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# Spatial-neighbour effects in the installation of solar photovoltaic technology in England and Wales*

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October 2025

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This article investigates spatial-neighbour effects in the deployment of small-scale solar photovoltaic (PV) systems, examining whether the installation rate in a given area is affected by the quantity of nearby solar PV systems. We study 1.4 million solar PV systems in England and Wales, analysing installations over the period 2010 – 2024. The results from 2010–2015 reveal that an additional solar PV system in a local authority is associated with an additional 0.128 installations 3 months later, suggesting a positive role of peer effects and observational learning. In contrast, from 2016–2024, spatial-neighbour effects are instead found to be negative, indicating saturation amongst the households likely to adopt solar PV. We further show that, by contrast, heat pumps do not exhibit any spatial-neighbour effects and that the collective buying scheme Solar Together did not appear to increase installations in the period 2015–2020.

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# 1 Introduction

The current UK Labour government has pledged to deliver a ‘rooftop revolution’, aiming to triple the UK’s solar capacity by 2030, as part of its plans to meet its legally binding target of reaching net zero carbon emissions by 2050 (Hansard, HC Deb., 2024; Labour Party, 2024).

Therefore, understanding the determinants of the installation rate of solar photovoltaic (PV) systems is of key policy relevance. This article focuses specifically on the role of spatial-neighbour effects, the impact of the quantity of solar PV systems in an area on future solar PV installation rates. These spatial-neighbour effects are highly pertinent to government policy, as they determine the ’multiplier effect’ of policies to increase solar PV installations.

Previous literature has interpreted these spatial-neighbour effects as peer effects. Richter (2014) suggested that solar PV systems create a persistent signal that neighbours and passers-by can observe, which may lead to observational learning by nearby households, reducing uncertainty around solar PV and causing a correlation of adoption decisions within local areas. Shakeel et al. (2023) highlighted two key factors; higher visibility of solar PV in the surrounding area firstly raises awareness of the technology and secondly develops greater confidence in the viability of the technology, as well as providing individuals with opportunities to ask their neighbours about their installation of solar PV. Baranzini et al. (2017) further suggested that greater visibility of solar PV will incentivise installations through the motivations of individuals to follow social norms. This indicates that households will have a greater probability of installing solar PV, ceteris paribus, if they have a greater installed base of solar PV - the cumulative number of completed installations - in their proximity. However, we diverge from this interpretation and also consider the possibility that a higher installed base of solar PV within an area may indicate *saturation*, suggesting that negative spatial-neighbour effects may be observed, where a higher installed base is associated with a lower current installation rate.

Saturation does not indicate that most households have solar PV systems: only 5.7% of households in the UK have installed solar PV as of December 2024 (MCS, 2025). Deciding whether to install solar PV involves a trade-off between the upfront cost of installation and the future cost savings through reduced energy bills, and this decision is determined by factors including the household’s discount factor, expected energy prices, subsidies to renewable electricity production, environmental preferences, wealth, liquidity constraints and housing characteristics (Balcombe et al., 2014). Saturation may therefore occur when the majority of households with characteristics such that they are likely to install solar PV have already done so. This also suggests that the degree of saturation in an area is dependent not only on the number of solar PV systems but also on factors such as energy prices and government subsidies, which may expand the pool of likely adopters of solar PV.

A further explanation for negative spatial-neighbour effects may be negative word-of-mouth, where households learn about the disadvantages of solar PV technology from previous adopters. Narayanan and Nair (2011) also suggest that 'snobbery' and desire for exclusivity may result in negative spatial-neighbour effects, but it is debatable how strong this effect would be in the case of solar PV.

We estimate spatial-neighbour effects using the first-difference method pioneered by Bollinger and Gillingham (2012) and Richter (2014), using data on 1.4 million solar PV systems, by far the largest dataset currently examined in the literature. The period we examine is 2010–2024, allowing us to study how spatial-neighbour effects change over time and after changes to subsidies or energy prices. As a robustness check, we extend our regression specifications by the squared installed base to investigate for non-linearities in spatial-neighbour effects and then evaluate spatial-neighbour effects at the postcode district level. For comparison, we also consider data on heat pump installations, which are a less visible technology than solar PV, but also a less common technology: only 0.94% of households in the UK have installed heat pumps as of December 2024 (MCS, 2025).

As an extension, the impact of the group-buying scheme "Solar Together" on installation rates is evaluated, given that the literature has suggested that these schemes can utilise spatial-neighbour effects to significantly increase the number of solar PV systems in an area.

The paper proceeds as follows. In section 2, we review the literature. In section 3, we present our dataset. We discuss our methodology in section 4, before proceeding to our results in section 5. Section 6 contains various robustness checks and extensions and section 7 offers a conclusion.

## 2 Literature Review

Spatial-neighbour effects can be motivated via Rogers' (1962) Diffusion of Innovations theory. Rogers identified a key determinant of the diffusion rate of an innovation as its observability: whether potential adopters can observe the innovation being used and the benefits of its use. Rai and Robinson (2013) distinguished between passive peer effects, where a greater installed base of a visible innovation within an area increases the observability of the innovation itself, therefore leading to more adoptions via observational learning and norm-following behaviour; and active peer effects, where a greater installed base can lead to more opportunities for direct communication with previous adopters, which can increase the observability of the *benefits* of the innovation. Positive spatial-neighbour effects may therefore arise in the case of solar PV due to the installed base of solar PV increasing the observability of both the technology and its benefits. However, Rogers also argued that the diffusion of a new technology tends to follow an "S-shaped" curve, where as total diffusion increases, the diffusion rate first increases and then decreases as saturation sets in. This suggests that negative spatial-neighbour effects may arise because higher installed bases can imply saturation; that the majority of individuals who are likely adopters have already adopted the innovation.

Positive spatial-neighbour effects have been identified for a variety of energy-related technologies, including electric vehicles (Narayanan and Nair, 2011; Liu et al., 2017; Min, 2025), heat pumps (Min, 2025), cookstoves (Beltramo et al., 2015) and energy efficient lightbulbs (Carranza and Meeks, 2016). However, solar PV is of particular interest because solar PV systems are highly visible to neighbours. It is therefore reasonable to expect, all else being equal, that the spatial-neighbour effects of solar PV will be more positive than other technologies due to the importance of the observability of the technology. This is supported by Min (2025), who, using data on Seattle and Vermont, found that spatial-neighbour effects were stronger for solar PV than for less visible technologies such as electric vehicles or heat pumps. For technologies that are not visible to neighbours, passive peer effects do not occur and only active peer effects can take place, where the benefits of the technology are communicated via word-of-mouth. These effects may be minimal; Narayanan and Nair (2011) found statistically significant positive spatial-neighbour effects in the case of the visually distinct Toyota Prius hybrid vehicle but reported no evidence of spatial-neighbour effects in the case of the Honda

Civic Hybrid, which was identical to the non-hybrid Honda Civic model.

The seminal work evaluating the impact of the installed base of solar PV on installation rates is Bollinger and Gillingham (2012), who found strong evidence for positive spatial-neighbour effects in their study of California using data at the zip-code level. The authors employed a first-difference model to estimate the impact of the installed base on day t on the fraction of owner-occupied households in the zip-code that had not previously adopted solar and decided to adopt solar that day. This specification addresses issues with simultaneity, self-selection and correlated unobservable variables, as will be discussed further in section 4.1. They reported that at the average number of 4,959 owner-occupied homes in a zip-code, an additional solar PV system in a zip-code is associated with 0.0078 further installations. They found that spatial-neighbour effects were stronger on the street level, suggesting that peer effects decrease with distance. In addition, they found that physically larger installations appeared to have a greater impact on the adoption rate of solar PV and that spatial-neighbour effects were greater in zip-codes where high proportions of their population have long commutes, and therefore spend more time in which they're likely to see solar PV installations. These findings therefore affirm the importance of the visibility of solar PV in spatial-neighbour effects. This is further corroborated by Bollinger et al. (2022), who used highly detailed data on the orientation of solar panels to show that solar PV systems which were more visible from the road led to stronger peer effects.

Richter (2014) carried out a similar study to Bollinger and Gillingham (2012) on postcode district level data in England and Wales over the period April 2010 to March 2013 and found evidence for positive spatial-neighbour effects. She implemented a first-difference panel regression of the number of installations of solar PV within a postcode district on the time-lagged installed base, the installed base 3 months prior, and found that one more solar panel in a postcode district increased the number of new installations per owner-occupied household 3 months later by 7.48e-6, therefore leading to 0.05 additional installations at the average number of 6,629 owner-occupied households. Richter also found a significant positive spatial-neighbour effect at the larger local authority level, reporting that at the average number of owner-occupied households, an additional solar PV system led to a further 0.075 installations. This is a contradiction of the general finding in the literature that spatial-neighbour effects are stronger on more localised levels. Richter then considered how spatial-neighbour effects changed over the 36 months of her study and found that spatial-neighbour effects initially increased but then decreased, even turning negative towards the end of the period, suggesting a degree of saturation in some areas.

To examine cross-boundary spatial-neighbour effects specifically, other papers have implemented a spatial econometric approach. Balta-Ozkan et al. (2015) used a spatial Durbin model to assess the determinants of the number of solar PV installations in each NUTS3 region in the UK and, controlling for a region's own explanatory variables, found that the coefficient of the spatially lagged dependent variable (solar PV installations in nearby areas) was statistically significant and that all spatially lagged explanatory variables were jointly significant, concluding that the uptake of PV in one region tended to spillover to neighbouring regions. Dharshing (2017) and Pronti & Zoboli (2024) also found evidence of spillover effects in solar PV deployment in Germany and Italy respectively. This further suggests the existence of peer and neighbouring effects for solar PV.

However, Bollinger and Gillingham (2012) and Richter (2014) do not consider these cross-boundary spatial-neighbour effects, restricting their attention to spatial-neighbour effects within fixed boundaries, whether zip-codes or postcode districts. Other papers have therefore used highly detailed geographic data to take all spatially proximate solar PV systems into account when estimating spatial-neighbour effects. Graziano and Gillingham (2015) examined the impact of spatial-neighbour effects on residential PV deployment in Connecticut at the Census block group level. Rather than use the installed base within each block group, for each PV system application they recorded how many PV systems had previously been installed within a certain distance of the installation and within a certain time frame prior to the application, and then averaged these spatiotemporal counts within each block group to create block group level "spatiotemporal neighbour" variables. This therefore takes into account peer effects from solar PV systems which are spatially proximate but across block group borders. The authors found strong evidence of significant positive spatial-neighbour effects and that this effect decreased with distance and with the time since surrounding solar PV installations were completed.

Baranzini et al. (2017) used a similar approach to analyse the adoption of solar PV in Switzerland and also found evidence for a positive role of the installed base on installation rates of households, diminishing with time since installation. They reasoned that new installations are more likely to catch people's attention and after some time, most households proximate to a solar PV system will have already observed the system, so observational learning has already occurred. In addition, the authors observed that spatial-neighbour effects decline in magnitude in later periods and suggest that, over time, as knowledge of solar PV becomes more widespread, the importance of observational learning and social effects for new installations decreases.

While Richter (2014) and Balta-Ozkan et al. (2015) have already examined peer effects in solar PV installations within England and Wales, there have been substantial changes in market conditions and government policy since their analyses. The total number of solar PV systems in England and Wales recorded by the Microgeneration Certification Scheme increased from approximately 756,000 by the end of 2015 to 1.4 million by the end of 2024. Therefore, there may be a greater probability of saturation within areas. Moreover, as solar panels become more common, the importance of learning from neighbours may decrease as information about solar PV is already widespread.

Furthermore, a key policy incentivising the installation of solar PV in the UK was the Feed-in-Tariff (FIT), which required energy suppliers to pay small renewable electricity generators (including owners of solar PV) a fixed sum per kWh of electricity generated and an additional sum for any electricity exported to the grid. The FIT was introduced in April 2010 and its tariff rates were cut over time before being closed to new applicants in March 2019. The most significant change was a dramatic cut in the FIT generation tariff in January 2016, where the higher tariff rate for the average 4kW retrofit PV system fell from 17.49p per kWh to 6.38p per kWh (Ofgem, 2024). Jenner et al. (2013) and Zhang et al. (2011) found that FIT policies lead to significant increases in PV deployment and so the reduction of the FIT over time may have dampened social-neighbour effects by reducing all households' incentives to adopt solar PV, reducing the pool of likely adopters and therefore increasing the degree of saturation.

Finally, the energy cost crisis unfolding from autumn 2021 would have conversely increased the return on investment of solar PV due to higher electricity prices and so may have led to a strengthening of social neighbour effects by instead increasing incentives to install solar PV.

In this paper, we therefore investigate whether, given these dramatic changes to policy, energy prices and the pre-existing stock of solar PV, there is still strong evidence of spatial-neighbour effects and whether the magnitude of these peer effects has changed over time. Our analysis has the advantages of studying the role of spatial-neighbour effects over the extended period of 2010–2024 and using a dataset containing 1.4 million solar PV systems, far more than previously analysed in the literature.

As an extension, we consider a particular implication for government policy of our findings on spatial-neighbour effects. Graziano and Gillingham (2015) investigated the “Solarize” programs in Connecticut, where group-buying is used to lower the price of solar PV installations, and found that by fostering social interactions about solar PV and by “seeding” areas with installations early on, thereby leading to further installations later on through spatial-neighbour effects, these programs could dramatically increase the number of PV systems in an area in a short amount of time. ”Solar Together” is a similar scheme in England, coordinated by local authority councils and the company iChoosr. Residents of a local authority currently running a scheme can register to join and the scheme then pre-vets solar PV installers and runs a reverse auction, securing installation contracts for participants at the lowest offered price. This scheme claims to have achieved ”average savings of 15-25% against the typical market price” (Solar Together, 2025), likely lowers the search costs of finding an installer for households, and possibly utilises peer effects, where households may be more likely to adopt solar PV if they are doing so alongside many others. We therefore evaluate whether Solar Together has led to a significant impact on installations.

The literature is summarised in Table 1. All papers find evidence for positive spatial-neighbour effects in the deployment of solar PV. However, Richter (2014) also reports negative spatial-neighbour effects towards the end of her period of study.

Table 1: Literature summary

| Paper | Location | Period | № of PV systems by end of period | Findings |
|---|---|---|---|---|
| Bollinger and Gillingham (2012) | California, US | January 2001 – December 2011 | 85,046 | An additional solar PV system in a zipcode is associated with 0.0078 further installations. Peer effects are found to be stronger on more localised levels. |
| Müller and Rode (2013) | Wiesbaden, Germany | 1992–2009 | 324 | Using a binary panel logit model, the authors find that the propensity to install PV increases with the number of systems in spatial proximity. The impact of each system decreases with distance from the new installation. |
| Richter (2014) | England and Wales | April 2010–March 2013 | 379,531 | An additional solar PV system in a postcode district leads to 0.05 further installations. Spatial-neighbour effects were found to decrease over time, even becoming *negative* at the end of the period. |
| Balta-Ozkan et al. (2015) | UK | April 2010 - June 2013 | 392,470 | Using a spatial econometric method, the authors found evidence of positive spillovers between regions in the uptake of solar PV |
| Graziano and Gillingham (2015) | Connecticut, US | January 2005 – September 2013 | 3,833 | If the households that install PV systems in a block group have on average one additional nearby installation within 0.5 miles in the previous 6 months, then the number of installations per quarter will increase by 0.44. Spatial-neighbour effects diminish with distance and time since installation. |
| Rode and Weber (2016) | Germany | 1992 – 2009 | 576,056 | Using an epidemic diffusion model, the authors found evidence for highly localised positive spatial-neighbour effects, fading after 1km. |

Table 1: (continued)

| Paper | Location | Period | № of PV systems by end of period | Findings |
|---|---|---|---|---|
| Baranzini et al. (2017) | Switzerland | January 2006 – December 2015 | 59,819 | For the average municipality, any additional installation in a radius of about 300 metres increases the number of adoptions by about 0.08 installations per quarter. Spatial-neighbour effects diminish with distance and time since installation. Over the period of study, spatial-neighbour effects fall in magnitude. |
| Bollinger et al. (2022) | Connecticut, US | January 2004 – February, 2016 | 17,291 | The total angle of visiblity of peer installations one the same street positively affects solar adoption decisions at distances of at least 500 metres. Non-visible solar arrays only have a positive spatial-neighbour effect within 100 metres. |
| Steadman et al. (2023) | UK | 2011 – 2016 | 808,239 | Using a spatial econometric model, the authors found that the presence of community energy groups in an area led to positive peer effects in solar PV installation, reporting that an additional installation by a community group (such as churches, schools and other non-profit community projects) was associated with 48 additional domestic installations the following year. |
| Min (2025) | Seattle and Vermont, US | 2011 – 2019 | 3,202(Seattle), 9,929(Vermont) | Using a binary logistic regression, Min found that solar PV exhibited stronger and wider positive spatial-neighbour effects than electric vehicles or heat pumps. |

# 3 Data

The Microgeneration Certification Scheme (MCS) Installation Database (2025) contains the details of every MCS certified small-scale (less than 50kWe) solar PV installation in the UK. MCS certification is not a mandatory requirement for the installation of a solar PV system and only began in 2008, so this database does not capture all small-scale solar PV systems in the UK. However, the vast majority of installations took place after the introduction of the Feed-in-Tariff in April 2010[1] and MCS certification was required for eligibility for the FIT and is now required for the Smart Export Guarantee, the financial incentives scheme that succeeded the FIT. Therefore, the MCS is "confident that [their] data represent a significant proportion of deployment in the UK" (MCS, 2025). This dataset is an improvement over the dataset used by Richter (2014), which covered installations from April 2010 onwards on the FIT register: a subset of the installations recorded in the MCS dataset.

Data on the total number of solar PV installations in each local authority[2] in England and Wales were obtained each month from January 2010 to December 2024 (MCS, 2025). We focus on England and Wales for comparability with Richter (2014). Similar data were obtained on request from the MCS on the more localised postcode district level and a balanced panel dataset created by dropping postcode districts without observations in all periods. Our main analysis uses the more complete local authority dataset. The summary statistics of these datasets are displayed in Table 2.

A limitation of these datasets is that we do not have access to the exact geographic locations of each solar PV system and therefore cannot calculate an exact installed base variable as in Graziano and Gillingham (2015). Consequently, we are only estimating spatial-neighbour effects within fixed boundaries, neglecting the influence of solar PV systems across borders.

[1] The installed capacity of domestic solar PV in the UK increased from 10.7 MW in January 2010 to 95.2 MW in January 2011, to 2958.1 MW in January 2016 (DESNZ, 2025).

[2] It is emphasised that the unit of observation is the area, in this case the local authority, rather than the household.

Table 2: Summary statistics

| | **Local authority data** | **Postcode district data** |
|---|---|---|
| Number of units | 318 | 2,273 |
| Years covered | 2010-2024 | 2010-2024 |
| Total observations | 57,240 | 409,140 |
| Mean number of solar PV systems* | 4,471 | 629 |
| Mean number of households** | 74,875 | 10,901 |

*As of December 2024
**Data obtained from the ONS (2021, 2022b)

Figure 1: Total monthly installations in England and Wales

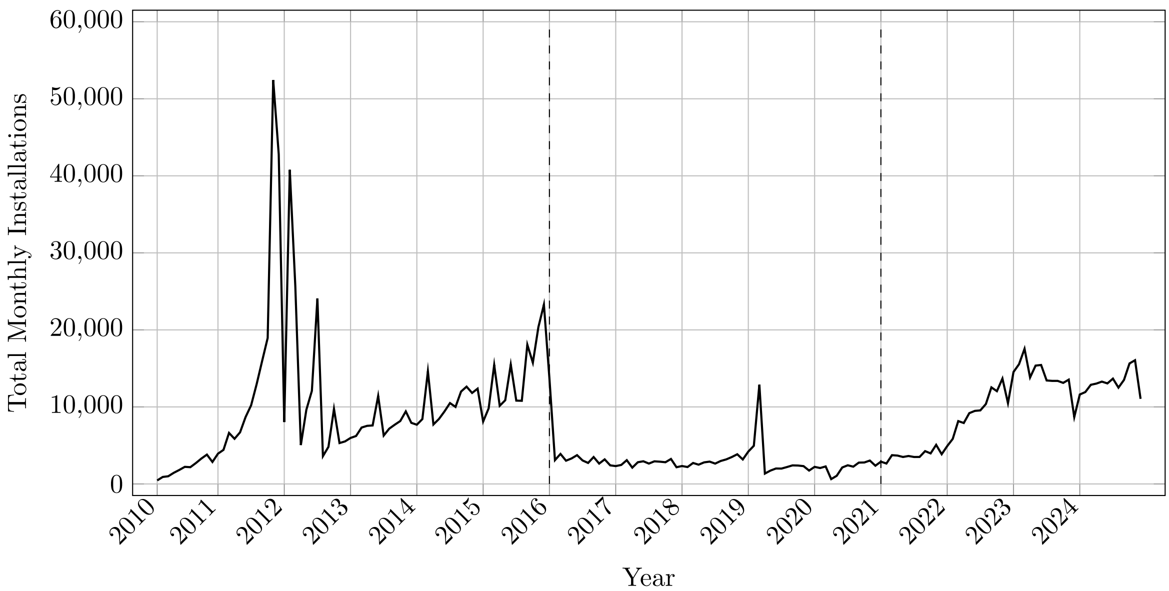


Figure 1 illustrates the monthly installation rates of solar PV in England and Wales from 2010 to 2014. As can be seen, this can be roughly decomposed into three periods. Firstly, from 2010-15 there are very high installation rates, and then a sharp decrease in installations in 2016. This is likely due to the significant cut in the Feed-in-Tariff in January 2016. From 2016 to 2020, there are relatively low installation rates and then from 2021 onwards, there is an increase in installations, likely partially caused by the energy cost crisis, which began in 2021, incentivising households to substitute away from consuming increasingly costly electricity from the National Grid. We therefore investigate spatial-neighbour effects separately for each of these periods.

One pattern that can also be observed is peaks in installation rates before the FIT rate is cut, such as in December 2015, or before the FIT was closed to new applicants, in March 2019. This is because these policy changes were announced in advance and installations before these changes were entitled to the previous rate of the Feed-in-Tariff. Consequently, we must control for these policy announcements because they would affect both the installed base and installation rate and so confound our estimation of spatial-neighbour effects.

So that we can compare the spatial-neighbour effects for solar PV and for a less visible technology, we also use data on the total number of heat pump installations in each local authority in England and Wales from January 2010 to December 2024, sourced from the MCS (MCS, 2025).

To investigate the impact of Solar Together, we contacted their owner organisation iChoosr and obtained a list of every Solar Together scheme implemented, starting with Solar Together Norfolk in 2015 (see Appendix B). These are subdivided into Spring, Summer, Autumn and Winter schemes and between 2015 and 2024, there have been 580 schemes (at the local authority level) carried out in 185 different local authorities. In 2023, over 10% of MCS accredited solar PV installations were under Solar Together schemes (Solar Together, 2024).

We also assembled a set of covariates to control for key determinants of solar PV adoption highlighted by Dharshing (2017), which are possible sources of omitted variable bias when estimating the impact of Solar Together. Although these data are not available on a monthly frequency, preventing their use in our estimation of peer effects, they are available on a yearly basis, on which the analysis of Solar Together is carried out. We acquired local authority level data on median age, median weekly pay, level of unemployment and the number of owner-occupied households at a yearly frequency from the Office of National Statistics (ONS, 2022; ONS, 2023; ONS, 2024a; ONS, 2024b) . Some of these data are not available for more recent years so we restrict our analysis to the Solar Together schemes carried out between 2015 and 2020, mostly coinciding with the period of low installation rates discussed above.

See Appendix A for more detail on the data sources used.

# 4 Methodology

## 4.1 Endogeneity and Identification

To estimate spatial-neighbour effects within a given area, we must address three key issues: simultaneity, self-selection, and correlated unobservables. To do so, we follow the example of Richter (2014).

The issue of simultaneity highlighted by Manski (1993) concerns a 'reflection problem' where a household's installation decision depends on the decisions of its neighbours and, in turn, impacts the decisions of its neighbours. Therefore, any correlation between any particular household's installation decision and the decisions of others cannot be solely attributed to the effects of others' decisions on that household's decision. However, this is not a problem in the case of solar PV installations. There is a time lag between the decision to adopt solar PV and the installation of a system and so at the time of its decision to adopt, a household is being impacted by the previous installations of its neighbours but did not impact their installations. To identify spatial-neighbour effects, we therefore need to find the effect of the installed base of solar PV at the time of the decision to install solar PV. Richter (2014) consulted the main solar PV suppliers in the UK and found that the time between first contact with the supplier and completion of the installation usually lies between two and three months. This is broadly consistent with other evidence; Sustainable Energy Engineering recently reported a timeframe spanning from 6 to 18 weeks (Sustainable Energy Engineering, 2024), and Project Solar, the largest solar PV installation company in the UK, reports that their process takes between 1 and 4 months (Project Solar, n.d.). We therefore follow Richter's example and estimate spatial-neighbour effects by evaluating the impact on installation rates of the size of the installed base three months prior.

Secondly, self-selection or homophily is where the characteristics of households leading them to choose to live in a certain area are also correlated with the solar PV installation rate. For example, environmentally conscious households may choose to relocate to areas with a high proportion of environmentally conscious households. This self-selection therefore can lead to clustering of environmentally conscious households within certain areas, which may increase both the installed base and the installation rate, leading to a spurious correlation which arises from self-selection rather than spatial-neighbour effects.

Finally, unobservable characteristics of an area may be correlated with both the installed base and the installation rate, leading to omitted variable bias if they are not controlled for. Dharshing (2017) highlights key determinants of solar PV installation rates that vary by area, such as income, age, number of houses, housing characteristics, unemployment, and green preferences; these factors will be correlated with all of an areas' installation rates over time, and may therefore affect both the amount of solar PV that has already been installed and current installation rates. However, data on these variables are rarely available at the granularity of time and area which we examine. Furthermore, other area-specific characteristics may be entirely unobserved, such as local advertising campaigns or the location of the headquarters of a specific installer within that area.

We therefore control for self-selection and correlated unobservables with a rich set of fixed effects. To address time-varying omitted variables which are constant across all areas, most importantly the contemporary FIT rate, we include month fixed effects. To address homophily and differences in correlated unobservables between areas, we use area-time fixed effects. These allow the fixed effect of an area to vary over time to reflect possible variation in correlated unobservables over time, such as a local advertising campaign ran over only a specific period. However, if we were to use area-month fixed effects, these would be perfectly collinear with the installed base and prevent identification of spatial-neighbour effects. Therefore, we use area-quarter fixed effects, controlling for characteristics that vary between quarters. These month and area-quarter fixed effects should control for the changes in policy and energy prices highlighted as driving significant changes in installation rates in section 3, allowing spatial-neighbour effects to be isolated.

### 4.2 Estimation strategy

Our model specification is therefore

$$Y_{it} = \alpha_t + \beta b_{it-3} + \alpha_{iq} + \varepsilon_{it} \tag{1}$$

$$where\ b_{it-3} = \sum_{\tau=1}^{t-3} Y_{i\tau} \tag{2}$$

This dynamic panel data model involves three dimensions: firstly, there are the areas $i$ in the cross-sectional dimension. Secondly, there are the months $t$ in a first time-dimension and, thirdly, the quarters $q$ in a second time-dimension. The months $t = 1, 2, 3$ are in quarter $q = 1$, the months $t = 4, 5, 6$ are in quarter $q = 2$ and so on. The outcome variable $Y_{it}$ is the number of new solar PV installations within an area $i$ in month $t$. Equation 2 defines $b_{it-3}$, the third lag of the installed base, as the cumulative number of solar PV systems within an area at the end of time period $t-3$. There are two types of fixed effect in this model. Firstly, the $\alpha_t$ are 180 dummies for each month from January 2010 to December 2024, which indicate month-specific effects that are constant across areas. Secondly, the $a_{iq}$ are area-quarter fixed effects, controlling for the issues of homophily and area-specific correlated unobservables discussed previously. Finally, $\varepsilon_{it}$ is an *i.i.d.* unobserved error term, where $E[b_{zt-3}\varepsilon_{zt}] = 0$

To eliminate the area-quarter effects, we use a first-difference estimator. First differencing on the month level alone however does not fully eliminate the area-quarter effects. First differencing of the first month of a quarter leads to a residual term equal to the change in area-quarter effects between quarters. We therefore drop the first month of each quarter from our analysis. This therefore leads to equation 3:

$$(Y_{it} - Y_{it-1}) = (\alpha_t - \alpha_{t-1}) + \beta(b_{it-3} - b_{it-4}) + (\varepsilon_{it} - \varepsilon_{it-1}) \tag{3}$$

$$\Delta Y_{it} = \Delta\alpha_t + \beta\Delta b_{it-3} + \Delta\varepsilon_{it} \tag{4}$$

If we carry out pooled OLS on this equation, we can then consistently estimate $\beta$ if the exogeneity condition is fulfilled:

$$E[\Delta b_{t-3}\Delta\varepsilon_{it} = 0] \tag{5}$$

As $\Delta b_{it-3} = \Delta \sum_{\tau}^{t-3} Y_{it} = \sum_{\tau}^{t-3} Y_{it} - \sum_{\tau}^{t-4} Y_{it} = Y_{it-3}$, this exogeneity condition can be rewritten as

$$E[Y_{it-3}\Delta\varepsilon_{it}] = E[Y_{it-3}\varepsilon_{it}] - E[Y_{it-3}\varepsilon_{it-1}] = 0 \tag{6}$$

Therefore, our estimator of $\beta$ will be consistent if $E[\varepsilon_{it}\varepsilon_{it-3}] = E[\varepsilon_{it}\varepsilon_{it-2}] = 0$; the order of auto-correlation of $\varepsilon_{it}$ is smaller than 2.

## 4.3 Extension: Methodology for policy evaluation

As an extension, we evaluate the impact of the group-buying scheme Solar Together on solar PV installations. Different local authorities have run Solar Together schemes at different times, some local authorities carrying out multiple schemes, starting with pilot schemes in local authorities in Norfolk in 2015 and in London, Essex, Suffolk and Norfolk in 2018. Therefore, a difference-in-differences strategy can be used to estimate the average treatment effect of running a Solar Together scheme. One possible way to do this is a Two-Way Fixed Effects (TWFE) regression. However, recent papers such as Goodman-Bacon (2021) and Sun and Abraham (2021) have highlighted that TWFE uses previously treated units as controls for later treated units, introducing bias if there are heterogeneous treatment effects, where the treatment effect varies over time. The treatment effect of Solar Together likely varies over time, first leading to households registered for the scheme installing solar PV and then influencing the installation decisions of other households through spatial-neighbour effects, and when local authorities run several consecutive schemes, these schemes may differ in effectiveness, leading to a time variant treatment effect. TWFE in this case would therefore be biased.

We therefore use the de Chaisemartin and D'Haultfoeuille (2020) heterogeneous treatment bias robust difference-in-differences ($DID$) estimators instead. Consider treated local authority $g$, and let $t$ denote the year $g$ switched into treatment. This method constructs a set of event-study estimators $DID_l$, which are the average, across all switchers $g$, of $DID$ estimators comparing the change in solar PV installation rates from year $t-1$ to year $t+l$ of $g$ to that of a set of controls which are not yet treated as of year $t+l$. $DID_l$ is therefore an estimator of the average treatment effect $l$ years after treatment.

We choose these estimators over alternatives such as those of Callaway and Sant'Anna (2021) and Wooldridge (2021) which assume staggered treatment, because the Chaisemartin and D'Haultfoeuille estimators do not assume treatment is permanent and allow for movement in and out of treatment, permitting local authorities to be considered treated only when a Solar Together scheme is run within a given year. We extend this definition of treatment, considering a local authority as treated if a Solar Together scheme has been run in that year or the previous year, to capture schemes running across years, delayed installations under schemes and the initial impact on installation rates through spatial-neighbour effects.

For difference-in-differences estimators to correctly identify the treatment effect of Solar Together, the common trends assumption must be satisfied: that if the local authorities which implemented Solar Together had not carried out these schemes, they would have followed parallel trends in solar PV installation rates to the local authorities which did not implement Solar Together. This assumption cannot be tested, but we check its plausibility by testing for parallel pre-trends.

# 5 Results

Table 3: First-difference regression results at the local authority level in England and Wales

| | Total installed base | | 6-month installed base | |
|---|---|---|---|---|
| | (1) Overall | (2) Period specific | (3) Overall | (4) Period specific |
| Installed base | 0.056** | | 0.076*** | |
| | (0.022) | | (0.024) | |
| 2010–2015 x installed base | | 0.128*** | | 0.145*** |
| | | (0.021) | | (0.018) |
| 2016–2020 x installed base | | -0.120*** | | -0.059*** |
| | | (0.022) | | (0.013) |
| 2021–2024 x installed base | | -0.023*** | | -0.022** |
| | | (0.006) | | (0.011) |
| Observations[3] | 37,524 | 37,524 | 36,252 | 36,252 |
| $R^2$ | 0.295 | 0.311 | 0.301 | 0.318 |

Cluster-robust standard errors in parentheses.
$***\, p < 0.01$, $**\, p < 0.05$, $*\, p < 0.1$

Table 3 indicates that over the entire period from 2010 to 2024, there are positive spatial-neighbour effects at the 5% significance level, where an increase of 1 in the installed base of solar PV within a local authority leads to an increase of 0.056 in the number of new installations 3 months later. This suggests that every 18 solar PV installations within a local authority results in one additional installation. This is lower than the spatial-neighbour effect estimated by Richter (2014), who found that one more solar PV system in a local authority increased the number of new installations by 0.075.

[3] There are fewer observations than in the dataset as the first month of each quarter is dropped.

Positive spatial-neighbour effects suggest that the positive effects of the installed base on nearby household's installation decisions through peer effects involving observational learning, imitation and positive word-of-mouth are greater than any negative impact of saturation.

However, when the spatial-neighbour effect is separately estimated for the periods 2010–2015, 2016–2020 and 2021–2024, the results differ significantly. From 2010–2015, our results are consistent with Richter's (2014) finding of positive spatial-neighbour effects, where an additional PV system in a local authority is associated with an additional 0.128 installations 3 months later, an effect even greater than that estimated by Richter, corresponding to an extra solar PV installation for every 8 installations carried out. Spatial-neighbour effects are therefore large and positive in this first period. However, spatial-neighbour effects are instead observed to be negative at a 1% significance level in both 2016–2020 and 2021–2024. This suggests that in these periods, the negative impacts of saturation outweigh the positive role of peer effects. This is in line with Baranzini et al.'s (2017) finding that spatial-neighbour effects declined over time in Switzerland. This may be due to the increase in the number of total solar PV systems increasing the likelihood of saturation and greater awareness of solar PV reducing the importance of observational learning. However, the decrease in spatial-neighbour effects is also likely a result of changes in government policy and market conditions. It is probable that the sharp decrease in spatial-neighbour effects between 2010–2015 and 2016–2020 is at least partially caused by the dramatic cut to the FIT in January 2016. This reduced the financial incentives to install solar PV and therefore also likely reduced the number of households which would consider adopting solar PV, thereby increasing the degree of saturation within local authorities. A key component of the positive peer effects in 2010–2015 may have been households learning about the FIT through their neighbours, but after the cut in FIT, word-of-mouth may have become more critical and contributed to the negative spatial-neighbour effects as households learned of their neighbour's negative experiences of falling subsidies and reduced returns on investment. Furthermore, the spatial-neighbour effect of -0.023 in 2021–2024 is significantly less negative than the effect of -1.20 in 2016–2020, which is likely due to the energy cost crisis unfolding from autumn 2021. This instead increased the financial incentives to adopt solar PV, likely expanding the pool of potential adopters and reducing saturation, as well as leading to more positive word-of-mouth. It is therefore suggested that the size and sign of spatial-neighbour effects are heavily dependent on the financial incentives to install solar PV, which themselves are determined by policy and market conditions.

Following Baranzini et al.'s (2017) finding that spatial-neighbour effects decline with the time since installation, we also estimate the spatial-neighbour effect using only solar PV systems installed between 9 and 3 months before installation as the (6-month) installed base. We indeed find that the estimates of the spatial-neighbour effects become more positive, but they still remain negative in 2016–2020 and 2021–2024, indicating that saturation seems to outweigh positive peer effects even for recent installations.

# 6 Robustness Checks & Extensions

## 6.1 Heterogeneous installed base effect

Table 4: Testing for a heterogeneous installed base effect

| | Total installed base | | 6-month installed base | |
|---|---|---|---|---|
| | (1) Overall | (2) Period specific | (3) Overall | (4) Period specific |
| Installed base | 0.0429 | | 0.0766*** | |
| | (0.0265) | | (0.0256) | |
| Installed base$^2$ | 0.0000 | | 0.0000 | |
| | (0.0001) | | (0.0000) | |
| 2010–2015 x installed base | | 0.03915 | | 0.1479*** |
| | | (0.0256) | | (0.0196) |
| 2010–2015 x installed base$^2$ | | 0.0002*** | | -0.0001*** |
| | | (0.0000) | | (0.000) |
| 2016–2020 x installed base | | -0.1375*** | | -0.0641*** |
| | | (0.3126) | | (0.0129) |
| 2016–2020 x installed base$^2$ | | 0.0000 | | -0.00003*** |
| | | (0.0000) | | (0.0000) |
| 2021–2024 x installed base | | -0.0035 | | -0.189* |
| | | (0.0145) | | (0.0110) |
| 2021–2024 x installed base$^2$ | | -0.0001 | | -0.0001 |
| | | (0.0001) | | (0.0002) |
| Observations | 37,524 | 37,524 | 36,252 | 36,252 |
| $R^2$ | 0.295 | 0.316 | 0.301 | 0.322 |

Cluster-robust standard errors in parentheses.
$***\, p < 0.01$, $**\, p < 0.05$, $*\, p < 0.1$

We now consider how spatial-neighbour effects differ with the level of the installed base and so extend our regression specifications by the squared installed base. Table 4 suggests that over the entire period, there is no significant effect of the installed base squared, contrasting Richter (2014) who found that there was a negative effect of the installed base squared. The result of a positive installed base effect that decreases with the size of the installed base is, however, replicated when considering the installed base within 6 months in 2010-15. Similarly, the 6-month installed base effect is negative in 2016–2020 and appears to become even more negative as the size of the installed base increases, possibly as a result of greater saturation within local authorities.

## 6.2 Postcode district analysis

Table 5: First-difference regression results at the postcode district level in England and Wales

| | Total installed base | | 6-month installed base | |
|---|---|---|---|---|
| | (1) Overall | (2) Period specific | (3) Overall | (4) Period specific |
| Installed base | 0.010 | | 0.018** | |
| | (0.013) | | (0.009) | |
| 2010–2015 x installed base | | 0.066*** | | 0.058*** |
| | | (0.019) | | (0.013) |
| 2016–2020 x installed base | | -0.100*** | | -0.048*** |
| | | (0.015) | | (0.011) |
| 2021–2024 x installed base | | -0.037*** | | -0.024*** |
| | | (0.007) | | (0.007) |
| Observations | 268,214 | 268,214 | 259,122 | 259,122 |
| $R^2$ | 0.130 | 0.136 | 0.131 | 0.135 |

Cluster-robust standard errors in parentheses.
$*** \, p < 0.01$, $** \, p < 0.05$, $* \, p < 0.1$

For robustness, we also estimate spatial-neighbour effects at the smaller postcode district level, displayed in Table 5. There is a similar pattern to the results on the local authority level, with positive spatial-neighbour effects in 2010–2015, strongly negative effects in 2016–2020 and less negative effects in 2021-2025. Consistent with Richter (2014), spatial-neighbour effects are observed to generally be lower in magnitude at the postcode district level than at the local authority level, in contrast to the findings of Bollinger and Gillingham (2012), Graziano and Gillingham (2015) and

Baranzini et al. (2017) that spatial-neighbour effects are stronger at more localised levels. We suggest that this contradictory finding may be because we are estimating spatial-neighbour effects only within fixed boundaries, neglecting cross-boundary spatial-neighbour effects. We therefore may not be capturing the full impact of the installed base on surrounding installations and this bias may be worse when analysing smaller areas, which may have a greater proportion of their households near their boundaries.

## 6.3 Heat pump analysis

Table 6: First-difference regression results on heat pump installations at the local authority level in England and Wales

| | Total installed base | | 6-month installed base | |
|---|---|---|---|---|
| | (1) Overall | (2) Period specific | (3) Overall | (4) Period specific |
| Installed base | 0.008 | | -0.014 | |
| | (0.009) | | (0.019) | |
| 2010–2015 x installed base | | 0.016 | | -0.031 |
| | | (0.014) | | (0.031) |
| 2016–2020 x installed base | | 0.016 | | -0.011 |
| | | (0.016) | | (0.021) |
| 2021–2024 x installed base | | 0.004 | | -0.001 |
| | | (0.012) | | (0.024) |
| Observations | 37,524 | 37,524 | 36,252 | 36,252 |
| $R^2$ | 0.050 | 0.050 | 0.050 | 0.050 |

Cluster-robust standard errors in parentheses.
$***\,p < 0.01$, $**\,p < 0.05$, $*\,p < 0.1$

For comparison, we also estimate spatial-neighbour effects for heat pumps at the local authority level. As suggested by Rogers (1952) and confirmed empirically by Bollinger and Gillingham (2012) and Bollinger et al. (2022), more observable technologies will have greater peer effects, which can lead to more positive spatial-neighbour effects. Because heat pumps are generally less visible than solar PV systems, we expect peer effects to be weaker for heat pumps than solar PV, if they exist at all. However, lower total adoption of heat pumps[4] suggests that there may also be lower saturation of heat pumps than solar PV.

[4]There were 1.4 million solar PV systems in England and Wales as of December 2025, but only 232 thousand heat pumps (MCS, 2025).

Our analysis finds that there is no evidence of spatial-neighbour effects on heat pump installations in any period. This suggests that neither peer effects nor saturation in the diffusion of heat pumps are sufficiently significant to lead to significant net spatial-neighbour effects.

## 6.4 Autocorrelation tests

As established in section 4.2, our estimator of spatial-neighbour effects will be consistent if $E[\varepsilon_{it}\varepsilon_{it-3}] = E[\varepsilon_{it}\varepsilon_{it-2}] = 0$; the order of autocorrelation of $\varepsilon_{it}$ is smaller than 2. We cannot test for autocorrelation in the level equation because the errors $\alpha_{iq} + \varepsilon_{it}$ are serially correlated through the area-quarter fixed effects $\alpha_{iq}$, so we test for autocorrelation using the first-differenced equation. However, the errors $\Delta\varepsilon_{it}$ are also autocorrelated of order 1 by construction, as $\varepsilon_{it-1}$ enters $\Delta\varepsilon_{it}$ as well as $\Delta\varepsilon_{it-1}$. Furthermore, first order autocorrelation of $\varepsilon_{it}$ leads to second order autocorrelation of $\Delta\varepsilon_{it}$ and second order autocorrelation of $\varepsilon_{it}$ leads to third order autocorrelation of $\Delta\varepsilon_{it}$, as illustrated by Equations 7 and 8.

$$E[\Delta\varepsilon_{it}\Delta\varepsilon_{it-2}] = E[\varepsilon_{it}\varepsilon_{it-2} - \varepsilon_{it}\varepsilon_{it-3} - \underbrace{\varepsilon_{it-1}\varepsilon_{it-2}}_{\text{First-order autocorrelation of } \varepsilon_{it} \text{ leads to second-order autocorrelation of } \Delta\varepsilon_{it}} + \varepsilon_{it-1}\varepsilon_{it-3}] \tag{7}$$

$$E[\Delta\varepsilon_{it}\Delta\varepsilon_{it-3}] = E[\varepsilon_{it}\varepsilon_{it-3} - \varepsilon_{it}\varepsilon_{it-4} - \underbrace{\varepsilon_{it-1}\varepsilon_{it-3}}_{\text{Second-order autocorrelation of } \varepsilon_{it} \text{ leads to third-order autocorrelation of} \Delta\varepsilon_{it}} + \varepsilon_{it-1}\varepsilon_{it-4}] \tag{8}$$

Therefore, to test for whether there is second order autocorrelation in $\varepsilon_{it}$, we test for whether there is third order autocorrelation in $\Delta\varepsilon_{it}$. We carry out Arellano-Bond autocorrelation tests on each of our regression specifications.[5]

[5] In these tests, the first month of each quarter is not omitted, so that the *nth* lag of an error is the error $n$ months prior. However, there is still evidence of third-order autocorrelation if the first month of each quarter is omitted.

Table 7: Testing for autocorrelation in the first-difference regressions

| | | Solar PV | | Heat pumps |
|---|---|---|---|---|
| | | Local authority dataset | Postcode district dataset | |
| Regression | Testing for | p-value | p-value | p-value |
| (1) Overall | AR(1) | 0.004 | 0.000 | 0.000 |
| | AR(2) | 0.015 | 0.000 | 0.004 |
| | AR(3) | 0.027 | 0.003 | 0.012 |
| | AR(4) | 0.022 | 0.009 | 0.050 |
| (2) Period specific | AR(1) | 0.003 | 0.000 | 0.000 |
| | AR(2) | 0.002 | 0.000 | 0.004 |
| | AR(3) | 0.006 | 0.001 | 0.012 |
| | AR(4) | 0.011 | 0.004 | 0.050 |
| (3) Overall 6 months | AR(1) | 0.000 | 0.000 | 0.000 |
| | AR(2) | 0.024 | 0.000 | 0.000 |
| | AR(3) | 0.113 | 0.048 | 0.008 |
| | AR(4) | 0.008 | 0.003 | 0.028 |
| (4) Period specific 6 months | AR(1) | 0.005 | 0.000 | 0.000 |
| | AR(2) | 0.058 | 0.000 | 0.001 |
| | AR(3) | 0.045 | 0.052 | 0.015 |
| | AR(4) | 0.004 | 0.001 | 0.047 |

As shown in Table 7, the null hypothesis that the order of autocorrelation of $\Delta\varepsilon_{it}$ is below 3 is rejected for each of our regression specifications, indicating that our estimators of spatial-neighbour effects may be inconsistent. This is the case for both our local authority level and postcode district level analyses of solar PV, but autocorrelation appears to be more severe in the postcode district data. Therefore, the strategy for estimating spatial-neighbour effects developed by Bollinger and Gillingham (2012) and extended by Richter (2014) is flawed in this case. This is a key concern for the literature; recent papers such as Graziano and Gillingham (2015) and Baranzini et al. (2017) do not test for autocorrelation in the errors of their regressions, despite lagged installation rates being included in their "spatiotemporal neighbour" variables, suggesting that their estimates of spatial-neighbour effects may also be inconsistent. Furthermore, while Richter (2014) rejects third order autocorrelation of her errors, she does not reject fourth order autocorrelation at the 5% significance level which suggests that there may also be higher order autocorrelation of $\varepsilon_{it}$ in her model, also leading to inconsistent estimates. We therefore conclude that there may be widespread bias in the estimation of spatial-neighbour effects in the literature and urge for these tests to be reported in future research such that possible inconsistency is taken into account.

### 6.5 Extension: Investigating group-buying policies

We now turn to our evaluation of the impact of the Solar Together program on solar PV installation rates in England, investigating whether these schemes utilised peer effects to dramatically increase solar PV installation rates as Graziano and Gillingham's (2015) "Solarize" program did.

We use the de Chaisemartin and D'Haultfoeuille (2020) estimators to evaluate the impact of Solar Together. As data for covariates are limited in recent years, we consider only the Solar Together schemes implemented before 2021. Treatment varies at the local authority level, so we carry out our analysis at this level. We use two specifications - model A does not control for any covariates, while model B controls for median age, median wage, the level of unemployment and the number of owner-occupied households. We ensure that the panel dataset is balanced by omitting local authorities dissolved or created in mergers over this period and local authorities for which data on covariates are unavailable. Solar Together has so far only been implemented in England, so we only consider English local authorities. This balanced panel has data on 283 local authorities, 85 of which are treated within the studied period.

Figure 2: Impact of Solar Together on solar PV installations

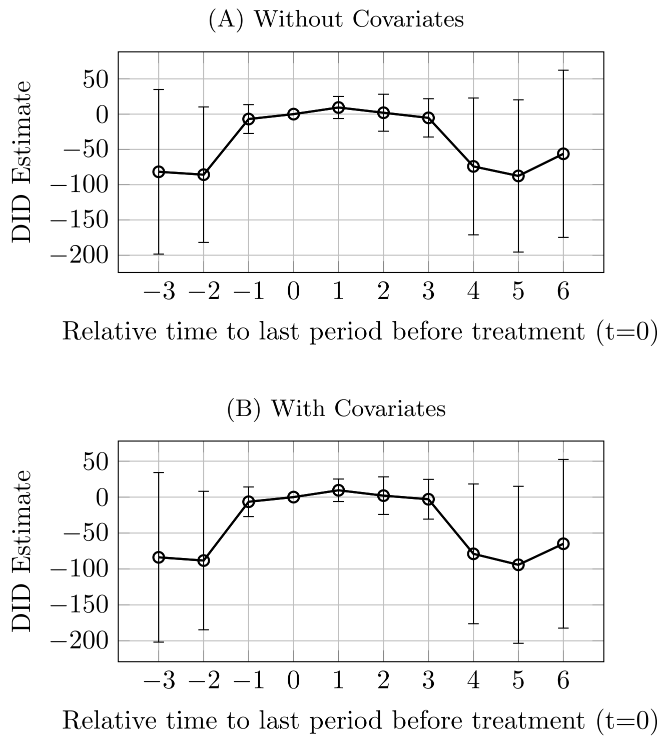


Table 8: Impact of Solar Together on installations between 2015 and 2020

| | (A) | (B) | N | Switchers[6] |
|---|---|---|---|---|
| $DID_1$ | 9.389 | 9.498 | 1047 | 85 |
| | (7.971) | (7.986) | | |
| $DID_2$ | 1.945 | 2.016 | 757 | 46 |
| | (13.367) | (13.353) | | |
| $DID_3$ | -5.308 | -3.011 | 506 | 32 |
| | (13.852) | (14.111) | | |
| $DID_4$ | -74.127 | -78.951 | 258 | 7 |
| | (49.475) | (49.606) | | |
| $DID_5$ | -87.624 | -94.234 | 244 | 7 |
| | (55.061) | (55.727) | | |
| $DID_6$ | -56.263 | -64.954 | 205 | 7 |
| | (60.447) | (59.875) | | |
| Covariates | No | Yes | | |

Cluster-robust standard errors in parentheses.
$***\, p < 0.01$, $**\, p < 0.05$, $*\, p < 0.1$

Table 8 and Figure 2 indicate that there is no statistically significant treatment effect of Solar Together in any year after treatment, differing from Graziano and Gillingham's finding that Solarize dramatically increased solar PV installations in Connecticut. These different treatment effects may be caused by differences in the price reduction offered by the two schemes, the extent of advertising or the ease of registry and installation. However, spatial-neighbour effects will also play a key role in determining the success of a scheme, as positive spatial-neighbour effects will mean that the initial wave of installations under the scheme will lead to additional installations by nearby households. The time-frame in which these Solar Together schemes are carried out is mostly within the period 2016–2020 in which we estimated spatial-neighbour effects to be negative, indicating saturation of solar PV amongst likely adopters. However, as shown previously, this estimation of peer effects is suspect because of inconsistency introduced by a high order of autocorrelation in the regression's errors. If this finding of negative spatial-neighbour effects is in fact valid, this is a possible reason for the insignificant impact of Solar Together; Solar Together may simply lead likely adopters of solar PV to move their installations forward, resulting in a following decrease in the installation rate.

Table 9: Test for pre-trends

| | (A) | (B) | N | Switchers |
|---|---|---|---|---|
| $PLACEBO_1$ | -6.981 | -6.490 | 1047 | 85 |
| | (10.432) | (10.520) | | |
| $PLACEBO_2$ | -85.833 | -88.288 | 757 | 46 |
| | (48.994) | (49.147) | | |
| $PLACEBO_3$ | -81.762 | -83.823 | 223 | 32 |
| | (59.515) | (60.190) | | |
| p-value of joint nullity | 0.377 | 0.353 | | |
| Covariates | No | Yes | | |

Cluster-robust standard errors in parentheses.
$***\,p < 0.01,\ **\ p < 0.05,\ *\,p < 0.1$

This estimation strategy is dependent on the common trends assumption for identification. Specifically, this requires that local authorities that implemented Solar Together schemes and those that did not would have followed parallel trends in solar PV installation rates, if the Solar Together

[6] *Switchers* is the number of units which we observe $l$ periods after they switched into treatment. $N$ is the sample size, including switchers and control units which have not yet been treated at the time of comparison.

scheme was not carried out. This assumption is untestable. Local authorities select into treatment and therefore there may be systematic differences between treated and non-treated local authorities. Councils of treated local authorities may be more willing to pursue other policies to encourage solar PV installation or if the population of a local authority is keen to install solar PV, they may lobby the council to carry out a Solar Together scheme to reduce the price of installations. We therefore test for parallel pre-trends to investigate whether there are differences in the rate of change of solar PV installation rates between treated and non-treated local authorities in the years before treatment occurs. Our results are contained in Table 9. We do not reject the null hypothesis of parallel pre-trends at the 10% significance level for either the model with or without covariates. Our result of parallel pre-treatment trends is not sufficient to indicate that parallel post-treatment trends hold but make the assumption of parallel post-treatment trends more plausible.

# 7 Conclusion

Taken at face value, these results lead to a clear set of conclusions. We confirm the presence of positive spatial-neighbour effects identified by other authors in the first period of study, 2010–2015, but identify negative spatial-neighbour effects in both 2016–2020 and 2021–2024. This is a concerning finding for the current Labour government's aim to triple solar capacity by 2030, suggesting that extremely high installation rates in 2010–2015 were aided by strong peer effects but these peer effects have diminished over time, possibly due to the mechanisms highlighted by Baranzini et al. (2017), where knowledge about solar PV technology becomes more widespread and so observational learning falls in importance. Negative spatial-neighbour effects instead suggest that there is a degree of saturation within the solar PV market, given the rise in the number of total solar PV systems in England and Wales to 1.4 million. These spatial-neighbour effects are the multiplier effects of government policy to increase solar PV capacity, and so given the most recent estimates, this suggests that extensive financial incentives may be required to increase solar PV capacity to the targeted level. The finding that schemes such as Solar Together have been unsuccessful in increasing solar PV installations given negative spatial-neighbour effects is a further cause of concern but these schemes may have been otherwise successful at reducing prices and search costs for participants.

However, this decrease in spatial-neighbour effects is likely not simply due to more widespread information about solar PV and the greater number of solar PV systems, but may also be caused by reductions in financial incentives to adopt solar PV, such as the cut in the FIT rate in January 2016. Reductions in these financial incentives may contribute to negative spatial-neighbour effects by reducing the pool of likely adopters of solar PV, thereby increasing saturation, and by leading to more critical word-of-mouth between neighbours around solar PV. This is indicated by the increase in spatial-neighbour effects in the period 2021–2024, following the energy cost crisis, which instead increased the financial incentives to adopt solar PV. This suggests that policies involving financial incentives to increase solar PV installation rates may increase the extent of their own multiplier effects and even lead to further installations as more positive spatial-neighbour effects increase the effectiveness of schemes such as Solar Together.

Further research can investigate spatial-neighbour effects with greater accuracy by obtaining the exact location of solar PV systems, allowing "spatiotemporal neighbour" variables to be constructed as in Graziano and Gillingham (2015) and Baranzini et al. (2017) such that cross-boundary spatial-neighbour effects are not neglected.

However, there is an important caveat. Autocorrelation in the errors of these regressions is sufficiently high to cause omitted variable bias in the estimation of these spatial-neighbour effects. If this bias is very large, our estimates of spatial-neighbour effects may be significantly incorrect. Recent works such as Graziano and Gillingham (2015) and Baranzini et al. (2017) neglect to report the results of such autocorrelation tests, suggesting that there may be widespread mis-estimation of spatial-neighbour effects in the literature. Further research should take care to report these tests to ensure that possible inconsistency in their results is taken into account.

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# Appendix A: Data sources

Table 10: Data sources

| Variable | Description and use | Source |
|---|---|---|
| Solar PV systems | The number of solar PV systems in each local authority / postcode district, by month. Used to evaluate peer effects at the local authority and postcode district level. | Local authority level: Obtained from MCS (2025). Only includes Solar PV, excludes Solar Heating.<br>Postcode district level: Obtained upon request from the MCS. |
| Heat pumps | The number of heat pumps in each local authority, by month. Used to evaluate peer effects for heat pumps. | Obtained from MCS (2025). Includes Air Source Heat Pump, Ground/Water Source Heat Pump and Other Heat Pump Types. |
| Solar Together schemes | A full list of Solar Together schemes carried out. Used to determine which local authorities were treated in the evaluation of Solar Together. | A full list of Solar Together schemes was obtained upon request from iChoosr and cross-referenced with the list of Solar Together London schemes in AECOM (2024). See Appendix B. |
| Number of households | The number of households in each local authority and postcode district. Used for summary statistics. | Local authority level: Obtained from ONS (2022b).<br>Postcode district level: Postcode level data obtained from Dataset P002 in ONS (2021). Postcode district level values calculated by taking the totals of postcodes within each postcode district. |
| Median age | Median age in each local authority by year. Used as a control in the evaluation of Solar Together. | Calculated from the data on ages in Mid-2011 to mid-2022 detailed time series in ONS (2024b). |
| Median weekly pay | Median weekly pay in each local authority by year. Used as a control in the evaluation of Solar Together. | Obtained from ONS (2024a). Query data for Geography: district / unitary local authorities, Pay and Hours: weekly pay - gross, Sex & Full/Part-Time: total, Variable: median. |
| Level of unemployment | Model-based estimates of unemployment in each local authority by year. Used as a control in the evaluation of Solar Together. | Obtained from ONS (2022a). |
| Number of owner occupied households | Estimates of the number of owner occupied households in each local authority by year. Used as a control in the evaluation of Solar Together. | Obtained from ONS (2023) |

# Appendix B: Solar Together schemes

Table 11: Solar Together schemes timeline

| Year | Season | Solar Together scheme |
|---|---|---|
| 2015 | Winter | |
| | Spring | |
| | Summer | Norfolk |
| | Autumn | |
| 2018 | Winter | |
| | Spring | London 1 |
| | Summer | Essex, London 2, Norfolk, Suffolk |
| | Autumn | |
| 2019 | Winter | |
| | Spring | |
| | Summer | |
| | Autumn | Suffolk, Norfolk, London 3, Manchester |
| 2020 | Winter | |
| | Spring | |
| | Summer | |
| | Autumn | Cambridgeshire, Devon, Suffolk, Norfolk, Kent, Sussex |
| 2021 | Winter | Essex, Hampshire, London 4, Warwickshire |
| | Spring | |
| | Summer | Surrey |
| | Autumn | Norfolk, Suffolk, Sussex, West of England |
| 2022 | Winter | |
| | Spring | Cambridgeshire, Essex, Kent, London 5 |
| | Summer | Bedfordshire, Buckinghamshire, Leicestershire, Wiltshire, Windsor & Maidenhead |
| | Autumn | Hampshire, Hertfordshire, Liverpool, Norfolk, Suffolk |

Table 11: (continued)

| Year | Season | Solar Together scheme |
|---|---|---|
| 2023 | Winter | Essex, Worcestershire, |
| | Spring | Kent, Sussex |
| | Summer | Bedfordshire, Berkshire, Leicestershire, Surrey, Wiltshire |
| | Autumn | Hertfordshire, Cheshire and Warrington, Hampshire, Kent, Liverpool, Norfolk, Suffolk, West of England |
| 2024 | Winter | Essex |
| | Spring | Buckinghamshire, Devon, Kent, Manchester |
| | Summer | West Yorkshire, Worcestershire, Berkshire, Leicestershire, Surrey, Wiltshire |
| | Autumn | Cheshire and Warrington, Hampshire, Kent, Liverpool, Norfolk, Suffolk, West of England |

Table 12: Solar Together schemes key

| Scheme | Local authorities |
|---|---|
| Bedfordshire | Bedford, Central Bedfordshire, Luton |
| Berkshire | Reading, Bracknell Forest, Wokingham, West Berkshire, Windsor & Maidenhead |
| Buckinghamshire | Buckinghamshire |
| Cambridgeshire | Cambridge, East Cambridgeshire, Fenland, Huntingdonshire, South Cambridgeshire |
| Cheshire and Warrington | Warrington, Cheshire East, Cheshire West and Chester |
| Devon | Exeter, East Devon, Mid Devon, North Devon, Torridge, West Devon, South Hams, Teignbridge |
| Essex | Basildon, Braintree, Brentwood, Castle Point, Chelmsford, Colchester, Epping Forest, harlow, Maldon, Rochford, Tendring, Uttlesford |
| Hampshire | Test Valley, Basingstoke and Deane, Hart, Rushmoor, Winchester, East Hampshire, New Forest, Southampton, Eastleigh, Fareham, Gosport, Havant |
| Hertfordshire | Broxbourne, Dacorum, East Hertfordshire, Hertsmere, North Hertfordshire, St Albans City, Stevenage, Three Rivers, Watford, Welwyn Hatfield |
| Kent | Ashford, Canterbury, Dartford, Dover, Folkestone and Hythe, Gravesham, Medway, Sevenoaks, Swale, Thanet, Tonbridge and Malling, Tunbridge |
| Leicestershire | Blaby, Charnwood, Harborough, Hinckley and Bosworth, Melton, North West Leicestershire, Oadby and Wigston |
| Liverpool | Halton, Knowsley, Liverpool, Sefton, St Helens, Wirral |
| London 1 | Brent, Ealing, Kingston upon Thames, Sutton, Merton |
| London 2 | Camden, Haringey, Islington, Kensington, Chelsea, Merton, Newham, Sutton, Waltham Forest, Westminster |
| London 3 | Brent, Camden, Croydon, Ealing, Hackney, Islington, Kensington and Chelsea, Kingston upon Thames, Lewisham, Merton, Newham, Sutton, Waltham Forest |
| London 4 | Barking and Dagenham, Barnet, Bexley, Brent, Bromley, Camden, Croydon, Ealing, Enfield, Greenwich, Hackney, Hammersmith and Fulhan, Haringey, Harrow, Havering, Hillingdon, Hounslow, Islington, Lambeth, Lewisham, Merton, Newham, Kensington and Chelsea, Kingston upon Thames, Redbridge, Richmon upon Thames, Southwark, Sutton, Tower Hamlets, Wandsworth, Waltham Forest, Westminster |

Table 12: (continued)

| Scheme | Local authorities |
| --- | --- |
| London 5 | Barking and Dagenham, Barnet, Bexley, Brent, Bromley, Camden, Croydon, Ealing, Enfield, Greenwich, Hammersmith and Fulham, Haringey, Hacknet, Harrow, Havering, Hillingdon, Hounslow, Islington, Kensington and Chelsea, Kingston upon Thames, Lewisham, Merton, Newham, Redbridge, Richmond upon Thames, Southwark, Sutton, Tower Hamlets, Wandsworth, Waltham Forest, Westminster |
| Manchester | Bolton, Bury, Manchester, Oldham, Rochdale, Salford, Stockport, Tameside, Trafford, Wigan |
| Norfolk | Breckland, Broadland, Great Yarmouth, North Norfolk, Norwich, King's Lynn and West Norfolk, South Norfolk |
| Suffolk | Babergh, East Suffolk, Ipswich, Mid Suffolk, West Suffolk |
| Surrey | Elmbridge, Epsom and Ewell, Guildford, Mole Valley, Reigate and Banstead, Runnymede, Spelthorne, Surrey Heath, Tandridge, Waverley, Woking |
| Sussex | Worthing, Arun, Chichester, Horsham, Crawley, Mid Sussex, Adur, Hastings, Rother, Wealden, Eastbourne, Lewes, Brighton & Hove |
| Warwickshire | North Warwickshire, Nuneaton and Bedworth, Rugby, Staford-on-Avon, Warwick |
| West of England | Bristol, South Gloucestershire, Bath and North East Somerset, North Somerset |
| West Yorkshire | Bradford, Calderdale, Kirklees, Leeds, Wakefield |
| Wiltshire | Wiltshire, Swindon |
| Windsor & Maidenhead | Windsor & Maidenhead |
| Worcestershire | Bromsgrove, Malvern Hills, Redditch, Worcester, Wychavon, Wyre Forest |