Performative State Capacity and Climate (In)Action

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Abstract

Climate action requires significant public and private sector investments to achieve meaningful reductions in carbon emissions. This paper documents that austerity, coupled with a lack of (digital) skills in (local) government, may have been a significant barrier to delivering climate action in the form of retrofitting. Decomposing heterogeneity in estimated treatment effects of a large scale energy efficiency program rolled out through a regression discontinuity design in the early 2010s, we find that both the extent of local budget cuts and poor digital connectivity may be responsible for up to 30% fewer retrofit installations that counterfactually would have taken place.

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JEL Codes: Q54, Q58, H76, C21, O33, R11, H54

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1 Introduction

The fight against climate change requires significant financial efforts by both the public and private sector to achieve the necessary emission reductions and transition to a net zero economy. Has the erosion of performative state capacity in the wake of austerity following the global financial crisis hampered decarbonization efforts? Following the global financial crisis, many governments implemented severe public spending cuts through a broad range of austerity measures. These aimed at reducing budget deficits and there was hope that the cuts would bring efficiency gains, boosting public sector productivity and the quality of public service. Although austerity may initially have been prudent macroeconomically (Born et al., 2020; Alesina et al., 2019, 2020; House et al., 2020; Jordà and Taylor, 2016), it also engendered many (un)intended consequences (see Fetzer, 2019; Cremaschi et al., 2022; Facchetti, 2023). This paper examines one such unintended consequence of austerity – how cuts to local government finances undermined efforts to shape climate action.

To study how austerity may have impeded efforts to promote climate action, we present evidence on the varied impacts of an energy efficiency program – the Energy Company Obligation (ECO), launched in 2011. This program, centrally designed but locally facilitated, offered support for home energy efficiency upgrades to households. This provides a unique setting for studying how austerity – measured as the extent of cuts in local government spending – limited local governments' ability to implement and manage centrally designed climate action policies. To do so, we use a regression discontinuity design within the ECO scheme roll-out that targeted low-income households in areas among the 15% most deprived in the UK. Local governments played a crucial role in facilitating the roll-out by reducing information asymmetries and barriers between households and energy companies that were legally compelled to deliver the retrofit measures. We argue that local governments' ability to carry out this role was hampered by two factors – austerity and limited (local) government digital and information processing skills.

We proceed in two steps. First, using detailed data on program delivery at the census-tract level and energy consumption data at the postcode level, we estimate an *average treatment effect* via a regression discontinuity. We find that the scheme led to increased uptake and reduced energy consumption in treated areas. Households in areas eligible for government grants saw an increase in the number of retrofit installations by about 25-30%, compared to households in comparable areas that were not targeted due to being slightly less economically deprived. Consequently, average household consumption in eligible areas decreased by 4-8%. The estimated treatment effects are likely downward biased given that we do not measure treatment at the individual household level. Recognizing the risk of ecological fallacy, we support these findings from aggregate data with a reduced-form exercise that leverages individual-level data in an Appendix.

Next, we explore *heterogeneous treatment effects*, estimating one treatment effect for each local authority containing some eligible lower layer super output area (LSOAs). We find significant variation in the estimated treatment effects: areas that were more affected by local spending cuts saw, on average, considerably smaller treatment effects, indicating weaker delivery of retrofits. Similarly, areas with poorer ICT connectivity in 2010 exhibited weaker retrofitting delivery. To consider both linear and non-linear interactions between austerity, digital connectivity and other area characteristics in treatment delivery, we use random forests. Through this exercise, we confirm that, in terms of variable importance, local budget cuts and ICT connectivity appear as primary factors capturing structure in the treatment effect heterogeneity.

The effects are economically significant. For every one-percent increase in local spending cuts, the likelihood that local authorities experienced an above-median treatment effect decreases by one percentage point. Similarly, for every one-percent increase in a local authority's share of households with slow internet, the probability of experiencing an above-median treatment effect decreases by three percentage points. Local authorities with greater spending cuts and a higher share of households with slow internet experienced significantly lower implementation levels. These findings underscore the pivotal role of local governments in executing centrally designed climate action programs and highlight how austerity measures have undermined their effectiveness, potentially impeding broader climate action initiatives.

This paper relates to three areas of research. First, it adds to our understanding of austerity and its unintended social and economic consequences. Most research has focused on the political ramifications of broad-based austerity after the global financial crisis (see, Alesina et al. (2023, 2020); Baccini and Brodeur (2021); Gabriel et al. (2023); Fetzer (2019); Galofré-Vilà et al. (2021); Kalbhenn and Stracca (2020); Ponticelli and Voth (2020); Bermeo and Pontusson (2012); Bermeo and Bartels (2014)). This paper contributes to an emerging literature studying the effects of austerity on public service delivery (Cremaschi et al., 2022; Fremerey et al., 2022), with broad-based austerity having been shown to cause more (hate) crimes (Bray et al., 2022; Facchetti, 2023), increased housing insecurity and homelessness (Fetzer et al., 2023), and a decrease in the quality of public services (Hoddinott et al., 2022). Those spending cuts were heavily biased towards deprived areas (Beatty and Fothergill, 2014; Gray and Barford, 2018). We trace out the unintended effects of austerity's erosion of performative state capacity to study the impact on the delivery of climate action.

Second, the paper relates to the climate policy literature. Prior work on the effectiveness of property-level climate action measures offers an ambiguous picture, with some studies finding positive and larger than expected effects (Clay, 2006; Webber et al., 2015) and others finding almost negligible or lower than estimated effects (Metcalf and Hassett, 1999; Davis et al., 2014; Levinson, 2016; Zivin and Novan, 2016; Houde and Aldy, 2017; Fowlie et al., 2018; Liang et al., 2018). We provide a mechanism for reduced effectiveness of climate policies – performative state capacity[1]. In line with existing studies emphasizing the state's role in facilitating individual climate action (Skidmore, 2022; Fetzer, 2023; IPCC, 2023; Nice and Sasse, 2023; CCC, n.d.; UK CCC, 2023a,b), we show how spending cuts decided on at the highest national level can undermine local efforts to decarbonize.

[1]Other explanations for failed climate policies can be classified into behavioral responses (Gillingham et al., 2013; Blonz, 2023) and market failure due to e.g. moral hazard or imperfect information (Giraudet et al., 2018). For a comprehensive overview of the energy efficiency gap and its determinants see Allcott and Greenstone (2012)

Austerity weakened local state capacity hindering the implementation of centrally designed programs, like ECO.[2]. This aligns with works arguing that a capable state is necessary to achieve climate targets by incentivizing behavioral changes at the individual leveland improving the implementation of climate policy (Willems and Baumert, 2003; Rau et al., 2020; Zwar et al., 2023).

Third, the paper relates to the growing literature on state capacity. Traditional models of state capacity have focused on governments' ability to implement and enforce policies (Besley and Persson, 2009, 2010; Johnson and Koyama, 2014; Dincecco, 2017; Lee and Zhang, 2017; Weigel, 2020; Balan et al., 2022; Schönholzer and Francois, 2023). This literature on performative state capacity has most recently been complemented by studies on informational state capacity (see e.g. Fetzer et al., 2024). This research highlights the importance of performative state capacity – the practical ability to implement policies effectively. Austerity eroded local government functions, undermining the effective roll-out of the ECO program. Similarly, lower digital skills hampered local governments' ability to efficiently carry out climate action policies. This complements existing literature examining how reduced resources, skills, and responsibilities can compromise the state's effectiveness in policy delivery and goal achievement (Huber and Shipan, 2002; Page and Pande, 2018; Serikbayeva et al., 2021; Dahlström and Lapuente, 2017, 2022; Best et al., 2023).

2 Context, Data and Motivating evidence

2.1 ECO and CSCO

The Energy Company Obligation (ECO) is a UK program requiring energy companies to support eligible households with energy-efficiency improvements to reduce their carbon emissions and to lower fuel poverty. The scheme first came into effect in 2012. To be eligible for financial support or grants to pay for retrofit measures

[2]This touches the literature on the trade-off between centralization and decentralization (Oates, 1972; Bjorvatn and Cappelen, 2003; Mazzaferro and Zanardi, 2008; Treisman, 2007) Previous work highlights the important complementary role local governments have to play in the path to net zero (Bulkeley and Betsill, 2005; Bulkeley and Kern, 2006; Aall et al., 2007; Sperling et al., 2011).

delivered under ECO, a household must claim some form of welfare benefits or meet other eligibility conditions.[3]

To aid implementation, councils were asked to coordinate and facilitate the flow of information to identify eligible households.[4] In the first iteration of ECO – the focus of this study – a spatial targeting approach was taken. Priority was given to lower layer super output areas (LSOAs) – statistically defined areas that are built from census tracts (so called, output areas) that encompass, on average, 1,700 residents – that rank particularly poorly on the Index of Multiple Deprivation (IMD). The IMD ranks each of the UK's roughly 40,000 LSOAs based on the deprivation of the resident population across a range of domains.[5] Initially, the ECO scheme targeted LSOAs within the most deprived 15% in England, Scotland, and Wales, based on IMD scores. In 2014, this threshold was increased to the 25th percentile.[6] Naturally, this creates the possibility of a regression discontinuity design around the deprivation cutoff, which we take advantage of here.

Eligibility for ECO To carry out the regression discontinuity design estimation, we leverage a list published by the UK's Department of Energy & Climate Change (DECC)[7] in June 2012 and contains all LSOAs eligible under the ECO1 CSCO scheme using the 15th percentile cutoff. As a running variable for the RDD, we obtained the deprivation score and ranking of each LSOA in 2011. This allows us to develop the RDD exercise using various cutoffs around the 15th percentile to facilitate comparison in the number of retrofit installation delievered between areas

[3]The precise legal text of the order can be found on `https://www.legislation.gov.uk/uksi/2012/3018/body/made`. More details on the scheme are discussed in Appendix A.1.

[4]This makes salient the informational boundaries of the state as it requires the processing and sharing of decentrally stored data from councils with centrally stored data on benefit receipt.

[5]The IMD comprises several deprivation measures, including income, employment, education, health, crime, housing, and living environment. See Bowie (2019) for more details on the IMD.

[6]To make sure that rural areas benefit as well from the CSCO, the government required firms to deliver 15% of their CSCO obligation to households in rural ares. A rural area was defined as a settlement with 10,000 households or less (Department of Energy and Climate Change, 2012). Firms, however, were permitted to deliver up to 20% of total activity to areas adjacent to those identified using the eligibility IMD cutoff.

[7]The department was dismantled and merged with the Department for Business, Energy and Industrial Strategy (BEIS) in 2016 and was partly resurrected in form of the Department for Energy Security and Net Zero (DESNZ).

that were not eligible. We focus mostly on a 5% and 10% cutoff for the estimation.

Measuring retrofit installations We obtained data on the installation of retrofit measures under the scheme from the Office of Gas and Electricity Markets (Ofgem) through several freedom of information (FOI) requests. The requested data is at the census tract – output area (OA) – level using 2021 census definitions. It covers all retrofit installations that were carried out under the various ECO schemes since its inception. More detail on the underlying data is provided in Appendix A.2. This allows us to measure the number of installations of retrofit measures at a spatially and temporally exceptionally granular level. The resulting dataset is a balanced annual panel, covering all retrofit installations in the UK at the output area level over the period from 2010 to 2023. Our main outcome variable of interest is the number of retrofit installations in a given output area and year.

2.2 Local government's coordinating role

The ECO scheme was decided on and designed at a national level. Yet, local governments were given a central role in its roll-out and delivery. The primary role of local governments was to leverage their informational capacity to reduce informational frictions between households and energy suppliers. Due to the administration of local taxes and benefits, local councils have significant hard data about their resident population. Their mandate involved leveraging this knowledge to identify eligible households and point them to energy suppliers. Local authorities typically would contact households they considered eligible based on their data and records within their jurisdiction and match them with an appropriate agent to facilitate the delivery of the retrofit measures via the energy companies and their network of installers.[8] We posit that the extent of austerity-induced cuts to local government funding, along with the often underdeveloped state of digital skills among civil servants in local administrations, may have directly impeded the delivery of the ECO scheme.

[8]Local authorities could also ask for specific installers, with which would then be brought to table by the managing agent firms.

Measurement of austerity Local government budgets saw some of the most drastic budget cuts after 2010.[9] Fetzer (2020) documents how spending across local governments and across core functions, such as housing and planning and development, saw nominal cuts in the neighborhood of up to 50%, relative to the level before the Global Financial Crisis.[10] The main mechanism by which the central government reduced the financial capacity of local governments was through across-the-board cuts in central government grants to local authorities.

At the same time, local governments' revenue-raising capacity remained limited, while statutory duties and service standards were raised, which may further limit the fiscal space for councils. The cuts were heterogeneous in their impact on spending, as some councils benefit from other sources of income arising, for example, from the ownership of assets. We leverage data on council spending that is reported across crude spending categories, indexed by i, for each budget year. We calculate an index to measure the relative change in average spending from 2007 to 2010, compared to average spending from 2011 to 2015.

That is, we measure:

$$austerity_{i,c} = \frac{\bar{x}_{i,c,2007-2010} - \bar{x}_{i,c,2011-2015}}{\bar{x}_{i,c,2007-2010}}$$

Here, i denotes the category of spend of council c. The higher this measure, the higher the austerity shock for a local authority c in category i.

Given the relatively coarse categorization of spending by activity, the main austerity measure we leverage is the change in current expenditure of total services less the net current expenditure in environmental and housing services. We deduct expenditures for environmental and housing services to ensure that the measure accounts for the austerity shock capturing service capacity and without conflating it

[9](Fetzer, 2019) focuses specifically on austerity-induced reforms to the welfare and various forms of benefits. These were realigned, producing significant cuts in benefit payments, in particular for the working-age adult population.

[10]The various cuts led to rather visible changes in the lived environment that exacerbated the fallout of structural change, for example in the retail sector. The negative spatial externalities – whether accurately perceived or not – is what populists are so adept at exploiting in their campaigning, benefiting from a fragmented and de-professionalized new (social) media ecosystem.

with expenditures that councils may incur due to the delivery of the ECO scheme.[11]

(Figure 1)

Panel A of Figure 1 displays the the spatial distribution of our main austerity measure across local authorities in England. The average local authority experienced a nominal spending cut of 17%. There is, however, substantial variation across local authorities with a standard deviation of 15%. Darker shades of red indicate a stronger austerity shock, i.e. higher cuts on total service expenditure. In Panel B of Figure 1, we present evidence suggesting that the level ECO-induced retrofit installations decreases in the extent of austerity that each local authority delivered. This suggests a negative relationship between climate action and the extent of austerity.

Broadband data As we will show, higher degrees of austerity across local councils implied a significantly weaker delivery of retrofit installations in eligible areas. Councils facing severe spending cuts may have struggled to fulfill their coordinating and facilitation role to deliver the ECO program. We also consider a second mechanism that may explain the low treatment effect: the lack of informational capacity within local governments to facilitate the flow of data and information necessary to coordinate action.[12] Unfortunately, we lack granular data that directly captures the level of digital literacy or skills at the local level. As a crude proxy, we use data measured in 2011 from the Office of Communication (Ofcom) in their Communications Infrastructure Report 2011 on broadband penetration.[13] The main measure we focus on is the share of homes receiving less than 2Mbit/s.

Other measures For our exercise where we use a random forest to decompose the heterogeneity in the treatment effects distribution, we leverage a broad vector

[11] In the Appendix, we show that our results are robust to using the measure that includes these expenditures.

[12] The pandemic highlighted significant deficiencies in skills and data processing capabilities across much of the world, which has resulted in significant and often times severe problems in the public sector being able to respond to the pandemic with agility and speed, see e.g. Fetzer and Graeber (2021) for a particularly stark example.

[13] See Appendix A.4 for more details on the processing of this data.

of other area-level (demographic) characteristics. Other controls include within-authority inequality, as measured by the standard deviation of the deprivation score (IMD), and the share of LSOAs classified as rural.

2.3 Energy consumption

Lastly, to document that the retrofit measures that were installed under ECO were effective, we leverage granular data on gas and electricity consumption – the main sources of domestic energy consumption – provided at the postcode level by the Department for Energy Security and Net Zero (DESNZ). This covers almost the universe of postcodes in the UK, except postcodes that are considered disclosive.[14] The data contains the number of domestic gas and electricity meters, total gas and electricity consumption per year, as well as median and mean annual gas consumption per meter. The data is only available for the years 2013, and 2015 - 2021. We aggregate the data to the output area level. To control for an OAs size we use gas and electricity consumption divided by the number of meters as outcome variables. Lastly, we build a combined energy index by adding up total annual gas and electricity consumption and dividing by the number of meters in a given OA.

For a robustness check, we also leverage anonymized household-level data from the National Energy Efficiency Data-Framework (NEED). This provides some data on the installation of measures, but we lack granular data on the exact location due to the potential disclosure risk involved. Nevertheless, we can emulate the regression discontinuity design with this data given that households energy consumption is reported across IMD quintiles. For more information on the Appendix exercise refer to Appendix section 2.

[14] Postcodes are considered disclosive if either the number of domestic electricity or gas meters is below 5 meters or the top two most consuming meters sum up to more than 90% of the total postcode consumption.

3 Empirical Approach and Results

3.1 Estimation of average treatment effects

Empirical Approach In the first step of our empirical analysis, we assess whether the CSCO policy under the ECO scheme achieved its goals to improve energy efficiency in the UK while focusing on low-income household areas (Department of Energy and Climate Change, 2012). To do so, we leverage the eligibility criteria of the CSCO that targeted households living in the 15 percent most deprived LSOAs to benefit from subsidized retrofit installations. We use this arbitrary cutoff to compare LSOAs just above the cutoff (treated) to LSOAs just below the cutoff (control).

The first stage of our analysis is to show that in areas eligible for CSCO retrofitting more installations were carried out. In the second stage, we estimate the effect of the CSCO eligibility on energy consumption of households, measured as combined gas and electricity consumption. To graphically show the relationship between retrofitting installations and eligibility we calculate the distance of each LSOA l to the cutoff as $d_l = IMDrank_l - cutoff$ where LSOAs with $d_l \leq 0$ are eligible for CSCO retrofitting measures. We use data on the number of installations at the OA level to assess the first stage. Figure 2 panel B shows a binned scatter plot of the log number of retrofit installations at the OA level just below and above the cutoff within a bandwidth of around 10% of all LSOAs below and above the cutoff[15]. The graph shows a clear and significant discontinuity at the cutoff. Panel A of figure 2 shows the selected sample in a spatial representation. Areas in brown are LSOAs that are below the 15th percentile cutoff but not within the chosen bandwidth. LSOAs in blue are treatment and control areas, that is, LSOAs below and above the 15th percentile cutoff that are within the bandwidth of 10% LSOAs above and below the cutoff.

(Figure 2)

We estimate this discontinuity in installations above and below the cutoff using

[15] 10% of all LSOAs above and below relates to including 3000 LSOAs above and below the cutoff.

the following baseline specification specification[16]:

$$y_{olt} = \beta \times 1(d_l \leq 0) + \mu_{itl1,t} + \epsilon_{olt} \tag{1}$$

where y_{otl} is either the number of installations within an OA or the energy consumption of an OA o in year t, in LSOA l. $1(d_l \leq 0)$ is an indicator function that equals one if LSOA l is among the 15 percent most deprived areas. Therefore, β is the coefficient of interest and gives us the causal effect of being eligible for retrofit measures. We cluster all standard errors at the LAD level to account for the level of local government at which decisions are made. $\mu_{itl1,t}$ are ITL1 $\times$ year fixed effects, and ϵ_{olt} is an idiosyncratic error term. ITL1 or International Territory Level 1 regions are the first level of the statistical subdivisions of the UK and correspond to the NUTS1 regions that the EU uses for geographical clustering. These are equivalent to the regions of England, which, until 2011, had administrative functions. Therefore, we control for ITL1-specific time trends. To ensure that we are picking up a robust effect of eligibility on installations and energy consumption, we use nine distinct specifications using different levels of fixed effects and controls. In a more demanding specification, we include ITL2 $\times$ year fixed effects as ITL2 regions in England correspond to counties (most of them grouped), which have some administrative responsibilities. Next, we isolate variation within years and within local authorities by including year and LAD fixed effects. In an even more restrictive approach, we include middle layer super output area (MSOA) fixed effects, one statistical level higher than our treatment. Lastly, we use property-level controls which are reported at the postcode level and aggregated at the OA level that could affect a household's demand for retrofitting installations and its energy consumption like household income, proxied by its council tax band, property age, and property type.[17] In our most restrictive specification, we control for ITL2 specific year trends, MSOA fixed effects, and property-level controls.

[16]We estimate all regressions in R using Laurent Bergé's amazing fixest R package. For more information, see Bergé (2018).

[17]The different house types are bungalow, maisonette flat, detached, semi-detached, and terraced.

Results Table 1 presents the results of these regressions. Panel A of the table shows the effect of CSCO eligibility on the number of retrofit installations. OAs that are part of LSOAs, which were eligible for CSCO measures, saw an additional 0.76-0.96 retrofitting installations depending on the specification. This represents a 25% - 30% increase over the mean in the number of retrofitting installation measures. This suggests that the number of installations of retrofit measures is notably higher in output areas that are part of LSOAs that are marginally eligible for the scheme.

In Panel B table 1, we study energy consumption data. This is postcode level aggregated data. On average, postcodes are more granular compared to output areas. Yet, we only have data on installations at the output area level and hence, for consistency, we work with data at the same spatial resolution. It goes without saying that aggregated energy consumption data combining electricity and natural gas consumption – the latter being the predominant source of space heating demand – means that potential effect sizes and variation may be more muted.

(Table 1)

We find that, among households living in areas eligible for retrofit measures, there was a reduction in average energy consumption across households linked to the OAs by around 4-8%. In absolute numbers, looking at electricity and natural gas combined, the effects range between 500 - 900 KWh, depending on the specification. Panel C focuses on natural gas consumption per meter more narrowly. We observe effect sizes in similar magnitudes. As indicated, these effect sizes are likely lower bounds, given the non-sharp measurement of both the outcome and the non-sharp measurement of the treatment.[18]

Robustness In Appendix tables A1 to A5, we show that the findings are robust to three exercises. First, our results hold when changing the bandwidth of the

[18] There are further reasons to believe that the effects may be muted due to spillover effects: installers were allowed to deliver up to 20% of the retrofit installations in areas adjacent to eligible ones which would mechanically depress the estimated differential treatment due to treatment in the control group.

RDD. Second, instead of using all retrofit installations, we use only CSCO installations, which again does not change our findings substantially. Finally, one might be concerned that our variables on energy consumption suffer from measurement error when aggregating from postcode to census tracts/OA level. In the Appendix, section B, we provide an additional exercise leveraging household-level energy consumption data.

3.2 Hypothesis driven decomposition of estimated treatment effect heterogeneity

We next estimate heterogeneous treatment effects and follow a hypothesis-driven approach to identify structure in treatment effect heterogeneity.

Estimating heterogeneous effects We estimate local-authority-specific heterogeneity in the treatment effects – rather than a common average treatment effect across areas. This is possible as there are eligible and non-eligible LSOAs across most local authorities.

We estimate the following equation

$$y_{olat} = \sum_{j=1}^{N_a} \beta_a \times \mathbb{1}(d_l \leq 0) + \nu_{itl1,t} + X_{olat} + v_{olat} \tag{2}$$

where $\beta_a = \beta \times \mathbb{1}(j = a), j \in \{1, ..., N_a\}$ is a local-authority-specific treatment effect for local authority a. As indicated, this is estimable for each local authority that has at least one eligible LSOA. The focus here is on program delivery, with the dependent variable y_{olat} measuring the number of retrofitting installations in each output area o, within each eligible LSOA l in a given local authority a. We include an ITL1 $\times$ year fixed effect that controls for region-specific time trends and account for property level controls by X_{olat}. Finally, v_{olat} denotes an idiosyncratic error term.

We then estimate a range of linear regressions to study the extent to which austerity- and/or digital skills help explain the estimated treatment effect heterogeneity $\widehat{\beta_a}$. We consider three transformations of the dependent variable $\widehat{\beta_a}$: i) the probability that the estimated coefficient from equation 2 is statistically significant at the 10% significance level, ii) the size of the estimated coefficient, and iii) the probability that the estimated coefficient is larger than the median coefficient. This is, we estimate variations of:

$$f(\widehat{\beta_a}) = X_a + \mu_{itl1} + \varepsilon_a \tag{3}$$

where $f(.)$ is either:

$$f(\widehat{\beta_a}) = \begin{cases} \mathbb{1}(\frac{\hat{\beta}_a - \beta_{a0}}{SE(\hat{\beta}_a)} \geq 1.65) \\ \hat{\beta}_a \\ \mathbb{1}(\hat{\beta}_a > \text{median}(\widehat{\beta_a})) \end{cases} \tag{4}$$

Specification 3 will consider two main measures X_a that vary at the local authority a level: the extent of austerity and the digital connectivity. We also run regressions with and without ITL1-region fixed effects.

Results Table 2 presents the results of these specifications for austerity and ICT connectivity. In columns (1), (3), and (5), we report specifications without ITL1 fixed effects but including a constant. In Panel A, we present results for heterogeneity by austerity shock. Looking at the first two columns, in local authorities that were more exposed to local budget cuts, we are less likely to detect statistically significant treatment effects of the first-wave of ECO program in eligible LSOAs. In columns (3) and (4) we estimate the relationship between austerity and the point estimate of the treatment effect – ignoring its precision. Again, higher exposure to local budget cuts is associated with a lower estimated value $\widehat{\beta_a}$, implying fewer retrofit installations under ECO in eligible deprived areas in local authority a. The last two columns estimate the relationship between austerity and the probability of retrofit installation take-up being larger than the median. This exercise is informative about the distribution of the treatment effect sizes and austerity. Higher austerity shocks indicate a statistically significantly lower probability of experiencing above median installation take-up in deprived areas.

Panel B performs the same exercise, with our proxy of digital connectivity, which can be construed as a proxy for the extent of digital skills in local administration. Throughout, we find a similar pattern: we are less likely to observe significant or sizable treatment effects in areas that have poor digital connectivity. Finally, in panel C, we allow for both factors to enter linearly in the same regression. This supports our hypothesis that authorities that fare worse with respect to performative state capacity experienced much lower treatment effects.

Robustness Naturally, there may be concerns that the proxies are poor measures of performative state capacity at the local level. In Appendix Table A6, we show that our findings do not depend on the definition of the austerity measure by allowing spending on environmental and housing services to be included – which could mechanically capture treatment effect heterogeneity. Appendix Table A7 shows that we do not find differential results when using other definitions of ICT connectivity, such as sync speed or superfast broadband availability. In Appendix section C and Appendix table A8, we show and present evidence that other plausible mechanisms or area characteristics do not appear to drive the effects such as, e.g., the relative urban/rural divide, the degree of inequality within a local authority, the demographic makeup of the population or their educational attainment.

Visualizing treatment effect heterogeneity The above analysis strongly suggests that both the extent of austerity and the lack of digital skills may be an important factor explaining treatment effect heterogeneity in program delivery. We visualize this in Figure 3: each dot represents a local-authority-specific treatment effect, where red dots are below-median and blue dots are above-median treatment effects. The x-axis captures the intensity of the austerity shock for each local authority, while the y-axis indicates the share of the population with low-speed internet in 2011. We partition the data into four quadrants based on the median exposure to austerity and broadband access. The figure suggests a notable partition of the data: in areas with both relatively little austerity exposure and relatively good digital connectivity, treatment effects are much more likely to be above-median while the opposite is true in other quadrants. This suggests that a random forest or tree-based approach may be suitable for analyzing treatment effect heterogeneity, given the apparent clustering of the treatment effect heterogeneity above- and below-median austerity and ICT skills.

3.3 Non-linear non-hypothesis driven analysis of treatment effect heterogeneity

We document that both austerity and broadband access are significant in understanding treatment effect heterogeneity. Further, the above analysis suggested that a tree-based decomposition may be particularly salient in segmenting the data. Yet, there may be concerns that the treatment effect heterogeneity is driven by other latent factors and that the austerity and broadband data, which we take as a digital skill or literacy proxy, may be confounding the analysis. In Appendix A8 we show that robustness of our main linear decomposition of treatment effect heterogeneity. Yet, there could be non-linear relationships between different features that may better help segment the underlying data.

To do so systematically – but in a hands-off fashion – we leverage random forests to identify the relative variable importance. For simplicity, we focus on the binary indicator that is: $\mathbb{1}(\hat{\beta}_a > \text{median}(\widehat{\beta_a}))$. A random forest (Breiman, 2001) is a machine learning algorithm that arrives at a prediction by averaging the predictions of multiple decision trees. A random forest draws a bootstrapped sample from the original dataset and grows a decision tree by recursively partitioning this sample. The recursive partitioning of the data produces (highly) non-linear interaction terms. We are not interested in inference here, but investigate the relative importance that each feature has in correctly classifying, in this case, whether a treatment effect stands out or not in the empirical distribution of estimated treatment effects.

To do so, we evaluate the relative importance of each variable by computing the increase in the misclassification rate if that variable is dropped from the forest. The more the accuracy of the random forests decreases when excluding a variable, the more important this variable is. This gives a sense of the likely empirical relevance of the features we are considering.[19]

Panel B of Figure 3 shows the ranking of the variables by how much the predictive power of the random forests decreases with their exclusion. This strongly suggests that among the ten features that are considered here (see also Appendix section C for discussion of these features separately), both the measure of austerity and the proxy of digital skills, are, relative to the other characteristics of the area or the housing stock that are considered, the two most important features.

This reinforces our preferred interpretation: the combination of austerity cuts and low levels of digital skills across local authorities contributes to a relatively poor and heterogeneous implementation of a centrally planned and decentrally administered energy efficiency savings program.

4 Conclusion

Recent crises, particularly the COVID pandemic, highlighted the struggles governments face in effectively delivering policies or interventions. In this paper, we study performative state capacity of local governments and climate (in)action in a two-fold analysis. First, we rely on a case study of the Carbon Saving Community Obligation (CSCO), a sub-obligation under the Energy Company Obligation (ECO) aimed at making energy efficiency measures affordable in the UK, to study the effect of climate action measures on take-up and energy consumption. We find that CSCO eligible households were more likely to install retrofit measures which in turn decreased their energy consumption. In a second step, we show that this effect masks substantial heterogeneity. Regions that saw higher austerity shocks and worse digital connectivity experienced a significantly lower treatment effect.

Our findings open several paths for future research. While we illuminate the interplay between austerity and skills in public administrations, more work is needed to study this nexus between austerity, digital capacities and public service delivery. Austerity-induced pressure on public wages lowers the competitiveness of public

[19] Appendix figure A6 focuses on another measure of variable importance that is often used to assess variable importance: decrease in mean squared error. We arrive at similar conclusions.

sector jobs versus the private sector – attracting less skilled workers. This limitation hampers the state's ability to leverage emerging technologies and data effectively (Fetzer et al., 2024).

Additionally, with our work, we showcase the potential conflict between national and local politics. We provide evidence suggesting that large-scale austerity may have hampered the ability of local governments to effectively implement centrally planned but decentrally administered climate policies. Another line of future work should study the public welfare implications of the trade-off between centralization and decentralization (Oates, 1972).

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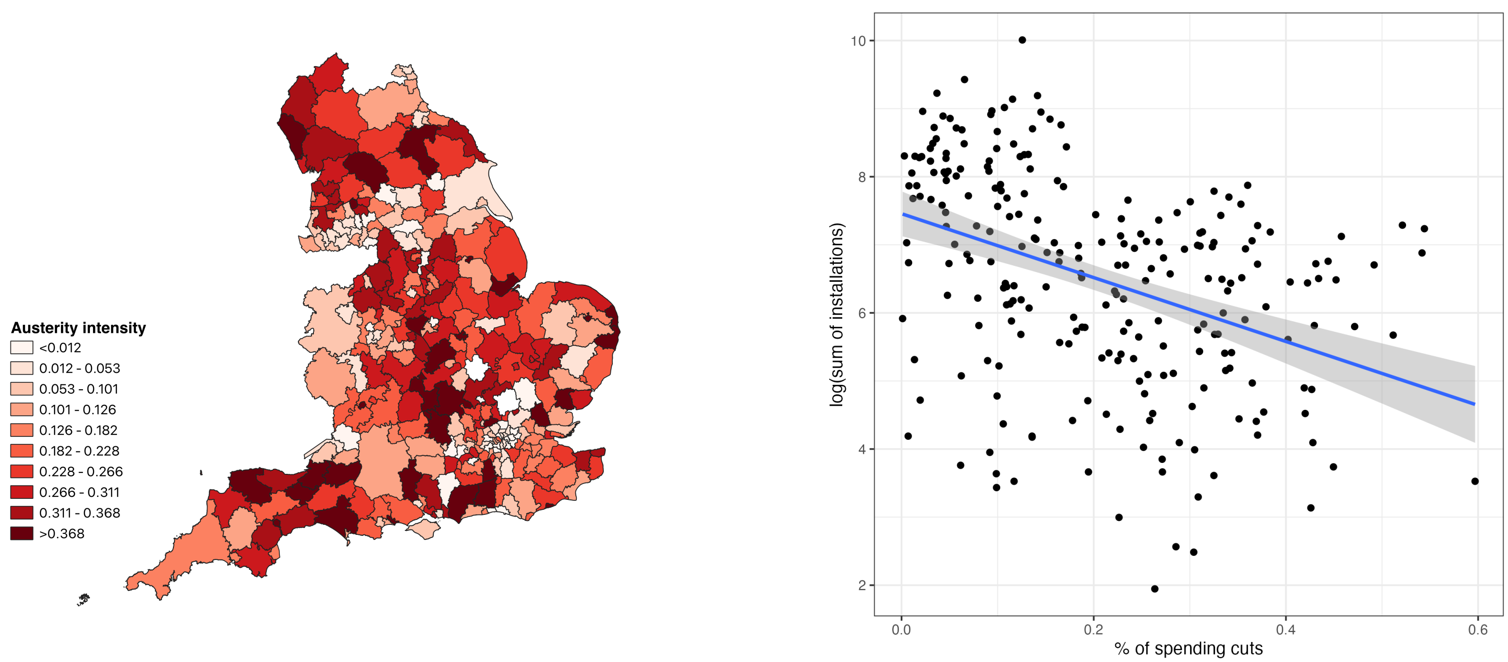
Figures and tables

Figure 1: Energy Company Obligation supported energy efficiency installations over time time and across local authorities by extent of budget cuts

Extent of austerity

Panel A: across local authorities *Panel B*: correlation with retrofit installations



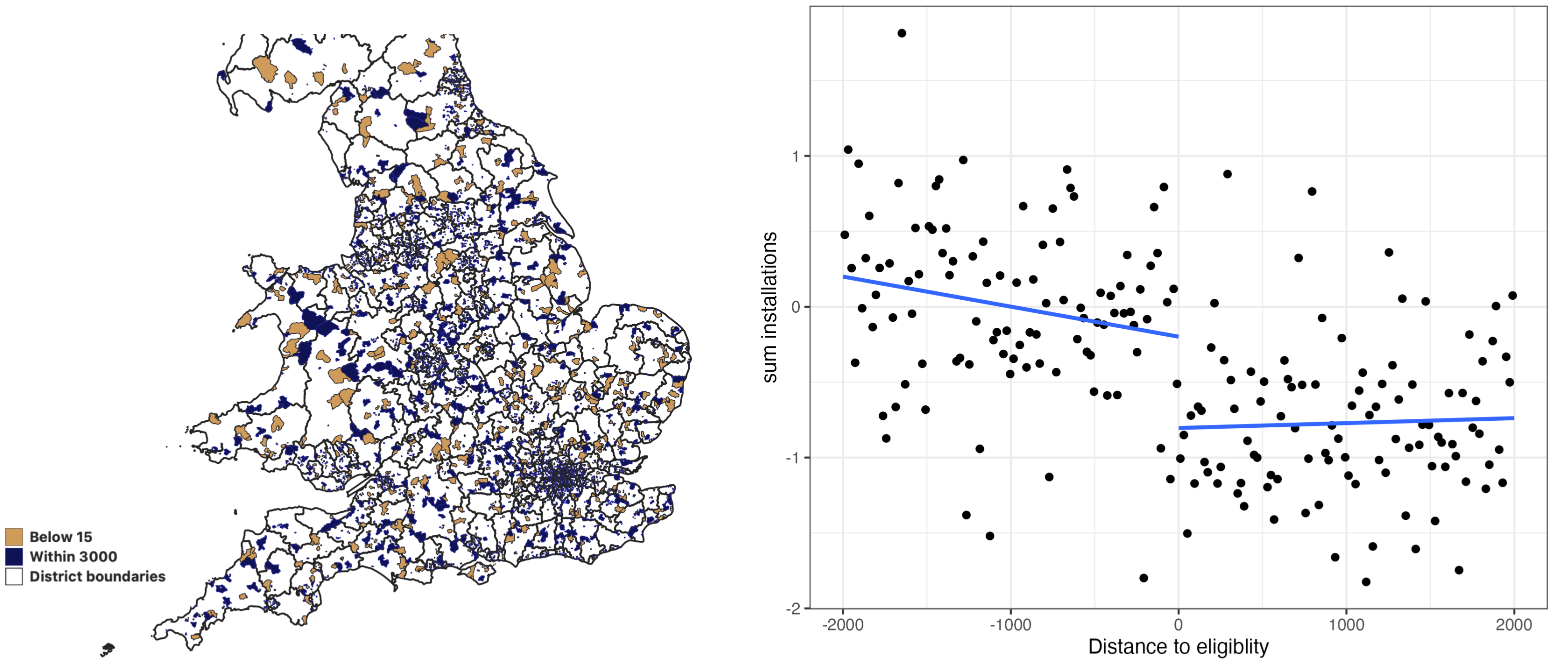
Notes: Panel A of the figure shows the spatial variation in our main austerity shock for the category total spending minus housing and environmental services across local authority districts in England. We calculate the shock as the relative change of the average spending between 2007 and 2010 and the average spending between 2011 and 2015 as described in section A.3 Thus the higher this measure is, the larger were the spending cuts after 2011. Darker shades represent higher austerity shocks. Panel B shows the correlation of local authorities' austerity shocks and the number of retrofitting installations. The austerity measure is the same as in panel A. The y-axis shows the log number of total retroffiting installations aggregated over all years at the local authority level.

Figure 2: Regression discontinuity around 15% deprivation cutoff

Illustration of regression discontinuity

Panel A: eligible LSOAs within bandwidth

Panel B: installations of retrofit measures around threshold

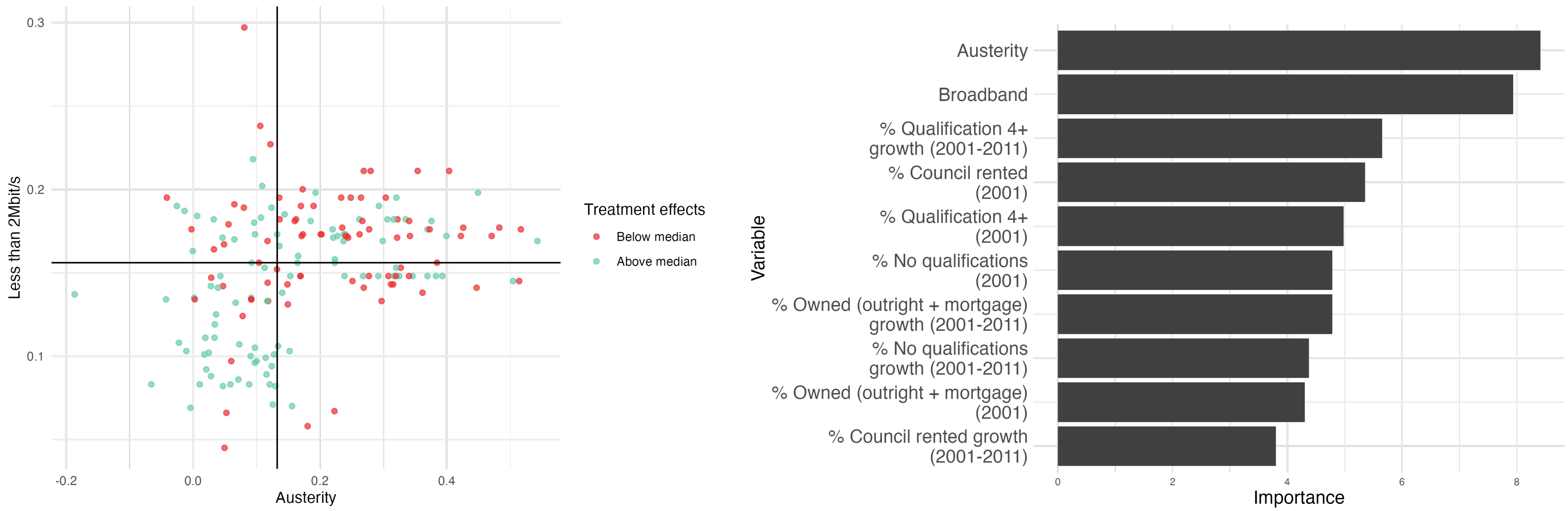


Notes: Panel A of the figure plots the spatial variation of the treatment and our sample selection across Lower Layer Super Output Areas (LSOAs) across England and Wales. Areas shaded in brown are LSOAs below the 15th percentile of the Index of Multiple Deprivation (IMD) and thus eligible for the Carbon Saving Community Obligation (CSCO). Areas shaded in dark blue are areas that are within a bandwidth of 3000 around the cutoff and are thus selected in our analysis sample. Panel B shows a binned scatterplot of the residuals of regressing the number of installations on local authority and ITL1 $\times$ year fixed effects for local regressions above and below the cutoff within a bandwith of 3000.

Figure 3: Decomposing Treatment Effect Heterogeneity

Panel A: Hypothesis driven

Panel B: Machine learning approach



Notes: Panel A of the figure plots authority specific treatment effects with with the colour indicating above and below median treatment effects. The x-axis measures our preferred austerity measure - the relative change in average spending on total services less environmental and housing before and after austerity was introduced in the UK in 2011. The y-axis our preferred ICT connectivity measure - the share of households with broadband slower than 2 Mbit/s. Panel B plots the relative variable importance of our random forest model where we predict the probability of a greater than median effects size. The variables with the highest importance have the highest predictive power.

Table 1: Impact of ECO eligibility on installed retrofit measures and energy consumption

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Sum of retrofit installations									
Eligible for CSCO	0.9687***	0.9430***	0.9549***	0.9549***	0.9549***	0.9792***	0.7945***	0.7945***	0.7692***
	(0.1131)	(0.1096)	(0.0962)	(0.0962)	(0.0962)	(0.1023)	(0.0938)	(0.0938)	(0.0973)
Dependent variable mean	3.1226	3.1226	3.1226	3.1226	3.1226	3.1226	3.1226	3.1226	3.1226
R^2	0.15656	0.16631	0.15948	0.17409	0.17989	0.18795	0.22505	0.23085	0.23228
Observations	130,976	130,976	130,976	130,976	130,976	130,976	130,976	130,976	130,976
Panel B: Combined Energy consumption per meter									
Eligible for CSCO	-603.3***	-623.3***	-813.0***	-813.0***	-813.0***	-472.6***	-916.0***	-916.0***	-538.7***
	(88.12)	(81.76)	(71.91)	(71.92)	(71.95)	(75.41)	(66.90)	(66.92)	(71.25)
Dependent variable mean	15,163.3	15,163.3	15,163.3	15,163.3	15,163.3	15,163.3	15,163.3	15,163.3	15,163.3
R^2	0.02765	0.05250	0.10511	0.10511	0.10511	0.16303	0.28076	0.28076	0.29977
Observations	31,599	31,599	31,599	31,599	31,599	31,599	31,599	31,599	31,599
Panel C: Natural Gas consumption per meter									
Eligible for CSCO	-613.8***	-637.4***	-779.9***	-779.9***	-779.9***	-367.5***	-866.9***	-866.9***	-451.3***
	(73.70)	(68.63)	(55.23)	(55.24)	(55.26)	(60.18)	(48.66)	(48.68)	(52.27)
Dependent variable mean	11,291.7	11,291.7	11,291.7	11,291.7	11,291.7	11,291.7	11,291.7	11,291.7	11,291.7
R^2	0.07571	0.10850	0.19037	0.19037	0.19037	0.28282	0.37737	0.37737	0.40600
Observations	31,648	31,648	31,648	31,648	31,648	31,648	31,648	31,648	31,648
Regression specification:									
ITL1 × Year FE	X			X			X		
ITL2 × Year FE		X			X	X		X	X
Year FE			X						
LAD FE			X	X	X	X			
MSOA FE							X	X	X
Property level controls						X			X

Notes: Table presents results from several regressions. Each observation refers to an output area (OA) in 2021. The regressions estimate a regression discontinuity design (RDD) where the control and treatment units are chosen within a bandwidth around an eligibility threshold. The bandwidth in this table is 3000. The dependent variables move across the panels and capture the sum of all retrofit installation measures (Panel A), and energy consumption measured as the sum of electricity and gas consumption in kWh per combined gas and electricity meters (Panel B). ITL stands for International Territorial Levels and is geocode used by the Office for National Statistics (ONS) to subdivide the UK into smaller units. ITL1 regions correspond to the regions of England. LAD stands for Local Auhtority District which are the local governments in the UK, and Middle-layer Super Output Areas (MSOA) is a statistical unit that is aggregated from census blocks (Output Areas). Property level controls include the property's council tax band, age band and type. Standard errors are clustered at the LAD level. 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 2: Heterogeneity wrt to effect size on number of installations by Austerity measures

Dependent variable	T-value > 1.65		Estimate		Estimate > Median	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:						
Austerity	-0.5611***	-0.5698***	-2.066***	-2.332***	-0.7113***	-0.6912**
	(0.1976)	(0.2042)	(0.6624)	(0.7638)	(0.2615)	(0.3048)
Dependent variable mean	0.16346	0.16346	0.77316	0.77316	0.50962	0.50962
R^2	0.03905	0.18633	0.03172	0.12931	0.03434	0.14310
Observations	312	312	312	312	312	312
Panel B:						
Less 2 Mbit/s	-0.8754	-0.6398	-11.10***	-10.78***	-3.533***	-3.397***
	(0.6772)	(0.5641)	(2.684)	(2.733)	(0.9291)	(0.9261)
Dependent variable mean	0.15891	0.15891	0.82478	0.82478	0.52326	0.52326
R^2	0.01038	0.17549	0.08630	0.16313	0.09055	0.20036
Observations	258	258	258	258	258	258
Panel C:						
Austerity	-0.5221**	-0.4435*	-2.336***	-1.750**	-1.028***	-0.6807**
	(0.2293)	(0.2314)	(0.8226)	(0.8200)	(0.2843)	(0.3157)
Less 2 Mbit/s	-0.4787	-0.2066	-9.437***	-9.259***	-2.692***	-2.743***
	(0.7097)	(0.5798)	(2.696)	(2.720)	(0.9560)	(0.9536)
Dependent variable mean	0.16270	0.16270	0.84018	0.84018	0.53571	0.53571
R^2	0.03674	0.21117	0.11243	0.18192	0.14239	0.22595
Observations	252	252	252	252	252	252
Regression specification:						
ITL1 FE		X		X		X

Notes: Table presents results from a regression. Each observation refers to an Local Authority District (LAD) in 2016. The dependent variables move across the columns and captures local authority specific treatment effects. Columns (1) and (2) measure the probability that the estimated LAD specific coefficient is statistically significant at the 10% significance level. Columns (3) and (4) measure the size of the LAD specific treatment effect. Columns (5) and (6) measure the probability that the LAD specific treatment effect is larger than the median treatment effect. Austerity is our preferred measure of expenditure cuts at the local authority level which we define as total expenditure minus expenditure on housing and environmental services. Less 2 Mbit/s is a measure of the percentage of households in a local authority that receive a broadband with a speed of less than 2 Mbit/s. Standard errors provided in parentheses are clustered at the district level with stars indicating *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Appendix to "Performative State Capacity and Climate (In)Action"

For Online Publication

A Further details on data

A.1 ECO Scheme

The UK Department of Energy & Climate Change (DECC) published in June 2012 a list with all LSOAs eligible under the Carbon Saving Community Obligation (CSCO ECO) scheme using the 15th percentile rule. It uses the 2001 LSOA coding. In 2014, the DECC published an updated file with all LSOAs eligible under the 25th percentile rule. To check whether the eligibility assignment by the DECC actually follows the rules, we calculate the cutoff ourselves using data on the indices of multiple deprivation (IMD) published by the Department for Levelling Up, Housing & Communities[1]. Based on the overall deprivation index, we calculate the cutoff to be the index value that is equivalent to the 15th percentile. We merge this with the eligibility data from the DECC to assess the discontinuity and find a clear cutoff at the 15th percentile.

The affordable warmth group defined households that received a range of benefits such as Child Tax Credit, Working Tax Credit, Universal Credit, Pension Guarantee Credit, Pension Savings Credit, Income Support, income-based Jobseeker's Allowance (JSA), income-related Employment and Support Allowance (ESA), Child Benefit, and Housing Benefit. The order gave multiple pathways to allow for more flexibility regarding individual eligibility. For example, there is in-fill eligibility that would provide retrofit measures to properties nearby clusters of households that are directly eligible. In this paper we will focus on the first iteration of ECO1, which

[1] At the time the CSCO came into effect the department was called Ministry of Housing, Communities & Local Government

included three streams: the Carbon Emissions Reduction Obligation (CERO), the Carbon Saving Community Obligation (CSCO) and the Home Heating Cost Reduction Obligation (HHCRO)

A.2 Retrofit installations

Data on the installation of retrofit measures were made available by the Office of Gas and Electricity Markets (Ofgem) following freedom of information (FOI) requests. The requested data is at the output area (OA) level using 2021 census definitions. It covers all retrofit installations that were funded or indirectly subsidized by public means. The installations were subsidized or financed under three different government schemes: the Domestic Renewable Heat Incentive (DRHI), the Feed-in Tariffs (FIT), and the Energy Company Obligation (ECO1) which itself was subdivided into three obligations which were the Carbon Emissions Reduction Obligation (CERO), the Carbon Saving Community Obligation (CSCO), and the Home Heating Cost Reduction Obligation (HHCRO). Furthermore, the data is differentiated by the type of installations[2].

We create a panel dataset of all retrofit installations in the UK at the OA level over the years 2010 - 2023 varying by government scheme and installation type. To assess the effectiveness of the CSCO as expressed by retrofit installations we create two different outcome variables. One is the sum of all installations done under the CSCO scheme in a given OA in a given year and second is the sum of all retrofit installations in a given OA in a given year. To match the installation data to our other data we map the OA 2021 definition to the OA 2011 definition using the crosswalk provided by the Open Geography Portal.

[2]The different installation types are air source heat pump, bio-methane, biogas, biomass, boiler, cavity wall insulation, community, district heating system, domestic, ground source heat pump, hard to treat cavity wall insulation, loft insulation, non-domestic (commercial), non-domestic (industrial), other heating, other insulation, park home external wall insulation, solar thermal, solid biomass boiler, solid biomass CHP, solid wall insulation, waste, and water source heat pump.

A.3 Austerity measures

To compute variables measuring a local authority's austerity intensity we rely on local authority service expenditure data collected by the Department for Levelling Up, Housing & Communities. The data is available for every year since 2007 up to 2022[3]. The data covers the twelve service categories education, highways and transport, social care[4], public health, housing, cultural and related services, environmental and regulatory services, planning and development, police, fire and rescue, central services, other services as well as total service expenditures. We use net current expenditure measures to isolate the net spending of local authorities. We match this data to the above mentioned datasets making use of the fact that OA 2011 codes match perfectly into local authority definitions between 2011 and 2021.

Austerity cuts in the UK were introduced from 2010 onwards (Fetzer, 2019). Thus, we calculate an austerity measure for category c in local authority r as the relative change of the average spending on category c between 2007 and 2010 and the average spending between 2011 and 2015:

$$austerity_{a,c} = \frac{\bar{x}_{a,c,2007-2010} - \bar{x}_{a,c,2011-2015}}{\bar{x}_{a,c,2007-2010}}$$

Hence, the higher this measure is the higher was the austerity shock for a local authority a.

Our main austerity measure is the change in the averages in net current expenditure of total services less the net current expenditure in environmental and housing services. We deduct expenditures for environmental and housing services to make sure that our austerity measure is not inflated by expenditures on installations carried out under the CSCO policy. In the Appendix we show that our results hold for the total service expenditure without deducting expenditures on housing and environmental services. Figure 1 panel A shows the spatial distribution of our

[3]More precisely, the first year is the financial year 2007/2008 which include April 2007 to March 2008. We define the financial year 2007/2008 to $t = 2007$ as the financial year covers more months of 2007 than of 2008.

[4]From 2007 - 2010 social care was one category. From 2011 onwards, the data distinguishes between children and adult social care. To have a harmonized series over time, we add up children and adult social care for the years 2010 - 2022.

main austerity measure across England. Darker shades of red indicate a stronger austerity shock, i.e. higher cuts on total service expenditure less housing and environmental services. There is substantial variation in the severity of austerity across space which we use to show the relationship of austerity and climate inaction in England. The right-hand panel of figure 1 shows a scatterplot of the aggregated number of retrofit installations in a local authority against the authority's austerity shock. The raw correlation suggests a negative relationship between climate action and spending cuts with higher spending cuts being associated with lower levels of energy efficiency installations.

(Figure 1)

A.4 Broadband data

We use data on broadband availability in 2011 by four different measures published by the Office of Communication (Ofcom) in their Communications Infrastructure Report 2011: Fixed Broadband Data. The data is provided at the upper tier local authority (UTLA) level[5]. This implies that the broadband data is at a higher spatial level than the local authorities that we use. More specifically, there are 116 UTLAs in England which we are able to merge to 176 LADs. The four broadband measures that the data provides are average modem sync speed, broadband take-up, superfast availability, and the the share of homes receiving less than 2Mbit/s. Sync speed is "the maximum rate at which data is transferred from the ISP [internet service provider] to the end users across their broadband connection" (Ofcom, 2011). The sync speed is measured in Mbit/s and excludes superfast connection which is defined as broadband connection running at over 24Mbit/s. Broadband take-up measures the share of all homes, residential and non-residential, that have a non-superfast broadband connection. Superfast availability represents the share of all homes with superfast broadband connection.

[5] Some local authorities in the UK are divided between a county council (upper tier or tier 1) and a district council (lower tier or tier 2).

A.5 Energy consumption

Data on gas and electricity consumption is provided at the postcode level by the Department for Energy Security and Net zero and the Department for Business, Energy & Industrial Strategy. This covers almost the universe of postcodes in the UK except postcodes that are considered to be disclosive[6]. The data contains the number of domestic gas and electricity meters, total gas and electricity consumption per year, as well as median and mean annual gas consumption per meter. The data is only available for the years 2013, and 2015 - 2021. We aggregate the data to the OA level using the fact that postcodes are perfect subdivisions of OAs. To control for an OAs size we use gas and electricity consumption divided by the number of meters as outcome variables. Lastly, we build a combined energy index by adding up total annual gas and electricity consumption and dividing by the total annual number of combined gas and electricity meters in a given OA.

Additional energy consumption that we use in robustness checks comes from the National Energy Efficiency Data-Framework (NEED). The data is at the household level and has information on gas and electricity consumption from 2005 - 2019. Moreover, the data provides variables on loft, cavity wall and solar PV installations, and the IMD quintile the household falls into.

B Household level exercise

To study the effect of the CSCO policy on energy consumption we use consumption data at the postcode level which we aggregate to the OA level. This can introduce measurement error in the outcome variable. To correct for this measurement error we can use property level energy consumption data from the National Energy Efficiency Data (NEED) framework which is provided by the Department for Business, Energy & Industrial Strategy. The anonymized dataset merges property level energy consumption with other property level information like property type and

[6] Postcodes are considered disclosive if either the number of domestic electricity or gas meters is below 5 meters or the top two most consuming meters sum up to more than 90% of the total postcode consumption.

age, floor area, conservatory, council tax band, IMD quintile, region, main heating fuel, as well as information on energy efficiency installations like loft insulation, cavity wall insulation and solar PV from 2005 - 2019.

We use this data to approximate our estimation strategy from above. Obviously, this data has no geographic information that can be merged to our main dataset. Thus, we don't know the LSOA and more importantly the treatment status coming from the CSCO eligibility criterion. We approximate the treatment status using the information on the IMD quintile. Recall that the most deprived 15 percent, that is the lowest 15 percent of the IMD, were eligible for retrofit installations. Hence, we classify properties as eligible that are in the lowest IMD quintile. Using an event study design we compare properties in the first quintile to properties in the second quintile before and after 2012. That is we estimate the following equation

$$y_{igrt} = \sum_{\tau=2008, t\neq 2011}^{2015} \beta_\tau D_{i\tau} + \gamma_i + \lambda_{gtr} + \epsilon_{igrt}$$

where y_{it} is either the log of gas, electricity or combined energy (gas + electricity) consumption of property i, belonging to group g, in region r and year t. $D_{i\tau}$ is an indicator variable that equals one for a property in the first quintile of the IMD from 2012 onwards. We include property level fixed effects γ_i to study only within property variation. Additionally, we include group-year-region fixed effects. A group is defined leveraging the additional property level information as the unique combination of property type, age, floor area band, conservatory, council tax band, loft insulation, cavity wall insulation, solar PV, and main fuel type. Doing so ensures that we compare properties that are similar in all those characteristics in the same year and region. We restrict our sample to the years between 2008 and 2015 to make sure that we don't capture additional upgrades or changes that are done to houses over time.

Figure A1 shows the estimated effects of being (approximately) eligible for receiving retrofit installations between 2008 and 2015. After the CSCO policy was introduced, properties in the lowest IMD quintile have a statistically lower energy (gas + electricity) consumption compared to properties in the second IMD quintile.

Importantly, there are no differential pre-trends in energy consumption.

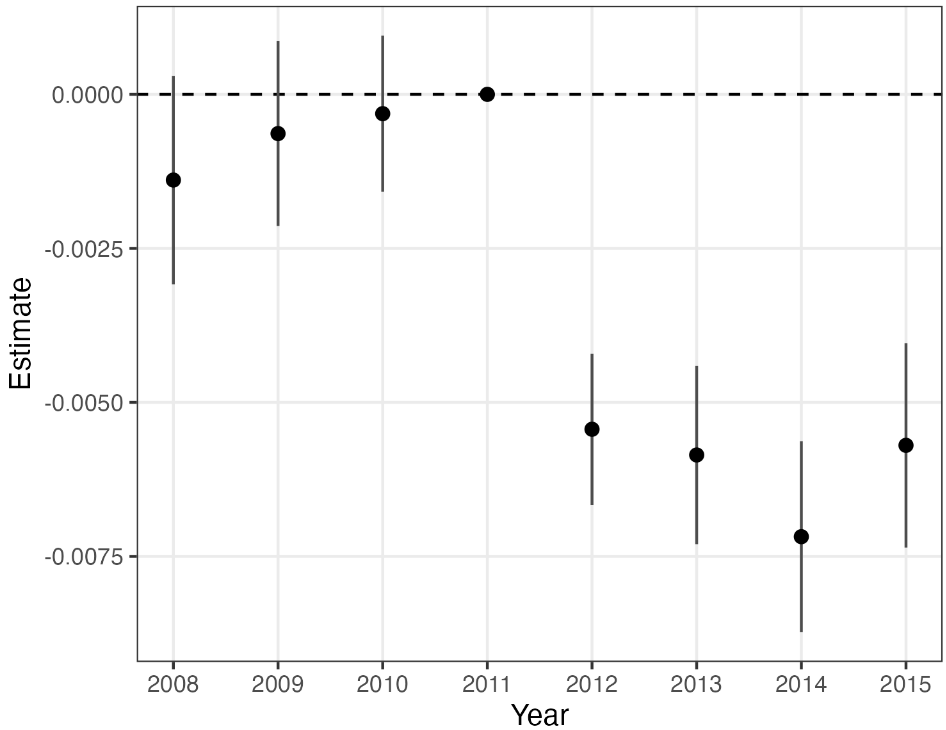


Figure A1: Event study energy consumption

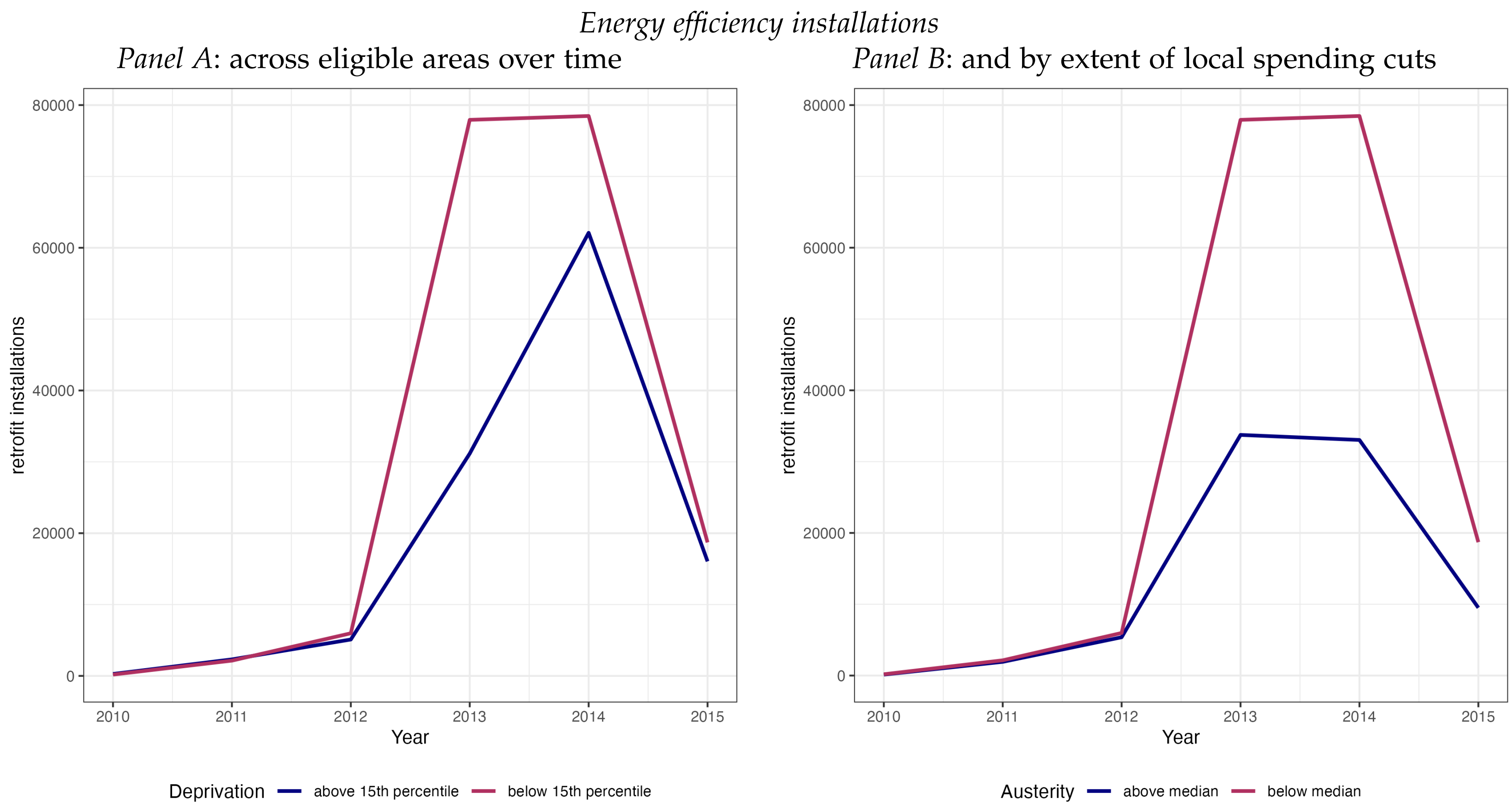
Using the IMD quintile to determine eligibility is only an approximation of treatment status as we classify the 20% most deprived areas as eligible for the CSCO policy instead of the actual 15% most deprived ones. This by itself introduces measurement error, this time in the explanatory variable. Evidently, there is a trade-off between having measurement error in the dependent or in the independent treatment variable. While measurement error in the independent variable attenuates our estimated coefficients, measurement error in the dependent variable can lead to biased estimates if the error is not random. Reassuringly, the findings of both strategies point in the same direction, giving rise to the interpretation that the CSCO policy had bite and reduced energy consumption in treated areas and properties.

C Discussion of local authority level confounders

We study a range of other features that could explain the observed treatment effect heterogeneity. We discuss these separately focusing on the austerity- and the broadband mechanism. In Appendix table A8 we include more local authority level controls that one might be concerned about confounding our findings. In panel A, we control for a local authority's share of LSOAs classified as rural to alleviate concerns that we are capturing an urban-rural divide. Panel B explores whether treatment effects are bigger in affluent LADs that have (some) isolated poor areas. It could be that in affluent but unequal areas, local governments did not put in effort to deliver a scheme that may disproportionately benefit deprived communities. To do so we construct a within LAD inequality measure in the deprivation score. We find, if anything, inequality to be positively associated with program delivery. The austerity main effect remains constant. It could be that policymakers were hesitant to deliver the scheme in areas with an old population that may be expected to move home and which, due to aging population, may have more severely been exposed to austerity due to age-specific budget pressures. This appears not the case. Lastly in panel D, we address the concern that our results might be biased by highly educated households demanding more retrofit installations. We include an LADs share of individuals with at least tertiary education in 2011 and showcase that our results do not change substantially.

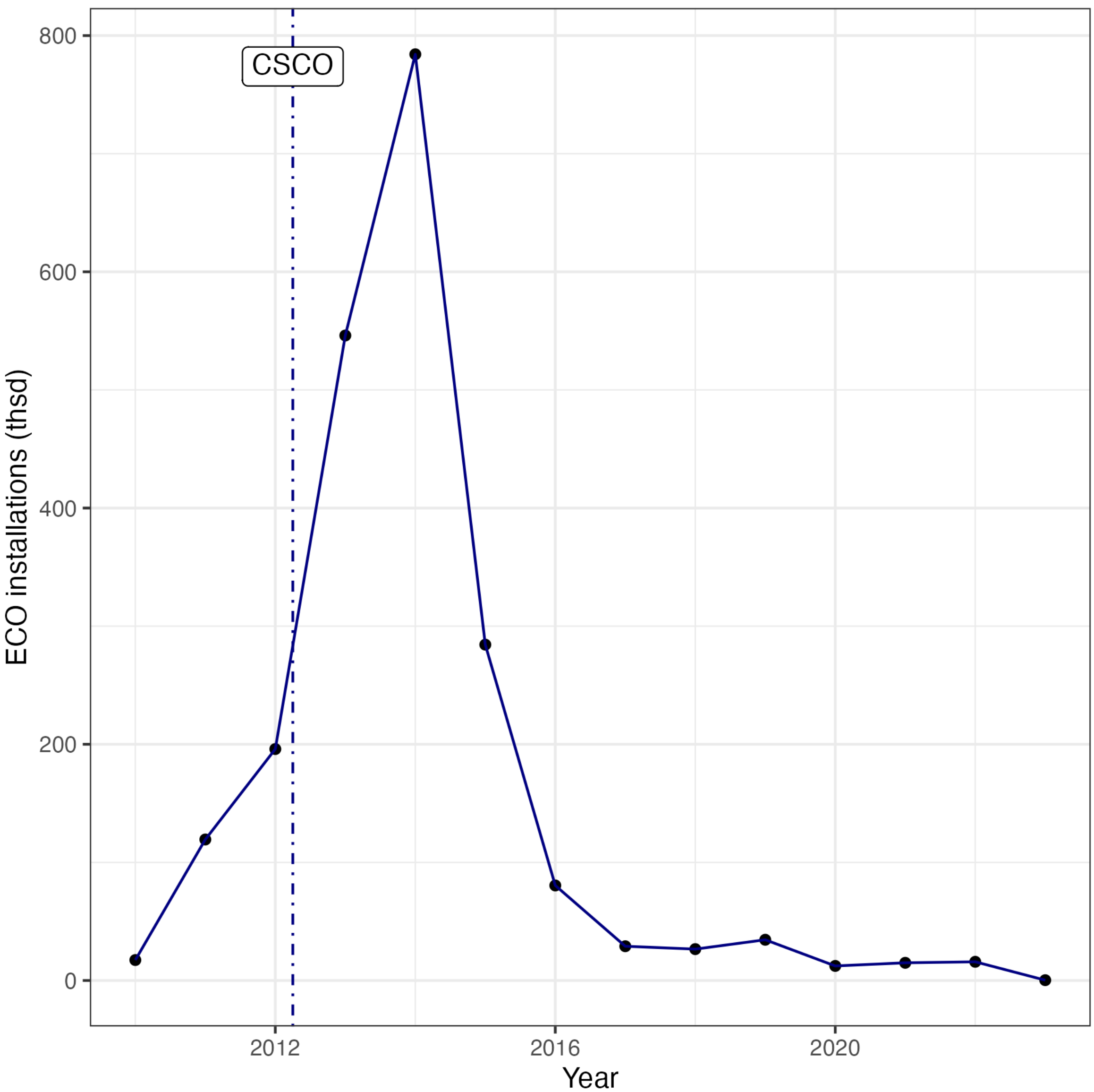
D Appendix figures

Figure A2: Energy Company Obligation supported energy efficiency installations over time time and across local authorities by extent of budget cuts



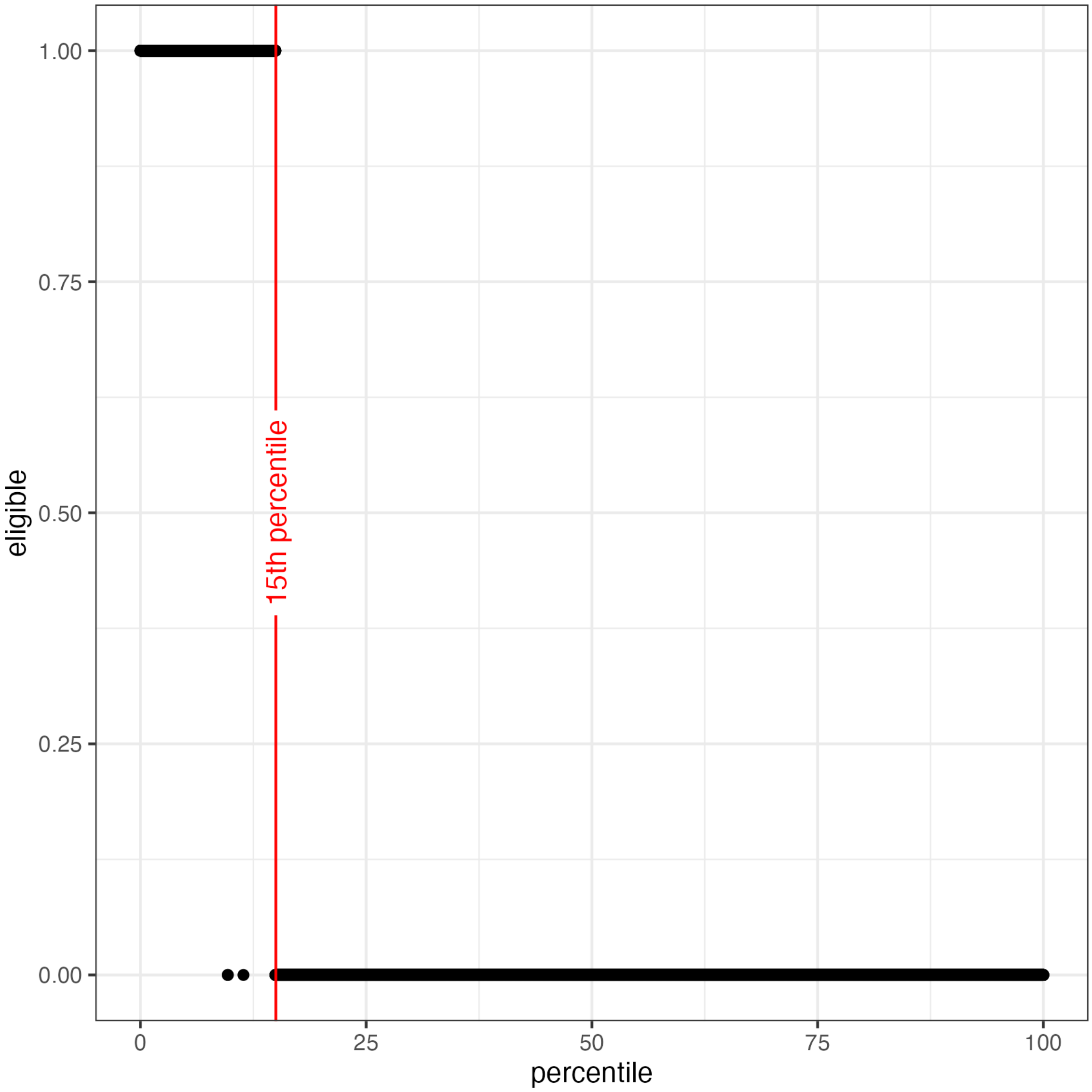
Notes: Panel A of the figure plots the aggregate number of Energy Company Obligation (ECO) supported retrofitting installations per year by Carbon Saving Community Obliation (CSCO) eligibility status. The red line represents areas that were below the 15th percentile of the index of multiple deprivation (IMD), and thus eligible for receiving retrofitting installations under the CSCO policy. Panel B plots the annual sum of ECO supported retrofitting installations measures by austerity intensity measured as below and above median austerity shock. We calculate the shock as the relative change of the average spending between 2007 and 2010 and the average spending between 2011 and 2015 as described in section A.3 Thus the higher this measure is, the larger were the spending cuts after 2011.

Figure A3: ECO installations over time



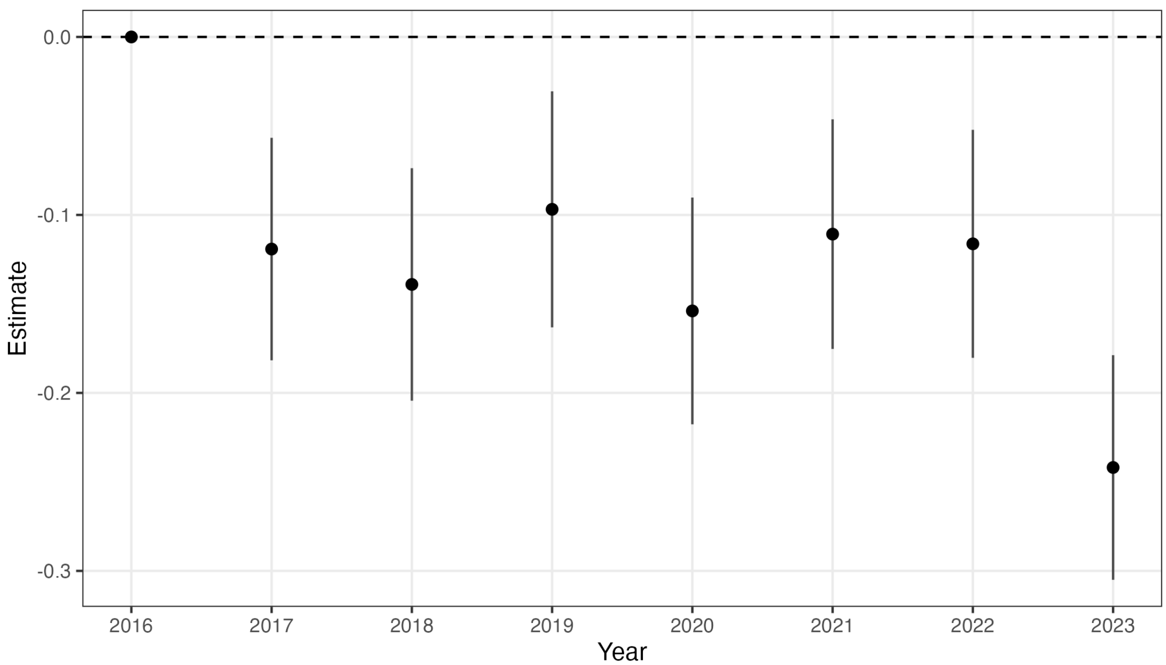
Notes:

Figure A4: CSCO eligibility and Deprivation Index rank



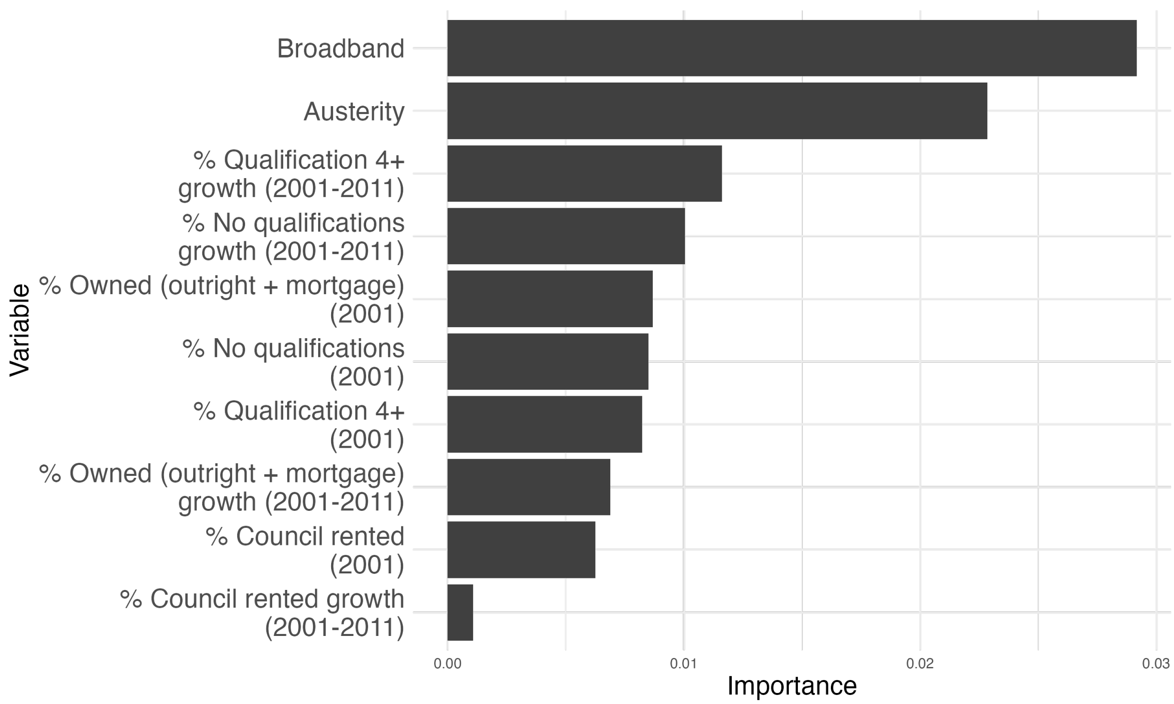
E Appendix tables

Figure A5: Trend of installations after 2015



Notes:

Figure A6: Machine learning approach - Mean Decrease Accuracy



Notes:The figure plots the relative variable importance of our random forest model where we predict the probability of a greater than median effects size. The variables with the highest importance have the highest predictive power.

Table A1: Impact of ECO eligibility on installed retrofit measures and energy consumption - threshold 2000

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Sum of retrofit installations									
Eligible for CSCO	0.8384***	0.8140***	0.8565***	0.8565***	0.8565***	0.8633***	0.7463***	0.7463***	0.7488***
	(0.1107)	(0.1076)	(0.1027)	(0.1027)	(0.1028)	(0.0963)	(0.1200)	(0.1201)	(0.1215)
Dependent variable mean	3.0786	3.0786	3.0786	3.0786	3.0786	3.0786	3.0786	3.0786	3.0786
R^2	0.15564	0.16583	0.15903	0.17260	0.17896	0.18797	0.22748	0.23384	0.23532
Observations	87,720	87,720	87,720	87,720	87,720	87,720	87,720	87,720	87,720
Panel B: Energy consumption per meter									
Eligible for CSCO	-291.7***	-331.6***	-509.8***	-509.8***	-509.8***	-297.1***	-594.4***	-594.4***	-357.2***
	(98.31)	(91.02)	(86.90)	(86.92)	(86.97)	(82.73)	(90.04)	(90.09)	(90.20)
Dependent variable mean	15,176.5	15,176.5	15,176.5	15,176.5	15,176.5	15,176.5	15,176.5	15,176.5	15,176.5
R^2	0.02383	0.04727	0.10529	0.10529	0.10529	0.16212	0.29838	0.29838	0.31483
Observations	21,110	21,110	21,110	21,110	21,110	21,110	21,110	21,110	21,110
Regression specification:									
ITL1 × Year FE	X			X			X		
ITL2 × Year FE		X			X	X		X	X
Year FE			X						
LAD FE			X	X	X	X			
MSOA FE							X	X	X
Property level controls						X			X

Notes: Table presents results from several regressions. Each observation refers to an output area (OA) in 2021. The regressions estimate a regression discontinuity design (RDD) where the control and treatment units are chosen within a bandwidth around an eligibility threshold. The bandwidth in this table is 2000. The dependent variables move across the panels and capture the sum of all retrofit installation measures (Panel A), and energy consumption measured as the sum of electricity and gas consumption in kWh per combined gas and electricity meters (Panel B). Regression specifications vary across the columns as indicated by the categories at the bottom of the table. ITL stands for International Territorial Levels and is geocode used by the Office for National Statistics (ONS) to subdivide the UK into smaller units. ITL1 regions correspond to the regions of England. LAD stands for Local Auhtority District which are the local governments in the UK, and Middle-layer Super Output Areas (MSOA) is a statistical unit that is aggregated from census blocks (Output Areas). Property level controls include the property's council tax band, age band and type. Standard errors are clustered at the LAD level. 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: Impact of ECO eligibility on installed retrofit measures and energy consumption - threshold 4000

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Sum of retrofit installations									
Eligible for CSCO	1.015***	0.9872***	0.9882***	0.9882***	0.9882***	1.052***	0.8053***	0.8053***	0.8152***
	(0.1159)	(0.1117)	(0.0970)	(0.0970)	(0.0970)	(0.1048)	(0.0823)	(0.0824)	(0.0954)
Dependent variable mean	3.0752	3.0752	3.0752	3.0752	3.0752	3.0752	3.0752	3.0752	3.0752
R^2	0.15721	0.16655	0.15801	0.17392	0.17968	0.18714	0.22063	0.22639	0.22804
Observations	174,844	174,844	174,844	174,844	174,844	174,844	174,844	174,844	174,844
Panel B: Energy consumption per meter									
Eligible for CSCO	-921.7***	-941.5***	-1,135.8***	-1,135.8***	-1,135.8***	-617.1***	-1,176.8***	-1,176.8***	-666.8***
	(91.26)	(81.23)	(69.45)	(69.46)	(69.48)	(87.96)	(65.23)	(65.25)	(79.32)
Dependent variable mean	15,169.1	15,169.1	15,169.1	15,169.1	15,169.1	15,169.1	15,169.1	15,169.1	15,169.1
R^2	0.03075	0.05691	0.10417	0.10417	0.10417	0.16335	0.26215	0.26215	0.28411
Observations	42,177	42,177	42,177	42,177	42,177	42,177	42,177	42,177	42,177
Regression specification:									
ITL1 × Year FE	X			X			X		
ITL2 × Year FE		X			X	X		X	X
Year FE			X						
LAD FE			X	X	X	X			
MSOA FE							X	X	X
Property level controls						X			X

Notes: Table presents results from several regressions. Each observation refers to an output area (OA) in 2021. The regressions estimate a regression discontinuity design (RDD) where the control and treatment units are chosen within a bandwidth around an eligibility threshold. The bandwidth in this table is 4000. The dependent variables move across the panels and capture the sum of all retrofit installation measures (Panel A), and energy consumption measured as the sum of electricity and gas consumption in kWh per combined gas and electricity meters (Panel B). Regression specifications vary across the columns as indicated by the categories at the bottom of the table. ITL stands for International Territorial Levels and is geocode used by the Office for National Statistics (ONS) to subdivide the UK into smaller units. ITL1 regions correspond to the regions of England. LAD stands for Local Auhtority District which are the local governments in the UK, and Middle-layer Super Output Areas (MSOA) is a statistical unit that is aggregated from census blocks (Output Areas). Property level controls include the property's council tax band, age band and type. Standard errors are clustered at the LAD level. 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: Impact of ECO eligibility on installed retrofit measures and energy consumption - threshold 2000

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Sum of CSCO installations									
Eligible for CSCO	0.8304***	0.8243***	0.8527***	0.8527***	0.8527***	0.8681***	0.8365***	0.8365***	0.8477***
	(0.0690)	(0.0681)	(0.0658)	(0.0658)	(0.0658)	(0.0611)	(0.0823)	(0.0823)	(0.0805)
Dependent variable mean	1.3205	1.3205	1.3205	1.3205	1.3205	1.3205	1.3205	1.3205	1.3205
R^2	0.13500	0.14567	0.14091	0.14840	0.15541	0.16064	0.18961	0.19662	0.19772
Observations	87,720	87,720	87,720	87,720	87,720	87,720	87,720	87,720	87,720
Panel B: Energy consumption per meter									
Eligible for CSCO	-603.3***	-623.3***	-813.0***	-813.0***	-813.0***	-472.6***	-916.0***	-916.0***	-538.7***
	(88.12)	(81.76)	(71.91)	(71.92)	(71.95)	(75.41)	(66.90)	(66.92)	(71.25)
Dependent variable mean	15,163.3	15,163.3	15,163.3	15,163.3	15,163.3	15,163.3	15,163.3	15,163.3	15,163.3
R^2	0.02765	0.05250	0.10511	0.10511	0.10511	0.16303	0.28076	0.28076	0.29977
Observations	31,599	31,599	31,599	31,599	31,599	31,599	31,599	31,599	31,599
Regression specification:									
ITL1 × Year FE	X			X			X		
ITL2 × Year FE		X			X	X		X	X
Year FE			X						
LAD FE			X	X	X	X			
MSOA FE							X	X	X
Property level controls						X			X

Notes: Table presents results from several regressions. Each observation refers to an output area (OA) in 2021. The regressions estimate a regression discontinuity design (RDD) where the control and treatment units are chosen within a bandwidth around an eligibility threshold. The bandwidth in this table is 2000. The dependent variables move across the panels and capture the sum of all CSCO retrofit installation measures (Panel A). In panel B, the number of CSCO retrofitting installations is instrumented by the eligibility for the Carbon Saving Community Obligation (CSCO). Regression specifications vary across the columns as indicated by the categories at the bottom of the table. ITL stands for International Territorial Levels and is geocode used by the Office for National Statistics (ONS) to subdivide the UK into smaller units. ITL1 regions correspond to the regions of England. LAD stands for Local Auhtority District which are the local governments in the UK, and Middle-layer Super Output Areas (MSOA) is a statistical unit that is aggregated from census blocks (Output Areas). Property level controls include the property's council tax band, age band and type. 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: Impact of ECO eligibility on installed retrofit measures and energy consumption - threshold 3000

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Sum of CSCO installations									
Eligible for CSCO	0.8629***	0.8568***	0.8753***	0.8753***	0.8753***	0.8876***	0.8398***	0.8398***	0.8392***
	(0.0746)	(0.0732)	(0.0655)	(0.0655)	(0.0655)	(0.0654)	(0.0613)	(0.0613)	(0.0623)
Dependent variable mean	1.3396	1.3396	1.3396	1.3396	1.3396	1.3396	1.3396	1.3396	1.3396
R^2	0.12866	0.13763	0.13425	0.14209	0.14793	0.15234	0.17906	0.18489	0.18586
Observations	130,976	130,976	130,976	130,976	130,976	130,976	130,976	130,976	130,976
Regression specification:									
ITL1 × Year FE	X			X			X		
ITL2 × Year FE		X			X	X		X	X
Year FE			X						
LAD FE			X	X	X	X			
MSOA FE							X	X	X
Property level controls						X			X

Notes: Table presents results from several regressions. Each observation refers to an output area (OA) in 2021. The regressions estimate a regression discontinuity design (RDD) where the control and treatment units are chosen within a bandwidth around an eligibility threshold. The bandwidth in this table is 3000. The dependent variable captures the sum of all CSCO retrofit installation measures (Panel A). ITL stands for International Territorial Levels and is geocode used by the Office for National Statistics (ONS) to subdivide the UK into smaller units. ITL1 regions correspond to the regions of England. LAD stands for Local Auhtority District which are the local governments in the UK, and Middle-layer Super Output Areas (MSOA) is a statistical unit that is aggregated from census blocks (Output Areas). Property level controls include the property's council tax band, age band and type. 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: Impact of ECO eligibility on installed retrofit measures and energy consumption - threshold 4000

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Sum of CSCO installations									
Eligible for CSCO	0.9568***	0.9529***	0.9773***	0.9773***	0.9773***	0.9831***	0.9398***	0.9398***	0.9295***
	(0.0711)	(0.0698)	(0.0632)	(0.0632)	(0.0632)	(0.0664)	(0.0575)	(0.0575)	(0.0632)
Dependent variable mean	1.2516	1.2516	1.2516	1.2516	1.2516	1.2516	1.2516	1.2516	1.2516
R^2	0.12453	0.13250	0.12837	0.13678	0.14194	0.14581	0.17098	0.17614	0.17706
Observations	174,844	174,844	174,844	174,844	174,844	174,844	174,844	174,844	174,844
Panel B: Energy consumption per meter									
Eligible for CSCO	-603.3***	-623.3***	-813.0***	-813.0***	-813.0***	-472.6***	-916.0***	-916.0***	-538.7***
	(88.12)	(81.76)	(71.91)	(71.92)	(71.95)	(75.41)	(66.90)	(66.92)	(71.25)
Dependent variable mean	15,163.3	15,163.3	15,163.3	15,163.3	15,163.3	15,163.3	15,163.3	15,163.3	15,163.3
R^2	0.02765	0.05250	0.10511	0.10511	0.10511	0.16303	0.28076	0.28076	0.29977
Observations	31,599	31,599	31,599	31,599	31,599	31,599	31,599	31,599	31,599
Regression specification:									
ITL1 × Year FE	X			X			X		
ITL2 × Year FE		X			X	X		X	X
Year FE			X						
LAD FE			X	X	X	X			
MSOA FE							X	X	X
Property level controls						X			X

Notes: Table presents results from several regressions. Each observation refers to an output area (OA) in 2021. The regressions estimate a regression discontinuity design (RDD) where the control and treatment units are chosen within a bandwidth around an eligibility threshold. The bandwidth in this table is 4000. The dependent variables move across the panels and capture the sum of all CSCO retrofit installation measures (Panel A). In panel B, the dependent variable is energy consumption per meter. Regression specifications vary across the columns as indicated by the categories at the bottom of the table. ITL stands for International Territorial Levels and is geocode used by the Office for National Statistics (ONS) to subdivide the UK into smaller units. ITL1 regions correspond to the regions of England. LAD stands for Local Auhtority District which are the local governments in the UK, and Middle-layer Super Output Areas (MSOA) is a statistical unit that is aggregated from census blocks (Output Areas). Property level controls include the property's council tax band, age band and type. 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: Heterogeneity wrt to effect size on number of installations by Austerity measures

Dependent variable	T-value > 1.65		Estimate		Estimate > Median	
	(1)	(2)	(3)	(4)	(5)	(6)
Total spending	-0.4727*	-0.4311	-0.8466	-1.356**	-0.2483	-0.4773
	(0.2700)	(0.2969)	(0.5850)	(0.6275)	(0.3584)	(0.3962)
Dependent variable mean	0.16987	0.16987	0.81823	0.81823	0.49359	0.49359
R^2	0.01489	0.12289	0.00896	0.17490	0.00232	0.14786
Observations	312	312	312	312	312	312
Planning and development	0.0264	-0.0551	0.0951	-0.0750	0.1299	0.0659
	(0.0770)	(0.0772)	(0.1699)	(0.1686)	(0.1001)	(0.0918)
Dependent variable mean	0.16987	0.16987	0.81823	0.81823	0.49359	0.49359
R^2	0.00049	0.11493	0.00120	0.15723	0.00671	0.14257
Observations	312	312	312	312	312	312
Regression specification:						
ITL1 FE		X		X		X

Notes: Table presents results from a regression. Each observation refers to an Local Authority District (LAD) in 2016. The dependent variables move across the columns and captures local authority specific treatment effects. Columns (1) and (2) measure the probability that the estimated LAD specific coefficient is statistically significant at the 10% significance level. Columns (3) and (4) measure the size of the LAD specific treatment effect. Columns (5) and (6) measure the probability that the LAD specific treatment effect is larger than the median treatment effect. Austerity measures vary across the panels and are defined in section A.3. 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 A7: Heterogeneity wrt to effect size on number of installations by broadband measures

Dependent variable	T-value > 1.65		Estimate		Estimate > Median	
	(1)	(2)	(3)	(4)	(5)	(6)
Sync speed	0.0508*	0.0372	0.4971***	0.4616***	0.1745***	0.1576***
	(0.0288)	(0.0264)	(0.1162)	(0.1267)	(0.0410)	(0.0416)
Dependent variable mean	0.15891	0.15891	0.82478	0.82478	0.52326	0.52326
R^2	0.01805	0.17916	0.08943	0.15655	0.11425	0.20641
Observations	258	258	258	258	258	258
Superfast broadband	0.2818***	0.2727***	1.699***	1.575***	0.4792***	0.4119***
	(0.0910)	(0.0861)	(0.3841)	(0.4202)	(0.1309)	(0.1315)
Dependent variable mean	0.15891	0.15891	0.82478	0.82478	0.52326	0.52326
R^2	0.04330	0.20895	0.08141	0.15161	0.06709	0.16701
Observations	258	258	258	258	258	258
Regression specification:						
ITL1 FE		X		X		X

Notes: Table presents results from a regression. Each observation refers to an Local Authority District (LAD) in 2016. The dependent variables move across the columns and captures local authority specific treatment effects. Columns (1) and (2) measure the probability that the estimated LAD specific coefficient is statistically significant at the 10% significance level. Columns (3) and (4) measure the size of the LAD specific treatment effect. Columns (5) and (6) measure the probability that the LAD specific treatment effect is larger than the median treatment effect. Sync speed is the average broadband sync speed in Mbit/s excluding superfast broadband within a local authority. Superfast broadband measures the share of households in a local authority that receive superfast broadband. The broadband data comes from the Communications Infrastructure Report 2011. 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: Heterogeneity - other measures

Dependent variable	T-value > 1.65		Estimate		Estimate > Median	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:						
Austerity	-0.4379**	-0.5279***	-1.105	-1.667**	-0.4719*	-0.5221*
	(0.1734)	(0.1934)	(0.7014)	(0.7089)	(0.2664)	(0.2822)
Rural	-0.1944*	-0.1236	-1.799***	-1.848***	-0.5217***	-0.5689***
	(0.1037)	(0.1053)	(0.4596)	(0.5145)	(0.1755)	(0.1746)
Dependent variable mean	0.16346	0.16346	0.77316	0.77316	0.50962	0.50962
R^2	0.04201	0.18921	0.06959	0.16811	0.06645	0.17941
Observations	312	312	312	312	312	312
Panel B:						
Austerity	-0.4877***	-0.5445***	-1.653**	-1.896***	-0.6077**	-0.5975**
	(0.1797)	(0.1927)	(0.6540)	(0.7013)	(0.2479)	(0.2860)
Inequality	0.0166**	0.0069	0.1240***	0.1084**	0.0439***	0.0321***
	(0.0072)	(0.0078)	(0.0292)	(0.0435)	(0.0084)	(0.0114)
Dependent variable mean	0.16346	0.16346	0.77316	0.77316	0.50962	0.50962
R^2	0.06412	0.18909	0.12907	0.17005	0.14993	0.17857
Observations	312	312	312	312	312	312
Panel C:						
Austerity	-0.4754***	-0.5181***	-2.227***	-2.302***	-0.8136***	-0.6904**
	(0.1688)	(0.1855)	(0.7403)	(0.7425)	(0.2712)	(0.2866)
65+	-0.4763	-0.7105	1.674	-0.6807	0.6127	-0.5523
	(0.7197)	(0.6983)	(2.512)	(2.960)	(1.007)	(1.078)
Dependent variable mean	0.16346	0.16346	0.77316	0.77316	0.50962	0.50962
R^2	0.03634	0.18988	0.03047	0.12967	0.03715	0.14713
Observations	312	312	312	312	312	312
Panel D:						
Austerity	-0.6024***	-0.5760***	-2.482***	-2.364***	-0.9508***	-0.7394***
	(0.1862)	(0.1968)	(0.7155)	(0.7509)	(0.2498)	(0.2802)
Pop. share qual. 4+	-0.4828	-0.4462	-3.409***	-2.011	-1.568***	-1.190**
	(0.3312)	(0.3938)	(0.9490)	(1.382)	(0.4213)	(0.5628)
Dependent variable mean	0.16346	0.16346	0.77316	0.77316	0.50962	0.50962
R^2	0.04495	0.19148	0.06131	0.13575	0.09799	0.16605
Observations	312	312	312	312	312	312
Regression specification:						
ITL1 FE		X		X		X

Notes: Table presents results from a regression. Each observation refers to an Local Authority District (LAD) in 2016. The dependent variables move across the columns and captures local authority specific treatment effects. Columns (1) and (2) measure the probability that the estimated LAD specific coefficient is statistically significant at the 10% significance level. Columns (3) and (4) measure the size of the LAD specific treatment effect. Columns (5) and (6) measure the probability that the LAD specific treatment effect is larger than the median treatment effect. Austerity is our preferred measure of expenditure cuts at the local authority level which we define as total expenditure minus expenditure on housing and environmental services. Rural is defined as the local authority's share of LSOAs that are classified as rural by the office for national statistics (ONS). Inequality is measured as the within authority standard deviation of the index of multiple deprivation (IMD). 65+ is the share of population aged 65 or older. Pop. share qual. 4+ measures the share of population with at least tertiary education. 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: Energy consumption - Difference in differences

	Energy consumption		Gas consumption		Electricity consumption	
	(1)	(2)	(3)	(4)	(5)	(6)
Eligible × Year = 2008	-19.08	-21.88*	-11.65	-14.27	-11.95***	-11.54***
	(12.88)	(12.98)	(11.83)	(11.91)	(4.425)	(4.459)
Eligible × Year = 2009	-7.429	-9.498	9.992	8.530	-11.13***	-11.32***
	(10.99)	(11.07)	(10.08)	(10.16)	(4.010)	(4.042)
Eligible × Year = 2010	-8.320	-6.843	-13.14*	-11.69	-4.438	-4.434
	(8.825)	(8.897)	(7.989)	(8.053)	(3.442)	(3.468)
Eligible × Year = 2012	-83.96***	-79.60***	-78.59***	-74.55***	-7.266**	-6.844**
	(8.155)	(8.220)	(7.336)	(7.393)	(3.297)	(3.322)
Eligible × Year = 2013	-94.63***	-87.77***	-97.24***	-91.24***	4.258	4.316
	(9.903)	(9.977)	(9.033)	(9.100)	(3.750)	(3.777)
Eligible × Year = 2014	-111.2***	-102.1***	-117.8***	-109.8***	4.970	5.300
	(10.96)	(11.04)	(9.962)	(10.04)	(4.075)	(4.105)
Eligible × Year = 2015	-90.79***	-82.51***	-97.22***	-89.36***	0.2200	0.0469
	(11.70)	(11.79)	(10.61)	(10.69)	(4.264)	(4.297)
Dependent variable mean	16,326.1	16,326.1	12,658.8	12,658.8	3,781.9	3,781.9
R^2	0.80328	0.80461	0.77824	0.77967	0.72698	0.72879
Observations	9,002,222	9,002,222	9,533,337	9,533,337	11,023,753	11,023,753
Regression specification:						
Installation controls		X		X		X
Group FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Household FE	X	X	X	X	X	X

Notes: Table presents the results from event study regressions. Each unit of observation refers to a household in England. The dependent variable moves across the columns. In columns (1) and (2) the dependent variable is the combined gas and energy consumption in KWh, in columns (3) and (4) only gas consumption, and in columns (5) and (6) only electricity consumption. Eligible is an indicator variable that equals one if the household is living in an LSOA that is within the 20% most deprived areas in the UK and 0 if it is between the 20 and 40% most deprived areas. Installation controls include indicator variables for loft insulation, cavity wall insulation and solar PV installations. Groupings for the group fixed effects are made by pooling all households with the same property type, property age, floor area, conservatory status, council tax band, region, and whether main heating is fuel. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.