# Local conditions for the decentralisation of energy systems

# Online Appendices

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# Appendix A

## A. Dataset and statistical properties

Our dataset contains information on 146 LES projects in the UK, started between 2010 to 2020, out of which we have identified the geographical location for 139 projects within Great Britain (GB). Figure 1 indicates the spatial distribution of LES projects across local authorities (380 in total) in GB. Figure A1 indicates that most of LAs (80%) have no LES, or in other words, about 1 in 5 LAs has at least one LES project. Figure A2 visualise depicts the number of LES projects changes significantly over time. Table A1 the annual and cumulative number of LES projects from 2010 to 2020. Overall, we can observe that the number of LES has been increasing steadily over time.

**Figure A1. Histogram of LES projects across local authorities in Great Britain.**

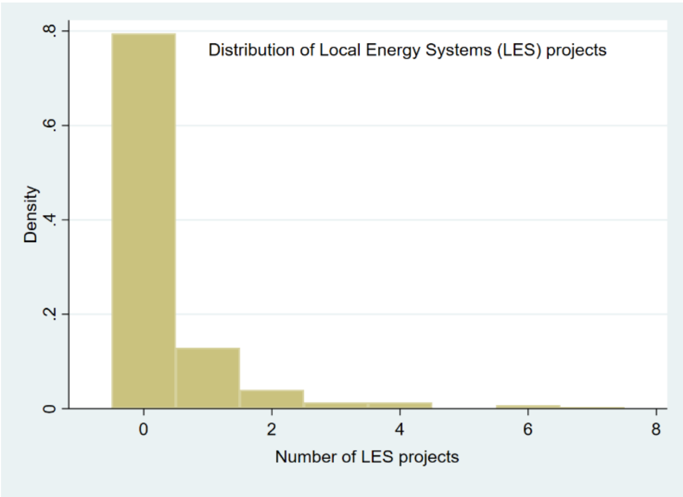



**Figure A2. Cumulative number of LES projects deployed from 2010 to 2020 local authorities in Great Britain.**

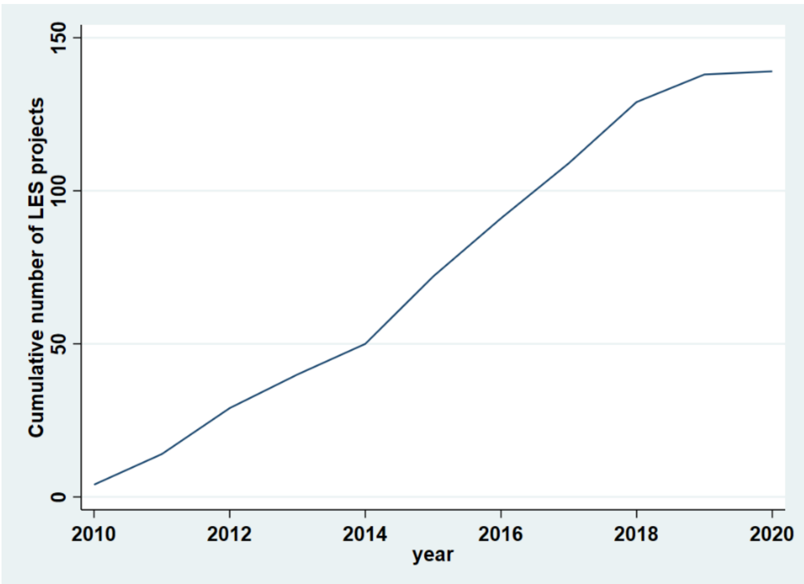


**Table A1. Cumulative and annual number of LES projects deployed from 2010 to 2020 local authorities in Great Britain.**

| Year | LES count cumulative | LES count annual |
|---|---|---|
| 2010 | 4 | 4 |
| 2011 | 14 | 10 |
| 2012 | 29 | 15 |
| 2013 | 40 | 11 |
| 2014 | 50 | 10 |
| 2015 | 72 | 22 |
| 2016 | 91 | 19 |
| 2017 | 109 | 18 |
| 2018 | 129 | 20 |
| 2019 | 138 | 9 |
| 2020 | 139 | 1 |

We have identified various data sources and compiled a large dataset that accounts for factors involving energy networks and systems, socioeconomics and housing stock, social capital, local government, local economy, and natural resources that may be responsible for the spatial diffusion of LES in the UK. Using this information, we have developed a methodological approach so that we test the validity of our empirical hypothesis outlined in Table 2. The goal is to control for all possible effects and identify the factors mainly responsible for the diffusion of LES. Restrictions in the availability/existence of specific data sources has constrained us from compiling quantifiable metrics for factors related the capacity of local government in capturing competitive of discretionary national funding, in-house expertise within local government and leadership with CE projects. We report in the Table A2 to Table A7 below all those factor that we have accounted for in our study along with all relevant information about the type of metrics used, temporal and spatial coverage and individual characteristics.

**Table A2. Data/variables tested on energy systems and associated hypotheses (Hyp. - column 1) reported in Table 1.**

| Hyp. | Energy variables | Metric type / number | Temporal coverage | Spatial coverage | Main metrics – *data source* |
|---|---|---|---|---|---|
| E1 | Electricity T&D network | Dummy / [2] | 2017 | LSOA / GB | [1] Presence of overhead transmission lines; [2] Presence of any electricity transmission infrastructure – *National grid, Ordnance survey* |
| E2 | Electricity substation capacity | Dummy, count / [3] | 2018 | LSOA / GB | [1-3] Number/dummy of substations with capacity available rated red (low), amber (medium), green (high) – *ADVENT* |
| E3 | Renewable power generation (utility) | Count, continuous / [2] | 2011-2020 | LSOA / GB | [1] Number of utility-scale renewable power projects; [2] Installed capacity of utility-scale renewable power projects – *BEIS Renewable Energy Planning Database (REPD)* |
| E3 | Renewable power generation (residential) | Count, continuous / [2] | 2011-2020 | LSOA / GB | [1] Number of domestic renewable power projects (with FiTs); [2] Installed capacity of domestic renewable power projects (with FiTs) – *OFGEM FiT installation report* |
| E1 | Major power generation | Count, continuous / [2] | 2013-2020 | LSOA / GB | [1] Number of major power projects; [2] Installed capacity of major power projects – *ADVENT* |
| E9 | Industrial CHP | Count, continuous / [2] | 2010-2018 | LSOA / GB | [1] Number of industrial CHP sites; [2] Installed capacity of industrial CHP sites – *BEIS CHP* Scheme database |
| E6 | Electricity demand | Count, continuous / [2] | 2010-2018 | LSOA / GB | [1] Total domestic electricity consumption (MW); [2] Total number of domestic electricity meters – *BEIS* |
| E7 | Power outages | Continuous / [2] | 2011-2019 | LA / GB[1] | [1] Number of customer interruptions; [2] Number of minutes per interruption – *OFGEM RIIO reports* |
| E9 | Capacity of industrial demand response | Count, continuous / [2] | 2013-2020 | LSOA / GB | [1] Count of DSR industrial CMU; [2] Installed capacity (MW) of DSR industrial CMU – *OFGEM CM Demand Side Response registry* |
| E5 | Gas T&D network | Dummy / [2] | 2019 | LSOA / GB | [1] Presence of gas pipeline infrastructure; [2] Presence of gas sites – *National grid* |
| E5 | Gas grid connections | Dummy, count / [2] | 2010-2018 | LSOA / GB | [1] Number of dwellings not connected to gas network; [2] Number of gas meters – *BEIS* |
| E5 | Gas demand volatility | Continuous, count / [2] | 2015-2020 | LSOA / GB | [1] Volatility of daily energy gas consumption (MW); [2] Number of LDZ gas offtake points – *National grid* |
| E5 | Gas demand | Continuous / [3] | 2010-2018 | LSOA / GB | [1] Total domestic gas consumption (MW); [2] Mean domestic gas consumption (MW) per meter; [3] Media domestic gas consumption (MW) per meter – *BEIS* |
| E8 | Heat pumps & other renewable heat | Count / [4] | 2015-2020 | LA / GB | [1-4] Number of heating installations with RHI incentive (air source heat pumps, ground source heat pumps, biomass, solar thermal) – *BEIS* |
| E11 | Electric vehicles | Count / [1] | 2011-2020 | LSOA / GB | [1] Number of electric vehicles – *DfT - Data on licensed EV* |
| E4 | Electric vehicle charging points | Count / [1] | 2012-2020 | LSOA / GB | [1] Number of electric vehicles charging points – *National Charge points Registry* |
| E10 | Smart meters | Count / [1] | 2012-2019 | LA / GB[1] | [1] Number of smart meters installed |

[1] Data available only at spatial resolution of DNO service territories and thus we used population index to disaggregate down information to local authorities. LSOA stands for Lower Spatial Output Area, LA stands for Local Authority and GB for Great Britain.

**Table A3. Data/variables tested on socioeconomic and housing stock, and associated hypotheses (Hyp. - column 1) reported in Table 1.**

| Hyp. | Socioeconomic and housing variables | Metric type/number | Temporal coverage | Spatial coverage | Main metrics – *data source* |
|---|---|---|---|---|---|
| S2 | Household income | Continuous / [1] | 2010-2016 | LA | [1] UK gross disposable household income; [2] UK gross disposable household income per head |
| S3 | Deprivation | Percentage / [1] | 2015 | LSOA[1] | [1] Lowest decile of LSOAs on multiple deprivation indices |
| S3 | Fuel poverty | percentage / [1] | 2012-2018[2] | LSOA or LA depending on country[2] | [1] Percentage of households in fuel poverty |
| S1 | Population density | percentage, continuous / [2] | 2011 | LSOA / LA[3] | [1] Number of people; [2] Number of households; [3] Persons per hectare |
| S1 | Urban-rural | percentage / [1] | 2011[4] | LSOA | [1] Percentage of population living in urban/rural areas |
| S5 | New building stock | percentage / [1] | 2015 | LA | [1] Percentage of dwellings built after 1983 |
| S5 | Energy efficiency rating | percentage / [1] | 2011-2018 | LA | [1] Percentage of dwellings with EPC= A, B, C |
| S4 | Efficiency improvements in fuel poor households | percentage, count / [9] | 2015-2019 | LA[5] | [1-5] ECO measures (including Carbon Saving Target, Carbon Savings Community, Affordable Warmth); [6-9] Flex ECO affordable warmth measures installed |
| S6 | Home energy audits | percentage, count / [4] | 2015-2019 | LA[5] | [1-4] GD measures (including Green Deal plans, assessments, assessors, providers, installers); |

[1] Deprivation indices constructed slightly differently for England for 2015, Wales for 2014 and Scotland for 2016. [2] Data available for England at the LSOA level from 2012 to 2018, for Wales at the LA level only for 2018 and for Scotland at the LA level from 2012 to 2018. Differences in the construction of the index between Scotland and England/Wales raise some concerns about the robustness of the constructed variable. [3] Persons per hectare [3] available only at the LA level. [4] England and Wales report cumulative for 2015 while Scotland reports annual data for years 2010 to 2019. [5] Cumulative data reported at different dates between 2015 and 2019 for each of the five metrics used to control for home energy audits.

**Table A4. Data/variables tested on local government and associated hypotheses (Hyp. - column 1) reported in Table 1.**

| Hyp. | Local government variables | Metric type / number | Temporal coverage | Spatial coverage | Main metrics – *data source* |
|---|---|---|---|---|---|
| L2 | Energy poverty funding | Continuous / [1] | 2012 | LA / England | [1] DECC funding for energy poverty |
| L1 | Sustainable energy action plans | Count / [3] | 2011-2020 | LA / GB | [1] Clean energy by 2050 pledge (UK100); [2] LEUKES data on energy plans; [3] Sustainable Energy (and Climate) Action Plans |
| L1 | Climate action plans | Count / [1] | 2020 | LA / GB | [1] Climate emergency pledge - Tingey & Webb 2020 Energy Policy |
| L2 | Financing & borrowing | Continuous / [6] | 2013-2018 | LA / GB | [1] Short-term borrowing; [2] Long-term borrowing for capital spending; [3] Borrowing for capital projects; [4] Borrowing for investment purposes; [5] Total service expenditure minus total income for services; [6] Total expenditure minus income |
| L2 | Municipality as an energy actor | Continuous, dummy / [2] | 2012 | LA / England | [1] Green Deal pioneer places funding; [2] Cheaper energy together (tariff switching) funding |

**Table A5. Data/variables tested on social capital and associated hypotheses (Hyp. - column 1) reported in Table 1.**

| Hyp. | Social capital variables | Metric type/number | Temporal coverage | Spatial coverage | Main metrics – *data source* |
|---|---|---|---|---|---|
| I1 | Social capital | Continuous, percentage / [17] | Years vary by indicator | LA / GB | [1] Number of close friends; [2] Borrow things from neighbours; [3] Talk regularly to neighbours; [4] Volunteering in last 12 months etc. – Data derived from the UK Understanding Society (2019) dataset. |
| I1 | Thriving places (local wellbeing) | Continuous / [3] | 2018-2020 | LA / GB | [1] Index on local conditions; [2] Index on equality; [3] Index on sustainability |
| I2 | Voter turnout - general election | Continuous / [2] | 2017 | LA / GB[1] | [1] Voter turnout; [2] Votes per party |
| I2 | Voter turnout - local election | Continuous / [1] | 2016-2018[2] | LA / GB | [1] Voter turnout |
| I2 | Political preference - general election | Dummy / [1] | 2017 | LA / GB[1] | [1] Winning party (first-past the post) |
| I2 | Political composition | Dummy, percentage / [2] | 2011-2019 | LA / GB | [1] Labour/Conservative control; [2] Share of Labour/Conservative councillors |
| I2 | Political stability | Dummy / [1] | 2011-2019 | LA / GB | [1] Same party in control |
| I3 | Property market prices | Continuous / [2] | 2010-2017 | LA / GB | [1] Average house prices (by type); [2] House price index (by type) |
| I3 | Property market activity | Continuous / [2] | 2010-2017 | LSOA / GB[3] | [1] Residential property sales volume; [2] Average price of dwellings sold |

[1] Reported at parliamentary constituency level – we used ONS tables to match those to the corresponding local authorities. [2] Year varies by nation – mainly reported for 2017. [3] Data available for Scotland from 2014 to 2018.

**Table A6. Data/variables tested on local economy and associated hypotheses (Hyp. - column 1) reported in Table 1.**

| Hyp. | Local economy variables | Metric type/number | Temporal coverage | Spatial coverage | Main metrics – *data source* |
|---|---|---|---|---|---|
| V1 | Economic activity | Continuous / [4] | 2010-2018 | LA / GB | [1-4] GDP or GVA variants |
| V1 | Economic activity by subsector | Continuous / [6] | 2010-2018 | LA / GB | [1-6] GVA in subsectors (including science, manufacturing, ICTs, engineering) |
| V2 | Number of firms by subsector | Continuous / [6] | 2014-2019 | LA / GB | [1-3] Number of enterprises in subsectors (production, ICTs, technology); [4-6] Number of business units in subsectors |
| V2 | Number of employees by subsector | Continuous / [6] | 2016-2019 | LA / GB | [1-3] Employment from VAT turnover in subsectors (production, ICTs, technology); [4-6] PAYE jobs in subsectors |
| V3 | Consumer lifestyle segmentation | Percentage / [8] | 2011 | LA | [1-8] Percentage of a LSOA lifestyle segment within an LA (e.g., industrious communities, multicultural living, University towns) |

**Table A7. Data/variables tested on natural resources/geographic variables and associated hypotheses (Hyp. - column 1) reported in Table 1.**

| Hyp. | Natural resources variables | Metric type/number | Temporal coverage | Spatial coverage | Main metrics – *data source* |
|---|---|---|---|---|---|
| G1 | Heating degree days | Continuous / [1] | Fixed[1] | GB / LSOA | [1] Long-term annual average of monthly Heating Degree Days (HHDs) |
| G1 | Temperature | Continuous / [1] | Fixed[2] | GB / LSOA | [1] Long term annual average temperature |
| G2 | Solar resource potential | Continuous / [2] | Fixed[3] | GB / LSOA | [1] Long term annual average of monthly solar irradiation; [2] Long term annual average of PV power output potential |
| G2 | Wind resource potential | Continuous / [1] | Fixed[4] | GB / LSOA | [1] Average wind speed |
| G2 | Geothermal resource potential | Count / [1] | Fixed | GB / LSOA | [1] Number of geothermal sites |
| G2 | Biomass resource potential | Continuous / [1] | Fixed[5] | GB / LSOA | [1] Miscanthus yield per hectare |

[1] Average annual HDD 1981-2010 assumed constant for 2010-2020. [2] Average annual temperature 1994-2018 assumed constant for 2010-2020. [3] Average annual solar irradiation and PV output 1994-2018 assumed constant for 2010-2020. [4] Average wind speed 2016-2018 assumed constant for 2010-2020. [5] Years of yield estimates unspecified.

**Figure A3. Temporal and spatial coverage of all metrics compiled.**

| | | *spatial and temporal coverage* | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **coverage** | **2010** | **2011** | **2012** | **2013** | **2014** | **2015** | **2016** | **2017** | **2018** | **2019** | **2020** |
| **OUTCOME VARIABLES** | | | | | | | | | | | | |
| Local energy system projects (UKERC+, n=147) | GB | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA |
| Community energy projects (n=400) | GB | | | | | | | | | | | |
| | | | | | | | | | | | | |
| **ENERGY VARIABLES** | | | | | | | | | | | | |
| Electricity T&D network | GB | | | | | | | | LSOA | | | |
| Electricity substation capacity | GB | | | | | | | | | LSOA | | |
| Renewable power generation (utility) | GB | | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA |
| Renewable power generation (residential) | GB | | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA |
| Major power generation | GB | | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | | | |
| Industrial CHP | GB | | | | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA |
| Electricity demand | GB | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | | |
| Power outages | GB | | LA | LA | LA | LA | LA | LA | LA | LA | LA | |
| Capacity of industrial demand response | GB | | | | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA |
| Gas T&D network | GB | | | | | | | | | | LSOA | |
| Gas grid connections | GB | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | | |
| Gas demand volatility | GB | | | | | | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA |
| Gas demand | GB | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | | |
| Heat pumps & other renewable heat | GB | | | | | LA | LA | LA | LA | LA | LA | LA |
| Electric vehicles | GB | | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA |
| Electric vehicle charging points | GB | | | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA |
| Smart meters | GB | | | LA | LA | LA | LA | LA | LA | LA | LA | |
| | | | | | | | | | | | | |
| **LOCAL GOVERNMENT VARIABLES** | | | | | | | | | | | | |
| Energy poverty funding | *En* | | | LA | | | | | | | | |
| Sustainable energy action plans | GB | | LA | LA | LA | LA | LA | LA | LA | LA | LA | LA |
| Climate action plans | GB | | | | | | | | | | | LA |
| Local authorities - political composition | GB | | LA | LA | LA | LA | LA | LA | LA | LA | LA | |
| Local authorities - political stability | GB | | LA | LA | LA | LA | LA | LA | LA | LA | LA | |
| Local authorities - financing & borrowing | GB | | | | LA | LA | LA | LA | LA | LA | | |
| Municipality as an energy actor | *En* | | | LA | | | | | | | | |
| | | | | | | | | | | | | |
| **LOCAL ECONOMY VARIABLES** | | | | | | | | | | | | |
| Economic activity | GB | LA | LA | LA | LA | LA | LA | LA | LA | LA | | |
| Economic activity by subsector | GB | LA | LA | LA | LA | LA | LA | LA | LA | LA | | |
| Number of firms by subsector | GB | | | | | LA | LA | LA | LA | LA | LA | |
| Number of employees by subsector | GB | | | | | | | LA | LA | LA | LA | |
| | | | | | | | | | | | | |
| **LOCAL SOCIETY VARIABLES** | | | | | | | | | | | | |
| Social capital | GB | | | LA | | LA | | | LA | | | |
| Thriving places (local wellbeing) | *En+Wa* | | | | | | | | | LA | LA | LA |
| Voter turnout - general election | GB | | | | | | | | LA | | | |
| Voter turnout - local election | GB | | | | | | | | | LA | | |
| Political preference - general election | GB | | | | | | | | LA | | | |
| Property market prices | GB | LA | LA | LA | LA | LA | LA | LA | LA | LA | LA | |
| Property market activity | GB | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | LSOA | |
| | | | | | | | | | | | | |
| **SOCIOECONOMIC VARIABLES** | | | | | | | | | | | | |
| Household income | GB | LA | LA | LA | LA | LA | LA | LA | | | | |
| Deprivation | *En+Wa+Sc* | | | | | | LSOA | | | | | |
| Fuel poverty | *En+Wa+Sc* | | | LA | LA | LA | LA | LA | LA | LA | | |
| Population density | GB | | LSOA | | | | | | | | | |
| Urban-rural | GB | | LSOA | | | | | | | | | |
| Housing stock - age | GB | | | | | | LA | | | | | |
| Housing stock - efficiency | GB | | LA | LA | LA | LA | LA | LA | LA | LA | | |
| Housing stock - efficiency improvements | GB | | | | | | LA | LA | LA | LA | LA | |
| Consumer lifestyle segmentation | GB | | LA | | | | | | | | | |
| | | | | | | | | | | | | |
| **GEOGRAPHIC VARIABLES** | | | | | | | | | | | | |
| Heating degree days | GB | LSOA* (geographic conditions assumed constant over observed time period) | | | | | | | | | | |
| Temperature | GB | LSOA* | | | | | | | | | | |
| Solar resource potential | GB | LSOA* | | | | | | | | | | |
| Wind resource potential | GB | LSOA* | | | | | | | | | | |
| Geothermal resource potential | GB | LSOA* | | | | | | | | | | |
| Biomass resource potential | GB | LSOA* | | | | | | | | | | |

We present below in Table A8 the descriptive statistics for the dependent variables (i.e., LES projects) and the subset of independent variables chosen by our model selection strategy.

**Table A8. Descriptive statistics of dependent variable and independent variables that explain LES diffusion across the UK.**

| Dependent variables | Metric type | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| Local energy systems (LES) projects | Count | 380 | 0.37 | 0.95 | 0 | 7 |
| **Independent variables** | **Metric type** | **Obs** | **Mean** | **Std. Dev.** | **Min** | **Max** |
| Renewable energy (RE) projects - utility | Count | 380 | 6.59 | 10.57 | 0 | 109 |
| Renewable energy (RE) projects - distributed | Count | 380 | 2,282 | 1,814.66 | 21 | 18,429 |
| Congested electricity substation | Count | 380 | 6.84 | 11.68 | 0 | 118 |
| Electric vehicle (EV) charging infrastructure | Count | 380 | 28.26 | 47.58 | 0 | 511 |
| Limited access to gas | % | 380 | 0.16 | 0.13 | 0.03 | 1 |
| Major power producers | Count | 380 | 0.61 | 3.38 | 0 | 59 |
| Energy and climate action plans | Dummy | 380 | 0.09 | 0.29 | 0 | 1 |
| Social capital | % | 380 | 0.16 | 0.05 | 0.06 | 0.36 |
| Tech businesses | Count | 380 | 558 | 645.53 | 5 | 5278 |
| Average household income | £ | 380 | 18,366 | 4708.46 | 11,545 | 54,768 |
| New building stock | % | 380 | 0.23 | 0.09 | 0.00 | 0.52 |
| Efficiency improvements in fuel poor households | % | 380 | 0.09 | 0.06 | 0.00 | 0.39 |
| Home energy audits | % | 380 | 0.03 | 0.01 | 0.00 | 0.09 |
| University towns | % | 380 | 0.03 | 0.07 | 0.00 | 0.51 |

For more information on the metric employed for each variable specified above, please check Table 2.

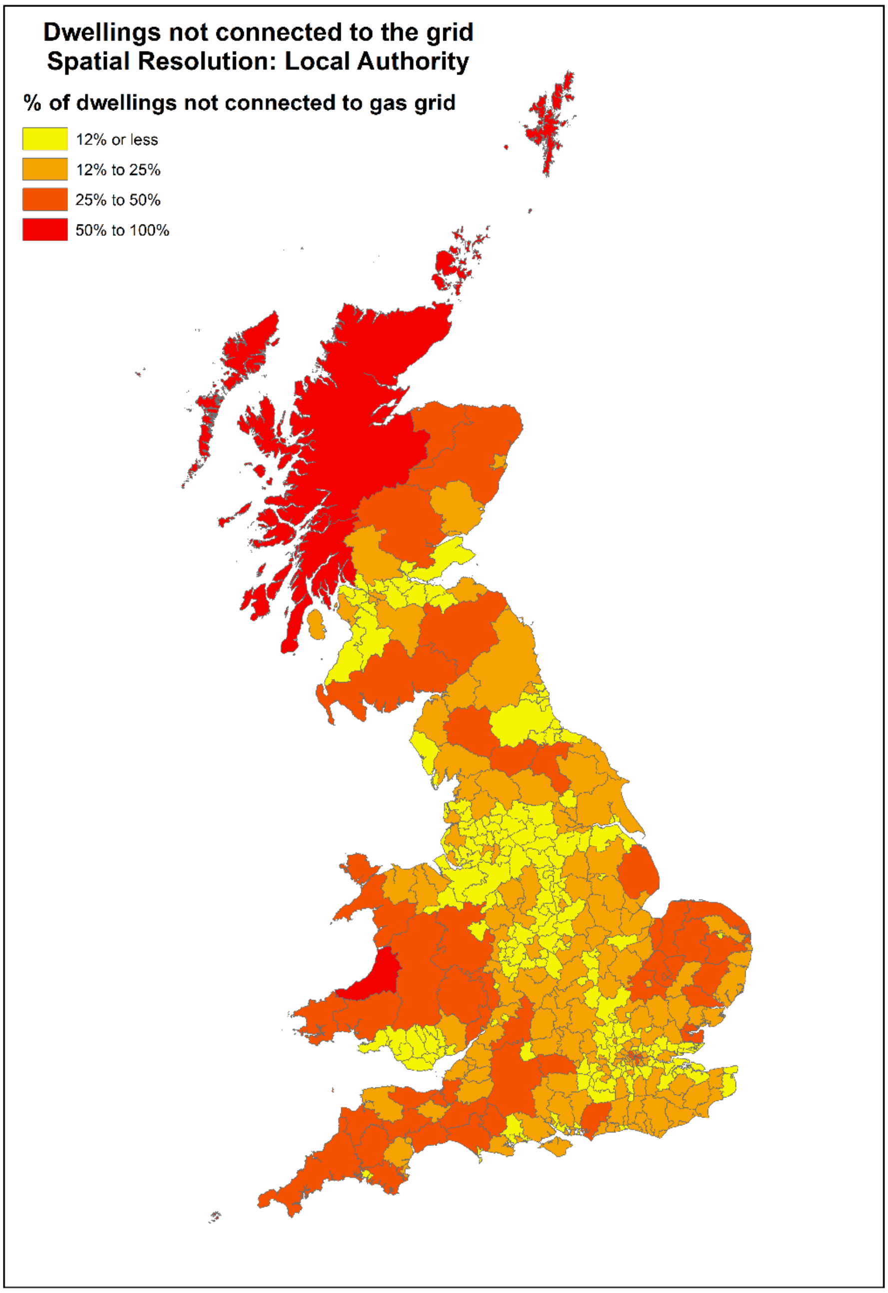
We present in Table A9, the inter-correlation coefficients between all variables specified in Table A8. Each cell of the table reports the corresponding correlation coefficient between two variables. We use bold ink and red paint to highlight those coefficients that indicate correlation equal or higher than 50%. We use yellow paint to highlight those coefficients that indicate correlation equal or higher than 30% and lower than 50%.

**Table A9. Inter-correlation matrix of dependent and independent variables per local authority across Great Britain.**

| Variables | **Local energy systems (LES)** | Renewable energy (RE) projects – utility-scale | Renewable energy (RE) projects - distributed | Electric vehicle (EV) charging infrastructure | Limited access to gas | Major power producers | Energy and climate action plans | Social capital | Tech businesses | Average household income | New building stock | Efficiency improvements in fuel poor households | Home energy audits | University towns | Congested electricity substation |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Local energy systems (LES) projects (count)** | 1.00 | | | | | | | | | | | | | | |
| Renewable energy (RE) projects – utility-scale | 0.18 | 1.00 | | | | | | | | | | | | | |
| Renewable energy (RE) projects - distributed | 0.23 | **0.58** | 1.00 | | | | | | | | | | | | |
| Electric vehicle (EV) charging infrastructure | 0.39 | -0.03 | 0.09 | 1.00 | | | | | | | | | | | |
| Limited access to gas | 0.25 | 0.31 | 0.05 | 0.00 | 1.00 | | | | | | | | | | |
| Major power producers | 0.01 | **0.54** | 0.12 | 0.00 | 0.25 | 1.00 | | | | | | | | | |
| Energy and climate action plans | 0.33 | 0.12 | 0.33 | 0.31 | -0.03 | -0.01 | 1.00 | | | | | | | | |
| Social capital | 0.02 | 0.15 | 0.05 | -0.14 | 0.33 | 0.05 | -0.08 | 1.00 | | | | | | | |
| Tech businesses | 0.24 | -0.12 | -0.03 | **0.68** | -0.02 | -0.06 | 0.12 | -0.05 | 1.00 | | | | | | |
| Average household income | 0.00 | -0.14 | -0.32 | 0.40 | 0.15 | -0.06 | -0.11 | 0.24 | **0.55** | 1.00 | | | | | |
| New building stock | -0.12 | 0.07 | 0.15 | -0.15 | 0.13 | -0.14 | -0.11 | 0.25 | -0.05 | 0.04 | 1.00 | | | | |
| Efficiency improvements in fuel poor households | 0.02 | 0.02 | 0.14 | -0.04 | -0.14 | 0.05 | 0.20 | -0.36 | -0.24 | **-0.52** | -0.39 | 1.00 | | | |
| Home energy audits | 0.15 | 0.16 | 0.14 | -0.14 | 0.08 | 0.15 | 0.09 | -0.10 | -0.34 | -0.43 | -0.33 | **0.58** | 1.00 | | |
| University towns | 0.19 | -0.13 | 0.05 | 0.15 | -0.03 | -0.03 | 0.31 | -0.03 | 0.15 | -0.03 | -0.15 | -0.01 | -0.03 | 1.00 | |
| Congested electricity substation | 0.11 | **0.62** | 0.42 | 0.00 | 0.24 | **0.55** | 0.17 | 0.04 | -0.08 | -0.14 | -0.01 | 0.06 | 0.15 | 0.00 | 1.00 |

The dependent variable (LES projects) is highlighted with bold ink and orange paint. Variables corelated more than 30% are highlighted with yellow paint, while variables correlated more than 50% are highlighted with bold ink and red paint.

**Figure A4. Proportion of dwellings not connected to gas grid per local authority across Great Britain.**



# Appendix B

## B. Supplementary material to baseline econometric analysis

Table B1 presents a set of alternative model specifications to prove the robustness of our proposed methodological approach. To do that, we focus on certain variables that are characterised by increased levels of inter-correlation and test whether the relationship between those variables might be spurious. We start by incorporating an additional regressor, namely 'congested electricity substation', and observe whether including it in our model specification significantly changes either the size or statistical significance of the rest of the coefficients of the independent variables. By comparing column 1 and 2 in Table B1, we observe that this is not the case. In fact, the coefficient for 'congested electricity substation' remains non-statistically significant.

We continue by removing from the model specification presented in column 3-Table B1 the variable 'renewable energy (RE) projects - utility-scale' and equivalently, we remove the variable 'renewable energy (RE) projects – distributed' from the model specification presented in column 4-Table B1. Once we remove 'renewable energy (RE) projects - utility-scale', we observe that 'renewable energy (RE) projects – distributed' becomes statistically significant. This finding, in conjunction to the fact that those two variables are correlated more than 50% (see Table A9.), indicate that they both control for similar effect on LES diffusion. This result is reasonable given there is certain degree of overlap between the RE projects reported in those two variables. Column 4 in Table B1 indicates that the coefficient for 'renewable energy (RE) projects - utility-scale' variable remains strongly significant, regardless of whether distributed RE is included in the model. Thus, we decide to keep 'renewable energy (RE) projects - utility-scale' variable (and discard 'renewable energy (RE) projects - utility-scale' variable) given the coefficient's value remain remarkably similar across various model specifications and it is always statistically significant. Finally, given that 'tech businesses' variable is highly correlated to 'EV charging infrastructure' variable (see Table A9), we further test the robustness of our empirical estimates by removing 'tech businesses' variable from our model in column 5 -Table B1. We can observe in column 5-Table B1 that all coefficients retain the same statistical properties to those in column 4 -Table B1 while we can observe no sizable changes in the values of the coefficients.

**Table B1. Re-estimation of alternative model specifications to model specification presented in column 1-table 3, performed as robustness check to baseline linear regression model.**

| | OLS (1) | OLS (2) | OLS (3) | OLS (4) | OLS (5) |
|---|---|---|---|---|---|
| Renewable energy (RE) projects – utility-scale | 0.014** | 0.015** | | 0.015*** | 0.014*** |
| | (0.006) | (0.006) | | (0.005) | (0.005) |
| Renewable energy (RE) projects - distributed | 0.000 | 0.000 | 0.000* | | |
| | (0.000) | (0.000) | (0.000) | | |
| EV charging infrastructure | 0.00692*** | 0.00688*** | 0.00678*** | 0.00693*** | 0.00828*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Limited access to gas | 1.839*** | 1.858*** | 2.015*** | 1.836*** | 1.817*** |
| | (0.348) | (0.350) | (0.342) | (0.345) | (0.346) |
| Major power producers | -0.0497*** | -0.0462*** | -0.0303** | -0.0499*** | -0.0502*** |
| | (0.015) | (0.016) | (0.013) | (0.014) | (0.015) |
| Energy and climate action plans | 0.504*** | 0.515*** | 0.517*** | 0.506*** | 0.497*** |
| | (0.165) | (0.166) | (0.165) | (0.161) | (0.162) |
| Social capital | 0.304 | 0.263 | 0.322 | 0.310 | 0.215 |
| | (0.858) | (0.861) | (0.863) | (0.852) | (0.854) |
| Tech businesses | 0.0002* | 0.0002* | 0.0002* | 0.0002** | |
| | (0.000) | (0.000) | (0.000) | (0.000) | |
| Average household income | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| New building stock | -1.217** | -1.221** | -1.247** | -1.211** | -1.239** |
| | (0.568) | (0.569) | (0.572) | (0.558) | (0.560) |
| Efficiency improvements in fuel poor households | -3.225*** | -3.247*** | -3.419*** | -3.221*** | -3.257*** |
| | (1.067) | (1.069) | (1.070) | (1.064) | (1.069) |
| Home energy audits | 14.41*** | 14.43*** | 14.81*** | 14.41*** | 13.04*** |
| | (4.347) | (4.351) | (4.370) | (4.341) | (4.302) |
| University towns | 1.056 | 1.066 | 0.761 | 1.059 | 1.183* |
| | (0.669) | (0.670) | (0.661) | (0.666) | (0.666) |
| Congested electricity substation | | -0.003 | | | |
| | | (0.004) | | | |
| Constant | 0.626* | 0.636* | 0.568 | 0.630* | 0.627* |
| | (0.365) | (0.366) | (0.367) | (0.358) | (0.359) |
| Observations | 380 | 380 | 380 | 380 | 380 |
| Moran test $\chi^2$ | 0.97 | 1.10 | 0.95 | 0.98 | 1.40 |
| P-value | 0.323 | 0.294 | 0.330 | 0.323 | 0.236 |
| R-squared | 0.359 | 0.360 | 0.349 | 0.359 | 0.352 |
| RMSE | 0.772 | 0.772 | 0.777 | 0.770 | 0.774 |

*** denotes statistical significance at 1%, ** at 5%, and * at 10%. Parentheses indicate standard errors for each coefficient.

To formally test whether these regressors are endogenous, we perform the Durbin-Wu-Hausman test. We start with model B1 specified below:

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 Z + u_i \qquad \text{B1}$$

where $y_i$ is the dependent variable, $x_1$ is the variable that we want to test for endogeneity, and $Z$ is a vector of exogenous variables. Following Wooldridge (2003, p. 483-484), the first step involves model B2 in which we regress the variable for which we are uncertain whether it is an endogenous predictor (i.e., $x_1$), with an additional exogenous variable i.e., the instrument variable $x_2$, and the vector of exogenous variables $Z$ incorporated in model B1:

$$y_2 = \pi_0 + \pi_1 x_2 + \beta_2 Z + v_i \qquad \text{B2}$$

The second step involves regressing model B3 in which we effectively estimate the original model A1, while also incorporating the residuals $v_i$ from model B2:

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 Z + \delta v_i + u_i \qquad \text{B3}$$

We then test the null hypothesis $H_0$ that the coefficient $\delta = 0$, which essentially means that $x_1$ is not endogenous as the two error terms are not correlated. The alternative hypothesis $H_0$under which $\delta \neq 0$ indicates that $x_1$ is endogenous.

Having set out the methodological approach to test for endogeneity (Wooldridge 2003), we now introduce the corresponding instrument for each of the variables that we want to test for endogeneity and estimate the associated regression modes. Starting with the number of ICT firms within each region, we use as an instrument the log of GVA for ICT firms within the same areas (in bold in Table B2). It is reasonable to assume that these two variables effectively control for the same effect on LES expansion. The log of GVA for ICT firms is positively correlated with the count of ICT firms. We perform a regression analysis using as dependent variable the count of ICT firms and independent variables the log of GVA of ICT firms and the rest of the exogenous regressors (see model B2 in Table B2). Then, we save the residuals from this first stage regression (model B2) and add them in the original regression model (model B3 in Table B2). We can see in model B3 in Table B2 that the coefficient for the Model B2 residual is not statistically significant. As a final test, we perform an f-test on the coefficient for the Model B2 residual that fails to reject the null. This further proves that the specific regressor is not endogenous. Beyond the econometrics test, we find supporting evidence in the literature that ICT firms that predate the deployment of LES, have a very similar geographic dispersion pattern across the UK as discussed on page 15 in the main manuscript.

**Table B2. Testing for endogeneity for the regressor controlling for the count of tech businesses in the linear regression model specified in Table 3.**

| | Model B1 | Model B2 | Model B3 |
|---|---|---|---|
| Renewable energy (RE) projects – utility-scale | 0.016*** | -1.065 | 0.000516 |
| | (0.005) | (2.739) | (0.006) |
| EV charging infrastructure | 0.007*** | 5.274*** | 0.006*** |
| | (0.001) | (0.490) | (0.001) |
| Limited access to gas | 1.836*** | 625.8*** | 1.523*** |
| | (0.345) | (179.2) | (0.368) |
| Major power producers | -0.05*** | -9.669 | -0.023 |
| | (0.014) | (7.123) | (0.01) |
| Energy and climate action plans | 0.506*** | -132* | 0.451*** |
| | (0.161) | (73.83) | (0.156) |
| Social capital | 0.310 | -278.1 | 0.704 |
| | (0.852) | (391.1) | (0.835) |
| **Tech businesses (count)** | 0.0002** | | 0.0003** |
| | (0.000) | | (0.000) |
| **Log of GVA of tech businesses (instrument)** | | 226.0*** | |
| | | (17.07) | |
| Average household income | -4.56e-05*** | 0.00928 | -4.97e-05*** |
| | (0.000) | (0.006) | (0.000) |
| New building stock | -1.211** | -935.8*** | -0.836 |
| | (0.558) | (262.7) | (0.546) |
| Efficiency improvements in fuel poor households | -3.221*** | -862.1* | -3.049*** |
| | (1.064) | (487.6) | (1.032) |
| Home energy audits | 14.41*** | -7,359*** | 18.24*** |
| | (4.341) | (1,981) | (4.39) |
| University towns | 1.059 | -581.0* | 0.948 |
| | (0.666) | (316.0) | (0.651) |
| **Model B2 residuals** | | | -0.0002 |
| | | | (0.000) |
| Constant | 0.630* | -1,881*** | 0.506 |
| | (0.358) | (220.9) | (0.353) |
| Observations | 380 | 378 | 378 |
| R-squared | 0.359 | 0.715 | 0.330 |

*** denotes statistical significance at 1%, ** at 5%, and * at 10%. Parentheses indicate standard errors for each coefficient.

For the number of renewable energy (RE) projects, we use as an instrument the sum of the capacity in MW of RE projects within the same LA (in bold in Table B3). It is reasonable to assume that these two variables effectively control for a very similar effect on LES expansion. The total capacity of RE projects is positively correlated with the count of RE projects. Thus, we estimate the model B2 that uses as a dependent variable the number of RE and as independent variable the capacity in MW of RE projects and the rest of the exogenous regressors (see model B2 in Table B3). The next step involves saving the residuals from this first stage regression (model B2) and adding then in the original regression model (model B1 in Table B3). We can see in model B3 in Table B3 that the coefficient for the Model B2 residual is not statistically significant. As a final test, we perform a f-test on the coefficient for the Model B2 residual that fails to reject the null. This further proves that the specific regressor is not endogenous.

**Table B3. Testing for endogeneity for the regressor controlling for the count of renewable energy (RE) projects in the linear regression model specified in Table 3.**

| | Model B1 | Model B2 | Model B3 |
|---|---|---|---|
| **Renewable energy (RE) projects – utility-scale** | 0.016*** | | 0.0007 |
| | (0.005) | | (0.014) |
| **Capacity in MW of RE projects (instrument)** | | 0.0144*** | |
| | | (0.002) | |
| EV charging infrastructure | 0.007*** | 0.009 | 0.007*** |
| | (0.001) | (0.012) | (0.001) |
| Limited access to gas | 1.836*** | 10.67*** | 2.018*** |
| | (0.345) | (3.418) | (0.385) |
| Major power producers | -0.05*** | 0.925*** | -0.0284 |
| | (0.014) | (0.152) | (0.025) |
| Energy and climate action plans | 0.506*** | 5.640*** | 0.594*** |
| | (0.161) | (1.591) | (0.182) |
| Social capital | 0.310 | 15.27* | 0.535 |
| | (0.852) | (8.506) | (0.878) |
| Tech businesses (count) | 0.007*** | -6.77e-05 | 0.0002* |
| | (0.001) | (0.001) | (0.001) |
| Average household income | -4.56e-05*** | -0.0003*** | -5.10e-05*** |
| | (0.000) | (0.000) | (0.000) |
| New building stock | -1.211** | 13.33** | -1.033* |
| | (0.558) | (5.561) | (0.582) |
| Efficiency improvements in fuel poor households | -3.221*** | -8.071 | -3.410*** |
| | (1.064) | (10.68) | (1.079) |
| Home energy audits | 14.41*** | 31.58 | 15.16*** |
| | (4.341) | (43.56) | (4.396) |
| University towns | 1.059 | -20.81*** | 0.716 |
| | (0.666) | (6.593) | (0.741) |
| **Model B2 residuals** | | | 0.016 |
| | | | (0.015) |
| Constant | 0.630* | 3.431 | 0.699* |
| | (0.358) | (3.584) | (0.363) |
| Observations | 380 | 380 | 380 |
| R-squared | 0.359 | 0.482 | 0.361 |

*** denotes statistical significance at 1%, ** at 5%, and * at 10%. Parentheses indicate standard errors for each coefficient.

For the number of EVs rechargers we use as an instrument the number of EVs registered within the same area. The number of registered EVs within an area is associated with the existence of EV charging point within the same area (in bold in Table B4). So effectively, the two variables control for the effect of EVs deployment on LES expansion. We estimate model B2 (Table B4) using the number of EV charging points as dependent and the number of EVs as independent, along with the rest of the exogenous controls. The next step involves saving the residuals from this first stage regression (model B2) and adding then in the original regression model (model A1 in Table B4). Once again, we can see in model B3 in Table B4 that the coefficient for the Model B2 residual is not statistically significant. As a final test, we perform a f-test on the coefficient for the Model B2 residual that fails to reject the null. This further proves that the specific regressor is not endogenous.

Beyond econometrics testing, this causal effect can be confirmed by the historical development of EV charging points and LES projects. Focusing specifically on the 'EV charging infrastructure' variable, almost all LES projects involving EVs were in areas with very high number of existing EV charging points (e.g., Westminster 511, Nottingham 202, Bristol 118, Milton Keynes 281). Exceptions (areas with low number of EV charging points reported till 2018) are Chelmsford (18), Isle of Wight (11), Huntingdonshire (12) and Southend-on-Sea (7). However, EV-related LES projects developed in these areas started in 2018 (exception Isle of Wight DIP091 started in 2017) so existing charging points were not related to LES projects in our sample. Therefore, we reject the reverse causal explanation that LES projects could involve and thus enable the diffusion of EV charging infrastructure in local areas.

**Table B4. Testing for endogeneity for the regressor controlling for the count of electric vehicle (EVs) charging infrastructure projects in the linear regression model specified in Table 3.**

| | Model B1 | Model B2 | Model B3 |
|---|---|---|---|
| Renewable energy (RE) projects – utility-scale | 0.016*** | 0.203 | 0.012** |
| | (0.005) | (0.206) | (0.00627) |
| **EV charging infrastructure** | 0.007*** | | 0.0175 |
| | (0.001) | | (0.019) |
| **Count of EVs (instrument)** | | -0.00171 | |
| | | (0.00140) | |
| Limited access to gas | 1.836*** | 3.828 | 1.786*** |
| | (0.345) | (14.59) | (0.358) |
| Major power producers | -0.05*** | 0.224 | -0.0521*** |
| | (0.014) | (0.613) | (0.015) |
| Energy and climate action plans | 0.506*** | 37.72*** | 0.117 |
| | (0.161) | (6.583) | (0.732) |
| Social capital | 0.310 | -100.7*** | 1.364 |
| | (0.852) | (35.59) | (2.117) |
| Tech businesses (count) | 0.007*** | 0.044*** | -0.0003 |
| | (0.001) | (0.003) | (0.001) |
| Average household income | -4.56e-05*** | 0.00203*** | -6.75e-05 |
| | (0.000) | (0.000) | (0.000) |
| New building stock | -1.211** | -8.397 | -1.071* |
| | (0.558) | (23.88) | (0.615) |
| Efficiency improvements in fuel poor households | -3.221*** | 75.30* | -3.988** |
| | (1.064) | (44.84) | (1.767) |
| Home energy audits | 14.41*** | 204.5 | 12.56** |
| | (4.341) | (184.5) | (5.526) |
| University towns | 1.059 | 4.490 | 0.995 |
| | (0.666) | (28.15) | (0.677) |
| **Model B2 residuals** | | | -0.0106 |
| | | | (0.019) |
| Constant | 0.630* | -31.72** | 0.954 |
| | (0.358) | (15.03) | (0.695) |
| Observations | 380 | 380 | 380 |
| R-squared | 0.359 | 0.547 | 0.359 |

*** denotes statistical significance at 1%, ** at 5%, and * at 10%. Parentheses indicate standard errors for each coefficient.

Overall, we are confident that our regressors are not endogenous and that our model is not misspecified. Our additional testing for endogeneity indicates that the direction of causality goes from socio-economic variables to LES expansion.

To further prove the robustness of our empirical estimates will also employ the Poisson quasi-MLE (or quasi-Poisson) model. The advantage of the quasi-Poisson model is that it relaxes the Poisson model's restrictive assumption of equidisperision between the mean and the variance. We can observe in

Table B5-column 1 that coefficient estimates, and associated margins are remarkably similar to the ones estimated suing the Poisson regression model in Table 3-collumn 2. Minor differences can be observed the statistical significance of the coefficient for 'Major power producers' that slightly increases while that for 'home energy audits' and 'energy and climate action plans' slightly decrease. Similar findings can be observed for the weighted quasi-Poisson model in Table B5-column 2 and the corresponding results for the weighted Poisson model in Table 3-collumn 4, in which the statistical significance of the coefficient for 'major power producers', 'limited access to gas' and 'university towns' increases. Overall, we can observe that model's fitness substantially increases under the quasi-Poisson model with highest value that for the weighted quasi-Poisson model ($R^2$=0.56).

**Table B5. Re-estimation of baseline Poisson regression model in collumn 2 and 4 in Table 3 employing instead the Poisson quasi-MLE estimator.**

| Variables | Quasi Poisson (2) | | Poison weighted (4) | |
|---|---|---|---|---|
| | **Coef.** | **Margins** | **Coef.** | **Margins** |
| Renewable energy (RE) projects | 0.0130*** | 0.00474*** | 0.00936*** | 0.0263*** |
| | (0.004) | (0.002) | (0.002) | (0.007) |
| Electric vehicle (EV) charging infrastructure | 0.00766*** | 0.00280*** | 0.00386*** | 0.0109*** |
| | (0.00194) | (0.001) | (0.000902) | (0.002) |
| Limited access to gas | 2.712*** | 0.992*** | 0.468** | 1.317** |
| | (0.556) | (0.200) | (0.237) | (0.645) |
| Major power producers | -0.0639*** | -0.0234*** | -0.0572** | -0.161** |
| | (0.0199) | (0.007) | (0.0285) | (0.08) |
| Energy and climate action plans | 0.679* | 0.248* | -0.0274 | -0.0770 |
| | (0.349) | (0.130) | (0.221) | (0.623) |
| Social capital | 1.886 | 0.690 | 0.411 | 1.157 |
| | (2.659) | (0.979) | (2.133) | (6.004) |
| Tech businesses | 0.000456** | 0.000167** | 4.99e-05 | 0.000140 |
| | (0.0001) | (6.61e-05) | (0.0001) | (0.001) |
| University towns | 1.374 | 0.502 | 2.548*** | 7.167*** |
| | (1.521) | (0.565) | (0.973) | (2.777) |
| Average household income | -0.000120*** | -4.38e-05*** | -4.82e-05** | -0.000136** |
| | (4.53e-05) | (1.66e-05) | (1.92e-05) | (5.59e-05) |
| New building stock | -3.322** | -1.215** | -0.665 | -1.870 |
| | (1.441) | (0.540) | (0.554) | (1.588) |
| Efficiency improvements in fuel poor households | -6.213*** | -2.273*** | -6.509*** | -18.31*** |
| | (1.668) | (0.648) | (1.565) | (4.656) |
| Home energy audits | 15.63* | 5.716* | 14.49*** | 40.76*** |
| | (8.177) | (3.010) | (3.639) | (10.41) |
| Constant | 0.283 | | 1.345*** | |
| | (1.188) | | (0.481) | |
| Observations | 380 | 380 | 78 | 78 |
| Log likelihood | -245.62 | | -110.16 | |
| $R^2$ | 0.532 | | 0.567 | |

*** denotes statistical significance at 1%, ** at 5%, and * at 10%. Parentheses indicate standard errors for each coefficient.

We re-estimate the baseline Poisson regression model using the panel dataset rather than the cross-section one. Since not all variables specified in the baseline model (Table 3 – column 2) are available as time series (Figure A3), we re-estimate the baseline linear regression model without specifying the variables: limited access to gas, major power producers, social capital and university towns. Results presented in Table B6 indicate that all predictors are strongly statistically significant. We observe no major differences between the coefficients estimated using the panel dataset (Table B6) and cross-section dataset (Table 3 – column 2) while we observe that the marginal effects of the two regression models are very similar. Only exception is the coefficient for 'Home energy audits' variable for which we observe a larger differentiation between the two models' marginal effects (Table B6 compared to Table 3 – column 2). Overall, we are confident about the robustness of the proposed econometric methodology while consistency checks prove that our cross-section results are stable across time.

**Table B6. Panel data poisson regression model perfromed as a consistency test to check the stability of our cross-section estimates (Table 3-collumn 2) over time.**

| | LES projects (t) | | LES projects (t+1) | |
|---|---|---|---|---|
| | Poisson | Margins | Poisson | Margins |
| Renewable energy (RE) projects | 0.009** | 0.002** | 0.012*** | 0.003*** |
| | (0.004) | (0.001) | (0.004) | (0.001) |
| Electric vehicle (EV) charging infrastructure | 0.006** | 0.001** | 0.006** | 0.002** |
| | (0.003) | (0.001) | (0.003) | (0.001) |
| Energy and climate action plans | 0.970*** | 0.208*** | 1.046*** | 0.275*** |
| | (0.242) | (0.054) | (0.216) | (0.0601) |
| Tech businesses | 0.001*** | 0.0002*** | 0.001*** | 0.0002*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Average household income | -0.0001*** | -0.000*** | -0.0001*** | -0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Efficiency improvements in fuel poor households | -16.55*** | -3.549*** | -16.23*** | -4.272*** |
| | (3.420) | (0.784) | (3.032) | (0.853) |
| Home energy audits | 49.67*** | 10.65*** | 49.61*** | 13.05*** |
| | (7.313) | (1.777) | (6.460) | (1.934) |
| Constant | -0.905 | | -0.594 | |
| | (0.599) | | (0.586) | |
| Observations | 760 | 760 | 760 | 760 |
| Log likelihood | -362.89 | | -417.82 | |
| Deviance | 463.68 | | 534.41 | |
| P-value | 1.0000 | | 1.0000 | |
| Pearson $\chi^2$ | 867.65 | | 932.99 | |
| P-value | 0.002 | | 0.000 | |

*** denotes statistical significance at 1%, ** at 5%, and * at 10%. Parentheses indicate standard errors for each coefficient.

Probit results (presented in Table B7) are almost identical to those estimated by the logit model in the main paper (Table 2 – column 3). Given we have no theoretical reasons to expect different results between probit and logit models, this further proves the consistency of our model and the robustness of our results.

**Table B7. Probit regression model results as a robustness test to Logit regression model results (Table 3-column 3).**

| | Probit | Margins |
|---|---|---|
| Renewable energy (RE) projects | 0.013 | 0.003 |
| | (0.010) | (0.002) |
| Electric vehicle (EV) charging infrastructure | 0.007*** | 0.002*** |
| | (0.002) | (0.001) |
| Limited access to gas | 1.816*** | 0.420*** |
| | (0.649) | (0.147) |
| Major power producers | -0.043 | -0.010 |
| | (0.029) | (0.007) |
| Energy and climate action plans | 0.436 | 0.101 |
| | (0.300) | (0.069) |
| Social capital | 1.703 | 0.393 |
| | (1.721) | (0.397) |
| Tech businesses | 0.000* | 0.000** |
| | (0.000) | (0.000) |
| Average household income | -0.000*** | -0.000*** |
| | (0.000) | (0.000) |
| New building stock | -3.073*** | -0.710*** |
| | (1.089) | (0.248) |
| Efficiency improvements in fuel poor households | -2.724 | -0.630 |
| | (2.279) | (0.524) |
| Home energy audits | 6.579 | 1.520 |
| | (8.232) | (1.897) |
| University towns | 0.853 | 0.197 |
| | (1.242) | (0.287) |
| Constant | 0.254 | |
| | (0.740) | |
| Observations | 380 | 380 |
| Log likelihood | -157.92 | |
| Pearson $\chi^2$ | 388.04 | |
| P-value | 0.216 | |

*** denotes statistical significance at 1%, ** at 5%, and * at 10%. Parentheses indicate standard errors for each coefficient.

Finally, we test a two-step model using our panel dataset so that we identify the "intensive" and the "extensive" margins. We start by estimating the probit model in column 2-Table B8 and the associated margins in column 3-Table B8. In the second step, we use one-year lagged independent variables and estimate a linear regression model presented in column 4-Table B8. The margins coefficients for the probit model identify the "extensive" effect while the coefficient in the linear regression model identify the "intensive" margins. We use those two coefficients two examine the contribute of the independent variables in the setting up and in the development of LES projects, respectively.

**Table B8. Two step model examining "extensive" and "intensive" margins using the panel dataset and employing a probit model and a linear regression model, respectively.**

| | **LES projects (Step 1)** | | **LES projects (t+1) (Step 2)** |
|---|---|---|---|
| | Probit | Margins | OLS |
| Renewable energy (RE) projects | 0.009 | 0.002 | 0.013*** |
| | (0.006) | (0.001) | (0.003) |
| Electric vehicle (EV) charging infrastructure | 0.006* | 0.002* | 0.006*** |
| | (0.004) | (0.001) | (0.00204) |
| Energy and climate action plans | 0.727*** | 0.148*** | 0.293*** |
| | (0.225) | (0.045) | (0.093) |
| Tech businesses | 0.001*** | 0.0001*** | 0.0003*** |
| | (0.000) | (0.000) | (0.000) |
| Average household income | -8.20e-05*** | -1.67e-05*** | -1.53e-05** |
| | (0.000) | (0.000) | (0.000) |
| Efficiency improvements in fuel poor households | -9.579*** | -1.956*** | -2.241*** |
| | (2.694) | (0.545) | (0.792) |
| Home energy audits | 24.89*** | 5.083*** | 18.04*** |
| | (6.553) | (1.329) | (3.067) |
| Constant | -0.0585 | | -0.0254 |
| | (0.492) | | (0.165) |
| Observations | 760 | | 760 |
| Log likelihood | -281.29053 | | |
| Pearson $\chi^2$ | 763.75 | | |
| P-value | 0.3751 | | |
| R-squared | 0.1514 | | 0.2266 |

*** denotes statistical significance at 1%, ** at 5%, and * at 10%. Parentheses indicate standard errors for each coefficient.

# Appendix C

## C. Community energy projects

### C.1 Modelling methodology

Below, we present the methodological approach employed for the community energy (CE) projects, the dependent variable in model C1. Since we find spatial autocorrelation in the regression residuals, we employ a spatial autoregressive model (Anselin, 2003) that accounts for spatial dependence both in the dependent variable (equation C1) and in the residual errors of the model (equation C2). More specifically:

$$CE_i = \rho WCE_i + \alpha + X_i\beta + u_i \tag{C1}$$

$$u_i = \lambda W u_i + \varepsilon_i \tag{C2}$$

where $WCE$ is the spatial lag vector that represents the values of the dependent variable for neighbouring LAs, $X_i$ is the vector of independent variables for LAs $i = 1,..,380$, and error $u_i$ accounts for spatial shocks $Wu_i$ in neighbouring LAs. We include two spatial dependence parameters $\rho$ and $\lambda$ that account for spatial dependence in the dependent variable and residuals, respectively. We estimate the model with the use of the Generalised 2 Stage Least Square (G2SLS) nonlinear estimator. Given the disproportionate spatial distribution of CE (Figure C.2-1) and the increased correlation between certain independent variables and dependent variable (Table C.2-2), we further spilt our sample to devolved administrations and re-estimate our models for England and Wales, and for Scotland separately, given we observe very high levels of correlation between CE and independent variables in Scotland (Table C.2-2). This is mainly due to extreme outliers[1], and due to the small sample properties[2].

### C.2 Empirical findings

Building on the Community Energy Hub and the Community energy Scotland datasets, we have identified the geographical location for 393 CE projects and mapped them using the 380 local authorities in England, Scotland and Wales as our spatial unit of analysis - see Figure C.2-1 and Table C.2-1 for descriptive statistics. We use CE projects as an external validity test to our proposed methodological approach given that using an alternative – but overall related – dataset should allow us to generate comparable findings. More specifically, we re-estimate our methodological approach using CE projects as a dependent variable and compare results to those for LES projects. We expect that a smaller set of predictors compared to LES would be able to explain the spatial diffusion of CE projects being significantly less complex than the equivalent LES ones. Figure C.2-1 indicates that CE projects are disproportionally allocated across GB with Scottish local authorities accounting for a significantly larger number of CE projects than England and Wales.

[1] For example, Highland LA has 90 CE while the mean number of CE per LA is 1.

[2] There are only 32 LAs for Scotland while 158 LAs for England and Wales.

**Figure C.2-1. Spatial distribution of community energy (CE) projects per local authority across Great Britain**

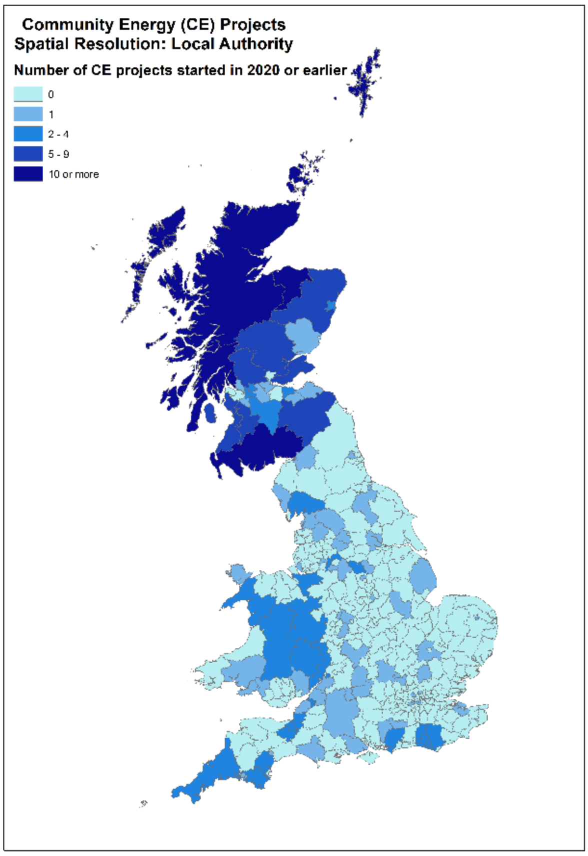



**Table C.2-1. Descriptive statistics for Community Energy projects per local authority across Great Britain**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Community Energy (CE) projects | 380 | 1.03 | 5.36 | 0 | 90 |

We present in Table C.2-2 the correlation coefficients between CE and independent variables. We use bold ink and red paint to highlight those coefficients that indicate correlation equal or higher than 50%. We use yellow paint to highlight those coefficients that indicate correlation equal or higher than 30% and lower than 50%. The highest correlation coefficient can be observed between CE projects and Major Powe Producers (MPPs). Given the disproportionate distribution of CE across GB, we further spilt our sample between England and Wales (on one side) and Scotland (on the other) and present the equivalent correlation coefficients for each subsample.

For Scotland in particular, we observe increased levels of correlation between CE projects and several energy and network related variables. This high level of correlation can be explained by i) the unique geographical characteristics of the Scottish landscape that result to extreme outliers (e.g. Highlands have 90 CE projects while the mean across GB is 1 CE per LA) and ii) small sample size properties (there are 348 LAs for England and Wales while only 32 LAs for Scotland). More specifically, Scottish LAs such as Highlands capture a (disproportionally to the rest of Scotland) large geographic area and account for a very large number of hydro-electric power stations mainly due the unique geological characteristics. Thus, we expect this extremely high correlation between major power producers and CE projects to be purely spurious. On the other hand, Highlands are mainly rural and sparsely populated areas, with higher renewable power generation, higher network capacity constraints in the local electricity network and reduced access to the gas grid. Similar characteristics are expected for areas such as the Scottish islands (such as Shetlands, Orkneys, etc.). Thus, these areas are more likely to deploy CE projects as way to deal effectively with supply constraints and to improve balancing between supply and demand (given increasing share of intermittent and distributed renewable generation technologies). Regarding England and Wales, we observe increased correlation between CE projects and distributed RE (e.g. solar panels funded by feed-in-tariffs) as one would expect according to the literature (Braunholtz-Speight et al., 2020).

**Table C.2-2. Inter-correlation ratios between community energy (CE) projects, local energy system (LES) projects and independent variables per local authority across Great Britain, England and Wales, and Scotland, respectively.**

| | Community energy (CE) projects (count) | | |
|---|---|---|---|
| | **Great Britain** | **England and Wales** | **Scotland** |
| Local energy systems (LES) projects | 0.14 | 0.18 | 0.10 |
| Renewable energy (RE) projects - utility-scale | **0.54** | 0.25 | **0.79** |
| Renewable energy (RE) projects - distributed | 0.10 | 0.30 | 0.41 |
| Congested electricity substation | **0.55** | 0.27 | **0.94** |
| Electric vehicle (EV) charging infrastructure | 0.01 | 0.06 | 0.09 |
| Limited access to gas | 0.39 | 0.19 | **0.56** |
| Major power producers | **0.87** | 0.03 | **0.91** |
| Energy and climate action plans | 0.04 | 0.06 | -0.00 |
| Social capital | 0.08 | 0.18 | 0.25 |
| Tech businesses | -0.06 | 0.04 | -0.11 |
| Average household income | -0.04 | -0.05 | -0.01 |
| New building stock | -0.21 | 0.03 | 0.22 |
| Efficiency improvements in fuel poor households | 0.07 | 0.01 | -0.17 |
| Home energy audits | 0.27 | -0.01 | 0.04 |
| University towns | -0.01 | 0.13 | -0.16 |

Variables correlated 30% or more are highlighted with yellow paint, while variables correlated more than 50% are highlighted with bold ink and red paint.

We re-estimate our methodological approach using CE as our dependent variable. Since we find evidence of spatial autocorrelation in our residuals (in contrast to LES projects), we employ the spatial autoregressive regression (SAR) model (Table C.2-3.-column 1). We start by estimating the SAR model for GB (full sample) and incorporating a spatial lag for the dependent variable and a spatial lag for the residuals, so that we deal effectively with spatial autocorrelation. Table C.2-3. indicates that spatial lag for the dependent variable is negative and statistically significant which means that CE deployment within an LA would generate in negative spillover effects to neighbouring areas (Table C.2-3.-column 1). Of course, this is not a reasonable result and therefore we try to identify the cause of misspecification in our model. Given the high correlation between CE and major 'power producers variable', we believe that including this variable produces spurious results (due to the inclusion of CE spatial lag with which it is highly correlated) and thus we remove 'major power producers' variable from our model. Indeed, once we discard it from our model (Table C.2-3.-column 2), we observe that the spatially dependent lag becomes non-statically significant, supporting our initial assumption of spurious relationship between CE and 'major power producers'. Since distributed and utility scale RE are correlated, when modelled together we observe that the coefficient of the former variable gets a negative value (Table C.2-3.-column 2). However, this is not a point of concern as we have already proved in our baseline model robustness test (Table B1.) that removing one of the two variables resolves similar modelling issues. Overall, we observe that existing RE projects, low surplus capacity, electricity network constraints, and energy inefficient housing stock are local conditions significantly associated with CE diffusion.

Given the i) disproportionate distribution of CE across GB and ii) the increased correlation between CE projects and energy systems variables for Scottish LAs, we further spilt our sample to devolved administrations and re-estimate our regression model for England/Wales and Scotland, separately. We can now observe in Table C.2-3 – column 3 and 5 that the number of major power producers becomes non-statistically significant further proving our claim about its spurious relationship with CE projects. We remove it from our model specifications in column 4 and 6, respectively. Focusing on England and Wales, distributed RE coefficient is statistically significant when modelled with utility-scale RE (column 2), indicating the relatively increased role of distributed RE for CE projects. We observe that volunteering rate (proxy for social capital) becomes statistically significant as expected according to literature. Capacity constraints remain significant and the proxy for university towns now becomes statistically significant. We also find that LAs with at least one CE project have positive spillover effects to their neighbouring LAs.

Concerning the case of Scotland, we find no spatial autocorrelation in the residuals for Scotland[3], and thus we use the linear regression model. We observe in Table C.2-3-column 6 that the coefficients of most the independent variables become non-statistically significant expect for that for 'Congested electricity substation' and 'limited access to gas'. Nonetheless, one needs to be careful not to overly on these findings due to the very small sample size properties (n=32) of this model. Overall, we observe that indeed a smaller set of factors (than that associated with LES projects in Table 3-collumn1 and 2) is associated with CE projects diffusion, validating this landscape transition from CE projects to more complex LES projects. In addition, we observe mainly energy related and social capital factors to be associated with CE diffusion. Further research in necessary for CE, and in particular for the case of Scotland, potentially employing spatially more granular observations (e.g., LSOAs), to identify the local conditions associated with CE diffusion.

[3] Moran test for spatial dependence does not reject the null hypothesis that errors are i.i.d. This means that there is no spatial autocorrelation in the residuals of the linear regression models for Scotland and thus we can use the OLS estimator.

**Table C.2-3. Regression results using the number of community energy (CE) projects per local authority across Great Britain, England and Wales, and Scotland, respectively, as dependent variable**

| | Great Britain | | England and Wales | | Scotland | |
|---|---|---|---|---|---|---|
| | SAR (1) | SAR (2) | SAR (3) | SAR (4) | OLS (5) | OLS (6) |
| Renewable energy (RE) projects - utility-scale | 0.0577*** | 0.215*** | 0.004 | 0.004 | -0.082 | -0.035 |
| | (0.018) | (0.029) | (0.005) | (0.006) | (0.168) | (0.160) |
| Renewable energy (RE) projects - distributed | -0.000** | -0.001*** | 0.000** | 0.000** | -0.001 | -0.001 |
| | (9.40e-05) | (0.000152) | (0.000) | (0.000) | (0.001) | (0.002) |
| Congested electricity substation | 0.0379*** | 0.183*** | 0.008** | 0.008** | 0.594** | 0.783*** |
| | (0.014) | (0.022) | (0.003) | (0.004) | (0.240) | (0.125) |
| Electric vehicle (EV) charging infrastructure | -0.000941 | 0.00402 | 0.001 | 0.001 | -0.035 | -0.002 |
| | (0.003) | (0.006) | (0.001) | (0.001) | (0.0853) | (0.077) |
| Major power producers | 1.164*** | | -0.009 | | 0.385 | |
| | (0.0444) | | (0.0402) | | (0.415) | |
| Limited access to gas | 7.484*** | 8.936*** | 0.487 | 0.521 | 13.13* | 10.69* |
| | (0.995) | (1.669) | (0.322) | (0.339) | (6.575) | (6.005) |
| Energy and climate action plans | 0.698 | -0.522 | -0.144 | -0.138 | 3.763 | 2.433 |
| | (0.464) | (0.776) | (0.135) | (0.141) | (4.588) | (4.342) |
| Social capital | 0.129 | 2.954 | 1.674** | 1.818** | -18.12 | -5.146 |
| | (2.372) | (3.987) | (0.698) | (0.712) | (32.47) | (29.20) |
| Tech businesses | 0.000212 | 0.000343 | 0.000 | 0.000 | 0.001 | 0.000 |
| | (0.000) | (0.000) | (0.00) | (0.00) | (0.004) | (0.004) |
| Average household income | 4.31e-07 | -6.99e-05 | -0.000 | -0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.00) | (0.00) | (0.00) | (0.00) |
| New building stock | -6.966*** | -10.20*** | -0.615 | -0.523 | 16.40 | 16.20 |
| | (1.779) | (2.997) | (0.522) | (0.546) | (21.67) | (21.58) |
| Efficiency improvements in fuel poor households | -5.451* | -2.929 | 0.809 | 0.770 | 10.67 | 13.57 |
| | (3.055) | (5.133) | (0.911) | (0.954) | (20.81) | (20.49) |
| Home energy audits | 66.21*** | 58.35*** | -5.942 | -5.409 | 28.87 | 28.90 |
| | (12.74) | (21.44) | (4.984) | (5.152) | (70.73) | (70.46) |
| University towns | 0.640 | 3.875 | 1.434*** | 1.409*** | 6.566 | 14.90 |
| | (1.796) | (3.015) | (0.537) | (0.544) | (25.69) | (23.97) |
| CE (dependent variable) spatial lag | -0.181** | -0.04 | 0.634*** | 0.529*** | | |
| | (0.0756) | (0.144) | (0.128) | (0.148) | | |
| Spatial error dependence | 0.498*** | 0.457*** | -0.278 | | | |
| | (0.128) | (0.136) | (0.182) | | | |
| Constant | -0.571 | 0.709 | -0.0837 | -0.130 | -4.500 | -7.931 |
| | (1.049) | (1.762) | (0.278) | (0.290) | (16.31) | (15.83) |
| Observations | 380 | 380 | 348 | 348 | 32 | 32 |
| Pseudo $R^2$ | 0.844 | 0.549 | 0.1935 | 0.1906 | | |
| $R^2$ | | | | | 0.951 | 0.949 |
| RMSE | | | | | 4.947 | 4.928 |
| Moran test $\chi^2$ | | | | | 0.05 | 0.04 |
| P-value | | | | | 0.822 | 0.85 |

*** denotes statistical significance at 1%, ** at 5%, and * at 10%. Parentheses indicate standard errors for each coefficient.

# Appendix D

## D. Cluster analysis and empirical findings

Using available information on energy technologies employed, funding source, and the participation of public/private/DNOs, of existing LES projects, we employ a cluster analysis to identify distinct groups of LES projects with homogenous characteristics. We find that LES projects form four clusters:

[1] 3rd or public sector-led projects covering demand sectors (n=41)
[2] private firm-led projects focusing on electricity supply integration and relatively small budgets (n=24)
[3] private firm-led projects involving multiple energy vectors and full system integration (n=34)
[4] DNO-led projects focusing on electricity networks (n=47)

We present more detailed information on the loading of the factors used to determine the clusters in Figure D1. For a more detailed analysis on the empirical findings of LES clusters please check (Wilson et al., 2020). Having identified the clusters of LES with homogenous characteristics, we distinguish in two groups with the first containing the historically older types of LES projects (i.e., Cluster 1 and 4) and the second the more recent ones (i.e., Cluster 2 and 3). We re-estimate the Poisson regression model using each of the two clusters of LES projects as dependent variable and present in Table D1 a detailed overview of regression results.

**Figure D1. % of LES projects with defined characteristics in each of four clusters. Between-cluster tests of difference for each characteristic (ANOVA) shown as significant (p<.01) or non-significant (n.s.). This figure is taken from (Wilson et al., 2020) that used the same dataset on LES projects and performed a detailed analysis on LES projects clusters.**

| | | GEOGRAPHIC & SCALE CHARACTERISTICS | | | | INSTITUTIONAL CHARACTERISTICS | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | *Location* | *Scale* | *Budget** | *Year Start* | *Lead Partner* | *Lead Partner* | *Lead Partner* | *Partners* | *Partners* |
| **Cluster** | **n** | **(sub)urban** | **dispersed** | **>=£2.5m** | **2016 or later** | **DNO or similar** | **private exc. DNO** | **3rd or public sector** | **public** | **3rd sector** |
| 1 | 41 | 76% | 61% | 58% | 59% | 0% | 0% | 100% | 51% | 90% |
| 2 | 24 | 75% | 38% | 45% | 67% | 0% | 96% | 0% | 38% | 71% |
| 3 | 34 | 79% | 44% | 66% | 47% | 0% | 100% | 0% | 56% | 82% |
| 4 | 47 | 70% | 53% | 45% | 28% | 100% | 0% | 0% | 34% | 68% |
| **ALL** | **146** | **75%** | **51%** | **53%** | **47%** | **32%** | **39%** | **28%** | **45%** | **78%** |
| | *ANOVA* | *n.s.* | *n.s.* | *n.s.* | *p<.01* | *(p<.01)*** | *p<.01* | *(p<.01)*** | *n.s.* | *n.s.* |

Notes: * undefined budgets for 20 projects so total n=126; ** insufficient heterogeneity for ANOVA, but clear difference

| | | TECHNOLOGICAL CHARACTERISTICS | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | *Sectors* | *Energy Vectors* | *Technology Groupings* | | | | | |
| **Cluster** | **n** | **multiple** | **multiple** | **Generation & Storage exc. Renewables** | **Variable Renewables** | **Electricity Grid Integration** | **Local Electricity Network** | **Energy Carriers & Coupling** | **Energy End-use** |
| 1 | 41 | 32% | 85% | 66% | 80% | 39% | 37% | 51% | 80% |
| 2 | 24 | 8% | 71% | 54% | 46% | 54% | 0% | 8% | 0% |
| 3 | 34 | 38% | 82% | 76% | 56% | 44% | 47% | 47% | 88% |
| 4 | 47 | 34% | 28% | 36% | 28% | 60% | 79% | 19% | 45% |
| **ALL** | **146** | **30%** | **64%** | **57%** | **52%** | **49%** | **47%** | **33%** | **58%** |
| | *ANOVA* | *n.s.* | *p<.01* | *p<.01* | *p<.01* | *n.s.* | *p<.01* | *p<.01* | *p<.01* |

**Table D1 – Poisson model regression results using clusters of LES projects as dependent variable.**

| Variables | Poisson - Cluster 1 & 4 | | Poisson - Cluster 2 & 3 | |
|---|---|---|---|---|
| | **Coef.** | **Margins** | **Coef.** | **Margins** |
| Renewable energy (RE) projects | 0.011* | 0.002* | 0.013* | 0.002 |
| | (0.006) | (0.001) | (0.008) | (0.001) |
| Electric vehicle (EV) charging infrastructure | 0.009*** | 0.002*** | 0.006** | 0.001** |
| | (0.002) | (0.0005) | (0.002) | (0.0004) |
| Limited access to gas | 3.110*** | 0.688*** | 1.818** | 0.258* |
| | (0.556) | (0.144) | (0.925) | (0.136) |
| Major power producers | -0.074 | -0.016 | -0.050 | -0.0072 |
| | (0.049) | (0.011) | (0.060) | (0.008) |
| Energy and climate action plans | 0.542 | 0.120 | 0.912** | 0.130** |
| | (0.364) | (0.081) | (0.442) | (0.065) |
| Social capital | 1.754 | 0.388 | 1.420 | 0.202 |
| | (2.794) | (0.619) | (3.486) | (0.496) |
| Tech businesses | 0.0004* | 8.08e-05* | 0.0006** | 8.54e-05** |
| | (0.0002) | (4.80e-05) | (0.0002) | (3.63e-05) |
| Average household income | -0.0001*** | -3.31e-05*** | -8.95e-05* | -1.27e-05* |
| | (4.61e-05) | (1.08e-05) | (4.64e-05) | (6.81e-06) |
| New building stock | -4.713*** | -1.042*** | -1.357 | -0.193 |
| | (1.486) | (0.348) | (1.694) | (0.242) |
| Efficiency improvements in fuel poor households | -4.961* | -1.097* | -11.10** | -1.578** |
| | (2.555) | (0.577) | (5.039) | (0.748) |
| Home energy audits | 11.31 | 2.500 | 25.14* | 3.573* |
| | (8.535) | (1.906) | (13.33) | (1.955) |
| University towns | 0.662 | 0.146 | 2.216 | 0.315 |
| | (1.579) | (0.349) | (1.660) | (0.240) |
| Constant | 0.631 | | -1.355 | |
| | (1.060) | | (1.347) | |
| Observations | 380 | 380 | 380 | 380 |
| Log likelihood | -175.667 | | -133.13976 | |
| Deviance | 224.8777 | | 181.7423 | |
| P-value | 1 | | 1 | |
| Pearson $\chi^2$ | 452.8758 | | 467.7525 | |
| P-value | 0.0015 | | 0.0003 | |

*** denotes statistical significance at 1%, ** at 5%, and * at 10%. Parentheses indicate standard errors for each coefficient.

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