Weathering the Energy Crisis: Can Tailored Information to Local Governments Spur Climate Action? *

Menna Bishop, Immanuel Feld, Thiemo Fetzer, Ludovica Gazze

September 24, 2026

Abstract

The United Kingdom ranks among the worst European countries in terms of residential energy efficiency and fuel poverty. Although local governments have the tools to influence building upgrades, lack of coordination across levels of government and a systemic under-funding have hindered councils' ability to foster energy efficiency investments. We implement a randomised controlled trial to test whether a bottom-up approach for disseminating academic and policy findings can influence adoption of local policies that deliver energy savings. Leveraging granular energy performance certificates (EPCs), local energy use, census, and property price data, we produced briefs containing rigorous, just-in-time analyses of the projected effects of the energy crisis on residents of districts in England and Wales and of the estimated local benefits of energy efficiency investments. We sent these briefs to councillors and council workers of 329 randomly selected districts. The outreach increased retrofit installations by 7 percent, without any detectable effect on energy consumption. The effects were highly localised around councillors' residential addresses, pointing to a highly local diffusion of the information.

Keywords: Energy Efficiency; Energy Prices; Field Experiment; Public Policy

JEL CODES: H1; Q48.

---

*Contact: Menna Bishop: menna.bishop@warwick.ac.uk; Immanuel Feld: immanuel.feld@warwick.ac.uk; Thiemo Fetzer: t.fetzer@warwick.ac.uk; Ludovica Gazze: ludovica.gazze@warwick.ac.uk. We thank Reuben Collins, Leon Beaufils, Natalia Tronina, Suraj Rajesh, and Tymoteusz Gozdzik for excellent research assistance. We acknowledge generous funding from Leverhulme Trust, the Policy Support Fund, and the Department of Economics and CAGE research centre at the University of Warwick. All remaining errors are our own.

1 Introduction

Improving the energy efficiency of residential buildings is one of the central challenges of the clean energy transition. Residential homes account for a substantial share of energy consumption, and energy-inefficient housing exposes households to both high energy bills and volatile energy prices. Residential retrofits are the result of private household decisions and public climate policy. While the decision to insulate a home or install energy-saving technologies is usually made by households, the information, trust, coordination, and political salience surrounding that decision are shaped by local political institutions and political support. This raises an important question: can informing local governments and politicians of the consequences of climate inaction change household investment behaviour?

The UK is a particularly relevant setting to study this question in. Its housing stock is especially old and dependent on fossil-fuel heating compared with other European countries with a high share of households under the threat of fuel poverty (Department for Business, Energy & Industrial Strategy, 2021; Department for Energy Security and Net Zero, 2026). This was especially salient during the 2022 energy price shock triggered by Russia's invasion of Ukraine. In the first few months after the attack, gas prices skyrocketed (see Appendix figure A1). This combination of an old housing stock, a large reliance on fossil fuels, and the spike in energy prices put even more people at risk of not being able to pay their bills and not be able to sufficiently heat their homes in the winter. While local governments in principle have the tools to help households through the energy transition, many councils lack coordination, information, and administrative capacities to do so effectively. These constraints became particularly salient during the energy crisis, when local governments had to respond quickly to sharply increasing energy costs. Retrofitting residential houses can reduce exposure to such shocks by lowering energy consumption, reducing reliance on fossil-fuel heating, and thus shielding households from future price volatility.

Because retrofit decisions are made by households, most policies, public programs, and scientific studies have focused on household-facing interventions like audits (Gillingham and Tsvetanov, 2018), subsidies (Boomhower and Davis, 2014; Holladay et al., 2019; Houde and Aldy, 2017), nudges (Allcott, 2011; Allcott and

Rogers, 2014; Allcott and Kessler, 2019), or information treatments (Papineau and Rivers, 2022). While this bottom-up approach is natural, it leaves political and institutional barriers underexplored. If households face barriers related to information acquisition, coordination, knowledge of local support, or trust, interventions that reach political actors who can legitimise and transmit information locally can be more effective than those targeted at individuals.

Local political actors in the UK are well-suited as a target for such interventions. They regularly communicate with the population in council hall meetings, by going door-to-door, or at public events. They can use these exchanges to diffuse ideas, connect households to relevant suppliers of retrofit technologies, activate local media, or simply make retrofitting a salient local topic. Similarly, they are locally embedded members of their community. They can transmit information through their neighbourhood networks, constituency-level casework, or party networks. This makes councillors and council workers a potentially relevant target for an informational treatment on climate action.

This paper tests whether disseminating tailored academic findings to local political and administrative actors can influence local energy savings policies. To do so, we ran a field experiment in November 2022 providing information via email to councillors and council workers in 329 randomly selected local authorities across England and Wales. The recipients in treated councils received tailored briefs on the potential savings in consumption and monetary terms that could arise from retrofitting homes in their constituencies. These briefs leveraged data from energy performance certificates (EPCs) to estimate the maximum attainable savings if a home upgrades to its highest potential (Fetzer et al., 2024b). First, we evaluate the immediate impacts of our information treatment on hard outcomes concerning the energy crisis using data on retrofit installations and energy consumption at the address and postcode level, respectively. Second, we study the political dimensions, like party affiliation, behind the engagement with the brief to understand which actors responded to the information and use councillors' residential locations to study whether and how the information treatment diffused from politicians to households.

We find that our outreach increased retrofit installations in treated authorities by 7% relative to the mean, corresponding to an increase of approximately one additional installation in an average local authority. This effect is statistically significant and robust across different specifications, spatial aggregations, and a randomisation-inference exercise. The increase is mainly driven by installations of solar panels. We do not detect, however, a statistically significant reduction in energy consumption in treated local authorities, which is perhaps unsurprising given the size of the retrofit installation response. Nevertheless, the results show that a low-cost information intervention targeted at local political and administrative actors affected realised investment behaviour, not only engagement with the brief or stated interest.

We then ask who engages with our information treatment and how the treatment may have diffused from politicians to households. We leverage information on whether councillors read the brief or even responded by getting in touch with our team. At the local authority level, richer authorities are less likely to engage. When looking at councillor level engagement, councillors from the Liberal Democrats and independent councillors are especially likely to engage with the information treatment. Using information on councillors' residential addresses, we find that the increase in retrofitting is highly localised in the immediate vicinity of councillor homes with no detectable spillovers to neighbouring areas. This is consistent with a highly local diffusion mechanism.

This paper contributes to five strands of the literature. First, we provide novel evidence on the determinants of the energy-efficiency gap, which studies why households underinvest in energy-efficiency upgrades despite their potential private and social benefits. The explanations of the existence of this gap range from behavioural frictions, market failures, adoption costs, or imperfect information (Allcott and Greenstone, 2012; Gerarden et al., 2017). These frictions and failures might explain why the realised savings from energy-efficiency programs often are below projected savings and the low take-up of these programs (Christensen et al., 2023; Fowlie et al., 2018). We add to this literature by shifting the focus from the household alone to the local political and institutional environment surrounding household decisions. Local political actors can lower informational barriers, leverage their roles as spokespersons for a constituency, or increase trust among the population, which might result in more households retrofitting their homes. While we cannot disentangle each of these mechanisms separately, we provide evidence on the role of political actors in diffusing the information treatment.

Second, we extend the literature studying energy-efficiency interventions that target households directly via information treatments, nudges, audits, or subsidies. Allcott (2011) and Allcott and Rogers (2014) show how home energy reports can incentivise households to consume less energy with the effect decaying over time. Similarly, Papineau and Rivers (2022) show that small nudges via heat loss visualisations and personalised information can induce changes in energy consumption. However, these effects from conservation nudges are not uniformly distributed: responses vary substantially in line with political leaning and affiliation, highlighting the role that political economy plays in this decision (Costa and Kahn, 2013). Lastly, Holladay et al. (2019) document a significant effect of both nudges and prices on energy audits, but not on retrofit installations. This body of academic work has focused on a bottom-up approach targeting households directly, while we add to this by implementing a top-down approach where we nudge local political actors to improve energy efficiency in their constituency via a locally tailored information treatment.

Third, a growing literature asks whether and how policymakers respond to evidence and if researchers can influence the policymaking process directly. Hjort et al. (2021) show evidence that politicians actually demand research evidence and that informing them about the effects of a policy makes them more likely to adopt it. Related, Pereira et al. (2024) study climate action policies and support for them. They show that politicians' responsiveness crucially depends on source credibility, their electorate and the policy's time horizon. This is in line with evidence by Ambuehl et al. (2023) who highlight the role of trade-offs that politicians face and how their welfare criteria can differ from technocratic benchmarks. Lastly, Geys and Sørensen (2018) and Nielsen (2014) provide evidence that local politicians and local bureaucrats react to information provided by academics. In contrast to the existing literature, our intervention does not include evidence recommending a direct policy that politicians can implement. Instead, our focus is on the role of politicians in disseminating information, increasing trust, or reducing informational barriers via their role as public bodies.

Fourth, we contribute to a nascent literature studying the role of state capacity and informational boundaries in the energy transition. Fetzer et al. (2024a) argue that state capacity is not only fiscal or in terms of bureaucratic capacity, but that there is an important informational component too. The ability to collect, process, and efficiently use granular information helps governments respond quickly to crises. Feld and Fetzer (2024) show how reduced state capacity, both in fiscal and informational terms, hindered local governments in England from effectively carrying out a nationally planned but locally administered climate action policy. We add to this literature by shedding more light on how local political actors handle new information that can help them saving energy.

Fifth, we add to the scientific body of work that analyses local embeddedness of politicians in their neighbourhood or jurisdiction. Local roots matter in the the election of candidates (Campbell et al., 2019) but also in subsequent policy outcomes like the allocation of local public goods (Harjunen et al., 2023) or the responsiveness to citizens' complaints (Kovarek, 2025). We show that also our information treatment works at a highly localised spatial scale around councillors' residential homes.

This paper proceeds as follows: In section 2, we present the intervention. In section 3, we introduce the dataset, before we present our main results on retrofit installations in section 4. In section 5, we show evidence on the engagement of local political actors, and in section 6, we analyse how the treatment diffused from recipients to households. Lastly, we conclude in section 7.

2 Experimental design

In November 2022, we conducted a randomised control trial (RCT) that carried out tailored outreach to randomly selected local governments and local media at the local authority district (LAD) level. We randomized the treatment across 329 Local Authorities, resulting in 165 treated local authorities. The outreach was in the form of an email that was sent to local councillors, local council workers and local media outlets in treatment local authorities. The email header read "New research: How will the energy crisis affect households in *Local Authority XY*?".

First, the body of the email contained results from an analysis of the impact of the energy crisis on households in that local authority, characterizing the needs of the local population in terms of energy expenditures. Second, the email suggested ways to save energy and estimated the average savings potential in that local authority in monetary and energetic terms, characterizing the energy efficiency investments that would lead to the largest savings. Third, the email linked to a 12-page brief with additional in-depth analyses and estimations. Specifically, the brief contained information on average increases in energy bills for the whole local authority, as well as along the empirical distribution of energy consumption, how energy saving measures can help fight climate change, the impact of energy saving installations on EPC ratings and other energy efficiency outcomes, and lastly on concrete steps individuals and local politicians can take to improve their energy efficiency.

At the end of the email, we outlined concrete, albeit non-tailored, steps local governments could take to facilitate take-up of energy efficiency investments that can reduce both energy use (thus alleviating the impacts of the energy cost crisis) and fossil fuel consumption (thus alleviating the impacts of pollution and climate change) in the residential sector. We also included contacts to get in touch with our team, offering to help identifying barriers to take-up of energy efficiency installations, as well as designing and testing programs to overcome those barriers. An example of such an email for the local authority of Darlington can be found in appendix section C.1 and of the respective brief in appendix section C.2.[1]

As part of our randomised evaluation, each council in our sample was assigned to one of two roughly equal-sized experimental groups: Treatment (outreach) or Control (no outreach). When randomising local authorities, we stratified on the following variables: availability of council contacts, availability of local media contacts,[2] an indicator for local elections being held in 2023, energy savings potential, energy performance certificate (EPC) coverage, an indicator for being located in England as opposed to Wales, and coverage by supra-regional media. First, having contacts for council administrators might make our outreach more powerful by reaching individuals with executive power. Similarly, having contacts for local media and having media that cover a district specifically, vs. multiple, might affect

[1]The Financial Times published an infographic with an analysis similar to the one in the brief which can be accessed here. These analyses are based on methods and findings published in Fetzer et al. (2024b).

[2]We compiled a list of local media sources from existing media contacts at the University of Warwick and web searches.

the reach and thus impact of our treatment; we do not have media contacts for 51 councils. Second, whether there will be a council election in 2023 might affect the ability of current officers to act or whether a party might want to include energy efficiency in their campaigns. Third, we anticipated that our outreach might have more substantial effects in areas with higher savings potential. Fourth, whether the council is below the median coverage of energy performance certificates relative to homes registered for council tax purposes affects the precision of the estimates included in our outreach. Finally, whether the council is in England is significant due to the institutional differences between England and Wales, including variations in fuel prevalence, which could affect the impact of our outreach campaign.

Table 1 reports randomisation balance across several variables of interest for heterogeneity analysis that we did not stratify on. These variables include average household income, population, homeownership rate, and the number of Ukrainian refugees who had arrived by the time of randomisation, given the connection between the war in Ukraine and energy prices. Furthermore, we examine indicators of whether the council is controlled by the Labour Party, the Conservative Party, another party, or if there is no overall control.

Exhibit 1: randomisation balance

(Table 1)

Table 1 shows that the treatment and control groups appear balanced in terms of almost all variables: local authorities in the control group are, on average, larger and host more Ukrainian refugees than those in the treatment group. To account for this, we will control for the general population and the Ukrainian refugee population in our analysis. Our randomisation procedure breaks ties within strata in favour of treatment assignment. Thus, there is one local authority more in the treatment group than in the control group.

3 Data

This project uses several data sources to obtain 1) important covariates for stratification and balancing and 2) key outcomes of interest. First, we study the effect of the outreach intervention on energy-saving measures. We interpret this as a direct outcome of the treatment. Second, we examine how local politicians and media engaged with the outreach materials. For each part of the analysis we use a separate set of variables and different levels of aggregation. We describe these data sources in detail below.

3.1 Stratification and balancing variables

To account for the energy efficiency of residential properties across local authorities, we use data from Energy Performance Certificates (EPC) provided by the UK Ministry of Housing, Communities & Local Government. EPCs assign a rating from A (most efficient) to G (least efficient) and include estimates of anticipated energy costs based on scores from 1 to 100. Since 2007, the requirement for buildings to have an EPC initially applied to houses for sale but was later extended to include all domestic and commercial properties (UK Government, 2012). The EPC data is at the property level and includes the EPC rating, hedonic characteristics such as floor area or the number of rooms, as well as consumption and monetary savings potentials derived from suggestions to improve the energy efficiency of a house. From this data, we compute two variables. First, as not every property has an EPC, we calculate EPC coverage by dividing the number of properties in a local authority that have an EPC by the total number of properties in a local authority as reported in council tax data. Second, we use the combined consumption savings potentials.[3] We discretise these measures into above or below median EPC coverage and above and below median savings potential, and we stratify our randomisation on these indicators.

Furthermore, we stratify on a binary variable indicating whether we have media contacts in a local authority, where these contacts were collected manually by web searches and combined with an existing list of media contacts from the University of Warwick, as well as coverage by supranational media, availability of council contacts,[4] hand-collected information on whether a local election was going to taking

[3]This measure is taken from Fetzer et al. (2024b) and is defined as the difference in actual and potential energy consumption combining space heating, hot water generation, and electricity use for lighting. The potential level refers to the energy consumption that would be expected if the energy-efficiency improvements recommended in the EPC were implemented.

[4]We acquired contacts of local officials and local council members from Oscar Research, a commercial data provider.

place in 2023, and an indicator for being in England as opposed to Wales to capture systematic differences in the two regions.

In addition, we explore heterogeneity and balance with respect to the following characteristics. We use population and home ownership data from the UK 2021 census, average household income from the Office for National Statistics small area income estimates, and the number of Ukrainian refugees an authority hosts from the Home Office. Also, we study heterogeneity in treatment engagement with respect to the political party controlling the local authority council. Council control is divided into Labour party councils, Conservative party councils, other control councils, and no overall control councils as measured in the proprietary Oscar Research data.

3.2 Energy efficiency installations

We are interested in whether sending out policy briefs to councillors, council workers, and media outlets increases energy efficiency investments in treated local authorities. To do so, we use data on energy efficiency installations, provided by MCS, a large UK firm that certifies low-carbon installations. The data covers a significant and representative proportion of retrofitting installations in the UK for the period November 2022 – May 2024, and is at the address level. In our main analysis, we focus on the subset of properties that ever had an MCS-registered installation, as not all installers might report to MCS. We present results for the full set of properties in the appendix. For every retrofitting installation carried out, the data records a variety of installation characteristics. Among them, and most important for our study, the type of technology, the cost of installing, and the installation type (either domestic or commercial use). Using the address postcode, we aggregate the number of installations over all types at the local authority and quarter-year level, as well as at the lower layer super output area (LSOA)[5] and quarter-year level. Then, we create two outcome variables: the natural logarithm of the total retrofitting installations, capturing the intensive margin, and a binary indicator equal to one if we record at least one installation in a given area (LAD or LSOA) and quarter-year observation and zero otherwise, capturing the extensive margin.

[5]LSOAs are statistical spatial units in the UK aggregated from census blocks to be comparable in terms of population. They host on average 1,500 inhabitants.

Energy consumption We gather information on energy consumption at the postcode level from the Department for Energy Security and Net Zero (DESNZ). The data reports total, mean, and median gas and electricity consumption in kWh for each postcode in the UK from 2013 – 2023. Additionally, the data provides information on the number of electricity meters per postcode area, which we treat as a proxy for the number of households. The data reports information for all postcodes that are not identified as disclosive to comply with privacy laws.[6] We create a "per household" measure of energy consumption by adding up total gas and electricity consumption and dividing by the number of domestic electricity meters in a postcode.

3.3 Measuring engagement with outreach

We employ different measures to examine whether and how local politicians and local media outlets react to information provided by researchers.

Local media engagement As for the media, we manually collect newspaper articles that report about our information treatment with the help of Google Alerts and the University of Warwick communications team. If the media outlet is clearly identifiable as a local newspaper it is assigned to the respective local authority. In cases of trans-regional or national media outlets reporting about the research, we classify them as national and do not use these media engagements in our analysis. From this manually collected list of media mentions, we create a binary indicator at the local authority level that equals one if a media outlet in that local authority reported about the brief and zero otherwise.

Local politicians' engagement To construct measures of local politicians' engagement we start from individual-level data, which we either aggregate to the local authority level or use at the individual level. We measure the engagement of local councillors and council officers – employees of the councils – with our treatment in

[6] A postcode is considered disclosive if it contains fewer than five domestic electricity or gas meters, or if the two highest-consuming meters together account for more than 90% of the postcode's total energy consumption.

three different ways. We create an extensive margin measure *Email read*, an intensive margin measure *Clicks*, and another binary measure *Engaged*.

The first two measures *Email read* and *Clicks* contain information on whether and how many times the policy brief with the extensive additional information on energy saving potential and retrofitting installations we sent to a given councillor or council officer was opened. To track whether recipients opened the briefs, we generated a unique link to the policy brief that contained an individual identifier. Recipients could only see a generalised link and were thus not aware of this identifier. The log files of the website where the briefs were stored record every time someone clicked on one of the links we sent out. Crucially, the log files provide information on the link via which the website was accessed. Thus, we are able to extract the unique identifier associated with the recipient of the link from which the ping in the log file originated. This way, we create the binary indicator *Email read* that equals one if we record at least one click from a given councillor and zero otherwise, and an intensive margin variable, *Clicks*, measuring the number of times the link associated with a given councillor was clicked on. We count the clicks for the period 19 December 2022 to 15 January 2023. In the individual-level engagement analysis, we use these measures, while at the local authority-level we calculate the share of links that were clicked on at least once by summing the individual-level variable that indicates whether a given personalised link was clicked over all recipients in a local authority and dividing this by the number of recipients in that local authority. We construct this measure separately for every type of recipient, councillor, council officer, and media contact.

Lastly, we create another binary variable, *Engaged*, for which we use information on email replies to our treatment. Our emails and briefs explicitly invited recipients to contact us for support with implementing energy-saving programs or for more information. Hence, we collect data on whether someone got in touch with us asking for help, more information on the treatment, or a meeting. We record this engagement by manually classifying all emails we received between 19 October and 9 November 2022 using the header and body of the email into whether it was genuine human engagement. This classification is necessary to exclude bouncebacks from emails that could not be delivered and auto-replies like out-of-office notifications, or confirmation of reception.

To study heterogeneity in engagement at the councillor level we use information on the party affiliation of each councillor – and if available – of council officers. As the Oscar Research data does not provide information on a councillor's party affiliation, we use data from the Local Elections Archive Project (LEAP). The data spans all local elections in the UK from 2002 onwards and has information on the candidate name, council, ward, and party, as well as election outcomes. Using the information on councillors' names, wards and councils, we match this dataset with the councillor-level Oscar Research data employing a Large Language Model. In cases where we observe the same councillor being affiliated with different parties, for instance because they switched parties, we keep only one councillor-party observation based on a random draw. Thus, each councillor's party affiliation can be interpreted as their party affiliation at a randomly selected point in time, acknowledging that this may not always reflect their most recent or longest-held affiliation. As we are interested only in the major parties, we code every councillor that does not belong to the Labour Party, Conservative Party, Liberal Democrats, Green Party, Independent Party, or UKIP as *Other party*.

Final datasets From these data sources, we construct different datasets for each part of the analysis – the estimation of the treatment effect on energy savings installations and the engagement analysis. To analyse the impact of the outreach on energy efficiency installations, we build four datasets that differ in the level of spatial aggregation. The first is at the Local Authority District (LAD) level, which represents local governments in the UK and is the unit of randomisation. The other three are at lower spatial scales using statistical units called Output Areas (OA), Lower Layer Super Output Areas (LSOA), and Middle Layer Super Output Areas (MSOA). These are aggregations from UK census blocks that are constructed such that each area is approximately comparable in terms of population size. OAs have an average population of 320 people, LSOAs of 1,700, and MSOAs of 8,200. We use these datasets at a more granular spatial scale for two reasons: First, we analyse how robust our results are to different spatial levels. Second, we study how the treatment diffused from councillors to the general population. Both datasets are at the quarter-year level and have variables on treatment status and the number of energy efficiency installations in total and disaggregated by type of installation. For the second part of the analysis, where we study who engages with the outreach, we have one dataset at the LAD level that contains LAD characteristics discussed above, as well as engagement outcomes aggregated at the local authority level. The second dataset is at the councillor level to study individual responses to the outreach.

4 Effect of outreach on energy saving measures

In the first part of our analysis, we focus on the impact of the information treatment on the installation of energy-saving measures. We estimate five difference-in-differences regression models differing in the levels of fixed effects we include. The most basic regression model we run, which does not include any fixed effects, is the following:

$$y_{it} = \beta_0 + \beta_1 D_i + \beta_2 Post_t + \beta_3 (D_i \times Post_t) + \sum_{t=2021Q1}^{2024Q1} \gamma_t \tau_t \cdot \mathbf{X_i} + \epsilon_{it} \tag{1}$$

where we regress the outcome y_{it}, measuring the intensive and extensive margins of retrofitting installations of local authority i in quarter-year t, on the interaction of the treatment status D_i that equals one for a treated local authority i and zero otherwise, and a binary indicator $Post_t$ being one for every quarter-year t after the third quarter of 2022 when we sent out the emails. The coefficient of interest is β_1, which captures the causal effect of our information treatment on retrofitting installations after we sent out the treatment. As we observe a slight imbalance in terms of population and the number of Ukrainian refugees hosted, we flexibly control for interactions of these variables – captured by $\mathbf{X_i}$ – with quarter-year dummies τ_t. Standard errors are clustered at the local authority level, the level of treatment assignment. Alternatively, we run this specification at the LSOA instead of the LAD level. Although this does not give us more variation in the treatment status – which varies at the LAD level – we get more power by increasing the sample size.

In addition, we run alternative specifications that control for increasingly stringent fixed effects. To control for differences across local authorities that are time invariant, we include local authority fixed effects in a next step in column (2). In a third specification, in column (3), we include strata fixed effects to evaluate only the variation within each stratum. In column (4), we add a quarter-year fixed effect to control for any time-specific shock that affects each local authority to the same extent. Lastly, in column (5), we allow for strata-specific time trends to take strata-specific shocks into account.

In table 2 we present the results of this regression. In both panels, the analysis is at the local authority level. In panel A, the dependent variable is the (log) number of total installations, while in panel B, we focus only on the total number of solar installations. We expect the effect to be driven by solar installations as these are the most common type of small scale retrofit installations in the UK (MCS, 2026). Across all columns in panel A, the estimated β_1 is similar in terms of size, positive, and statistically significant at the 10% significance level. These results suggest that informing local governments and local media about the expected costs of the energy crisis and the savings potential in their jurisdiction increases the number of retrofitting installations in treated authorities in the six quarters after the treatment was sent. The log number of installations increased by 0.0678 - 0.0763, implying an increase of roughly one additional installation in an average local authority. This translates into an increase of 7.02% - 7.9% over the mean.[7] Panel B of table 2 shows the estimated coefficients for the same specification but with only solar PV installations as the outcome. The results are largest and most precisely estimated for solar PV installations, suggesting that this type of installation accounts for a substantial share of the overall pattern. In appendix tables A1 – A4, we present results for a number of further regressions where we change either the spatial unit of observation from MSOA, LSOA, OA, to property level and/or the dependent variable, looking at an extensive margin measure equal to one if an area saw any new installation. As we would expect, the results show that the extensive margin becomes more important at lower spatial levels. Most LADs will have seen some new installation somewhere, so the binary indicator is not informative. This becomes more important when comparing neighbourhoods or even properties. Appendix figures A3 – A6 show event study plots for the most stringent specification 1 with LAD and strata x quarter-year fixed effects. The effect of the information brief kicks in almost immediately, in the first or second quarter after the treatment was delivered, and then vanishes afterwards. Given that our results are primarily driven by solar

[7] As this regression is a log-linear specification, we get to these numbers by plugging in the estimated coefficients into the exponential function e^x.

PV installations, this is in line with information by suppliers on the timeframe for solar PV installations, which varies between four to eight weeks.[8]

Exhibit 2: Treatment effects on retrofit installations

(Table 2)

However, due to the small number of clusters, the data obtained from the RCT does not meet the required assumptions that asymptotic theory is based on (Young, 2019). To show robustness to this issue, we perform a randomisation inference exercise. Randomisation inference was introduced by Fisher (1935) and later further elaborated upon by Rosenbaum (2002). It allows us to test precise hypotheses by computing a distribution of a test statistic under said hypothesis. The beauty of randomisation inference is that it computes a precise test regardless of the sample size, the specification of the regression, or the distribution of the error term.

In practice, we re-randomise the treatment for 20,000 iterations to create a distribution of treatment effects and compare our true treatment to those. In a first step, we randomise a placebo treatment within each stratum discussed in section 2. Then we run our main specification with log number of installations from table 2 column (5), i.e. equation 1 with LAD and strata $\times$ quarter-year fixed effects. For every permutation we extract the coefficient of interest β_1 and re-run this procedure 20,000 times. Figure 1 shows the cumulative distribution function of these coefficients. The vertical line in red represents our true treatment effect. It intersects the cumulative distribution function (CDF) of the placebo treatment effects at a value of 0.96905. In other words, the effect we estimate for our true treatment lies within the top 5% of placebo treatments, reassuring us that it is not likely due to chance only.

Exhibit 3: Robustness – Permutation test

(Figure 1)

Impact on Energy Consumption After looking at the effect of the information treatment on energy savings installations, it is only natural to study energy consumption itself. We rely on the postcode-level data on energy consumption per

[8] https://samsoenergy.co.uk/how-long-does-it-take-to-install-solar-panels, https://heatiq.co.uk/article/solar-panel-installation-timeline-what-to-expect-from-start-to-finish

domestic meter, which we aggregate to the local authority district level, at which we randomised our treatment. We run the same regression at the local authority level as in equation 1, just with energy consumption per meter as the dependent variable. Table A6 displays the resulting treatment effects of this regression and shows a very precise null-effect of our information treatment on energy consumption per meter.

We speculate that there are at least two explanations that can explain this null effect on energy consumption. First, there might be a rebound effect of solar panel adoption, a behavioural effect, such that households, in expectations of lower energy bills due to the solar PV installation, shift their energy demand curve upwards, yielding a zero net effect of solar PV (Aydın et al., 2023). Second, the aggregate energy-consumption data do not reveal whether energy generated by newly installed solar PV systems is consumed by the installing household, exported to the grid, or consumed outside the LAD. Consequently, an increase in local solar PV generation need not produce a detectable change in measured LAD-level domestic energy consumption, which may help explain the null effects in these outcomes. Finally, we note that even if we were to observe savings from switching to solar-powered energy directly, a back-of-the-envelope calculation suggests that the effect would not be economically significant. In treated areas, we observe one additional installation in a quarter after the treatment happened. MCS states that an average solar PV system working at peak capacity generates 3,700 kWh of electricity per year, which is 925 kWh per quarter. Given that we have about 79,000 meters in an average LAD, the electricity saving effect that we would be able to detect amounts to 0.011 kWh per meter. Thus, the data provide no evidence of a detectable reduction in aggregate electricity consumption, which is consistent with the effect being too small to observe at the LAD level

5 Who engages with the information treatment?

With our information treatment, we test whether it is possible to spur local action by providing politicians and media outlets with information; similar to previous research (Hjort et al., 2021; Pereira et al., 2024). Furthermore, we are interested in who engages with it. To this end, we collect data both at the council level and at the individual councillor level as described in section 3. The analysis in this section is correlational.

Council level evidence We create a local council-level dataset to correlate local engagement with local authority characteristics. At the council level, we measure engagement with the share of emails read, that is, the sum of instances for which the binary indicator *Email read* equals one divided by the total emails sent to each local authority. We construct this measure for each recipient type, i.e. councillors, council officials, and media contacts. Then we run the following regression

$$EmailsRead_c = \alpha + \mathbf{X_c}'\beta + \varepsilon_c \tag{2}$$

where **X** is a vector of covariates that includes binary indicators for savings potential below median and EPC coverage below median, population, household income, ownership share, share of Ukrainians hosted, whether there was an election in 2023, and binary indicators for conservative council control, labour council control, and other council control where the left out category is no overall council control. Evidently, we can perform this analysis only for the subsample of treated local authorities. For the analysis on media recipients only, the sample is even smaller, as we don't have media contacts for every local authority.

Table 3 presents the results of this regression. Two clear overall patterns of engagement at the council level emerge. First, average household income in the local authority is negatively related to the total share of emails read, overall and separately by councillors and council officials. For politicians, a one standard deviation increase in average household income is associated with a decrease of 15 percentage points in the share of emails read. For council employees, an average increase in an authority's household income of one standard deviation translates into a 12 percentage point lower share of emails read. These are decreases of 26% and 19% over the mean, respectively. Second, the share of Ukrainians who migrated to a local authority after the Russian invasion of Ukraine is positively and statistically significantly related to the engagement of recipients with the information brief in that authority. The engagement rate of councillors is associated with an increase of 1.1 percentage points for every additional Ukrainian refugee and by 1.3 percentage points for council employees. A last remarkable fact is that for media outlets, the share of emails read does not correlate with any of the covariates: the estimated coefficients are smaller than those estimated for the other recipient types.

Exhibit 4: Heterogeneity by local authority characteristics

(Table 3)

Councillor-level evidence At the councillor level, we compiled a dataset using information on engagement outcomes from our email replies and log files, combined with data on party affiliation by the Local Election Archive Project and overall council control. In this analysis, we regress the three engagement variables measuring the extensive margin of reading the email, the intensive margin of the number of clicks on the brief, and a binary measure of getting into contact with us on dummy variables of party affiliation. That is we run the following regression:

$$\begin{aligned} y_p = \alpha + \beta_1 Labour_p + \beta_2 Libdem_p + \beta_3 Green_p \\ + \beta_4 UKIP_p + \beta_5 Indep_p + \beta_6 Other_p + \varepsilon_p \end{aligned} \tag{3}$$

where $Labour_p$, $Libdem_p$, $Green_p$, $UKIP_p$, $Indep_p$, and $Other_p$ are binary variables for councillor p being a member of the Labour party, the Liberal Democrats, the Greens, UKIP, independent councillors, or any other party members. The reference category is Conservative Party members. y_p is one of the outcomes named above and ε_p is an idiosyncratic error term.

Politicians from different parties might be differentially likely to engage with our outreach and to take action depending on the political power balances they are facing in their local authority. On one hand, politicians of parties that are in the minority or opposition might have greater incentives to take action in order to distinguish themselves, especially if an election is upcoming. On the other hand, their propensity to engage and act might be lower if the majority party would obstruct change. To test which of these effects dominates empirically, we run the regression in (3) for two different samples: councils that are controlled by the Labour party and councils that are controlled by the Conservative party.

Table 4 displays the results of these three sets of regressions. One clear pattern emerges regarding the engagement behaviour of councillors from the Green

Party. No matter whether the council is controlled by the Labour or Conservative parties, or whether there is no control at all, Green politicians are significantly more likely to engage and are engaging more intensely with the information brief than Conservative councillors (who serve as the reference group).[9] We observe the highest difference in the propensity to engage with us for Green councillors in Labour-controlled councils. By contrast, Labour councillors in Conservative control councils appear to be statistically significantly less likely to read the information brief than Conservative councillors in the first place. Another interesting pattern arises for councillors from the Liberal Democrats and for independent councillors. They are more likely to engage with our outreach, compared to Conservative councillors, in two out of three engagement measures in both Labour and Conservative dominated councils, however, less likely in councils without overall control. Similarly, vis-à-vis Conservative politicians, members of other parties are more likely to engage in Labour dominated councils but less likely to engage in councils without overall control.

One possible explanation for this pattern might be that party council control defines the political returns to engage with evidence from researchers. In councils controlled by the Labour or Conservative Party, Liberal Democrats and independent councillors might have interests to use the evidence to distinguish themselves from the party in power. This can signal responsiveness to locally salient topics.

Exhibit 6: Heterogeneity by party affiliation and council control

(Table 4)

6 How does the information treatment diffuse from politicians to the population?

So far, the question remains as to how our treatment, which targeted politicians, council workers, and media, led to households undertaking retrofits. One hypothesis is that politicians talked to their neighbours after reading the brief, spreading

[9]This result is confirmed in appendix table A11 where we present the results for regression 3 for the full sample without splitting into different council controls.

information on the benefits of retrofitting. To test this hypothesis, we conduct a heterogeneity analysis using information on councillors' home addresses and their party affiliation. We start with a list of councillors' residential postcodes and link them to 2021 Output Areas (OAs), Lower Layer Super Output Areas (LSOAs) and Middle Layer Super Output Areas (MSOAs) using the official postcode to geography lookup. This allows us to aggregate the councillors' residences to our main analyses' units of observation. Our main variables of interest are an indicator equal to one if at least one councillor lives in the area (extensive margin) and a count of the number of resident councillors (intensive margin).

We then use these variables to test whether our treatment effects are larger in places where councillors reside. That is, we run the following equation

$$Y_{iat} = \beta_1 \left(\text{Post}_t \times \text{Treat}_a \times C_i\right) + X'_{at}\gamma + \alpha_i + \lambda_{\text{Treat}_a t} + \mu_{C_i t} + \varepsilon_{iat} \qquad (4)$$

where we regress the number of new retrofit installations in small area i, authority a, and quarter-year t on a triple interaction of the treatment indicator, the post indicator, and one of the councillor residence measures. In addition, we include small-area fixed effects, as well as treatment-by-quarter-year fixed effects to control for common time trends across all treated units, and councillor-residence-by-quarter-year fixed effects, which alleviate concerns that councillors live in richer areas that, in general, have more resources to install retrofit upgrades. The coefficient of interest β_1 captures whether OAs in treated authorities with a resident councillor saw a different post-intervention change in retrofit installations than OAs in treated authorities without one. Lastly, we again include the interactions of quarter-years with population and the number of Ukrainian refugees as control variables.

Table 5 reports the results of these regressions for all three levels of small areas (OA, LSOA, and MSOA) for the resident councillor indicator as the main mechanism variable. The results are statistically indistinguishable from zero for the regressions at the LSOA and MSOA level. However, for the smallest statistical area, we detect a marginally statistically significant positive effect indicating an increase of one percentage point in the likelihood that we observe a new installation in an area where a councillor lives. We expect the effect of resident councillors to play out at a very local spatial scale. If councillor residence matters because they are more visible or have more information about nearby households or talk to their neighbours, then we should see the effect of the treatment to concentrate in the immediate vicinity of their homes. Aggregating to LSOAs or MSOAs would wash out this variation by combining households located close to councillors and households living too far away to be meaningfully exposed to them. Such aggregation may introduce measurement error into the exposure variable, which weakens the proposed relationship.

This interpretation motivates a further empirical investigation. If the relevant mechanism is local proximity, the effect may not stop exactly at the OA boundary. Thus, we consider whether the local exposure spills over to neighbouring areas. We construct three spillover variables: an indicator variable for whether at least one neighbouring OA is home to a councillor, an intensive margin variable counting the number of adjacent OAs with resident councillors and the share of neighbouring OAs with councillor residences. We interact these variables again with the post and treatment indicators as shown in the regression equation below, where S_i is one of the three spillover measures that we are using.

$$Y_{iat} = \beta_1 \left(\text{Post}_t \times \text{Treat}_a \times C_i\right) + \beta_2 \left(\text{Post}_t \times \text{Treat}_a \times S_i\right) + X'_{at}\gamma + \alpha_i + \lambda_{\text{Treat}_a t} + \mu_{C_i t} + \nu_{S_i t} + \varepsilon_{iat} \tag{5}$$

While the ceteris paribus interpretation of β_1 is the same as before, β_2 captures whether treatment effects extend beyond councillor residence areas into neighbouring OAs.

We present the results of this regression in table 6. On all three spillover variables, the coefficients are small and statistically insignificant. If anything, the effect in neighbouring areas seems to be negative. This reinforces the interpretation that our information treatment played out at a highly local spatial scale, potentially clustering only around the treated councillors' own homes.

We interpret the results of this heterogeneity analysis as suggestive evidence on a potential diffusion channel rather than a separate causal estimate of councillor-to-household diffusion. Councillors' residence locations are not randomly assigned, and the interaction terms should therefore not be interpreted as isolating only direct communication from councillors to nearby households. Still, our specification absorbs general quarter-specific differences between councillor-residence and noncouncillor-residence areas through the $C_i \times t$ fixed effects, as well as quarter-specific differences by spillover exposure through the $S_i \times t$ fixed effects. The identifying variation therefore comes from whether areas associated with treated councillors change differentially after treatment relative to comparable areas associated with control councillors.

A remaining concern is that the treatment may be more likely to diffuse through other channels in the places where treated councillors live. For example, households near treated councillors may become attentive to council politics, more connected to local civic or party networks, or more likely to receive information through neighbourhood groups, local media, or online communication due to initiatives spurred by the treatment. In that case, the estimated coefficient would still capture geographically concentrated diffusion of the treatment, but not necessarily direct councillor-to-household communication. Conversely, the coefficient could be attenuated if councillors transmit information outside their own residential areas, for instance through council meetings, online channels, party networks, or ward-level activities. We therefore interpret the estimates as evidence consistent with a highly localised diffusion mechanism, while remaining cautious about attributing the pattern exclusively to direct interpersonal diffusion from councillors to their immediate neighbours.

Exhibit 7: Heterogeneity by councillor residence

(Table 5) (Table 6)

7 Conclusion

In this paper, we study if and how locally tailored information sent to local political actors increases their constituencies' energy efficiency. We carried out an information intervention in November 2022, providing local councillors and council workers with tailored evidence on the distributional impact of the energy crisis and how retrofitting homes in their authority can help to cushion the effects of this shock. Using a randomised field experiment across local authorities in England and Wales, we find that treated authorities see a significant increase in retrofit installations. We do not find any impact on energy consumption. The effects are highly localised around councillors' residential addresses.

References

Allcott, Hunt, "Social norms and energy conservation," *Journal of Public Economics*, October 2011, *95* (9-10), 1082–1095.

— **and Judd B. Kessler**, "The Welfare Effects of Nudges: A Case Study of Energy Use Social Comparisons," *American Economic Journal: Applied Economics*, January 2019, *11* (1), 236–276.

— **and Michael Greenstone**, "Is There an Energy Efficiency Gap?," *Journal of Economic Perspectives*, February 2012, *26* (1), 3–28.

— **and Todd Rogers**, "The Short-Run and Long-Run Effects of Behavioral Interventions: Experimental Evidence from Energy Conservation," *American Economic Review*, October 2014, *104* (10), 3003–3037.

Ambuehl, Sandro, Sebastian Blesse, Philipp Doerrenberg, Christoph Feldhaus, and Axel Ockenfels, "Politicians' Social Welfare Criteria An Experiment With German Legislators," 2023. Institution: American Economic Association.

Aydın, Erdal, Dirk Brounen, and Ahmet Ergün, "The rebound effect of solar panel adoption: Evidence from Dutch households," *Energy Economics*, April 2023, *120*, 106645.

Boomhower, Judson and Lucas W. Davis, "A credible approach for measuring inframarginal participation in energy efficiency programs," *Journal of Public Economics*, May 2014, *113*, 67–79.

Campbell, Rosie, Philip Cowley, Nick Vivyan, and Markus Wagner, "Why Friends and Neighbors? Explaining the Electoral Appeal of Local Roots," *The Journal of Politics*, July 2019, *81* (3), 937–951.

Christensen, Peter, Paul Francisco, Erica Myers, and Mateus Souza, "Decomposing the Wedge between Projected and Realized Returns in Energy Efficiency Programs," *Review of Economics and Statistics*, July 2023, *105* (4), 798–817.

Costa, Dora L. and Matthew E. Kahn, "Energy Conservation "Nudges" and Environmentalist Ideology: Evidence from a Randomized Residential Electricity Field Experiment: Energy Conservation "Nudges" and Environmentalist Ideology," *Journal of the European Economic Association*, June 2013, *11* (3), 680–702.

Department for Business, Energy & Industrial Strategy, "Heat and Buildings Strategy," Technical Report, HM Government 2021.

Department for Energy Security and Net Zero, "Annual Fuel Poverty Statistics Report: 2025," Technical Report, Department for Energy Security and Net Zero August 2026.

Feld, Immanuel and Thiemo Fetzer, "Performative State Capacity and Climate (In)Action," *SSRN Electronic Journal*, 2024.

Fetzer, Thiemo, Callum Shaw, and Jacob Edenhofer, "Informational Boundaries of the State," *SSRN Electronic Journal*, 2024.

_ , Ludovica Gazze, and Menna Bishop, "Distributional and climate implications of policy responses to energy price shocks," *Economic Policy*, July 2024, p. eiae038.

Fisher, Ronald A., *The Design of Experiments*, Edinburgh: Oliver & Boyd, 1935.

Fowlie, Meredith, Michael Greenstone, and Catherine Wolfram, "Do Energy Efficiency Investments Deliver? Evidence from the Weatherization Assistance Program*," *The Quarterly Journal of Economics*, August 2018, *133* (3), 1597–1644.

Gerarden, Todd D., Richard G. Newell, and Robert N. Stavins, "Assessing the Energy-Efficiency Gap," *Journal of Economic Literature*, December 2017, *55* (4), 1486–1525.

Geys, Benny and Rune J. Sørensen, "Never Change a Winning Policy? Public Sector Performance and Politicians' Preferences for Reforms," *Public Administration Review*, 2018, *78* (2), 206–216. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/puar.12824.

Gillingham, Kenneth and Tsvetan Tsvetanov, "Nudging energy efficiency audits: Evidence from a field experiment," *Journal of Environmental Economics and Management*, July 2018, *90*, 303–316.

Harjunen, Oskari, Tuukka Saarimaa, and Janne Tukiainen, "Love Thy (Elected) Neighbor? Residential Segregation, Political Representation, and Local Public Goods," *The Journal of Politics*, July 2023, *85* (3), 860–875.

Hjort, Jonas, Diana Moreira, Gautam Rao, and Juan Francisco Santini, "How Research Affects Policy: Experimental Evidence from 2,150 Brazilian Municipalities," *American Economic Review*, May 2021, *111* (5), 1442–1480.

Holladay, Scott, Jacob LaRiviere, David Novgorodsky, and Michael Price, "Prices versus nudges: What matters for search versus purchase of energy investments?," *Journal of Public Economics*, April 2019, *172*, 151–173.

Houde, Sébastien and Joseph E. Aldy, "Consumers' Response to State Energy Efficient Appliance Rebate Programs," *American Economic Journal: Economic Policy*, November 2017, *9* (4), 227–255.

Kovarek, Daniel, "Neighbors with benefits: How politicians' local ties generate positive externalities when bureaucratic oversight is limited," *Governance*, January 2025, *38* (1), e12867.

MCS, "UK homes installing a small-scale renewable every 90 seconds," Technical Report 2026.

Nielsen, Poul Aaes, "Learning from Performance Feedback: Performance Information, Aspiration Levels, and Managerial Priorities," *Public Administration*, 2014, *92* (1), 142–160. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/padm.12050.

Papineau, Maya and Nicholas Rivers, "Experimental evidence on heat loss visualization and personalized information to motivate energy savings," *Journal of Environmental Economics and Management*, January 2022, *111*, 102558.

Pereira, Miguel M., Nathalie Giger, Maria D. Perez, and Kaya Axelsson, "Encouraging politicians to act on climate: A field experiment with local officials in six countries," *American Journal of Political Science*, 2024, *n/a* (n/a). _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/ajps.12841.

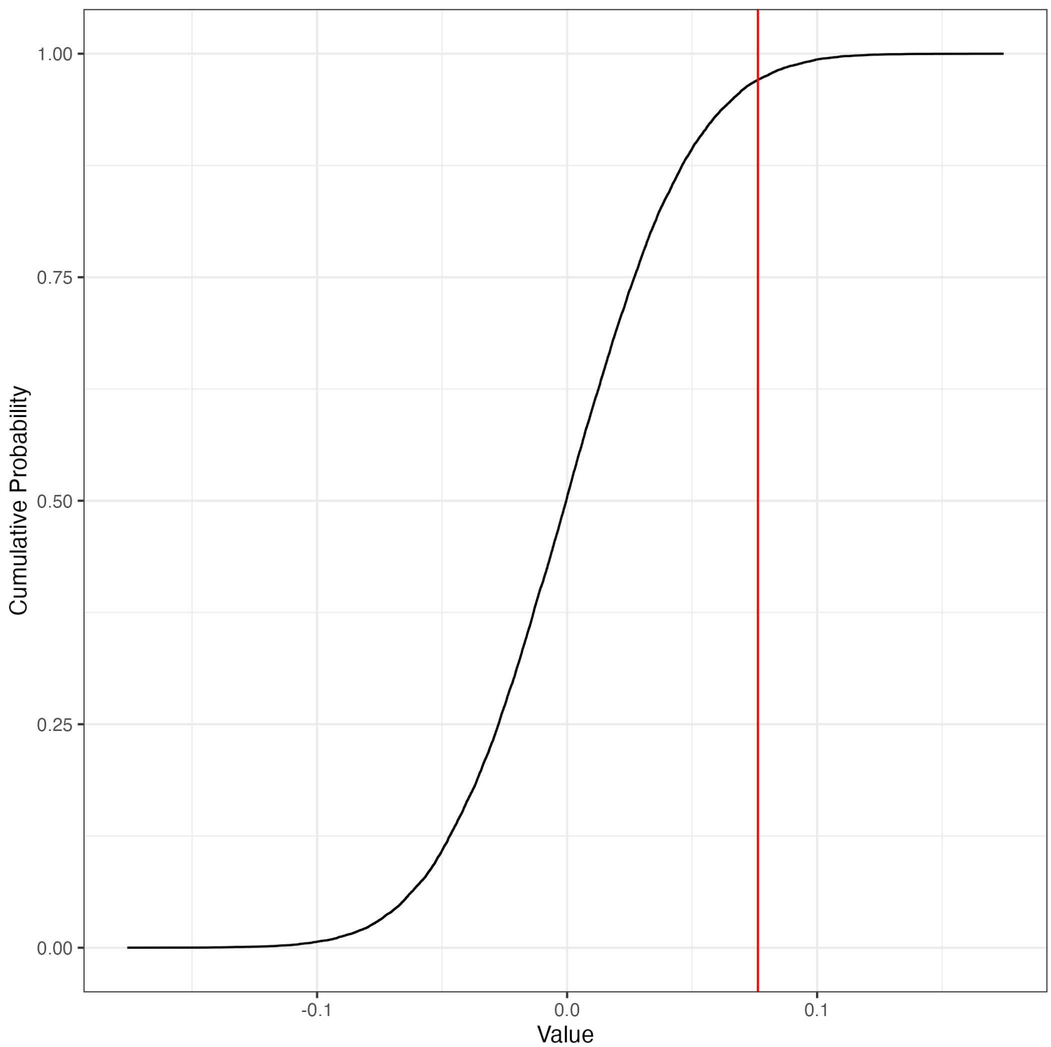
Rosenbaum, Paul R., *Observational Studies*, 2 ed., New York: Springer, 2002.

UK Government, "The Energy Performance of Buildings (England and Wales) Regulations 2012," 2012.

Young, Alwyn, "Channeling Fisher: Randomization Tests and the Statistical Insignificance of Seemingly Significant Experimental Results*," *The Quarterly Journal of Economics*, May 2019, *134* (2), 557–598.

Figures

Figure 1: Permutation test of treatment



Notes: The figure plots the cumulative distribution function of the treatment effects of a permutation test with 20,000 iterations. For each iteration, we create a random "placebo" treatment and run a regression corresponding to the regression in panel A of table 2 column (5), i.e. we include LAD, strata, and strata $\times$ quarter - year fixed effects. The red vertical line represents the "true" estimated treatment effect with the true randomisation.

Tables

Table 1: Randomisation Balance

Variable	Treatment	Control	P-Value
Has Media Contact	0.824 (0.382)	0.866 (0.342)	0.378
Election in 2023	0.626 (0.485)	0.544 (0.5)	0.197
Media at Lower Spatial Resolution	0.291 (0.456)	0.311 (0.464)	0.857
In England	0.933 (0.25)	0.933 (0.251)	0.903
Savings Potential below Median	0.491 (0.501)	0.512 (0.501)	0.944
EPC Coverage below Median	0.521 (0.501)	0.481 (0.501)	0.515
Average HH Income in 2023	43696 (7725)	43924 (7841)	0.998
Population	63264 (37826)	74854 (51434)	0.033
Ownership Rate	0.682 (0.107)	0.663 (0.106)	0.373
# Ukranian Refugees	200.576 (146.083)	238.866 (186.434)	0.061
Conservative Council	0.38 (0.487)	0.363 (0.482)	0.735
Labour Council	0.233 (0.424)	0.256 (0.438)	0.947
No Overall Control in Council	0.288 (0.454)	0.256 (0.438)	0.702
Other Party Control in Council	0.098 (0.298)	0.125 (0.332)	0.344
N	165	164	

The table reports mean and standard deviation of selected variables not used in the stratification among treatment and control councils, as well as the p-value of the difference between treatment and control units.

Table 2: Effect of treatment on installations - LAD level, quarterly data

	(1)	(2)	(3)	(4)	(5)
Panel A: log(total installations)					
Post × Treatment	0.0754*	0.0854*	0.0854*	0.0709*	0.0828**
	(0.0412)	(0.0444)	(0.0445)	(0.0409)	(0.0397)
Dependent variable mean	4.2486	4.2486	4.2486	4.2486	4.2486
R^2	0.33159	0.78942	0.78942	0.84907	0.86873
Observations	3,766	3,766	3,766	3,766	3,766
Panel B: log(solar installation)					
Post × Treatment	0.0969**	0.0990**	0.0990**	0.0789*	0.0840*
	(0.0458)	(0.0499)	(0.0501)	(0.0444)	(0.0441)
Dependent variable mean	3.9714	3.9714	3.9714	3.9714	3.9714
R^2	0.36857	0.73387	0.73387	0.82930	0.85244
Observations	3,763	3,763	3,763	3,763	3,763
Regression specification:					
LAD FE		X	X	X	X
Strata FE			X	X	
Quarter-Year FE				X	
Strata x Quarter-year FE					X
Controls	X	X	X	X	X

Notes: The table presents results from OLS regressions of retrofit installations on the treatment dummy interacted with a post dummy. The data covers all quarters between 01-2021 and 01-2024. Controls include the interaction of quarter-year dummies with population and with the number of Ukranian refugees arrived. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table 3: **Engagement by recipient and by LAD characteristic**

	(1)	(2)	(3)	(4)
	Emails read			
	All	Councillor	Council officer	Media
Sav. pot < med.	0.0191	0.1627	0.1775	0.0115
	(0.0343)	(0.1226)	(0.1164)	(0.0311)
EPC cov. < med	-0.0240	-0.0923	-0.1701	-0.0274
	(0.0325)	(0.1162)	(0.1103)	(0.0303)
Population	-0.0480*	-0.0947	-0.1184	0.0337
	(0.0271)	(0.0968)	(0.0918)	(0.0238)
HH income	-0.0507**	-0.1498**	-0.1242*	0.0058
	(0.0205)	(0.0733)	(0.0696)	(0.0196)
Ownership	-0.1728	-0.9766	-0.4898	-0.1112
	(0.1891)	(0.6759)	(0.6413)	(0.1710)
Ukrainians	0.0004**	0.0011*	0.0013**	-1.56×10^{-5}
	(0.0002)	(0.0006)	(0.0006)	(0.0001)
Election 2023	-0.0048	-0.0036	0.0093	0.0053
	(0.0364)	(0.1301)	(0.1235)	(0.0329)
Conservative council	0.0286	-0.1937	-0.2367*	0.0208
	(0.0396)	(0.1414)	(0.1342)	(0.0362)
Labour council	-0.0062	-0.0642	-0.1312	-0.0086
	(0.0459)	(0.1640)	(0.1556)	(0.0419)
Other control council	0.0835	0.0405	0.1068	0.0472
	(0.0534)	(0.1907)	(0.1809)	(0.0494)
Dependent variable mean	0.16742	0.56464	0.62856	0.08202
R^2	0.06950	0.11745	0.12044	0.06702
Observations	156	156	156	127

Notes: This table shows the results of multivariate regressions that measure the engagement of local authority districts (LAD) with our policy brief by different LAD characteristics. The dependent variable is the share of emails read in the aggregate (All) and by the three recipient types: Councillor, Council Officer, and Media. The measure is calculated by dividing the number of times a policy brief recipient clicked on the link using information from log files by the amount of emails which were sent to recipients within a LAD. The sample is restricted to only treatment LADs. For control LADs this measures are zero. The explanatory variables are the following: There are energy related variables like the savings potential as calculated in Fetzer, Gazze, and Bishop (2022), the energy price certificate coverage as well as indicators for being below the median savings potential or EPC coverage. Furthermore, we control for LAD characteristics like population, average household income, ownership rate, the number of Ukrainian refugees an LAD received, and whether there are local elections in 2023. The variables savings potential, population and household income are standardized by dividing each variable by its standard deviation. In addition we add controls for the party controlling the LADs council. The left-out reference category is "no overall control council". Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table 4: Engagement of councillor by party affiliation and council control

	(1)	(2)	(3)	(4)	(5)	(6)
Council control	Labour			Conservative		
	Email read	Clicks	Engaged	Email read	Clicks	Engaged
Conservative	-0.0282	0.0489	-0.0056			
	(0.0300)	(0.0846)	(0.0048)			
Libdem	0.2323***	0.1851	0.0179**	0.0799***	0.1706***	0.0057
	(0.0554)	(0.1564)	(0.0089)	(0.0282)	(0.0515)	(0.0036)
Green	0.1453	-0.0906	0.0658***	-0.0142	0.1480*	0.0054
	(0.0948)	(0.2674)	(0.0152)	(0.0453)	(0.0828)	(0.0058)
Independent	0.1445***	-0.0131	-0.0056	0.1060***	0.0705	0.0157***
	(0.0529)	(0.1492)	(0.0085)	(0.0399)	(0.0730)	(0.0051)
Other party	0.1034	0.8597***	0.0379**	-0.0415	-0.0600	-0.0026
	(0.1044)	(0.2945)	(0.0168)	(0.0544)	(0.0994)	(0.0070)
Labour				-0.0666**	0.0710	-0.0026
				(0.0278)	(0.0509)	(0.0036)
UKIP				-0.0729	0.7067*	-0.0026
				(0.2006)	(0.3665)	(0.0257)
Dependent variable mean	0.42240	0.50669	0.00467	0.41143	0.49884	0.00399
R^2	0.01444	0.00504	0.01499	0.00811	0.00604	0.00445
Observations	1,998	1,998	1,998	3,009	3,009	3,009

Notes: This table presents the results from multivariate regressions. The dependent variables capture the engagement of a councillor on the extensive and intensive margin. Columns (1) and (4) measure the extensive margin whether a councillor read the brief. This is a binary measure that is one if we record either one or more clicks in the log files or the recipient replied to us by email confirming the reception of the brief. Columns (2) and (5) measure the intensive margin of engagement by calculating the number of times a recipient clicked on the brief. Columns (3) and (6) also measure an extensive engagement margin by measuring whether a councillor got into contact with us by replying to our email brief. The outcome measures are regressed on dummy variables indicating the party affiliation of the councillor. We split the sample by council control into Labour and Conservative controlled councils. This information is taken from the Local Elections Archive Project (LEAP), which is kindly collected by Andrew Teale. The sample is restricted to councillors for which we could find information on the party affiliation. The omitted party affiliation is the party in power. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table 5: Treatment effect and councillor-residence heterogeneity

Dependent variable: $\mathbb{1}$(New Installations)	ATE only (1)	ATE + residence (2)	Saturated FE (3)
Panel A: Output Area			
Post × Treatment	-0.0016	-0.0036	
	(0.0064)	(0.0064)	
Post × Councillor residence		0.0081	
		(0.0132)	
Post × Treatment × Councillor residence		0.0225*	0.0229*
		(0.0136)	(0.0137)
Dependent variable mean	0.10408	0.10408	0.10408
R^2	0.20266	0.20272	0.20278
Observations	3,151,640	3,151,640	3,151,640
Panel B: Lower Layer Super Output Area			
Post × Treatment	0.0092	0.0017	
	(0.0109)	(0.0114)	
Post × Councillor residence		0.0021	
		(0.0255)	
Post × Treatment × Councillor residence		0.0234	0.0234
		(0.0262)	(0.0262)
Dependent variable mean	0.40535	0.40535	0.40535
R^2	0.32788	0.32795	0.32805
Observations	386,448	386,448	386,448
Panel C: Middle Layer Super Output Area			
Post × Treatment	0.0250**	0.0422**	
	(0.0123)	(0.0178)	
Post × Councillor residence		-0.0638***	
		(0.0231)	
Post × Treatment × Councillor residence		0.0353	0.0351
		(0.0273)	(0.0273)
Dependent variable mean	0.65840	0.65840	0.65840
R^2	0.38004	0.38020	0.38061
Observations	133,820	133,820	133,820
Regression specification			
Area FE	X	X	X
Quarter-year FE	X	X	
Treatment × Quarter-year FE			X
Councillor residence × Quarter-year FE			X
Controls	X	X	X

Notes: Column 1 reports the average treatment effect from a difference-in-differences specification with area and quarter-year fixed effects. Column 2 adds the councillor-residence interaction; the coefficient on Post × Treatment is the treatment effect outside councillor-residence units, while Post × Treatment × Councillor residence is the additional effect at councillor residences. Column 3 includes treatment-by-quarter-year and councillor-residence-by-quarter-year fixed effects, so the main treatment effect is absorbed. Standard errors in parentheses are clustered at the district level. Stars indicate *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 6: Effect of treatment on installations by councillor residence and spillovers – Output Area (OA) level

	(1)	(2)	(3)
Dependent variable: $\mathbb{1}$(New Installations)			
Post × Treatment × Own councillor	0.0223*	0.0221*	0.0219
	(0.0130)	(0.0131)	(0.0134)
Post × Treatment × Spillover (any)	-0.0026		
	(0.0078)		
Post × Treatment × Spillover (count)		-0.0033	
		(0.0061)	
Post × Treatment × Spillover (share)			-0.0093
			(0.0352)
Dependent variable mean	0.09866	0.09866	0.09866
R^2	0.18766	0.18777	0.18851
Observations	3,011,800	3,011,800	3,011,800
Regression specification:			
Area FE	X	X	X
Treatment x Quarter-year FE	X	X	X
Councillors Residence x Quarter-year FE	X	X	X
Spillover x Quarter-year FE	X	X	X
Controls	X	X	X

Notes: This table shows the results of three multivariate regressions from equation 5. The unit of analysis is an Output Area (OA). The dependent variable in all three regressions is an indicator equal to one for whether an OA gets an additional retrofit installation in a quarter-year. Own councillor is an indicator equal to one if a councillor lives in the area. Spillover (any) is an indicator equal to one if an area neighbors a councillor residence area. Spillover (count) counts the number of neighbouring areas with a resident councillor. Spillover (share) is the share of all neighbouring areas that are residence of a councillor. Standard errors in parentheses are clustered at the district level. Stars indicate *** p <0.01, ** p <0.05, and * p <0.1.

Appendix to "Weathering the Energy Crisis: Can Tailored Information to Local Governments Spur Climate Action?"

For Online Publication

A Appendix figures

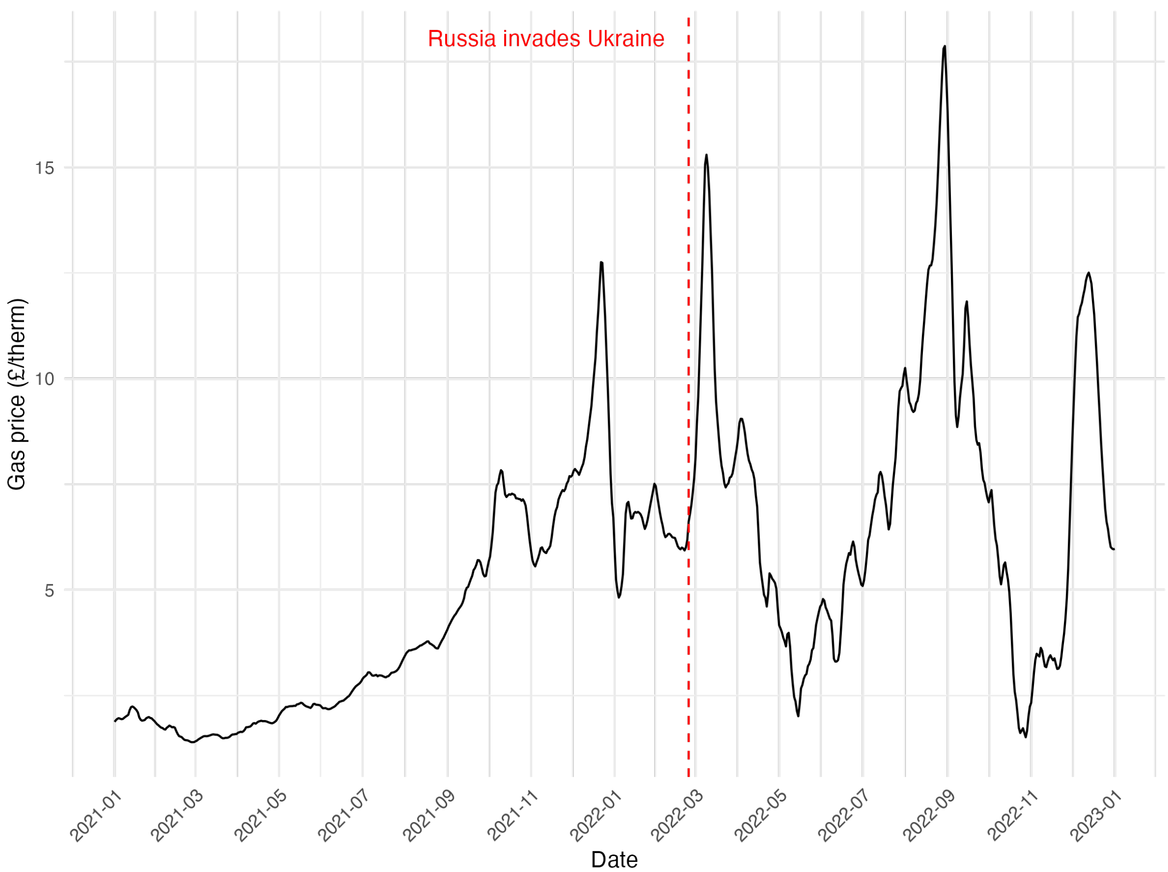
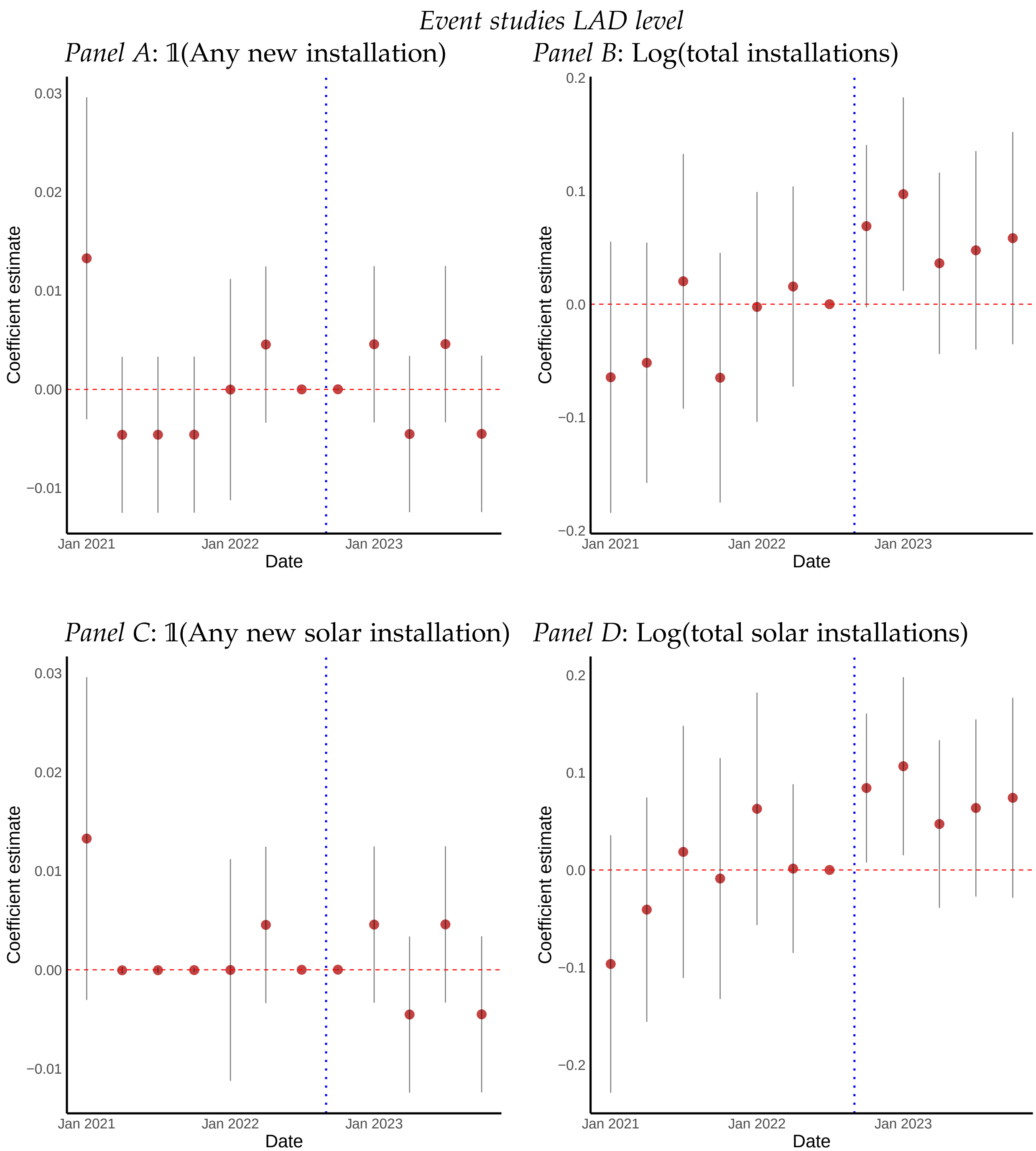


Figure A1: Gas prices around the Russian invasion of Ukraine

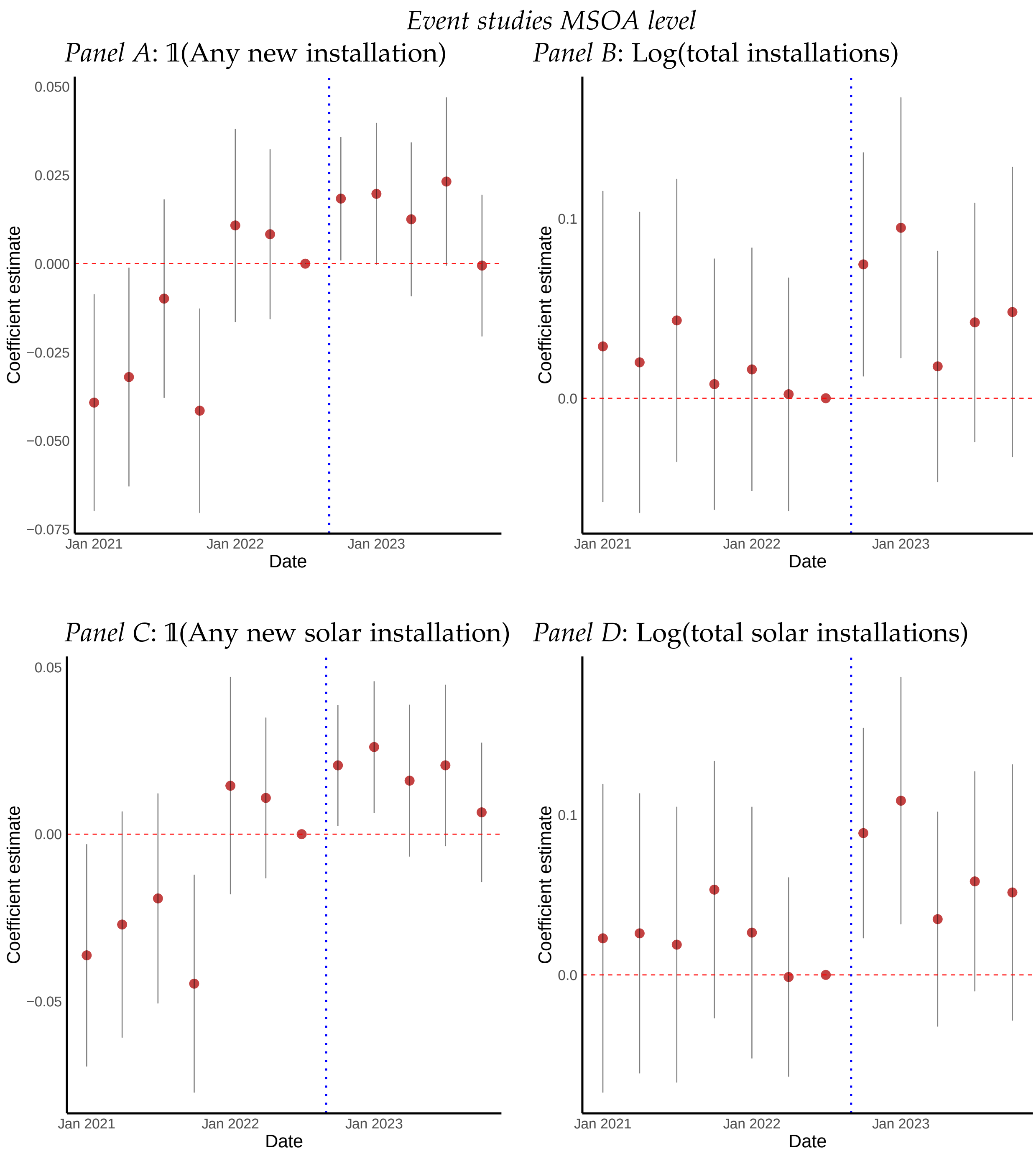
Notes: The graph shows monthly gas prices in England in £ per kilowatt hours for 2021-2023. Source: Office for National Statistics.

Figure A2: Event studies LAD level, quarterly data



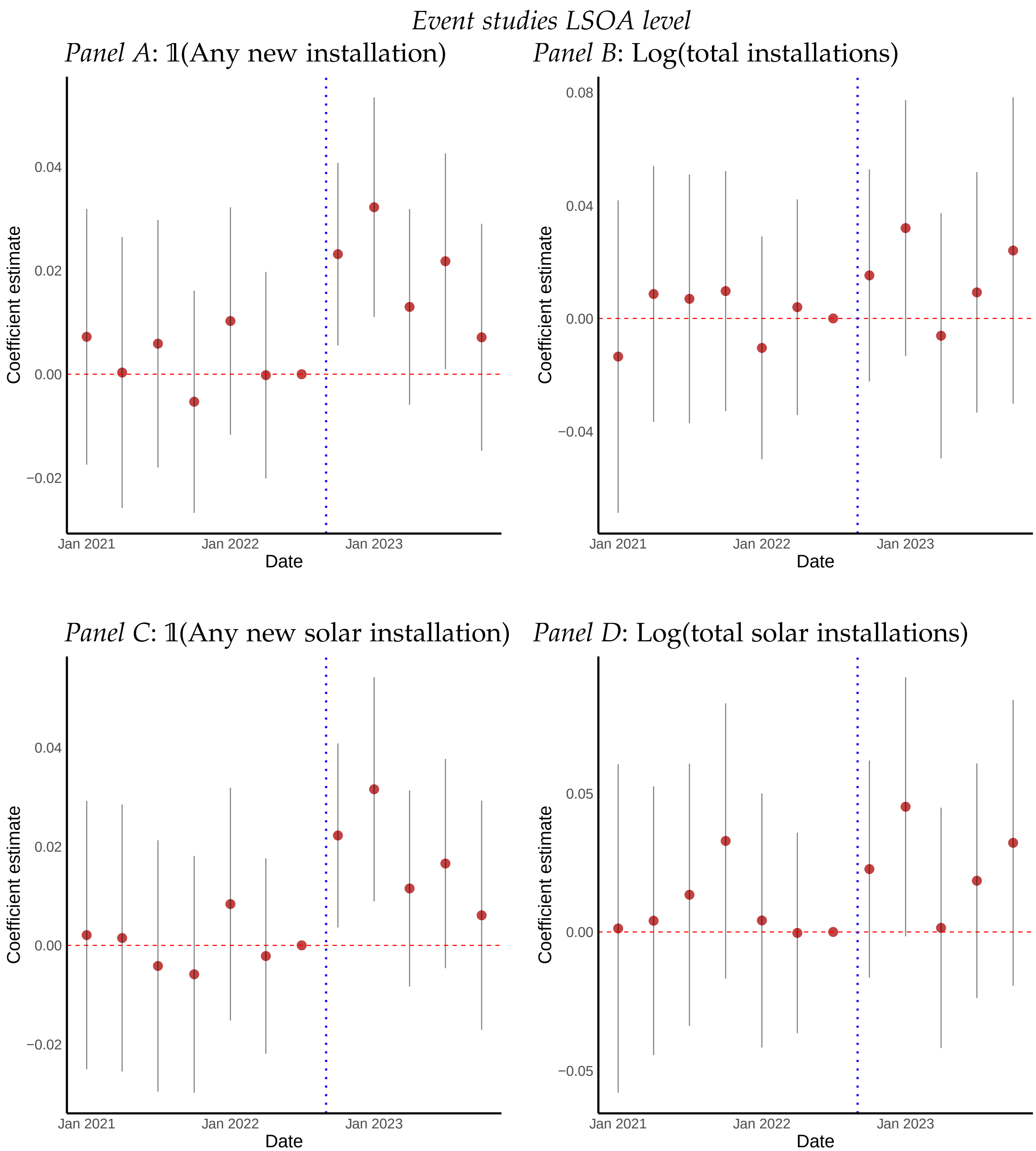
Notes: The graph shows event studies for OLS regressions of different measures of retrofit installations on the treatment dummy interacted with year-quarter dummies. The most stringent specification from equation is estimated, i.e. 1 with LAD and strata x quarter-year fixed effects. The unit of observation is a UK local authority (LAD). The dots depict point estimates and the bars 90% confidence intervals.

Figure A3: Event studies MSOA level, quarterly data



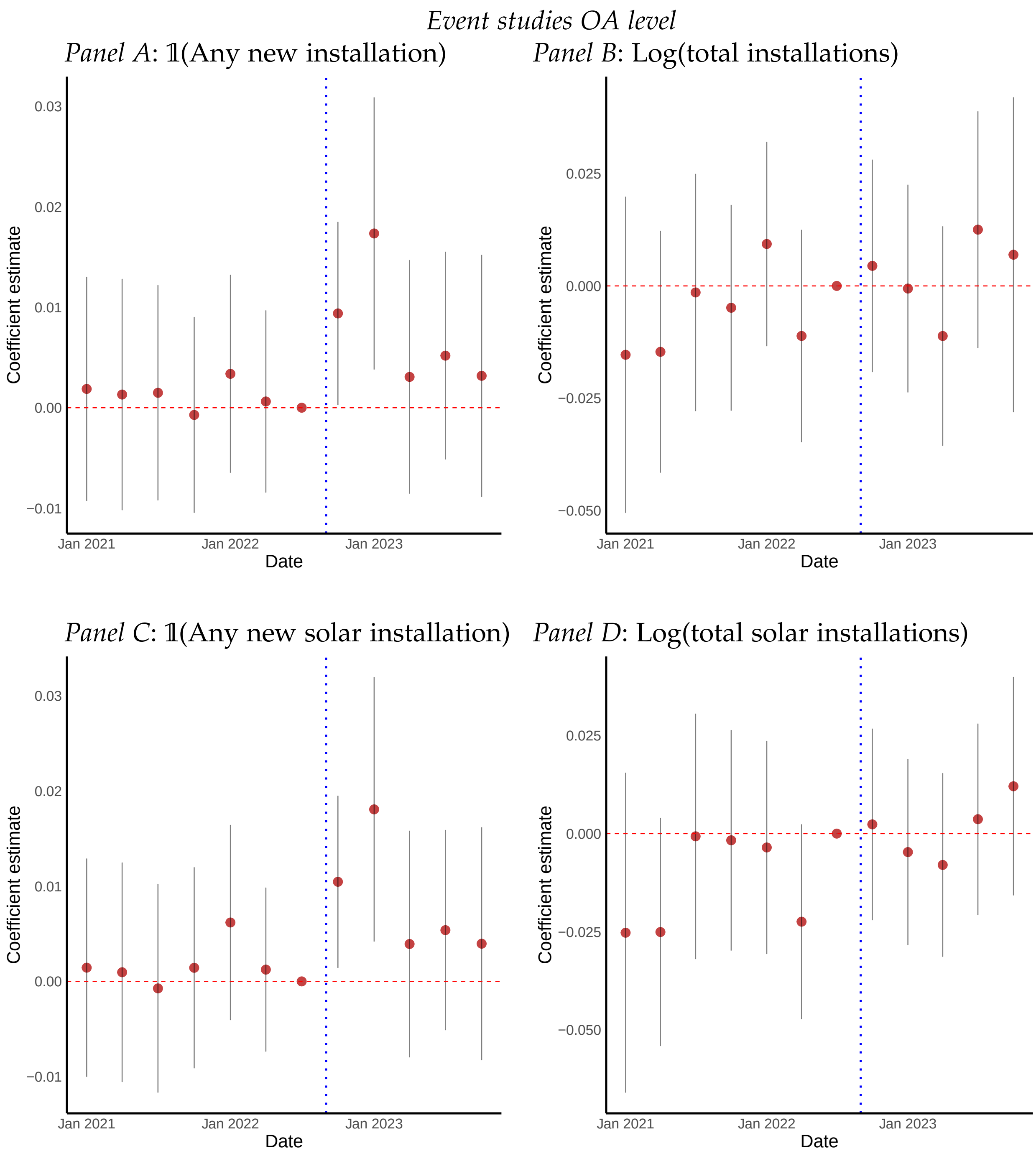
Notes: The graph shows event studies for OLS regressions of different measures of retrofit installations on the treatment dummy interacted with year-quarter dummies. The most stringent specification from equation is estimated, i.e. 1 with LAD and strata x quarter-year fixed effects. The unit of observation is a UK middle layer super output area (MSOA). The dots depict point estimates and the bars 90% confidence intervals.

Figure A4: Event studies LSOA level, quarterly data



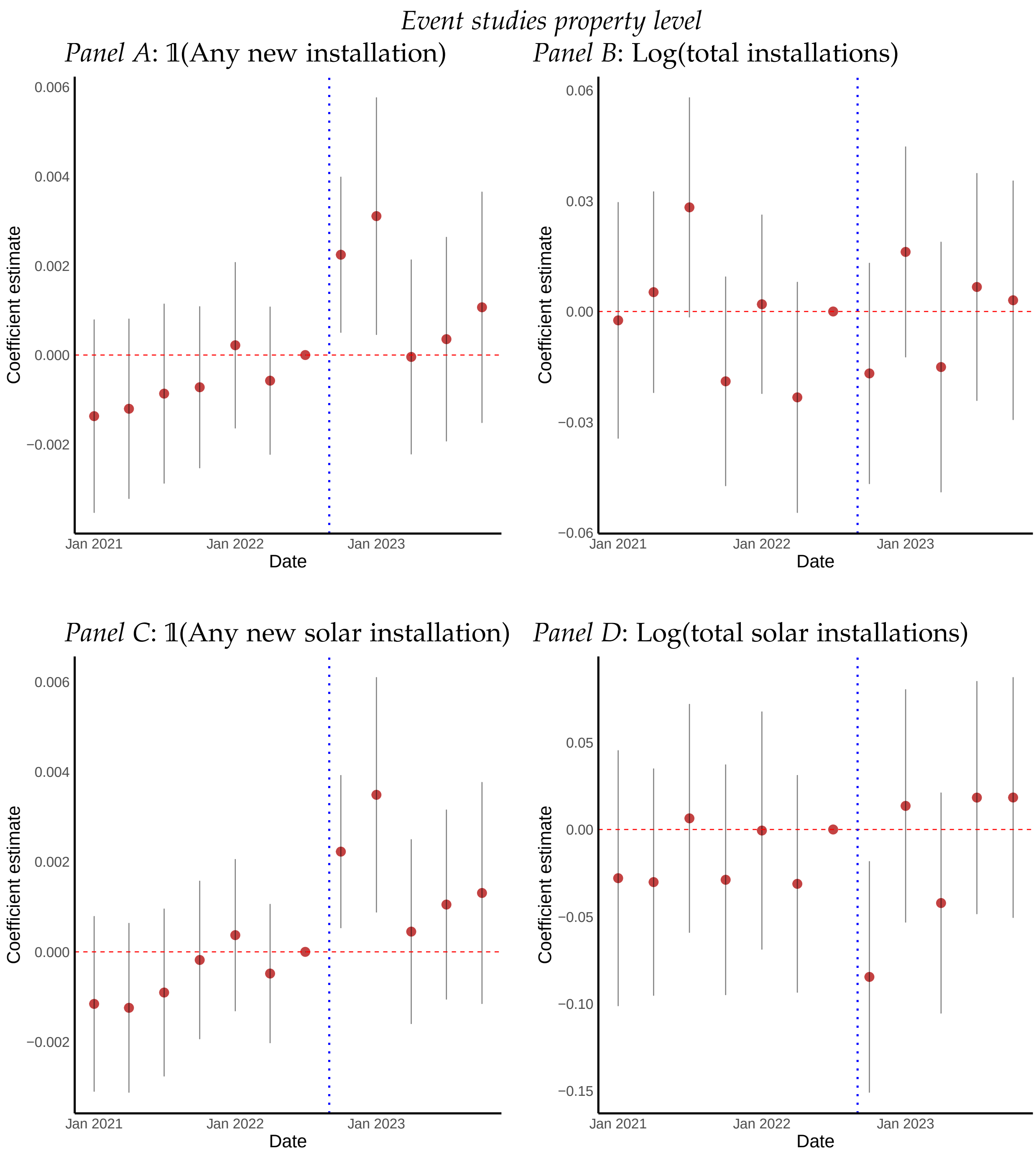
Notes: The graph shows event studies for OLS regressions of different measures of retrofit installations on the treatment dummy interacted with year-quarter dummies. The most stringent specification from equation is estimated, i.e. 1 with LAD and strata x quarter-year fixed effects. The unit of observation is a UK lower layer super output area (LSOA). The dots depict point estimates and the bars 90% confidence intervals.

Figure A5: Event studies OA level, quarterly data



Notes: The graph shows event studies for OLS regressions of different measures of retrofit installations on the treatment dummy interacted with year-quarter dummies. The most stringent specification from equation is estimated, i.e. 1 with LAD and strata x quarter-year fixed effects. The unit of observation is a UK output area (OA). The dots depict point estimates and the bars 90% confidence intervals.

Figure A6: Event studies property level, quarterly data



Notes: The graph shows event studies for OLS regressions of different measures of retrofit installations on the treatment dummy interacted with year-quarter dummies. The most stringent specification from equation is estimated, i.e. 1 with LAD and strata x quarter-year fixed effects. The unit of observation is a property. The dots depict point estimates and the bars 90% confidence intervals.

B Appendix tables

Table A1: Effect of treatment on installations - MSOA level, quarterly data

	(1)	(2)	(3)	(4)	(5)
Panel A: log(total installations)					
Post × Treatment	0.0214	0.0313	0.0313	0.0217	0.0401
	(0.0381)	(0.0387)	(0.0387)	(0.0355)	(0.0295)
Dependent variable mean	1.3175	1.3175	1.3175	1.3175	1.3175
R^2	0.15179	0.56543	0.56543	0.59780	0.61154
Observations	63,851	63,851	63,851	63,851	63,851
Panel B: log(solar installation)					
Post × Treatment	0.0497	0.0456	0.0456	0.0363	0.0497
	(0.0448)	(0.0428)	(0.0429)	(0.0406)	(0.0357)
Dependent variable mean	1.1690	1.1690	1.1690	1.1690	1.1690
R^2	0.16204	0.50039	0.50039	0.55110	0.56922
Observations	60,335	60,335	60,335	60,335	60,335
Panel C: $\mathbb{1}$(any new installation)					
Post × Treatment	0.1878*	0.2533**	0.2533**	0.2603**	0.2374**
	(0.0964)	(0.1091)	(0.1092)	(0.1118)	(0.1013)
Dependent variable mean	0.79957	0.72216	0.72216	0.72216	0.72118
No. of area FE	2	5,109	5,109	5,109	5,109
No. of time FE	2	2	32	42	366
Observations	85,764	61,308	61,308	61,308	61,094
Panel D: $\mathbb{1}$(any new solar installation)					
Post × Treatment	0.1811*	0.2306**	0.2306**	0.2381**	0.2346**
	(0.0967)	(0.1061)	(0.1061)	(0.1083)	(0.0991)
Dependent variable mean	0.75568	0.70416	0.70416	0.70416	0.70309
No. of area FE	2	5,828	5,828	5,828	5,828
No. of time FE	2	2	32	42	367
Observations	85,764	69,936	69,936	69,936	69,684
Regression specification:					
LAD FE		X	X	X	X
Strata FE			X	X	
Quarter-Year FE				X	
Strata x Quarter-year FE					X
Controls	X	X	X	X	X

Notes: The table presents results from OLS regressions of retrofit installations on the treatment dummy interacted with a post dummy. The data covers all quarters between 01-2021 and 01-2024. Controls include the interaction of quarter-year dummies with population and with the number of Ukranian refugees arrived. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table A2: Effect of treatment on installations - LSOA level, quarterly data

	(1)	(2)	(3)	(4)	(5)
Panel A: log(total installations)					
Post × Treatment	0.0088	0.0069	0.0069	0.0056	0.0140
	(0.0224)	(0.0243)	(0.0243)	(0.0243)	(0.0181)
Dependent variable mean	0.60256	0.60256	0.60256	0.60256	0.60256
R^2	0.06901	0.44341	0.44341	0.45986	0.47086
Observations	156,645	156,645	156,645	156,645	156,645
Panel B: log(solar installation)					
Post × Treatment	0.0199	0.0107	0.0107	0.0113	0.0176
	(0.0250)	(0.0238)	(0.0238)	(0.0242)	(0.0200)
Dependent variable mean	0.51536	0.51536	0.51536	0.51536	0.51536
R^2	0.06785	0.40602	0.40602	0.42924	0.44072
Observations	139,748	139,748	139,748	139,748	139,748
Panel C: $\mathbb{1}$(any new installation)					
Post × Treatment	0.0704	0.0970	0.0970	0.0986	0.1205**
	(0.0454)	(0.0692)	(0.0692)	(0.0702)	(0.0596)
Dependent variable mean	0.41091	0.41445	0.41445	0.41445	0.41445
No. of area FE	2	31,757	31,757	31,757	31,757
No. of time FE	2	2	32	42	372
Observations	412,116	381,084	381,084	381,084	381,084
Panel D: $\mathbb{1}$(any new solar installation)					
Post × Treatment	0.0884*	0.1161	0.1161	0.1197	0.1389**
	(0.0507)	(0.0731)	(0.0731)	(0.0743)	(0.0645)
Dependent variable mean	0.36632	0.38558	0.38558	0.38558	0.38558
No. of area FE	2	32,080	32,080	32,080	32,080
No. of time FE	2	2	32	42	372
Observations	412,116	384,960	384,960	384,960	384,960
Regression specification:					
LAD FE		X	X	X	X
Strata FE			X	X	
Quarter-Year FE				X	
Strata x Quarter-year FE					X
Controls	X	X	X	X	X

Notes: The table presents results from OLS regressions of retrofit installations on the treatment dummy interacted with a post dummy. The data covers all quarters between 01-2021 and 01-2024. Controls include the interaction of quarter-year dummies with population and with the number of Ukranian refugees arrived. Standard errors provided in parentheses are clustered at the district level with stars indicating *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A3: Effect of treatment on installations - OA level, quarterly data

	(1)	(2)	(3)	(4)	(5)
Panel A: log(total installations)					
Post × Treatment	-0.0009	-0.0051	-0.0051	-0.0033	0.0058
	(0.0141)	(0.0160)	(0.0160)	(0.0161)	(0.0098)
Dependent variable mean	0.28885	0.28885	0.28885	0.28885	0.28885
R^2	0.02680	0.47634	0.47634	0.48943	0.49623
Observations	267,375	267,375	267,375	267,375	267,375
Panel B: log(solar installation)					
Post × Treatment	0.0089	0.0038	0.0038	0.0059	0.0100
	(0.0111)	(0.0106)	(0.0106)	(0.0108)	(0.0091)
Dependent variable mean	0.23739	0.23739	0.23739	0.23739	0.23739
R^2	0.01885	0.50522	0.50522	0.52407	0.52844
Observations	226,135	226,135	226,135	226,135	226,135
Panel C: $\mathbb{1}$(any new installation)					
Post × Treatment	0.0476	0.0494	0.0494	0.0504	0.0813*
	(0.0393)	(0.0512)	(0.0512)	(0.0516)	(0.0439)
Dependent variable mean	0.13803	0.20079	0.20079	0.20079	0.20079
Observations	1,937,100	1,329,372	1,329,372	1,329,372	1,329,372
Panel D: $\mathbb{1}$(any new solar installation)					
Post × Treatment	0.0679	0.0735	0.0735	0.0754	0.1063**
	(0.0478)	(0.0600)	(0.0600)	(0.0607)	(0.0523)
Dependent variable mean	0.11674	0.17890	0.17890	0.17890	0.17890
Observations	1,937,100	1,262,772	1,262,772	1,262,772	1,262,772
Regression specification:					
LAD FE		X	X	X	X
Strata FE			X	X	
Quarter-Year FE				X	
Strata x Quarter-year FE					X

Notes: The table presents results from OLS regressions of retrofit installations on the treatment dummy interacted with a post dummy. The data covers all quarters between 01-2021 and 01-2024. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table A4: Effect of treatment on installations - Property level, quarterly data

	(1)	(2)	(3)	(4)	(5)
Panel A: log(total installations)					
Post × Treatment	-0.0124	-0.0076	-0.0076	-0.0085	-0.0008
	(0.0092)	(0.0109)	(0.0109)	(0.0106)	(0.0103)
Dependent variable mean	0.10256	0.10256	0.10256	0.10256	0.10256
R^2	0.05792	0.95459	0.95459	0.95738	0.95827
Observations	367,449	367,449	367,449	367,449	367,449
Panel B: log(solar installation)					
Post × Treatment	-0.0035	-0.0247	-0.0247	-0.0299	-0.0078
	(0.0027)	(0.0224)	(0.0224)	(0.0226)	(0.0212)
Dependent variable mean	0.07092	0.07092	0.07092	0.07092	0.07092
R^2	0.03420	0.96161	0.96161	0.96323	0.96597
Observations	300,781	300,781	300,781	300,781	300,781
Panel C: $\mathbb{1}$(any new installation)					
Post × Treatment	0.0667	0.0711	0.0711	0.0713	0.0960**
	(0.0444)	(0.0478)	(0.0478)	(0.0479)	(0.0430)
Dependent variable mean	0.02106	0.08731	0.08731	0.08731	0.08731
Observations	17,444,100	4,208,376	4,208,376	4,208,376	4,208,376
Panel D: $\mathbb{1}$(any new solar installation)					
Post × Treatment	0.0950*	0.1009*	0.1009*	0.1015*	0.1307**
	(0.0544)	(0.0584)	(0.0584)	(0.0587)	(0.0537)
Dependent variable mean	0.01724	0.08475	0.08475	0.08475	0.08475
Observations	17,444,100	3,549,108	3,549,108	3,549,108	3,549,108
Regression specification:					
LAD FE		X	X	X	X
Strata FE			X	X	
Quarter-Year FE				X	
Strata x Quarter-year FE					X

Notes: The table presents results from OLS regressions of retrofit installations on the treatment dummy interacted with a post dummy. The data covers all quarters between 01-2021 and 01-2024. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table A5: Effect of treatment on installations, quarterly data – Robustness across spatial levels

Spatial level	LSOA	MSOA	LAD
	(1)	(2)	(3)
Panel A: log(total installations)			
Post × Treatment	0.0129	0.0485	0.0763*
	(0.0198)	(0.0337)	(0.0389)
Mean of DV	1.0363	4.9798	108.18
R^2	0.46886	0.61235	0.87311
No. of area FE	32,707	7,134	329
No. of time FE	372	372	372
Observations	169,342	68,574	3,934
Panel B: $\mathbb{1}$(any new installation)			
Post × Treatment	0.0217**	0.0253**	-0.0006
	(0.0101)	(0.0112)	(0.0014)
Mean of DV	1.0363	4.9798	108.18
R^2	0.33349	0.32779	0.60079
No. of area FE	34,343	7,147	329
No. of time FE	372	372	372
Observations	412,116	85,764	3,948
Regression specification:			
LSOA FE	X		
MSOA FE		X	
LAD FE			X
Strata x Quarter-year FE	X	X	X

Notes: The table presents results from OLS regressions of retrofit installations on the treatment dummy interacted with a post dummy. The data covers all quarters between 01-2021 and 01-2024. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table A6: Effect of treatment on energy consumption - LAD level, annual data

	(1)	(2)	(3)	(4)	(5)
Panel A: log(energy consumption per meter)					
Post × Treated	0.0010	0.0010	0.0010	0.0010	0.0019
	(0.0015)	(0.0015)	(0.0018)	(0.0015)	(0.0015)
Dependent variable mean	9.4260	9.4260	9.4260	9.4260	9.4260
R^2	0.32009	0.91461	0.91294	0.99271	0.99432
Observations	1,490	1,490	1,490	1,490	1,490
Regression specification:					
LAD FE		X	X	X	X
Strata FE			X	X	
Quarter-Year FE				X	
Strata x Quarter-year FE					X
Controls	X	X	X	X	X

Notes: This table shows the effect of the information treatment on log energy consumption. Energy consumption is measured as combined electricity and gas consumption divided by the number of meters in a Local Authority District. *** p <0.01, ** p <0.05, and * p <0.1.

Table A7: Mechanisms - LSOA level, quarterly data

	(1)	(2)	(3)	(4)	(5)
Dependent variable: log(total installations +1)					
Panel A: 𝟙(Engaged)					
Post × Treatment	-0.0202	-0.0204	-0.0204	-0.0204	-0.0133
	(0.0362)	(0.0363)	(0.0363)	(0.0363)	(0.0360)
Post × Treatment × d_engaged	-0.0987***	-0.0821**	-0.0821**	-0.0821**	-0.0517**
	(0.0352)	(0.0316)	(0.0316)	(0.0316)	(0.0231)
Dependent variable mean	0.32920	0.32920	0.32920	0.32920	0.32920
R^2	0.09526	0.37482	0.37482	0.41095	0.42658
Observations	312,660	312,660	312,660	312,660	312,660
Panel B: 𝟙(Engaged within 200m)					
Post × Treatment	0.0543	0.0542	0.0542	0.0542	0.0382
	(0.0339)	(0.0339)	(0.0339)	(0.0339)	(0.0289)
Post × Treatment × d_engaged_200	-0.0410	-0.0141	-0.0141	-0.0141	0.0009
	(0.0545)	(0.0471)	(0.0471)	(0.0471)	(0.0359)
Dependent variable mean	0.31313	0.31313	0.31313	0.31313	0.31313
R^2	0.08826	0.37235	0.37235	0.40602	0.42179
Observations	319,320	319,320	319,320	319,320	319,320
Panel C: 𝟙(Engaged within 500m)					
Post × Treatment	0.0550	0.0548	0.0548	0.0548	0.0385
	(0.0339)	(0.0339)	(0.0339)	(0.0339)	(0.0289)
Post × Treatment × d_engaged_500	-0.0903**	-0.0703*	-0.0703*	-0.0703*	-0.0446
	(0.0441)	(0.0382)	(0.0382)	(0.0382)	(0.0283)
Dependent variable mean	0.31313	0.31313	0.31313	0.31313	0.31313
R^2	0.08837	0.37238	0.37238	0.40605	0.42180
Observations	319,320	319,320	319,320	319,320	319,320
Panel D: 𝟙(Engaged within 1000m)					
Post × Treatment	0.0556	0.0553	0.0553	0.0553	0.0386
	(0.0340)	(0.0340)	(0.0340)	(0.0340)	(0.0289)
Post × Treatment × d_engaged_1000	-0.1120***	-0.0912***	-0.0912***	-0.0912***	-0.0457
	(0.0348)	(0.0290)	(0.0290)	(0.0290)	(0.0290)
Dependent variable mean	0.31313	0.31313	0.31313	0.31313	0.31313
R^2	0.08846	0.37241	0.37241	0.40608	0.42181
Observations	319,320	319,320	319,320	319,320	319,320
Regression specification:					
LAD FE		X	X	X	X
Strata FE			X	X	
Quarter-Year FE				X	
Strata x Quarter-year FE					X
Controls	X	X	X	X	X

Notes: The table presents results from OLS regressions of retrofit installations on the treatment dummy interacted with a post dummy. The data covers all quarters between 01-2021 and 01-2024. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table A8: Mechanisms - LAD level, quarterly data

	(1)	(2)	(3)	(4)	(5)
Dependent variable: log(total installations +1)					
Panel A: $\mathbb{1}$(Media coverage)					
Post $\times$ Media coverage	-0.0154	0.0532	0.0532	0.2066*	0.2093*
	(0.1373)	(0.1181)	(0.1190)	(0.1248)	(0.1141)
Dependent variable mean	4.2004	4.2004	4.2004	4.2004	4.2004
R^2	0.35885	0.80854	0.80854	0.86836	0.89967
Observations	1,896	1,896	1,896	1,896	1,896
Regression specification:					
LAD FE		X	X	X	X
Strata FE			X	X	
Quarter-Year FE				X	
Strata x Quarter-year FE					X
Controls	X	X	X	X	X

Notes: The table presents results from OLS regressions of retrofit installations on the treatment dummy interacted with a post dummy. The data covers all quarters between 01-2021 and 01-2024. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table A9: Mechanisms - LSOA level, quarterly data

	(1)	(2)	(3)	(4)	(5)
Dependent variable: log(installations)					
Panel A:					
Post × Treatment	0.0679**	0.0388	0.0388	0.0401	0.0199
	(0.0319)	(0.0296)	(0.0296)	(0.0290)	(0.0277)
Post × Clicks 200m	0.1364***	0.0541**	0.0541**	0.0480*	0.0542**
	(0.0437)	(0.0258)	(0.0258)	(0.0246)	(0.0266)
Post × Treatment × Clicks 200m	-0.1292***	-0.0485*	-0.0485*	-0.0433*	-0.0500*
	(0.0442)	(0.0264)	(0.0264)	(0.0252)	(0.0269)
Dependent variable mean	0.53769	0.53769	0.53769	0.53769	0.53769
R^2	0.04960	0.38702	0.38702	0.41032	0.42803
Observations	95,591	95,591	95,591	95,591	95,591
Regression specification:					
LSOA FE		X	X	X	X
Strata FE			X	X	
Quarter-Year FE				X	
Strata x Quarter-year FE					X

Notes: The table presents results from OLS regressions of retrofit installations on the treatment dummy interacted with a post dummy. The data covers all quarters between 01-2021 and 01-2024. Standard errors provided in parentheses are clustered at the district level with stars indicating *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A10: Mechanisms - LAD level, quarterly data

	(1)	(2)	(3)	(4)	(5)
Dependent variable: log(total installations +1)					
Panel A: HH income					
Post × Treatment	0.0703*	0.0808*	0.0808*	0.0666	0.0772**
	(0.0408)	(0.0437)	(0.0439)	(0.0407)	(0.0391)
Post × Treatment × HH income (std.)	0.0021	-0.0323	-0.0323	-0.0068	0.0200
	(0.0668)	(0.0340)	(0.0341)	(0.0330)	(0.0261)
Dependent variable mean	4.2563	4.2563	4.2563	4.2563	4.2563
R^2	0.38262	0.80266	0.80266	0.85720	0.87642
Observations	3,780	3,780	3,780	3,780	3,780
Panel B: Ukrainians					
Post × Treatment	0.1610	0.3208***	0.3208***	0.0882	0.0973
	(0.1099)	(0.0672)	(0.0674)	(0.0671)	(0.0661)
Post × Treatment × Ukrainians	-0.0004	-0.0012***	-0.0012***	-0.0001	-9.14×10^{-5}
	(0.0005)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Dependent variable mean	4.2563	4.2563	4.2563	4.2563	4.2563
R^2	0.32933	0.80554	0.80554	0.85722	0.87640
Observations	3,780	3,780	3,780	3,780	3,780
Panel C: < Median(Savings potential)					
Post × Treatment	0.1108*	0.1457***	0.1457***	0.1055**	0.0885*
	(0.0639)	(0.0501)	(0.0503)	(0.0474)	(0.0516)
Post × Treatment × < Median Savings Potential	-0.0843	-0.1361**	-0.1361**	-0.0806	-0.0214
	(0.0980)	(0.0574)	(0.0576)	(0.0537)	(0.0766)
Dependent variable mean	4.2563	4.2563	4.2563	4.2563	4.2563
R^2	0.32768	0.80315	0.80315	0.85741	0.87639
Observations	3,780	3,780	3,780	3,780	3,780
Panel D: Conservative council					
Post × Treatment	0.0416	0.0474	0.0474	0.0435	0.0469
	(0.0565)	(0.0503)	(0.0505)	(0.0462)	(0.0418)
Post × Treatment × Conservative	0.0872	0.0994*	0.0994*	0.0701	0.1040*
	(0.0934)	(0.0550)	(0.0552)	(0.0533)	(0.0534)
Dependent variable mean	4.2563	4.2563	4.2563	4.2563	4.2563
R^2	0.33211	0.80283	0.80283	0.85734	0.87666
Observations	3,780	3,780	3,780	3,780	3,780
Regression specification:					
LSOA FE		X	X	X	X
Strata FE			X	X	
Quarter-Year FE				X	
Strata x Quarter-year FE					X

Notes: The table presents results from OLS regressions of retrofit installations on the treatment dummy interacted with a post dummy. The data covers all quarters between 01-2021 and 01-2024. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table A11: Engagement of councillor by party affiliation

	(1)	(2)	(3)
	Email read	Clicks	Engaged
Labour	0.0205	0.1103***	0.0021
	(0.0133)	(0.0288)	(0.0019)
Libdem	0.0197	0.1210***	0.0085***
	(0.0169)	(0.0366)	(0.0025)
Green	0.0493	0.2775***	0.0248***
	(0.0303)	(0.0657)	(0.0044)
UKIP	0.0392	0.3103	-0.0022
	(0.1337)	(0.2893)	(0.0195)
Independent	0.0544**	0.0164	0.0026
	(0.0219)	(0.0473)	(0.0032)
Other party	-0.0417	-0.0322	0.0031
	(0.0272)	(0.0589)	(0.0040)
Dependent variable mean	0.47417	0.60916	0.00536
R^2	0.00163	0.00432	0.00476
Observations	8,208	8,208	8,208

Notes: This table presents the results from multivariate regressions. The dependent variables capture the engagement of a councillor on the extensive and intensive margin. Column (1) measures the extensive margin whether a councillor read the brief. This is a binary measure that is one if we record either one or more clicks in the log files or the recipient replied to us by email confirming the reception of the brief. Column (2) measures the intensive margin of engagement by calculating the number of times a recipient clicked on the brief. Column (3) also measures an extensive engagement margin by measuring whether a councillor got into contact with us by replying to our email brief. The outcome measures are regressed on dummy variables indicating the party affiliation of the councillor. This information is taken from the Local Elections Archive Project (LEAP) which is kindly collected by Andrew Teale. The sample is restricted to councillors for which we could find information on the party affiliation. The omitted party affiliation is the conservative party. Standard errors provided in parentheses are clustered at the district level with stars indicating *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

C Example of treatment outreach

C.1 Email to Darlington

Subject:	New Research: How will the energy crisis affect households in Darlington?
Date:	Tuesday, 25. October 2022 at 19:46:43 Central European Summer Time
From:	Fetzer, Thiemo on behalf of energycrisis, resource
To:	FELD, IMMANUEL (PGR)
Attachments:	PNG image.png, PNG image.png

How will the energy crisis affect households in Darlington?

Dear Mr. Feld,

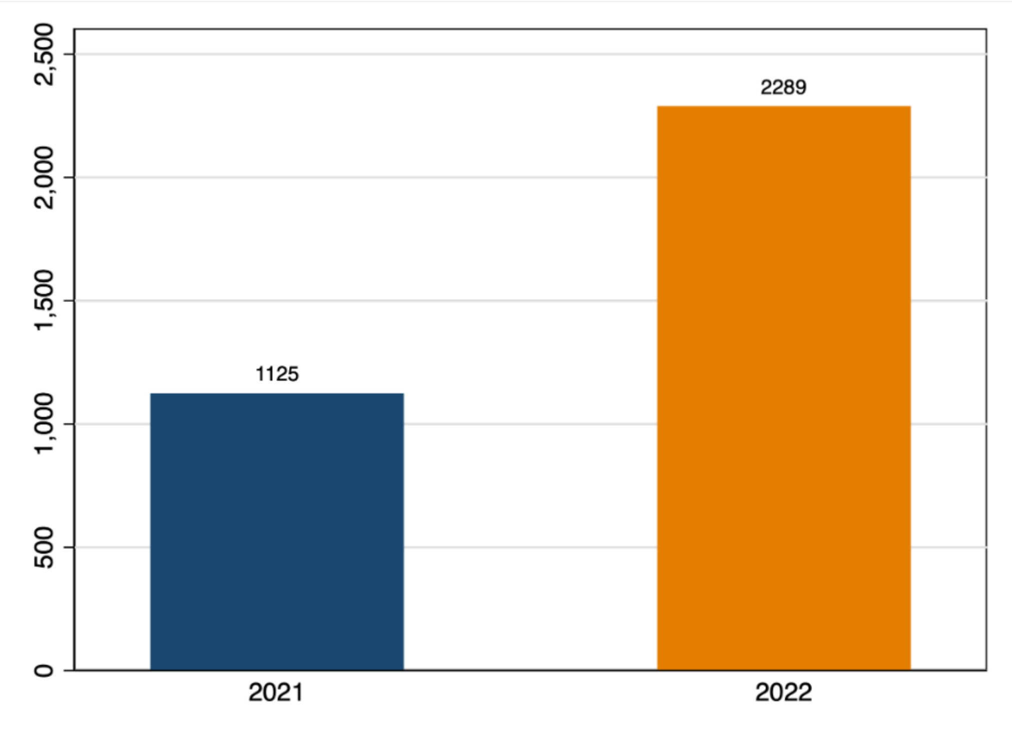
We are a group of economists at the University of Warwick who have analysed the impacts of the energy crisis for Darlington. Our data analysis **specific to Darlington**, along with more detail is available here:

https://warwick.ac.uk/fac/soc/economics/staff/lagazze/energycrisis/brief_district_e06000005.pdf.

The energy crisis is a **broad-based economic shock** that can threaten social and economic stability in the UK. Households in Darlington will be **hit hard**. Even with government support through the Energy Price Guarantee, we estimate that households in Darlington will see **an increase in their energy bills by, on average, £1164** relative to energy prices from October 2021.

This is an economic shock that affects **all households in Darlington**, even households who consume very little energy, which may threaten the social and economic stability in this country and your community.

Figure 1: Impact of energy crisis on households in Darlington: Increase in annual average energy bills

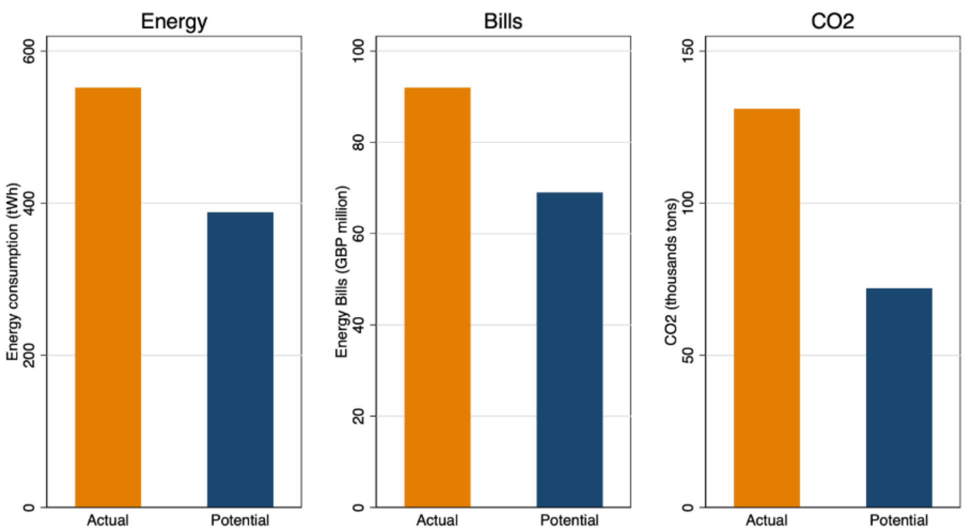


Government intervention, for example through the **Energy Price Guarantee** may **temporarily reduce the burden** on households, but ultimately, the higher price for energy will be paid either by households directly, or indirectly, through the government, which needs to **raise taxes, cut spending or borrow** in order to cover the cost.

But there is another alternative: to **save energy**. And the savings potential in Darlington is large. We estimate that all households in Darlington combined could save **more than £23 million in energy bills per year** at current market prices. In fact, if homes for which we do not have data are comparable to those for which we do have data, financial savings could be as high as £36 million per year.

This savings potential exists because we estimate that the residential building stock in Darlington could save up to **30% of its primary energy consumption** if buildings were **properly insulated**. We estimate that the building stock in Darlington alone could save at least **60000 tons of CO2 per year**. The CO2 savings themselves have a monetary value: at present emissions trading prices of £78 per ton of CO2, we estimate that the 60000 tons of CO2 emissions that could be saved are worth £4.7 million per year.

Figure 2 – Energy, financial and CO2 savings potential in Darlington's building stock



Helping households insulate their properties could be a win-win-win as households could **permanently save money**; it would support the **fight against the climate crisis** and it could help reduce our **vulnerability to foreign powers** that may use energy as leverage or as a weapon in a hybrid war.

With the crisis unfolding, households may feel helpless and even more disconnected from the central government. Yet, our research highlights that empowering households to unlock the savings potential in their own homes is key to their wellbeing and to the country's decarbonisation goals.

Therefore, it is imperative for local government and local councils to devise ways to ensure that the existing schemes reach households. Our team will be happy to assist in identifying barriers to take-up of energy efficiency investments, in designing programs to overcome these barriers, and in finding out "what works". Such a partnership can make your district an example to follow in the whole country.

We have prepared more **analysis specific to Darlington** that is available as a brief *here*.

Thiemo Fetzer
Ludovica Gazze
Menna Bishop

University of Warwick
CAGE Research Centre

C.2 Brief to Darlington

How will the energy crisis affect households in UK districts?

Thiemo Fetzer, Ludovica Gazze, Menna Bishop (University of Warwick, *energycrisis@warwick.ac.uk*.)

25 Oct 2022

The energy crisis in Darlington: Executive Summary

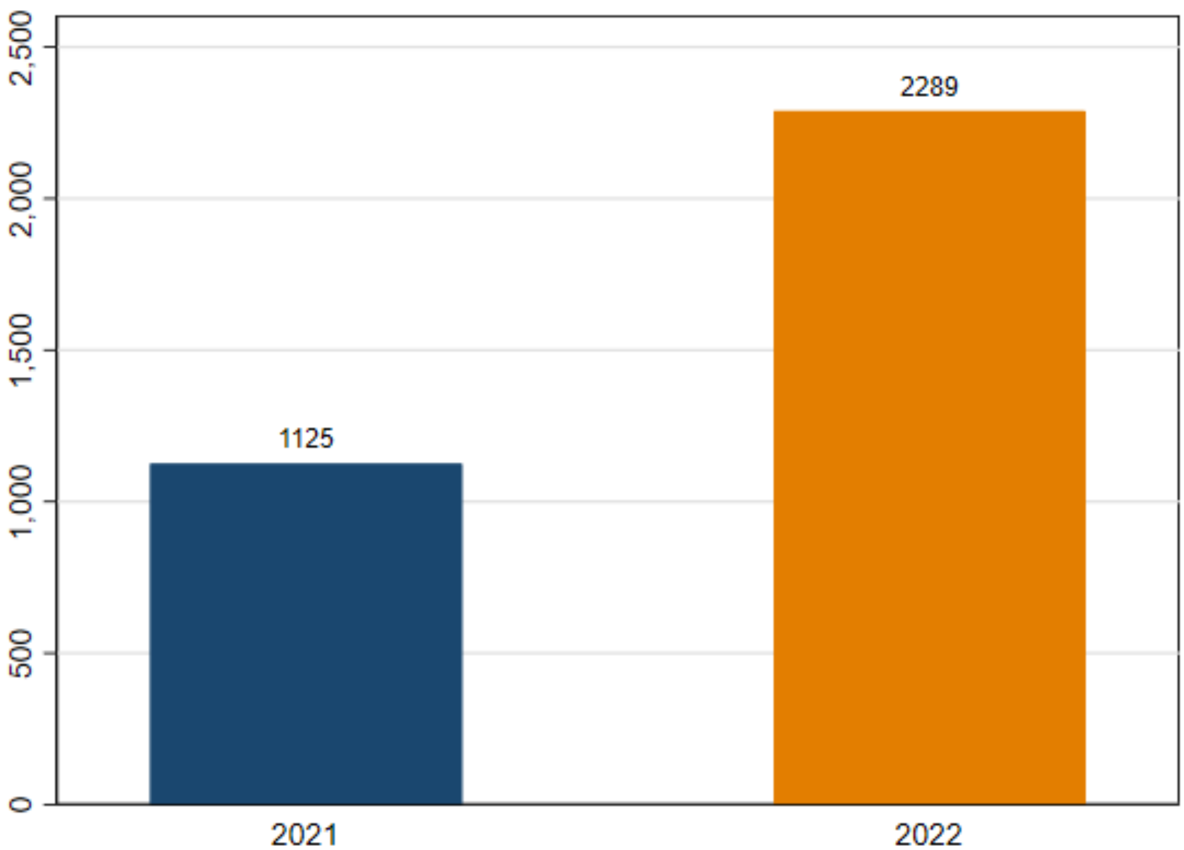
This report provides a summary of research that is carried out at by economists at the University of Warwick. We have modelled what the impact of the energy crisis is going to be across households in England and Wales and have developed this specific brief for Darlington. We find that the **average household in Darlington may see increases in energy bills of £1164 per year**, even with the existing government support in place through the Energy Price Guarantee (EPG). Without the EPG, average energy bills would increase **by as much as £2036** when measuring prices as per the Ofgem October announced prices. Naturally, the difference between the cost increase that households face vis-à-vis the market prices of energy will need to be paid somehow by the government, which invariably means **higher taxes, lower public spending or more public debt**. The shock is broad based and will virtually affect all households.

Our estimates suggest that the energy shock may take **out a combined £53 million from residents in Darlington**, if homes for which we do not have data are comparable to those for which we have data. Rather than spending public money to subsidize energy consumption, we identify that there is a **large potential for energy savings** that could be mobilized in Darlington. We estimate that residents in Darlington could save at least 30% energy permanently if energy efficiency upgrades were implemented to the building stock; this corresponds to **realizing financial savings valued at market prices of at least £23 million per year**, along with CO2 emissions reductions of 60000 tons. In fact, if homes for which we do not have data are comparable to those for which we do have data, financial savings could be **as high as £36 million per year**. An estimate of the investment cost of making such upgrade investments in the 25635 properties for which the data suggests there is an energy efficiency improvement potential, focusing particularly on insulation and boiler upgrade measures, is £163 million.

How will the energy crisis affect Darlington and its residents?

The energy crisis is a broad-based economic shock that can threaten social and economic stability in the UK and it will see **households in Darlington hit hard.** Even with government support, for example, through the Energy Price Guarantee in place: we estimate that the average household in Darlington will see an increase in their energy bill of £1164 relative to prices from October 2021. Importantly, the government financial support to households is not itself without costs, as the government either will have to **borrow, cut spending, or raise taxes** in order to finance the energy price support package. As such, households will have to pay the price of higher energy either directly, or indirectly.

Figure 1: Impact of energy crisis on households in Darlington: Increase in annual average energy bills

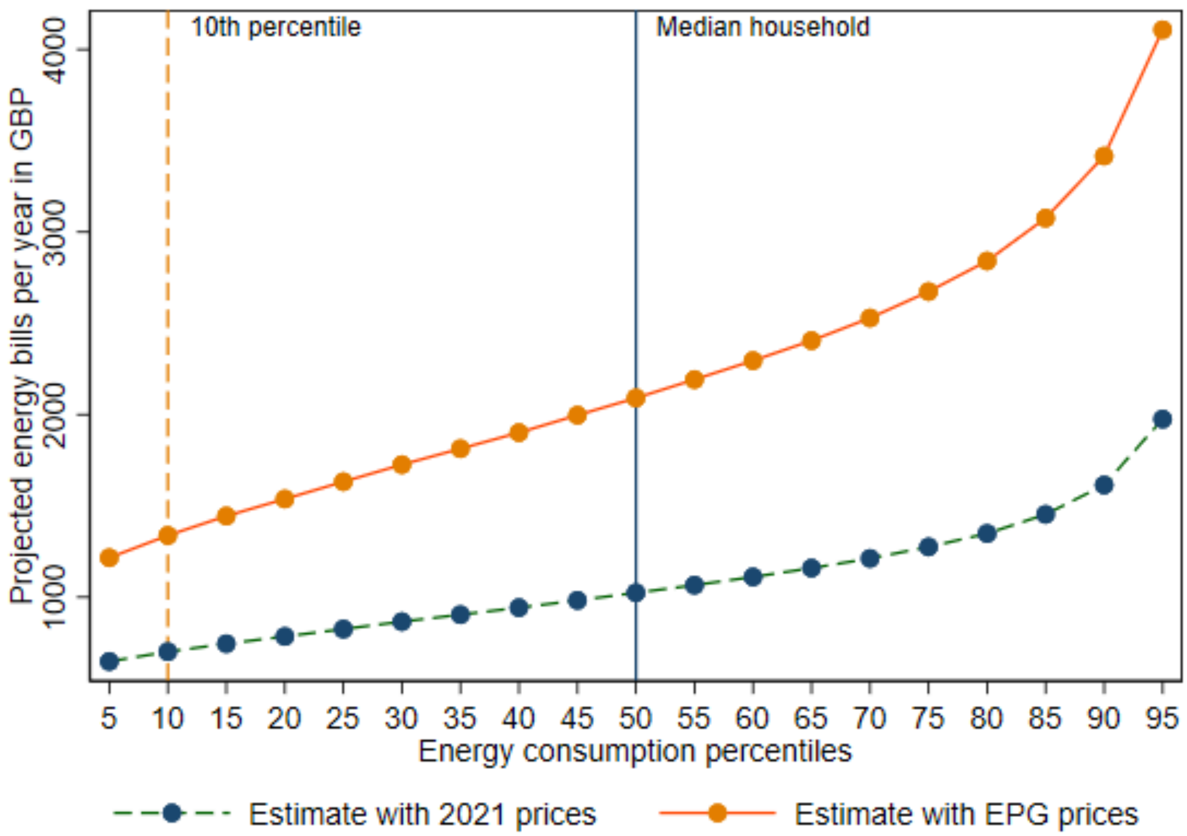


Importantly, **many households may be caught off guard by this drastic increase in energy bills.** Research has shown that many households **do not know how much energy they consume** (see Attari et al, 2010). The prime reason for this is that energy use simply was not top-of-mind, as energy prices have been very low for a long period of time. The absence of awareness to one's own energy consumption raises the importance for local government, local media, and local politicians to raise such awareness.

Moreover, **all households in Darlington will be affected by the energy price shock.** Even households who consume very little energy are projected to see a steep increase in their energy bills. These increases are expected to happen despite government support packages, such as the Energy Price Guarantee. Figure 2 illustrates the projected impact of the energy price shock in Darlington across the distribution of households based on their respective energy consumption. The median household in Darlington may expect to see an increase in their energy bills by up to £1067. That is, 50% of households will see their energy bill increase by more than £1067 per year, while 50% will see their increase in energy prices by less than that.

Still, **even households who already consume very little energy – which are typically among the poorest – will be hit hard.** Households at the 10th percentile of the energy consumption distribution (that is, 90% of households consume more energy than them while 10% consume less than them) are **projected to see an increase in energy bills of £637** despite the support from the Energy Price Guarantee. Households who have such low energy consumption typically live on a household income of less than £15,000 per year. For these households this shock, in the context of broader inflationary pressures, may cause a drastic decline in real standards of living which may threaten social cohesion and social stability.

Figure 2: Distribution of the projected change in energy bills across households in Darlington



To put things in perspective, the median household in Darlington lives in a mid terrace property that was built during the 1900-1929 period with 4 habitable rooms and an approximate floor area of 85 square meters (915 sqft). Thus, it is clear that this energy crisis will affect many very regular families and citizens in your community.

Many households are already **financially squeezed due to the economic fallout from the pandemic,** more than a decade of **stagnant productivity growth,** and the resulting **falling real incomes.** This energy crisis thus may affect the material well-being of broad swathes of society, many of whom do not have a financial cushion to accommodate the shock.

Why is this happening?

The increase in energy prices is brought about by the Russian War on Ukraine and the subsequent dislocations in energy markets. This has been made most apparent in recent destruction of pipeline infrastructure in the Baltic Sea. It is a broad foreign policy expert consensus that energy is used as leverage in this conflict to sow an economic crisis in the West and through that, undermine the Western resolve to support Ukraine in its self-defence against Russia's aggression. This threatens the global peace order that was established after World War 2.

Why does saving energy make so much sense both in the short and long run?

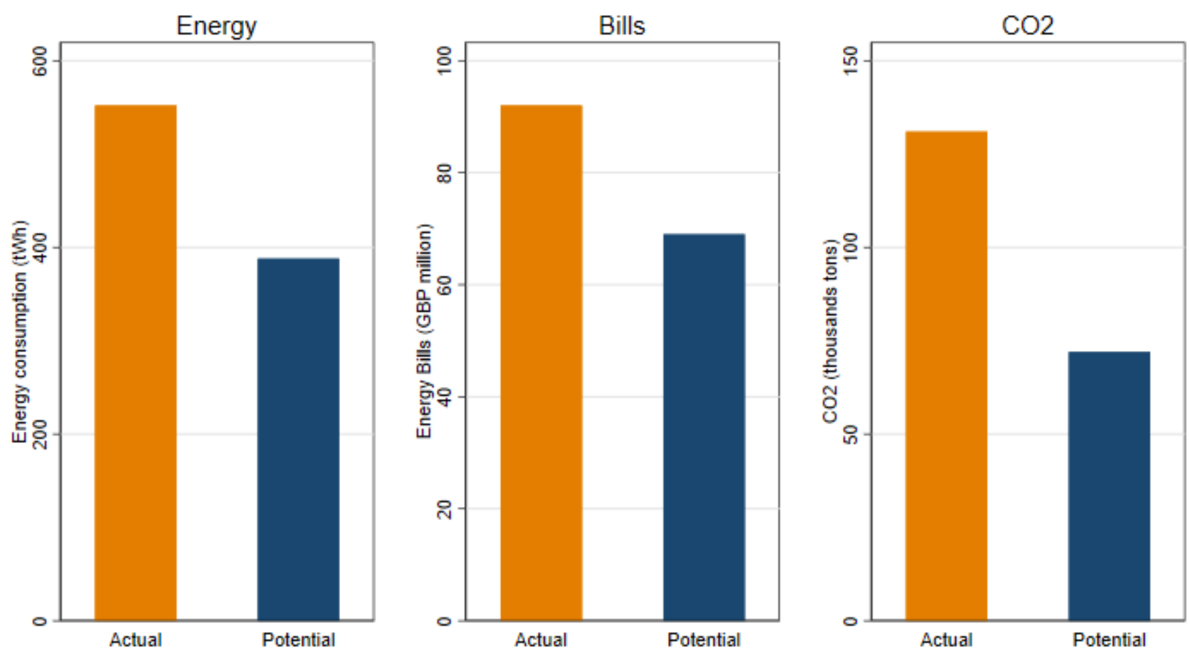
Irrespective of the motivations, the energy crisis is also an opportunity to rebalance the UK economy. Saving energy makes a lot of sense both economically and environmentally. And there is a lot of energy savings potential right here in Darlington. One of the main reasons why Darlington and its population will be so severely affected by the energy crisis is because of decades of **underinvestment in the existing building stock.** We estimate that at least 49% of Darlington's building stock could, if adequately retrofitted, contribute permanently to saving energy. Why has this not happened before? The answer is simple: the economics of energy saving investment were not there. For many homeowners, businesses, and the community in general, it simply did not financially make sense to invest in improving the energy efficiency of their property.

The dashed line in Figure 2 highlights this quite nicely: prior to the war, energy bills between the highest consuming households and the lowest energy consuming households hardly differed. Because **energy was very cheap** it didn't make a huge difference for households to save energy. The incentives to do so were very weak. In England and Wales, before the Ukraine war, households on incomes less than £15,000 had average annual energy bills to the tune of £1,161 per year, which contrasts to estimated energy bills among the highest earners with household incomes of £150,000 or more of £2,809 per year. So, despite the annual incomes between these two socio-economic groups differing by a factor of 10, energy bills between highest and lowest earners were only, on average, 2.5 times higher among the highest earners. That is why many people didn't pay much attention to energy. And as highlighted, many households, especially in the middle of society are not aware of the shock that may be coming because many do not know how much energy they use (see Attari, 2010)

The Russian war on Ukraine and the resulting energy price increases **have changed this.** And it is our view that the increase in energy prices will be **permanent.** Even with large scale natural gas imports through liquified natuaral gas (LNG) or with higher domestic production, possibly using methods with a questionable environmental track record such as fracking (see Alvarez, 2018), it is unlikely that energy will become as cheap as it was before the war. Physics is one factor in this equation: the process of liquification and regasification uses up a lot of energy implying a natural minimum markup on any LNG imports. Further, climate change and the need to **reduce our carbon footprint** will elevate energy prices structurally in the long run through the much-needed system of carbon taxation.

We estimate that all households in Darlington combined **could save more than £23 million in energy bills per year at current market prices.** In fact, if homes for which we do not have data are comparable to those for which we do have data, financial savings could be as high as £36 million per year. This savings potential arises because we estimate that the residential building stock in Darlington **could save up to 30%** of its primary energy consumption if buildings were properly insulated. We estimate that the building stock in Darlington alone **could save at least 60000 tons of CO2 per year.** The CO2 savings themselves have a monetary value: at present emissions trading prices of GBP 78 per ton of CO2, we estimate that the 60000 tons of CO2 emissions that could be saved are worth £4.7 million per year. With increased carbon prices, which will be added on to consumer bills in the future, these carbon costs will **raise future energy prices,** even if the war in Ukraine comes to an end and European energy supplies normalize. As such, saving energy is not just sensible in the short-term but also the longer term.

Figure 3: Energy, financial and CO2 savings potential in Darlington's building stock



It is also important to point out that **there is no free lunch.** Short term interventions in energy markets have a price tag. The government's **Energy Price Guarantee temporarily reduces energy prices** for consumers in a way that disproportionately benefits better-off households (see Fetzer, 2022). Yet, as a society, the cost of the energy price guarantee or any price-support mechanisms will need to be paid for. The government would pay for the difference between the market price and the subsidized prize. It needs to finance this subsidy somehow. From a budget perspective, this can take the form of either **higher taxes or cuts in government spending.** Yet, there is a third way which is to ensure that households consume permanently less energy. This has several advantages because saving energy:

- **Saves** households large amounts of **money permanently** not just as a one off
- **Reduces our carbon footprint** accelerating the net zero transition to avert the worst consequences of climate change which itself has a monetary value
- Can help **avert higher taxes and/or further budget cuts** that may be needed to fund energy subsidies such as the Energy Price Guarantee that often benefit households that are better off and consume more energy and that are distorting incentives to save energy

- Can help **build resilience** and blunt the ability of Russia or other energy suppliers which often are non-democratically governed to use energy as weapon or leverage

- Lastly, there is some work that suggests that energy efficiency can also pay off in the long term by **boosting property values** (see Dalton and Fuerst, 2017) and reduce the default risk of mortgage borrowers (Guin et al, 2022) thereby contributing to financial stability.

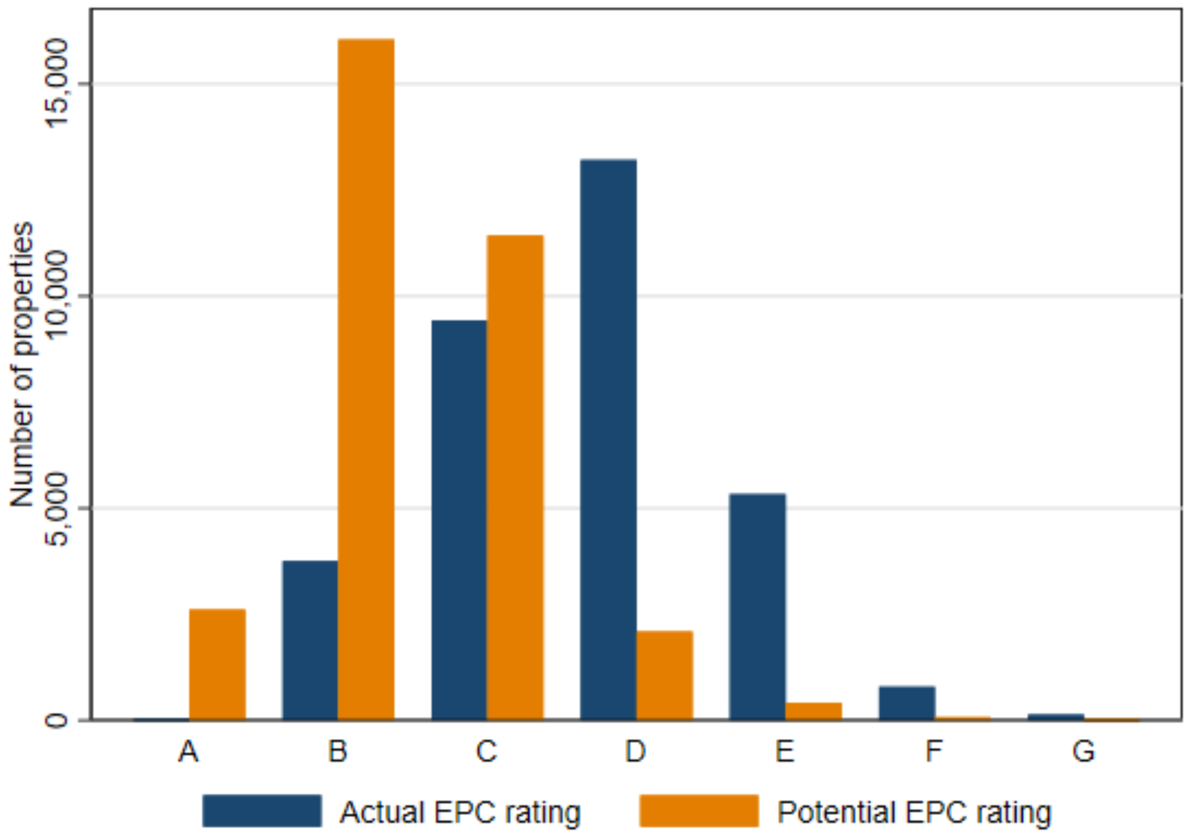
What can be done in Darlington to mobilize the energy savings potential?

As we quantified, there is a lot of energy savings potential in Darlington that can be mobilized and tapped into. Energy savings measures will have two components: **short-term and medium- to longer term measures.**

Permanent energy savings measures

Darlington has around 51980 residential properties as per the council tax register. We have granular data that allows us to study energy consumption from a sample of about 63% of Darlington's building stock, that is 32671 properties. Research from the Office of National Statistics suggests that the data we work with here is broadly representative of the overall building stock. Most of the properties have notable improvement potential in terms of their energy performance certificate as is shown in Figure 4 tabulating the actual and the potential energy performance certificate (EPC) rating of the building stock for which we have data. In total, there is improvement potential in 25635 of the 32671 properties for which we have data.

Figure 4: Number of properties by their current and potential EPC rating in Darlington

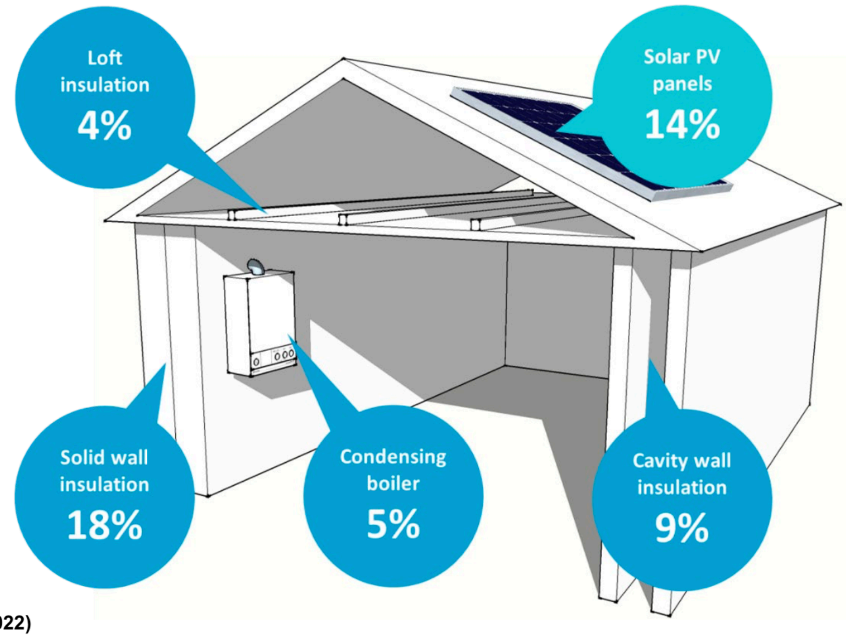


The most common measures to improve the energy efficiency of properties that have been shown to have real impact are:

- Cavity wall insulation
- Solid wall insulation
- Floor, roof and loft insulation
- Condensing boiler replacements

The UK's Department of Business, Environment and Industrual Strategy (BEIS) regularly studies the energy savings potential using real data on actual consumption. These are based on individual level meter-reading data and not just modelled energy savings that draw on laws of physics and thermodynamics (see BEIS, 2022). They are visually summarized in Figure 5.

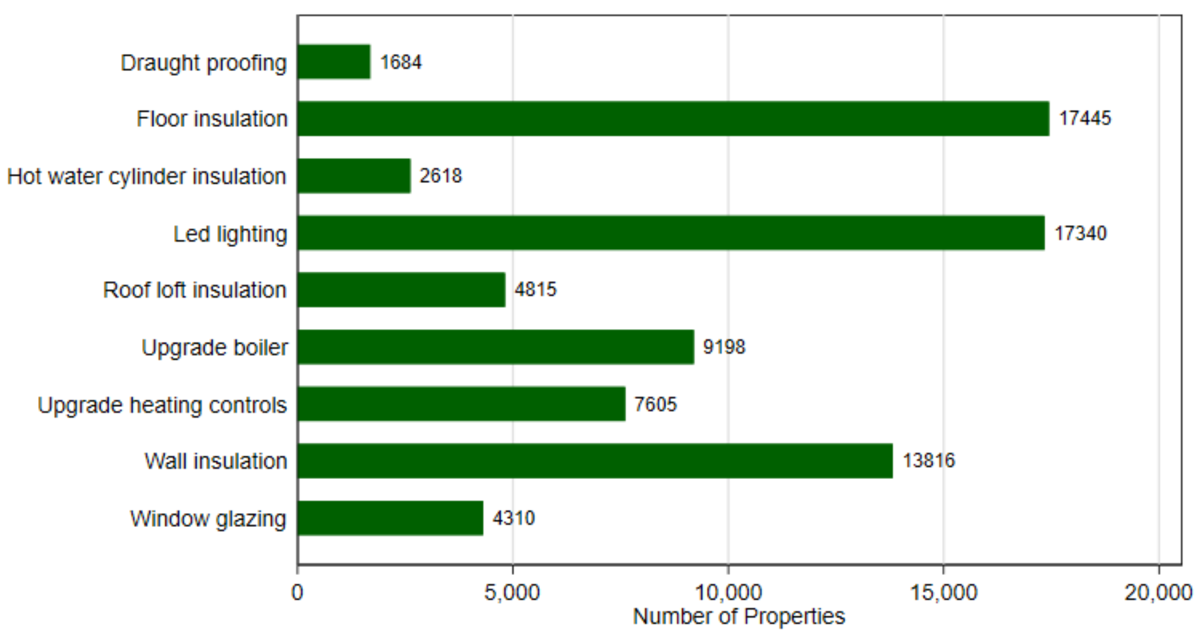
Figure 5: Typical gas savings in 2019 from energy-efficiency upgrades installed in 2018 in England and Wales (electricity savings are shown for Solar PV installations)



Source: BEIS (2022)

So what can be done in Darlington in the at least 25635 properties for which we identified energy-savings potentials? The data on the EPC's provides a range of measures that are quoted. This can give an idea of the scale of the task at hand to realize these energy savings to shape a more sustainable future.

Figure 6: Number of energy efficiency improvement recommendations by recommendation type in Darlington



In Darlington, we estimate that at least 13816 properties would benefit from improved wall insulation such as solid- or cavity wall insulation. Further, 4815 properties would benefit from roof- or loft insulation, while 17445 properties could benefit from floor insulation. Further, there are at least 9198 properties that could benefit from condensing boiler upgrades. There are smaller measures that may be less invasive and less costly, but the savings could add in the short- and long-run.

This suggests that there is a lot of room for improvement in terms of energy savings. Here are 4 steps you can take to secure resources to make these investments happen right here in **Darlington**:

- Local councils could secure funding from their *local net zero hub* to promote energy efficiency investments in your council.
- Local councils could refer households to large energy suppliers for retrofits under the *ECO Flexible Eligibility scheme*.
- Local councils could refer households to existing *government energy efficiency schemes*.
- Local councils could help people navigate the retrofitting process with simple permitting procedures, lists of contractors, and schemes to support training of new contractors.
- Local councils could secure funding to retrofit social housing through *BEIS-backed Social Housing Retrofit Accelerator* designed to support you to successfully bid into the Government's Social Housing Decarbonisation Fund.

Households can also save money through ***temporary energy savings measures,*** including:

- Local councils could identify energy savings potentials in buildings that are managed by the council or through the social rented sector. Councils could offer a reward scheme or a cut to service charge that is communicated to all residents if they achieve a certain energy savings target.
- Local councils could encourage other private and social rented providers similar incentives. These would mostly self-fund as the lower energy bills can be passed on.
- There is large energy savings potential simply arising from changing daily routines, for example encouraging households to lower the cooling temperature settings on their thermostats by 1 degree (19C) like many other European countries are doing, turning off devices on standby, changing lightbulbs or using electrical appliance use, such as dishwashers or laundry machines to off-peak hours.

Way forward

With the crisis unfolding, households may feel helpless and even more disconnected from the central government. Yet, our research highlights that empowering households to unlock the savings potential in their own homes is key to their wellbeing and to the country's decarbonisation goals. Therefore, it is imperative for local government and local councils to devise ways to ensure that the existing schemes reach households. Our team will be happy to assist in identifying barriers to take-up of energy efficiency investments, in designing programs to overcome these barriers, and in finding out "what works". Such a partnership can make your district an example to follow in the whole country.

Methodology

This section briefly summarizes the methodology that we used to produce this report and the data that went into this. A (much) more detailed presentation of this can be found in Fetzer, Gazze and Bishop (2022). A detailed policy brief on the economic implications of the Energy Price Guarantee and other measures that could be taken to boost energy savings is outlined in Fetzer (2022).

Energy Performance Certificates

The UK collects data on the energy performance certificates (EPCs) and makes these available in the public domain for research purposes and non-commercial use. This data provides, for each property that is listed, an estimate of the total energy consumption along with an estimate of potential energy consumption, coupled with the recommendations that are needed to be implemented in order to attain that lower level of energy consumption. The modelled measures of energy consumption are taking into account a range of factors but is mostly relying on the physical attributes of the building such as the materials that were used for construction; the types of windows; the ventilation along with a range of other factors. The engineering view arrives at an estimated volume of energy consumption measured in kWh. We have broken this down into the energy requirement for space heating, hot water generation and electricity use for lighting.

Naturally, the physical energy consumption of a property not only depends on the attributes of the properties, but also of who lives there. The EPC data falls short, because it does not incorporate who and how many people live in a property. Each of these unobservable factors could drive energy consumption above- and beyond what is captured by the physical attributes of the property.

We leverage additional data to anchor the theoretical energy consumption with actual meter-reading based data from actual energy consumption that we match and link to the EPC data. This effectively rescales the energy consumption and can help bring the data closer in line with actual consumption data.

NEED Anonymized Household Energy Consumption Micro Data

Through the National Energy Efficiency Data Framework (NEED) data on energy consumption is analysed by the Department for Business, Energy & Industrial Strategy (BEIS). Anonymized meter-level micro-data is shared with the research community. This provides the annual gas- and electricity consumption of around 4 million households. The data is augmented to include a range of building characteristics such as the property age, the built type, the region- and a few other characteristics that can also be found in the EPC data.

We rescale the EPC-implied energy consumption measure to capture consumption data that is actually found in this meter-reading data based on the percentiles. That is, if a property has similar characteristics in the EPC and the NEED data and is in a similar percentile of the energy-consumption distribution, we rescale the EPC measure to match the actual energy consumption data. This method is called matching-moments in econometrics. This rescaling takes into account property characteristics and actual consumption information but may still fail to account for the demographics of areas and the ensuing energy consumption preferences. To do so, we also use a second rescaling method.

Local Area Consumption Data

BEIS publishes very granular energy consumption data down to the individual postcode level both for electricity- and natural gas as long as a postcode has at least 5 readings. For each postcode, the data provides both the mean- as well as the median energy consumption. We compute the corresponding matching moment – that is the mean or median – in the EPC data and then derive a rescaling factor that is mapping the EPC-NEED augmented mean/median to ensure that this mean/median coincides with the mean/median from the postcode-level energy consumption.

Potential mismeasurement

It goes without saying that this approach is not without measurement error. Yet, this is the best approach that can be used to construct local energy demand measures in a way that we can link to energy savings potential in the UK housing stock. More could be done with more granular data that is available for research use. In fact, BEIS could provide for a linked dataset that matches the EPC data with actual meter-reading data. Yet, it has so far not done so and such a linked dataset is also not available in the Secure Research Service (SRS) of the Office of National Statistics, which is a pathway for academics to work with microdata under a strict, but very slow and bureaucratic access control protocol.

References

Attari, Shahzeen Z., Michael L. DeKay, Cliff I. Davidson, and Wändi Bruine de Bruin. "Public perceptions of energy consumption and savings." Proceedings of the National Academy of sciences 107, no. 37 (2010): 16054-16059.

BEIS – Department for Business Energy and Industrial Strategy. (2021). National Energy Efficiency Data-Framework (NEED): Summary of Analysis, Great Britain, 2021. June 2021.

Dalton, B., Fuerst, F. (2017). The Green Real Estate Premium: A Meta-Analysis. In: Wilkinson et al: The Routledge Handbook of Sustainable Real Estate. Routledge, 9781138655096.

Fetzer, Gazze and Bishop (2020), How big is the UK's energy savings potential?, CAGE working paper.

Fetzer (2022). Beyond the Energy Price Guarantee. With or Without? CAGE Policy Briefing Paper.

Guin, B., Korhonen, P., & Moktan, S. (2022). Risk differentials between green and brown assets? Economics Letters, 213, 110320. *https://doi.org/10.1016/j.econlet.2022.110320*

Intercontinental Exchange (ICE), UKA Futures Price for Emissions Trading Scheme, *https://www.theice.com/products/80216150/UKA-Futures/data?marketId=6675113, accessed October 10, 2022*.