Demand Correlation and PV Solar Panel Investment[*]

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Abstract

The globe is entering an age of electricity, with renewable sources at the forefront of growth in investment in the transition. This study takes a novel step by theoretically and empirically contributing to our understanding of how investment in residential solar photovoltaics (PV) increases with demand correlation, and the extent to which this relationship is shaped by demand uncertainty. We bring together a unique dataset of relevant information about solar PV investment and electricity demand in GB between 2015 and 2020. This allows us to test our theoretical predictions and empirically show that i) households invest more when demand correlation increases and that ii) this relationship is amplified when demand is uncertain.

Keywords: Investment; demand correlation; demand uncertainty; households; renewable technology

JEL codes: D11, D12, E22, L94, Q42

1 Introduction

Global energy systems are "entering the age of electricity" [1]. Electricity demand is expected to continue rising as countries invest in electrification, boosted by emerging economies; however, while the United States' (US) electricity demand has returned to growth for now, European Union demand is faltering in the face of high electricity prices [1]. Great Britain (GB), the focus of our empirical analysis, despite also reeling from significant gas price volatility [2], has seen an uptick in domestic electricity consumption following recent colder winters and increasing numbers of electric vehicles [3]. Renewables made up just over 46 per cent of the United Kingdom's (UK[1]) total electricity generation in the first quarter of 2025, with solar photovoltaics (PV) contributing most to the overall change in electricity capacity and generation compared to the same quarter of 2024 [3]. Our study contributes to the literature with theoretical and empirical evidence on how demand correlation and uncertainty impact investments, focusing on GB's residential market for solar PV.

Over the last decade the inflation adjusted cost of installing domestic solar panels, specifically small-scale solar technology below 50 kilowatts (kW), has decreased by around 23 per cent in the UK [4]. During the same period, the capacity of domestic solar installations has more than doubled, rising from under 2000 megawatts (MW) to just over 5000 MW, with over 1.4 million installations in the UK and almost 1.2 million deployed in England alone [5]. Regardless of the UK Government's flagship Feed-in-Tariff scheme coming to an end in early 2019 – which subsidised electricity exported to the grid – the recent strong price and policy incentives led to the UK witnessing a record number of solar panel installations in the first half of 2025, up 36 per cent on the previous year [6].

To motivate our empirical analysis, we first build a theoretical model to investigate PV investment decisions of households. In our model, households invest in PV, maximising their utility with respect to capital costs, and/or buy electricity from the grid when needed. This reflects the fact that few households are self-sufficient throughout the year without battery storage. As time-of-use (ToU) tariffs, which incentivise shifting demand from expensive to cheaper periods of the day, have started to become more available in recent years in GB, prices in our model are allowed to vary between on-peak and off-peak. Household demand for electricity, measured here in kilowatt hours (kWh), is uncertain but correlated. Each household's demand can be high or low [2]. Demand correlation occurs – defined here as the extent to which households exhibit synchronous demand – with peaks when households have high demand and troughs when they have low demand. This process leads to spatial clustering or dispersion where similar or differing demand patterns geographically co-exist, whilst demand uncertainty – which we define as the stochastic variability in electricity demand profiles – may arise from economic (e.g., prices), socio-demographic (e.g., pandemics), and temperature/climate shocks.

Indeed, demand correlation can be observed in daily patterns of consumption, which are shaped by consumer archetypes (profiles) including households consuming electricity all day or those consuming mainly in the morning and/or evening – as well as observed seasonally or annually following the "rhythms" of local communities and societies, e.g., patterns of work, school, annual events/festivals [7]. Similarly, correlations in demand for products and services could also arise from social networks reacting to such external stimuli, including temperature [8]. The strength of peer-to-peer or neighbourhood effects, previously identified as drivers of PV investment (see, e.g., [9], [10], [11]), may also intensify correlation in demand, particularly amongst those with similar household and dwelling characteristics, thereby shaping the adoption of behaviours and technologies that manage demand at similar times of day across different seasons of the year. Crucially, whilst peer and neighbourhood effects may be correlated with adoption, our focus is on how the synchronisation of electricity demand, i.e. the demand correlation, is associated with investment in solar PV.

Our theoretical model leads to two testable predictions. The first is that households invest more in PV as demand correlation increases. And the second implies that this effect becomes stronger when demand uncertainty is greater. Both are due to the difference between on-peak and off-peak prices becoming more significant as demand correlation increases, which increases the benefit of PV investment, and higher

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[1] I.e., GB and Northern Ireland.

[2] To provide some context, using the first and last year of our data as an example, GB's energy regulator – the Office for Gas and Electricity Markets (Ofgem) – routinely updates and publishes "typical domestic consumption values" (TDCVs) and defined low (high) electricity profiles as 2,000 (4,600) kWh in 2015 and 1,800 (4,300) kWh in 2020 reflecting continued falling electricity consumption.

uncertainty amplifies this.

To test the theoretical predictions, we have constructed a unique dataset bringing together several sources of official information. Electricity consumption and residential solar PV installation data at high levels of spatial disaggregation are retrieved from the UK Government and GB's energy regulator, respectively.[3]. The structure of the dataset naturally leads to the estimation of a our measure of demand correlation: Moran's I. This statistic captures the spatial autocorrelation (dispersion and clustering) in demand. This is estimated using the postcode level residential electricity data, between 2015 and 2020, at the postal outward code (the next level of spatial aggregation after postcode).[4] We use this information to investigate whether demand correlation is associated with the total capacity of accredited solar PV installed by households, at the outward code level. Furthermore, we augment our model in order to investigate how this association is affected by demand uncertainty. In line with our theoretical framework, we find i) a positive association between demand correlation and solar PV investment by households, and ii) that this positive association becomes stronger when demand is more uncertain. A series of robustness and specification checks are conducted to test the veracity of the findings, including controlling for key market features of our theoretical framework, i.e., capital costs, prices, temperature, individual, time, and regional effects.

Altogether our theoretical and empirical findings contribute to this nascent literature in two important ways. First, we address a gap recently emphasised by Song, Miao, and Xia [12]. Their study establishes that climate change, while leading to increased electricity demand, affects demand correlation differently depending on local climates, with demand being positively affected in warmer, and negatively affected in colder, regions. The authors state that the changes in demand correlation are likely to impact investment plans. The primary objective of the present paper is to reveal both theoretically and empirically the association between demand correlation and investment. Indeed, our study is the first – to our best knowledge – to show that higher (lower) demand correlation indeed yields greater (fewer) investments in renewables (solar PV) by households. Our theoretical model, while yielding insights into modern (clean) electricity systems, also relates to the broader discussion on cloud infrastructure investments needed to support the continued growth of technologies [13] [14].

Second, as Wang and Zheng argued in 2024 [15], there is a dearth of research that investigates the interplay between demand correlations and uncertainty in energy systems, more specifically, between the respective distributions of electricity and heat demand. Their study integrated uncertainties and correlations in scenario-based simulations of hybrid energy systems that aim to improve predictions of seasonal electricity and heat loads and the evaluation of the economic impacts of hybrid systems. This approach considers a static level of technology and therefore does not attempt to investigate how demand correlation and uncertainty impact investment decisions. Our secondary objective addresses this literature gap, that is, by theoretically and empirically generating new insights that shed further light on the combined effect of demand correlation and uncertainty on investment.

The rest of the paper is organised as follows: section 2 presents the theoretical framework, whilst the data and empirical methodology are described in section 3. The main results are discussed in section 4 and section 5 offers conclusions and recommendations.

2 Theoretical Framework

To motivate our empirical study, we consider a simple yet flexible model to capture demand correlation, time-varying pricing and investment in solar panels.[5] There is a unit mass of households. The demand of

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[3]We have brought together this data because the main UK household surveys only contain either relevant information about electricity consumption patterns or investment but not both; furthermore, they are not able to match the sub-regional coverage or representativeness of our dataset.

[4]In GB, unit postcodes are separated into two alphanumeric codes, the outward code (2-4 characters, e.g. AB10) and inward code (3 characters, e.g. 1BA). Unit postcodes (e.g. AB10 1BA) represent the lowest level of postal aggregation, above individual addresses, and typically contain between 1 and 100 addresses.

[5]This model builds upon the classic peak-load pricing literature, which analyses capacity and pricing decisions with varying demands. See, for example, [16]. A key difference to this literature is the consideration of investment in solar panels in addition to on-grid investment. Moreover, the model provides general results that hold for different market structures.

each household i can be either high (h) or low (l):

$$D_i = \begin{cases} q_h, & \text{with probability } \alpha; \\ q_l, & \text{with probability } 1 - \alpha. \end{cases}$$

We denote the average demand by $\bar{q} = \alpha q_h + (1 - \alpha)q_l$. The demands are correlated as follows: a proportion β of all households have the same consumption patterns and their demands are high or low simultaneously; the demands of the rest $1 - \beta$ are independently and identically distributed as above. Therefore, the peak demand occurs when all households with correlated demands demand q_h of electricity, and the off-peak demand occurs when they all demand q_l of electricity.

Each household can invest in solar panels K_i and, if demand exceeds what the solar capacity can handle, buy on-demand energy $q_j - K_i$ (where $j = h$ or l) from an on-grid energy provider, who charges a peak price p_h and an off-peak price p_l. For each individual household, it takes the on-grid electricity price as given. The cost of installing a capacity K_i of solar panel is $C_i(K_i)$, which is assumed to be increasing and convex. For simplicity, we assume it takes the quadratic form $C_i(K_i) = \frac{K_i^2}{2c_i}$.[6] This cost includes the material cost of solar panels as well as other costs, such as labour and opportunity costs. Hence, the utility of each household is given by:

$$\begin{aligned} \max_{K_i} U_i =& \alpha\Big[u_i(q_h) - [\beta p_h + (1 - \beta)(\alpha p_h + (1 - \alpha)p_l)](q_h - K_i)\Big] \\ &+ (1 - \alpha)\Big[u_i(q_l) - [\beta p_l + (1 - \beta)(\alpha p_h + (1 - \alpha)p_l)](q_l - K_i)\Big] - C_i(K_i) \\ =& \alpha u_i(q_h) + (1 - \alpha)u_i(q_l) - \beta[\alpha p_h(q_h - K_i) + (1 - \alpha)p_l(q_l - K_i)] \\ &- (1 - \beta)(\alpha p_h + (1 - \alpha)p_l)[\alpha(q_h - K_i) + (1 - \alpha)(q_l - K_i)] - C_i(K_i). \end{aligned}$$

To understand this utility function: With probability α, the demand is high and the household enjoys a utility of $u_i(q_h)$. Furthermore, with probability β, this household belongs to the group of households with correlated demands and faces a price p_h; with probability $1 - \beta$, this household falls outside of the correlated group and faces an average price $\alpha p_h + (1 - \alpha)p_l$. Similarly, with probability $1 - \alpha$, the demand is low and the households enjoys a utility of $u_i(q_l)$, and the price it faces for on-grid electricity is either p_l when it belongs to the correlated group or the average price when it falls outside of the correlated group. The last term captures the cost of investment.

Differentiating U_i with respect to K_i yields:

$$\alpha p_h + (1 - \alpha)p_l = C_i'(K_i) = \frac{K_i}{c_i}. \tag{1}$$

That is, the household invests up to the point where the marginal cost of investment equals the marginal benefit from saving on the average electricity price. Denote the optimal investment of household i by $K_i(p_h, p_l)$ and the aggregate investment in solar panel by all households by $K(p_h, p_l) = \sum_i K_i(p_h, p_l) = \sum_i c_i(\alpha p_h + (1 - \alpha)p_l)$. In equilibrium, households have rational expectation about the on-grid price during peak and off-peak times, which satisfies:

$$S(p_h) = \beta q_h + (1 - \beta)\bar{q} - K(p_h, p_l), \tag{2}$$

in the peak state, and

$$S(p_l) = \beta q_l + (1 - \beta)\bar{q} - K(p_h, p_l), \tag{3}$$

in the off-peak state. The left hand side is the aggregate supply $S(p)$ and the right hand side is the aggregate demand. Assume $S'(\cdot) > 0$ and $S''(\cdot) < 0$.[7] Equations (1), (2) and (3) then define the equilibrium prices and investments. We can show that:

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[6]The main result holds for more general convex costs.

[7]This is related to the increasing marginal cost of electricity generation; in the UK, this corresponds to the price of the marginal generator within the merit order stack.

Proposition 1. *An increase in the degree of correlation β increases investment in solar panels K, and the impact is stronger when demand is more uncertain.*

Proof. From the equilibrium characterisation, we obtain:

$$\frac{\partial K(p_h, p_l)}{\partial \beta} = \sum_i c_i [\alpha \frac{\partial p_h}{\partial \beta} + (1 - \alpha) \frac{\partial p_l}{\partial \beta}].$$

From Equation (2), we have:

$$\frac{\partial p_h}{\partial \beta} = \frac{q_h - \bar{q} - \partial K / \partial \beta}{S'(p_h)};$$

From Equation (3), we have:

$$\frac{\partial p_l}{\partial \beta} = \frac{q_l - \bar{q} - \partial K / \partial \beta}{S'(p_l)}.$$

Therefore, we have:

$$\frac{\partial K}{\partial \beta} = (\sum_i c_i) \Big[\frac{\alpha(q_h - \bar{q}) - \alpha \frac{\partial K}{\partial \beta}}{S'(p_h)} + \frac{(1 - \alpha)(q_l - \bar{q}) - (1 - \alpha) \frac{\partial K}{\partial \beta}}{S'(p_l)} \Big].$$

Rearranging this yields:

$$\frac{\partial K}{\partial \beta} = \frac{\sum_i c_i \alpha (1 - \alpha)(q_h - q_l)(\frac{1}{S'(p_h)} - \frac{1}{S'(p_l)})}{1 + \sum_i c_i (\frac{\alpha}{S'(p_h)} + \frac{1 - \alpha}{S'(p_l)})}.$$

Since $S'' < 0$ and $p_h > p_l$, we have $\frac{1}{S'(p_h)} > \frac{1}{S'(p_l)} > 0$. Therefore, we have $\partial K / \partial \beta > 0$. That is, the equilibrium investment in solar panels is higher when demand is more correlated. Furthermore, ceteris paribus, we have $\partial K / \partial \beta$ increasing in $\alpha(1 - \alpha)(q_h - q_l)$, which is positively related to demand uncertainty as the variance of our Bernoulli demand distribution is $\alpha(1 - \alpha)(q_h - q_l)^2$. Therefore, the impact of demand correlation on investment is higher when demand uncertainty is higher. $\qquad \square$

3 Data and empirical methodology

This section provides an overview of the data sources and empirical methods used to explore the association between electricity demand correlation and domestic solar PV investment. [8] The time period spans 2015 to 2020, determined by the earliest available and relevant electricity consumption data (i.e., 2015), as well as the final publication of relevant solar PV installation data (i.e., 2020). The spatial dimension, as discussed in the introduction and in detail below, is defined by the postal outward code level. The final sample for our analysis is 15,371; reflecting around 2,562 outward-code-year observations.

3.1 *Domestic solar PV installations*

The data on domestic solar PV installed in GB is retrieved from the Ofgem's Feed-in-Tariff installation reports [17]. The report contains information about accredited installations made by domestic (household or community/school) and non-domestic entities. We investigate installed capacity of solar PV of less than 50 kW by domestic households within a given unit postcode[9], which is then aggregated to the postal outward code to coincide with the spatial dimension of analysis. Summary statistics of domestic solar PV installations are presented in Table 1. The mean total installations of domestic solar PV per annum by households within postal outward codes between 2015 and 2020 is around 61 kW (standard deviation, 128 kW). Figure A1 (Appendix) shows however that compared to between 2015 and 2017, total capacity installed in a given year from 2018 to 2020 has decreased in most regions of GB.

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[8]The authors used StataNow Version 18/19. Data is available upon request.

[9]Only 36 observations are above the 50 kW threshold. This upper threshold is in line with the definition of and available data on micro-generation [18].

Table 1: Summary statistics: annual total solar PV installations
in GB postal outward codes (2015-2020).

Variables	Mean	Standard Deviation	Min	Max
Domestic solar PV installations (kW)	60.94	127.51	0	2348.14
- Winsorised*	58.08	103.38	0	644.39
Observations=15,371				

*Note: *Domestic solar PV has been winsorised at the 99th percentile.*

3.2 *Electricity consumption and demand correlation (Moran's I)*

Our electricity consumption data is retrieved from the UK Government's Department of Energy Security and Net Zero (DESNZ) [19]. Electricity consumption data is published by DESNZ at the postcode level for all domestic meters[10]. The data also contains information on total electricity consumption (kWh) metered within a given unit postcode during the period of interest (2015-2020).

We use the postal unit code electricity consumption data to estimate demand correlation at the postal outward code level[11]. This data contains 1.127 million observations at the lower (postal unit) level of aggregation. The mean (median) postal unit contains 16 (20) unique domestic electricity meters, and a typical meter consumes around 3848 kWh (3553 kWh) of electricity per annum. At the postal outward code level, i.e., the spatial dimension of our main analysis, the mean annual electricity consumption in GB outward postcodes between 2015 and 2020 is around 30 gigawatt hours (GWh). Average electricity consumption fell from 30.4 GWh in 2015 to 29.3 GWh in 2019, before reverting to 31.6 GWh during the period of the COVID-19 pandemic lockdowns in 2020.

Using the postal unit code data, we compute a measure of spatial dependence for electricity consumption. Specifically, we calculate the global Moran's I iteratively within the boundaries of each outward code for a given year between 2015 and 2020. This allows us to capture the spatial autocorrelation (clustering or dispersion) of consumption values local to each outward code area, which serves as our final unit of analysis. Our measure of spatial dependence, Moran's I, is defined as [21]:

$$I = \frac{z^T W z}{z^T z} \tag{4}$$

Where z represents the N-vector of standardised electricity consumption for postal units i; and, W is the (N x N) spatial weight matrix (SWM), whilst N denotes the number of observations. Moran's I ranges between -1 (perfect negative spatial autocorrelation) and 1 (perfect positive spatial autocorrelation), and asymptotically takes a value of zero when the electricity consumption across units are randomly distributed within outward codes. We test for spatial autocorrelation under the null hypothesis of spatial randomisation; the test statistic follows a standard normal distribution [22]. The SWM is specified using k-nearest neighbours, where k=2, and a radius (d) equal to 20 miles.

Table 2 presents the summary statistics for our measure of demand correlation (Moran's I) estimated at the outward code level. The correlation in demand appears reasonably positive with a mean of 0.151, with spatial correlation in energy consumption ranging between -0.58 and 0.65. Later, in an additional check for robustness, Moran's I is set equal to zero if the null of spatial randomisation cannot be rejected at the 10 percent level of statistical significance, this only has a small impact on the sample mean and standard deviation (0.146 and 0.118, respectively) and does not have a material impact on the main results below. Figure A2 (Appendix) shows that demand correlation with respect to an area being positively or negatively correlated is quite stable across GB local authorities over time.

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[10]Including standard meters. Economy-7 meters are excluded from the analysis as they are used by a limited set of consumers on differential tariffs, typically off-grid households with storage heaters. It is also important to note that some meters are excluded by DESNZ to avoid disclosure of consumers, e.g., meters which have recorded annual consumption of less than 100 kWh (for a detailed overview see [19]).

[11]Latitude and longitudinal coordinates are assigned to unit postcodes using the UK's Office of National Statistics Postcode Directory [20].

Table 2: Summary statistics of Moran's I
at GB postal outward code level (2015-2020).

Variables	Mean	Standard Deviation	Min	Max
Moran's I	0.151	0.120	-0.577	0.647
- Winsorised*	0.151	0.117	-0.426	0.470
Observations=15,371				

*Note: *Moran's I has been winsorised at the 99th percentile.*

3.3 Econometric analysis

Our empirical strategy leverages the panel structure of our data in order to employ pooled ordinary least squares (OLS) and fixed effects (FE) regressions, allowing us to estimate the association between capacity and demand correlation. The general econometric specification can be defined as follows:

$$C_{it} = \beta_0 + \beta_1 DC_{it} + X'_{it}\gamma + \omega_t + \mu_r + \alpha_i + \epsilon_{it} \tag{5}$$

where C_{it} is capacity (C) of solar PV installations at the outward code level i in year t, and $t = 2015, \ldots, 2020$. DC_{it} represents our measure of demand correlation, captured by Moran's I (denoted by $MORANSI$ hereafter). Equation 5 is estimated sequentially introducing layers of robustness, such as winsorisation, geographical region (μ_r) fixed effects and Local Authority (LA) fixed effects, annual time effects (ω_t) capturing aggregate time-varying shocks and seasonality in C_{it}, LA-specific trends, and a matrix of covariates X_{it}. The vector of regression coefficients to be estimated for the covariates is represented by γ, whilst α_i denotes the time-invariant unobserved heterogeneity. Finally, ϵ_{it} denotes the error term, clustered at the outward code level.[12]

Covariates

According to *Proposition* 1, we anticipate that higher levels of demand uncertainty increase investment in solar PV given higher levels of demand correlation. Therefore, we augment Equation 5 with the standard deviation of total consumption in outward codes as a measure of demand uncertainty ($LNELECDSD$), in order to estimate its potential role in explaining the variation in PV installations in GB.[13]

In addition, by matching various data sources, we also control for an array of factors expected to be correlated with capacity and demand correlation. Since Ofgem's Feed-in-Tariff reports do not contain information on the upfront cost of installing solar PV, we capture this using data published by DESNZ [23] [14] on the mean cost per kilowatt (£/kW) of solar PV micro-generation installed per annum across three size ranges, that is, 0-4 kW, 4-10 kW, and 10-50 kW ($LNCOSTKW$). We also control for the mean price of electricity (£/kWh) at the geographic region and annual level ($LNELECPRICE$), using data on standard variable tariffs[15] collected from DESNZ [25]. Both sets of data allow us to capture the influence of the upfront cost of solar investment and the marginal cost of purchasing electricity from the grid. All covariates so far are logarithmically transformed prior to their inclusion, attenuating the influence of outliers, and can be interpreted as semi-elasticities.

Finally, as mentioned in the introduction, our theoretical model captures the high (low) price of energy corresponding to high (low) demand. Empirically, this relationship is partially proxied by annual temperature variations. Since temperature is highly correlated with electricity demand and price changes (where colder years are often associated with periods of higher prices and demand), we control for temperature at the geographic office regional level in our final specification, more specifically the polynomial of mean temperature, collected via the UK Met Office [26].[16] This further controls for seasonality over and above

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[12]The main analysis holds using robust standard errors (SE) and without robust or clustered SEs.

[13]Figure A3 (Appendix) shows the regional dispersion of energy demand across GB.

[14]Costs represent Feed-in-Tariff accredited installations in GB and are reflective of the upfront cost of solar PV equipment, its connection to the electricity grid, and VAT [23].

[15]In 2018, around two-thirds of customers paid for their energy using standard variable tariffs; these customers were protected by a price cap from January 2019 [24].

[16]Note that the results are robust using annual duration of bright sunshine [26].

the inclusion of regional and time fixed effects.

4 Results

4.1 *Empirical analysis of capacity and demand correlation*

Table 3 presents our pooled OLS and fixed effects models of the capacity of domestic solar PV installed by households on our spatial measure of demand correlation (Moran's I) estimated at the GB outward code level between the years of 2015 and 2020.

In line with our theoretical model (*Proposition* 1), we find a positive association between capacity installed and demand correlation across all specifications (Table 3, Columns 1-8). For example, controlling for geographical office regions (Table 3, Column 1), on average an increase in Moran's I by 0.1 is associated with an increase in capacity installed by 3.21 kW, all else constant. This association is statistically significant at the 1 per cent level.

Upon controlling for local authority (LA) effects (Column 2) and time effects using year indicators (Column 3), the point estimate remains very similar to our baseline model (Column 1). Our findings hold after winsorising capacity and Moran's I to further account for the potential influence of outliers (Column 4)[17] and are consistent with flexibly controlling for regional and time effects with LA specific trends (Column 5). Given the high correlation between national time-varying shocks and our annual unit-level demand correlation measure, we prioritise the use of LA-specific trends in subsequent specifications (Columns 5 to 8) to further investigate the association from differential local growth paths.[18]

Table 3: Pooled ordinary least squares (OLS) and fixed effects (FE) regressions of installed domestic PV capacity (C) on demand correlation (Moran's I) in GB outward codes

Specifications Dependent variable	(1) Capacity (GOR)	(2) Capacity (LA)	(3) Capacity (Time)	(4) Capacity (Winsorised)	(5) Capacity (LA trends)	(6) Capacity (LA trends)	(7) Capacity (Controls)	(8) Capacity (Temp.)
	OLS					FE		
MORANI	32.06***	48.07***	35.81***	32.15***	33.55***	116.3***	57.50**	51.27**
	(9.401)	(10.635)	(10.607)	(8.091)	(8.203)	(22.358)	(25.894)	(25.612)
LNELECTDSD							457.5***	432.2***
							(23.208)	(22.956)
LNELECPRICE							1246.5***	1204.9***
							(28.191)	(28.816)
LNCOSTKW							-82.65***	-84.13***
							(7.536)	(7.615)
GOR effects	Y	N	N	N	N	N	N	N
LA effects	N	Y	Y	Y	Y	Y	Y	Y
Time effects	N	N	Y	Y	Y	Y	Y	Y
LA specific trends	N	N	N	N	Y	Y	Y	Y
Temp. polynomial	N	N	N	N	N	N	N	Y
R^2	0.0351	0.114	0.404	0.496	0.448	0.453	0.580	0.586
BIC	192228.9	194341.8	188314.3	179272.2	184031.1	178515.1	174482.9	174282.1
Observations=15,371								

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the outcode level in parentheses. Specifications: (1) includes geographical regional (GOR) indicators; (2) includes local authority (LA) indicators, replacing GOR; (3) includes year indicators alongside LA indicators (without LA specific trends); (4) is specification (3) with winsorised capacity (99th percentile) and Moran's I (1st and 99th percentile); (5) uses winsorised capacity and Moran's I together with LA effects and LA-specific trends, replacing year indicators; (6) estimates specification (5) using fixed effects regression; (7) adds controls to specification (6); while (8) includes temperature (temp.) polynomials alongside the controls in (7).

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[17]The baseline results also remain robust when using the Inverse Hyperbolic Sine and the log(Y+1) transformations, as well as Poisson regression (see Appendix Table A1).

[18]Whilst only 5.5 per cent of outcodes record zero PV installations, Tobit regressions estimated using LA-specific trends indicates that there is a slight underestimation in the baseline pooled OLS regressions (Table A2, Column 1). The results are robust when using Tobit random effects regression (Table A2, Column 2). As mentioned above, as an additional check for robustness, Moran's I is set equal to zero if the null of spatial randomisation cannot be rejected at the 10 per cent level of significance. Setting such values to zero, the concomitant findings suggest a slight underestimation in our baseline results (Table A3, Column 1), and again when controlling for potential outliers upon winsorising this outcome (Table A3, Column 2). Hence our main estimates may be considered a lower bound.

Continuing with LA effects and LA-specific trends, our fixed effects regressions which eliminate unobserved time-invariant heterogeneity also suggest that pooled OLS underestimates the association between our measure of demand correlation and capacity installed (Column 6). The larger point estimate (116.3) however is somewhat explained by other time-varying covariates, i.e., demand uncertainty, the cost of capital, the marginal price of electricity, and temperature (Columns 7 to 8). Focusing on the most robust specification (Column 8), an increase in Moran's I by 0.1 is associated with an increase in PV capacity installed by 5.13kW, on average, *cetris paribus*, and is statistically significant at the 5 per cent level. This supports our theoretical prediction of and primary objective to establish an association between demand correlation and investment.

The covariates' estimated coefficients signs are as expected and are statistically significant at the 1 per cent level. More specifically, our estimates support that households install solar PV when marginal domestic electricity prices are higher, since a 1 per cent increase in regional electricity unit rate is associated with an approximate 12.5 kW rise in domestic solar PV installed. In contrast, the upfront cost of investment acts as a disincentive, as our findings suggest that a 1 per cent increase in the cost of installation is associated with an approximate 0.83 kW decrease in domestic solar PV installed. The estimated coefficient for our measure of demand uncertainty ($LNELECDSD$) is also intuitive, since on average a 1 per cent increase in the standard deviation of outward code electricity consumption is associated with a 4.3 kW increase in domestic solar PV installed, all else constant. [19]

Compared to the baseline pooled OLS regressions presented in Table 3, the fixed effects regressions with LA-effects and LA-specific time trends (Column 6) and the fixed effects regressions with controls and temperature polynomials (Column 8) fit the data best, according to the Bayseian Information Criterion (BIC) presented in Table 3. Therefore, we utilise these empirical specifications in the next section to further analyse the influence of demand uncertainty.

Before moving onto the role of demand uncertainty, we show that our main findings also hold in Table A4 (Appendix) when controlling for the price paid to small-scale domestic solar generators when exporting electricity to national grid. However, these results should be interpreted with some caution because the export price, set nationally, changed only once per year under the UK Government's flagship scheme – the "Feed-in Tariff" (FiT). In addition, this scheme launched in 2010 and closed to new applications as of 1st April 2019. New low-carbon installations had to wait until the launch of its successor – the "Smart Energy Guarantee" (SEG) – on 1 January 2020, which requires some electricity suppliers to pay small-scale low-carbon generators (given certain criteria) for electricity exported to the grid. We use the monthly mean FiT for each year from 2015 to 2018 [28], the mean SEG price in 2020 [29], and the mean of the FiT in 2018 and SEG 2020 to proxy for the year-long gap in 2019. Given the lack of variation in this variable we are only able to control for region (LA) and time (year) effects in our fixed effects regressions while excluding another year fixed effect due to collinearity (Table A4, Column 1). Nonetheless, we show these results to be robust to the inclusion of the log of export prices in Column 2 (at the 5% level), and further hold (at the 10% level) when controlling for potential uncertainty in electricity costs captured by including the log difference in the import (standard variable) price and export (FiT) price in our regression (Column 3).

4.2   The role of demand uncertainty

In this section we investigate the role of demand uncertainty in the association between capacity and demand correlation. We test the second theoretical prediction in *Proposition* 1 that the relationship between demand correlation is stronger when demand uncertainty increases. To this end we utilise fixed effects regressions, while including LA-effects and LA-specific trends without and with controls and temperature polynomials, as mentioned earlier. The regressions presented in Table 4 are estimated separately while interacting our spatial measure of demand correlation ($MORANI$) and quintiles of demand uncertainty ($LNELECDSD\_Q2-LNELECDSD\_Q5$) or interacting deciles of demand uncertainty ($LNELECDSD\_D2-LNELECDSD\_D10$). Table 4 also provides the F-statistic to test the joint significance of the interaction terms.

Our findings yield two more important results. Firstly, the interactions across all specifications support the theoretical prediction that the impact of demand correlation on capacity installed is larger at higher levels

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[19]Our results are robust to the inclusion of population size or the total number of meters within an outcode. In line with previous literature, we find the potentially counterintuitive finding that less densely populated areas have a greater propensity to invest in solar PV (e.g., [9], [27]); therefore, these results are available upon request.

Table 4: Fixed effects regressions interacting Moran's I with
quintiles and deciles of demand uncertainty

Specifications Dependent variable	(1) Capacity	(2) Capacity	(3) Capacity	(4) Capacity
Panel A				
MORANI	63.80**	7.306		
	(27.496)	(28.613)		
MORANI x LNELECTDSD_Q2	38.34	35.15		
	(27.134)	(26.956)		
MORANI x LNELECTDSD_Q3	64.07**	70.20**		
	(32.494)	(31.754)		
MORANI x LNELECTDSD_Q4	97.10***	93.88***		
	(35.118)	(34.648)		
MORANI x LNELECTDSD_Q5	97.18***	129.9***		
	(36.235)	(36.861)		
Panel B				
MORANI			33.85	-33.38
			(29.813)	(31.353)
MORANI x LNELECTDSD_D2			37.53	36.71
			(32.299)	(33.108)
MORANI x LNELECTDSD_D3			70.58*	61.88*
			(37.405)	(36.348)
MORANI x LNELECTDSD_D4			80.16**	92.40**
			(39.467)	(39.222)
MORANI x LNELECTDSD_D5			112.6***	128.2***
			(41.879)	(41.106)
MORANI x LNELECTDSD_D6			107.9***	133.8***
			(40.010)	(39.603)
MORANI x LNELECTDSD_D7			154.5***	174.1***
			(41.344)	(41.275)
MORANI x LNELECTDSD_D8			133.4***	145.1***
			(44.930)	(45.367)
MORANI x LNELECTDSD_D9			147.2***	199.9***
			(43.938)	(46.068)
MORANI x LNELECTDSD_D10			153.7***	218.5***
			(43.657)	(46.651)
Controls	N	Y	N	Y
Temp. polynomial	N	Y	N	Y
R^2	0.459	0.577	0.463	0.584
BIC	178401.8	174687.0	178404.1	174502.0
F(4, 2631)	2.099	3.213		
- p-value	0.078	0.048		
F(9, 2631)			1.900	3.257
- p-value			0.012	0.001
Observations=15,371				

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the outcode level in parentheses. All regressions include LA-effects and LA-specific trends. Controls include $LNELECPRICE$ and $LNCOSTKW$. Capacity is winsorised at the 99th percentile, Moran's I is winsorised at the 1st and 99th percentile. The coefficients estimated for the categories $LNELECTDSD\_Q2 - 5$ and $LNELECTDSD\_D2 - 10$ are excluded from the table for brevity and available upon request. The F-statistics and respective p-values test the joint significance of the interaction terms.

of demand uncertainty. For example, the interaction with the 10th decile of demand uncertainty (compared to the 1st decile) implies that the *additional* effect of a 0.1 increase in demand correlation leads to a 15.4 kW increase in capacity installed, on average.

Secondly, the sign and statistical significance of the base coefficient on $MORANI$ reveals that at low levels demand uncertainty (e.g., the first quintile or first decile) the association between demand correlation and capacity appears individually statistically insignificant once adjusting the regressions for temperature and other controls. Despite this, the second quintile and second decile of demand uncertainty, interacted with our measure of demand correlation, remains jointly significant with all other interaction terms.

Overall these results are in line with our theoretical predictions, and our secondary objective, that households invest more when demand correlation increases and, more specifically, this relationship is amplified when demand is uncertain.

5   Conclusion

Global spending on renewable generation has doubled since 2020 and investment in utility-scale and decentralised solar is expected to have reached 450 billion US$; indeed, the "age of electricity" is being led by solar and wind generation, accounting for 98% of the growth in total electricity generation investment over the last decade [30]. In line with our objectives, this study is the first of its kind – to the authors' knowledge – that shows both theoretically and empirically the relationship between investment and demand correlation, and how this relationship is shaped by demand uncertainty. Our findings contribute to the literature first by theoretically proposing that households are likely to invest more in solar PV in response to higher levels of (positive) demand correlation, and that this relationship becomes stronger when there is more uncertainty in electricity demand. We test these theoretical predictions empirically.

By assembling a unique dataset of relevant information about solar PV investment and electricity demand in GB between 2015 and 2020, we use geographically rich postcode-level data in order to estimate a spatial measure of electricity demand correlation. This, in turn, allows us to investigate its association with solar PV installed by domestic consumers at the next (outcode) level of regional aggregation. Controlling for an array of economic, time, and regional characteristics, our empirical models support the theoretical prediction that demand correlation is associated with higher levels of solar PV capacity installed. Furthermore, by interacting demand correlation with our measure of demand uncertainty, we find that the association between investment and demand correlation is amplified when demand is more uncertain.

Altogether, this allows us to further contribute to the gaps in the literature (as noted in [12] and [15]) by showing empirically that households i) invest more when demand is correlated and ii) that this relationship is amplified when demand is uncertain. Importantly, both the theoretical model and empirical evidence aligns in highlighting the importance of considering profiles of demand for solar PV adoption.

Our study, while departing from traditional approaches of examining demand profiles using "clustering" techniques applied to high-resolution smart meter electricity data (see, e.g., [31]), complements this relevant literature by taking advantage of the spatial correlation in systematic demand profile archetypes identified by such studies. In the context of GB, Pullinger and colleagues [7] uncovered significant heterogeneity within average electricity demand profiles characterised, for example, by households using electricity at all times of the day, mid-morning and evening, or mainly evenings. The authors established in GB that these profiles, though distinct, are influenced over longer horizons by weekly societal "rhythms" of work and school, exposure to seasonal variation, national holidays (e.g., Christmas), and shocks (e.g., COVID-19). Naturally, studies relying on high-frequency demand data are unable to investigate how such profiles and patterns determine investment behaviour, as they rely on static surveys of technology adoption. Therefore we make an important contribution to this related literature by investigating how correlation in demand not only matters across time *but also* space. This fundamental shift in perspective is what allows us to establish how correlation in demand and its uncertainty is associated with solar PV investment.

The "rooftop revolution" is a mainstay in the current UK Government's energy policy landscape, joining the global *photovoltaic revolution* [32]. However, given a tight fiscal outlook and stubbornly high energy prices, it is necessary for energy interventions to be targeted towards households who are in the most need of support - especially in light of evidence of the central role of subsidies in driving the energy transition to date [33]. This year saw a shift in the UK Government's focus under the "Warm Homes Plan" [34],

which earmarks £15 billion for public investment in homes that are yet to benefit from the energy transition in an effort to meet Net Zero targets while cutting energy bills and improving living conditions. Through a combination of measures focusing primarily on deploying low-carbon technologies, including subsidies for those on low-incomes, low-interest loans for homeowners, and regulating standards in the social and privately rented sectors, the WHP harnesses ambitions to deploy solar on as many rooftops as possible – a tripling (roughly 46GW) by 2030. However, delivering solar at scale hinges on effectively targeting homes through area-based coordination and planning.

Our findings suggest two ways forward. The first is to target vulnerable households living in regions likely to exhibit low investment, that is, regions characterised by low demand correlation, particularly if demand is less uncertain, including areas in England (e.g., Norfolk, West Devon), Scotland (e.g., Dumfries and Galloway, Highlands) and mid-Wales. And the second is to target vulnerable households who live in areas conducive to high investment where the region is characterised by strong demand correlation, and higher levels of demand uncertainty, particularly if the latter makes the risks too large for lower income households who are unable to afford the cost of capital e.g. North East England and South Wales. These patterns can be observed in the spatial distribution of total domestic PV capacity installed in local authorities and their mean demand correlation between 2015 and 2020 - see Appendix (Figure A4). Targeted support in areas with rapid investment and high demand correlation is crucial not only because of the growing evidence that inequalities in low-carbon technology still remain high despite falling for specific socioeconomic groups [35], but also to ensure that installations are not delayed due to constraints in local networks and upgrades to the network are not unfairly borne by households yet to adopt low-carbon technology. Whilst our findings provide useful policy insights about investment in rooftop solar by households, they also point towards potential opportunities for investigating and targeting other domestic (e.g., schools) and non-domestic buildings, such as hospitals and car parks, and serve as future avenues of research.

One limitation of our study is the use of a parsimonious theoretical model; however, this is to clearly demonstrate the relationship between demand correlation and investment through a simple yet robust mathematical framework that generates testable predictions rather than developing a full-fledged model with too many "moving parts" that aims to perfectly fit reality. Nevertheless, we believe the intuition and results would continue to hold in a more general model. Another potential limitation is that our empirical findings do not aim to address the potential endogeneity biases or establish any causal interpretation on the association between solar PV investment and demand correlation, but instead provide strong empirical evidence consistent with the mechanisms proposed by our theoretical predictions. Although causality with full certainty is a challenge when using observational data, future research with access to longitudinal data on both the intertemporal demand *and* investment patterns of households will allow researchers to account for additional sources of unobserved heterogeneity and, thus, facilitate a potentially more causal interpretation of the findings.

References

[1] IEA (2025a). *Electricity 2025*. Paris, France: IEA.

[2] Burlinson, A., Giulietti, M., Waterson, M., Ajayi, V. (2025). The impact of the energy price crisis on GB consumers: a difference-indifferences experiment. *CAGE working paper no. 727.*

[3] Department for Energy Security and Net Zero (2025). *Energy trends UK January to March 2025*. London, UK: HM Government.

[4] Department for Energy Security and Net Zero (2024a). Solar photovoltaic (PV) cost data. [online] Available at: Postcode level domestic gas and electricity consumption: about the data - GOV.UK.

[5] HM Government (2025). New Homes (Solar Generation) Bill 2024-25. House of Commons Library.

[6] MCS (2025). Record number of renewables being installed in UK homes.

[7] Pullinger, M., Zapata-Webborn, E., Kilgour, J., Elam, S., Few, J., Goddard, N., Hanmer, C. et al. (2024). Capturing variation in daily energy demand profiles over time with cluster analysis in British homes (September 2019 – August 2022). *Applied Energy*, 360, 122683.

[8] Oestreicher-Singer, G., Sundararajan, A. (2012). The visible hand? Demand effects of recommendation networks in electronic markets. *Management Science*, 58(11), 1963-1981.

[9] Bollinger, B., Gillingham, K. (2012). Peer effects in the diffusion of solar photovoltaic panels. *Marketing Science*, 31(6), 900-912.

[10] Rai, V., Robinson, S.A. (2013) *Environmental Research Letters*, 8014044.

[11] Steadman, S., Bennato, A.R., Giulietti, M. (2023). From energy consumers to prosumers: the role of peer effects in the diffusion of residential microgeneration technology. *Journal of Industrial and Business Economics*, 50, 321–346.

[12] Song, F., Miao, X., Xia, F. (2025). Fighting climate change together: The regional heterogeneous impacts of climate change and potentials of regional power markets. *Energy Economics*, 141, 108115.

[13] Lam, W. (2015). Competition in the Market for Flexible Resources: An Application to Cloud Computing, LCII Policy Brief.

[14] Biglaiser, G., Cremer, J., Mantovani, A. (2024). The Economics of the Cloud. *TSE Working Paper*.

[15] Wang, J., Zheng, Y. (2024). Data-driven seasonal scenario generation-based static operation of hybrid energy systems. *Energy*, 309(15), 133030.

[16] Zöttl, G. (2010). A Framework of Peak Load Pricing with Strategic Firms. *Operations Research*, 58(6), 1637-1649.

[17] Office of Gas and Electricity Markets (2021). Feed-in-tariff installation report: 31 December 2020. [online] Available at: Feed-in Tariff Installation Report 31 December 2020 — Ofgem.

[18] Department for Business, Energy, and Industrial Strategy (BEIS) (2022). *Review of solar PV capacity publications.* London, UK: HM Government.

[19] Department for Energy Security and Net Zero (2024b). Sub national electricity consumption data. [data] Available at: https://www.gov.uk/government/collections/sub-national-electricity-consumption-data

[20] Office for National Statistics (2022). ONS Postcode Directory. [online] Available at: Open Geography Portal.

[21] Moran, P. (1950). A Test for the Serial Independence of Residuals. *Biometrika*, 37, 178-181.

[22] Kondo, K. (2015). Spatial persistence of Japanese unemployment rates. *Japan and the World Economy*, 36, 113-122.

[23] Department for Energy Security and Net Zero (2023a). Solar photovoltaic (PV) cost data. [online] Available at: Solar photovoltaic (PV) cost data - GOV.UK.

[24] Office of Gas and Electricity Markets (2018). *Decision: Default tariff cap – Overview document.* London, UK: Ofgem.

[25] Department for Energy Security and Net Zero (2023b). Average variable unit costs and fixed costs for electricity for regions in the United Kingdom. [online] Available at: Annual domestic energy bills - GOV.UK.

[26] Met Office (2023). Climate and climate change: UK and regional series. [online] Available at: UK and regional series - Met Office.

[27] Balta-Ozkan, N., Yildirim, J., Connor, P.M. (2015). Regional distribution of photovoltaic deployment in the UK and its determinants: A spatial econometric approach. *Energy Economics*, 51, 417-429.

[28] Office of Gas and Electricity Markets (2025). *Feed-in Tariff: RPI Adjusted Tariffs.* London, UK: Ofgem.

[29] Office of Gas and Electricity Markets (2021b). *Smart Export Guarantee (SEG) Annual Report.* London, UK: Ofgem.

[30] IEA (2025b). *World Energy Investment 2025, 10th Edition.* Paris, France: IEA.

[31] Yilmaz, S., Chambers, J., Patel, M.K. (2019). Comparison of clustering approaches for domestic electricity load profile characterisation - Implications for demand side management. *Energy*, 180: 665-677.

[32] Haas, R., Duic, N., Auer, H., Ajanovic, A., Ramsebner, J., Knapek, J., Zwickl-Bernhard, S. (2023). The photovoltaic revolution is on: How it will change the electricity system in a lasting way. *Energy*, 265, 126351.

[33] Zhang, Y., Zahoor, Z. (2025). The role of energy subsidies, savings, and transitions in driving energy transformations toward net-zero emissions. *Energy*, 320, 135209.

[34] HM Government *Warm Homes Plan.* London, UK: HM Government.

[35] Burlinson, A., Davillas, A., Giulietti, M. (2025). Socioeconomic inequality in low-carbon technology adoption. *Energy Economics*, 143, 108244.

Appendix

Tables

Table A1. Pooled ordinary least squares (OLS) and Poisson regressions of installed PV capacity on Moran's *I*.

Specifications	(1)	(2)	(3)
Dependent variable	Capacity Inverse Hyperbolic Sine	Capacity Log(Capacity+1)	Capacity Poisson
MORANI	0.918***	0.816***	0.640***
	(0.206)	(0.181)	(0.165)
Observations = 15,371			

*Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the outcode level in parentheses. All regressions include LA-effects and LA-specific trends. Specifications: (1) tests the robustness of the hypothesis that capacity and demand correlation is positively correlated while using the inverse hyperbolic sine transformation of capacity in the baseline specification that includes LA specific trends; (2) is the same as (1) but uses a log transformation of capacity+1; (3) is the same as (1) with capacity in levels while using Poisson regression. Capacity is winsorised at the 99th percentile. The coefficient estimates can be interpreted as semi-elasticities.*

Table A2. Tobit and Tobit Random Effects regressions of installed domestic PV capacity (C) on demand correlation (*Moran's I*) in GB outward codes

Specifications	(1)	(2)
Dependent variable	Capacity (Tobit)	Capacity (Tobit Random Effects)
MORANI	50.40***	51.68***
	(10.932)	(9.087)
Observations = 15,371		

*Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the outcode level in parentheses. All regressions include LA-effects and LA-specific trends. Specifications: (1) and (2) include LA-specific trends, and both use winsorised capacity (99th percentile) and Moran's I (1st and 99th percentile).*

Table A3. Fixed effects (FE) regressions of installed domestic PV capacity (*C*) on demand correlation (*Moran's I*) in GB outward codes when (1) estimates of Moran's I set to zero if non-statistically significant at 10% level, and (2) augments (1) by winsorisation.

Specifications	(1)	(2)
Dependent variable	Capacity (MI-Zero)	Capacity (MI-Zero-99)
	Fixed effects	
MORANI	92.69***	109.6***
	(19.540)	(21.684)
Observations = 15,371		

*Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the outcode level in parentheses. All regressions include LA-effects and LA-specific trends. Specifications: (1) considers all statistically insignificant (p>0.1) estimates of Moran I as zero; and winsorised Moran's I (1st and 99th percentile); (2) adjusts (1) by winsorising the adjusted Moran I used in (1).*

Table A4. Fixed effects (FE) regressions of installed domestic PV capacity (*C*) on demand correlation (*Moran's I*) in GB outward codes when (1) controlling for local authority (LA) and time effects and (2) the log of Feed-in-Tariffs (FiT), and or (3) the log of the difference in standard variable tariffs and FiTs.

Specifications	(1)	(2)	(3)
Dependent variable	Capacity	Capacity	Capacity
	Fixed effects		
MORANI	59.48**	59.48**	54.50*
	(30.157)	(30.157)	(28.460)
LNELECTDSD	40.43*	40.43*	49.61**
	(21.867)	(21.867)	(20.816)
LNELECPRICE	180.9***	180.9***	489.6***
	(52.741)	(52.741)	(50.185)
LNCOSTKW	-88.61***	-88.61***	-89.33***
	(7.745)	(7.745)	(7.759)
LNFIT		188.1***	
		(9.737)	
LNSVTFIT			-92.04***
			(12.661)
Observations = 15,371			

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors clustered at the outcode level in parentheses. Specifications: (1) includes regional (LA) effects and time (year) effects; (2) adjusts (1) by controlling for the log of the Feed-in-Tariff (FiT); and (3) adjusts (1) by controlling for the difference between the log of the difference between the standard variable tariff and the FiT.

Figures

Figure A1. Total capacity (kW) installed by local authority between 2015-2017 and 2018-2020
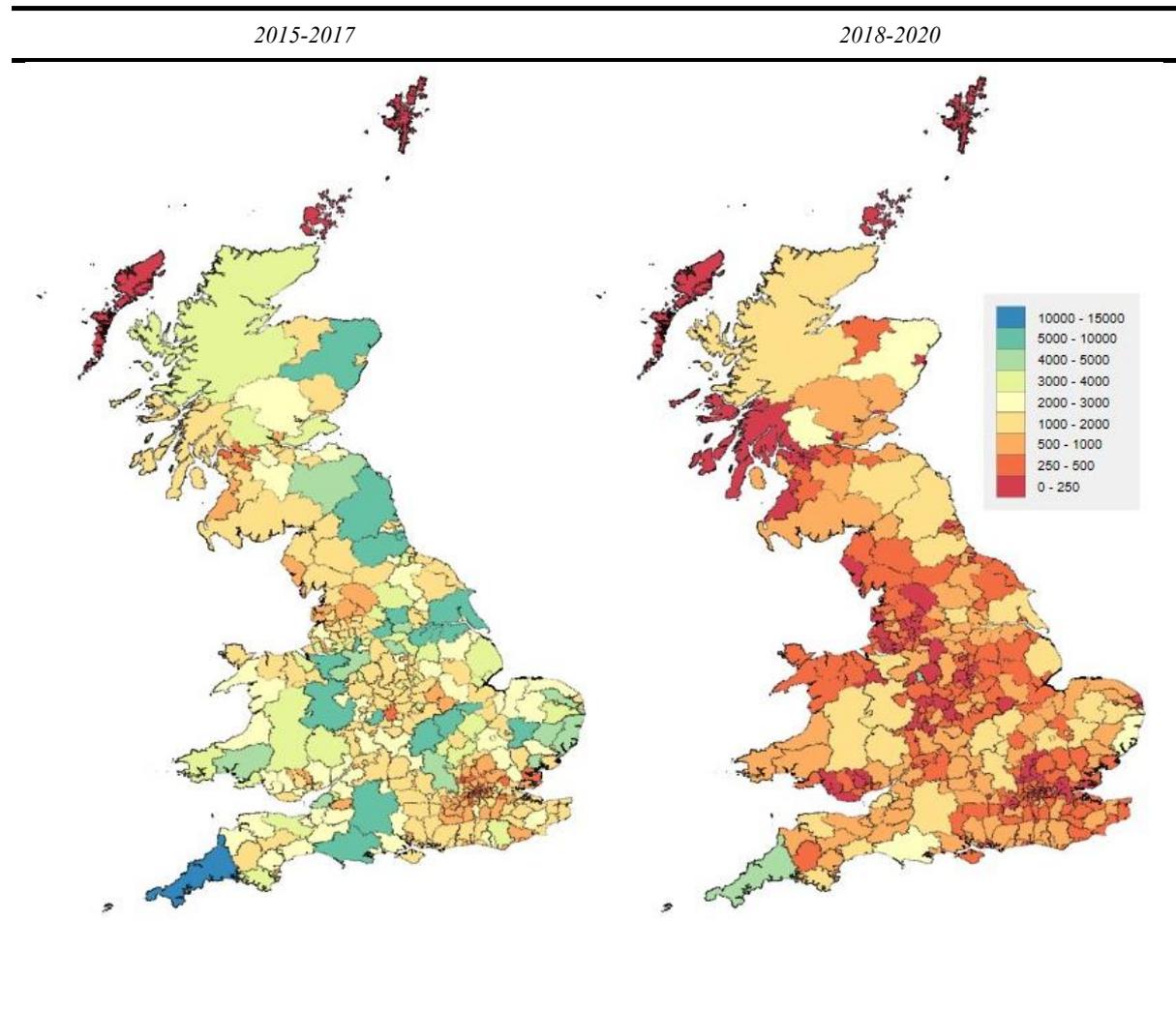
2015-2017	*2018-2020*

10000 - 15000
5000 - 10000
4000 - 5000
3000 - 4000
2000 - 3000
1000 - 2000
500 - 1000
250 - 500
0 - 250

Figure A2. Mean Moran's I [-1, 1] by local authority between 2015-2017 and 2018-2020
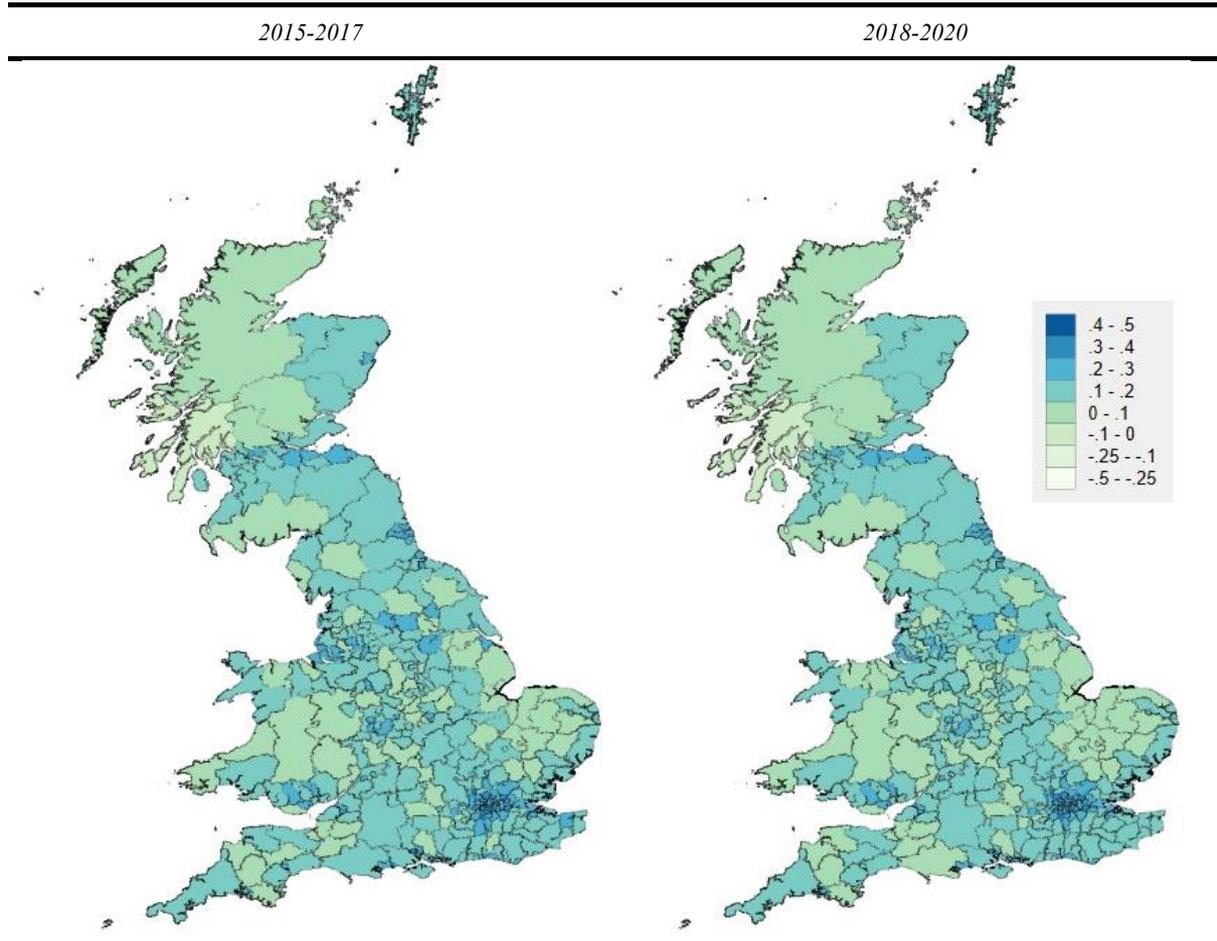
2015-2017	*2018-2020*

Figure A3. Mean of standard deviation of electricity consumption (GWh)
by local authority between 2015-2017 and 2018-2020

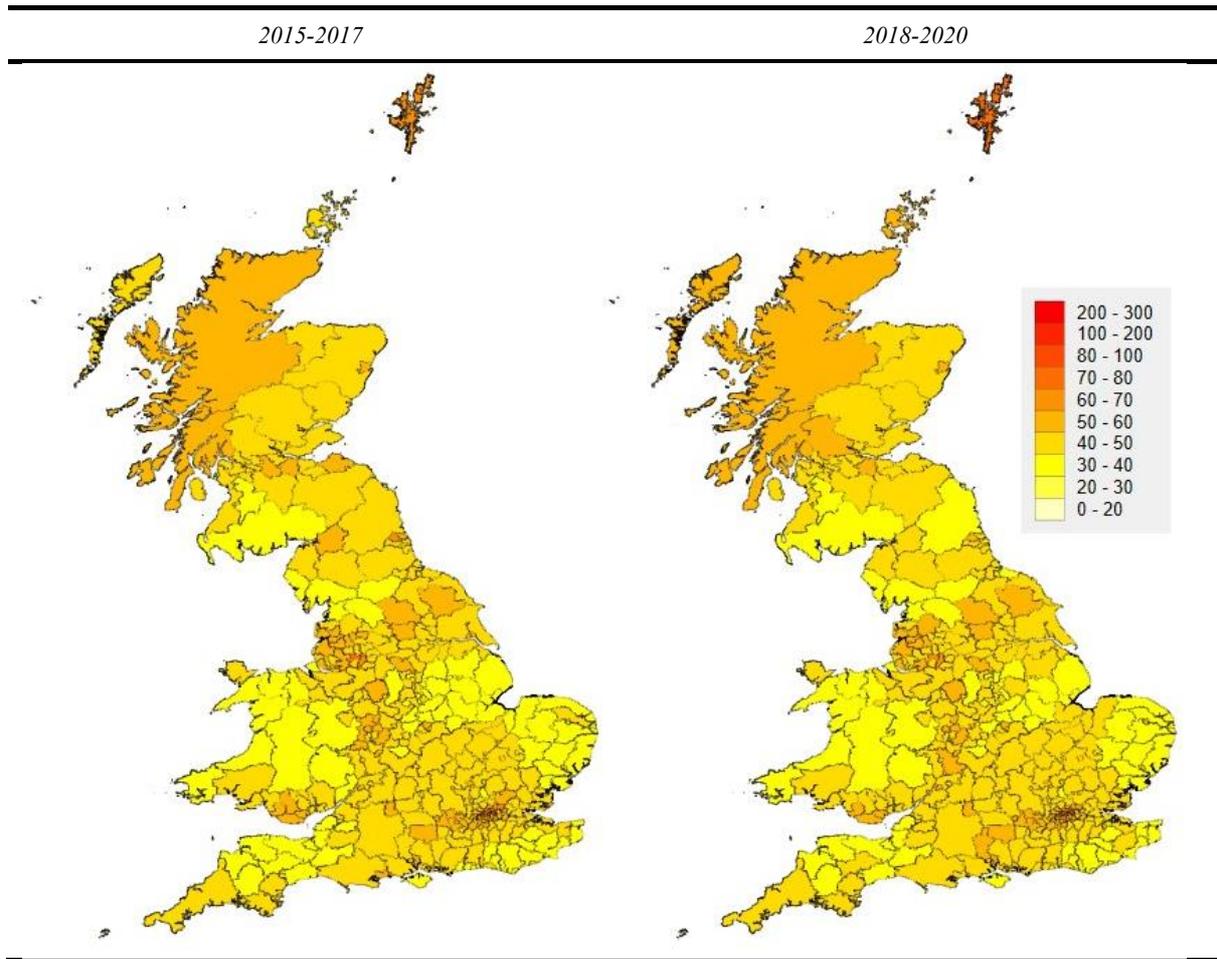| *2015-2017*	*2018-2020*