Performative State Capacity and Climate (In)Action

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Abstract

Climate action requires significant public and private sector investments to reduce carbon emissions. This paper documents that post global financial crisis austerity and a lack of (digital) skills in (local) government were substantial barriers to climate action in the form of retrofitting homes. We estimate causal heterogenous treatment effects for a large scale energy efficiency program leveraging a regression discontinuity in the UK. We find that both the extent of local budget cuts and poor digital connectivity may explain up to 30% fewer retrofit installations that would have taken place counterfactually.

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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? After 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 services. 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 implemented, offered grants or large subsidies for home energy efficiency installations (cavity wall insulations, boiler upgrades, solar installations etc.) to households. We use a regression discontinuity design (RDD) within the ECO scheme roll-out that targeted households living in small areas that were considered to be the among the 15% economically 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 of performative state capacity: austerity – measured as the extent of cuts in local government spending – and limited (local) government digital skills.

We proceed in two steps. First, using exceptionally granular data on program delivery at the census-tract level and energy consumption data at the postcode level, we estimate a causal *average treatment effect* via a regression discontinuity design. We find that the scheme led to increased uptake and reduced energy consumption in treated areas. Households in areas eligible for central 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 energy consumption in eligible areas decreased by 4-8%.

Next, we break down the causally estimated average treatment effect to explore causal estimates of *heterogeneous treatment effects*. For every local authority with at least one treated area we can estimate a causal authority specific treatment effect exploiting the arbitrary eligibility threshold. We find significant variation in the estimated treatment effects: authorities that were more affected by local spending cuts saw, on average, considerably smaller treatment effects, indicating weaker delivery of retrofits, despite these being financed out of central government budgets unaffected by the local government spending cuts. That is: lower treatment effects can not be explained by less central government resource availability but by worse program delivery. 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 a random forest to study the variation in the causal heterogenous treatment effects. Our analysis confirms that, in terms of variable importance, local budget cuts and ICT connectivity are primary drivers of treatment effect heterogeneity in random forests.

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 worse internet connectivity together experienced the worst program implementation. These findings under-score 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.[1]

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 the performative capacity of local governments in effectively channel central government funds for climate action into their communities.

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[2]. In line with existing studies emphasizing the state's role in facilitating individual climate action (Skidmore, 2022; Fetzer, 2023; IPCC, 2023; Nice

[1]Appendix D supports our analysis with an instrumental variables strategy, leveraging the sharper austerity impact on older communities due to rising social care costs.

[2]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)

and Sasse, 2023; CCC, n.d.; UK CCC, 2023a,b), we show how spending cuts for local governments that were decided on at the highest national level can undermine local efforts to decarbonize. Austerity weakened effective delivery of fiscally expansive centrally designed retrofit programs, like ECO[3]. This aligns with works arguing that a capable state is necessary to achieve climate targets by encouraging action at the individual level and by improving the implementation of climate policy (Willems and Baumert, 2003; Rau et al., 2020; Zwar et al., 2023). In our case, local governments in areas hit hardest by spending cuts failed to actively ensure residents benefited from government grants.

Third, the paper relates to the growing literature on state capacity. Traditional models of state capacity have focused on governments' ability to extract resources and 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 work emphasising the deployment of informational state capacity (Fetzer et al., 2024). This research highlights the importance of performative state capacity – the practical ability to implement and deliver policies effectively. Austerity eroded local government functions, undermining the effective roll-out of the ECO grants that offered free retrofits to eligible households. 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).

[3]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).

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.[4]

A spatial targeting approach was employed to roll out the program to render all households effectively eligible that live in lower layer super output areas (LSOAs)—areas with roughly 1,700 residents—based on their rank 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, households within the most deprived 15% of LSOAs across England, Scotland, and Wales were eligible for grants. This threshold was later expanded to the 25th percentile. Importantly, this geographic targeting meant that all households living in the most deprived areas, regardless of individual income or benefits received, became eligible for energy efficiency grants under ECO.[6] We take advantage of the arbitrary threshold of 15% to employ a regression discontinuity design (RDD).

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

[4]The 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.

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

[6]The broad eligibility also applied to the Carbon Saving Community Obligation (CSCO), part of the ECO program. Under Article 13, energy suppliers funded energy-efficiency measures in designated low-income areas without individual income criteria. A rural sub-obligation required 15% of CSCO funds to target households with at least one member receiving income-related benefits in settlements with 10,000 households or less. Firms could allocate up to 20% of total activity to areas adjacent to eligible ones.

(DECC)[7] in June 2012 that contains all LSOAs eligible under the ECO1 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 delivered between areas that were eligible and those that were not. 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 output area (OA) level using 2021 census definitions. Output areas are the most granular census geography with, on average, each census tract including around 100 residents that perfectly map into the coarser LSOAs. The data 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 OA level from 2010 to 2023. Our main outcome variable of interest is the number of retrofit installations in a given OA and year.

2.2 Local government's coordinating role

The ECO scheme was designed at the national level, but local governments played a central role in its roll-out and implementation. Their primary role was to leverage their informational capacity to reduce frictions between households and energy suppliers. Local councils, due to their administration of local taxes, benefits, and housing records, hold comprehensive data about their resident populations, including those in deprived areas in which all households were deemed

[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).

eligible for ECO grants. Local authorities would contact households living in eligible areas to draw attention to the grant program and connect them with energy suppliers or agents responsible for retrofit installations. Beyond this, they coordinated energy-efficiency improvements, managing logistical challenges and overseeing community-wide projects, particularly in areas where eligibility was tied to geographic deprivation. We posit that the extent of austerity-induced cuts to local government funding, along with the often underdeveloped digital skills among civil servants in local administrations, may have directly impeded the delivery of the ECO scheme. Resource limitations could have compromised the ability of councils to fully leverage their data and coordinate with energy companies, especially in reaching vulnerable households that may most benefit from energy-efficiency upgrades.

Measurement of austerity Local government budgets saw some of the most drastic cuts after 2010.[8] 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. 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.

Meanwhile, local governments faced revenue-raising constraints as increased service standards and growing statutory duties – especially in old-age social care, which we exploit for robustness in an instrumental variables analysis in the Appendix – further limited their fiscal space. As a result, the cross-the-board cuts had an exogenously given heterogeneous impact on spending across councils, as some councils may have benefited from other sources of income such as 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

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

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 spending category 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 use is the change in net current expenditure of total services less the net current expenditure in environmental and housing services. We deduct these categories to ensure that the measure accounts for the austerity shock capturing service capacity without conflating it with expenditures that councils may incur due to the delivery of the ECO scheme.[9]

(Figure 1)

Panel A of Figure 1 displays the spatial distribution of our main austerity measure across local authorities in England. The average local authority experienced a *nominal* spending cut of 17%, implying even greater real term cuts. There is, however, substantial variation across local authorities. Darker shades of red indicate a stronger austerity shock, i.e. higher cuts on total service expenditure. Panel B of Figure 1 plots the temporal evolution of local public spending by different categories indexed to 100 in 2007. After broad based austerity started 2010, expenditure was cut across all categories except spending on old age care, which as a statutory duty falls on councils and was growing drastically due to the aging society. Thus, communities with an older population, for the same level of central government spending cuts, likely experienced greater reductions in their public spending in areas that could have benefited the delivery of retrofit programs.

We document this in in panels C and D. Panel C suggests that the austerity shock was larger in areas with an older population, while Panel D presents the fact

[9] In the Appendix, we show that our results are robust to using a measure including these expenditures.

that ECO-induced retrofit installations are notably lower in local authorities that exhibited more austerity. This suggests that austerity and the local demographic make-up of an authority may have played an important role in the delivery of local climate action.

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.[10] 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.[11] The main measure we focus on is the share of homes receiving less than 2Mbit/s.

Other measures For the random forest exercise to decompose the heterogeneity in the treatment effect distribution, we employ a broad vector of other authority-level 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 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

[10]The pandemic highlighted significant deficiencies in skills and data processing capabilities across the world, which has resulted in significant severe problems in the public sector's ability to respond adequately to the pandemic, see e.g. Fetzer and Graeber (2021) for a particularly stark example.

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

for Energy Security and Net Zero (DESNZ). This covers almost the universe of postcodes in the UK, except postcodes that are considered disclosive.[12] 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. 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[13].

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 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). We leverage the eligibility criterion that targeted households living in the 15 percent most deprived LSOAs. 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 ECO retrofitting more installations were carried out. In the second stage, we estimate the effect of the eligibility on energy consumption of households. 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 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

[12] 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.

[13] For a robustness check, we use anonymized household-level data from the National Energy Efficiency Data-Framework (NEED). or more information on the Appendix exercise refer to Appendix section B

the cutoff within a bandwidth of around 10% of all LSOAs below and above the cutoff[14]. 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 the following baseline specification[15]:

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

where y_{otl} is either the number of installations 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 five 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 admin-

[14] 10% of all LSOAs above and below relates to including 3000 LSOAs above and below the cutoff.

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

istrative responsibilities. Next, we isolate variation within years and within local authorities by including year and LAD fixed effects. 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.[16] In our most restrictive specification, we control for ITL2 specific year trends, middle layer super output area (MSOA) fixed effects – just one statistical geography level coarser than our treatment, and property-level controls.

Results Table 1 presents the results of these regressions. Panel A of the table shows the effect of ECO eligibility on the number of retrofit installations. OAs within LSOAs that were eligible for ECO 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. The results are remarkably stable across the specification path moving from least to most demanding specification. This suggests that the number of installations of retrofit measures is notably higher in OAs that are part of LSOAs that are marginally eligible for the scheme.

In Panel B, we study energy consumption data aggregated from postcode level. 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 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

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

gas combined, the effects range between 500 - 900 KWh, depending on the specification. 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.[17]

Robustness In Appendix tables A1 to A3, we show that the findings are robust to three exercises. First, our results hold when changing the bandwidth of the RDD. Second, instead of using all retrofit installations, we use only installations under the CSCO subscheme, which again does not change our findings substantially. Finally, one might be concerned that the energy consumption variables suffer from measurement error when aggregating from postcode to census tracts/OA level. Appendix section B presents a property-level analysis using anonymized data, leveraging variation around the deprivation threshold in a difference-in-differences design to support our findings.

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 treatment effects – rather than a common average treatment effect across authorities. This is possible as there are eligible and non-eligible LSOAs across most local authorities.

We estimate the following equation

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

[17]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.

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. Panel C of Figure 2 links the first and second steps of our analysis. The vertical red line represents the average treatment effect from the first step, while the blue curve shows the distribution of local authority-specific heterogeneous treatment effects.

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 digital connectivity. We 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 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 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.

(Table 2)

Panel B performs the same exercise with 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 A4, Panel A shows that including spending on environmental and housing services in the austerity measure does not affect our findings, while Panels B and C indicate no differential results when using alternative definitions of ICT connectivity. In Appendix section C and Table A5, we provide evidence that other plausible mechanisms or area characteristics, such as the urban-rural divide, local inequality, demographic makeup, or educational attainment, do not appear to drive the effects. Lastly, in

Appendix section D, we use an instrumental variable strategy leveraging exogenous variation in austerity driven by the greater spending pressures in areas with aging populations and rising statutory social care costs. The results suggest that areas experiencing more demographically induced austerity show weaker treatment effects.

Visualizing treatment effect heterogeneity Our analysis suggests that both austerity and lack of digital skills play a significant role in explaining treatment effect heterogeneity in program delivery. This is visualized in Panel D of Figure 2, where each dot represents a local authority's treatment effect—red for below-median and blue for above-median. The x-axis represents austerity shock intensity, while the y-axis shows the share of the population with low-speed internet in 2011. The data, split into four quadrants based on median austerity exposure and broadband access, reveals a clear pattern: areas with less austerity and better digital connectivity are more likely to have above-median treatment effects, while the opposite holds for other quadrants. This clustering suggests applying a random forest or tree-based approach to analyze treatment effect heterogeneity.

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

We document that both austerity and broadband access are important in understanding treatment effect heterogeneity with the above analysis suggesting that a tree-based decomposition may be particularly salient in segmenting the data. HHowever, latent factors may drive this heterogeneity, and non-linear relationships could more effectively capture the underlying patterns in the data.

To explore this systematically, we use random forests to identify the relative variable importance among a large set of other features that could conceivably be driving heterogeneity in treatment effects. For simplicity, we focus on the binary indicator: $\mathbb{1}(\hat{\beta}_a > \text{median}(\widehat{\beta_a}))$. A random forests is an ensemble method, where predictions are obtained from an ensemble of classification trees that have been built through binary recursive splitting. This produces (highly) non-linear interaction terms. We are interested in the relative importance that each feature has in correctly classifying whether a treatment effect stands out or not in the empirical distribution of estimated treatment effects. 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.[18]

Panel A of Figure 3 shows one ranking of the variables by how much the predictive power of the random forests decreases with their exclusion. This strongly suggests that, among the features considered (see Appendix section C for a detailed discussion), the austerity measure and the proxy for digital skills are the two most important factors. We run multiple random forests with different levels of fixed effects or outcome variables in equation 3, and focus on different measures of variable importance. Panel B of Figure 3 shows the distribution of importance ranks of the two measures. Both, the austerity and the broadband measure, consistently rank among the top three most important features in explaining treatment effect heterogeneity.[19][20]

(Figure 3)

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.

[18] Appendix figure A3 focuses on another measure of variable importance: mean decrease in Gini importance. We arrive at similar conclusions.

[19] To show the interdependency of the two state capacity measures in explaining treatment effect heterogeneity, we plot conditional CDFs in Appendix figure A4.

[20] In Appendix Figure A5, we provide centered individual conditional expectation plots for the size of local authority estimates. The plots show how increases in austerity and worse internet access, on average, across the distribution are associated with lower treatment effects.

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 Energy Company Obligation (ECO) program that aimed at providing grants to households in deprived parts of the UK to finance retrofits. We find that households living in areas eligible for ECO grants were more likely to install retrofit measures which in turn decreased their energy consumption. In a second step, we show that the delivery of the retrofit program masks substantial regional heterogeneity. Areas that saw higher austerity shocks and worse digital connectivity experienced a significantly lower treatment effects. Local governments played a vital role in facilitating the roll out of the ECO grants scheme. Our analysis suggests that there have been notable program delivery failures particularly concentrated in parts of the UK that had experienced the most significant cuts to public spending and where public budgets were coming under increasing strain from demographic change.

Our findings open several paths for future research. One that we find most promising and interesting is the nexus between austerity, skills, and public service delivery amidst demographic change. Austerity-induced pressure on public wages lowers the competitiveness of public 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).

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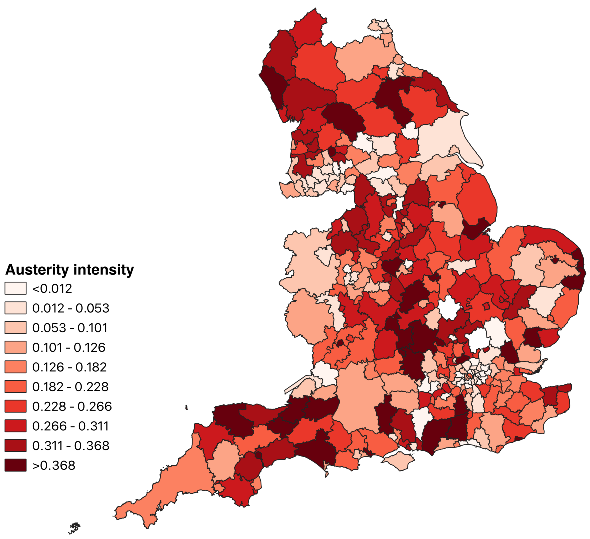
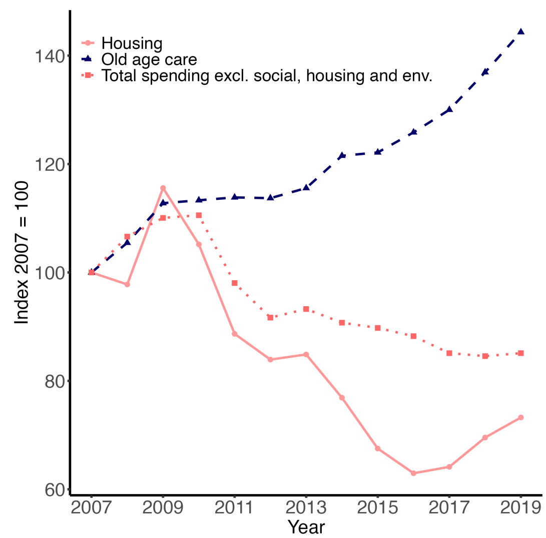
Figures and tables

Figure 1: Local government budget cuts varied notably across space and is associated with worse retrofit program delivery

Extent of austerity

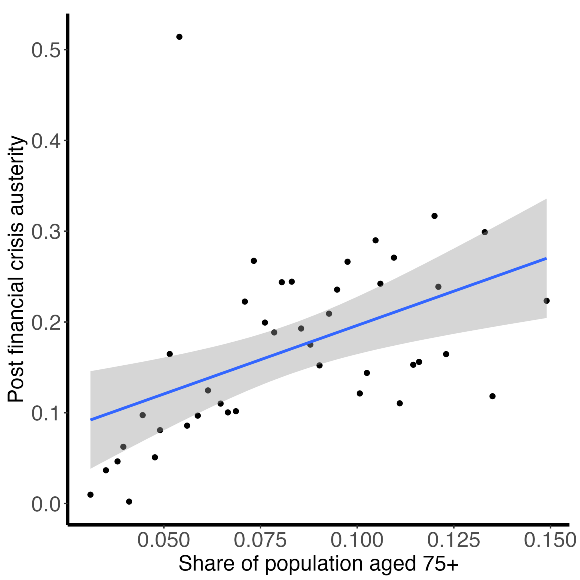
Panel A: Variation in austerity across space *Panel B*: and over time by local function

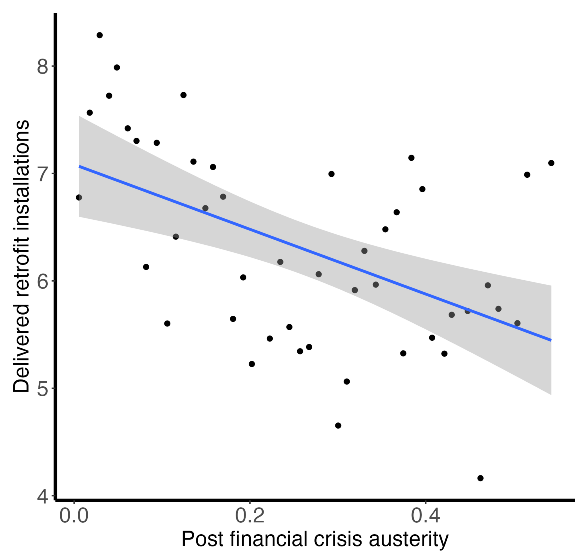




Panel C: with spending cuts sharper in areas with an older resident population

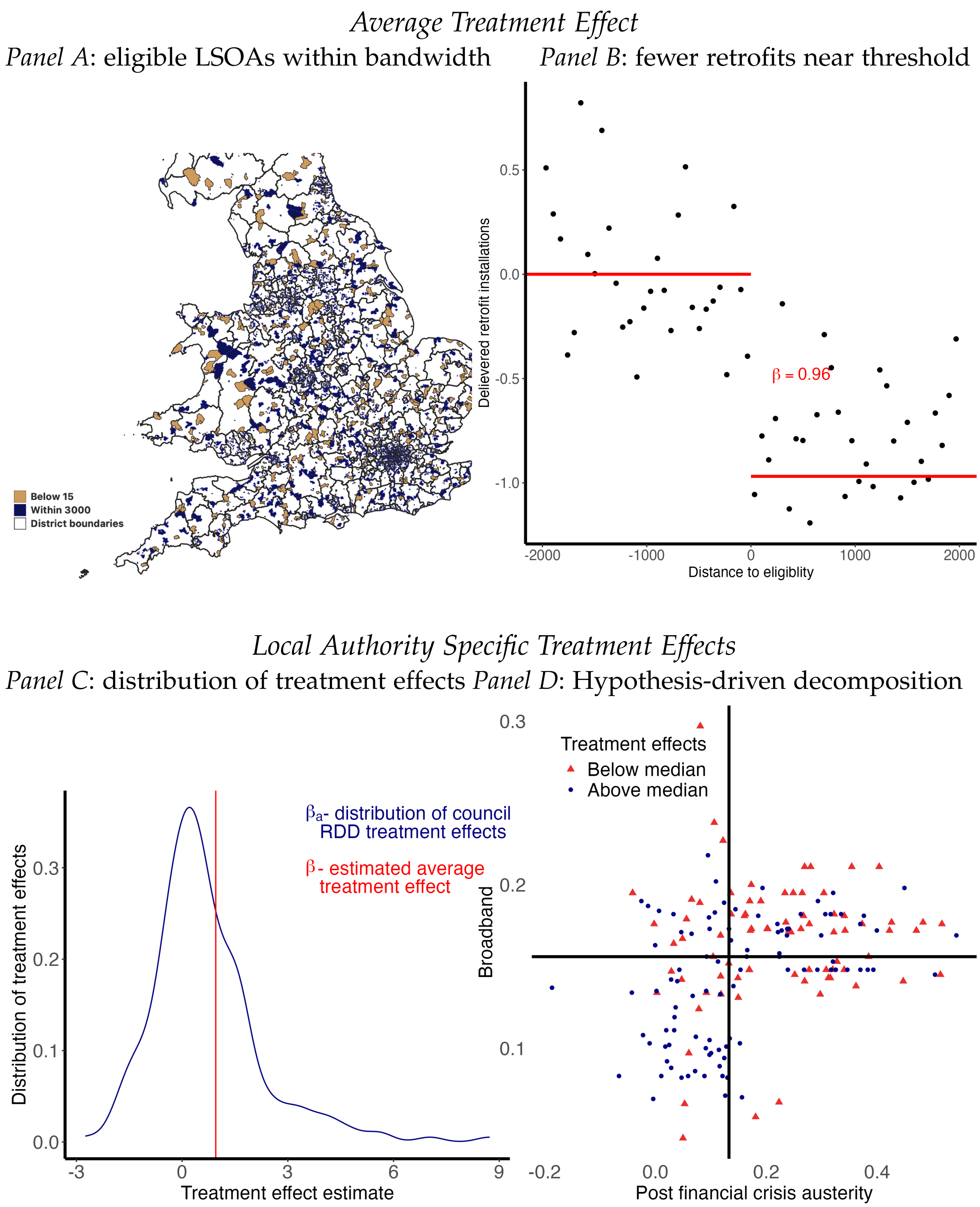
Panel D: spending cuts associated with notably fewer retrofit installations





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 plots the time series of post financial crisis local authority spending by broad categories between 2007 and 2019 where 2007 is indexed to be 100. Panel C shows in a binned scatterplot the correlation of local authorities' spending shock on the x-axis and the percentage of residents of age 75 or more. Panel D shows in a binned scatterplot 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 analysis and exploration of variation in causal council-specific treatment effects

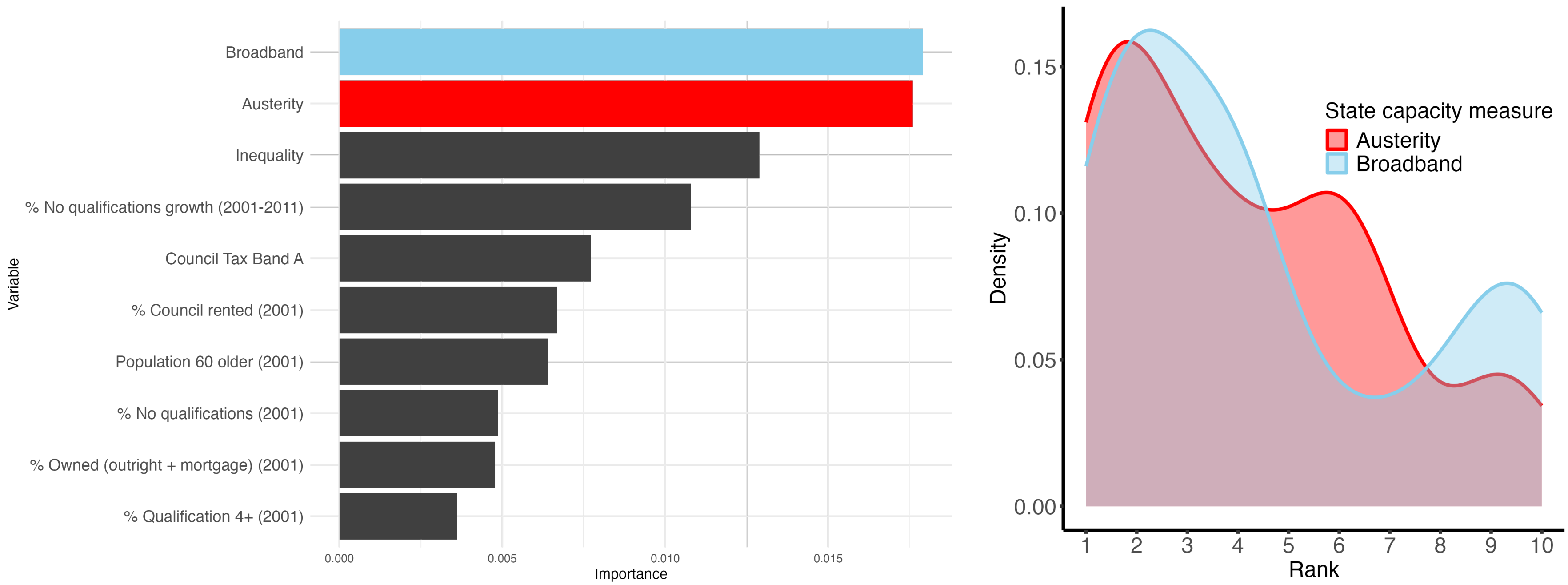


Notes: Panel A of the figure plots the spatial variation of the treatment and our sample selection across Lower Layer Super Output Areas (LSOAs) across England and Wales. Areas shaded in brown are LSOAs below the 15th percentile of the Index of Multiple Deprivation (IMD) and thus eligible for the Carbon 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 × year fixed effects for local regressions above and below the cutoff within a bandwith of 3000. **Notes:** Panel C of the figure plots the distribution of authority specific treatment effects in blue and the average treatment effect from our preferred specification in red. Panel D plots authority specific treatment effects 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 shows our preferred ICT connectivity broadband measure - the share of households with broadband slower than 2 Mbit/s.

Figure 3: Variable importance measures showcasing the empirical relevance of austerity measure explaining variation in treatment effect heterogeneity across random forests

Panel A: Variable importance

Panel B: Robustness of variable importance rank



Notes: Panel A of the figure plots the relative variable importance of our random forest model pertaining to the most preferred specification. The random forest is classifying districts into whether they have an above or below median effect size. The variables with the highest importance have the highest predictive power. Panel B presents a probability density function of the rank of the austerity and broadband variables across a set of 54 random forests with different austerity measures for robustness. In the vast majority of random forests the austerity measure appears in the top one or two of the random forest models. Appendix Figure A4 further highlights that the rank of the austerity- and digital connectivity measures appear negatively correlated across random forests suggesting that the information content in the two variables is quite similar. This is evidenced in panel D of Figure 2 highlighting that high versus low treatment effects can be separated out well through either the austerity measure (horizontal axis) or the broadband access measure (vertical axis).

Table 1: Regression discontinuity design estimates around the retrofit scheme eligibility cutoff

	(1)	(2)	(3)	(4)	(5)
Panel A: Sum of retrofit installations					
Eligible for retrofit scheme	0.9687***	0.9430***	0.9549***	0.9549***	0.7692***
	(0.1131)	(0.1096)	(0.0962)	(0.0962)	(0.0973)
Dependent variable mean	3.1226	3.1226	3.1226	3.1226	3.1226
R^2	0.15656	0.16631	0.15948	0.17409	0.23228
Observations	130,976	130,976	130,976	130,976	130,976
Panel B: Combined Energy consumption per meter					
Eligible for retrofit scheme	-603.3***	-623.3***	-813.0***	-813.0***	-538.7***
	(88.12)	(81.76)	(71.91)	(71.92)	(71.25)
Dependent variable mean	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	0.29977
Observations	31,599	31,599	31,599	31,599	31,599
Regression specification:					
ITL1 $\times$ Year FE	X			X	
ITL2 $\times$ Year FE		X			X
Year FE			X		
LAD FE			X	X	
MSOA FE					X
Property level controls					X

Notes: Table presents results from several regressions estimating the effect of a retrofit eligibility scheme called CSCO in the UK. 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 in retrofit-scheme delivery: Decomposition of RDD estimates across local authorities highlighting role of austerity and digital connectivity

Dependent variable	T-value > 1.65		Estimate β_a		Estimate β_a > Median	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:						
Austerity	-0.4359***	-0.4299***	-2.000***	-2.278***	-0.5934**	-0.5491**
	(0.1420)	(0.1538)	(0.5944)	(0.6980)	(0.2393)	(0.2696)
Dependent variable mean	0.13208	0.13208	0.68595	0.68595	0.50000	0.50000
R^2	0.03308	0.15277	0.03246	0.11290	0.02811	0.11108
Observations	212	212	212	212	212	212
Panel B:						
Less 2 Mbit/s	-1.131*	-0.8649	-12.16***	-11.56***	-3.877***	-3.584***
	(0.6314)	(0.5460)	(2.701)	(2.822)	(0.8991)	(0.9002)
Dependent variable mean	0.13068	0.13068	0.72415	0.72415	0.51136	0.51136
R^2	0.01732	0.14460	0.08308	0.14700	0.09261	0.19337
Observations	176	176	176	176	176	176
Panel C:						
Austerity	-0.3547**	-0.3687**	-1.472**	-1.333*	-0.6488**	-0.4038
	(0.1671)	(0.1785)	(0.7082)	(0.7355)	(0.2836)	(0.2933)
Less 2 Mbit/s	-0.7142	-0.4054	-10.48***	-9.910***	-3.122***	-3.118***
	(0.6581)	(0.5708)	(2.748)	(2.874)	(0.9562)	(0.9463)
Dependent variable mean	0.13295	0.13295	0.73408	0.73408	0.51445	0.51445
R^2	0.03427	0.17207	0.09453	0.15953	0.11912	0.20273
Observations	173	173	173	173	173	173
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.

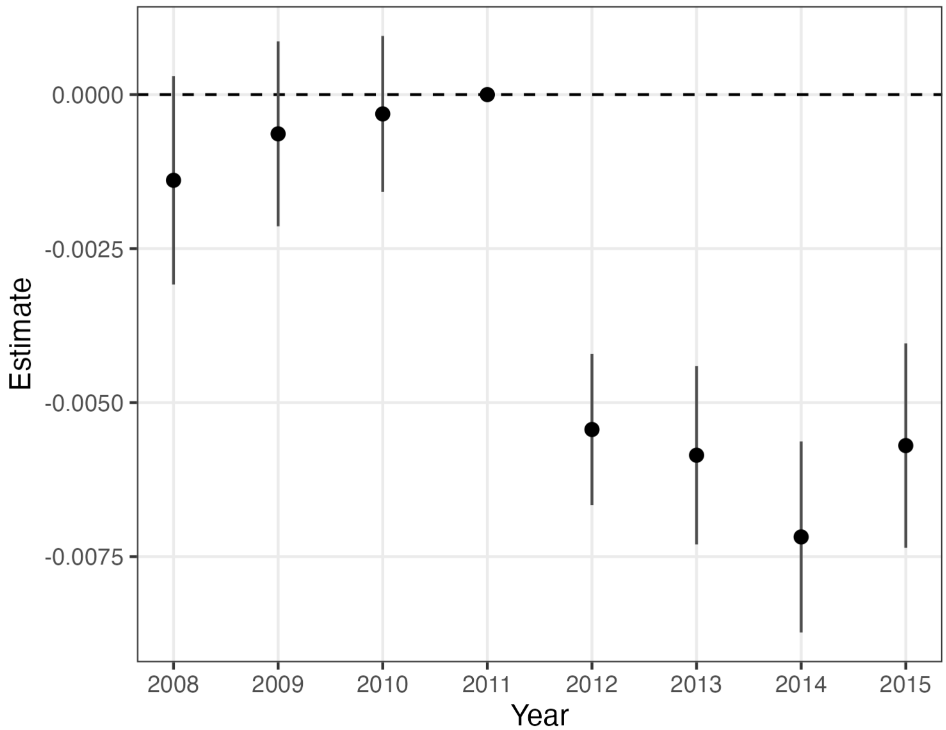


Figure A1: Event study energy consumption

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 A5 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.

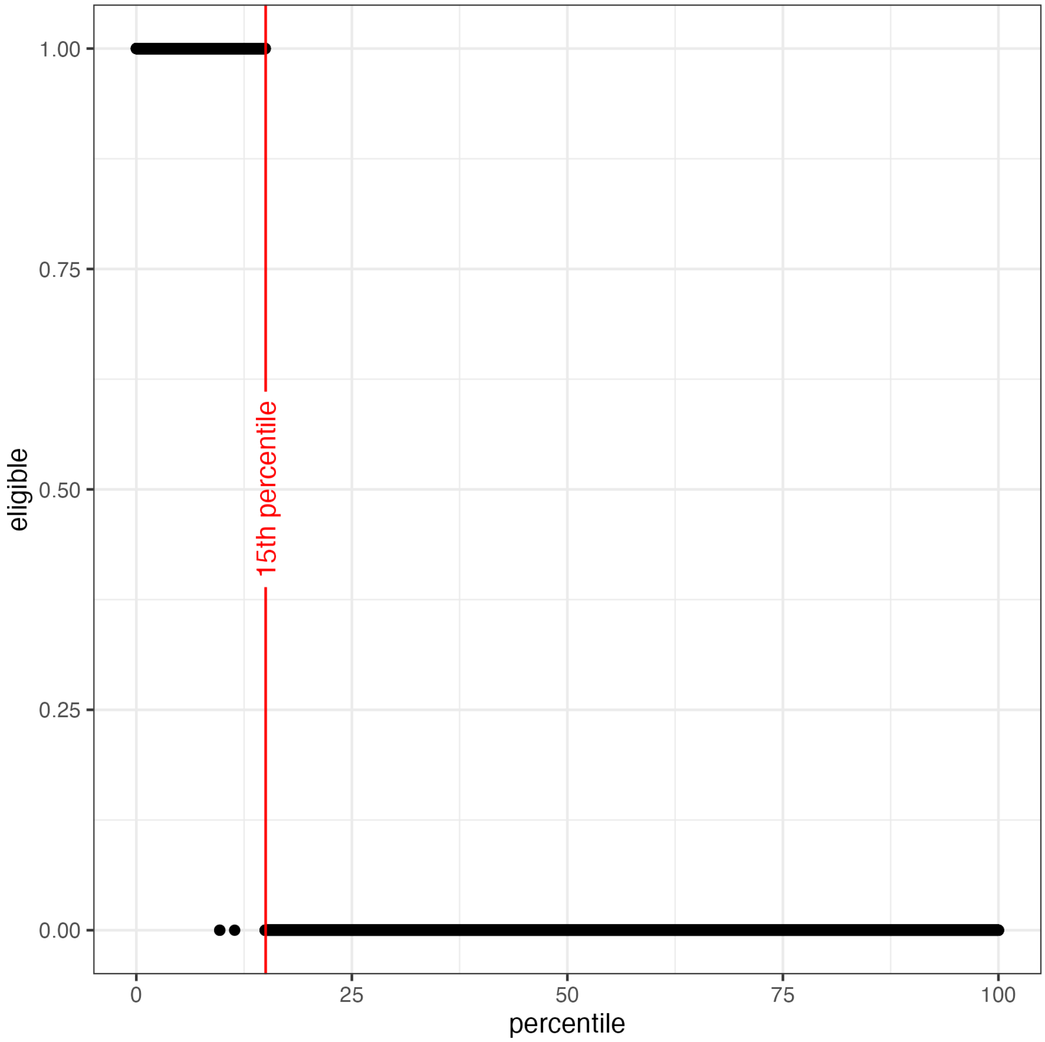
D Instrumental variable strategy

When estimating treatment effect heterogeneity with respect to austerity measures there might be concerns of potential endogeneity issues and as such our estimated coefficients in table 2 don't reflect causality. Confounding factors that have an impact on the effectivitiy of climate action as well as on the pressure of local authority to cut public expenditures can bias our findings. To alleviate these concerns we employ an instrumental variable strategy using local health and age patterns as an exogenous demand shifter for the extent of the local austerity shock. More precisely, we use the share of individuals of age 85 or older that report to suffer from long term health problems such that day-to-day activities are limited, measured in 2011 as an instrument for the austerity shock. All of the data come from the 2011 UK census.

To satisfy the identifying assumptions of an instrumental variable strategy, the instruments need to be, first, strongly related with the endogenous variable, and second, exogenous with respect to the outcome. As a large part of local authority expenditure falls on social care, the health related and demographic make-up of an authority is a significant demand factor for local government spending. This is confirmed by the first stages in table A6. Further, the instrument should affect the outcome – the efficiency of the CSCO program – only via its impact on austerity. As we use data from 2011 and thus prior to the implementation of the ECO programme, age and health distributions are pre-determined and should therefore not be relevant for the roll-out of the CSCO program. One might worry that local authorities strategically rolled out the retrofit installation scheme in some local neighborhoods with an e.g. younger population than in neighborhoods with an older population or vice versa. This could violate the validity of the instrument. To take this into account, we control for an output area's demographic make-up in 2011 with the data coming from the 2011 census in the estimation of the local authority specific treatment effects. Table A6 presents the results of this identification strategy. As the outcome variable, we focus here only on the probability to observe a statistically significant treatment effect. With this we capture systematically different take-up of the treatment across local authorities. In addition, we show that the effect is robust to our definition of austerity with the austerity measure varying across the columns. In columns (1) and (2) we exclude environmental and housing spending to not inflate our austerity measure with spending in relation to the policy we're studying. In columns (3) and (4) we exclude only social care spending to make sure we use only variation that is not directly due to an aging local population but we want to look at the externality of rising old age care costs. In the last two columns we then exclude all three categories environmental, housing and social care. The estimated coefficients confirm our findings from table 2 that the extent of authority is an important factor in explaining the heterogeneity in the treatment effect of the CSCO program. When including ITL1 fixed effects the estimated coefficients are not statistically significant anymore. This is likely due to low power in out setting. As we only have 209 local authorities with at least one treated LSOA and ITL1 regions include between 12 and 67 LADs we might end up with too little variation to detect an effect.

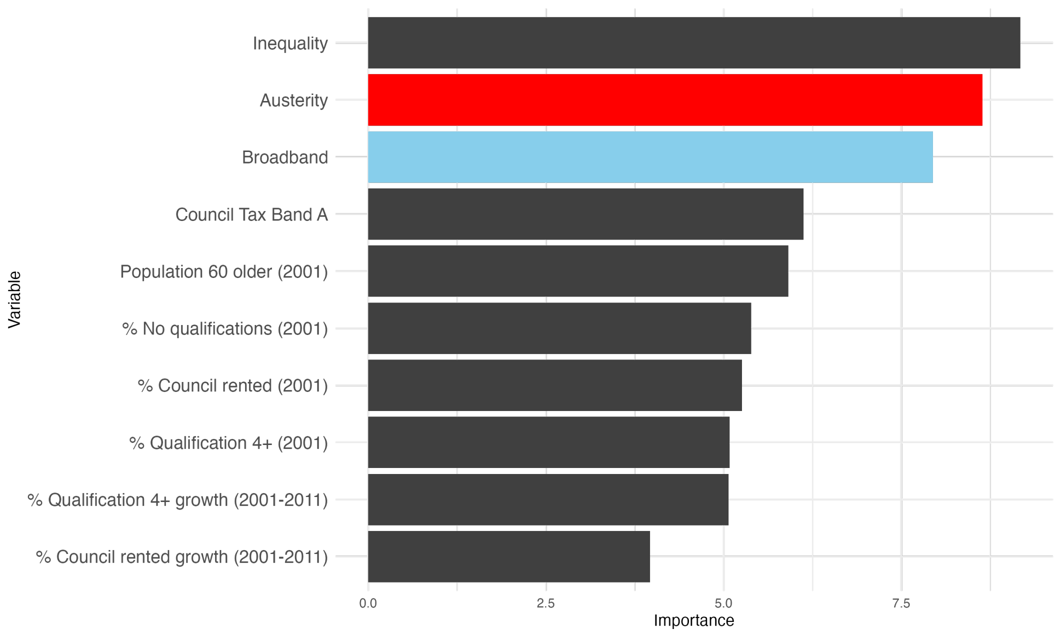
E Appendix figures

Figure A2: CSCO eligibility and Deprivation Index rank



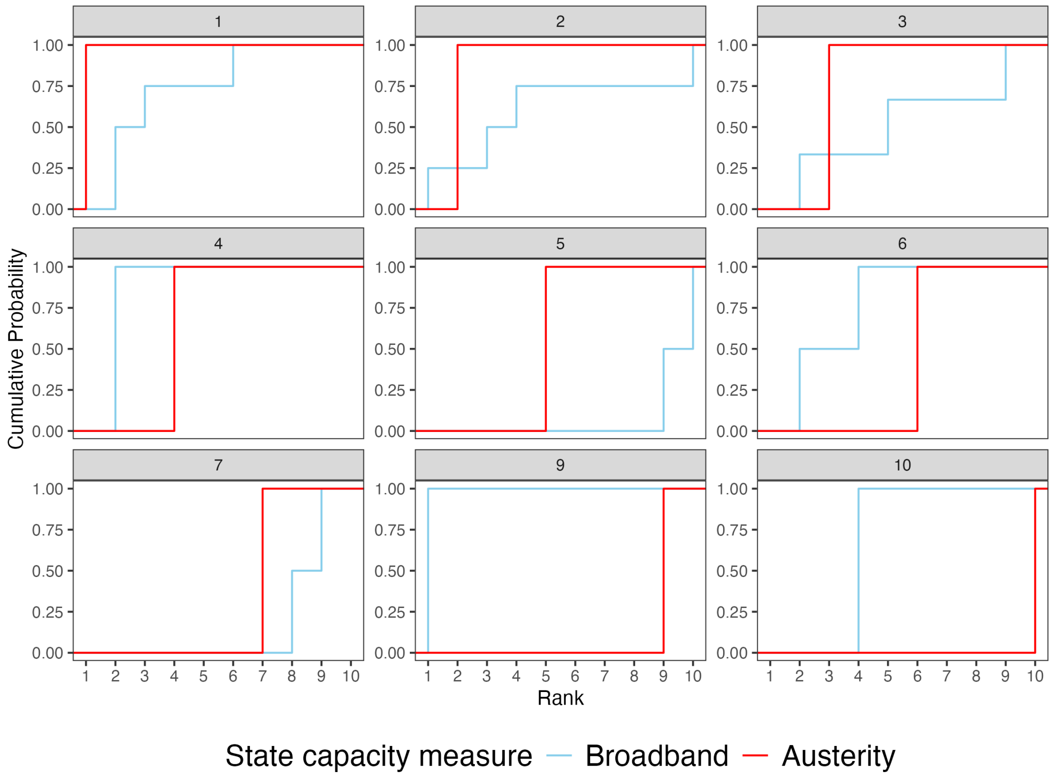
Notes: The figure plots the ranking of LSOAs along their deprivation score percentile along the x-axis with lower ranks corresponding to more deprived areas. The y-axis shows the eligibility status for the CSCO program. The red line depicts the 15th percentile of the deprivation index below which LSOAs were eligible for the program.

Figure A3: Machine learning approach - Mean Decrease Gini



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.

Figure A4: Conditional Cumulative Distribution Function

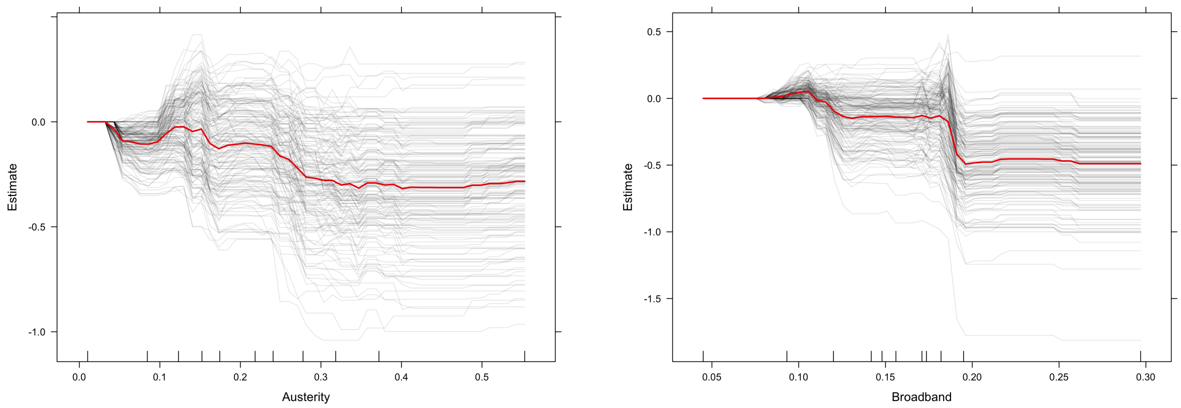


Notes: The figure shows conditional Cumulative Distribution Functions (CDF) for the broadband state capacity measure. In each panel, the realized variable importance rank of austerity is fixed and plotted against the CDF of the broadband measure. This shows the interdependency of the two state capacity measures. It highlights that the high rank of the austerity measure in the variable importance, on average, is associated with a lower rank of the broadband measure and vice versa highlighting the joint significance in shaping the estimated treatment effect heterogeneity.

Figure A5: Machine learning approach - Individual Conditional Expectation plots highlighting monotonicity in the impact of austerity and poor broadband's association with lower program treatment effects

Panel A: Estimate - Austerity

Panel B: Estimate - Poor Broadband Connectivity



Notes: The figure plots the centered individual conditional expectation plot from the random forest and shows how a local authority specific estimate changes with increasing levels of austerity (Panel A) and broadband (Panel B). Each line depicts a unique observation and thus a combination of the covariates used in the random forest. The red line is the median observation. It highlights both, higher austerity and higher share of households with worse internet access is associated with lower treatment effects of the retrofit program

F Appendix tables

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

	(1)	(2)	(3)	(4)	(5)
Panel A: Sum of retrofit installations					
Eligible for retrofit scheme	0.8384***	0.8140***	0.8565***	0.8565***	0.7488***
	(0.1107)	(0.1076)	(0.1027)	(0.1027)	(0.1215)
Dependent variable mean	3.0786	3.0786	3.0786	3.0786	3.0786
R^2	0.15564	0.16583	0.15903	0.17260	0.23532
Observations	87,720	87,720	87,720	87,720	87,720
Panel B: Energy consumption per meter					
Eligible for retrofit scheme	-291.7***	-331.6***	-509.8***	-509.8***	-357.2***
	(98.31)	(91.02)	(86.90)	(86.92)	(90.20)
Dependent variable mean	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	0.31483
Observations	21,110	21,110	21,110	21,110	21,110
Regression specification:					
ITL1 × Year FE	X			X	
ITL2 × Year FE		X			X
Year FE			X		
LAD FE			X	X	
MSOA FE					X
Property level controls					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)
Panel A: Sum of retrofit installations					
Eligible for retrofit scheme	1.015***	0.9872***	0.9882***	0.9882***	0.8152***
	(0.1159)	(0.1117)	(0.0970)	(0.0970)	(0.0954)
Dependent variable mean	3.0752	3.0752	3.0752	3.0752	3.0752
R^2	0.15721	0.16655	0.15801	0.17392	0.22804
Observations	174,844	174,844	174,844	174,844	174,844
Panel B: Energy consumption per meter					
Eligible for retrofit scheme	-921.7***	-941.5***	-1,135.8***	-1,135.8***	-666.8***
	(91.26)	(81.23)	(69.45)	(69.46)	(79.32)
Dependent variable mean	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	0.28411
Observations	42,177	42,177	42,177	42,177	42,177
Regression specification:					
ITL1 × Year FE	X			X	
ITL2 × Year FE		X			X
Year FE			X		
LAD FE			X	X	
MSOA FE					X
Property level controls					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 3000

	(1)	(2)	(3)	(4)	(5)
Panel A: Sum of CSCO installations					
Eligible for retrofit scheme	0.8629***	0.8568***	0.8753***	0.8753***	0.8392***
	(0.0746)	(0.0732)	(0.0655)	(0.0655)	(0.0623)
Dependent variable mean	1.3396	1.3396	1.3396	1.3396	1.3396
R^2	0.12866	0.13763	0.13425	0.14209	0.18586
Observations	130,976	130,976	130,976	130,976	130,976
Panel B: Energy consumption per meter					
Eligible for retrofit scheme	-603.3***	-623.3***	-813.0***	-813.0***	-538.7***
	(88.12)	(81.76)	(71.91)	(71.92)	(71.25)
Dependent variable mean	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	0.29977
Observations	31,599	31,599	31,599	31,599	31,599
Regression specification:					
ITL1 × Year FE	X			X	
ITL2 × Year FE		X			X
Year FE			X		
LAD FE			X	X	
MSOA FE					X
Property level controls					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 A4: 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:						
Total spending	-0.4821*	-0.4710*	-1.025*	-1.678**	-0.5623*	-0.7880**
	(0.2501)	(0.2829)	(0.5896)	(0.6457)	(0.3386)	(0.3597)
Dependent variable mean	0.15271	0.15271	0.78779	0.78779	0.49754	0.49754
R^2	0.01867	0.09837	0.01455	0.16826	0.01315	0.13940
Observations	203	203	203	203	203	203
Panel B:						
Sync speed	0.0552**	0.0412*	0.5358***	0.4857***	0.1763***	0.1514***
	(0.0262)	(0.0244)	(0.1148)	(0.1278)	(0.0393)	(0.0404)
Dependent variable mean	0.13068	0.13068	0.72415	0.72415	0.51136	0.51136
R^2	0.02244	0.14636	0.08777	0.14108	0.10419	0.18781
Observations	176	176	176	176	176	176
Panel C:						
Superfast broadband	0.2327***	0.2519***	1.649***	1.562***	0.4629***	0.3920***
	(0.0802)	(0.0814)	(0.3806)	(0.4280)	(0.1291)	(0.1341)
Dependent variable mean	0.13068	0.13068	0.72415	0.72415	0.51136	0.51136
R^2	0.03406	0.17282	0.07088	0.13521	0.06127	0.15885
Observations	176	176	176	176	176	176
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 A5: Heterogeneity - other measures

Dependent variable	T-value > 1.65		Estimate		Estimate > Median	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:						
Austerity	-0.3873***	-0.4326***	-1.179*	-1.719**	-0.4854*	-0.4753*
	(0.1439)	(0.1626)	(0.6393)	(0.6828)	(0.2631)	(0.2779)
Rural	-0.1226	-0.0802	-1.632***	-1.668***	-0.4348**	-0.4240**
	(0.1022)	(0.1009)	(0.4568)	(0.5109)	(0.1680)	(0.1779)
Dependent variable mean	0.13793	0.13793	0.69800	0.69800	0.50246	0.50246
R^2	0.03577	0.15174	0.06553	0.14674	0.06170	0.14796
Observations	203	203	203	203	203	203
Panel B:						
Austerity	-0.3986***	-0.4305***	-1.597***	-1.904***	-0.5719**	-0.4955*
	(0.1490)	(0.1612)	(0.6062)	(0.6898)	(0.2510)	(0.2818)
Inequality	0.0154**	0.0073	0.1100***	0.0885*	0.0382***	0.0300***
	(0.0065)	(0.0074)	(0.0329)	(0.0501)	(0.0083)	(0.0113)
Dependent variable mean	0.13793	0.13793	0.69800	0.69800	0.50246	0.50246
R^2	0.05983	0.15383	0.09735	0.13791	0.11808	0.15551
Observations	203	203	203	203	203	203
Panel C:						
Austerity	-0.4181***	-0.4453***	-2.074***	-2.240***	-0.7552***	-0.6181**
	(0.1363)	(0.1565)	(0.6745)	(0.7270)	(0.2715)	(0.2890)
65+	-0.2250	-0.2095	1.595	0.3139	0.7193	0.2696
	(0.6522)	(0.6676)	(2.581)	(3.151)	(0.9472)	(1.107)
Dependent variable mean	0.13793	0.13793	0.69800	0.69800	0.50246	0.50246
R^2	0.03195	0.15042	0.02937	0.11119	0.03816	0.12542
Observations	203	203	203	203	203	203
Panel D:						
Austerity	-0.4894***	-0.4569***	-2.247***	-2.223***	-0.8537***	-0.6036**
	(0.1572)	(0.1662)	(0.6831)	(0.7359)	(0.2573)	(0.2828)
Pop. share qual. 4+	-0.3948	-0.4551	-2.836***	-1.482	-1.452***	-1.380***
	(0.3037)	(0.3551)	(1.046)	(1.644)	(0.4141)	(0.5121)
Dependent variable mean	0.13793	0.13793	0.69800	0.69800	0.50246	0.50246
R^2	0.03869	0.15591	0.04609	0.11414	0.08252	0.15087
Observations	203	203	203	203	203	203
Panel E:						
Austerity	-0.2883**	-0.3527**	-1.099*	-1.235*	-0.4813*	-0.3362
	(0.1454)	(0.1697)	(0.6517)	(0.6980)	(0.2822)	(0.2858)
Less 2 Mbit/s	-0.2465	-0.2768	-7.880***	-8.270***	-2.216**	-2.545**
	(0.6926)	(0.6299)	(2.946)	(3.135)	(1.003)	(1.003)
Inequality	0.0159**	0.0054	0.0844**	0.0590	0.0299***	0.0202*
	(0.0069)	(0.0082)	(0.0409)	(0.0561)	(0.0096)	(0.0121)
Dependent variable mean	0.13143	0.13143	0.72537	0.72537	0.51429	0.51429
R^2	0.06399	0.17546	0.12861	0.17229	0.16100	0.21348
Observations	175	175	175	175	175	175
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 A6: Two Stage Least Squares estimation exploiting variation in demography-induced austerity pressures in driving ECO program delievery treatment effect heterogeneity

	Total spending excluding					
	enviro & housing		social		enviro, housing, & social	
Dep var: T-value $>$ 1.65	(1)	(2)	(3)	(4)	(5)	(6)
2SLS:						
Austerity	-1.055**	-1.188	-1.452**	-1.820	-1.078**	-1.460
	(0.4963)	(0.9283)	(0.7008)	(1.487)	(0.5026)	(1.171)
Dependent variable mean	0.13397	0.13397	0.13397	0.13397	0.13397	0.13397
R^2	-0.03221	0.07299	-0.04869	0.04482	-0.02665	0.01270
Observations	209	209	209	209	209	209
First Stage:						
Limited 85+	10.57***	6.003***	7.678***	3.918**	10.35***	4.884**
	(1.909)	(2.240)	(1.604)	(1.740)	(2.028)	(2.249)
Dependent variable mean	0.16206	0.16206	0.16821	0.16821	0.18945	0.18945
R^2	0.10883	0.22633	0.10986	0.25132	0.10989	0.22154
Observations	209	209	209	209	209	209
F-test (1st stage)	25.279	6.1094	25.549	5.1406	25.554	4.2321
Wald (1st stage)	30.641	7.1821	22.915	5.0682	26.042	4.7151
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 variable measures the probability that the estimated LAD specific coefficient is statistically significant at the 10% significance level. The independent variables move across the columns and captures austerity measures. Columns (1) and (2) measure the austerity shock excluding spending on environmental and housing services. Columns (3) and (4) exclude spending on old age care. Columns (5) and (6) exclude old age care spending as well as spending on environmental and housing services. Limited 85+ measures the share of the local authority's population that is of age 85 or older and experiences long term health problems such that day-to-day activities are limited and is between 0 and 1. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.