Figure 1: Renewable Energy Projects in the UK



Notes: These figures show the location of projects and the timing of when they were submitted for planning permission. Project sizes are determined by their capacity (in MW). Projects are classified by their development status. "Pending" are projects that have submitted a planning application but have yet to receive a final decision. "Approved" are projects that have been approved and are either awaiting construction, under construction, operational or have been subsequently decommissioned. "Refused" are projects that were refused planning permission or were otherwise withdrawn or halted. The administrative boundaries depicted are the local planning authorities responsible for processing planning applications.

generous subsidies spurred the expansion of solar power and offshore wind.

In 2015 several reforms were introducted that led to a decline in new investment for both solar power and onshore wind, including freezing the UK carbon tax, cutting renewable subsidies and requiring greater consensus from local residents for projects to be approved. Some of these changes were driven in part by the vocal opposition of rural voters to onshore wind turbines, with then-prime minister David Cameron vowing to "rid" the countryside of these "unsightly" structures. Notably offshore wind was not subjected to the same withdrawl of policy support. In recent years some of these subsidy cutbacks have been reversed, although the issue remains politically contentious.

2.2 Permitting Process for Renewable Energy

In most countries the planning and permitting process is a key determinant of the deployment of any large-scale infrastructure, including renewable energy projects. Like many jurisdictions, the UK decides the overwhelming majority of planning applications at the local level through local planning authorities. Local authorities are the primary unit of local government in the UK and are broadly analogous to counties or municipalities in other countries. Project developers submit a planning application to the relevant local authority. The proposal is reviewed in line with national and local planning guidelines. A public consultation period is required where affected residents and stakeholders have the opportunity to provide comments. The local authority then decides to either approve or refuse the planning application.

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

A common approach in many countries is to set out certain zoning criteria that restrict development (e.g., setbacks stating how far projects must be from nearby properties or quotas for the number of projects in a certain area). The planning process in the UK is generally less prescriptive, but officials do still have a lot of scope to deem certain siting decisions to be harmful. Planning authorities may also seek amendments to planning applications, or approve them with conditions aimed at mitigating concerns.

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

2.3 Renewable Energy Planning Database

The primary dataset used in this paper is a UK government database on the planning applications for renewable energy projects. The Renewable Energy Planning Database includes all projects with a capacity of 1MW or greater that have been proposed since 1990 (BEIS, 2022). Small-scale residential or commercial systems (e.g. rooftop solar) are excluded. I limit my analysis to wind and solar projects as these are the two largest sources of renewable energy, and are expected to provide the vast majority of future capacity additions both in the UK and globally (NGET, 2022; IEA, 2022).

Figure 1 shows where projects have been located and when they were submitted for planning approval. Table 1 provides additional summary statistics on planning outcomes for the projects in the database.

The projects in the planning database comprise the overwhelming majority of wind and solar capacity in the UK. There is a roughly even split across the two technology types, although wind projects are larger and so account for most of the total capacity. Despite this, it is noticeable from Table 1 just how much tougher the planning process is for wind projects. Receiving a planning decision takes three to four times longer for wind projects. The approval rate is much lower as well, with 41% of wind projects being approved compared to 73% for solar projects. Accounting for appeals causes this to rise to 51% of wind projects and 78% for solar projects.

To further highlight some of the factors that correlate with projects successfully receiving planning permission, Table 2 shows the results of regressing a binary indicator for whether a project was approved on a range of project characteristics.

As expected, there is a marked drop in wind project approvals post-2015, but not

Table 1: Summary Statistics on Project Planning Outcomes

	Solar	Wind
Number of Projects	2025	1885
Total Capacity (MW)	20756	73133
Average Capacity (MW)	10.2	38.8
Length of Planning Process to Initial Decision (days)	156	546
Length of Planning Process to Final Decision (days)	192	644
Initial Decision Approval Rate	0.73	0.41
Share of Projects subject to National Authority Decision	0.01	0.14
National Authority Initial Decision Approval Rate	0.75	0.67
Local Authority Initial Decision Approval Rate	0.73	0.37
Share of Projects Appealed	0.11	0.23
Appeal Success Rate	0.46	0.48
Final Decision Approval Rate	0.78	0.51

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

for solar. This corresponds to changes made to the planning process that gave local residents more power to block onshore wind projects. In general, approvals appear less likely for larger projects, projects sited in conservative areas, projects near national parks or areas with high property values, and projects proposed in areas where large amounts of capacity have previously been constructed. Conversely, offshore wind projects, those proposed by large developers and those decided at the national level are more likely to be approved.[1]

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

[1]The largest fifty developers in the sample comprise 90% of offshore wind capacity, 55% of onshore wind capacity and 41% of solar capacity.

Table 2: Planning Process Regressions for Project Characteristics

	Wind		Solar	
Model:	(1)	(2)	(3)	(4)
Variables				
Post-2015	-0.1152***		0.0599***	
	(0.0357)		(0.0200)	
log(Project Capacity (MW))	-0.0481***	-0.0508***	-0.0285**	-0.0341**
	(0.0118)	(0.0136)	(0.0110)	(0.0136)
log(Cumulative Capacity (MW))	-0.0069	-0.0427*	0.0165*	-0.0411
	(0.0084)	(0.0223)	(0.0092)	(0.0267)
Large Developer	0.1276***	0.1493***	0.0255	0.0471**
	(0.0260)	(0.0273)	(0.0202)	(0.0216)
Distance to National Park (km)	0.0015***	0.0016**	0.0004	0.0012
	(0.0004)	(0.0007)	(0.0004)	(0.0007)
National	0.1467***	0.1383***	-0.0191	-0.0213
	(0.0361)	(0.0361)	(0.1130)	(0.1310)
Conservative	-0.1113***	-0.0655	-0.0292	-0.0731
	(0.0426)	(0.0702)	(0.0251)	(0.0621)
Avg. Property Value (thou. £)	-0.0005	-0.0001	-0.0004**	-0.0009***
	(0.0003)	(0.0005)	(0.0002)	(0.0003)
On/Offshore	0.3167***	0.3355***		
	(0.0613)	(0.0865)		
Fixed-effects				
Year		Yes		Yes
Local Authority		Yes		Yes
Fit statistics				
Observations	1,879	1,879	1,988	1,988
R^2	0.06889	0.24762	0.01651	0.25508
Within R^2		0.04340		0.01690
Technology	Wind	Wind	Solar	Solar

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

Notes: This table shows the impact on approval probability of various project characteristics. "Post-2015" is a dummy for whether a project was due to come online after 2015. "Capacity" refers to the capacity in MW of a project. "Cumulative Capacity" refers to the capacity in MW of all previously approved projects in a local authority. "Large Developer" refers to whether a project was proposed by one of the fifty largest developers in the sample. "National" coefficients capture whether a project's planning application was decided at the national level. "Conservative" captures whether a local authority is politically conservative. "Avg. Property Value" captures the average residential property value within 6km of a project. "On/Offshore" is a dummy for whether a project is located Offshore and is only relevant for wind projects.

The planning outcome data described here makes clear that a big challenge for the deployment of renewable energy is getting permitting approval. A key determinant of success is likely to be the extent of opposition from local residents and firms. In many ways this makes renewable energy projects similar to most other large-scale infrastructure projects, and so the findings here may be instructive for other sectors.

However, the particular importance of national and global factors (e.g., climate change) makes wind and solar projects an especially challenging case when planning processes are so dominated by local decisionmakers. Unlike more traditional local infrastructure like transport or housing, most of the benefits of wind and solar projects are spread diffusely throughout wider society while certain key costs remain concentrated locally. Quantifying the economic impacts arising from this misalignment between local and wider social incentives is the primary aim of this paper.

3 Empirical Strategy

To examine the potential economic impact of NIMBYism and local planning restrictions I conduct four pieces of analysis. First, I quantify the key costs and benefits of each project. This includes conducting a hedonic analysis to estimate the local external costs of these project as reflected in changes to nearby property values. The goal is to understand how large the local impacts are relative to the other wider social impacts that motivate the deployment of renewable energy. Second, I conduct a regression analysis to understand how responsive planning officials are to economic impacts that are local or non-local. This builds on the earlier exploratory regressions on project characteristics. Third, I estimate the costs of inefficient planning decisions in the form of misallocated investment. I do this by looking at the gains from reallocating across the range of proposed projects to see if beneficial ones are systematically denied planning permission. Lastly, I examine the feasibility of a key policy solution: making transfer payments to affected local residents.

3.1 Estimating project-level costs and benefits

3.1.1 Benefits of Installation and Electricity Production

Estimating Electricity Production

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 35% for wind projects and 10% for solar projects.

To estimate the capacity factors for wind and solar projects I use estimates from Renewables Ninja (Pfenninger and Staffell, 2016; Staffell and Pfenninger, 2016), which I complement with data from the Wind and Solar Atlases produced by the World Bank (World Bank, 2022*a*,*b*). The analysis produces a unique capacity factor profile for each project at the month-of-year by hour-of-day level. This captures the key sources of seasonal and within-day variation in wind and solar output. In each case the capacity factor is project specific in that it is based on the wind or solar resource at a project's precise location and the nature of the technology installed (i.e. the turbine size and characteristics for wind projects). I also make adjustments to the wind capacity factors to ensure they better match improvements in observed performance over time (IRENA, 2022; Smith, 2023). Full details on the estimation of the hourly project specific capacity factors can be found in the appendix. Total electricity production in MWh is calculated as the project specific capacity factor multipled by the capacity of a project multiplied by the total number of hours in its 25 year lifetime.

Market Value of Electricity

To value the electricity produced by each project I primarily rely on data from the UK government's guidance on cost benefit analysis and the valuation of climate change policies (BEIS, 2021). I measure the market value of the electricity produced by each project using the wholesale price of electricity. To capture long-term annual trends I use pre-2022 data on observed traded wholesale market prices and post-2022 data on projections out to 2050 that were made by the UK government.[2]

There is also significant spatial and temporal variation in the private value of electricity production, even on an hour-to-hour basis. To capture hourly variation in the private value of electricity production I supplement the annual data with observed hourly wholesale electricity prices from 2004 to 2022. I then train a machine learning model using this historical data that I use to make plausible predictions of hourly wholesale electricity prices across my entire sample period from 1990 to 2050. To capture spatial variation in rely on a recent study of locational marginal pricing to adjust prices to reflect congestion rents, most notably those associated with the transfer of power from the north (where there is an excess of supply) to the south (where demand centers are located) (Ofgem, 2022). Full details on this are provided in the appendix.

Wind and solar projects do also receive production subsidies in addition to any wholesale market revenues. I do not include subsidy revenues in my estimates of the market

[2]These projections are based on modeling of the future electricity grid that includes forecasting fuel prices, demand and investment in new capacity, and then running a dispatch model to solve for clearing market prices.

value of the electricity produced because from the perspective of a social planner they are simply transfers.

External Value of Emissions and Local Pollution Abated

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

To calculate the emissions intensity of the electricity being displaced by new wind and solar production, I start with historical data on annual total electricity generation and annual power plant emissions by source type (i.e. coal, gas, oil etc.). I use this to calculate annual average emissions factors for each source type for CO_2, SO_2, $PM_{2.5}$, PM_{10} and NO_X. For future values I project these emissions factors for each source type forward to 2050. I then weight these source level emissions factors by the relative generation shares of the different flexible sources of electricity supply that are assumed to be displaced by new wind or solar output (i.e. coal, oil, gas, other thermal, storage and interconnectors). This gives annual estimates of marginal emissions factors.

As with wholesale electricity prices, there is also significant within-year variation in the emissions intensity of electricity production, and this can have important implications for the value of additional wind and solar output (Borenstein and Bushnell, 2018; Callaway, Fowlie and McCormick, 2018). To capture hourly variation in the external value of electricity production I supplement the annual data with hourly observed data on total demand and electricity production by source type from 2009 to 2022. I then estimate a simple econometric model using this historical data in order to make plausible predictions of hourly fluctuations in total demand and electricity generation by source type across my entire sample period from 1990 to 2050. I use the combination of observed and predicted values and the annual average emissions factors for each source type to estimate the marginal emissions intensity for each pollutant in each hour-of-sample. Full details on this are provided in the appendix.

Lastly, I multiply the estimated emissions intensities by the assumed damages from additional carbon and local pollution emissions. Marginal abated carbon emissions are valued at £73/ton and local pollution emissions are valued at £8,152/ton for SO_2, £5,487/ton for $PM_{2.5}$, £3,616/ton for PM_{10}, and £2,272/ton for NO_X. These values are taken from UK government guidance (BEIS, 2021).[3]. Importantly, the assumptions for the local pollutants are underpinned by UK government modelling of air pollution transport and damages.[4] Additional details on the approach taken can be found in the appendix.

[3]My analysis relies on the 2019 guidance and all the values cited are given in real 2021 prices for the year 2020.

[4]For all air pollutants I use the baseline national damage assumptions, except for $PM_{2.5}$ and NO_X

Capacity Value

The capacity value reflects the value a project provides in being available to match demand, particularly during peak demand periods when supply is tight. As such it is calculated per MW capacity installed. For this I rely on data from National Grid's Capacity Market Auction, as well as analysis by Harrison et al. (2015). The result is a capacity value for each project in £/MW/year. In practice the capacity value estimates are very small and do not meaningfully affect the results.

Learning-By-Doing

As well as their static benefits, constructing a new wind or solar project has important dynamic effects through learning-by-doing. This is often one of the key reasons cited for subsidizing renewable energy in the early years of its development, beyond any direct emissions reduction benefits. The rapid declines in the costs of both wind and solar do point to significant scope for learning-by-doing effects.

Unfortunately quantifying these benefits is incredibly challenging. Here I rely on a method set out by Newbery (2018), which produces learning-by-doing 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. Ultimately these estimated learning-by-doing benefits are highly uncertain, but fortunately in most instances do not meaningfully drive my results. More details on their calculation is found in the appendix.

3.1.2 Costs of Construction and Operation

Capital Costs

It is particularly challenging to get detailed project-level data on costs as this is usually treated as commercially confidential. Therefore to estimate capital costs I rely primarily on data from the International Renewable Energy Agency (IRENA), which provides country-level annual average installed capital costs for onshore wind and solar projects (IRENA, 2022). These values are based on confidential records of the actual capital costs of completed projects who then submit data to IRENA.

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 likely to be a decent approximation of costs for the UK. However, due to the size and relatively small number of offshore wind projects I am able to use direct project specific estimates of the capital costs for these projects taken from various industry sources and news reports. I

where more detailed assumptions are available that better reflect the chimney stack heights of large power plants.

sense check these against the official IRENA annual averages to make sure this approach is reasonable.[5]

Once I have an initial estimate for the unit capital costs of each project based on annual averages, I then make a further adjustment to account for economies-of-scale. To do this I use data from Lawrence Berkeley National Laboratory (LBNL) on relative capital costs by project size (Wiser et al., 2022; Bolinger et al., 2022; Barbose et al., 2022). For example, they show that the per MW capital costs for a 50MW solar project are around 20% lower than those for a 5MW solar project. The difference is even more pronounced for wind projects where the equivalent cost reduction is 45%. I therefore use the LBNL data to scale the unit capital costs of large projects relative to small ones.[6]

I convert my final estimates to consistent £/MW unit capital costs and multiply by the capacity of each project to get project-level values for total installed capital costs.[7]

Operating Costs

To calculate project specific estimates of ongoing operating and maintainence (O&M) costs I also rely primarily on data from IRENA. Here UK specific data is not consistently available and so for onshore wind I use US values while for solar I use the values for projects in developed countries (IRENA, 2022). Fortunately variation in average operating costs across developed countries is fairly minimal, and so using non-UK values is appropriate. 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. I compare to UK government estimates to ensure my approach is reasonable throughout.[8]

An important additional contributor to O&M costs are grid connection and transmission 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.[9] This includes accounting for the additional grid infrastructure costs associated with the offshore wind.[10]

I multiply my £/MW/year unit O&M cost estimates by the capacity and lifetime of

[5]See Appendix A.4 for details.

[6]Specifically, for wind projects I distinguish different unit capital costs for size bands of: 1-5MW, 5-20MW, 20-50MW, 50-100MW, 100-200MW and 200+MW. For solar projects the size bands are: 1-2MW, 2-3MW, 3-4MW, 4-5MW, 5-20MW, 20-50MW, 50-100MW and 100+MW.

[7]Where the available data does not span the full sample period from 1990 to 2025 I extrapolate using the observed rates of growth/decline over the nearest ten-year period.

[8]See Appendix A.4 for details.

[9]For example, the locational portion of transmission charges can vary from more than £20,000/MW/year in Scotland to less than -£10,000/MW/year near London.

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

each project to get project-level values for O&M costs.[11]

3.1.3 Costs to Local Residents

Finally, renewable energy projects create a number of local economic impacts. Of primary interest here are the visual and noise disameneties associated with these projects. Credibly estimating these impacts is challenging. Here I draw on empirical evidence of how wind and solar projects affect nearby residential property values. I apply these hedonic effects to the value of nearby properties to calculate the local impacts.

I focus on capitalization into residential property values as this likely captures a significant portion of the local impacts of interest.[12] These effects on nearby residents also seem important in the UK context given the extent to which visual and noise concerns are raised during the planning process. Other potential local costs and benefits (e.g. impacts on employment, taxes or wildlife) are discussed at the end of this section on estimating costs and benefits.

Project and Property Locations

Key to conducting this analysis is determining which properties are close to each project. For property locations I use data from the Office for National Statistics (ONS) on the centroid of each post code. These are a very granular geographic measure in the UK context, with each post code representing around 15 properties.

For project locations I use the centroid of each project. This information is provided directly in the planning database. Where possible I check these locations against more detailed spatial information available from Open Street Map. For many larger projects OSM provides information on the overall footprint of a project (e.g. the area covered by solar panels or the location of individual wind turbines). Where this information is not available I approximate the footprint based on the capacity of the project and the size of the turbines installed. I calculate the distance from each nearby post code to the edge of the footprint taken up by a given project. I also calculate the direct line-of-sight visibility from each project to the same set of nearby post codes (see appendix for details).

Hedonic Analysis of Property Value Impacts

A number of studies have used hedonic methods to study the local impacts of wind projects. Parsons and Heintzelman (2022) conduct a comprehensive review of the literature and find negative effects of 5%, 4%, 2.6% and 1.2% at distances of within 1km, 2km, 3km and 4km respectively. Gibbons (2015) is the most relevant study for this context

[11] Where the available data does not span the full sample period from 1990 to 2025 I extrapolate using the observed rates of growth/decline over the nearest ten-year period.

[12] There is no research on effects on commercial property values. Haan and Simmler (2018) examine capitalization of wind energy subsidies into agricultural land values, but not the effect of project siting.

and finds pronounced effects in the UK for directly visible properties, with reductions of 5% within 2km, increasing to 12% for some of the largest projects. The evidence for solar projects is less extensive with only two studies finding relatively limited evidence of reductions of 1-3% at distances of around 1km Dröes and Koster (2020); Gaur and Lang (2020).

I conduct a new hedonic analysis that builds on these prior studies and makes a number of novel contributions. to do this I rely on residential property transactions data taken from Her Majesty's Land Registry (HMLR) that covers virtually all sales of residential properties in England & Wales since 1995 (Her Majesty's Land Registry, 2022). I collapse the data to postcode annual averages and employ a quasi-experimental difference-in-difference approach. This hinges on comparing changes in property values for locations that have a new renewable energy project constructed nearby to changes in property values for other similar locations that do not have a new renewable energy project constructed nearby. My preferred specification is an event study of the form:

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

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

Prior studies in this area have generally conducted a simple difference-in-difference analysis with a single post-period dummy variable. Unfortunately this makes it challenging to see how the estimated effects evolve over time, or to provide any reassurance that the parallel trends assumption is likely to hold. Here I improve on prior work by estimating an event study with a set of dummy variables indicating whether a given observation is s years before (pre) or after (post) the year when a project became operational. I include ten years of pre-periods ($S_{pre} = -10$) and five years of post-periods ($S_{post} = 5$).[13] Unless otherwise specified the treatment effect coefficients, β, capture the percent change in property values from a new project of capacity c being completed in distance bin d.

In all regressions I limit the sample to properties in locations that are ever within 6km of a project by the end of the period. I focus on properties that are ever near to a single project to avoid issues of properties being treated multiple times. I also drop any projects from my sample that do not have observations at least ten years prior and five

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

years after their start date. Given my property value data spans 1995 to 2022 this means my sample of projects includes those built between 2005 and 2017. This period is when the large majority of wind and solar capacity in the UK was completed.

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

Numerous studies have shown that difference-in-difference estimates can be biased when there is variation in treatment timing (Goodman-Bacon, 2018; Borusyak and Jaravel, 2017; Callaway and Sant'Anna, 2019). Here I estimate my effects using the approach developed by Callaway and Sant'Anna (2019) to tackle this problem. This paper is therefore the first paper using hedonic methods to quantify the local impacts of renewable energy projects that has accounted for this potential source of bias. It appears from comparing the new estimates with those from a standard two-way fixed effects model that this source of bias is potentially important in this context. This makes sense given the extent to which treatment effects are heterogenous and that deployment of projects rolled out over many years.

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

Finally, I examine a key source of heterogeneity in my analysis: the line-of-sight visibility of a project. The visual impact of wind and solar projects is consistently cited as a key reason that projects are refused planning permission. Prior work has also found that negative impacts on local property values are primarily due to visual disamenity (Gibbons, 2015; Sunak and Madlener, 2016). To examine this I conduct a geospatial analysis to determine whether a property has direct line-of-sight to a project. I then conduct my analysis seperately for visible and non-visible projects. Full details on the hedonic approach used can be found in the appendix.

Assumed Capitalization Effects

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

I therefore pick a set of capitalization effects that produces a reasonable range of property value impacts that can match the hedonic estimates I find, as well as drawing on those found in the wider literature (Gibbons, 2015; Jensen et al., 2018; Dröes and Koster, 2020; Gaur and Lang, 2020; Parsons and Heintzelman, 2022). I allow effects to increase with greater proximity to a project, to increase with project size, and to be concentrated at properties with direct line-of-sight visibility. Full details can be found in the appendix.

Property Values by Post Code

To calculate the local external costs of each project, I multiply the assumed capitalization effects by the total value of any properties in the relevant surrounding area. Unfortunately no dataset exists that provides a consistent panel for the value of all properties at each postcode in the UK over my sample period. As such I estimate the total value of all properties at each post code in the UK by starting with more aggregated data and then downscaling these to the post code level.

To get the number of properties in each post code I start with data on annual total counts of properties at the local authority level from the Valuation Office Agency (VOA) for England & Wales and from the National Registers of Scotland (NRS) for Scotland. To downscale the property counts to each post code 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.

To get the average price of properties in each post code I start with data on annual average prices published by the UK Office for National Statistics (ONS) at the local authority level for all local authorities in England, Wales and Scotland. These are originally constructed using property transaction data, adjusted to reflect the overall composition of the property stock.

To downscale the average property prices to each post code I once again use property transaction data from HMLR. I merge a range of other variables that are likely to be correlated with prices while also being consistently available at the post code level. This includes measures of whether a post code is rural or urban, index scores of social deprivation and census data on the socioeconomic status of residents. I then using machine learning to fit a predictive model with the transaction price as my outcome variable and these various post code-level characteristics as my covariates. The fitted model achieves an out-of-sample R-squared of 0.57. Once this model is fitted, I make predictions of the average property price for every post code.

Finally I downscale the local authority annual average prices using my predicted post code-level prices to get a set of annual average residential property prices at the post code-level that also remain consistent with the original local authority values. These are multiplied by the relevant capitalization effects to get the impact of each project on local property values. Further details can be found in the appendix.

3.1.4 Other Factors and Limitations

There are some limitations to the various costs and benefits estimated here. With regard to the hedonic approach to valuing the local external costs, the difference-in-difference method used for estimation will not capture that hedonic price functions may change over time, introducing a risk of bias (Kuminoff and Pope, 2014). Similarly, assuming the capitalization effects are equivalent to marginal willingness to pay and multiplying them by the change in the amenity may not be appropriate for non-marginal changes (Bishop et al., 2020). Unfortunately it is challenging to make alternative assumptions that can directly tackle these issues in this context and so these limitations must be kept in mind when considering the local property value costs.

Local property values may also fail to reflect real external impacts if people are misinformed. For instance, there are studies that have tried to understand whether the disturbance from wind turbine noise could have adverse impacts on human health (Schmidt and Klokker, 2014). While the evidence remains inconclusive, if these health impacts are meaningful they will likely not be reflected in property values as they are not widely known.

The focus on reductions to local property values does risk obscuring some of the local benefits these projects can provide. For instance, projects involve land lease payments to the landowner of the site. There are also property and business taxes, some of which may be levied by local government. Some projects provide direct payments to local communities as well. Importantly though many of these local revenue streams are captured by my estimates of operating costs and can be thought of as transfers. I will return to the role of local taxation, compensation and ownership as possible policy solutions in the final portion of the paper.

With regard to other more indirect local effects, persistent impacts on local employment appear to be limited (Costa and Veiga, 2019). This is consistent with wind and solar projects requiring minimal direct employment for ongoing maintainence and much of the upstream supply chain being located away from the project site. There is some evidence from the US of broader economic benefits at the county-level, primarily driven by boosts to local tax revenues (De Silva, McComb and Schiller, 2016; Brunner and Schwegman, 2022). In the UK these effects are likely to be muted as the relevant taxes have historically gone directly to the central government budget, rather than remaining in the local area. Lastly, impacts on wildlife are another factor often cited by opponents of wind projects in particular, although evidence on the economic nature of these effects is lacking and so can't be incorporated here.

Each of the costs and benefits I do estimate are still subject to significant uncertainty. To deal with this I conduct a sensitivity analysis for some of the most uncertain categories (i.e., the local property costs and the environmental benefits). One further source of uncertainty is the discount rate used when converting to present value levelized quantities. Here I examine a baseline real discount rate of 3.5% in line with UK Treasury guidance, but conduct a sensitivity analysis using 1.5% and 7%. Beyond examining the sensitivity of the results to changing specific cost and benefit assumptions, I also examine a sensitivity to check for the risk of systematic error in the estimation for projects that were not completed. Lastly, I conduct robustness checks to explore the sensitivity of the results to more general noise in the estimates.

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, and so for the purpose of this paper the scenarios analysed later should be interpreted with this in mind. Treating each project as a marginal project does have the benefit of mirroring the governmental guidance that planning officials should be following when individually valuing these projects. I revisit the implications of this assumption later during the discussion of the results and conduct additional sensitivity analysis to ensure my findings are robust to this assumption.

An important final limitation is that the data and approaches used are based on current understanding, which may be quite different from the state of knowledge available to decisionmakers at the time they were considering a project. Moreover, a mixture of observed and forecasted data is used when in reality decisionmakers would be relying on forecasts made at the time. Fully tackling these issues is beyond the scope of this paper. As such I continue to use values based on current knowledge and methods, but this should be kept in mind when considering the results.

3.2 Determinants of Planning Approvals

Armed with a comprehensive assessment of the costs and benefits of each project, I next move to evaluating how effectively policymakers balance these different impacts. To do this I employ a fixed effects regression model that links variation in project costs and benefits with the likelihood of a project being approved.

$$approve_{iat} = \beta_1 C_i^{prop} + \beta_2 C_i^{other} + \beta_3 B_i^{elec} + \theta_t + \lambda_a + \epsilon_{iat} \tag{2}$$

The observations here are the roughly four thousand wind and solar projects in my sample. The dependent variable is a binary approval decision indicator, *approve*, for each project, i, in local authority, a, in year, t and it is regressed on the local property costs, C^{prop}, the other capital and operating costs, C^{other}, and the benefits of the electricity production, B^{elec}.[14]

In line with the earlier descriptive analysis in Table 2, the baseline model I estimate does not include any controls or fixed effects. The goal is to get a sense for how the entire variation in costs and benefits aligns with the approval decisions made across the permitting process. I then examine how the findings change once I include a set of fixed effects for each year-of-sample, θ, and local authority, λ. This ensures the variation in costs and benefits more explicitly relates to decisionmaking within a given local authority.

Naturally including these fixed effects does absorb a lot of the available variation which may present challenges with statistical power. To give some context, once the included fixed effects are accounted for the remaining variation in property costs is driven by within-local-authority variation in property values, population density, project size and project visibility. The remaining variation in project benefits is primarily due to differences in the electricity productivity of each project, which in turn is a function of within-local-authority variation in wind conditions (i.e. how windy it is on average and how hourly fluctuations differ from other projects) and technology choice (i.e. which turbine is installed). The variation in other projects costs comes from within-local-authority variation in project sizes (i.e. the way their unit capital costs are subject to economies-of-scale across several size categories) while the locational variation in operational costs takes place across regions at a more aggregated level than a local authority.

In the context being studied we might expect an idealized global social planner to find that an equivalent change in costs or benefits should have the same impact on approval likelihood, irrespective of where it occurs (i.e. $-\beta_1 = -\beta_2 = \beta_3 > 0$). A national planner

[14] I examine specifications where the costs and benefits enter linearly or in logs. My main specifications are estimated using a linear probability model. Estimation using a logit model gives qualitatively similar results. Results for alternative specifications can be found in the appendix.

is likely to get pretty close to this, although most of the carbon emission reduction benefits do accrue to other countries. However, for a local planner we might reasonably expect them to only pay attention to the local net benefits as these are the ones that directly affect constituents in their jurisdiction (i.e. $-\beta_1 > -\beta_2 = \beta_3 = 0$).[15]

To be clear, the main local impacts for the local planning authorities are the property value impacts arising for their nearby residents. All other costs and benefits can be viewed as externalised or diffuse from the perspective of the local authority where a wind or solar project is being sited. It is true that displacing electricity from fossil power plants can lead to changes to air pollution that are geographically concentrated. However, the UK grid is relatively well integrated and most wind and solar projects are not sited in industrial areas near existing fossil power plants. As such any benefits from changes to air pollution will almost certainly be concentrated far from the local authority where a new wind or solar project is being sited.

Lastly, I extend the analysis to look at differential effects to see whether planning decisions differ based on: 1) whether a project is in a wealthy area; 2) whether the local authority was politically conservative; and 3) whether the decision was made nationally or locally. Areas were classified as wealthy based on data from the UK's Index of Multiple Deprivation.[16] For the political makeup of a local authority, I use data on local elections to identify areas that have a majority of Conservative party councillors.[17] National control can be directly observed in the planning data.

3.3 Quantifying Misallocated Investment

If the planning and permitting process places outsize emphasis on avoiding certain costs (e.g. reductions in local property values) then socially beneficial projects will be consistently refused, leading to under-investment. Even if aggregate deployment is unaffected, a systematic bias towards approving more expensive projects could still emerge. This could take the form of building solar power instead of wind; building more remote wind projects or even moving projects offshore.

To try and quantify the potential for insufficient or misallocated investment, I use my estimates of project specific costs and benefits to find an alternative "best" set of proposed projects. I do this in two main ways.

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

[16] The index assigns neighborhoods a score based on their level of deprivation on a range of measures, where high scores indicate high levels of deprivation. The average deprivation score was calculated for post codes in a 10km radius of each project, with scores below the national median being classed as wealthy.

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

First, I find the set of proposed projects that can produce the observed deployment of renewable energy at least cost. I start by grouping projects by the local authority where they are located and their actual or expected start year. I then rank them in order of social net present value. I sum up the least cost set of projects necessary to reproduce the observed increase in renewable energy production for each local authority in each year. I then compare the cumulative total costs and benefits between this least cost set of projects and the actual ones that were built. After looking at reallocation within local authorities within each year, I then examine the gains from allowing reallocation across local authorities and across years. Preserving the existing level of aggregate deployment and considering reallocation across space and time in this way also helps bolster the plausibility of assuming that existing prices and costs can be used in the valuation analysis, as set out earlier.

Second, I seperately examine the potential gains from approving and constructing all positive net present value projects. This latter approach is particularly valuable for understanding possible under-investment. One challenge this does raise is that it necessarily involves assuming a different (and generally larger) deployment of renewable energy than already seen to date. Where these changes are non-marginal this does raise potential concerns with the original valuation analysis that relies on existing prices and costs. I cover this issue in more detail in the discussion of the results.

3.4 Transfer Payments to Local Residents

A range of policy solutions could help resolve the misalignment between local and wider social incentives, from permitting process reforms to increased local ownership. One natural solution may be to introduce some form of direct transfers to affected local residents. This practice does already happen for some projects, with voluntary payments being made by wind and solar developers to local communities in the form of grants to fund public services or discounts on electricity bills.

I use my estimates of household specific impacts on property values to examine a range of simple transfer schemes. At the most basic these involve making lump sum payments to all affected households within a certain distance. Increasing complexity involves allowing payments to vary based on the capacity of the project, how close a resident is to the project, line-of-sight visibility and average local property values.

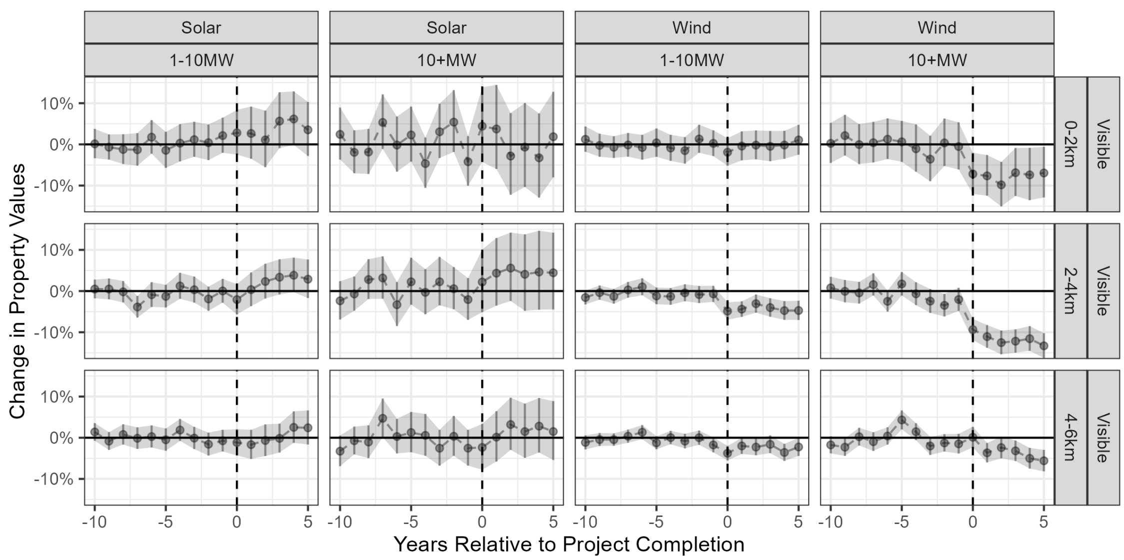
The goal here is to understand if it is feasible to offset the bulk of the local external costs to nearby residents using a few simple project and property characteristics, and how cost effective transfers might be for developers. Full details can be found in the appendix.

4 Results

4.1 Project Costs and Benefits

Figure 2 provides the results of the hedonic analysis. I find strong evidence of a reduction in property values for properties located within 4km of a new wind project and with direct line-of-sight visibility. These effects are much more pronounced for larger projects, with reductions of 8-10% for projects larger than 10MW. There is also some limited evidence of potentially smaller effects out to 6km. As for solar projects, I find no clear evidence of any reduction in property values. In all cases though the event study provides supportive evidence that the treated and control group are on similar trajectories in the pre-period. Further details on the results of the hedonic analysis, and the estimation of the other categories of costs and benefits, can be found in the appendix.

Figure 2: Estimated Capitalization into Nearby Property Values



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

Figure 3 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.

4.2 Determinants of planning approvals

Table 3 presents the results of the planning approvals analysis. The purpose is to understand how responsive planning officials are to different costs and benefits when deciding whether to approve a project. Given the lack of any local external impacts for solar projects I only present the results for wind projects.

Table 3: Planning Process Regressions for Project Costs and Benefits

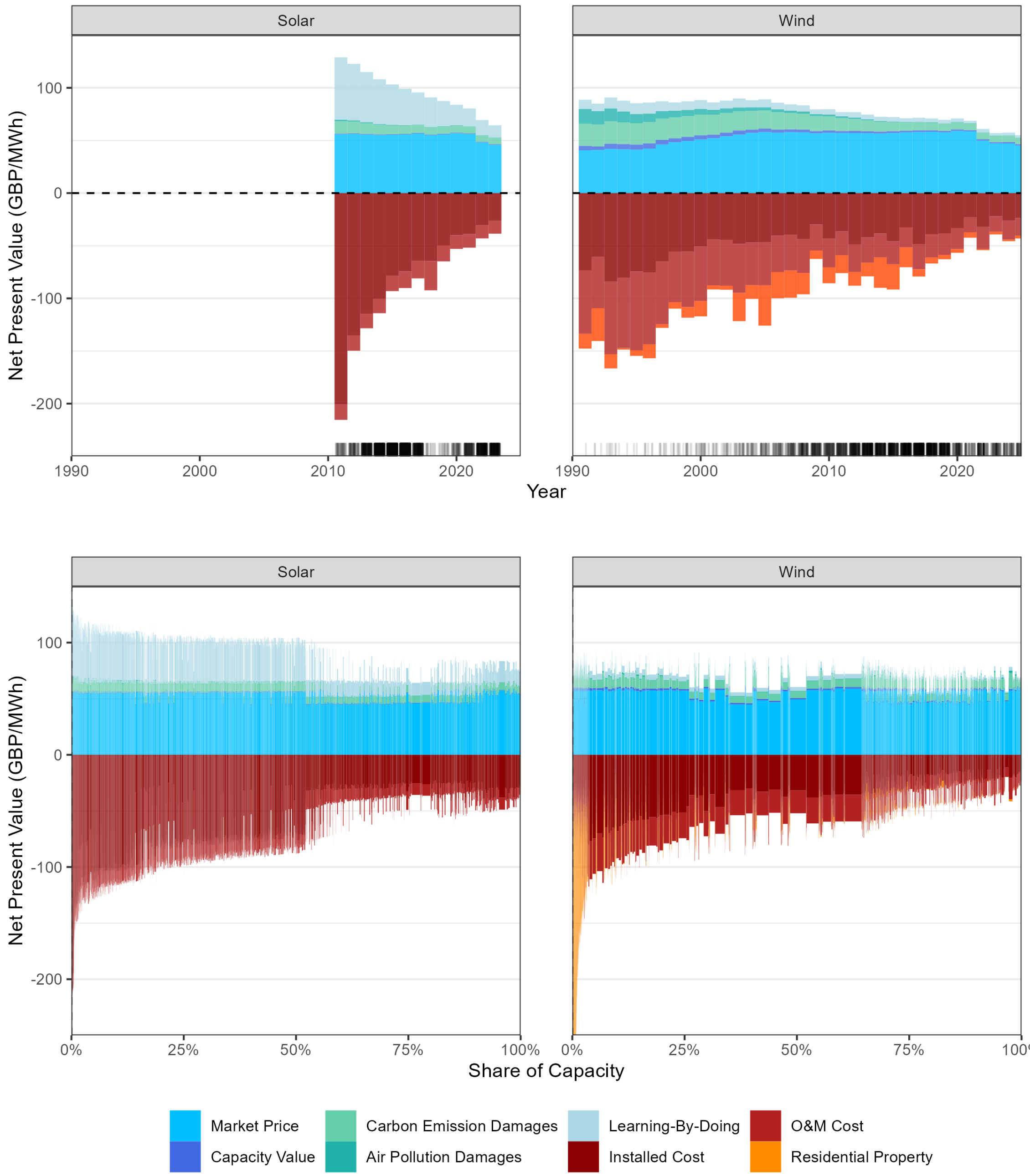
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Cost Property (£10m)	-0.0071*	0.0014	-0.0024	-0.0098**	-0.0014	0.0069	0.0025	-0.0039
	(0.0038)	(0.0046)	(0.0051)	(0.0041)	(0.0061)	(0.0069)	(0.0063)	(0.0065)
Cost Other (£10m)	0.0022***	0.0042	0.0022***	0.0295***	0.0023***	0.0011	0.0025***	-0.0094
	(0.0007)	(0.0040)	(0.0008)	(0.0105)	(0.0008)	(0.0039)	(0.0009)	(0.0133)
Benefits (£10m)	-0.0013**	-0.0012	-0.0013**	-0.0270***	-0.0015**	0.0002	-0.0017**	-0.0030
	(0.0006)	(0.0026)	(0.0007)	(0.0072)	(0.0007)	(0.0031)	(0.0008)	(0.0090)
Cost Property (£10m) x Interaction		-0.0236**	-0.0108	0.0342***		-0.0289**	-0.0138	0.0266**
		(0.0094)	(0.0075)	(0.0122)		(0.0122)	(0.0122)	(0.0128)
Cost Other (£10m) x Interaction		0.0042	-0.0001	-0.0276***		0.0087	-0.0011	0.0117
		(0.0082)	(0.0020)	(0.0106)		(0.0083)	(0.0018)	(0.0133)
Benefits (£10m) x Interaction		-0.0042	0.0001	0.0260***		-0.0074	0.0011	0.0015
		(0.0051)	(0.0017)	(0.0073)		(0.0051)	(0.0016)	(0.0089)
Interaction: Wealthy	No	Yes	No	No	No	Yes	No	No
Interaction: Conservative	No	No	Yes	No	No	No	Yes	No
Interaction: National	No	No	No	Yes	No	No	No	Yes
Fixed-effects								
Local Authority					Yes	Yes	Yes	Yes
Year					Yes	Yes	Yes	Yes
Fit statistics								
Observations	1,942	1,889	1,936	1,942	1,942	1,889	1,936	1,942
R^2	0.01340	0.00969	0.01435	0.02570	0.22330	0.22141	0.22171	0.23033
Within R^2					0.01068	0.00737	0.01150	0.01963
$-\beta_1$=$-\beta_2$ p-value	0.0177	0.6450	0.3829	0.0007	0.5410	0.4299	0.9990	0.7134
$-\beta_1$=β_3 p-value	0.0300	0.9778	0.4742	7.84×10^{-6}	0.6353	0.3186	0.8997	0.5206
$-\beta_1$=$-\beta_2$ p-value (Interaction)		0.0083	0.0106	0.0519		0.0138	0.2284	0.0823
$-\beta_1$=β_3 p-value (Interaction)		0.0055	0.0149	0.0444		0.0082	0.2595	0.0717

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

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

For wind projects, the baseline results reveal fairly consistent evidence of a statistically significant effect for local property values. The coefficient indicates that a £10 million

Figure 3: Estimated Project Costs and Benefits



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

increase in losses to nearby residential property values reduces the likelihood of project approval by 0.7%. By comparison, the coefficients on other non-local costs and benefits are much smaller and actually have the wrong sign, indicating that projects that are less costly to build or more productive are *less* likely to be approved.[18] Tests of the equality of coefficients reveal that there is statistical evidence that local property value impacts are indeed treated differently to other non-local costs and benefits.

Furthermore, the results with interaction effects reveal additional interesting findings. I find that it is wealthy areas where the sensitivity to local property value impacts is concentrated. Here a £10 million increase in losses to nearby residential property values reduces the likelihood of project approval by 2.4%. In less wealthy areas there is no significant effect. The tests of the equality of coefficients also indicate it is only wealthy areas where the sensitivity to local property impacts differs significantly from the sensitivity to other costs and benefits.

When focusing on political makeup, more conservative areas appear to be the ones where the sensitivity of approval decisions to local property value impacts differs significantly from the sensitivity to other costs and benefits. Similarly, when decisionmaking authority rests at the local level I again find that sensitivity to local propery value impacts differs from the sensitivity to other costs and benefits. Where decisions are made nationally the mismatch is counteracted, in keeping with the idea that national decisionmakers pay attention to a broader array of factors than local decisionmakers.

I also explore whether equivalent findings emerge when only focusing on within-local-authority variation. Directionally many of the estimated effects remain the same, although the more limited within-local-authority variation in costs and benefits does reduce the statistical power of the analysis. Notably though, the results that focus on wealthy areas continue to be the ones that most clearly hold. This is further supported by the tests on the equality of coefficients, with wealthy areas again appearing to be more sensitive to local property impacts than to other non-local costs and benefits.

Overall, the particular sensitivity of approval decisions to local property costs is consistent with the idea that local decisionmakers are incentivized to focus on costs to local actors. This appears to be especially true in wealthy areas that are more inclined and better able to resist new wind power deployment. By contrast, the other non-local costs and benefits do not appear to have the same impact on approval probability, and often the sign of the coefficients is reversed. This is consistent with the idea that planning

[18] This is a consistent pattern in much of the analysis. It is notable that local property costs are negatively correlated with other non-local costs and positively correlated with non-local benefits. This is the case when considering variation across all projects and when accounting for local authority and year fixed effects. To the extent there are some unobserved local costs being picked up by these measures of non-local costs and benefits this might help rationalize these effects and provide further support for the role of local factors in guiding planning decisions.

officials are not responsive to these wider impacts, perhaps because they are externalized to non-local actors.

These findings are robust to a range of alternative specifications, such as considering logarithmic changes in costs and benefits (rather than linear) and when estimating using logit instead of a linear probability model. Results with alternative specifications can be found in the appendix. Furthermore, the costs and benefits used in this regression analysis are necessarily uncertain. It is difficult to say whether any such measurement error is classical or systematically related to project characterisitcs. If it is the former, this would tend to lead to attenuation bias. I check this by instrumenting for local property costs with a historic measure of population density. I do indeed find that the results have the same pattern as found in the main analysis but with even larger effects for the local property value costs. These additional results can be found in the appendix. That I find significant coefficients and differences even in the presence of potential measurement error suggests the main findings may understate the level of disparity between the way planners account for local and non-local factors.

Lastly, to further support the idea that the particular sensitivity of planning decisions to local property impacts is indicative of local opposition or NIMBY attitudes I gathered information on the numbers of public comments submitted for a subset of wind projects in Scotland. Here I do indeed find evidence that the number of public comments is higher for projects that have larger local impacts on nearby property values. I also find that projects with more public comments are less likely to be approved, with ten additional objecting comments reducing approval probability by 1.2%. Further detail on this analysis can be found in the appendix.

4.3 Misallocated Investment

4.3.1 Main Misallocation Findings

Table 4 shows that the potential gains from more efficiently reallocating investment amongst the set of proposed projects. A range of possible scenarios are examined to understand the likely drivers of misallocation.

To begin with we can see the observed actual set of projects comprise 41GW of wind and solar capacity, and have a lifetime electricity output of 2,904 TWh. The costs of constructing and operating these projects is £142 billion, and yields benefits of £160 billion. Local property value costs are around £8.5 billion. The result is a social net present value of £9 billion.

Now I consider several counterfactual scenarios. If the planning process is producing efficient outcomes we would expect relatively small differences between the observed set of

Table 4: Misallocated Investment Results

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

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

projects and some hypothetical alternative set of proposed projects. If the planning process is producing inefficient outcomes we would expect there are many socially beneficial projects that did not go ahead after failing to receive permitting approval. Importantly, this entire analysis is conditional on the set of projects that were actually proposed, and so in the likely case where the planning process deters projects from being proposed in the first place this analysis will understate the likely cost of misallocation.

To start let us consider the scope for reallocation across projects to be highly constrained. If reallocation is only possible within a given local authority and within a given year, we see that social net present value can be increased by just over £6 billion (Scenario 1). When compared to observed total capital and operating costs this is equivalent to a 4% cost saving. Importantly, these gains are possible despite the fact that very few local authorities have more than one project proposed in a given year.[19]

Moving to allowing reallocation within a given local authority but across all years causes social net present value to rise more significantly by £26 billion (Scenario 2). This is equivalent to a cost saving of 18%. Focusing on within-local-authority reallocation in this way indicates there is significant inefficiency in local authority decisionmaking when considering the range of projects proposed in a given area. Again though, for most local authorities this still entails reallocating across a relatively small pool of proposed projects.[20]

[19]Only 4% of local authorities in a given year have more than one proposed wind project and only 5% of local authorities in a given year have more than one proposed solar project.

[20]Each local authority sees an average of seven wind projects and eight solar projects over the sample period. The distribution is heavily skewed with only 13% of local authorities having more than ten wind projects and only 24% of local authorities having more than ten solar projects.

Moving to allowing reallocation across local authorities but within a given year leads to an even larger increase in social net present value of £38 billion (Scenario 3). This is equivalent to a cost saving of 26%. As with the first scenario this approach preserves the existing deployment of capacity over time. While less of a direct test of the role of decisionmaking from individual local authorities, this scenario does help illuminate inefficiencies from the lack of coordination in planning decisions across space.

Finally, I examine the result of allowing full reallocation. This is equivalent to considering the impact of approving and constructing all positive net present value projects. Here I find that total lifetime output from wind and solar increases by 55% from observed levels (Scenario 4). This is potential evidence of substantial under-investment in renewable energy, particularly for wind power, with many socially beneficial projects failing to go ahead. Notably, total local property value costs also increase in this case, suggesting there are many projects worth pursuing even where they create adverse external costs to nearby residents.

4.3.2 Discussion of Misallocation Results

The large misallocation costs found here raise important questions about how effectively decisions are being made about which renewable energy projects to build and where. These costs can also be clearly attributed to failings in the permitting process. When a socially beneficial project fails to be built, this could be for two main reasons: 1) the project was refused planning permission, or 2) the project was approved for planning permission but did not go ahead for other reasons (e.g. failure to secure financing). In all scenarios the significant majority of socially beneficial projects that failed to be built were refused planning permission.

A subsequent question is: what aspects of planning decisionmaking are leading to these inefficient outcomes? The first explanation discussed most directly here has been the role of local opposition or NIMBYism, either from residents or from planners themselves. Put another way, the incentives local communities and politicians have to resist projects in their area that they perceive as having concentrated harms, while notionally supporting the deployment of renewable energy more generally. As discussed previously, planners in this context have strong incentives to pay attention to local impacts given that decisions are mostly made by local planning authorities. These jurisdictions also do not capture many of the benefits of renewable energy projects. The value of the electricity produced and the reductions in carbon emissions and local pollution are not concentrated in the local area, and often arise regionally, nationally or even globally. There are also minimal boosts to local tax revenues in the UK and a lack of long-term impacts on employment. In this setting it is the direct external costs on nearby residents through visual and noise disamenities that are likely to be most salient, and these are reflected here by impacts on local property values. The regression analysis of approval decisions provided support for this explanation, highlighting the sensitivity of planning decisions to local property value costs, especially in wealthy areas. I also find evidence that projects with larger property value impacts are subject to more public comments, and that increased public comments are associated with a lower chance of approval.

If the local opposition story does apply here we would expect the misallocation analysis to reveal that under an optimal scenario many more projects would be approved. This is indeed what I find: many socially desirable projects were refused planning permission and under an optimal scenario the lifetime output from wind and solar would be 55% higher than observed levels (Scenario 4). We would also expect there to be significant gains available simply from reallocating projects within a local authority, which again is what I find (Scenarios 1 and 2).

Lastly, we might also expect that after reallocation the total local property value costs should increase, which would be compensated for by changes to the other non-local costs and benefits that were not being adequately accounted for. I do find that the share of project capacity imposing local property costs increases substantially across the various reallocation scenarios. However, reallocation does not increase total local property value costs - instead these fall across reallocation scenarios which seems at odds with the NIMBYism explanation. This can largely be explained by the fact that the reductions in total local property costs in the base case are mostly driven by several small projects that are significant outliers in terms of their local property costs. Often these are individual turbines constructed on industrial sites near urban centers and so may reflect imperfections in the application of the capitalization effects in this context. For instance, it is possible these kinds of projects may have unobserved local benefits (i.e. they are directly owned by a local industrial firm) or may not impose as severe visual disamenity if already located in an industrial area. Planners may also be more inclined to approve small projects in general as seen in the earlier descriptive analysis. This might be because they view several small projects as preferable to approving a single larger one that exposes one community to a more substantial degree of external impacts.

To further explore this issue I conduct a sensitivity analysis focusing only on the larger projects. I find that projects smaller than 10MW (1% of existing output) are responsible for almost two thirds of local property value impacts. Limiting the analysis to reallocation amongst projects greater than 25MW (84% of existing output) yields similar social net present value gains to the base case across the various reallocation scenarios while also consistently increasing total local property costs. The earlier planning approval regression results also hold when focusing on larger projects in a similar manner. Full details on the sensitivity results are in the appendix.

A second explanation for the observed misallocation costs could be a lack of regional coordination. With most decisions being made by local authorities, the fragmented nature of the planning process means decisionmakers in one jurisdiction are not considering the relative merits of similar projects in other jurisdictions, some of which may be more worthy of approval. If this is the case we would expect there to be significant gains available simply from reallocating projects across local authorities, which I do find (Scenario 3). However, this explanation does not necessarily imply that planners would systematically approve too few projects overall, where as I do find evidence of underinvestment (Scenario 4).

A third explanation is that planners simply lack the expertise to distiguish “good” projects from “bad” ones. However, if this was the case we would expect their decisions to be largely unresponsive to the various costs and benefits quantified here. The planning approvals regression analysis showed that decisions are actually systematically related to variation in certain impacts (i.e. local property costs) and if anything have the wrong sign when it comes to the other non-local costs and benefits. This explanation also does not necessarily imply that planners would systematically approve too few projects overall, and yet that is what I find (Scenario 4).

Overall it is hard to say definitively to what extent each of these competing explanations is most responsible for the observed costs from misallocation. In practice it is likely some combination of all three. However, given the earlier planning approvals regression analysis and some key features of the observed misallocation analysis it does seem that local opposition and incentives for planners to focus on local factors is a significant driver of inefficient permitting for renewable energy.

Importantly there are a few caveats to note with this misallocation analysis. The first is that my findings reflect the set of proposed projects that even made it to the planning submission stage. Misallocation costs are likely to be considerably larger when accounting for the the full range of hypothetical projects that could have been proposed. For instance, changes made to the planning process for onshore wind projects in England & Wales after 2015 led to a significant drop in planning applications, over and above any fall in the approval rate (Windemer, 2023). If onshore wind projects had continued to be proposed in England & Wales at the rate seen in the decade before 2015, as they did in Scotland, an additional 5.6GW would have been proposed by 2022, representing a 13% increase on the current total in the sample. Moreover, current forecasts anticipate that installed onshore wind power capacity will double from existing levels to around 23GW by 2050 (NGET, 2022), and the technical potential for the UK is projected to be twenty times that level (Eurek et al., 2017). The proposed projects in my sample therefore represent a partial picture of the full set of optimal locations potentially available.

A second caveat is that the various scenarios explored (especially the final one) may entail non-marginal changes in renewable investment that alter the pace, scale and sequencing of deployment. This could have dynamic effects on electricity prices, capital costs or cumulative impacts on property values which are not fully accounted for. It is difficult to say if this will tend to bias the estimates of misallocation costs upwards or downwards. On the one hand, a larger deployment of renewable energy will tend to depress wholesale prices, and in concentrated locations there can be negative spillovers across projects, such as through transmission congestion or wake effects for wind turbines (Lundquist et al., 2018). Failing to account for these factors would lead the current analysis to overstate the potential gains from reallocation. On the other hand, there may be economies-of-scale and learning-by-doing effects from adding many projects, especially if these are located in a specific area. This could arise through the build-out of the necessary supply chain capacity or where expanded deployment facilitates spreading transmission costs over more projects. Failing to account for these factors would lead the current analysis to understate potential gains from reallocation. The sign of any bias this might create in the misallocation analysis is therefore ambiguous. Ultimately accounting for these different dynamics would require making complex alternative assumptions about equilibrium prices and costs in ways that are not feasible here.

To provide further reassurance that these non-marginal changes are not unduly affecting the findings I conduct a sensitivity analysis that adjusts downwards the private value of electricity output for each project. This adjustment is designed to reflect a plausible reduction to wholesale prices that would be caused by the expanded deployment of renewable energy envisaged under the full reallocation scenario. This sensitivity does indeed reduce the gains from reallocation, but the effect is very small, with full reallocation resulting in a 45% increase in deployment, rather than the 55% found in the base case. Overall the core findings of the analysis remain robust to this change. Full details are in the appendix.

The third caveat is that these findings are understandably subject to uncertainties in the underlying estimates of costs and benefits. The concern here may be that key costs and benefits could plausibly be calculated using alternative assumptions and that this might meaningfully alter the core findings. There is also a risk that measurement error more generally could bias the calculation of misallocation by making it appear as if there are greater inefficiencies than may be the case. As a robustness check I therefore examine a range of sensitivities to the underlying estimates of costs and benefits (i.e., with regard to local property value costs, environmental benefits, discount rates, error in the attractiveness of cancelled projects, more general noise in the estimates, restricting reallocation across technology types, dropping small projects, and spatial variation in wholesale prices). Across all of these various sensitivities it is striking that the same broad findings emerge: that there is evidence of significant inefficiencies in the observed allocation and scale of investment, with the planning process acting as a key barrier. Further detail on the sensitivity analyses are in the appendix.

Overall then, I consistently find evidence that the fragmented and localized nature of the planning process does risk significant spatial misallocation of infrastructure investment. In terms of under-investment, the analysis here indicates that building 55% more wind and solar power to date would have been socially desirable. That these projects were not built, and that the refusal decisions that blocked them are systematically linked to impacts on local property values, suggests local opposition and NIMBYism does play a role here. Even when constraining the analysis to reproduce the observed deployment of total wind and solar output, significant cost savings are still plausible.

4.4 Transfer Payments to Local Residents

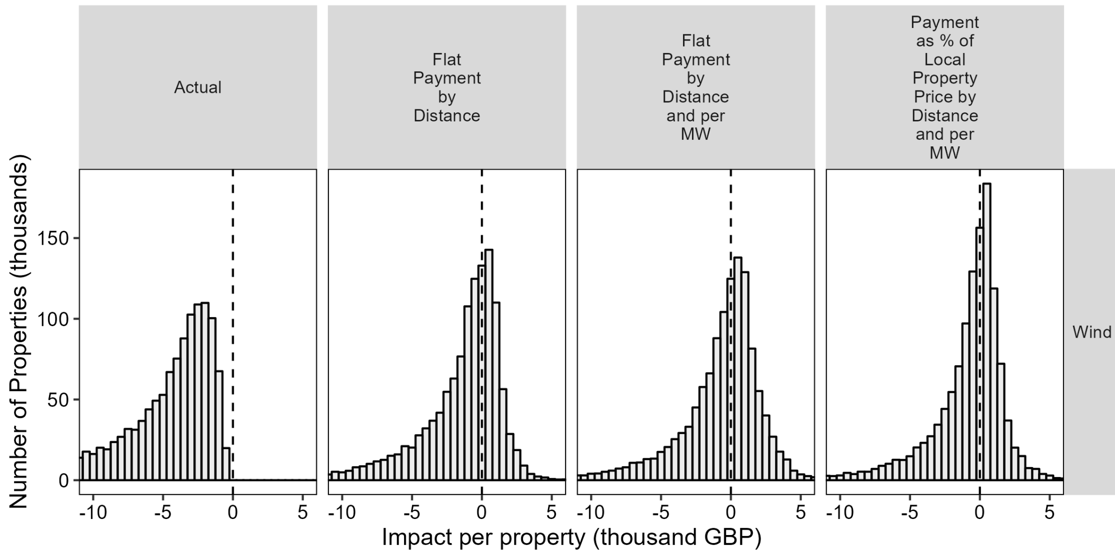
One possible policy solution that could help remedy some of the inefficiencies in the planning process is to make transfer payments to local residents in order to better align local and wider social incentives. Figure 4 shows the external costs to local property values for all nearby residents affected by the socially desirable wind projects in the sample. For most residents the impacts are relatively minor, although there is a long tail of larger impacts for those near particularly expensive properties.

Figure 4 then illustrates how relatively simple schemes for targeting payments to local residents can help offset the impacts on affected households. These range from simple flat payments based on distance, to payments that account for project size and are made proportional to the average local authority property value. Most individual payments to households end up being on the order of a few hundred pounds, but some can reach several thousand pounds. Of course, there are limits to the extent to which a policy can target heterogeneous affected individuals without distorting household incentives (Sallee, 2019). It is not clear that significantly increasing complexity further to improve targeting would be desirable from an economic, political or administrative standpoint.

From the developer perspective, the capacity-weighted average cost of these transfer schemes for the socially beneficial projects is around £6,500/MW/year. This masks significant variation with the bottom 10% of projects making virtually zero payments and the top 10% of projects making payments in excess of around £20,000/MW/year.

These overall costs are actually quite similar in size to the voluntary payments that some developers have already made. In Scotland, onshore wind projects with voluntary community benefits funds have made payments of around £2,000-4,000/MW/year. The latest government guidance calls for developers to adopt funds with a value of

Figure 4: Local Compensation Schemes



Notes: This figure shows the net external costs incurred by local residents due to the socially desirable set of wind projects in the sample. The left-most panel shows a histogram of the observed uncompensated distribution of impacts on local residents. The three remaining panels then show the net impact on local residents after accounting for several different compensation schemes of varying levels of complexity.

£5,000/MW/year and there are even some projects making payments of more than £10,000/MW/year. The similarity between my estimates of required transfers and actual voluntary payments could suggest that the status quo of Coasian bargaining is actually functioning fairly well.

However, some caution is warranted. Available data is based on a selected sample of developers that self-report information on their community engagement for successful projects. Whether all local communities are receiving these kinds of opportunities remains unclear. It is possible there are many communities that are poorly placed to negotiate a desirable settlement. Moreover, most existing community benefits funds appear to provide grants to local community organisations. Very few make direct payments to nearby residents. Examining the effectiveness of these community payment schemes is an important area for further study.

5 Conclusion

In this paper I estimate the economic costs of NIMBYism and local planning restrictions by examining the case of renewable energy projects. First I estimate the full range of costs and benefits for each project and find significant heterogeneity. This is particularly the case for the local external costs of these projects, which I estimate here using a hedonic analysis of the impacts on local property values. I then show how planning decisions are particularly responsive to local factors, especially in wealthier areas. This is consistent with the localized nature the planning and permitting process, but raises the risk that the wider social benefits of renewable energy are systematically overlooked. In fact I find that inefficiencies in planning and permitting decisions have contributed to a significant misallocation of investment. The same rate of deployment could likely have been achieved at much lower cost, and evidence of significant underinvestment indicates that a much more expansive rollout of wind and solar power would have been socially desirable.

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

Ultimately though the siting of any new infrastructure project is at some level a political decision. Reforming the extent of local control over planning and permitting decisions is therefore an important issue that is raised by the findings in this paper. Of course, shifting more control over siting decisions to regional or national policymakers could backfire if it results in affected residents believing their concerns are not being heeded. But recent evidence that boosts to local tax revenues can increase the attractiveness of new wind and solar projects is encouraging (Germeshausen, Heim and Wagner, 2021; Brunner and Schwegman, 2022). It may be that pairing decisionmaking reforms with favorable tax changes could help offset the objections of local residents and officials.

Managing the differences between local and national decisionmaking is a significant challenge, and is not unique to renewable energy. For many other forms of infrastructure there is a tension between meeting the needs of local residents and the needs of society as a whole. Finding policies to resolve those tensions will require further research and experimentation. The findings in this paper on the shortfalls of the current planning and permitting process suggest this work is sorely needed.

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Online Supplementary Appendix

Contents

A Project Costs and Benefits

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

A.1 Electricity production

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

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

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

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

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

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

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

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

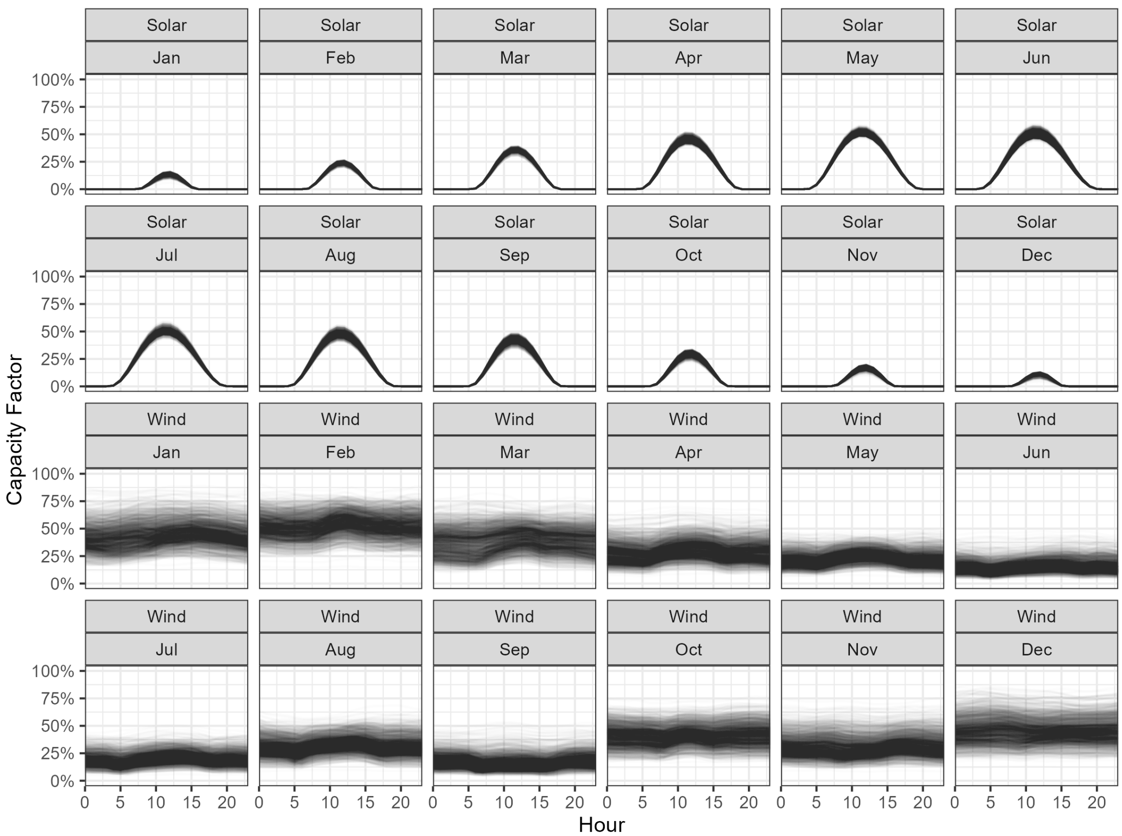
[3]To reduce the noise from year-to-year variation in this ratio value I use a five-year rolling average.

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

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

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

Figure A.1: Estimated Hourly Capacity Factor Profiles

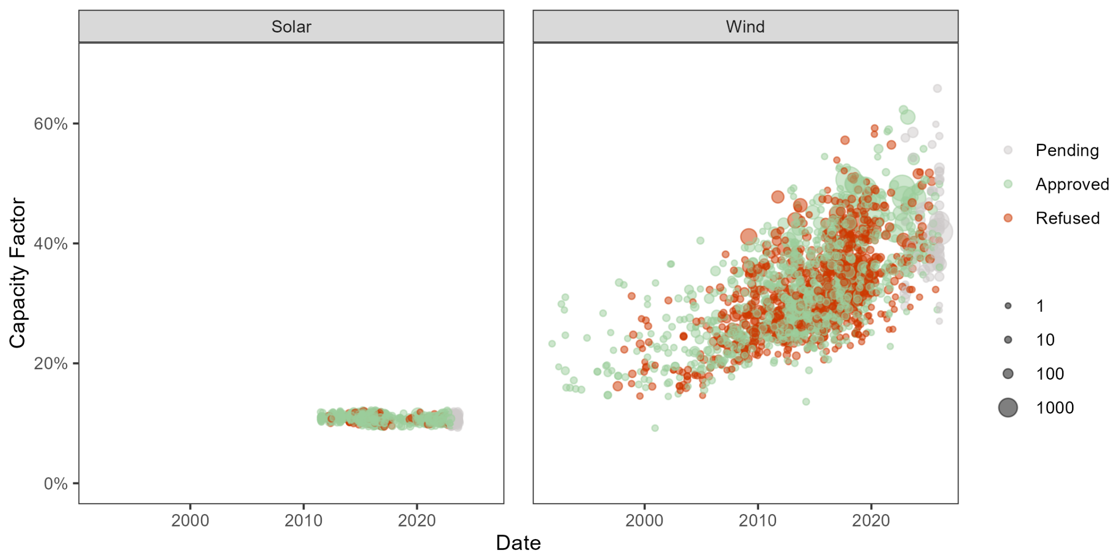


Notes: This figure shows the month-of-year by hour-of-day capacity factor profiles for all projects in my sample. Each line refers to a project. The top panels are for solar projects and the bottom panels are for wind projects.

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

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

Figure A.2: Estimated Project Capacity Factors



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

A.2 Market and Environmental Value of Electricity

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

A.2.1 Wholesale Electricity Prices

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

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

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

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

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

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

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

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

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

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

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

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

A.2.2 Carbon Emissions and Local Pollution Damages

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

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

relationship holds out to 2050.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

A.2.3 Marginal Value Results

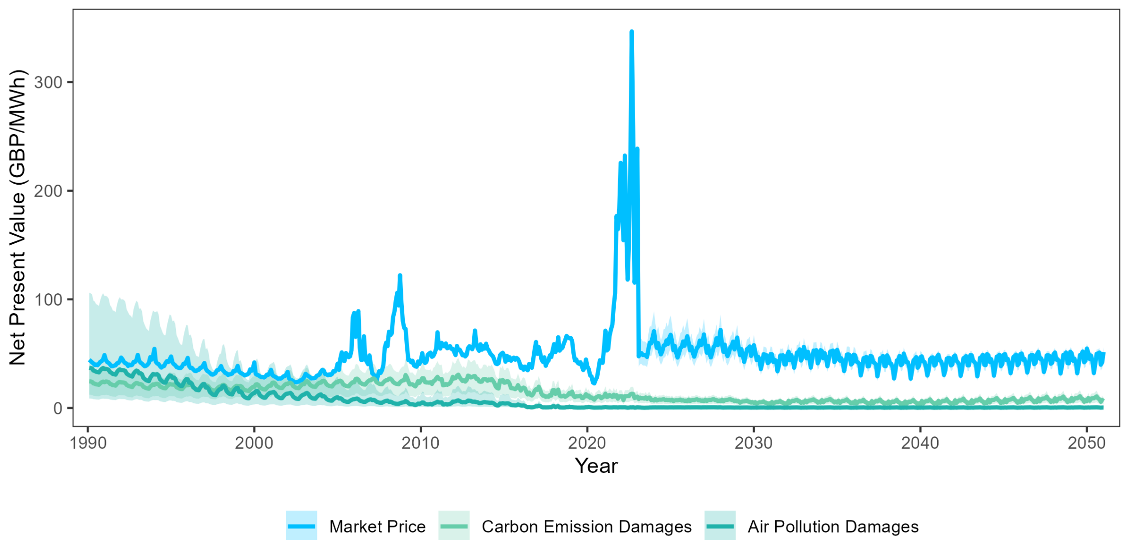
The resulting marginal values per MWh of electricity produced are shown in Figure A.3. These monthly averages convey both the long-term trends and the seasonal fluctuations in both private and external benefits from new wind and solar output. The shaded range also indicates the bounds created by the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

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

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

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

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



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

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

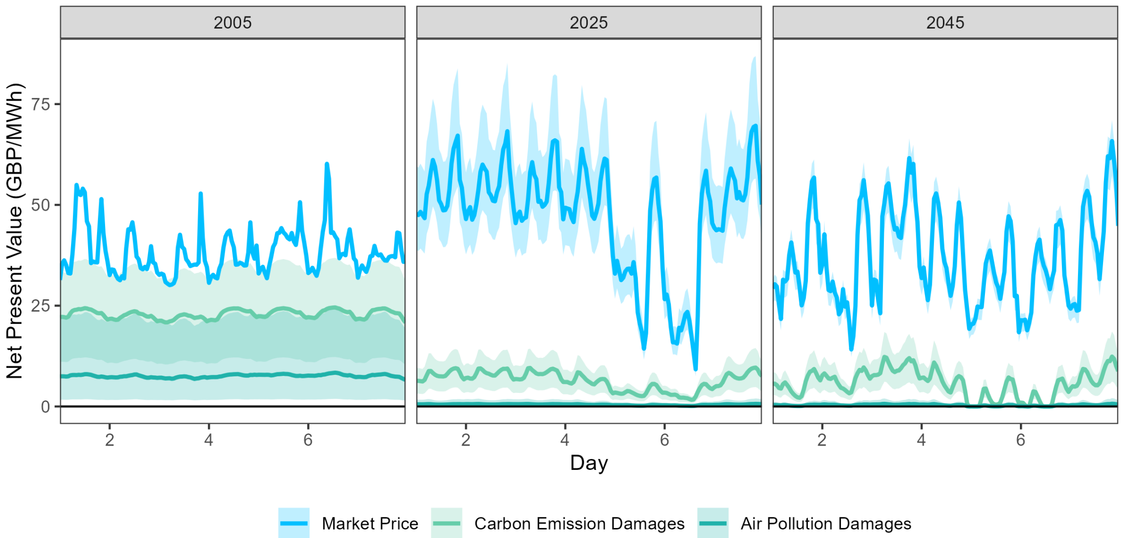
Of course, simulating hourly variability in demand, generation and prices over such a long time period still has some limitations. For instance, shifts in demand that were not observed pre-2022 will be challenging to capture, such as the uptake of electric vehicles and heat pumps. Similarly a growing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

A.3 Capacity Value

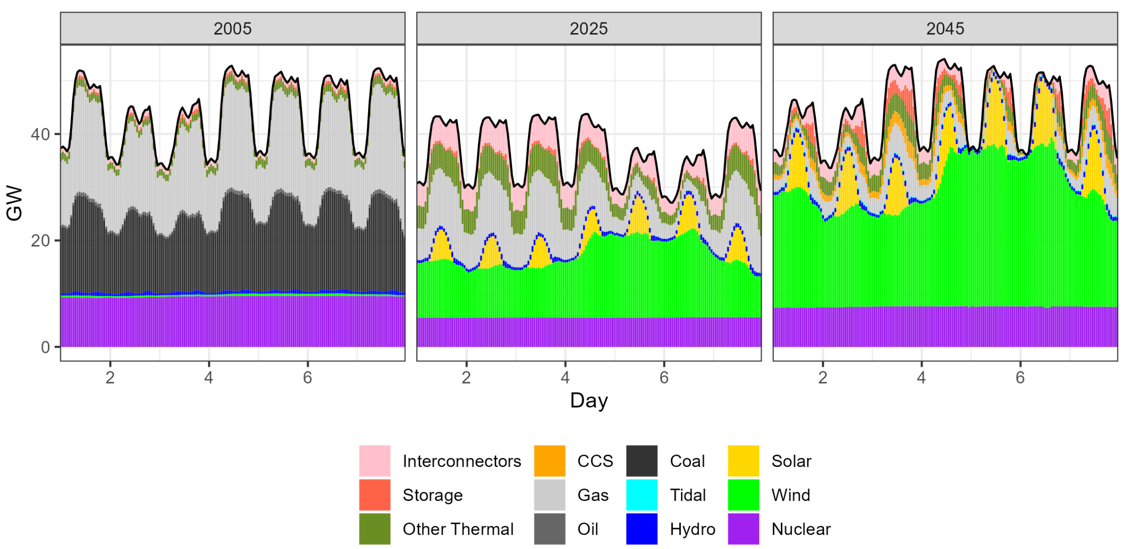
Further detail and figures on the estimation of capacity value is provided here. For intermittent power sources like wind or solar the capacity value is generally thought of in relative terms by starting with the capacity value of a conventional dispatchable generator (e.g. a gas-fired power plant) and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

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

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



(a) Marginal Value of Electricity Output



(b) Generation by Source Type

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

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

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

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

A.4 Capital and Operating Costs

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

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

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

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

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

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

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

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

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

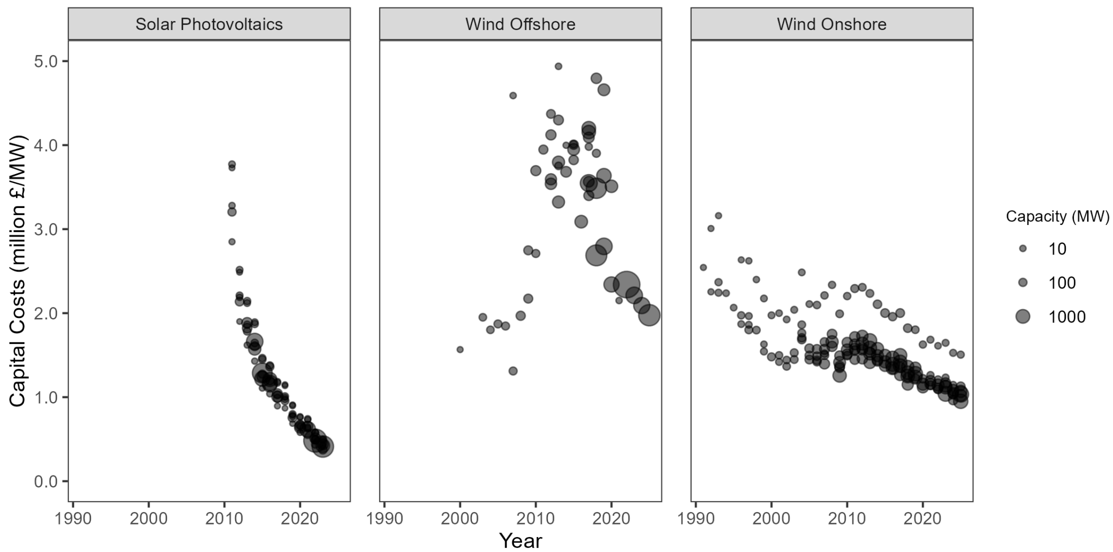
[18]Note that IRENA assumes onshore wind operating costs for the UK in 2021 of $37,000/MW/yr which is basically identical to the $38,000/MW/yr value they assume foir the US.

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

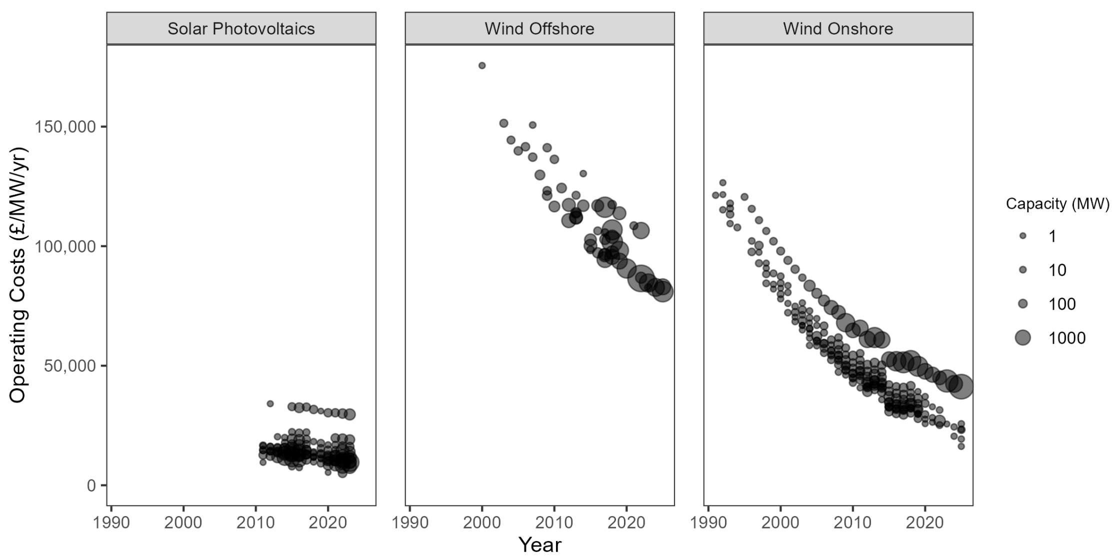
[20]In this instance the regions are South West, South East, London, East of England, East Midlands, West Midlands, Wales, North West, Yorkshire and The Humber, North East and Scotland.

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

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



(a) Capital costs



(b) Operating costs

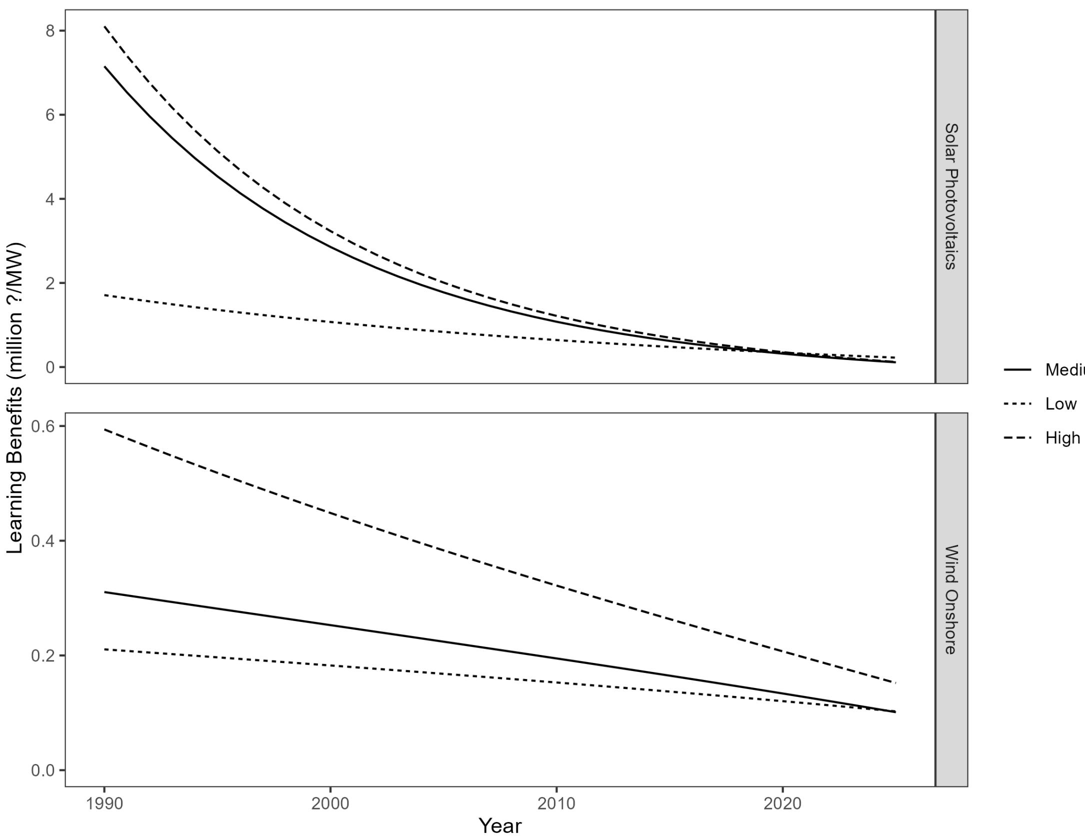
Notes: This figure shows the estimated costs over time. Each point represents the total amount of proposed capacity of a given technology type at a given cost level. Capital costs are at the top and operating costs are at the bottom. Panels refer to three different technology types: solar, onshore wind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

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

A.5 Learning-by-doing

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

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



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

A.6 Costs to Local Residents

A.6.1 Project and property locations

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

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

A.6.2 Visibility analysis

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

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

For wind projects the height of the turbines is far more heterogenous, particularly as turbines have increased substantially in size over time. The planning dataset also does not include information on wind turbine tip heights. Fortunately it is possible to calculate the average capacity of the turbines installed by dividing the total capacity by the number of turbines. Turbine capacity has a fairly stable relationship to turbine size. I use data on thousands of different turbine models in The Wind Power Turbine Database to fit a simple regression model that traces out the effectively quadratic relationship between turbine capacity and turbine height (The Wind Power, 2019). I then apply this to the information on turbine capacity in the project database. The resulting turbine tip heights range from around 50m to in excess of 200m. This is the height off the ground that I use for the project locations.

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

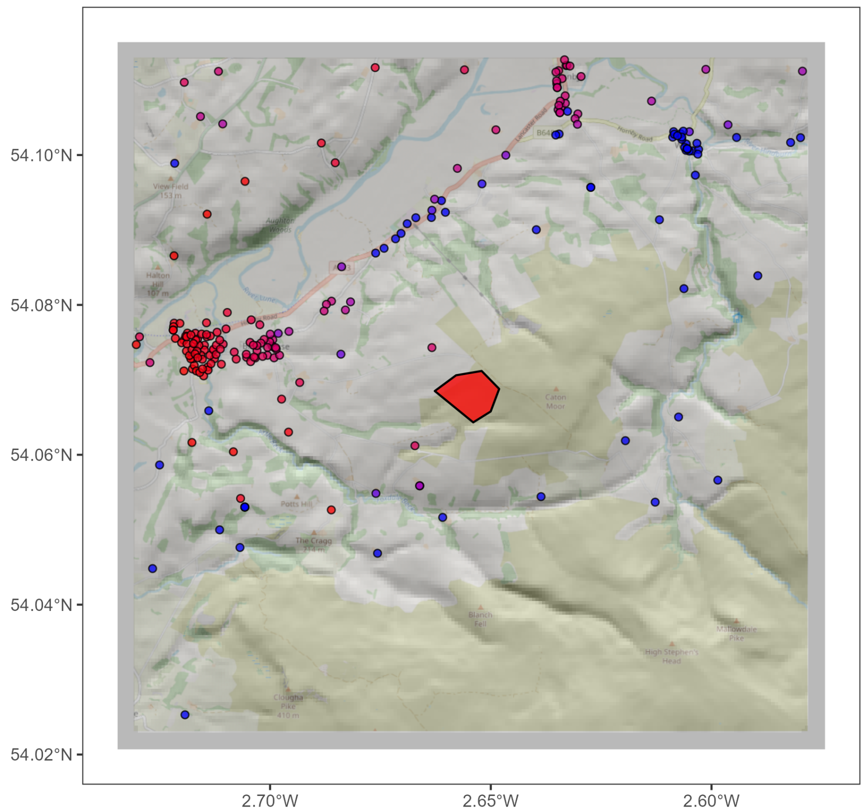
An illustration of this analysis can be seen in Figure A.7. This figure shows a map of the area surrounding the Caton Moor Wind Farm, denoted by the red polygon in the center. The red/blue points denote the post codes where properties are located. Postcodes in blue have no direct line-of-sight to the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

A.6.3 Empirical strategy for hedonic analysis

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

I focus on capitalization into residential property values as this likely captures a large portion of the local impacts of interest. Wind and solar projects have been shown to have minimal persistent impacts on local employment (Costa and Veiga, 2019). Projects do generate rents for landowners, and prior research has found positive capitalization of wind energy subsidies into agricultural land values (Haan and Simmler, 2018). Unfortunately I lack the necessary data on land values to study this directly, although given the concentration of landholdings this is likely to only affect a very small number of local individuals. The impact of a project on local tax revenues is likely minimal in the UK

Figure A.7: Illustration of Postcode to Project Visibility



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

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

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

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

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

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

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

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

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

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

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

The hedonic analysis conducted here improves on prior studies in important ways. Numerous studies have shown that difference-in-difference estimates can be biased when there is variation in treatment timing (Goodman-Bacon, 2018; Borusyak and Jaravel, 2017; Callaway and Sant'Anna, 2019). Here I estimate my effects using the approach developed by Callaway and Sant'Anna (2019) to tackle this problem. This paper is therefore the first paper using hedonic methods to quantify the local impacts of renewable energy projects that has accounted for this potential source of bias. It appears from comparing the new estimates with those from a standard two-way fixed effects model that this source of bias is potentially substantial in this context. This makes sense given the extent to which treatment effects are heterogenous and that deployment of projects rolled out over many years.

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

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

A.6.4 Detailed Hedonic Regression Results

Figure A.8 provides additional detail on the results presented in the main text. The clearest evidence of an impact on property values still arises for properties within 4km of a directly visible wind project, particularly a larger wind project of 10+MW. In these cases there is a sudden negative jump at the year of project completion that deviates from the prior flat pre-period trend, with an effect size on the order of 8-10%. There is also some potential evidence of a small effect in the 4-6km distance bin, and for smaller projects in the 1-10MW capacity bin, although these are not quite as conclusive. There is no clear evidence of an effect for visible solar projects of any size in any distance bin.

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

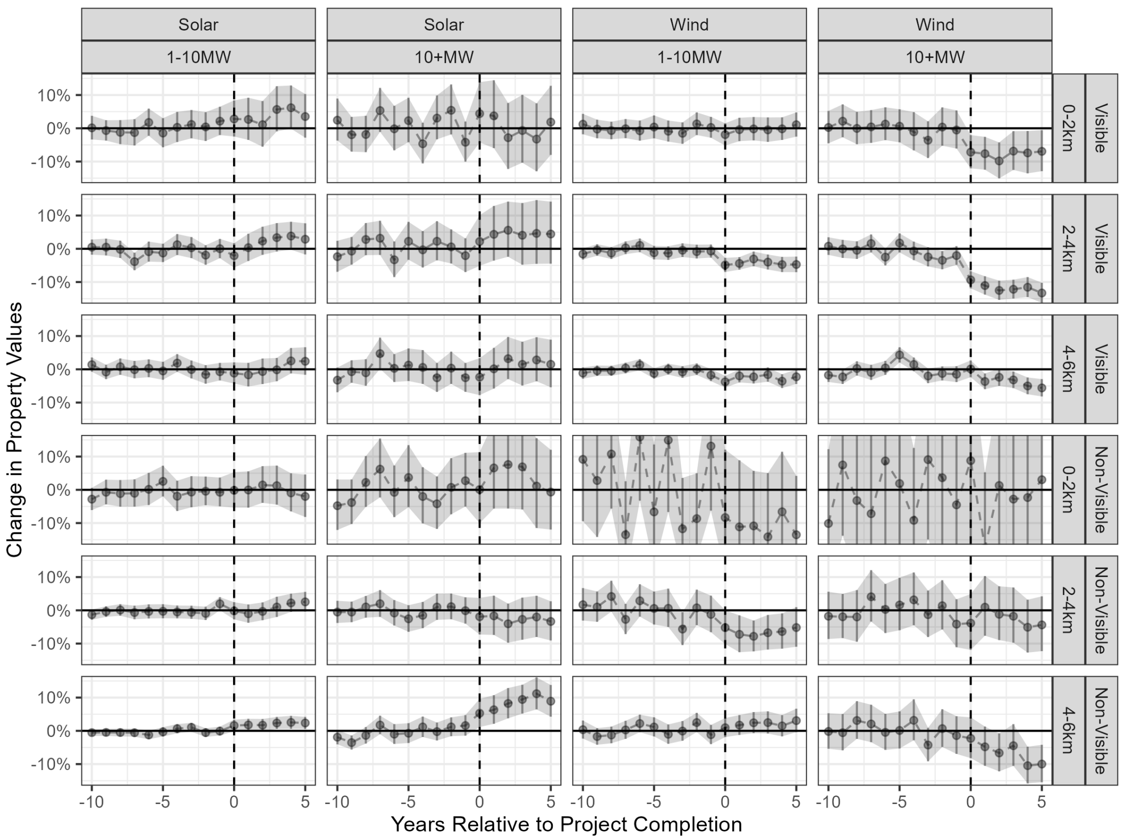
To check for possible sorting I repeat my regression analysis but this time the dependent variable is the number of sales per postcode-year. I make sure to expand the dataset to include zero values for postcode-years where there are no sales. Figure A.9 shows that across both wind and solar projects and various margins of heterogeneity I find no consistent evidence of a change in the frequency with which properties are sold.

A.6.5 Assumed capitalization effects

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

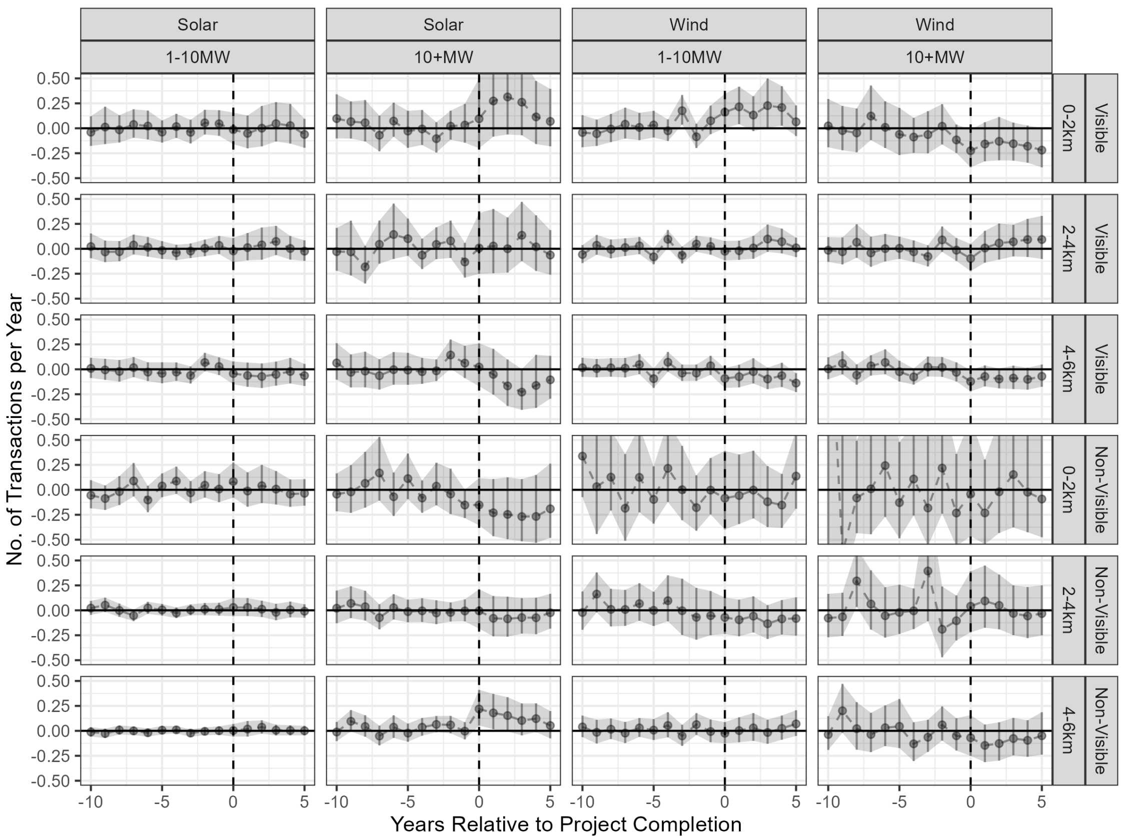
I therefore pick a set of capitalization effects, β, that produces a reasonable range

Figure A.8: Estimated Capitalization of Wind and Solar Projects into Nearby Property Values



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

Figure A.9: Estimated Effect of Wind and Solar Projects on Frequency of Property Transactions



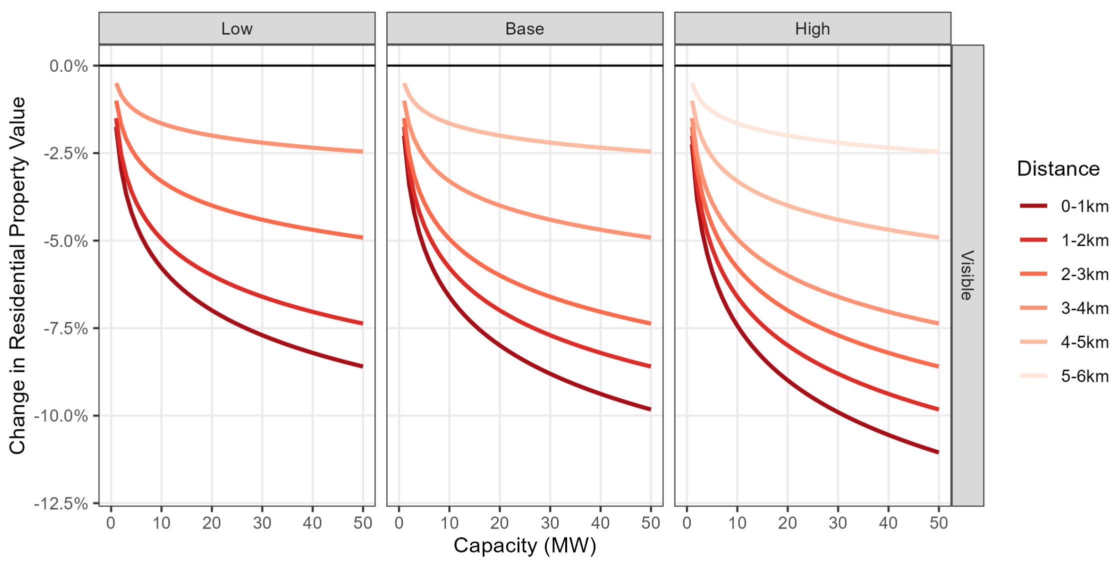
Notes: This figure shows the estimated effects of new wind and solar projects on the frequency of property transactions. The left panels are for solar projects and the right panels are for wind projects, with subpanels by capacity bin. The top panel shows visible projects and the bottom panel shows non-visible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

of property value impacts that can approximate the hedonic estimates I find, and those found in the wider literature (Gibbons, 2015; Jensen et al., 2018; Dröes and Koster, 2020; Gaur and Lang, 2020; Parsons and Heintzelman, 2022). Here I assume a log relationship between project capacity and the effect size, consistent with prior work (Jensen et al., 2018). This conveniently produces a smooth increase that lends itself to the kind of extrapolation exercise envisaged here. It also captures the fact that the first few turbines installed are likely to be quite costly, but that there is a diminishing marginal impact as the extent of deployment increases. In using a log relationship I also make a slight adjustment to ensure the smallest projects have sensible effects. The resulting approach is set out below.

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

In my central scenario, properties within 5km of a wind project with direct visibility have β values of -0.02, -0.0175, -0.015, -0.01 and -0.005 at distances of 0-1km, 1-2km, 2-3km, 3-4km and 4-5km respectively. See Figure A.10 for an illustration of how these assumptions translate into property value changes.

Figure A.10: Illustration of Assumed Capitalization Effects by Project Capacity



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

A.6.6 Property values by post code

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

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

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

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

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

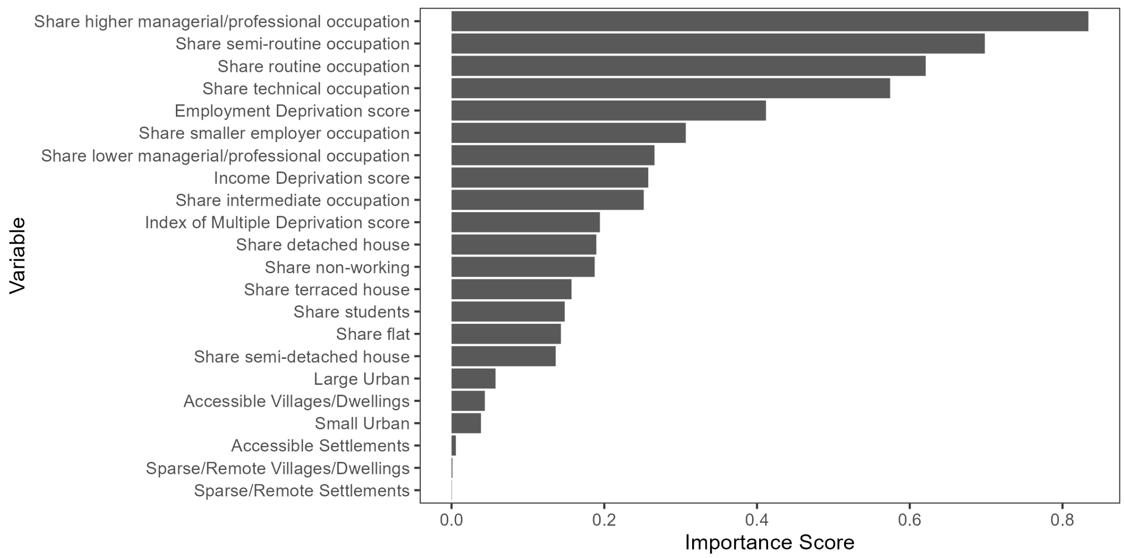
Next I download and merge a range of other variables, X_p, that are likely to be correlated with prices while also being consistently available at the post code level. This includes measures of whether a post code is rural or urban, index scores of social deprivation and census data on the socioeconomic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

I then fit a machine learning model of my "post code price ratio" outcome variable, R_{ip}, on the range of post code-level covariates, X_p. For this I use the random forest algorithm.[23]

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

The model achieves an out-of-sample R-squared of 0.57. The relative importance of different covariates to the overall predictive power of the model can be seen in Figure A.11. The most important covariates are those associated with the prevelance of different types of occupation and aggregated scores of deprivation. The least important covariates are those capturing differences between urban and rural areas.

Figure A.11: Postcode Price Ratio Predictive Model Importance Scores



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

Lastly, I use the model to make predictions of the "post code price ratio" for every post code in my sample, including those in Scotland which were not in the original transaction dataset. I then calculate the predicted post code-level price in a given year by rescaling the local authority average price using the predicted "post code price ratio".

$$P_{pt} = P_{at} \times \frac{\hat{R}_p}{\hat{R}_a} \quad (4)$$

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

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

B Determinants of Planning Approvals

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

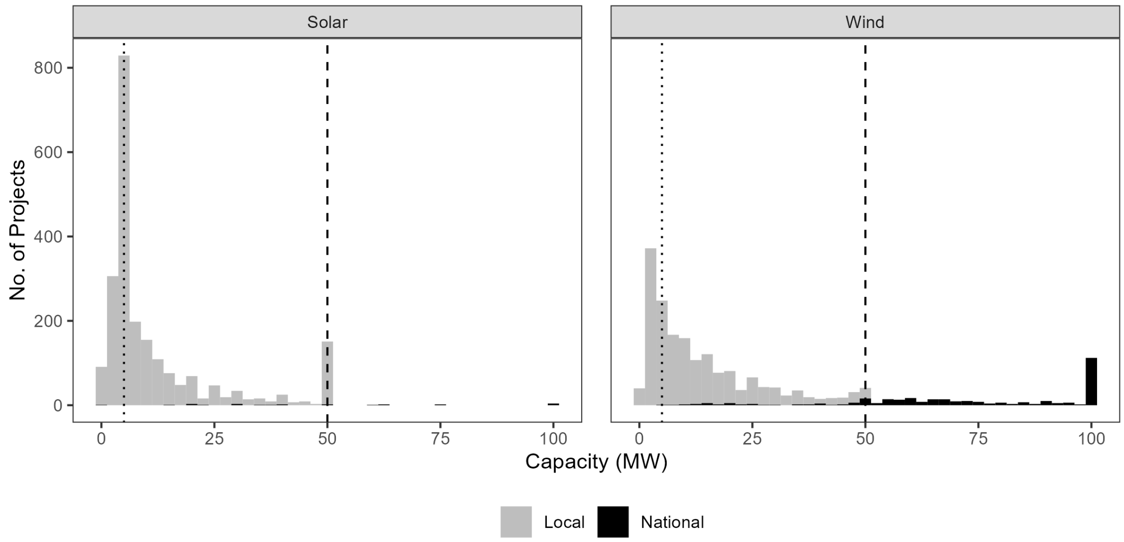
B.1 Threshold for National Significance

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

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

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

Figure B.1: Wind and Solar Projects by Size



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

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

B.2 Additional Regression Results

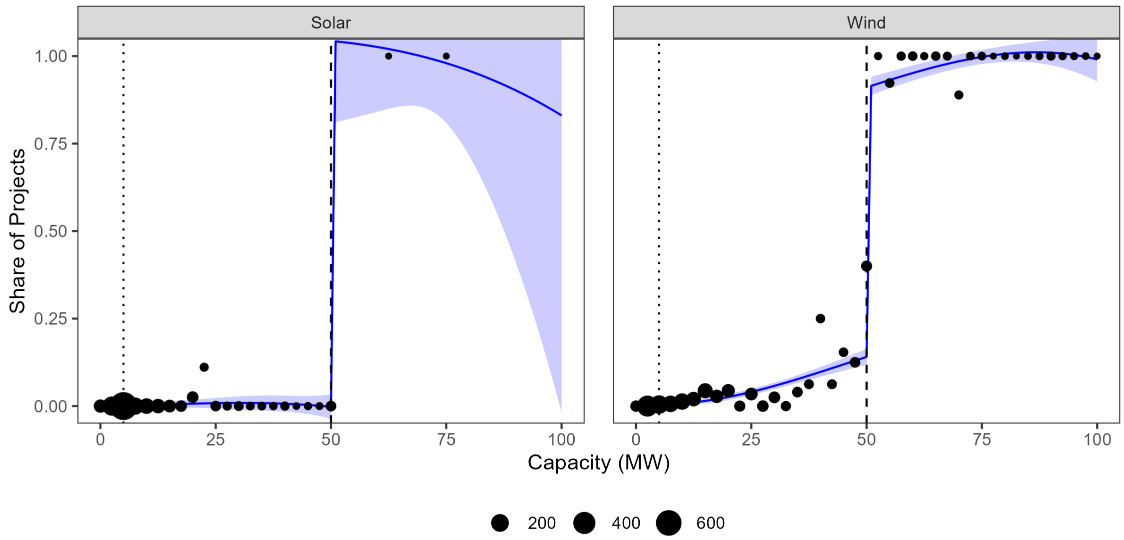
Table B.1 examines the robustness of the planning process results in the main text to alternative specifications. I examine the impact of using using a logit specification rather than a linear probability model and of using a log instead of linear functional form.

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

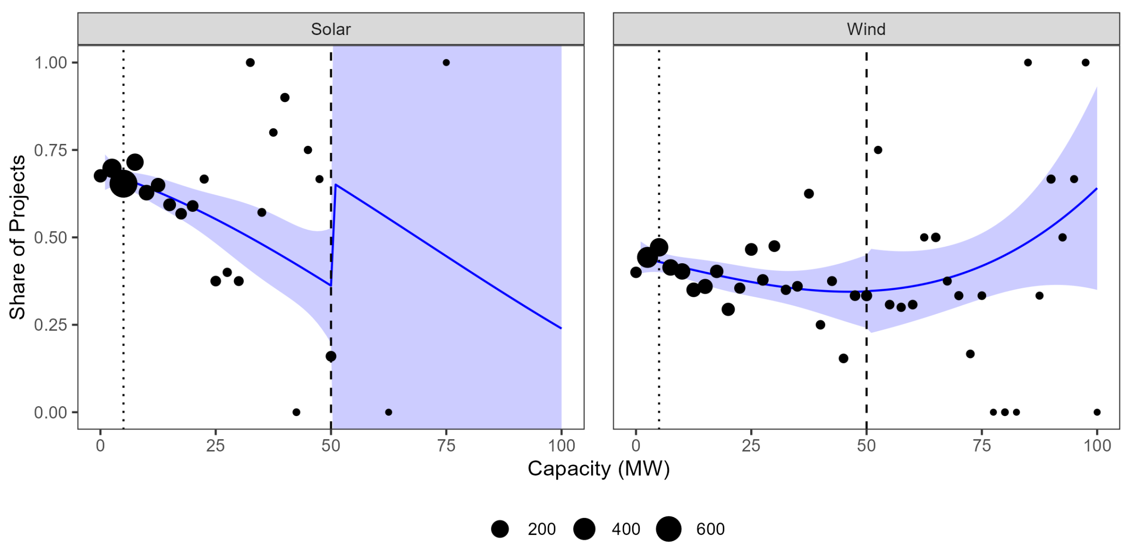
Unlike the linear functional form models, the log functional form does still have highly significant negative coefficients on the property value costs across all specifications. This is likely due to the high degree of dispersion in the estimates of property value costs. The tests of equality of the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

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

Figure B.2: Wind and Solar Projects by Size



(a) Share Decided Nationally by Size



(b) Share Approved by Size

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

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

Model:	(1) OLS	(2) OLS	(3) Logit	(4) Logit	(5) OLS	(6) OLS	(7) Logit	(8) Logit
Variables								
Cost Property (£10m)	-0.0071*	-0.0014	-0.0287*	-0.0069				
	(0.0038)	(0.0061)	(0.0169)	(0.0296)				
Cost Other (£10m)	0.0022***	0.0023***	0.0123**	0.0130**				
	(0.0007)	(0.0008)	(0.0061)	(0.0061)				
Benefits (£10m)	-0.0013**	-0.0015**	-0.0067	-0.0077				
	(0.0006)	(0.0007)	(0.0046)	(0.0051)				
log(Cost Property)					-0.0159***	-0.0177***	-0.0699***	-0.0868***
					(0.0029)	(0.0036)	(0.0139)	(0.0190)
log(Cost Other)					0.2367***	0.1885**	1.030***	1.124***
					(0.0478)	(0.0778)	(0.2168)	(0.4307)
log(Benefits)					-0.2282***	-0.1877**	-0.9854***	-1.095***
					(0.0444)	(0.0747)	(0.1990)	(0.4081)
Fixed-effects								
Local Authority		Yes		Yes		Yes		Yes
Year		Yes		Yes		Yes		Yes
Fit statistics								
Observations	1,942	1,942	1,942	1,718	1,942	1,942	1,942	1,718
Squared Correlation	0.01340	0.22330	0.01660	0.12804	0.05296	0.24240	0.05324	0.15005
Pseudo R^2	0.00929	0.17409	0.01177	0.10085	0.03749	0.19124	0.04000	0.11871
BIC	2,823.0	4,152.9	2,690.7	3,214.1	2,743.5	4,104.5	2,614.7	3,171.6
β_1=β_2 p-value	0.0177	0.5410	0.0254	0.5078	5.47×10^{-8}	0.0063	2.23×10^{-7}	0.0041
β_1=β_3 p-value	0.0300	0.6353	0.0482	0.6257	1.75×10^{-8}	0.0047	6.84×10^{-8}	0.0031

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

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

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

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

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

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Cost Property (£10m)	-0.0087**	-0.0023	-0.0021	-0.0099**	0.0002	0.0076	0.0050	-0.0023
	(0.0043)	(0.0052)	(0.0054)	(0.0044)	(0.0058)	(0.0063)	(0.0059)	(0.0062)
Cost Other (£10m)	0.0020***	0.0018	0.0019***	0.0258**	0.0028***	0.0009	0.0029***	-0.0019
	(0.0006)	(0.0032)	(0.0006)	(0.0130)	(0.0007)	(0.0036)	(0.0008)	(0.0142)
Benefits (£10m)	-0.0015***	-0.0004	-0.0015***	-0.0250***	-0.0022***	-0.0003	-0.0024***	-0.0078
	(0.0005)	(0.0021)	(0.0005)	(0.0089)	(0.0006)	(0.0026)	(0.0007)	(0.0098)
Cost Property (£10m) x Interaction		-0.0191**	-0.0153*	0.0314***		-0.0257**	-0.0170	0.0263**
		(0.0092)	(0.0078)	(0.0117)		(0.0121)	(0.0108)	(0.0104)
Cost Other (£10m) x Interaction		0.0015	0.0006	-0.0240*		0.0058	-0.0002	0.0047
		(0.0079)	(0.0020)	(0.0130)		(0.0092)	(0.0019)	(0.0142)
Benefits (£10m) x Interaction		-0.0030	-0.0004	0.0237***		-0.0060	0.0004	0.0056
		(0.0048)	(0.0017)	(0.0089)		(0.0057)	(0.0016)	(0.0097)
Interaction: Wealthy	No	Yes	No	No	No	Yes	No	No
Interaction: Conservative	No	No	Yes	No	No	No	Yes	No
Interaction: National	No	No	No	Yes	No	No	No	Yes
Fixed-effects								
Local Authority					Yes	Yes	Yes	Yes
Year					Yes	Yes	Yes	Yes
Fit statistics								
Observations	1,942	1,889	1,936	1,942	1,942	1,889	1,936	1,942
R^2	0.09006	0.08095	0.09179	0.09978	0.28429	0.27828	0.28304	0.29040
Within R^2					0.08837	0.07987	0.08940	0.09615
$-\beta_1$=$-\beta_2$ p-value	0.0133	0.4942	0.4749	0.0060	0.6572	0.3356	0.7207	0.9805
$-\beta_1$=β_3 p-value	0.0179	0.6280	0.5218	0.0001	0.7307	0.2647	0.6589	0.3544
$-\beta_1$=$-\beta_2$ p-value (Interaction)		0.0273	0.0020	0.0903		0.0648	0.1094	0.0307
$-\beta_1$=β_3 p-value (Interaction)		0.0101	0.0025	0.0840		0.0300	0.1257	0.0269

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

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

It may also be that the findings are driven by smaller projects that are assumed to impose large property costs because they are located on industrial sites near to urban areas. To test this and examine a set of projects more in line with larger utility-scale wind projects I repeat the analysis using only projects that are larger than 10MW. Here again the results show much the same core findings as in the main analysis.

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

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Cost Property (£10m)	-0.0101**	0.0016	-0.0129	-0.0152***	-0.0034	0.0079	-0.0088	-0.0128
	(0.0047)	(0.0074)	(0.0082)	(0.0054)	(0.0087)	(0.0083)	(0.0096)	(0.0105)
Cost Other (£10m)	0.0019***	0.0032	0.0019**	0.0168	0.0026***	0.0063**	0.0026***	0.0127
	(0.0007)	(0.0042)	(0.0008)	(0.0105)	(0.0006)	(0.0027)	(0.0007)	(0.0141)
Benefits (£10m)	-0.0010*	0.0002	-0.0010	-0.0185***	-0.0018***	-0.0021	-0.0018***	-0.0157
	(0.0006)	(0.0031)	(0.0006)	(0.0069)	(0.0005)	(0.0027)	(0.0006)	(0.0095)
Cost Property (£10m) x Interaction		-0.0222**	0.0058	0.0372***		-0.0455***	0.0543***	0.0334**
		(0.0105)	(0.0097)	(0.0132)		(0.0152)	(0.0192)	(0.0159)
Cost Other (£10m) x Interaction		0.0072	1.89×10^{-5}	-0.0149		0.0128	0.0005	-0.0100
		(0.0076)	(0.0020)	(0.0105)		(0.0088)	(0.0014)	(0.0141)
Benefits (£10m) x Interaction		-0.0057	-4.39×10^{-5}	0.0174**		-0.0098*	-0.0004	0.0137
		(0.0047)	(0.0017)	(0.0070)		(0.0056)	(0.0012)	(0.0094)
Interaction: Wealthy	No	Yes	No	No	No	Yes	No	No
Interaction: Conservative	No	No	Yes	No	No	No	Yes	No
Interaction: National	No	No	No	Yes	No	No	No	Yes
Fixed-effects								
Local Authority					Yes	Yes	Yes	Yes
Year					Yes	Yes	Yes	Yes
Fit statistics								
Observations	994	943	993	994	994	943	993	994
R^2	0.02759	0.01744	0.02787	0.04437	0.24635	0.23992	0.24965	0.25675
Within R^2					0.01774	0.02257	0.02307	0.03130
$-\beta_1$=$-\beta_2$ p-value	0.0110	0.8522	0.0705	0.0107	0.4824	0.8448	0.2292	0.1527
$-\beta_1$=β_3 p-value	0.0179	0.8149	0.0882	0.0002	0.5448	0.4907	0.2664	0.0329
$-\beta_1$=$-\beta_2$ p-value (Interaction)		0.0036	0.1020	0.0798		0.0016	0.0197	0.1338
$-\beta_1$=β_3 p-value (Interaction)		0.0044	0.1343	0.0692		0.0024	0.0174	0.1197

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

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

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

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

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Cost Property (£10m)	-0.0161	0.0046	-0.0096	-0.0243*	-0.0261	-0.0047	-0.0265	-0.0326
	(0.0129)	(0.0128)	(0.0148)	(0.0133)	(0.0320)	(0.0279)	(0.0345)	(0.0333)
Cost Other (£10m)	0.0021***	0.0040	0.0022***	0.0289***	0.0022***	0.0003	0.0024***	-0.0082
	(0.0007)	(0.0038)	(0.0008)	(0.0106)	(0.0008)	(0.0042)	(0.0008)	(0.0134)
Benefits (£10m)	-0.0013**	-0.0016	-0.0014**	-0.0269***	-0.0014**	0.0005	-0.0016**	-0.0027
	(0.0006)	(0.0024)	(0.0006)	(0.0072)	(0.0007)	(0.0032)	(0.0008)	(0.0091)
Cost Property (£10m) x Interaction		-0.0698***	-0.0249	0.0403		-0.1040**	-0.0022	0.0464
		(0.0216)	(0.0173)	(0.0274)		(0.0405)	(0.0284)	(0.0313)
Cost Other (£10m) x Interaction		0.0059	-0.0005	-0.0271**		0.0114	-0.0010	0.0104
		(0.0078)	(0.0020)	(0.0107)		(0.0082)	(0.0018)	(0.0134)
Benefits (£10m) x Interaction		-0.0043	0.0005	0.0258***		-0.0083	0.0010	0.0012
		(0.0049)	(0.0017)	(0.0073)		(0.0051)	(0.0016)	(0.0090)
Interaction: Wealthy	No	Yes	No	No	No	Yes	No	No
Interaction: Conservative	No	No	Yes	No	No	No	Yes	No
Interaction: National	No	No	No	Yes	No	No	No	Yes
Fixed-effects								
Local Authority					Yes	Yes	Yes	Yes
Year					Yes	Yes	Yes	Yes
Fit statistics								
Observations	1,942	1,889	1,936	1,942	1,942	1,889	1,936	1,942
R^2	0.01115	-0.01124	0.00778	0.02007	0.21640	0.18925	0.21382	0.22205
Within R^2					0.00190	-0.03363	0.00149	0.00909
Wald (1st stage), Cost Property (£10m)	77.849	36.577	40.517	37.109	36.553	18.166	26.977	18.101
Wald (1st stage), Cost Property (£10m) x Interaction		19.750	33.598	15.179		34.375	54.612	15.304
$-\beta_1$=$-\beta_2$ p-value	0.1613	0.9674	0.4253	0.0018	0.3758	0.8517	0.4007	0.5073
$-\beta_1$=β_3 p-value	0.1811	0.8181	0.4568	0.0003	0.3900	0.8765	0.4137	0.2795
$-\beta_1$=$-\beta_2$ p-value (Interaction)		0.0024	0.0198	0.6094		0.0385	0.3128	0.7332
$-\beta_1$=β_3 p-value (Interaction)		0.0032	0.0229	0.5914		0.0429	0.3260	0.7181

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

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

B.3 Local Opposition and Public Comments

To further examine what might be driving the observed sensitivity to local impacts, and whether this can be linked to local opposition, I gathered information from local authority websites on the number of public comments for a subsample of onshore wind projects in Scotland. Specifically, the data was collected using the Improvement Service database that includes detailed information on every planning application submitted to local authorities in Scotland (Improvement Service, 2022). I use this dataset to identify possible wind project applications through a keyword search of the application details.[24] I then extract key information on each project from the relevant local authority website at the URLs provided in the dataset. One piece of information I can extract is the number of individual public comments that are recorded on the website. I then match the projects in the Improvement Service database to those in my sample using the planning reference code used for the local planning authority.

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

Table B.5 shows the results of regressing the number of comments a project received on the estimated local and non-local costs and benefits. Here I find evidence that projects with larger local costs, as measured by changes to property values, appear to receive higher numbers of public comments. A £10 million increase in local property value costs is associated with around 12 additional public comments. The association continues to be statistically significant after including local authority and year fixed effects. There is no significant relationship between the other non-local costs and benefits and the number of public comments. In fact the coefficients also have the wrong sign, mirroring the findings in the main planning process regressions that focus on the likelihood of approval.

Table B.6 shows the results of regressing whether a project was approved on the

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

Table B.5: Planning Process Regressions for Project Costs and Benefits (Comments)

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

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

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

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

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

Table B.6: Planning Process Regressions for Project Public Comments

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

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

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

C Misallocated Investment

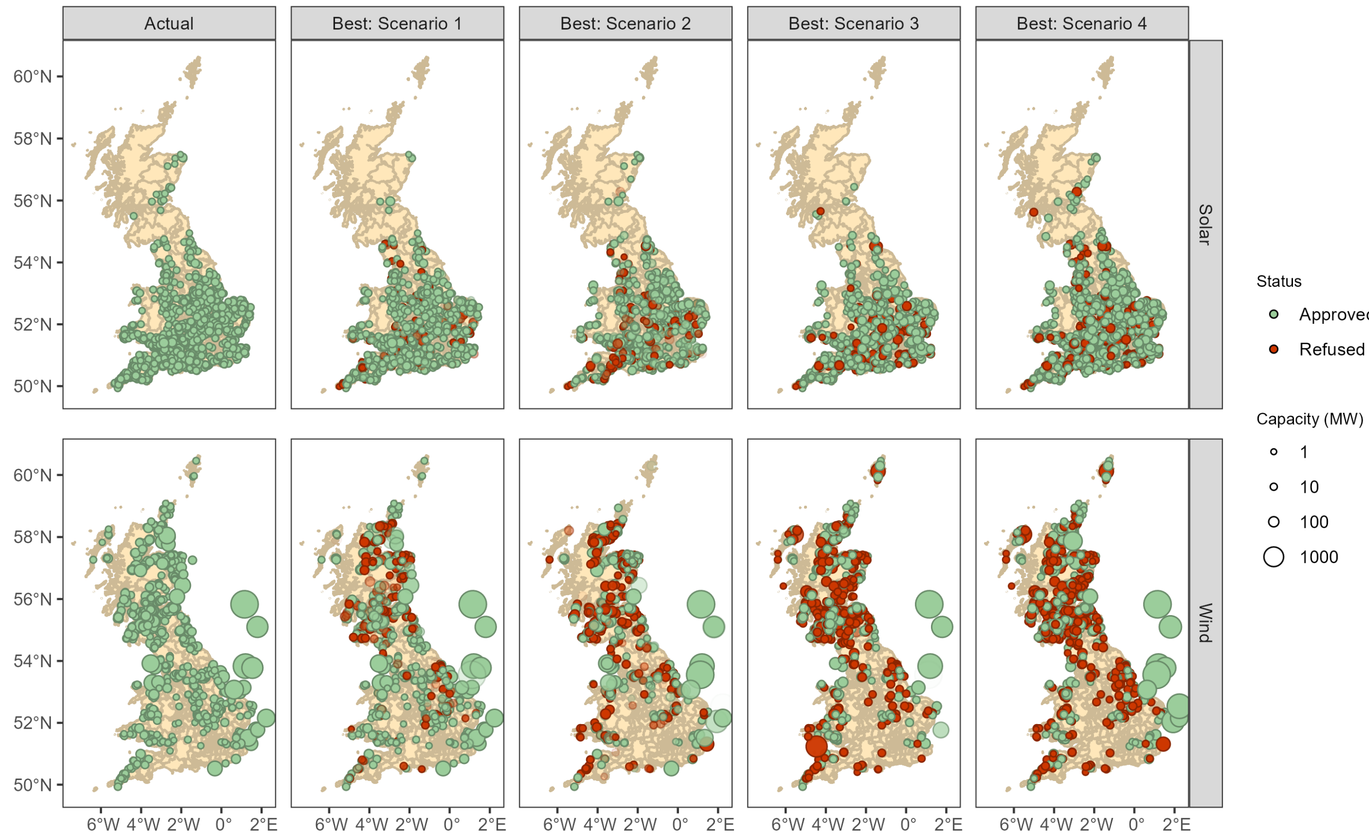
My primary approach to analyzing misallocated investment entails finding the set of projects that can produce the observed annual deployment of renewable energy at least cost. To further illustrate the findings in the main text, Figure C.1 plots the actual or best set of projects across the range of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

Naturally my analysis is potentially subject to uncertainties in the underlying estimates of costs and benefits.[25] As robustness checks, Tables C.1, C.2, C.3, C.4, C.5, C.6, C.7, C.8 and C.9 reproduce the findings from the main text for a range of sensitivities. The aim is to convey the extent to which the overall findings are affected by varying key assumptions. In the base case the central estimates for local property value costs and social market and environmental benefits are used, with a discount rate of 3.5%. The sensitivies are therefore as follows.

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

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

Figure C.1: Misallocated Investment Results Detail



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

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

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

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

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

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

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

Table C.7 provides the results for the "Project Size" sensitivity. Here the analysis is the same as the base case except now the analysis is limited to larger projects. Specifically, I use the same four misallocation scenarios but first conduct the analysis only using projects larger than 10MW and then only using projects larger than 25MW. In general the potential gains to social net present value only decline modestly relative to the base case. The big difference relates to local property value impacts which are frequently concentrated at a limited number of small projects. Focusing on larger wind farms with multiple turbines removes these outliers such that total local property costs fall from £8.5 billion in the base case to £3.2 billion and £0.9 billion in the sensitivities. Focusing on larger projects also results in total local property costs increasing in the full reallocation scenario when compared to current levels.

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

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

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

I take my measure of the sensitivity of wholesale prices to the share of renewables and combine this with the increase in the renewable share that is anticipated by the full reallocation scenario. So in the mid-2020s I calculate that the projected 20 percentage point increase in the share of renewables (relative to observed levels) should depress wholesale prices by around 4%. I then re-run the misallocation analysis, assuming each project earns a lower private value for their electricity in accordance with the annual adjustments they would be exposed to over their lifetime. This means a project built in 2000 would see a 1.2% reduction in the private benefits of their output due to non-marginal price adjustments, while a project built in 2020 would see a 3.6% reduction.

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

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

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

(a) Base

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

(b) Low Local Property Cost

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

(c) High Local Property Costs

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

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

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

(a) Base

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

(b) Low Social Benefits

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

(c) High Social Benefits

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

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

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

(a) Base

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

(b) Low Discount Rate

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

(c) High Discount Rate

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

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

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

(a) Base

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

(b) Low Extrapolation Error (10%)

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

(c) High Extrapolation Error (25%)

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

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

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

(a) Base

No.	Scenario Constraints			Project Characteristics						Project Costs and Benefits			
		Year	Local Authority	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	2904	41	1883	0.78	0.30	0.26	-8.5	-141.4	162.8	12.8
1	Best	Fixed	Fixed	2904	40	1767	0.79	0.30	0.29	-6.9	-138.5	159.7	14.3
2	Best	-	Fixed	2904	40	1407	0.76	0.28	0.32	-3.9	-114.9	156.7	37.9
3	Best	Fixed	-	2904	43	1684	0.77	0.47	0.47	-3.3	-106.3	157.2	47.6
4	Best	-	-	4543	66	2526	0.74	0.38	0.38	-4.2	-173.4	245.9	68.3

(b) Low Noise (10%)

No.	Scenario Constraints			Project Characteristics						Project Costs and Benefits			
		Year	Local Authority	Output (TWh)	Capacity (GW)	Projects	Wind (%)	Scotland (%)	Any Property Cost (%)	Cost Property (£bn)	Cost Other (£bn)	Benefits (£bn)	Social NPV (£bn)
0	Actual	Fixed	Fixed	2904	41	1883	0.78	0.30	0.26	-8.4	-131.7	163.8	23.7
1	Best	Fixed	Fixed	2904	40	1773	0.79	0.30	0.29	-7.0	-135.5	163.6	21.1
2	Best	-	Fixed	2904	40	1465	0.76	0.29	0.33	-4.2	-114.6	165.2	46.3
3	Best	Fixed	-	2904	42	1720	0.79	0.44	0.46	-3.2	-105.4	173.9	65.3
4	Best	-	-	3672	55	2276	0.73	0.44	0.42	-4.3	-136.5	205.7	65.0

(c) High Noise (25%)

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

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

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

(a) Base

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

(b) Wind / Solar

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

(c) Onshore Wind / Offshore Wind / Solar

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

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

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

(a) Base

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

(b) Projects > 10MW

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

(c) Projects > 25MW

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

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

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

(a) Base

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

(b) No Spatial Variation

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

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

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

(a) Base

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

(b) Non-Marginal Adjustment

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

D Transfer Payments to Local Residents

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

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

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

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

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

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

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

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

The total costs to developers can then be calculated by summing up the value of all payments relevant to each project. I compare these to observed voluntary payments from community benefits funds as listed in Scotland's Community Benefits Register (Local Energy Scotland, 2022). The latest government guidance for Scotland calls on developers to adopt funds with a value of £5,000/MW/year, and this increasingly appears to be followed for the most recent projects (Scottish Government, 2019).

Table D.1: Local Compensation Scheme Regression Results

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

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

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

E Programming

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

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