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REGULATORY BARRIERS TO CLIMATE ACTION: EVIDENCE FROM CONSERVATION AREAS IN ENGLAND

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Preserving heritage is an important part of maintaining collective identity for future generations. Yet, culturally defined notions of "heritage'' or "character'', in the context of the climate crisis, may be a barrier to individual and collective climate action to tackle a much more existential threat to those future generations. Studying data for more than half of the English housing stock, I show that conservation area status – a rather fluffy area-based designation that intends to protect the unique character of a neighborhood – not to be confused with preservation of historic buildings – in England may be responsible for up to 3.2 million tons of avoidable CO2 emissions annually. Using a suite of micro-econometric methods and alternative identification strategies ranging from saturated specifications, border discontinuity, matching estimation and an instrumental variables approach leveraging World War II wartime destruction in London – I show that properties in conservation areas have a notable worse energy efficiency; experience lower investment in retrofitting and consume notably higher levels of energy owing to poor energy efficiency. Effect sizes are very consistent comparing engineering based energy consumption estimates with actual consumption data. Effects can be directly attributed to planning requirements for otherwise permitted development that only apply to properties by virtue of them being located inside a conservation area.

JEL Classification: Q54, Q55, R14, R48, N74

Keywords:

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Regulatory barriers to climate action: Evidence from Conservation Areas in England

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March 1, 2023

Abstract

Preserving heritage is an important part of maintaining collective identity for future generations. Yet, culturally defined notions of "heritage" or "character", in the context of the climate crisis, may be a barrier to individual and collective climate action to tackle a much more existential threat to those future generations. Studying data for more than half of the English housing stock, I show that conservation area status – a rather fluffy area-based designation that intends to protect the unique *character* of a neighborhood – not to be confused with preservation of historic buildings – in England may be responsible for up to 3.2 million tons of avoidable CO2 emissions annually. Using a suite of micro-econometric methods and alternative identification strategies ranging from saturated specifications, border discontinuity, matching estimation and an instrumental variables approach leveraging World War II wartime destruction in London – I show that properties in conservation areas have a notable worse energy efficiency; experience lower investment in retrofitting and consume notably higher levels of energy owing to poor energy efficiency. Effect sizes are very consistent comparing engineering based energy consumption estimates with actual consumption data. Effects can be directly attributed to planning requirements for otherwise permitted development that only apply to properties by virtue of them being located inside a conservation area.

Keywords: CLIMATE CRISIS, COLLECTIVE ACTION, ZONING, CLIMATE ADAPTATION
JEL Classification: Q54, Q55, R14, R48, N74

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1 Introduction

The climate crisis is rapidly accelerating with the risk of irreparable damage becoming more and more likely by the year – not the decade. Yet, action to drastically reduce emissions has still failed to materially take off. The last decade – despite accommodating factors such as record low interest rates – has not helped the (Western) world make significant headway into greening their economies and reducing its carbon footprint. It is imperative for research in the social and economic sciences to identify and quantify the many barriers to climate action *right at home*. These barriers can be manifold and can undermine individual action, for example, retrofitting ones own home. The fabric of our societies, its laws, regulations and customs – many of which originate from a time in which climate change was at best seen as a distant threat – without intending to do harm, may constitute a significant barrier to individual action. And, individual action may be even more important given that politics has been very slow to rise to the challenge.

This paper provides an illustration of the type of research that may be important going forward. It identifies a specific historically grown barrier to climate action. It documents and quantifies how this barrier is *causing* higher levels of energy consumption mostly from a hydrocarbon source: natural gas for space heating. It showcases how this barrier is impeding individual action to lower carbon emissions. It highlights how a constraint, which has its origin in a societal articulation to limit drastic change to the lived environment in the 1960s is now contributing to an even bigger threat to the lived environment – climate change – and is thus, inherently contradicting its very own original motivations. The paper further provides an important illustration of how open data can empower policy relevant research for the collective good. Lastly, the work presented here is planned to feed into a randomized controlled trial that can help seed collective action, encourage coordination and may contribute to helping finding scalable solutions at the local level.

The paper focuses on a barrier to climate action: the impact that conservation area status in the UK has on reducing take up of retrofit measures to homes that, counterfactually, would be taken up in similar properties outside conservation areas (albeit, still at a far too low rate). Conservation areas were introduced through the Civic Amenities Act 1967. This was a time when planning authorities proposed drastic redevelopment schemes to account for the growing *carbonisation* of transportation in light of rising car ownership to adapt towns and cities designed for horse and cart. Conservation area status does not imply that properties inside such an area are recognized as listed buildings. Quite to the contrary – more than 95% of properties inside conservation areas are not in listed buildings. Conservation areas are defined as "areas of special architectural or historic interest, the character or appearance of which it is desirable to preserve or enhance". Local planning authorities have the statutory duty to identify, designate, preserve and enhance conservation areas while undertaking their planning duties. This area definition extends well beyond policies aimed to preserve historic buildings. Many conservation areas include buildings and architectural styles that can be found both inside- as well as outside conservation areas. What is judged to make up the *character* of a conservation area is the combination of different features such as the *density of buildings styles* that follow the built-form of a specific era, street patterns, the combination of trees, boundary walls, the existing open spaces, views or even sites of human activity such as market places, which combine to provide special character. This highlights: the definition of *character* is rather a fuzzy one that does not have its origin in a sharp architectural feature.

Yet, while the concept of what makes up *character* is rather fuzzy, the restrictions to retrofitting that come with conservation area status are sharp. I trace this specifically to the planning requirements that apply to retrofit measures inside conservation areas – which do not normally apply outside conservation areas, where retrofit measures such as exterior wall insulation, photovoltaic installations or window replacements typically do not require any permission. In conservation areas, in most cases, these changes require planning permission, often involving consultation and local consent. It is this regulation-induced *added retrofit gap* over and above the poor energy efficiency standard of English homes – irrespective of conservation area status that I quantified in Fetzer et al. (2022) – that this paper identifies.

I leverage a suite of micro-econometric methods ranging from saturated specifications, border regression discontinuity designs, (refined) matching approaches and – for London – an instrumental variables strategy to quantify the causal impact of conservation area status has on the retrofit gap. Most of the substantive analysis considers the treatment – whether a given property is located inside a conservation area – as exogenous. This is entirely appropriate and any concerns can be addressed using a suite of micro-econometric approaches. Yet, for London, I also present a novel instrumental variables approach exploiting quasi-exogenous variation in conservation area status. I leverage data that was extracted using machine learning methods from an exceptionally granular historic map of World War II destruction from aerial bombardment. I find that surviving properties in areas that were heavily bombed during World War II are less likely to be located in present-day conservation areas and, by virtue of not being subject to conservation area restrictions, are retrofit to a higher standard. This is not unexpected since conservation area status is an *area designation* that requires *density*.

Using these empirical approaches, I estimate that the retrofit gap that can be attributed to the regulatory restrictions that owners face in conservation areas can explain easily between 5 to 15% of the total energy efficiency gap. This added retrofit gap is driven by worse retrofit standards owing to the added planning restrictions that particularly restrict retrofit that may alter the outside appearance: (exterior) wall insulation, window replacements and PV installations. Counterfactually, properties that are very similar in terms of their built form, age, location, property value, local tax status, tenure and physical size outside conservation areas do not have this *additional* retrofit gap.

Not only does there exist such a conservation-area specific *additional* retrofit gap as a status quo, I also document that this conservation area status retrofit penalty has *widened* over the last 10-15 years. Properties that are very similar but located outside a conservation area have seen a higher rate of retrofit investments compared to properties inside conservation areas which, again, is mostly driven by the very specific nature of the restrictions that apply to the exterior appearance that prohibit or significantly limit the cost-effective installation of double-glazed windows, exterior wall insulation or PV installations that may be visible from the street. Lastly, while much of the analysis is done on energy certificate data, all results documented here are also detectable in exceptionally granular actual energy consumption data at the postcode level along with some retrofit installation data, in particular concerning photovoltaic installations that is coming from other data sources.

The numbers are not negligible. The added retrofit gap that arises from the planning burden to carry out retrofits in conservation areas is large, economically meaningful and growing. Overall, the 2,033,354 properties inside conservation areas in the 239 English local authority for which boundary data is available are estimated to consume between 500 to 1500 kWh more in natural gas that is used mostly for space heating purposes. Smaller effects are detectable also for electricity consumption. This amounts to between 5 to 15% of all energy consumed, on average. This figure is quite consistently estimated when comparing both, estimated energy consumption from energy performance certificates along with granular actual energy consumption data. Combined, this amounts to between 1,020 to 3,033 GWh of added natural gas consumption coming at a monetary annual cost (domestic energy use is exempt from carbon taxation presently) of around £ 104 to 314 million per annum. This is not a small number especially in light of the fact that it could be tackled with *the stroke of a pen*.

This paper documents a specific driver of the retrofit gap. In 2020, the residential sector contributed 23% of the UK's greenhouse gas emissions (90 MtCO2e) once end-use reallocation is accounted for, mainly due to fuel combustion for heating and cooking, and electricity consumption (ONS, 2022).[1] In the EU, buildings account for about 40% of the EU's final energy consumption and the building stock represents the the single biggest potential domain for energy saving. Across the EU, roughly 75% of the EU building stock is deemed to be energy inefficient.[2] Yet, progress on reducing the carbon footprint of housing has been very slow. A big emphasis has been on the monetary- and non-monetary cost to retrofitting with seminal work by Fowlie et al. (2018, 2015) suggesting that the cost of retrofitting may outweigh its benefits to homeowners. Alternative explanations for low rates of retrofitting have been suggested, such as, credit market failures, coordination failures, or general split incentive problems e.g. between a landlord and a resident, along with a broad range of other mechanisms (see Allcott and Greenstone, 2012; Gerarden et al., 2017; Christensen et al., 2021). This paper makes a contribution identifying a specific mechanism that drives the *cost of retrofit investments* for individuals interested in pursuing this: the required additional planning needed solely

[1] https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1064962/annex-1-1990-2020-uk-ghg-emissions-final-figures-by-end-user-sector-fuel-uncertainties-estimates.pdf

[2] See https://commission.europa.eu/news/focus-energy-efficiency-buildings-2020-02-17_en, accessed 01.02.2023.

by virtue of the conservation area designation.[3]

This paper is hardly the first that studies the economic effects of (conservation) area designation. One line of work here has sought to identify whether conservation area designation has an impact on property prices. Ahlfeldt et al. (2017) find no effect of English conservation area designation on property prices, while Ahlfeldt and Holman (2018) finds a 6% premium; Koster and Rouwendal (2017), Been et al. (2014), Zhou (2021) using a variety of approaches find positive effects in Netherlands, New York and Denver, Colorado, respectively. Yet, empirically, a consensus on the impact of (conservation) area zoning on property prices has not emerged.[4] This paper takes an agnostic view on the issue as it focuses on retrofit investments and the energy efficiency gap, treating property values as an important proxy variable that may capture many observable and unobservable factors about the underlying property; the character of the area; the socio-economic characteristics of the residents. I construct a counterfactual by zooming in on properties that are identical in regards to many hard observables such as age, built-form, property-type, tenure, main source of fuel, listed building status, legal status, local tax treatment, and at least, very similar in terms of size measured in square meters, property value, number of bedrooms and importantly, physical location. The prime challenge with understanding variation in energy consumption is due to unobservable socio-economic characteristics of the residents living in a property. By exploiting variation between statistically identical or very similar properties along a broad set of dimensions within very granular neighbourhoods I effectively account for many unobservable factors that may capture the socio-economic status of the local population. The findings bear on this: while energy performance certificates are often critiqued to provide unreliable estimates of actual consumption (see e.g. Cozza et al., 2020), in fact, in my analysis of the energy efficiency gap identified

[3] The paper, unlike the work of Hilber et al. (2019), analyises the retrofit gap at the property level (not the area level); distinguishes listed from non-listed buildings; exploits quasi-exogenous variation in conservation area status; identifies specific mechanism of how conservation area status causes less retrofit investments

[4] Relatedly, whether energy efficiency is adequately priced in asset prices is an important empirical question with quite mixed results: Guin et al. (2022) find a positive effect of energy efficiency on health of underlying mortgages; Dalton and Fuerst (2018) present a meta-analysis of the "green premium" of higher property and rents for more energy efficient homes. For the US, Myers et al. (2022) finds a positive impact of mandatory disclosure of energy efficiency ratings while Myers (2020) suggests that landlords are unable to charge higher rents for more energy efficient properties.

from actual energy consumption data vis-a-vis the certificates aligns quite nicely. I attribute this tot he fact that the empirical framework effectively accounts for many of the potential omitted factors that may drive a gap between hypothetical and actual energy consumption.

The paper is also related to the literature that aims to understand the logic and economic impacts of place based policies in general (see e.g. Busso et al., 2013 for a prominent example). Directly relevant to conservation areas, Ahlfeldt et al. (2017) argue that conservation area zoning provides a benefit in form of reduced uncertainty about future area development, and through that mechanism, provides a return to local residents, which is offset with the cost implied by the restrictions that come with it on local residents. This may have a positive effect of encouraging residents to invest in their community, resulting in improved public goods and increased social cohesion (for early cross-country work on the relevance of cohesion for public good quality see e.g. Alesina and Zhuravskaaya, 2011). The long term economic benefits of neighbourhood effects have been of interest to economists for a long time (see e.g. Jacob, 2004; Ludwig et al., 2013; Chyn, 2018). In the context of climate change, the reality of higher energy prices – induced by the war in Ukraine and the much needed higher carbon taxation – the trade-off studied by Ahlfeldt et al. (2017) could have changed where now the cost of restrictions outweigh their (perceived) benefits. Yet, as restrictions are institutionally enshrined, challenging them requires *collective action*, which may suffer from free riding problems (in this context, understanding free riding and coordination frictions as a barrier to collective action is vital Hager et al., 2021). This can explain the persistence of an equilibrium of high energy consumption and low retrofit investments.

More broadly, there is a growing recognition that planning restrictions may be an impediment to urban development and renewal. Cheshire (2018) provides an overview of recent research relating to the British Planning system's impact on the supply of development. Kulka et al. (2022) studies, using data from the United States, how various zoning regulations interact to affect housing supply and affordability and which regulations policymakers should relax if they want to reduce housing prices. Land use restrictions may also affect spatial sorting and thereby contribute to segregation (see e.g. Kulka, 2019) for which Bologna Pavlik and Zhou (2022) present evidence in the context of the US.

The work is related to the growing literature in urban economics that makes use of exceptionally granular spatial data to understand the emergence of the modern city using historical and contemporaneous data (see Hanlon and Heblich, 2022 for a recent review and Henderson and Becker, 2000 for early work). This research is particularly important as developing countries are experiencing rapid rates of urban transformation (see for example Henderson et al., 2021) and climate change is an important driver of this (Henderson et al., 2017). A lot of focus has been put on the impact that transport infrastructure has on shaping spatial development (see e.g. Storeygard, 2016; Heblich et al., 2020). Leveraging war time destruction as a source of exogenous variation of density that affects present day conservation area designation is novel but wartime destruction has been used before e.g. by Redding and Sturm (2016) to estimate neighbourhood effects. Yet, the built environment may provide further amenity value that may be important to factor in, when carrying out cost-benefit calculations and, as the framework developed by Ahlfeldt et al. (2019) suggests, these effects are quantifiably large. Yet, climate change and the risks associated may turn some amenities – for example, proximity to water bodies – into costly disammenities (see e.g. Garbarino et al., 2022).

The research is relevant far beyond the UK as there exist area-based designations in many countries which may impede climate action. The current EU energy efficiency directive 2012/27/EU states that buildings account for about 40% of the EU's final energy consumption, and identifies the existing building stock as "the single biggest potential sector for energy saving". Policy makers are encouraged to formulate strategies to increase the renovation rate, and to encourage "cost-effective deep renovations [...reducing] the delivered and final energy consumption of a building by a significant percentage." Understanding the specific drivers of barriers to *individual* retrofit action is vital.

In the following section, I describe the institutional context and the underlying data that was used in this paper.

2 Context and Data

2.1 Conservation areas

A Conservation Area is defined as an 'area of special architectural or historic interest the character or appearance of which it is desirable to preserve or enhance' (Section 69 of the Planning (Listed Buildings and Conservation Areas) Act 1990). The purpose of a Conservation Area is to acknowledge significant historic places and to cherish the local distinctiveness of areas that are valued by communities. 2017 sees the 50th anniversary of the Civic Amenities Act 1967 which established the concept of Conservation Areas nationally. Whilst Conservation Areas usually contain individual buildings, structures or monuments of importance, these tend to be protected through the listed building or scheduling process, a Conservation Area designation responds to wider townscape and landscape issues. In looking at Conservation Areas, views, vistas and other aspects of context are significant to consider in addition to individual historic fabric. In a conservation area, local authorities must take in to account the need to preserve or enhance the area's special character when deciding whether to grant planning permission. Applications are considered against conservation policies and can be refused on conservation grounds alone. The fact that external considerations such as the change of appearance of a property impacting the "character" of an area significantly raises the risks that cost and time going into planning processes is null and void for consideration of soft characters. It further gives significant weight to other parties to effectively impose constraints on others. This directly applies to retrofit investments or installations, which may require planning permission inside conservation areas that would otherwise not require such permission.

Solar panels can be installed on a house or flat, or on a building within the curtilage as long as panels are not be fitted to a wall which fronts a highway or are visible from the street. *Insulation* which also preserves the character or appearance a building in a conservation area is encouraged. Loft or internal wall insulation does not require planning permission. External wall insulation may suit some buildings but may harm the appearance of others - for instance, of a house that is part of a terrace, and does require planning permission. This implies that, in most instances, changes to insulation are made impossible in conservation areas. One general rule that is the case in most conservation areas, is that the property owner can make changes to their *windows* without permission as long as they change them with an identical replacement. Some conservation areas have 'Article 4 Directions' in place which may require owners to apply for planning permission if they wish to alter the windows in their homes.

2.2 Conservation area boundary definitions

Conservation Areas can be created where a local planning authority identifies an area of special architectural or historic interest, which deserves careful management to protect that character. Local authorities play a special role in the establishment and management of conservation areas. This starts from designation which has to follow a due process to ensure that conservation area status can later not be challenged. Prior to designation, a local authority carries out an appraisal that typically involves a photographic survey of buildings. There is further a need for a management plan which regular reviews of the conservation area and its boundaries are carried out and proposals for the preservation and enhancement of the area are being formulated. All owners in an area are informed about the conservation area status as residents need to be informed about the restrictions that this may entail.

In this paper I use data on conservation area boundaries that have been collated from most English local authorities or councils. The data is available most completely as boundary definitions as of 2022 as geographic shapes or polygons.[5] For each property, I know the exact latitude and longitude due to the unique identification. This enables me to construct an indicator T_i indicating whether a property lies inside- or outside a conservation area. Statistically speaking, I will be constructing a range of different counterfactuals comparing how properties inside and outside conservation areas appear in terms of their energy efficiency and the retrofit gap. Further, I similarly compare actual energy consumption of postcodes that fall inside conservation areas with those that lie outside conservation areas. I next describe the data that is used to measure outcomes.

[5] Appendix Figure A1 presents the time series in the data that is most complete: the 2022 boundary definitions. In total 285 conservation areas have been newly designated and 1,508 have had an update since 2008. Unfortunately, exact boundaries of the changes are not available.

2.3 Energy Performance Certificates (EPCs)

In order to measure the energy (in)efficiency of properties this paper leverages data from energy performance certificate (EPC) data. EPCs provide buyers and tenants with information on the energy efficiency rating of residential properties as well as estimates of likely energy costs. EPCs also contain recommendations of measures to improve the properties' energy efficiency, including estimates of the costs and impact on energy demand of these measures. It provides information on *actual* and *potential* energy consumption by a property. The potential measure captures an estimate of how much energy would be consumed, all else equal, if all recommended energy savings measures were implemented.

The requirement for properties to have an EPC was introduced in 2007 following the EU Directive on the energy performance of buildings (Department for Levelling Up, Housing & Communities, 2017). This requirement was initially applied just to homes for sale, but has since been extended to all domestic and commercial properties being sold, constructed, or rented (Department for Levelling Up, Housing & Communities, 2021). EPCs for all domestic and commercial buildings are available to download online from the national database of all registered EPCs.[6] In this paper, which focuses on England, I use data pertaining to 10,379,775 unique properties capturing around 57% of the English housing stock in the local authorities for which I have conservation area boundaries. For a subset of 2,977,510 properties, I have multiple EPC certificates owing to the fact that EPCs are valid for 10 years implying that many of the earliest certificates that were issued from 2007 onwards will have to be updated from around 2016 onward. The subset of properties for which there are at least two certificates implies that, not only can we look at levels, but we can also look at changes over time.[7]

In Appendix Figure A2 I show that for more than 50% of the properties, the most recent EPC is more recent than 2016. The lower quartile stands at 2013, the upper quartile is 2019. Importantly, throughout this work, I will confirm that the results

[6] Data are available here `https://epc.opendatacommunities.org/`.

[7] The EPC data is not perfect. In Fetzer et al. (2022) I show that around 50 to 70% of the variation in actual energy consumption can be explained by the property and its characteristics; the remainder is likely driven by socioeconomics of the resident population and the interaction with the building characteristics chiming with the analysis of Hårsman et al. (2016) using Swedish data and a review by Pasichnyi et al. (2019).

hold true using actual granular energy consumption data, which should alleviate concerns that the energy efficiency gap that is found here is an artefact of the data being potentially outdated.

2.3.1 Representativeness and reweighing

A potential concern is that the EPC data may not be representative of the building stock that is not included. A comparison by the ONS of the EPC data representing 51% the building stock vis-a-vis the population of properties from the Valuation Office Agency (VOA) data, built for council tax purposes, suggests that the data are very similar on observables.[8] Through the National Energy Efficiency Data framework (NEED) data framework and a Freedom of Information request, I was able to obtain a breakdown of the population of properties in England and Wales that can be characterized by their combination of at least six factors: the main heating fuel, the property type, the property age band, the floor area band, the deprivation profile of the area in which a property is located and the geographic region.[9] This, while not perfect, allows me to reweigh the EPC data to match the population of properties at least, along these characteristics. Throughout results pertaining to the unweighted sample are available in the appendix. The features on which basis the weights are computed does not include the conservation area status, albeit, a freedom of information request has been launched to obtain this information.

2.3.2 Main dependent variable from EPC certificates

The EPC certificates provide a broad range of data about an individual property. A central measure that the EPC provides is an estimate of annual energy consumption based on a model that incorporates the physical attributes of a property.[10]. At the

[8] See Office of National Statistics, Energy efficiency of housing in England and Wales: 2021, https://www.ons.gov.uk/peoplepopulationandcommunity/housing/articles/energyefficiencyofhousinginenglandandwales/2021. Still, Department for Business, Energy & Industrial Strategy (2020) suggests that that the EPC database under-represents medium-sized properties and bungalows and over-represents smaller properties and flats.

[9] The FOI can be found here https://www.whatdotheyknow.com/request/stratification_bin_counts_for_an.

[10] This data and the underlying measurement framework are discussed in much more detail in Fetzer et al. (2022)

property level i an EPC certificate that was issued at time t provides us with an estimate of the *estimated energy consumption* in kWh along with the *estimated CO2 emissions* for a property over the course of a year. I refer to the estimated energy consumption as $E^{EPC}_{i,t,est}$. In addition to the estimated energy consumption, the EPC also provide with an estimate of the *potential energy consumption* in kWh denoted here as $E^{EPC}_{i,t,pot}$. This potential energy consumption takes into account the likely effect that energy efficiency upgrades have on the estimated energy consumption: for example, upgrades of windows from single- to double-glazing, by reducing the heat loss, will lower the energy demand, all else equal.

Cross sectional variation For the cross-sectional analysis, I am making use of data pertaining to 10,379,775 unique properties that are located in one of the 239 districts for which conservation area boundary data is available studying their *most recent* EPC certificate in case a property has multiple certificates attached to it. I then statistically compare the estimated energy consumption of a property i, $E^{EPC}_{i,t,est}$, that lies *inside a conservation area* with that of a property j, $E^{EPC}_{j,t,est}$, that lies outside a conservation area. This difference captures differences in estimated energy consumption owing to, e.g. the lower energy efficiency standard of a property i inside a conservation area vis-a-vis a property j outside. It further can capture inherent differences in the energy consumption e.g. due to the physical attributes of the property that may be more difficult to change through *any* retrofit measures.

I also study to what extent properties inside conservation areas have a larger energy efficiency gap captured as the difference between the estimated and the potential energy consumption:

$$Gap^{EPC}_{i,t} = E^{EPC}_{i,t,est} - E^{EPC}_{i,t,pot}$$

For both, I also have a measure of CO2 emissions associated with the energy consumption as secondary outcome measure. To study retrofit investments, I also explore and exploit within property variation.

Within property variation For a subset of 2,977,510 properties, I observe multiple EPC certificates at different points in time t. This implies that I have some *within property* time variation. Suppose t_{min} indicates the first year I observe a property in the EPC database and suppose t_{max} indicates the most recent time-point for which a new EPC certificate is available. I can then compute the *within property change* as

$$\Delta E_{i,est}^{EPC} = E_{i,t_{max},est}^{EPC} - E_{i,t_{min},est}^{EPC}$$

Similarly, I measure changes in the energy efficiency gap across certificates:

$$\Delta Gap_{i}^{EPC,E} = Gap_{i,t_{max}}^{EPC,E} - Gap_{i,t_{min}}^{EPC,E}$$

2.3.3 Other property-level attributes related to energy efficiency

In addition to the main outcome measures discussed in the previous section there are a range of additional outcome data. The vast majority of them are derived from the EPC themselves. The first set refers of binary variables indicating whether the energy efficiency of the roof or loft, the walls, the main heating system, the hot water generation and the windows are judged to be (very) poor. In addition, I study whether a property has retrofit recommendations for roof- or loft-insulation measures, wall insulation (interior or exterior), a boiler upgrade, improvements in window glazing or window replacements and solar panel installation. In addition to the EPC-derived measure I also leverage actual photovoltaic installation data at the property level. These certificates are obtained from MCS via a data sharing agreement. They indicate whether an installation has been designed, installed & commissioned to some minimum service standards by a certified installer. This data has been matched to individual properties. I focus, in particular, on solar and photovoltaic installations as these are subject to planning restrictions in conservation areas as was outlined earlier.

2.4 Energy consumption data

One of the shortcomings of the EPC data is that the energy consumption of a property i is an estimate that may be different from the actual energy consumption for a range of reasons. To overcome this, this paper also draws on very granular energy consumption data, in particular, natural gas consumption data at the full postcode level. England has around 1,475,641 individual postcodes and around 24.6 million residential properties. For 928,322 postcodes, annual total, mean and median natural gas consumption data is available from 2017 onwards.

A postcode is not a well defined spatial concept. A postcode typically represents a street or a part of a street, a single address or a group of properties or a single a single property with e.g. multiple units. The energy consumption data is available if there are at least five meters reporting natural gas consumption for a postcode. This is to reduce the risk of statistical disclosure. The median postcode has around 18 properties with 90% of postcodes having less than 41 properties associated with them. In the econometric exercises where I study postcodes as unit of observation I classify a postcode as being inside a conservation area if the centroid of all properties associated with that postcode is located inside a conservation area.

2.5 Other data

I leverage a range of other data sources to construct other features or measures at the individual property level that are used in various empirical exercises.

Listed building classification Conservation areas, on average, include more properties that are classified as listed buildings. For listed buildings, the planning restrictions are even more severe compared to properties that are in a conservation area. To account for this, I add a flag for every property that is listed or that lies in very close proximity to a listed building, to ensure that the analysis is adequately accounting for listed buildings as specially protected category of buildings.

Price Paid Data The UK tax authority publishes transaction level data for all real estate transactions that take place in the UK with the full address information. I merge this address data with the EPC register. Not all properties with an EPC appear in the price-paid dataset but a large number do. This gives some additional control variables to match on which is most informative for the underlying socio-economic characteristics of the likely residents. For 63% of unique properties in the EPC data do I have some price paid information.

Council Tax Band Residents in the UK have to pay council tax which pays for local services such as garbage collection. The council tax due on each property is determined, among others, by the council tax band in which a property falls under. The underlying council tax band classification is based on property valuations based on 1991 values. I obtained this data from an address based lookup service that is available on `https://www.tax.service.gov.uk/check-council-tax-band/search`. Again, the data is available with the full address and I have linked this with the EPC register to add the council tax band information.The council tax band information is available for around 88% of the unique properties that I observe.

2.6 Visualisation of data

The empirical approaches taken here are best visually illustrated. Figure 2 illustrates the data in the context of the Buntingford conservation area in East Hertfordshire. There are several visual elements on this map exhibit. Circles refer to locations of specific properties. This is mapping the population of all properties that exist in the UK using a database that lists all properties with their respective latitude and longitudes. Some of the circles are solid. This represents a property for which the data has at least one energy performance certificate allowing me to measure the energy efficiency and the gap vis-a-vis the potential. As indicated, in some instances there are several EPCs for the same property.

In Figure 2, the boundary of the Buntingford conservation area, which was established in 1968, is indicated through the solid black line. The figure further also adds the census tract or output-area boundaries from the 2011 census. This is the most granular geographic unit at which census data for the 2011 census was reported. Output area's constitute the building blocks of other coarser statistical, electoral and political geographies that are used. Lastly, the red stars indicate the centroid of properties that are associated with each unique postcode – the most granular level at which I observe energy consumption data.

2.7 London case study of World War II bombing

I carry out a separate instrumental variables exercise focusing on London as a case study. This makes use of exceptionally granular war time destruction data in which individual properties have been hand colored on a high resolution map capturing their extent of wartime destruction. To the best of my knowledge, this data has so far only been used in Redding and Sturm (2016) and is not in the public domain. A digitized version of the map was made available as a raster image. Subsequently, the data was processed using machine learning methods. A training dataset was built in which, for a random selection of image tiles, a sample of polygons were drawn that trace out the color coding of the bomb damage. With this training dataset I build a random forest classifier that predicts a binary indicator for each pixel in the raster image whether the pixel is likely to be colored indicating wartime destruction. This results in many stray pixels false-positives along with clustered true positives. A neighborhood kernel smoothing is subsequently applied that assigns the modal value of each pixel within a 10m neighborhood results in a cleanly classified pixel. The processing steps are illustrated in Appendix Figure A4. For the econometric use, I construct, for each surviving and present day property the average level of wartime destruction within a 50m radius.

I next present the empirical approaches and results.

3 How large and why is there a conservation area specific energy efficiency gap?

I begin by documenting that properties inside conservation areas, relative to very comparable properties outside conservation areas, have an added energy efficiency gap. This analysis is carried out on the cross section of 10,379,775 properties for which I have an EPC certificates that are located in each of the 239 districts for which I have data on the conservation areas. For properties for which I have multiple EPC certificates, I focus on the most recent certificate. This analysis will thus provide a view of the *status quo*. I first describe the empirical approaches. All subsequent analysis follows very similar steps.

3.1 Description of empirical approaches

Throughout the paper I present results pertaining to several different empirical approaches. The ultimate hypothesis to test is whether and to what extent conservation area status is associated with worse energy efficiency and lower retrofit investments, which, in relative terms, results in higher energy consumption.

Full sample estimation A first exercise consists of studying the full sample contrasting properties that lie either inside- with properties outside a conservation area. I estimate specifications of the form:

$$y_i = \beta \times T_i + \nu \times X_{i,c} + \epsilon_{d(i)} \tag{1}$$

where

$$T_i = \begin{cases} 1 & \text{inside conservation area} \\ 0 & \text{outside conservation area} \end{cases}$$

the estimating sample in this section focuses on the 10,379,775 properties and their most recent EPC certificate. The dependent variable is either the EPC estimated current energy consumption $E^{EPC}_{i,t_{max},est}$ or the energy efficiency gap $Gap^{EPC,E}_{i,t_{max}}$, along with a range of other property characteristics that are indicative of the retrofit gap. The most salient observable characteristic being the share of windows that are multi glazed or whether a property has a PV installation that has been linked to a property based on the full address.

I saturate this specification with a broad range of additional control variables. These range from area fixed effects that e.g. remove census tract fixed effects (there are around 180,000 census tracts across the UK). Further, we naturally also control for a vector of (mostly) invariant property characteristics. In the data these are mostly categorical, such as the age band that a property was built, the built form and the property type and the main source of heating fuel, the number of habitable rooms and the floor area. These characteristics either enter the regression additively or interactively (that is, we allow each combination of characteristics to define its own group) to ensure we only exploit cross-sectional variable in the treatment status among properties with similar set of characteristics. Importantly, since the methodology to measure energy efficiency and consumption has changed over time, throughout we control for fixed effects capturing the year a certificate was issued (or the two sets of year fixed effects for the analysis of changes).

I implement three additional empirical approaches. Appendix Figure A3 provides an illustration of these approaches.

Regression around conservation area boundary For each property, in addition to identifying wether a property is inside- or outside a conservation area, I also calculate the as-the-crow-flies *distance to the nearest conservation area boundary*. This allows a focusing on the sample for the analysis to focus on properties that are just inside a conservation area vis-a-vis properties just outside a conservation area. This may take into account area specific idiosyncratic factors such as building materials commonly used in an area or unobserved area specific characteristics that may affect the energy efficiency or retrofit status of properties in an area that share many common factors and amenities.

In addition to estimating regressions on the subsample of properties that fall within 250, 500, or 1000 m of a conservation area boundary, I can also visualize the extent to which there is a discontinuous difference in the (estimated) energy consumption or the energy efficiency gap for properties inside and outside and present the result graphically.

Matching within district A potential concern may be unobservable factors that may affect the retrofitting status of properties across locations differentially. Further, since the appraisal of conservation areas and potential approaches to conservation areas is a responsibility of local authorities, focusing the estimation on data from within the same local authority seems a natural approach.

To do so, I carry out a propensity score matching approach. Three sets of matching exercises are carried out focusing on comparisons *within district* whereby a property inside a conservation area is matched with a property that shares similar characteristics that could be *anywhere else* in the same local authority district. Throughout, a vector of characteristics is used for exact matching: the listed building status, the property type, tenure, the main heating fuel, the construction age and the built form. This ensures that only properties that share the same unique combination of characteristics are being compared. This is akin to controlling for the *interaction* of these features in the full sample regressions. Within each subgroup that is defined by a unique combination of features, I estimate propensity scores focusing on the following numeric features: the number of habitable rooms, the number of heated rooms, the total floor area and the year in which the EPC certificate was issued. In the second matching approach, the exact matching is augmented to incorporate the council tax band of a property. In the third matching approach, I also match on the numeric feature capturing the price paid per square meter along with the year of last sale.

Matching around conservation area boundary A further set of matched pairs is constructed that focuses on properties that are clustered within a band of 250, 500 or 1000 meters *around a conservation area boundary*. This way, we combine the local area context, the specific proximity as well as making sure that we carry out as close as possible a like-for-like comparison based on the observable characteristics. The empirical specifications that study matched pairs only include matched pairs in the estimating sample whose propensity score is in the first quartile of the empirical distribution. Further, I control for matched-pair fixed effects and the numeric matching characteristics that are not matched on exactly to account for any remaining imbalance.

London case study I carry out a case study for London that exploits quasi exogenous variation in present day conservation area status and war time damage. For this exercise I narrow the estimating sample to buildings constructed prior to World War II that survived the bombing. For each surviving property I have measured the extent of wartime destruction within a 50 meter radius. This measure is used to instrument the present day conservation area status of a property i in the first stage:

$$T_{i,c} = \alpha_{d(i)} + \xi \times \text{Bomb Damage}_i + \nu_{d(i)}$$

The fitted values are used for the second stage of model 1. The relevance of the instrument is obvious given the technical definition of a conservation area. It can be nicely visualized, for example, in Figure 3 which visually suggests that conservation area boundaries appear to include areas that, on average, saw less bomb damage. An alternative way to visualize the strength of the first stage is provided in Appendix Figure A13. This, in essence, contrasts the distribution of the bomb damage around a conservation area boundary. We note that there is notably less WWII bomb damage in areas that would subsequently become conservation areas. Surviving isolated buildings that have not become part of a conservation area, as we will see, are notably more energy efficient owing to a higher rate of retrofit relative to their statistically equivalent peers inside conservation area owing to the additional retrofitting regulatory barriers.

Advantages and disadvantages of each approach and ensemble estimator The various empirical approaches each take into account different sets of information and may address a broad set of potential concerns about the validity of the estimation approach to measure the energy efficiency gap that can be *causally* attributed to the conservation-area status. The full sample estimation provides the overarching estimation framework. Yet there is a natural concern that properties, even after accounting for property characteristics in a very parsimonious way, that there may be unobserved differences that give rise to *omitted variable bias*.

For example, it could be that the estimated energy efficiency gap is very much local context specific. Refining the sample to focus on properties near a conservation area boundary provides an alternative sample cut. Properties near a conservation area boundary may share similar characteristics and similar character. Further, the people living nearby may share similar socio-economic characteristics, which is not unreasonable given the huge literature studying neighborhood sorting in economics (see Eeckhout et al., 2014; Galiani et al., 2015; Kulka, 2019). The fact that conservation area boundaries do change suggests that local geographic context and local architectural context are somewhat flexible contexts implying that properties outside conservation areas may conceivably become part of conservation areas. As such a geographic regression discontinuity approach may provide for an alternative way to construct a counterfactual and specifically focus on capturing very localized area specific differences where the full set of additional control variables that are included in the full sample estimation are also included but they are estimated off a different subsample, in essence allowing these control variables to became area specific estimates.

The matching approach is an alternative way to construct a counterfactual. Focusing on matching properties that are inside conservation areas with those that are outside but are part of the same local authority district ensures that we focus on a subsample of matched pairs of properties that are subject to the same overarching planning regulations which may produce area-specific differences in the retrofit gap. It further constitutes a sample refinement again, with the purpose of controlling for potential observable and unobservable factors more generously. This matching approach, especially when augmented with data on the council tax band and the property value is further very useful to account for the unobservable differences in energy consumption that arise from different property values.

The fourth approach combines the geographic sample focus explicit with the matching approach. Each of these approaches will yield a point estimate $\hat{\beta}$ capturing the energy efficiency gap that can be attributable to the legal status and the restrictions that come with a property being in a conservation area. In total there will be ten different estimates $\hat{\beta}$ and I will arrive at an *ensemble average* as preferred point estimate of the energy efficiency gap that is causally attributable to the conservation area status.

The instrumental variables exercise can only be done for London owing to data constraint. This serves not much wider purpose, but there is an affinity in the profession for such exercises and it can also be particularly effective in conveying research to a broader audience. The point estimates from the instrumental variables exercise should not be over-interpreted as they capture a local average treatment effect as it is estimated on a specific subpopulation

I next present the results from this analysis.

3.2 Results

I begin by discussing the empirical results pertaining to the full sample comparing the energy efficiency (gap) of properties inside conservation areas vis-a-vis those outside conservation areas.

Estimates across exercises I present these results in Table 1. Panel A studies the estimated current energy consumption. I observe that properties inside conservation areas, on average, are estimated to consume between 700 to 900 kWh more in energy. The prime source of energy use is for space heating with natural gas being the most common source of space heating technology. In relative terms this is between 3-4% higher. Panel B focuses specifically on the *energy efficiency gap*, that is, the difference between the estimated- and the potential energy consumption of a property. Across specifications the estimated energy efficiency gap or, the retrofit gap between properties inside and outside conservation areas amounts to between 200 to 400 kWh. This is to say that the gap between the current estimated energy consumption and the potential energy consumption is notably higher for properties inside conservation areas highlighting that the retrofit gap, all else equal is notably higher for properties inside conservation areas.

In Panel C and Panel D I focus on the emissions gap as an outcome measure which aims to proxy for the CO2 emissions. Relative to properties outside conservation areas, after accounting for a broad range of characteristics, we find that properties inside conservation areas produce, on the upper end, up to 170kg more in CO2 compared to properties outside conservation areas. On the lower end a precise estimated measure is around 40kg of CO2. It is worth highlighting that this is all relative. In Fetzer et al. (2022), I document the low energy efficiency standard of the UK housing stock in general. Properties inside conservation areas stand out even further in terms of poor environmental and energy efficiency performance.

The results pertaining to the equivalent regression carried out on the subsample of properties that lie within 500 meters of a conservation area boundary are presented in Table 2 (Appendix Tables A3 and A2 present results for the 250 and 1000 meter bandwidth). The estimates suggest an energy efficiency gap of between 300 to 700 kWh. Table 3 presents the results from the various matching approaches. The estimate suggests an energy efficiency gap ranging from 300 to 700 kWh. All estimates are quite precise and it is worth highlighting that, despite the variability in the point estimates, there is a high degree of consistency.

The results from the London exercise are presented in Table 4. The point estimates are notably higher as the properties that are included in the estimating sample are, on average, older. Owing to the worse energy efficiency of the older housing stock, the added retrofit gap that is arising from the planning requirements appears to be wider - nearly three to six times as much. The IV is, not surprisingly, very strong as it is plain obvious even in the raw data as is illustrated in Figure 3 and in Appendix Figure A13..

Visualization of (matched) geographic discontinuity Figure 4 presents the regression results in visual form akin to a geographic regression discontinuity design. Properties that lie on the interior of a conservation area, on average, have much higher estimated energy consumption and a more pronounced energy efficiency gap. The results for the emissions and the emissions gap are very similar. The geographic discontinuity that the conservation area status has on the energy efficiency gap is even more apparent in Figure 5 which presents the results pertaining to the matching-augmented geographic border regression discontinuity design.

Coefficient plot across exercises and ensemble estimate While the less saturated specifications exhibit, on average, a higher point estimate, there is a good reason to believe that the more saturated specifications help remove any bias in the estimate of the *conservation area-induced retrofit gap* that this paper aims to identify. Figure 6 provides a coefficient plot that presents the most preferred specification from each of the exercises and auxiliary regression results that are presented in Appendix tables in a concise form. The ensemble average across these exercises – the average of the estimates across the coefficients presented in Panel A and B would suggest a midpoint estimate of the energy efficiency gap with a lower bound being 400 kWh and an upper bound estimate being 800 kWh. The equivalent measure for the emissions gap lies between 80kg to 160kg of extra CO2 emissions that is attributable to the conservation area status induced retrofit gap.

To double down on the fact that the retrofit gap that I identify in the above specifications is driven by the planning restrictions that are specific to conservation areas, I next turn to studying the underlying drivers of what specific property attributes retrofit status is driving the conservation area status induced energy efficiency gap that is measured through the increased estimated energy use and the higher CO2 emissions documented here.

3.3 What causes the conservation-area status induced retrofit gap?

The energy efficiency gap is driven by the fact that properties inside conservation areas have a retrofit gap that is unique and specific to the conservation areas and can, to a significant extent, be traced back to the specific *restrictions on retrofit measures* that are in place in conservation areas. These impact the ability of property owners to bring the energy efficiency standards of properties in line with the (marginally) better energy efficiency standards of comparable properties that are not located in conservation areas.

To shed light on which features are driving the conservation-area induced energy efficiency gap, I carry out the above exercises on a suite of additional dependent variables that are derived from the EPC data and other data merged to these records. There are three groups of outcomes that I study: the first set of outcomes is a binary indicator that captures whether the energy efficiency standard of walls, windows, roof or loft, the hot water and heating technology are considered to be "poor" or "very poor". The second set of measures captures whether a property has recommendations attached to it, for example, wall insulation measures are being recommended. These recommendations should take into account whether certain improvements can physically be implemented on said property. Lastly, I also study hard measures such as a measure capturing the share of a properties windows that are multi glazed (as opposed to single glazed) and whether a property has solar photovoltaic panels installed – this information stems from auxiliary address level data on micro generation installations.

Drivers of the retrofit gap The analysis is carried out on this multitude of outcomes using a preferred specification from each of the four approaches and is visually presented as a coefficient plot in Figure 7. Each panel presents regression results on a set of naturally nested and related outcome measures that drive the energy efficiency gap through a specific dimension. It implements a *most preferred* specification from the previous analysis.

The synthesis of results is quite sharp: properties inside conservation areas that are similar to properties outside conservation areas stand out in terms of the energy efficiency gap being driven by three factors: lower energy efficiency of window installations, wall insulation and, to a moderate degree worse roof- or loft insulation. This pattern emerges both along the qualification of these features in terms of energy efficiency as poor or very poor. Further, also on the recommended measures to be implemented to improve the energy efficiency from the current estimated energy consumption to the lower, potential energy consumption, provides a clear signature: window retrofits and wall insulation stand out explicitly. For the energy efficiency of windows, the direct measure is the share of windows that are multi glazed and there, relative to similar properties outside conservation areas we see that the share of windows that are multi glazed is notable lower.

Lastly, while on the recommendations side, I do not see that properties inside conservation areas are distinctly different in terms of whether they have a recommendation for PV installation, there is a notable difference in terms of *actual PV installations* detectable. These were identified through merging full address level PV installation data to the individual properties.

Ensemble average Turning to the effect sizes, as before, I characterise these as an ensemble average of the estimated coefficient across the main empirical exercises. Properties inside conservation areas are more likely to be considered (very) poor in terms of the energy efficiency of the roof or loft by 0.8 percentage points; by 3 percentage points in terms of the energy efficiency of the walls; by 9 percentage points in terms of the energy efficiency of the windows. They have a 2.4 percentage points higher chance of having a retrofit recommendation for wall insulation measures and a 8 percentage points higher chance of having a retrofit recommendations for the windows. Looking at actual installations: properties inside conservation areas, when measuring the share of the window glazing that is multi glazed have that share being 7 percent lower. In terms of solar PV installations this is 1.1 percentage points lower. The latter two estimates are particularly relevant if expressed in relative terms as only for around 4 percent of properties have a solar PV installation; in conservation areas the 1.1 percentage points lower chance thus means, in relative terms, more than 25% lower PV installations.

This analysis is based on the *status quo* dataset capturing how, in their most recent EPC certificate a property is presented at least for the data that is derived from the EPC certificates - the solar panel installation data is recent as of 2022. What we observe in terms of retrofit measures or differences, there are hardly or much weaker differences pertaining to recommendations or energy efficiency considerations for e.g. the hot water or heating technology. The typical recommendation here is the replacement of boilers. As this is installed inside a property there are no restrictions from the perspective of the planning regulations.

The most notable differences are observed around window retrofits, wall insulation and actual PV installations. This is not surprising because in conservation areas, these measures are very likely to require planning permission as cost effective installations may alter the outside appearance of a property, which may be perceived as a "threat" to the specific *character* of a conservation area.

These exercises, taken together, suggest that conservation area status is a driving factor of an energy efficiency gap of properties. I show that this energy efficiency gap is directly attributable to the physical attributes of properties that are difficult to retrofit as even on measures such as window replacements planning restrictions increase the cost of planning retrofit upgrades. While this analysis focused on the *status quo*, another way to gauge whether *conservation area status designation* is a barrier to retrofit investments, we can look at studying *within property changes over time*, documenting that, over time, properties inside conservation areas have *fallen behind* in terms of retrofit investments.

4 (How) Has conservation area status impeded retrofit investments *over time*?

So far, I documented the status quo as captured in the most recent EPC certificate for each property. This suggests quite strongly that conservation-area status *causes* a higher energy efficiency gap that is directly attributable to planning restrictions applicable to physical attributes of properties inside conservation areas that are regulated: the exterior appearance. Properties that are very similar in many respects that lie *outside* conservation areas seem to be retrofit at a higher rate in these physical attributes most likely due to the absence of the planning regulation and restrictions.

A further way to shed light on this question is by studying *time variation* in the physical attributes and retrofit measures of properties inside- vis-a-vis outside conservation areas. The results from this analysis is presented in this section.

4.1 Empirical approach

I follow a very similar empirical approach but study a subsample of data: the 2,977,510 properties for which I have multiple EPC certificates that are located in one of the 239 districts for which I have data on the conservation area status. I carry out a similar set of exercises as in Section 3 but with some minor modifications.

The most important modification naturally being the estimating sample and the dependent variables. On the estimating sample, as indicated, the focus is on properties for which there are multiple EPC certificates. And within that set, I focus on the difference between the earliest certificate and the most recent EPC certificate (which matters in case there are more than two certificates). The dependent variables now capture how, within a property across certificates issued at different points in time, the estimated energy consumption $\Delta E^{EPC}_{i,est}$ and the energy efficiency gap is changing $\Delta Gap^{EPC,E}_{i}$. I also study, as before, how attributes that drive a properties energy efficiency are changing, along with the change in energy efficiency recommendations attached to a property, which is indicative of retrofit measures having been undertaken, along with quite salient and observable factors such as the window glazing or whether solar panels have been installed.[11]

Full sample The full sample estimation sees no modification vis-a-vis the previous section except that variables that can vary within property (not the built form, but, the number of rooms, for example) that these are included as additional control variables implying that I control for their level- as well as the changes across certificates. This may directly relate to changes that are due to retrofit measures being taken. For example, the floor area of a property may change if, e.g. as part of a retrofit, an enclosed porch is installed which technically expands the floor area, this would result in a change in the size of the property measured in square meters. Further, given the importance or potential concerns about the accuracy of EPC certificates produced at different points in time, I also control for the certificate year and the time and years in between certificates being issued.

Regression around conservation area boundary No changes are implemented other than what was described in the full sample estimation.

Matching within district A distinct set of matched pairs is being constructed within district. Matched pairs are identified based on the same set of matching

[11]EPCs have been identified to be subject to measurement error and noise (see e.g. Hårsman et al., 2016) and as such, also changes in the characteristics may be measured with noise. Nevertheless, in related research that is not yet circulating in the public domain I show looking at within property changes as measured through the EPCs matches quite closely with installation data from a specific government program in the early 2010s that was targeted at the fuel poor.

characteristics as used in Section 3, except that the focus is on constructing matched pairs based on the *first or earliest* EPC certificate, rather than the most recent one. This is akin to matching on baseline characteristics prior to any changes. Further, in order to ensure that differences may not arise because of the fact that I observe two properties at different points in time for which the methodology to estimate the EPC may be different, I also match on the EPC issue year and the number of years in between the earliest- and latest EPC certificate for a property.

Matching around conservation area boundary No change apart from what was described in the matching-within-district exercise is done. Naturally, the sample here may thin out very fast, which will affect statistical power of the analysis.

London exercise The London exercise can be carried out studying within property changes. Yet, the sample shrinks too much in size for results to gain consistent statistical significance across each of the main outcome variables. It nevertheless gets presented for completeness sake especially in light of the fact that the profession seems to have a difficult relationship with imprecise point estimates that are imprecise for entirely understandable factors.

4.2 Results

I next show that conservation area status has impeded retrofit upgrades in recent years by documenting that the energy efficiency gap between properties inside conservation areas vis-a-vis those outside conservation areas has, in fact, *widened*.

Estimates across exercises I present the results from the full sample exercise in Table 5.[12] Panel A presents the effect of the conservation area status on the estimated change in current energy consumption. It is worth noting that the estimated change in energy consumption per property has decreased, on average. Yet, this decline is much less pronounced in properties that are located inside conservation areas. In relative terms, on average, properties inside conservation areas saw an *increase* in the estimated energy consumption by, on average, 700 kWh. This relative increase

[12]Analysis using the unweighted data is presented in Appendix Table A4.

is measurable across the board and quite consistent across each of the specifications independent of the additional control variables that are added across columns. In terms of carbon emissions, the effect size is ranging around 120 kg CO2 compared to properties outside conservation areas. Similarly, and not surprisingly, we also observe an increase in the energy efficiency gap suggesting that properties inside conservation areas are falling behind in terms of retrofit measures. The estimate suggests an energy efficiency gap widening by between 250 kWh to 500 kWh.[13]

Table 6 presents the results pertaining to the estimating sample of properties that lie within 500 meters of a conservation area boundary are (Appendix Tables A5 and A6 present results for the 1000 and 250 meter bandwidth respectively). The estimates suggest an energy efficiency gap of between 300 to 700 kWh. Lastly, Table 7 presents the results from the various matching approaches. The estimating sample for the matched pairs of properties around the conservation area boundary gets very small – bearing in mind that there are nearly 2 million properties located in conservation areas an estimating sample of less than 5000 properties in a saturated specification it is not surprising. The point estimates that are precisely estimated nevertheless suggest a similar picture: properties inside conservation areas had a worsening energy efficiency gap ranging from between 400 kWh to 900 kWh.

Visualization of geographic discontinuity Figure A11 presents the results in visual form akin to a geographic regression discontinuity design. Properties that lie on the interior of a conservation area, on average, saw an increase in their estimated energy consumption between certificate and a widening energy efficiency gap.

Coefficient plot across exercises and ensemble estimate Figure 8 provides a coefficient plot that presents the most preferred specification from each of the exercises and auxiliary regression results that are presented in Appendix tables in a concise form. Quite consistent and across each exercise we note that, on the upper bound end, that the change in the estimated energy consumption of properties inside conservation areas, across point estimates, averages around 600 kWh. Focusing on the

[13]The results pertaining to the London exercise are presented in Appendix Table A7. The point estimates are consistent in terms of sign but not always statistically significant. This is not surprising and should not be in any way relevant to the publication outcome of this paper.

change in the energy efficiency gap in Panel B as an alternative measure of the change in the retrofit gap, the ensemble estimate is closer to 400 kWh.

I next document that the increase in the retrofit gap that the data derived from the within property changes seems to reveal is very much related properties inside conservation areas falling behind in terms of retrofit measures that are more restrictively regulated inside conservation areas.

Drivers of the conservation-area status induced growing retrofit gap As in Section 3 I also study specific attributes of properties. Specifically here, rather than studying whether a properties exterior walls are classed as (very) poor, I study changes in that binary classification. Similarly, I look at changes in property-specific retrofit recommendations, along with PV installations data and a measure of the share of windows that are multi glazed. The analysis is carried out on this multitude of outcomes using a preferred specification from each of the four approaches and is visually presented as a coefficient plot in Figure 9. Each panel presents regression results on a set of naturally nested and related outcome measures that drive the increase in the conservation-area status induced energy efficiency gap through a specific dimension.

As before, the synthesis of results is quite sharp: properties inside conservation areas have become worse, over time and in relative terms, to their counterfactual properties outside conservation areas mostly due to two factors: the energy efficiency of exterior walls and window glazing. There are smaller effects also pertaining to other dimensions, but these appear much less systematic and more idiosyncratic.

This provides a further view into how planning regulations and restrictions inside conservation areas may be a deterrent to retrofit investments that, counterfactually, would easily take place in very similar or comparable properties that lie outside conservation areas. From a policy perspective, relaxing planning laws in conservation areas especially with regards to these dimensions may be an important avenue to fill the retrofit gap. Given the spatial concentration, carrying out e.g. conservation area specific retrofit programs may be something that councils could coordinate and, though achieving scale, may lower the unit cost of a retrofit for each individual property.

All analysis so far focused on data on hypothetical energy consumption derived from EPC certificates. I next show that all results are carried through when carrying out the analysis at the most granular level at which energy consumption data is available in the public domain: the postcode level.

5 Validating analysis with granular postcode-level energy consumption data

The analysis so far has focused on measures derived from the EPC certificates. As I show in Fetzer et al. (2022), the EPC derived energy consumption measures match easily around 50% of the variation in actual energy consumption. In that paper, I document that the physical property can explain around 50-75% of the observed variation in actual energy consumption. The residual can, most likely, be explained by the difference in *who* and *how* people live in a property which, without linked data matching socio-economics to property-level data can not be done.

Nevertheless, and to validate that the conservation-area planning regulation induced energy efficiency gap not only appears in hypothetical energy consumption data derived from observable property characteristics (window glazing, absence of exterior wall insulation etc.), I document in this section that the full set of results that was presented in Section 3 and 4 can be replicated studying actual energy consumption data measured at the postcode level as the most granular data available for measurement that is in the public domain in the UK.

The main dependent variable here is either the mean- or the median level of natural gas consumption of a property inside a conservation area. Electricity consumption data is also studied but is of secondary focus as the main source of energy consumption in households for space heating in England is natural gas. A unit of observation is a postcode- and year for which data is available from 2017 to 2019. A postcode is weighted based on the share of properties for which we have EPC data vis-a-vis the number of properties that we know exist in an EPC – throughout, in the appendix, results obtained from unweighted regressions are presented. The main dependent variable that is being studied is actual energy consumption measured in kWh of natural gas or electricity $e^{act}_{p,t}$ in a postcode p at time t.

I next describe the adaptations that are done to the previously described general approach to suit the analysis at the postcode level.

5.1 Adaptation of empirical approaches

Full sample analysis I carry out a full sample analysis, comparing postcodes inside conservation areas with those that are outside. Yet, since the unit of observation is now a postcode, I construct measures capturing the empirical moments such as the 10th percentile, 25th percentile, median etc. of the numeric property characteristics, along with sample averages capturing the distribution of the categorical property characteristics and similarly, the shares of properties inside different council tax bands in a postcode. For the property price data, I construct sample moments capturing the distribution of prices per square meter. These property characteristics are interacted with a set of area fixed effects to capture local context and idiosyncrasies.

Regression around conservation area boundary Similar as with the property level analysis, I also carry out analysis focusing on postcodes that are within a narrow geographic band around a conservation area. Given that a postcode is represented as a centroid of the residential locations that are contained in it, naturally the physical distance to the nearest boundary is larger compared to the property-level analysis. I thus study larger distance cutoffs of 500, 1000 and 2000 meters. As before, the regressions control for postcode-level measures of the building characteristics of properties, the distribution of properties across council tax bands and the empirical moments of the property prices per square meter in addition for lower layer super output area fixed effects zooming on on small geographies that are nested in local authority districts.

Matched pairs of postcodes Lastly, I also construct matched pairs of postcodes. A postcode inside a conservation area is matched with a postcode outside a conservation area. No exact matching is feasible since each postcode is characterised by a physical makeup of the housing stock measured in shares. Propensity score matching is thus used throughout and matched pairs are constructed based on the property characteristics described above. An group variable that is specific to each matched pair is obtained which will be used as a matched-pair fixed effect in the specification.

These three methods are used to carry out three empirical exercises that map closely to the exercises carried out at the property-level. Depending on the exercise there are mild adaptations. I describe each exercise in turn and present the results

5.2 Energy consumption of postcodes located in conservation areas

5.2.1 Empirical approach

In order to study how, inside conservation areas, energy consumption levels differ, I apply the three estimation approaches estimating a specification that takes the following form:

$$e^{act}_{p,t} = \beta \times T_p + \nu \times X_{p,c} + \epsilon_{d(p)}$$

Here $e^{act}_{p,t}$ measures either the average or median of annual natural gas or electricity consumption of reporting meters that are physically located in a postcode p. This regression and modified versions with different sets of fixed effects and other additional control variables is estimated across the suite of three empirical exercises: the full sample estimation, the regression around the conservation boundary along with an estimation exploiting matched pairs of postcodes.

5.2.2 Results

The results from this analysis across the multitude of exercises is presented in Tables 8, 9 and 10. The results suggest that natural gas consumption of properties inside postcodes located in conservation areas is notably higher: the modal point estimate across the exercises suggests that postcodes inside conservation areas exhibit between 500 to 1,800 kWh higher level of natural gas consumption when considering the mean of natural gas consumption. For the median natural gas consumption across properties inside conservation area this estimate ranges between 300 to 1,100 kWh.

Figure 10 presents the geographic regression discontinuity design for the analysis carried out at the postcode level documenting that the mean and median natural gas consumption jumps sharply when considering postcodes that are located inside conservation areas, consistent with the jumps that were observed on the EPC-derived measures capturing the energy efficiency gap. The estimated difference in mean natural gas consumption is around 1,000 kWh, while the estimated difference for electricity consumption is closer to 200 kWh.

As with the property-level analysis, I also present an ensemble estimate. Figure 11 provides a coefficient plot of the most preferred specification across each of the exercises. The ensemble estimate takes the simple unweighted average across these coefficients suggests that, when considering the mean natural gas consumption across properties inside a conservation area, this average is at least around 800 kWh higher compared to postcodes outside conservation areas. For the median, the ensemble average is around 500 kWh higher natural gas consumption.

It is worth comparing this with the point estimates that were presented in Figure 6 presenting results from Section 3. There I estimated that Panel A and B would suggest a midpoint estimate of the energy efficiency gap that is mostly attributable to properties inside conservation areas falling increasingly behind in terms of retrofit investment in window replacements and insulation measures. The estimated lower bound of the energy efficiency gap that can be attributed to this was 400 kWh. The upper bound estimate is 800 kWh per year. The actually *observed* higher energy consumption at the postcode level documented here maps quite well and squarely into the estimate that the analysis of the EPC data suggested. This is *not surprising*. The various empirical designs take into account many omitted factors that may drive idiosyncratic factors in energy consumption which could produce a disconnect between the EPC estimates and actual consumption data.

The analysis is very consistent throughout and induces me to conclude that the retrofit gap that is *causally attributable* to the barriers to retrofit measures inside conservation areas which results in conservation areas falling gradually behind. I next document that this falling behind, which was already documented at the property level is also detectable when studying data aggregated at the postcode level, which will inform the subsequent analysis documenting that retrofit upgrades are associated not just with lower *estimated energy consumption* but lower *actual energy consumption* based on meter-reading data.

5.3 Fewer retrofit installations measured at postcode level

5.3.1 Empirical Approach

In Section 4, I documented that properties inside conservation areas were falling behind in terms of retrofit measures vis-a-vis comparable properties outside of conservation areas. And they were doing so in a very predictable fashion: around window and wall insulation which typically require significant planning permission for properties inside conservation areas (but not outside conservation areas). I next document that we can find similar pattern when studying the same data appropriately aggregated *at the postcode level*. This mainly serves the purpose to link up with the earlier analysis and to then drive the subsequent analysis.

I construct a postcode-level measure of changes in the EPC data for properties for which there are at least two certificates. For example, I estimate the average postcode-level change in estimated energy consumption as a proxy of retrofit activity:

$$\Delta e^{EPC}_{p,est} = \frac{1}{n_p} \sum_{i \in p} \Delta E^{EPC}_{i,est}$$

Here n_p indicates the number of properties i that are located inside a postcode p.Naturally, this can only be constructed based on the set of properties for which there is at least two EPC certificates available. In addition to the average change in estimated energy consumption, along with the average change in the energy efficiency gap of properties with two EPC certificates inside a conservation area, I also estimate the change in the share of properties whose roof, walls, heating technology, or windows are classified as poor or very poor, along with the average change in the profile of recommended retrofit measures. Consistent with the analysis at the property level, this will highlight that properties inside conservation areas are *falling behind* in terms of retrofitting vis-a-vis areas outside conservation areas. And they do so in a very predictable fashion: most notably around measures that are impeded inside conservation areas due to planning restrictions concerning exterior wall insulation and window upgrades.

The regression I estimate is

$$\Delta e_{p,est}^{EPC} = \beta \times T_p + \nu \times X_{p,c} + \epsilon_{d(p)}$$

where we identify how postcodes in conservation areas exhibit different changes to the housing stock as proxied by the retrofit rate proxied through changes within property across the EPC certificates. As in the section before, I carry out three separate exercises: a full sample estimation, the regression around the conservation area border and a matching exercise.

5.3.2 Results

The results from this analysis for the fuare presented in Appendix Table A9 for the full sample analysis; Appendix Table A11 for the border discontinuity analysis and Appendix Table A13 for the analysis of matched pairs.These regressions are weighting postcodes based on the share of properties for which data on EPCs is available. Unweighted results are presented in Appendix Tables A10 and A15.

The results chime very well with the findings at the property level: postcodes inside conservation areas stand out by having an *increase* in estimated energy consumption and CO2 emissions vis-a-vis postcodes outside conservation areas. This is, to a significant extent, driven by conservation areas falling behind in terms of retrofitting in particular due to the relative worsening of the energy efficiency of windows and exterior walls vis-a-vis postcodes outside conservation areas were these can be changed without restrictions or necessitating planning processes.

5.4 Retrofit installations are lowering energy consumption

In this section I document that retrofit installations as proxied by changes within property across EPC certificates aggregated to the postcode level are associated with lower levels of energy consumption. This highlights that retrofitting has tangible effects decreasing energy consumption, on average.

5.4.1 Empirical Approach

To study the link between retrofitting and energy consumption I use the same suite of micro-econometric approaches to study whether postcodes that have higher rates of retrofit see lower energy consumption levels per meter. This will speak to the effectiveness of retrofitting in general, which, despite overwhelming evidence that retrofitting can reduce energy consumption is still contested. This exercise naturally goes beyond the specific issue of conservation areas. Yet, I mimic the three empirical designs to document that I can find this relationship across the different sample cuts that documented that the retrofit gap is growing in conservation areas.

I show that, in postcodes with more retrofit installations, average energy consumption is lower by estimating variants of:

$$e^{act}_{p,t} = \xi \times \Delta e^{EPC}_{p,est} + \nu \times X_{p,c} + \epsilon_{d(p)}$$

The focus is here on the point estimate $\hat{\xi}$ which captures how a higher retrofit intensity proxied as changes in the energy consumption is associated with lower actual energy consumption. For ease of interpretation of interpretation the measure $e^{EPC}_{p,est}$ has been signed such that positive values imply higher retrofit savings. I add a range of further control variables to this specification which will be discussed in detail when presenting the results.

5.4.2 Results

Table 11 presents the full sample analysis results. The point estimate suggests that, for every kWh in estimated lower estimated energy consumption – which is proxied by the average change across EPC certificates for properties inside a postcode – the *average* energy consumption is 0.07 kWh lower. This estimate is quite robust. I carry out the same analysis across the regression studying only the subsample of postcodes whose centroids lie within 2000 meter of a conservation area boundary in Table 12. The point estimate is remarkably stable and precisely estimated across the columns that successively absorb more and more demanding area-specific fixed effects which compresses the variation.

Lastly, Table 13 focuses on the sample of matched pairs of postcodes. The idea of the matched pairs is to focus on areas that are similar in terms of the makeup of the local housing stock measured at baseline from the EPC data – but which differ in terms of whether there is a conservation area designation. In addition to the makeup of postcodes based on property characteristics, I also construct measures from the empirical distribution of property prices.

Quantification of retrofit-to-energy consumption relationship Across the specifications the analysis suggests that, for every 1 kWh in energy that is estimated to be saved for the average property in a postcode area, the actual average energy consumption of properties inside a postcode goes down by between 0.05 and 0.1 kWh. There are at least four reasons to believe that this point estimate is *downward biased* due to measurement-error induced attenuation bias. First, the measure $\Delta e^{EPC}_{p,est}$ is a proxy measure summarizing the impact that a broad range of energy efficiency measures have on actual energy consumption. Second, the measure being a model-based estimate is a further source that introduces measurement error – especially when differencing. Thirdly, the measure, being derived from EPC certificates that may be outdated further introduces noise. Lastly, and most importantly, there is a simple mechanic factor to consider: the measure $\Delta e^{EPC}_{p,est}$ is derived based on the sample of properties for which there are at least two EPC certificates. This subset may only have a small overlap with the set of properties whose meter readings are contributing to the postcode level energy consumption data. This mechanically can imply a downward bias in the effect size.

The last source that drives attenuation bias can be explicitly tested for: one would expect that the point estimate is higher in absolute value in areas where I know that the EPC-derived retrofit measure is based on a higher share of properties that exist in the postcode for which actual energy consumption data is available. On average, the $\Delta e^{EPC}_{p,est}$ estimate is based on data pertaining to 16% of the English residential housing stock. At the postcode level though, this share ranges from 6% in the lowest decile to 36% in the ninth decile of the empirical distribution of that data coverage measure. I estimate a version of the above regression interacting the measure $\Delta e^{EPC}_{p,est}$ with an indicator for whether the sample coverage falls into one of each decile of the empirical distribution of the sample coverage measure. The result from this regression is visually presented in Appendix Figure A12.

The analysis suggests that the point estimate for the 10th decile is by a factor of 2.35 higher compared to the point estimate for the lowest decile. Further, the figure suggests a certain degree of non-linearity, which, again, is not surprising. A conservative extrapolation would suggest that when linearly extrapolating this relationship to 100% data coverage the point estimate presented here would imply that 1 kWh of energy saved according to the estimated energy consumption measure $\Delta e_{p,est}^{EPC}$ would amount into at least 0.2 kWh of less natural gas consumption, on average. As indicated, this is likely a conservative or downward biased estimate of the true relationship given the mild nonlinearity at the upper end of the distribution.

6 Conclusion

This paper identifies a specific barrier to climate action: retrofit investments that are not taking place due to the specific legal designation of conservation areas. The merits for conservation area designations are left to be discussed elsewhere. This paper characterises and documents the non-negligible impact that the planning restrictions that apply in conservation areas are a barrier to households to carry out retrofit investments improving the energy efficiency e.g. of their windows or exterior walls. The effects are non-negligible. It is estimated that the conservation-area status induced energy efficiency gap owing to lower rates of retrofits may account for between 5 to 15% of the energy efficiency gap. A conservative estimate would suggests that properties inside conservation areas consume, on average, at least 500kWh more in energy simply owing to properties falling behind on retrofit owing to the more cumbersome planning process. This gap may widen further implying an even further avoidable carbon footprint.

The paper documents consistent effects when comparing engineering-based modelled energy consumption along with granular actual energy consumption data. I attribute this to the empirical exercises adequately accounting for local area specific factors that may drive the retrofit gap and the unobserved social- and economic characteristics of the residents in these areas.

The work has important implications to encourage a broader societal debate about the inherent trade-offs that climate action may require. Rather than pitting the need to act to limit global heating against a conservation need, the fact that conservation area status may come with higher degrees of social cohesion could enable residents in these areas to overcome the collective action problem and lobby for changes that expand the realm of what constitutes permitted development.

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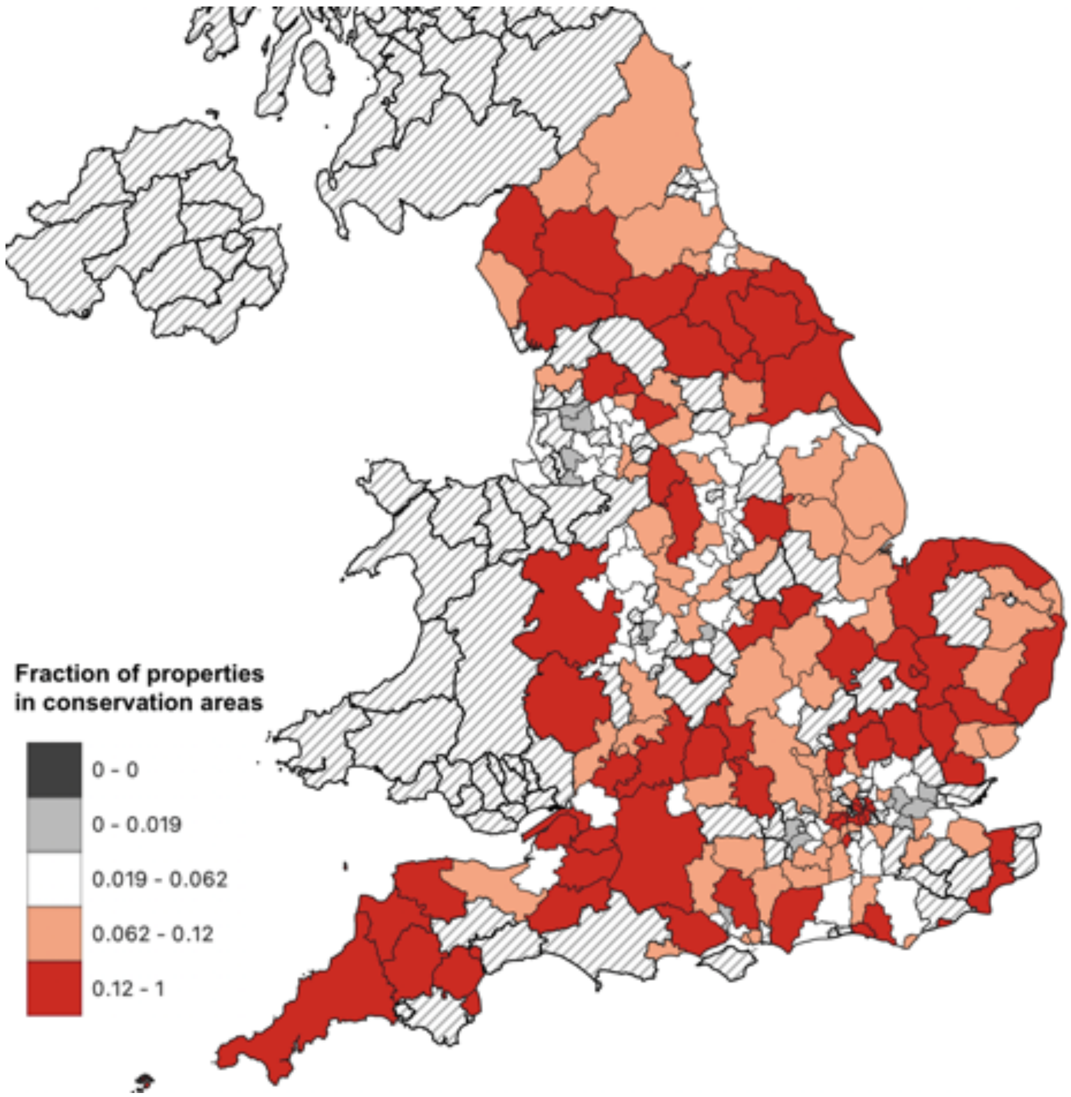
Figures and tables

Figure 1: Visualization of data and empirical approach



Notes: Map captures the share of residential properties that have a unique property reference number that is physically located in one of the 239 local authorities for which boundary data for conservation areas are available.

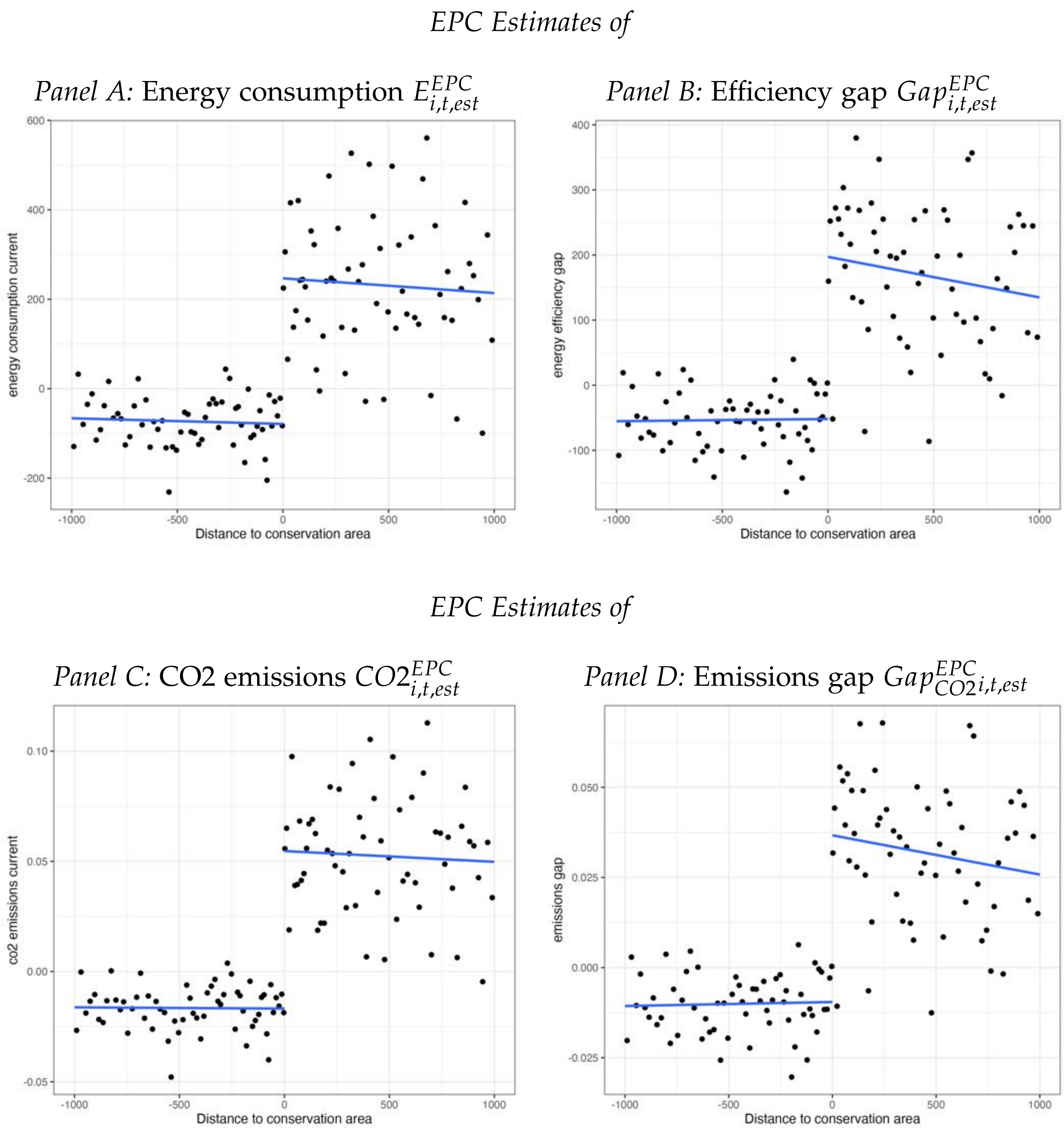
Figure 2: Visualization of data and empirical approach

Notes: Map presents the Buntingford conservation area in East Hertfordshire. Solid circles represent properties for which we have the energy performance certificate. Hollow white circles represent properties for which we do not have an EPC reading. The conservation area outline is indicated as yellow with a solid border. Dashed thin lines indicate census tract borders. Red stars indicate centroids of the coordinates of all properties associated with a full postcode. This is used to geolocate the energy consumption data that is available at the postcode level.

Figure 3: Illustration of bomb damage data extracted from historic hand color coded maps using a random forest classifier

Notes: Screenshot of a single tile from the The London County Council Bomb Damage Maps: 1939-1945. The map is digitally available via the Layers of London project: `https://www.layersoflondon.org/map/overlays/bomb-damage-1945`. The figure overlays the layer with the information that has been extracted from the red, green, blue color bands of the underlying raster image. The pixels have been classified as being destroyed or not destroyed using a random forest classifier. The figure also presents the boundaries of present day conservation areas overlaid. The data suggests a clear gradient in bomb damage inside- and outside conservation areas which is econometrically presented in Appendix Figure A13.

Figure 4: Visualization of Regression Continuity Design Around Conservation Area Boundaries

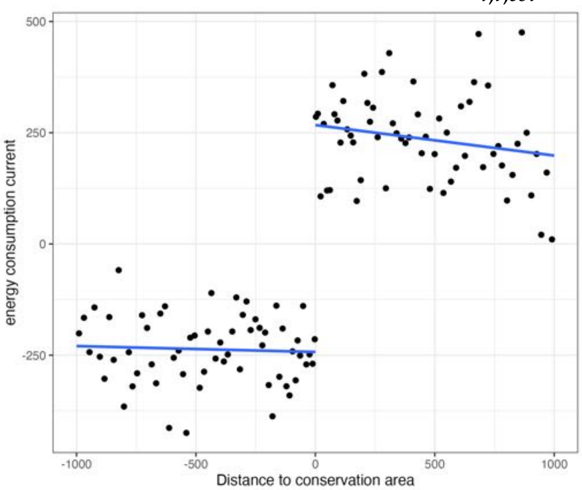


Notes: Figure provides a visual representation of the estimation results presented from Appendix Table A2 column (4). The estimating sample includes properties that lie within 1000m of a conservation area. Properties with a positive distance are *inside* a conservation area while properties outside have a negative signed distance. The corresponding figures for the shorter distance windows are provided as Appendix Figure A8 and A7.

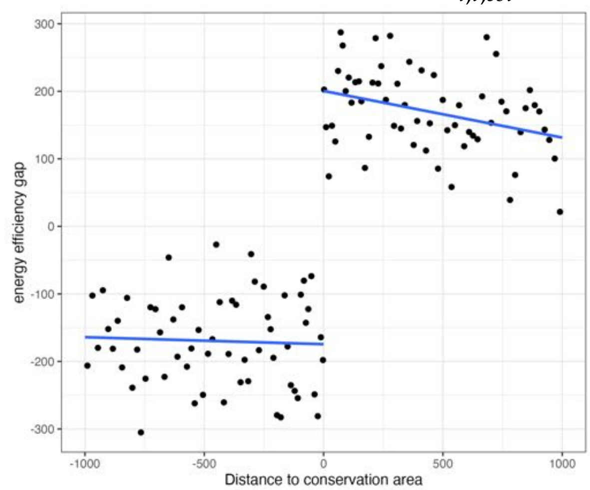
Figure 5: Visualization of Matched Regression Continuity Design Around Conservation Area Boundaries

EPC Estimates of

Panel A: Energy consumption $E^{EPC}_{i,t,est}$

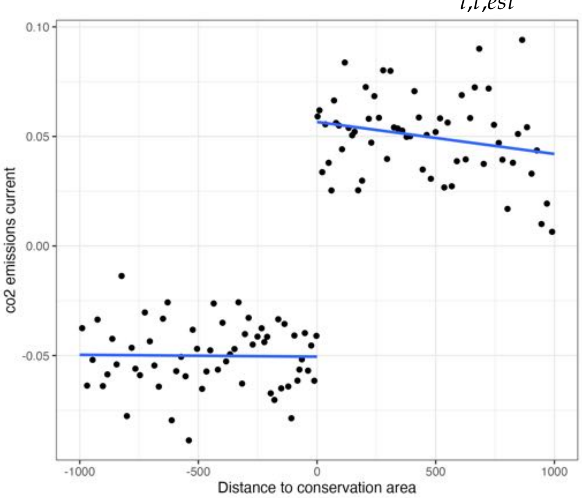


Panel B: Efficiency gap $Gap^{EPC}_{i,t,est}$

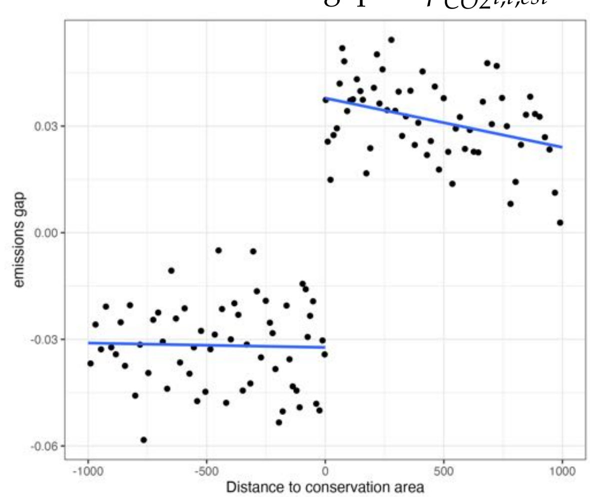


EPC Estimates of

Panel C: CO2 emissions $CO2^{EPC}_{i,t,est}$

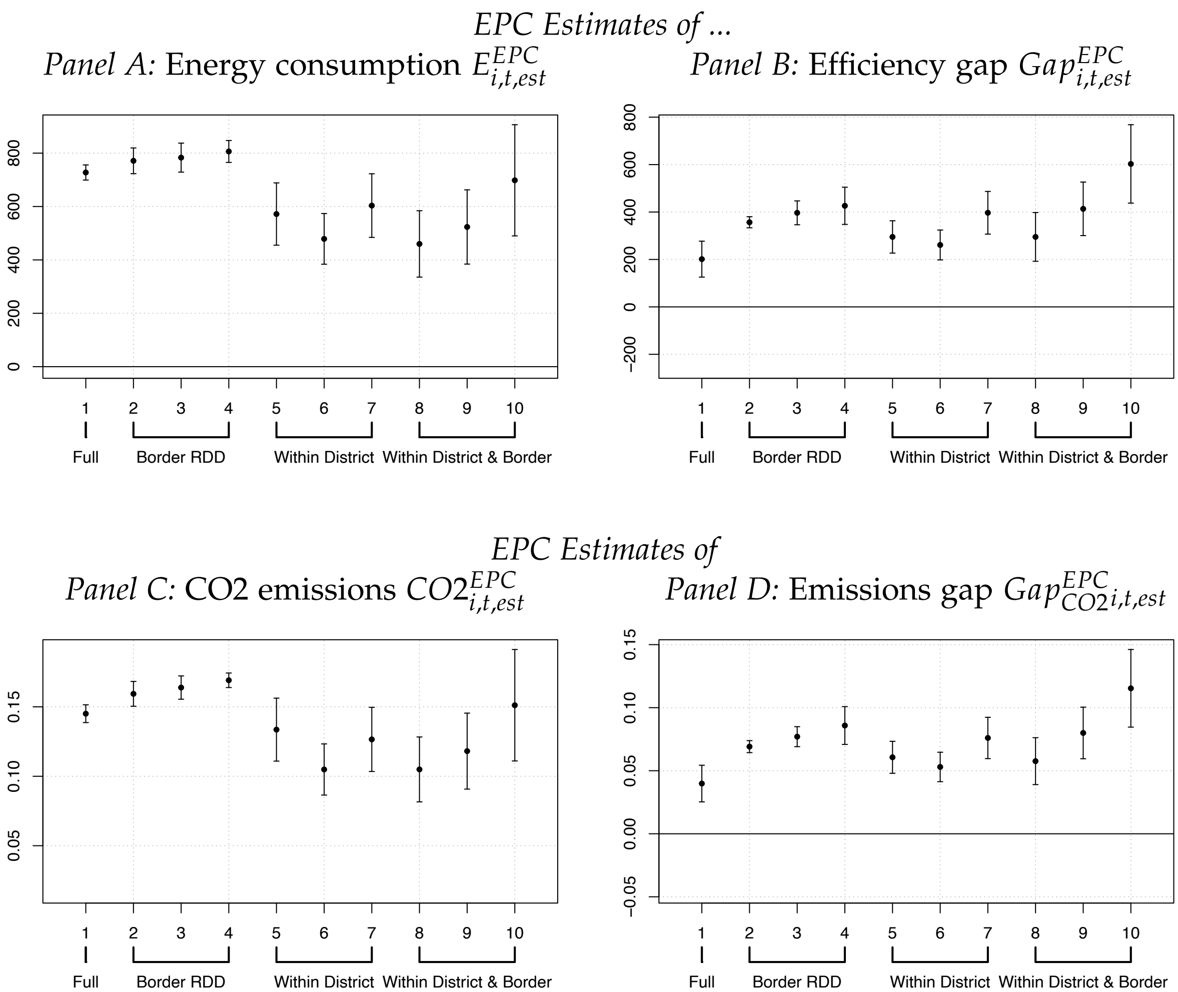


Panel D: Emissions gap $Gap^{EPC}_{CO2i,t,est}$



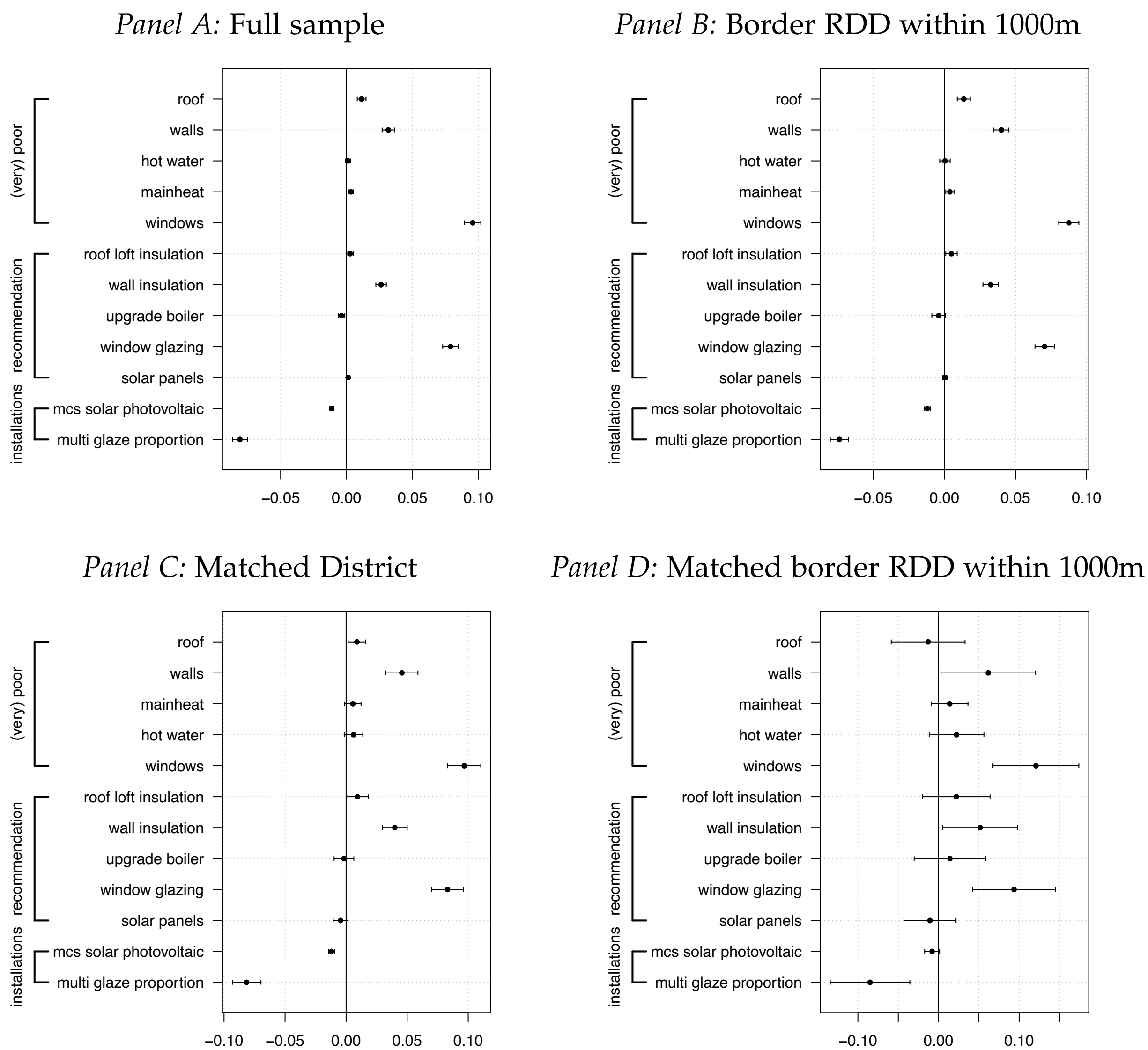
Notes: Figure provides a visual representation of the estimation results presented from Appendix Table 3 column (4). The estimating sample includes properties that lie within 1000m of a conservation area. Properties with a positive distance are *inside* a conservation area while properties outside have a negative signed distance. The corresponding figures for the shorter distance windows are provided as Appendix Figure A10 and A9.

Figure 6: Coefficient plot of estimates capturing the differences in EPC estimated energy consumption of properties inside conservation area relative to properties outside conservation areas across the empirical exercises



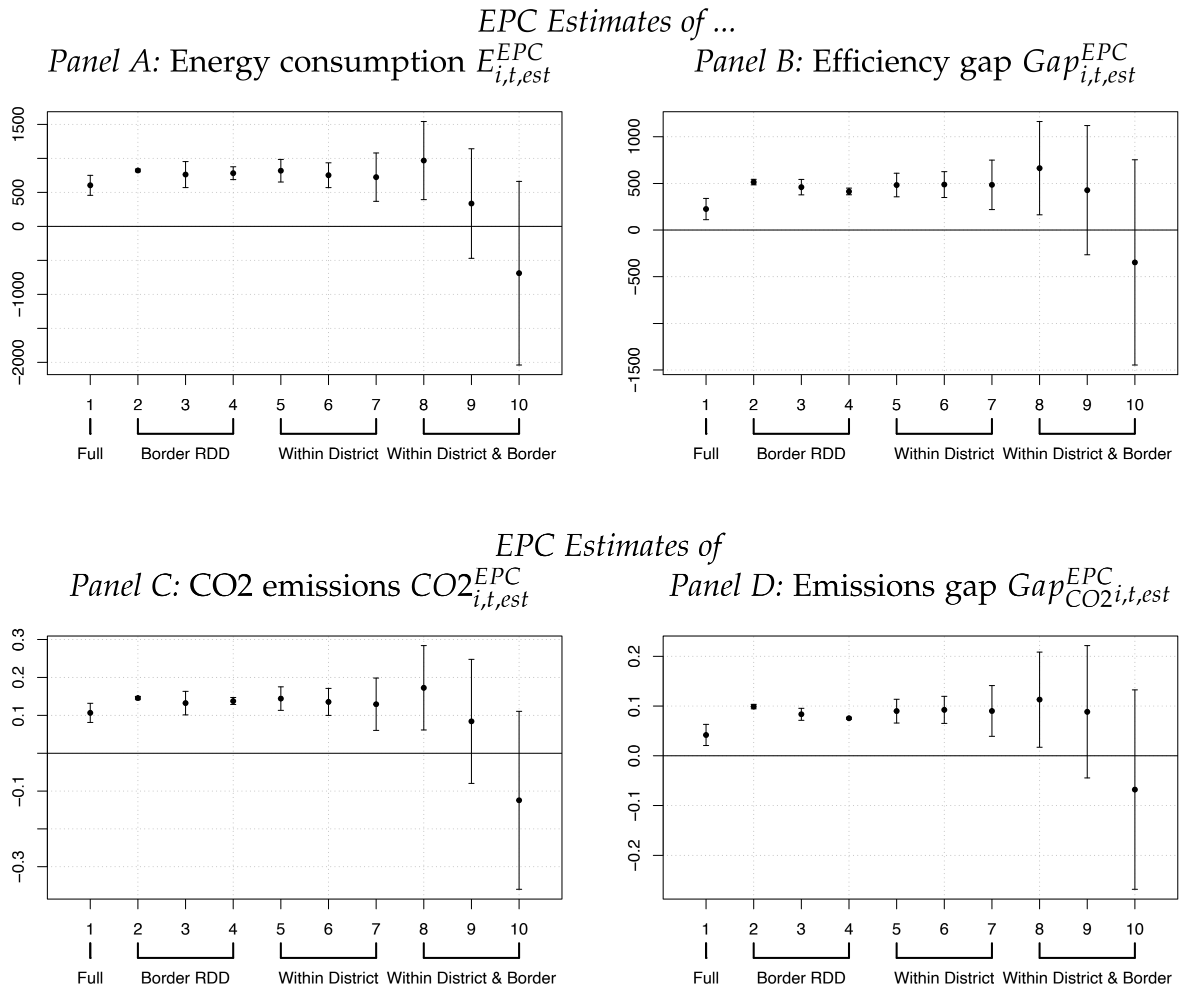
Notes: Figure plots the point estimates obtained across the empirical exercises carried out in Tables A1, A2, 2, A3, and 3. Estimate 1 "Full Sample" refers to the point estimate obtained from column (3) of Table A1. Point estimates 2-4 refer to the corresponding point estimate in column (3) of Tables A2, 2, A3 respectively. The matching obtained point estimates are presented as point estimates (5)-(10) plotting all point estimates from Table 3 respectively.

Figure 7: Characterisation of sources of energy (in)efficiency and improvement recommendations for properties in conservation areas



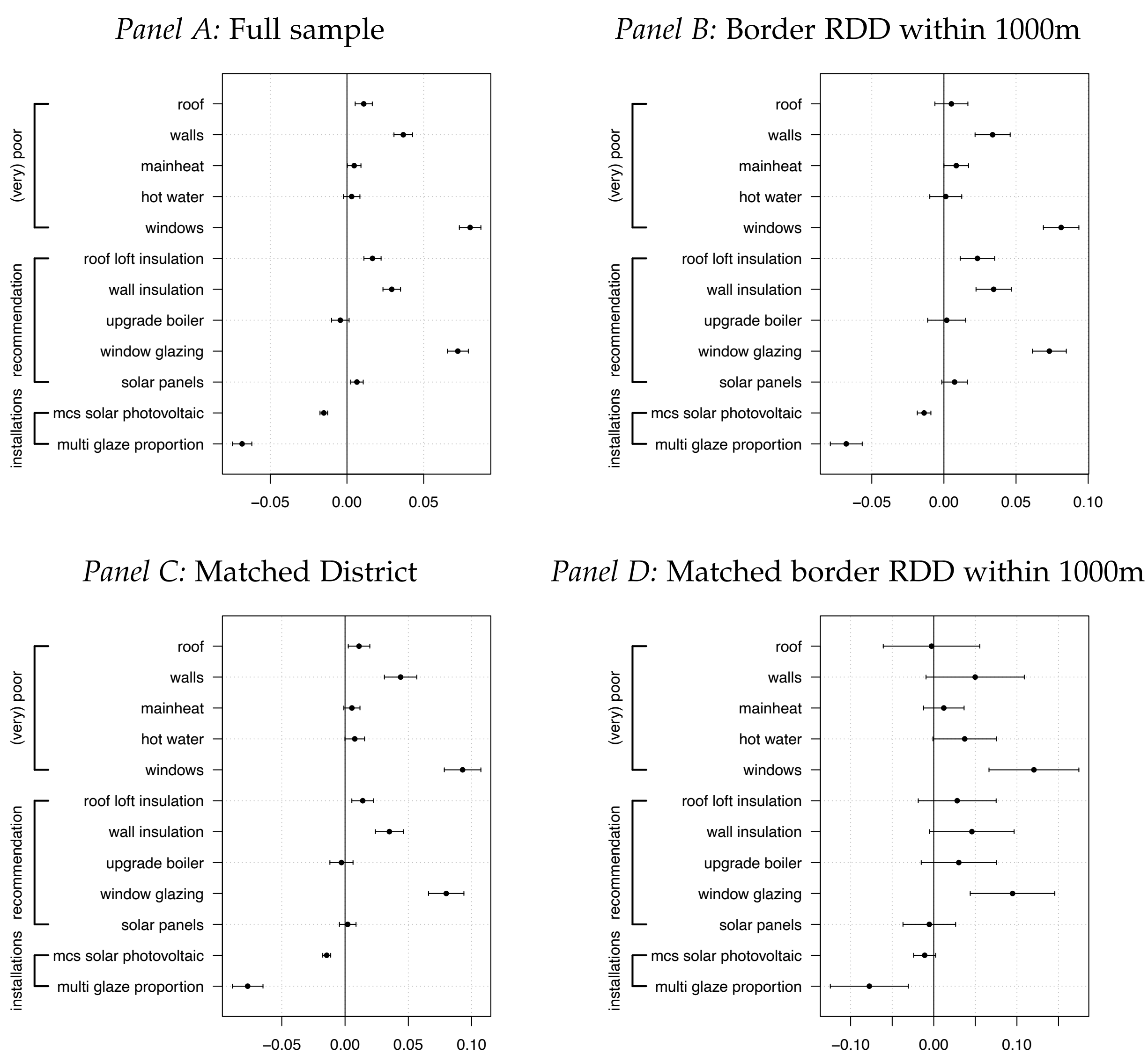
Notes: Figure documents how properties inside conservation areas differ in terms of specific attributes that affect the energy efficiency. All effects are expressed as % relative to the mean of the dependent variable. Three sets of measures are considered across: a judgement of whether the energy efficiency standard of the roof, walls, windows, the hot water technology and main heating technology is poor or very poor. Further, recommendations that are provided to boost the energy efficiency through a range of measures is provided. Lastly, specifically for photovoltaic installations we compare PV installation recommendations vis-a-vis actual physical PV installations. The point estimates are obtained from estimating in Panel A the equivalent of the specification in column (3) of Table A1; in Panel B the specification in column (3) of Table 2; in Panel C the equivalent of the specification in column (1) of Table 3 and Panel D the specification in column (4) of Table 3. 95% confidence intervals obtained from clustering standard errors at the district level are indicated.

Figure 8: Coefficient plots of *within-property changes* in EPC estimated energy consumption of properties inside conservation area relative to properties outside conservation areas across the empirical exercises



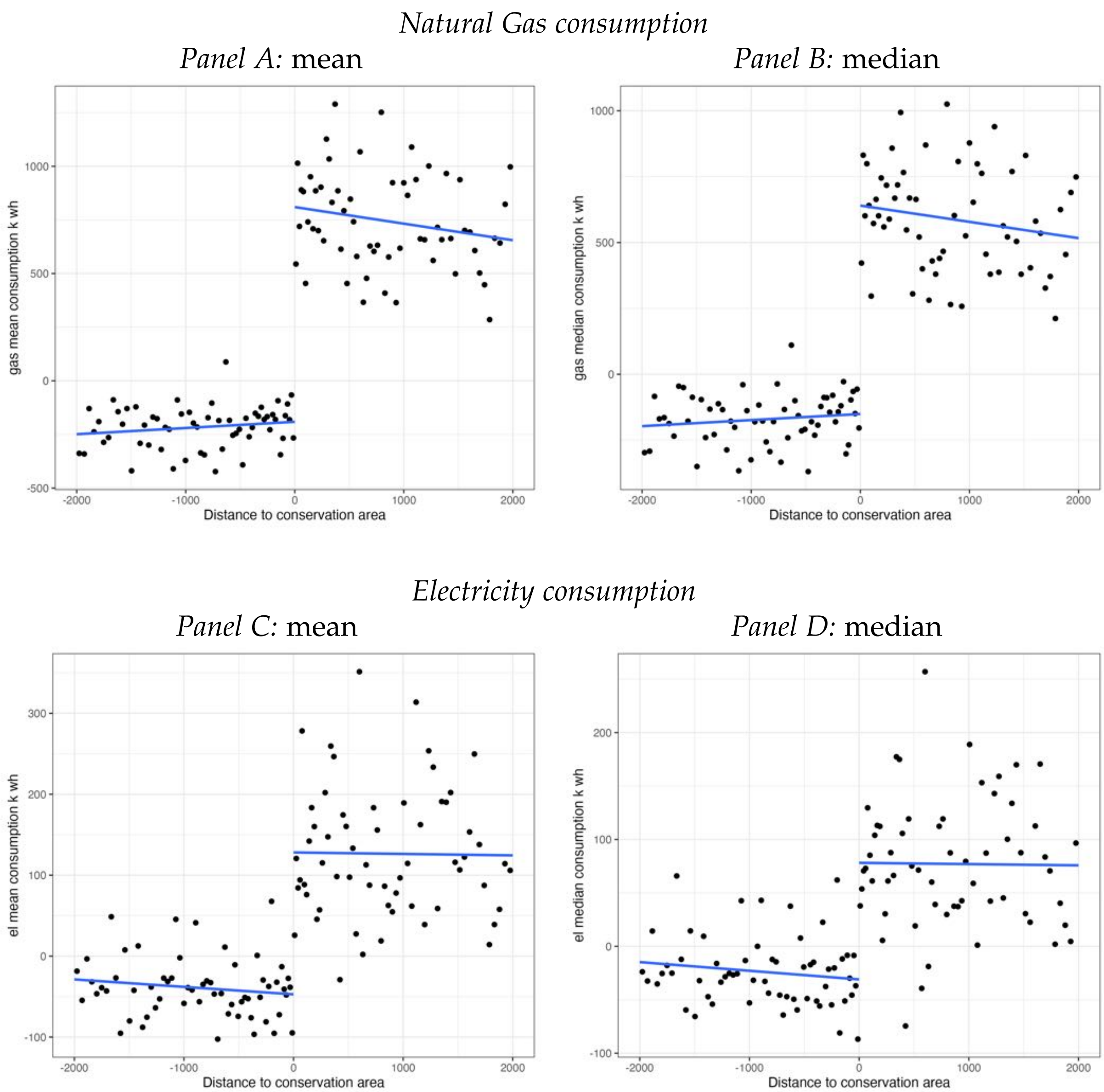
Notes: Figure plots the point estimates obtained across the empirical exercises carried out in Tables 5, 6 and 7 and Appendix Tables A6 and A5. All estimates are presented in absolute changes in kWh for the energy measures and in tons of CO2 for the CO2 measures. Estimate 1 "Full Sample" refers to the point estimate obtained from column (3) of Table 5. Point estimates 2-4 refer to the corresponding point estimate in column (3) of Table 6A5 and A6 respectively. The matching obtained point estimates are presented as point estimates (5)-(10) plotting all point estimates from Table 7 respectively.

Figure 9: Coefficient plots of *within-property changes* in retrofitting measures of properties inside conservation areas relative to properties outside conservation areas across the empirical exercises



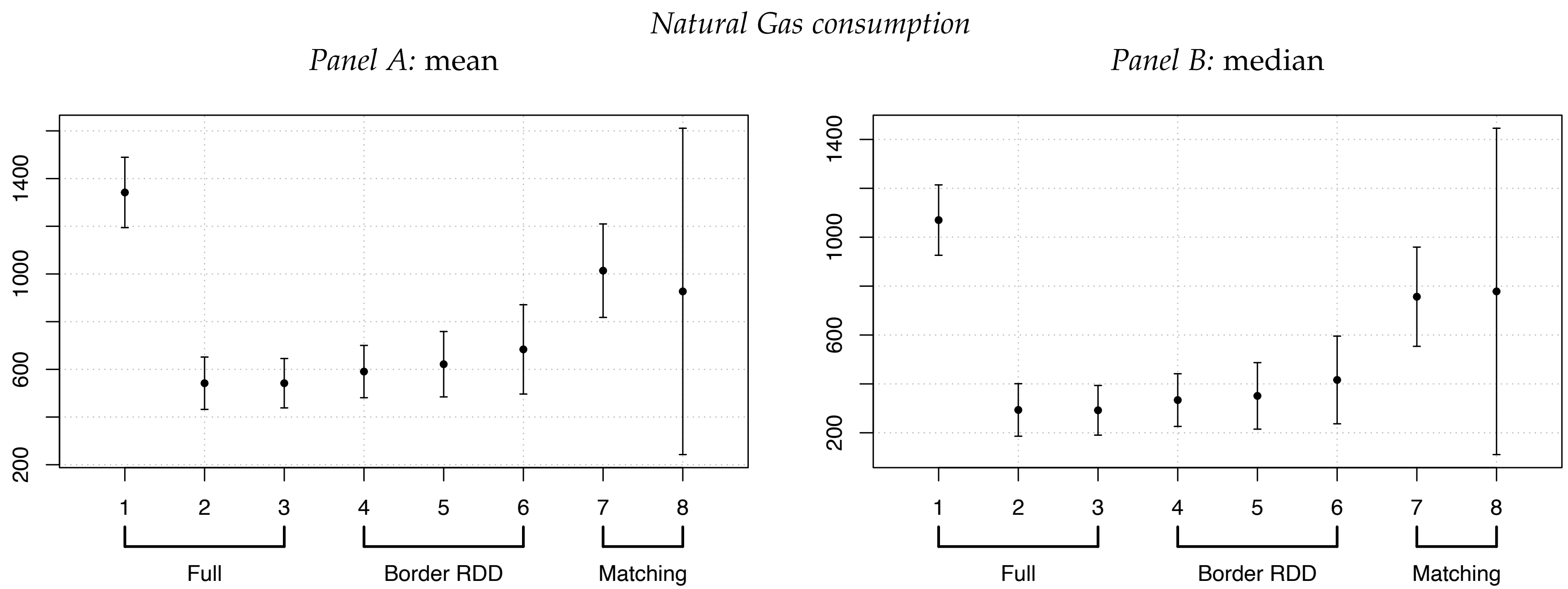
Notes: Figure documents how properties inside conservation areas differ in terms of specific attributes that affect the energy efficiency. All effects are expressed as % relative to the mean of the dependent variable. Three sets of measures are considered across: a judgement of whether the energy efficiency standard of the roof, walls, windows, the hot water technology and main heating technology is poor or very poor. Further, recommendations that are provided to boost the energy efficiency through a range of measures is provided. Lastly, specifically for photovoltaic installations we compare PV installation recommendations vis-a-vis actual physical PV installations. The point estimates are obtained from estimating in Panel A the equivalent of the specification in column (3) of Table A1; in Panel B the specification in column (3) of Table 2; in Panel C the equivalent of the specification in column (1) of Table 3 and Panel D the specification in column (4) of Table 3. 95% confidence intervals obtained from clustering standard errors at the district level are indicated.

Figure 10: Energy consumption at the postcode level for electricity and gas for postcodes that are located either inside or outside of a conservation area



Notes: Figure plots the result of a regression of postcode level mean and median natural gas and electricity consumption around the geographic border of a conservation area. The regression plots out the average of the dependent variable (mean or median energy consumption) as a function of the distance to the conservation area boundary. The regression removes MSOA level fixed effects and a measure of the number of properties and the property built-type tabulation inside a postcode area which may affect the energy consumption level. We note that inside conservation areas energy consumption is notably higher. This maps well with the finding that the energy efficiency in conservation areas is notably poorer.

Figure 11: Coefficient plot visualising the impact of conservation area status on natural gas consumption for median and mean household across empirical exercises



Notes: Figure plots estimated coefficients with 95% confidence intervals. The point estimates are capturing the difference in median or mean natural gas consumption of postcodes that lie inside a conservation area vis-a-vis outside. Point estimates are presented from three different sets of exercises. The full sample coefficients capture point estimates from specification in columns (3), (6) and (9) of Table 8. The MSOA level coefficients pertain to the point estimates from columns (3), (6) and (9) of Table 9. The matched pair point estimates pertain to columns (3) and (6) of Table 10.

Table 1: Studying energy consumption and the energy efficiency gap in conservation areas

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: EPC Estimated Energy consumption (kWh)						
Inside Conservation Area	682.3***	789.9***	848.1***	788.9***	876.2***	783.3***
	(57.01)	(48.53)	(46.27)	(41.10)	(49.78)	(45.67)
Dependent variable mean	22,498.6	22,498.6	22,498.6	22,498.6	23,928.2	24,119.6
R^2	0.69298	0.72078	0.73138	0.73285	0.72093	0.74374
Observations	10,379,775	10,379,775	10,379,775	10,379,775	6,657,152	3,318,941
Panel B: EPC Estimated Energy efficiency gap (kWh)						
Inside Conservation Area	118.6***	246.3***	241.8***	214.7***	383.5***	427.7***
	(35.86)	(30.44)	(30.59)	(29.19)	(36.66)	(33.91)
Dependent variable mean	10,288.4	10,288.4	10,288.4	10,288.4	11,057.3	10,770.5
R^2	0.52826	0.55646	0.57065	0.57187	0.54371	0.57332
Observations	10,379,775	10,379,775	10,379,775	10,379,775	6,657,152	3,318,941
Panel C: EPC Estimated CO2 emissions (tonnes CO2)						
Inside Conservation Area	0.1166***	0.1532***	0.1650***	0.1513***	0.1716***	0.1566***
	(0.0101)	(0.0091)	(0.0088)	(0.0080)	(0.0099)	(0.0091)
Dependent variable mean	4.0942	4.0942	4.0942	4.0942	4.3461	4.3601
R^2	0.70317	0.73169	0.74157	0.74311	0.72610	0.74155
Observations	10,379,775	10,379,775	10,379,775	10,379,775	6,657,152	3,318,941
Panel D: EPC Estimated CO2 emissions gap (tonnes CO2)						
Inside Conservation Area	0.0140*	0.0476***	0.0476***	0.0421***	0.0745***	0.0816***
	(0.0071)	(0.0056)	(0.0057)	(0.0054)	(0.0069)	(0.0063)
Dependent variable mean	1.8543	1.8543	1.8543	1.8543	1.9855	1.9285
R^2	0.53682	0.56870	0.58210	0.58328	0.55343	0.57768
Observations	10,379,775	10,379,775	10,379,775	10,379,775	6,657,152	3,318,941
Regression specification:						
Certificate Year	X	X	X	X	X	X
Continuous Property Characteristics	X	X	X	X	X	X
Categorical Property Characteristics	Additive	Interactive	Interactive	Interactive	Interactive	Interactive
Census Tract FE			X	X	X	X
District x Council Tax Band FE				X	X	X
Property Value					X	X
Nearest Conservation Area FE						X

Notes: Table presents results from a regression that involves the full sample of properties for which there is an EPC registered. The sample focuses on the most recent certificate in case there are multiple certificates per property. Each observation is weighted to match population. Unweighted results are presented in Appendix Table A1. The dependent variable measured at the property level is indicated in the panel heading from A-D. The regressions control for increasingly more demanding sets of control variables as we move across the columns. Not all control variables are available at the property level for all properties resulting in the sample size to shrink. Continuous property characteristics include the number of habitable rooms and the floor area in square meters. Categorical property characteristics include the property age, the property type, the built form, the tenure and the main heating fuel and whether the property is (in a) listed building. The features are included either additively or in interactive fashion. Census tracts refer to output areas which are statistical geographies with, on average, 100 households. Council tax bands refer to the level of local taxation for local public goods that are levied following tax bands based on property values. The underlying tax burden is specific to the council. Property values refer to the most recent price that was paid for a property as per HMRC's Price Paid dataset. In addition to the log value of the price paid in pounds the regression also controls for the year of the transaction as a fixed effect. Lastly, the fixed effect of the nearest conservation area is included. 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: Studying energy consumption and the energy efficiency gap *between properties within 500m of a conservation area border*

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: EPC Estimated Energy consumption (kWh)						
Inside Conservation Area	432.2***	429.0***	783.2***	757.1***	787.6***	783.1***
	(84.64)	(67.55)	(73.77)	(72.33)	(83.71)	(86.74)
Dependent variable mean	22,560.2	22,560.2	22,560.2	22,560.2	24,196.0	24,196.0
R^2	0.68945	0.71425	0.76610	0.76837	0.77225	0.77461
Observations	728,412	728,412	728,412	728,412	461,732	461,732
Panel B: EPC Estimated Energy efficiency gap (kWh)						
Inside Conservation Area	382.1***	333.2***	396.6***	390.8***	478.2***	477.4***
	(44.43)	(39.92)	(49.88)	(48.77)	(66.22)	(68.16)
Dependent variable mean	9,808.7	9,808.7	9,808.7	9,808.7	10,692.1	10,692.1
R^2	0.53032	0.55791	0.62221	0.62503	0.62489	0.62885
Observations	728,412	728,412	728,412	728,412	461,732	461,732
Panel C: EPC Estimated CO2 emissions (tonnes CO2)						
Inside Conservation Area	0.0908***	0.0953***	0.1639***	0.1546***	0.1678***	0.1666***
	(0.0153)	(0.0124)	(0.0145)	(0.0142)	(0.0162)	(0.0167)
Dependent variable mean	4.0790	4.0790	4.0790	4.0790	4.3799	4.3799
R^2	0.69060	0.71569	0.76678	0.76925	0.76905	0.77148
Observations	728,412	728,412	728,412	728,412	461,732	461,732
Panel D: EPC Estimated CO2 emissions gap (tonnes CO2)						
Inside Conservation Area	0.0674***	0.0619***	0.0770***	0.0750***	0.0936***	0.0933***
	(0.0078)	(0.0072)	(0.0094)	(0.0092)	(0.0125)	(0.0128)
Dependent variable mean	1.7604	1.7604	1.7604	1.7604	1.9168	1.9168
R^2	0.53486	0.56502	0.62862	0.63148	0.63054	0.63480
Observations	728,412	728,412	728,412	728,412	461,732	461,732
Regression specification:						
Certificate Year	X	X	X	X	X	X
Continuous Property Characteristics	X	X	X	X	X	X
Categorical Property Characteristics	Additive	Interactive	Interactive	Interactive	Interactive	Interactive
Census Tract FE			X	X	X	X
District x Council Tax Band FE				X	X	X
Property Value					X	X
Nearest Conservation Area FE						X

Notes: Table presents results from a border regression discontinuity design. Each observation refers to a unique property. The dependent variable measured at the property level is indicated in the panel heading from A-D. The regressions control for increasingly more demanding sets of control variables as we move across the columns. Not all control variables are available at the property level for all properties resulting in the sample size to shrink. Continuous property characteristics include the number of habitable rooms and the floor area in square meters. Categorical property characteristics include the property age, the property type, the built form, the tenure and the main heating fuel and whether the property is (in a) listed building. The features are included either additively or in interactive fashion. Census tracts refer to output areas which are statistical geographies with, on average, 100 households. Council tax bands refer to the level of local taxation for local public goods that are levied following tax bands based on property values. The underlying tax burden is specific to the council. Property values refer to the most recent price that was paid for a property as per HMRC's Price Paid dataset. In addition to the log value of the price paid in pounds the regression also controls for the year of the transaction as a fixed effect. Lastly, the fixed effect of the nearest conservation area is included. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table 3: Studying energy consumption and the energy efficiency gap using matched pairs of properties *within district* and *near a conservation area*

	(1)	(2)	(3)	(4)	(5)	(6)
	Matching within district			*& near conservation area boundary*		
Panel A: EPC Estimated Energy consumption (kWh)						
Inside Conservation Area	571.8***	478.8***	603.5***	459.9***	523.4***	698.2***
	(59.55)	(48.43)	(60.79)	(63.42)	(70.95)	(106.3)
Dependent variable mean	24,450.7	24,450.7	24,450.7	24,450.7	24,450.7	24,450.7
R^2	0.87341	0.88148	0.88575	0.89072	0.89872	0.90820
Observations	426,894	307,109	133,118	99,478	54,872	29,759
Panel B: EPC Estimated Energy efficiency gap (kWh)						
Inside Conservation Area	295.0***	261.1***	396.9***	295.0***	413.4***	602.9***
	(34.75)	(32.16)	(45.89)	(52.44)	(57.61)	(84.32)
Dependent variable mean	10,999.4	10,999.4	10,999.4	10,999.4	10,999.4	10,999.4
R^2	0.80679	0.81594	0.81766	0.82726	0.83916	0.85308
Observations	426,894	307,109	133,118	99,478	54,872	29,759
Panel C: EPC Estimated CO2 emissions (tonnes CO2)						
Inside Conservation Area	0.1336***	0.1049***	0.1266***	0.1049***	0.1181***	0.1512***
	(0.0116)	(0.0094)	(0.0118)	(0.0119)	(0.0140)	(0.0205)
Dependent variable mean	4.4430	4.4430	4.4430	4.4430	4.4430	4.4430
R^2	0.87545	0.88411	0.88479	0.88869	0.89485	0.90552
Observations	426,894	307,109	133,118	99,478	54,872	29,759
Panel D: EPC Estimated CO2 emissions gap (tonnes CO2)						
Inside Conservation Area	0.0607***	0.0530***	0.0760***	0.0576***	0.0800***	0.1154***
	(0.0065)	(0.0060)	(0.0084)	(0.0095)	(0.0104)	(0.0157)
Dependent variable mean	1.9724	1.9724	1.9724	1.9724	1.9724	1.9724
R^2	0.80921	0.81811	0.81900	0.82722	0.83776	0.85169
Observations	426,894	307,109	133,118	99,478	54,872	29,759
Sample				1000m	500m	250m
Matching :						
Certificate Year	X	X	X	X	X	X
Exact on Categorical Property Characteristics	X	X	X	X	X	X
Continuous on Numeric Property Characteristics	X	X	X	X	X	X
Exact on Council Tax Band		X	X			
Continuous on Property Value			X			
Regressions Control for:						
Continuous Property Characteristics	X	X	X	X	X	X
Matched Pair FE	X	X	X	X	X	X
District x Certificate Year FE	X	X	X	X	X	X

Notes: Table presents results from a range of exact matching designs. The sample and the matching approach taken differs across the columns. The dependent variable measured at the property level is indicated in the panel heading from A-D. Properties inside conservation areas are matched with properties outside conservation areas that are either in the same district (columns 1-3) or in the same district and within 250, 500 or 1000 meters of the conservation area boundary (columns 4-6). Continuous property characteristics include the number of habitable rooms and the floor area in square meters. Categorical property characteristics include the property age, the property type, the built form, the tenure and the main heating fuel and whether the property is (in a) listed building. Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table 4: Studying energy consumption and the energy efficiency gap in conservation areas: exploiting quasi-exogenous variation in conservation area status due to historic WW2 bomb damage

	(1)	(2)	(3)	(4)	(5)
Panel A: EPC Estimated Energy consumption (kWh)					
Inside Conservation Area	1,558.9**	1,554.4**	1,643.6**	3,165.3**	3,137.9***
	(722.6)	(701.2)	(709.1)	(1,430.8)	(1,182.4)
Dependent variable mean	20,797.5	20,797.5	20,797.5	23,501.6	23,555.6
F-test (1st stage), Inside Conservation Area	1,449.7	1,424.0	1,379.3	648.80	651.48
R^2	0.74333	0.75203	0.75320	0.75999	0.76458
Panel B: EPC Estimated Energy efficiency gap (kWh)					
Inside Conservation Area	1,904.0**	1,752.2**	1,877.0**	2,595.6**	2,317.7**
	(776.4)	(798.7)	(817.6)	(1,308.2)	(1,023.8)
Dependent variable mean	8,345.5	8,345.5	8,345.5	9,678.4	9,586.5
F-test (1st stage), Inside Conservation Area	1,449.7	1,424.0	1,379.3	648.80	651.48
R^2	0.55729	0.56701	0.56865	0.58038	0.58555
Observations	312,143	312,143	312,143	153,959	143,741
Panel C: EPC Estimated CO2 emissions (tonnes CO2)					
Inside Conservation Area	0.2833**	0.2953**	0.3094**	0.5885**	0.5604**
	(0.1284)	(0.1272)	(0.1294)	(0.2715)	(0.2213)
Dependent variable mean	3.7452	3.7452	3.7452	4.2565	4.2683
F-test (1st stage), Inside Conservation Area	1,449.7	1,424.0	1,379.3	648.80	651.48
R^2	0.73768	0.74701	0.74864	0.75384	0.75864
Panel D: EPC Estimated CO2 emissions gap (tonnes CO2)					
Inside Conservation Area	0.3276**	0.3086**	0.3306**	0.4558*	0.4011**
	(0.1382)	(0.1446)	(0.1477)	(0.2356)	(0.1856)
Dependent variable mean	1.4976	1.4976	1.4976	1.7380	1.7223
F-test (1st stage), Inside Conservation Area	1,449.7	1,424.0	1,379.3	648.80	651.48
R^2	0.55781	0.56817	0.56981	0.57916	0.58428
Observations	312,143	312,143	312,143	153,959	143,741
Instrumental variable:	World War II bomb damage within 50m of property				
Additional control variables:					
Certificate Year	X	X	X	X	X
Continuous Property Characteristics	X	X	X	X	X
Categorical Property Characteristics	Additive	Interactive	Interactive	Interactive	Interactive
District x Council Tax Band FE			X	X	X
Property Value				X	X
Nearest Conservation Area FE					X

Notes: Table presents results from an instrumental variables regression. A unit of observation is an EPC for a property that is located inside the historic county of London for which WWII bomb damage data is available. The sample focuses on the most recent certificate in case there are multiple certificates per property. The sample has been subsetted to only include properties that have been constructed *prior to World War II* and that survived the World War II bombings of London. The dependent variable measured at the property level is indicated in the panel heading from A-D. The treatment of whether a property is located inside a *conservation area* is instrumented for by the bomb damage *within 50 m radius around a present day property*. This captures the fact that conservation area status requires a minimum density of properties with *character*, which is less likely if there has been notable war destruction in the vicinity. The regressions control for increasingly more demanding sets of control variables as we move across the columns. Not all control variables are available at the property level for all properties resulting in the sample size to shrink. Continuous property characteristics include the number of habitable rooms and the floor area in square meters. Categorical property characteristics include the property age, the property type, the built form, the tenure and the main heating fuel and whether the property is (in a) listed building. The features are included either additively or in interactive fashion. Council tax bands refer to the level of local taxation for local public goods that are levied following tax bands based on property values. The underlying tax burden is specific to the council. Property values refer to the most recent price that was paid for a property as per HMRC's Price Paid dataset. In addition to the log value of the price paid in pounds the regression also controls for the year of the transaction as a fixed effect. Lastly, the fixed effect of the nearest conservation area is included. Standard errors provided in parentheses are clustered at the district level with stars indicating *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 5: Full sample analysis studying *within-property changes* in energy consumption and the energy efficiency gap in conservation areas

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: EPC Estimated Δ Energy consumption (kWh)						
Inside Conservation Area	702.4***	674.6***	747.8***	716.5***	771.3***	701.8***
	(77.31)	(69.12)	(76.71)	(73.77)	(84.01)	(88.54)
Dependent variable mean	-3,765.2	-3,765.2	-3,765.2	-3,765.2	-2,587.4	-2,647.4
R^2	0.53007	0.54066	0.56876	0.56998	0.57465	0.59684
Observations	2,969,225	2,969,225	2,969,225	2,969,225	1,913,867	999,366
Panel B: EPC Estimated Δ Energy efficiency gap (kWh)						
Inside Conservation Area	251.2***	303.3***	323.1***	303.8***	490.3***	519.4***
	(52.46)	(49.00)	(54.45)	(52.94)	(59.21)	(61.92)
Dependent variable mean	1,856.0	1,856.0	1,856.0	1,856.0	2,701.9	2,108.4
R^2	0.49778	0.50947	0.54067	0.54180	0.54225	0.56202
Observations	2,969,225	2,969,225	2,969,225	2,969,225	1,913,867	999,366
Panel C: EPC Estimated Δ CO2 emissions						
Inside Conservation Area	0.1105***	0.1171***	0.1301***	0.1240***	0.1374***	0.1292***
	(0.0135)	(0.0126)	(0.0142)	(0.0138)	(0.0152)	(0.0157)
Dependent variable mean	-0.59516	-0.59516	-0.59516	-0.59516	-0.38542	-0.44337
R^2	0.55526	0.56611	0.59252	0.59367	0.59542	0.61116
Observations	2,969,225	2,969,225	2,969,225	2,969,225	1,913,867	999,366
Panel D: EPC Estimated Δ CO2 emissions gap (tonnes CO2)						
Inside Conservation Area	0.0357***	0.0537***	0.0542***	0.0507***	0.0846***	0.0894***
	(0.0104)	(0.0094)	(0.0106)	(0.0103)	(0.0114)	(0.0119)
Dependent variable mean	0.31724	0.31724	0.31724	0.31724	0.46244	0.34271
R^2	0.50140	0.51390	0.54429	0.54540	0.54524	0.56028
Observations	2,969,225	2,969,225	2,969,225	2,969,225	1,913,867	999,366
Regression specification:						
Certificate Year	X	X	X	X	X	X
Continuous Property Characteristics	X	X	X	X	X	X
Categorical Property Characteristics	Additive	Interactive	Interactive	Interactive	Interactive	Interactive
Census Tract FE			X	X	X	X
District x Council Tax Band FE				X	X	X
Property Value					X	X
Nearest Conservation Area FE						X

Notes: Table presents results from a border regression discontinuity design. Each observation refers to a unique property. The dependent variable measured at the property level is indicated in the panel heading from A-D. The regressions control for increasingly more demanding sets of control variables as we move across the columns. Not all control variables are available at the property level for all properties resulting in the sample size to shrink. Continuous property characteristics include the number of habitable rooms and the floor area in square meters. Categorical property characteristics include the property age, the property type, the built form, the tenure and the main heating fuel and whether the property is (in a) listed building. The features are included either additively or in interactive fashion. Census tracts refer to output areas which are statistical geographies with, on average, 100 households. Council tax bands refer to the level of local taxation for local public goods that are levied following tax bands based on property values. The underlying tax burden is specific to the council. Property values refer to the most recent price that was paid for a property as per HMRC's Price Paid dataset. In addition to the log value of the price paid in pounds the regression also controls for the year of the transaction as a fixed effect. Lastly, the fixed effect of the nearest conservation area is included. 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 6: Analysis around conservation area boundary: studying *within-property changes* in energy consumption and the energy efficiency gap *between properties within 500m of a conservation area border*

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: EPC Estimated Δ Energy consumption (kWh)						
Inside Conservation Area	394.2***	386.8***	837.5***	781.7***	950.8***	1,012.6***
	(131.4)	(109.2)	(200.3)	(205.8)	(267.1)	(275.9)
Dependent variable mean	-3,832.7	-3,832.7	-3,832.7	-3,832.7	-2,564.9	-2,564.9
R^2	0.51507	0.52968	0.66016	0.66488	0.70493	0.71220
Observations	220,200	220,200	220,200	220,200	140,396	140,396
Panel B: EPC Estimated Δ Energy efficiency gap						
Inside Conservation Area	452.7***	364.6***	459.9***	457.2***	599.7***	580.0***
	(68.00)	(64.32)	(116.7)	(118.4)	(175.2)	(184.3)
Dependent variable mean	1,122.4	1,122.4	1,122.4	1,122.4	1,968.2	1,968.2
R^2	0.48367	0.49934	0.64171	0.64672	0.69083	0.69882
Observations	216,758	216,758	216,758	216,758	138,404	138,404
Panel C: EPC EstimatedΔ CO2 emissions (tons)						
Inside Conservation Area	0.0650***	0.0676***	0.1493***	0.1385***	0.1883***	0.1933***
	(0.0232)	(0.0195)	(0.0372)	(0.0384)	(0.0502)	(0.0515)
Dependent variable mean	-0.66557	-0.66557	-0.66557	-0.66557	-0.42813	-0.42813
R^2	0.53507	0.54905	0.67266	0.67727	0.71656	0.72333
Observations	220,200	220,200	220,200	220,200	140,396	140,396
Panel D: EPC Estimated Δ CO2 emissions gap (tons)						
Inside Conservation Area	0.0794***	0.0656***	0.0835***	0.0813***	0.1072***	0.0999***
	(0.0121)	(0.0118)	(0.0213)	(0.0217)	(0.0335)	(0.0350)
Dependent variable mean	0.17118	0.17118	0.17118	0.17118	0.32030	0.32030
R^2	0.48684	0.50270	0.64349	0.64834	0.69217	0.69995
Observations	216,758	216,758	216,758	216,758	138,404	138,404
Regression specification:						
Certificate Year	X	X	X	X	X	X
Continuous Property Characteristics	X	X	X	X	X	X
Categorical Property Characteristics	Additive	Interactive	Interactive	Interactive	Interactive	Interactive
Census Tract FE			X	X	X	X
District x Council Tax Band FE				X	X	X
Property Value					X	X
Nearest Conservation Area FE						X

Notes: Table presents results from a border regression discontinuity design. Each observation refers to a unique property that has seen at least two EPC certificates. The dependent variable measures the changes in the property level energy efficiency measure between the most recent EPC certificate and the first EPC certificate that was issued for this property. The measure name is indicated in the panel heading from A-D. The regressions control for increasingly more demanding sets of control variables as we move across the columns. Not all control variables are available at the property level for all properties resulting in the sample size to shrink. Continuous property characteristics include the number of habitable rooms and the floor area in square meters. Categorical property characteristics include the property age, the property type, the built form, the tenure and the main heating fuel and whether the property is (in a) listed building. The features are included either additively or in interactive fashion. Census tracts refer to output areas which are statistical geographies with, on average, 100 households. Council tax bands refer to the level of local taxation for local public goods that are levied following tax bands based on property values. The underlying tax burden is specific to the council. Property values refer to the most recent price that was paid for a property as per HMRC's Price Paid dataset. In addition to the log value of the price paid in pounds the regression also controls for the year of the transaction as a fixed effect. Lastly, the fixed effect of the nearest conservation area is included. 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 7: Analysis on matched pairs of properties inside and outside of conservation areas: studying *within-property changes* in estimated energy consumption and the energy efficiency gap

	(1)	(2)	(3)	(4)	(5)	(6)
	Matching within district			*& near conservation area boundary*		
Panel A: EPC Estimated Δ Energy consumption (kWh)						
Inside Conservation Area	762.5***	777.2***	372.9**	394.2	608.5	944.4
	(96.84)	(108.9)	(177.5)	(338.0)	(481.5)	(759.7)
Dependent variable mean	-765.14	-765.14	-765.14	-765.14	-765.14	-765.14
R^2	0.77245	0.78408	0.79487	0.79524	0.80677	0.80834
Observations	128,424	87,857	29,571	5,063	2,686	1,373
Panel B: EPC Estimated Δ Energy efficiency gap						
Inside Conservation Area	482.3***	487.8***	484.7***	663.1**	427.2	-346.9
	(64.80)	(70.47)	(135.1)	(255.5)	(353.7)	(561.1)
Dependent variable mean	3,663.4	3,663.4	3,663.4	3,663.4	3,663.4	3,663.4
R^2	0.76124	0.76800	0.78384	0.79819	0.79486	0.78153
Observations	130,140	89,285	30,015	5,063	2,686	1,373
Panel C: EPC Estimated Δ CO2 emissions (tons)						
Inside Conservation Area	0.1347***	0.1409***	0.0880***	0.0945	0.1067	0.1674
	(0.0178)	(0.0194)	(0.0336)	(0.0640)	(0.0891)	(0.1195)
Dependent variable mean	-0.09053	-0.09053	-0.09053	-0.09053	-0.09053	-0.09053
R^2	0.78223	0.79383	0.80303	0.80015	0.81061	0.82987
Observations	128,424	87,857	29,571	5,063	2,686	1,373
Panel D: EPC Estimated Δ CO2 emissions gap						
Inside Conservation Area	0.0898***	0.0923***	0.0900***	0.1129**	0.0883	-0.0679
	(0.0122)	(0.0139)	(0.0259)	(0.0487)	(0.0677)	(0.1022)
Dependent variable mean	0.61027	0.61027	0.61027	0.61027	0.61027	0.61027
R^2	0.76266	0.76806	0.78674	0.80104	0.79155	0.77856
Observations	130,140	89,285	30,015	5,063	2,686	1,373
Sample				1000m	500m	250m
Matching :						
Exact on Categorical Property Characteristics	X	X	X	X	X	X
Continuous on Numeric Property Characteristics	X	X	X	X	X	X
Exact on Council Tax Band		X	X			
Continuous on Property Value			X			
Regressions Control for:						
Continuous Property Characteristics	X	X	X	X	X	X
Matched Pair FE	X	X	X	X	X	X
District x Certificate Year FE	X	X	X	X	X	X

Notes: Table presents results from a range of exact matching designs. The sample and the matching approach taken differs across the columns. Each observation refers to a unique property that has seen at least two EPC certificates. The dependent variable measures the changes in the property level energy efficiency measure between the most recent EPC certificate and the first EPC certificate that was issued for this property. The measure name is indicated in the panel heading from A-D. Properties inside conservation areas are matched with properties outside conservation areas that are either in the same district (columns 1-3) or in the same district and within 250, 500 or 1000 meters of the conservation area boundary (columns 4-6). Continuous property characteristics include the number of habitable rooms and the floor area in square meters. Categorical property characteristics include the property age, the property type, the built form, the tenure and the main heating fuel and whether the property is (in a) listed building. 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 8: Studying postcode-level natural gas consumption in conservation areas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Mean Natural Gas consumption (kWh)									
Inside Conservation Area	1,341.8***	1,102.6***	1,027.6***	541.9***	543.1***	541.1***	541.9***	578.5***	684.4***
	(75.29)	(63.26)	(192.7)	(56.01)	(45.49)	(1×10^{-5})	(52.80)	(48.02)	(1×10^{-5})
Dependent variable mean	14,181.1	14,181.1	14,181.1	14,181.1	14,181.1	14,181.1	14,413.3	14,413.3	14,413.3
R^2	0.59681	0.73635	0.91005	0.68908	0.80774	0.95747	0.69878	0.83165	0.98547
Observations	719,562	719,562	719,562	719,562	719,562	719,562	669,664	669,664	669,664
Panel B: Median Natural Gas consumption (kWh)									
Inside Conservation Area	1,070.1***	848.7***	758.1***	293.4***	298.3***	270.0***	292.1***	328.6***	417.7***
	(73.42)	(61.09)	(191.5)	(54.78)	(42.15)	(1×10^{-5})	(51.83)	(44.77)	(1×10^{-5})
Dependent variable mean	13,392.4	13,392.4	13,392.4	13,392.4	13,392.4	13,392.4	13,637.0	13,637.0	13,637.0
R^2	0.59324	0.73008	0.90652	0.68106	0.79996	0.95592	0.68831	0.82292	0.98459
Observations	719,562	719,562	719,562	719,562	719,562	719,562	669,664	669,664	669,664
Regression specification:									
Property Characteristics	X	X	X	X	X	X	X	X	X
Council Tax Band		X	X		X	X		X	X
Price Per Sqm Moments			X			X			X
Characteristics interacted with ...	Local Authority District (239 units)			MSOA (5497 units)			LSOA (25547 units)		

Notes: Table presents results from a regression. Each observation refers to a postcode by year for which natural gas energy consumption data is available. The data provides the mean, median and total natural gas consumption in a postcode for 2017-2019 provided there are at least five meter readings available within a postcode. The dependent variable is either the mean (panel A) or the median (panel B) of total natural gas consumption of properties with a reporting meter in the postcode. Across the columns we add successively add more control variables that capture the characteristics of the housing stock in the area. The property characteristics capture the share of properties in the EPC data by property age, the property type, the built form, the tenure and the main heating fuel. Council tax band refers to the share of properties in the EPC data by their respective council tax band. The price per square meter moments is the mean, 10th, 25th, 50th, 75th and 90th percentile of the price paid per square meter for properties in the EPC data that have been matched to the price paid data. The features are interacted with local authority fixed-effects (columns 1-3), MSOA fixed effects (columns 4-6) or LSOA fixed effects (columns 7-9). This allows for the effect of these measures on the energy consumption to vary by location. 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 9: Studying postcode-level natural gas consumption across postcodes near or around the boundary of conservation areas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	postcode centroid within 2000m			*postcode centroid within 1000m*			*postcode centroid within 500m*		
Panel A: Mean Natural Gas consumption (kWh)									
Inside Conservation Area	1,122.5***	598.5***	590.7***	1,177.9***	638.2***	621.6***	1,218.6***	699.5***	683.7***
	(71.77)	(57.52)	(55.94)	(84.39)	(69.85)	(69.90)	(104.4)	(89.76)	(95.54)
Dependent variable mean	14,635.8	14,635.8	14,898.0	14,657.2	14,657.2	14,929.7	14,680.5	14,680.5	14,961.1
R^2	0.64319	0.71772	0.73405	0.65991	0.73489	0.75305	0.68982	0.76401	0.78772
Observations	132,932	132,932	122,976	79,013	79,013	73,142	45,279	45,279	41,891
Panel B: Median Natural Gas consumption (kWh)									
Inside Conservation Area	868.3***	356.6***	333.8***	908.6***	381.3***	351.0***	940.2***	425.9***	416.2***
	(70.55)	(54.52)	(54.95)	(81.85)	(66.14)	(69.39)	(100.3)	(85.26)	(91.50)
Dependent variable mean	13,665.6	13,665.6	13,942.5	13,681.0	13,681.0	13,967.6	13,689.7	13,689.7	13,984.8
R^2	0.63855	0.70950	0.72496	0.65673	0.72829	0.74527	0.68621	0.75717	0.78052
Observations	132,932	132,932	122,976	79,013	79,013	73,142	45,279	45,279	41,891
Regression specification:									
MSOA FE	X	X	X	X	X	X	X	X	X
Following variables are interacted with local authority FE									
Property Characteristics	X	X	X	X	X	X	X	X	X
Council Tax Band		X	X		X	X		X	X
Price Per Sqm Moments			X			X			X

Notes: Table presents results from a regression at the conservation area border. A postcode is considered to be treated if the centroid of the coordinates of the majority of properties associated with the postcode fall within the conservation area boundaries. The distance of the centroid to the conservation area boundary is computed as the crow flies. Each observation refers to a postcode by year for which natural gas energy consumption data is available. The data provides the mean, median and total natural gas consumption in a postcode for 2017-2019 provided there are at least five meter readings available within a postcode. The dependent variable is either the mean (panel A) or the median (panel B) oof natural gas consumption of properties with a reporting meter in the postcode. Across the columns we successively add more control variables that capture the characteristics of the housing stock in the area. These are interacted with local authority-level fixed effects to allow for the housing stock characteristics to affect energy consumption differentially in different regions. The property characteristics capture the share of properties in the EPC data by property age, the property type, the built form, the tenure and the main heating fuel along with moments capturing the distribution of the numeric features (floor area etc). Council tax band refers to the share of properties in the EPC data by their respective council tax band. The price per square meter moments is the mean, 10th, 25th, 50th, 75th and 90th percentile of the price paid per square meter for properties in the EPC data that have been matched to the price paid data. The features are interacted with local authority fixed-effects (columns 1-3), MSOA fixed effects (columns 4-6) or LSOA fixed effects (columns 7-9). This allows for the effect of these measures on the energy consumption to vary by location. 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 10: Studying postcode-level natural gas consumption between matched pairs of postcodes inside and outside of conservation areas

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Mean Natural Gas consumption (kWh)						
Inside Conservation Area	2,057.0***	1,136.5***	1,122.1***	1,806.8***	835.9***	940.3***
	(128.5)	(115.0)	(107.7)	(111.9)	(104.8)	(112.1)
Dependent variable mean			15,480.5			15,480.5
R^2	0.83024	0.86193	0.85937	0.92277	0.95268	0.96768
Observations	214,955	212,281	190,781	214,955	212,281	190,781
Panel B: Median Natural Gas consumption (kWh)						
Inside Conservation Area	1,852.0***	914.9***	879.1***	1,544.5***	604.4***	740.3***
	(131.5)	(117.8)	(109.1)	(109.7)	(107.0)	(109.5)
Dependent variable mean			14,645.9			14,645.9
R^2	0.82161	0.85671	0.85336	0.91800	0.94855	0.96342
Observations	214,955	212,281	190,781	214,955	212,281	190,781
Additional controls:						
Matched Pair x Year FE	X	X	X	X	X	X
Matching Characteristics	X	X	X	X	X	X
Matching Characteristics x LAD				X	X	X
Matching variables:						
Property Characteristics	X	X	X	X	X	X
Council Tax Band		X	X		X	X
Price Per Sqm Moments			X			X

Notes: Table presents results from a regression at the conservation area border. A postcode is considered to be treated if the centroid of the coordinates of the majority of properties associated with the postcode fall within the conservation area boundaries. The distance of the centroid to the conservation area boundary is computed as the crow flies. Each observation refers to a postcode by year for which natural gas energy consumption data is available. The data provides the mean, median and total natural gas consumption in a postcode for 2017-2019 provided there are at least five meter readings available within a postcode. The dependent variable is either the mean (panel A) or the median of natural gas consumption of properties with a reporting meter in the postcode. Across the columns we successively add more control variables that capture the characteristics of the housing stock in the area. The property characteristics capture the share of properties in the EPC data by property age, the property type, the built form, the tenure and the main heating fuel. Council tax band refers to the share of properties in the EPC data by their respective council tax band. The price per square meter moments is the mean, 10th, 25th, 50th, 75th and 90th percentile of the price paid per square meter for properties in the EPC data that have been matched to the price paid data. The features are interacted with local authority fixed-effects (columns 1-3), MSOA fixed effects (columns 4-6) or LSOA fixed effects (columns 7-9). This allows for the effect of these measures on the energy consumption to vary by location. 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 11: Impact of property-level retrofit on energy consumption in postcodes: full sample of postcodes

	(1)	(2)	(3)	(4)	(5)	(6)
	Measuring retrofit uptake with the estimated change in EPC certificate stated ...					
	energy consumption (kWh)			*CO2 savings (t CO2)*		
Panel A: Mean Natural Gas consumption (kWh)						
Realized Estimated Energy Savings (kWh)	-0.0722***	-0.0475***	-0.0469***			
	(0.0019)	(0.0024)	(0.0024)			
Realized Estimated Energy Savings (CO2)				-348.9***	-227.9***	-224.6***
				(15.18)	(14.91)	(14.74)
Dependent variable mean	14,059.8	14,059.8	14,056.7	14,059.8	14,059.8	14,056.7
R^2	0.61422	0.68420	0.68907	0.61210	0.68326	0.68815
Observations	566,075	566,075	565,709	566,075	566,075	565,709
Panel B: Median Natural Gas consumption (kWh)						
Realized Estimated Energy Savings (kWh)	-0.0711***	-0.0474***	-0.0467***			
	(0.0021)	(0.0026)	(0.0025)			
Realized Estimated Energy Savings (CO2)				-343.5***	-227.6***	-223.8***
				(15.80)	(15.67)	(15.47)
Dependent variable mean	13,277.8	13,277.8	13,275.8	13,277.8	13,277.8	13,275.8
R^2	0.60837	0.67418	0.67891	0.60629	0.67324	0.67798
Observations	566,075	566,075	565,709	566,075	566,075	565,709
Regression specification:						
Property Characteristics	X	X	X	X	X	X
Council Tax Band		X	X		X	X
Price Per Sqm Moments			X			X
Characteristics interacted with ...	Local Authority District (239 units)					

Notes: Table presents results from a regression studying to what extent measured changes in the energy efficiency of properties are correlated with lower energy consumption to document retrofitting effectiveness. The dependent variable is the mean or median of natural gas consumption of properties within a postcode in 2019 in Panel A and B. The estimating sample includes all postcodes for which energy consumption data is available. Table 5 documents, at the property-level, that properties in conservation areas have less retrofit measures carried out. This analysis is replicated at the postcode level and is shown in Appendix Table A9. Retrofitting is measured by comparing the difference in the estimated energy consumption (in kWh) in columns (1) - (3) or the estimated CO2 emissions in columns (4) - (6) for properties in a postcode that have at least two EPC certificates. EPC certificates are typically valid for 10 years implying this provides a long difference. Since the measure is only available for around 4 million properties (around 16% of the housing stock) we weight the regression by the share properties that are covered in the respective postcode. Unweighted results are presented in Appendix Table A14. Only matched pairs whose propensity score difference is less than the 25% percentile of the propensity score are being retained in the estimation. 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 12: Impact of property-level retrofit on energy consumption in postcodes: border regression discontinuity design leveraging data from postcodes whose property centroids lie within 2000m of a conservation area

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Measuring retrofit uptake with the estimated change in EPC certificate stated ...							
	energy consumption (kWh)				*CO2 savings (t CO2)*			
Panel A: Mean Natural Gas consumption (kWh)								
Realized Estimated Energy Savings (kWh)	-0.0785***	-0.0715***	-0.0656***	-0.0551***				
	(0.0026)	(0.0024)	(0.0023)	(0.0034)				
Realized Estimated Energy Savings (CO2)					-394.1***	-360.1***	-330.7***	-277.6***
					(13.80)	(12.42)	(12.08)	(18.27)
Dependent variable mean	14,441.0	14,441.0	14,441.0	14,441.0	14,441.0	14,441.0	14,441.0	14,441.0
R^2	0.62989	0.67026	0.72345	0.85442	0.62847	0.66922	0.72269	0.85410
Observations	104,344	104,344	104,344	104,344	104,344	104,344	104,344	104,344
Panel B: Median Natural Gas consumption (kWh)								
Realized Estimated Energy Savings (kWh)	-0.0773***	-0.0706***	-0.0642***	-0.0541***				
	(0.0029)	(0.0027)	(0.0025)	(0.0036)				
Realized Estimated Energy Savings (CO2)					-388.0***	-355.8***	-324.2***	-272.9***
					(14.86)	(13.61)	(13.05)	(18.99)
Dependent variable mean	13,469.8	13,469.8	13,469.8	13,469.8	13,469.8	13,469.8	13,469.8	13,469.8
R^2	0.62411	0.66326	0.71622	0.84975	0.62270	0.66222	0.71549	0.84944
Observations	104,344	104,344	104,344	104,344	104,344	104,344	104,344	104,344
Regressions Control for:								
Fixed Effect	LAD	MSOA	LSOA	OA	LAD	MSOA	LSOA	OA
Property characteristics	X	X	X	X	X	X	X	X
Property interacted with ...	Local Authority District (239 units)							

Notes: Table presents results from a regression studying to what extent measured changes in the energy efficiency of properties are correlated with lower energy consumption to document retrofitting effectiveness. The dependent variable is the mean or median of natural gas consumption of properties within a postcode in 2019 in Panel A and B. The estimating sample includes postcodes whose centroid lies within 2000m of a conservation area. Table 6 and Appendix Tables A5 and **??** documents, at the property-level, that properties in conservation areas have less retrofit measures carried out. This analysis is replicated at the postcode level and is shown in Appendix Table A11. Retrofitting is measured by comparing the difference in the estimated energy consumption (in kWh) in columns (1) - (3) or the estimated CO2 emissions in columns (4) - (6) for properties in a postcode that have at least two EPC certificates. Since the measure is only available for around 3 million properties (around 16% of the housing stock) we weight the regression by the share properties that are covered in the respective postcode. Unweighted results are presented in Appendix Table A15. Property characteristics captures the age, built form, the average floor area, the number of habitable rooms of properties in a postcode. 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 13: Impact of property-level retrofit on energy consumption in postcodes: empirical design leveraging matched pairs of postcodes that lie in- and outside conservation areas

	(1)	(2)	(3)	(4)	(5)	(6)
	Measuring retrofit uptake with the estimated change in EPC certificate stated ...					
	energy consumption (kWh)			*CO2 savings (t CO2)*		
Panel A: Mean Natural Gas consumption (kWh)						
Realized Estimated Energy Savings (kWh)	-0.0893***	-0.0800***	-0.0840***			
	(0.0103)	(0.0093)	(0.0072)			
Realized Estimated Energy Savings (CO2)				-415.2***	-406.9***	-410.7***
				(53.67)	(47.57)	(39.73)
Dependent variable mean			14,937.0			14,937.0
R^2	0.91151	0.91751	0.90245	0.91056	0.91724	0.90177
Observations	24,527	24,327	25,781	24,527	24,327	25,781
Panel B: Median Natural Gas consumption (kWh)						
Realized Estimated Energy Savings (kWh)	-0.0904***	-0.0763***	-0.0837***			
	(0.0108)	(0.0092)	(0.0071)			
Realized Estimated Energy Savings (CO2)				-419.2***	-384.0***	-409.8***
				(56.10)	(48.14)	(37.92)
Dependent variable mean			14,077.2			14,077.2
R^2	0.90781	0.91561	0.90210	0.90678	0.91529	0.90142
Observations	24,527	24,327	25,781	24,527	24,327	25,781
Additional controls:						
Matched Pair x Year FE	X	X	X	X	X	X
Matching Characteristics	X	X	X	X	X	X
Matching variables:						
Property Characteristics	X	X	X	X	X	X
Council Tax Band		X	X		X	X
Price Per Sqm Moments			X			X

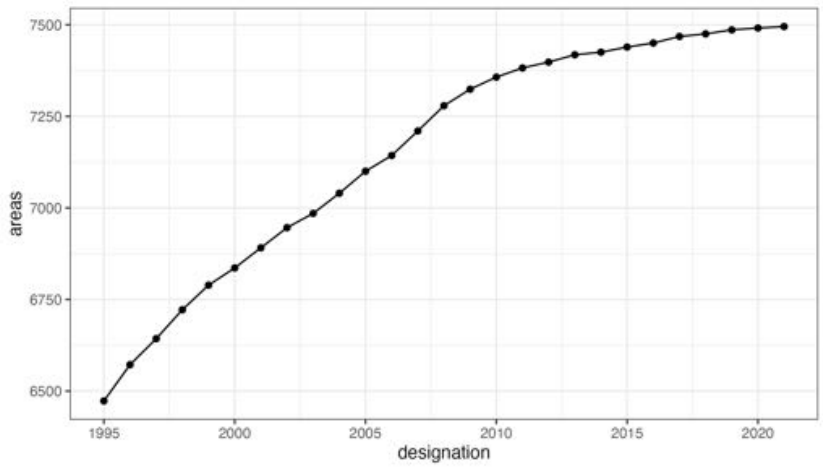
Notes: Table presents results from a regression studying to what extent measured changes in the energy efficiency of properties are correlated with lower energy consumption to document retrofitting effectiveness. The dependent variable is the mean or median of natural gas consumption of properties within a postcode in 2019 in Panel A and B. Matched pairs consist of postcodes that are similar in terms of their make-up of the physical housing stock, the council tax bands and the underlying empirical moments of the house prices. The set of matched pairs considered is the same as used in Table 10. Table 7 documents, at the property-level, that properties in conservation areas have less retrofit measures carried out. This analysis is replicated at the postcode level and is shown in Appendix Table A13. Retrofitting is measured by comparing the difference in the estimated energy consumption (in kWh) in columns (1) - (3) or the estimated CO2 emissions in columns (4) - (6) for properties in a postcode that have at least two EPC certificates. EPC certificates are typically valid for 10 years implying this provides a long difference. Since the measure is only available for around 4 million properties (around 16% of the housing stock) we weight the regression by the share properties that are covered in the respective postcode. Unweighted results are presented in Appendix Table A16. Only matched pairs whose propensity score difference is less than the 25% percentile of the propensity score are being retained in the estimation. 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 “Regulatory barriers to climate action: Evidence from Conservation Areas in England”

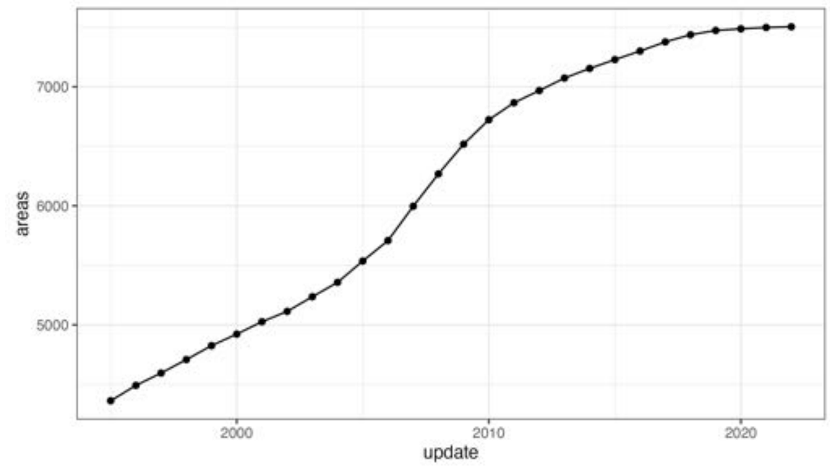
For Online Publication

Figure A1: Time series of number of conservation areas by year of designation and by year of update

Panel A: Designation



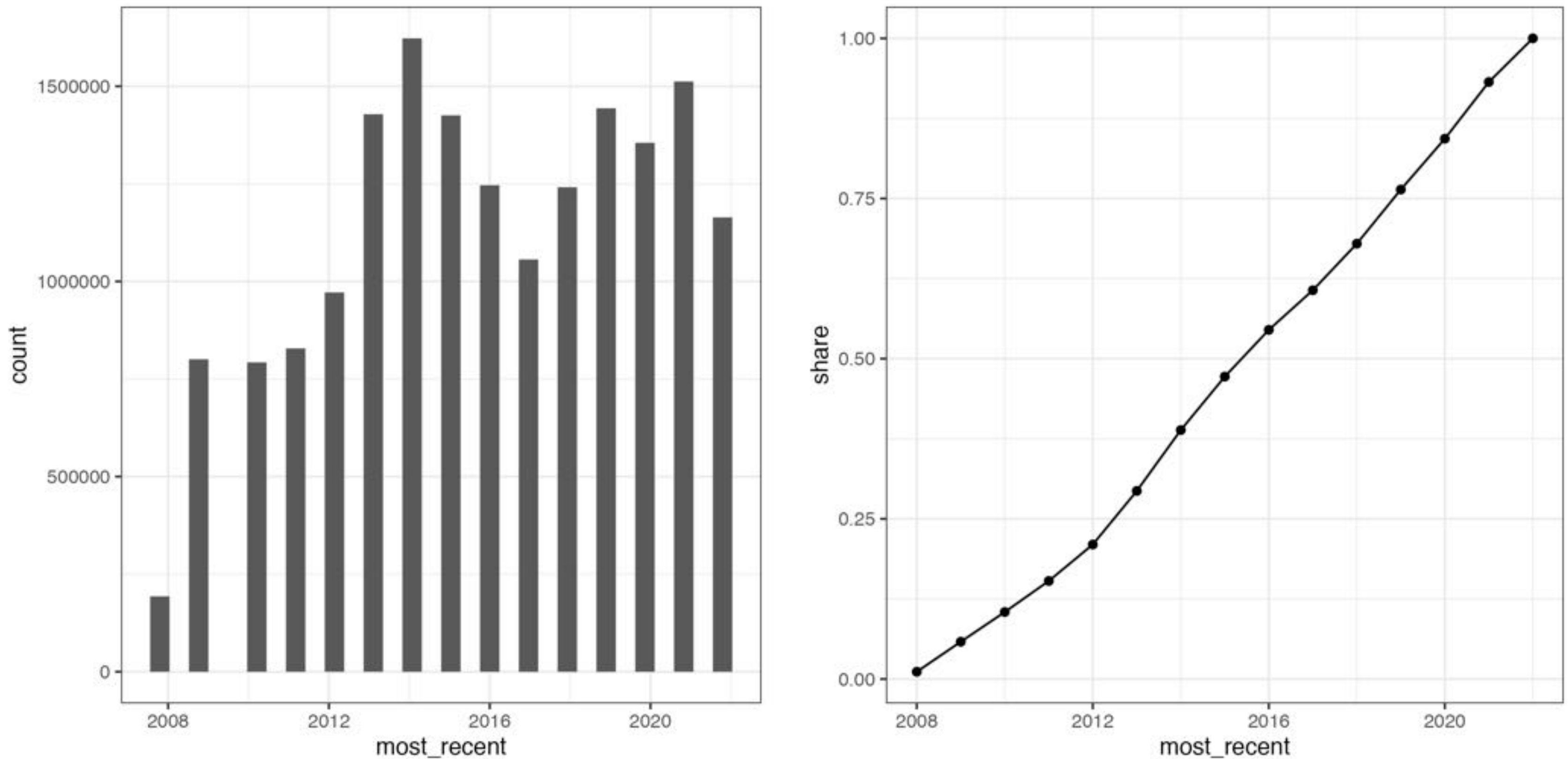
Panel B: Update



Notes: Left panel displays the number of conservation areas by year of designation among the population of conservation areas that have been identified. There has been a marginal addition of conservation areas on the extensive margin since 2008 when the EPC register was introduced. The right panel presents the number of conservation area designations or updates. This reveals that in the early 2000s there was a wave of updates of existing conservation area boundaries but in general there has been a fair bit of stability. In total 285 conservation areas have been newly designated and 1,508 have had an update since 2008.

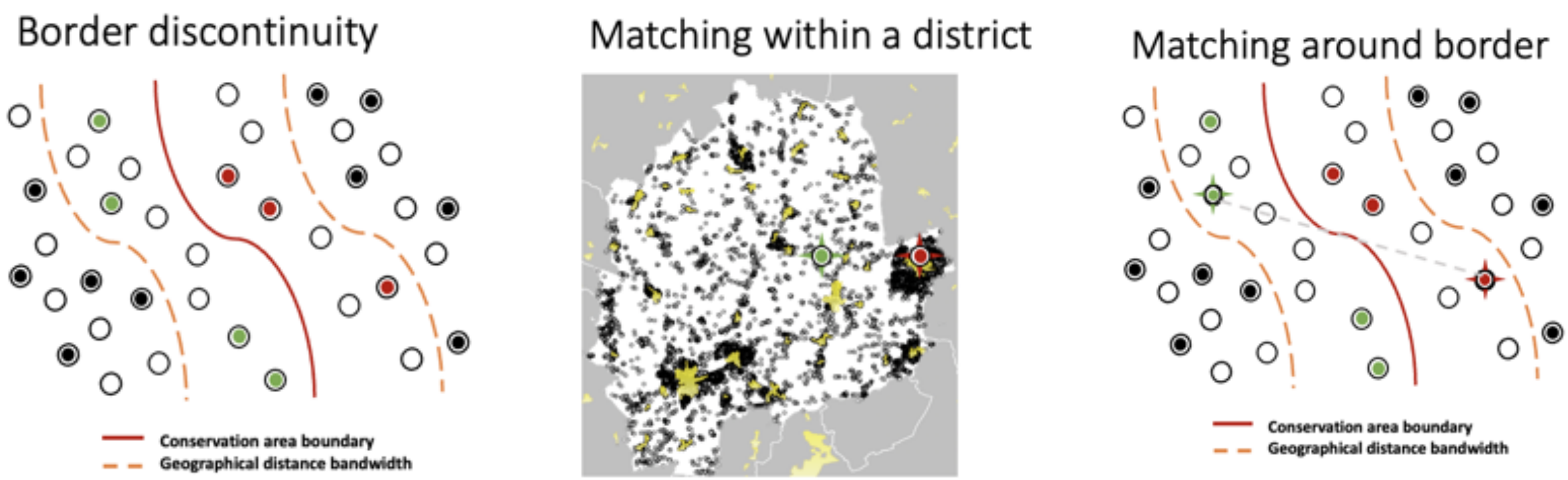
Figure A2: Visualization of age of stock of 17,082,698 EPC certificates covering unique properties

Panel A: Histogram *Panel B:* Cumulative Distribution



Notes: Figure displays tabulations and summary statistics of the stock of EPC properties in the data that is being used for the analysis. The left panel plots the histogram capturing the distribution of the year of most recent EPC certificate for each unique property. The right panel plots the cumulative distribution capturing the share of unique properties with an assessment year. This highlights that more than 50% of the properties in the data have an assessment that happened after 2016.

Figure A3: Visualization of three approaches to measuring the energy efficiency gap of properties inside conservation areas

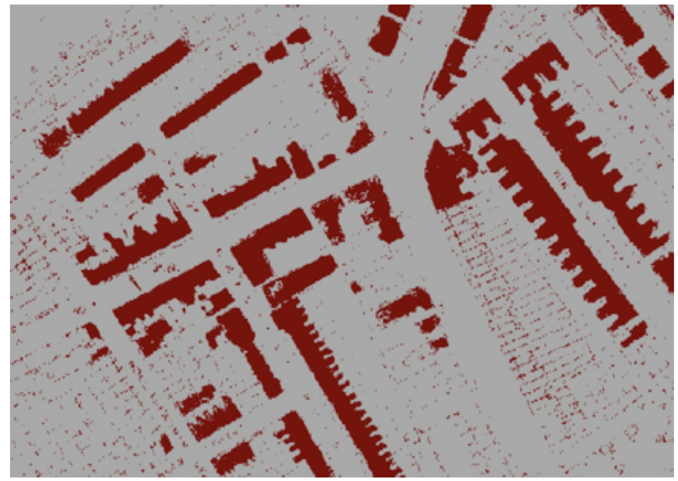


Notes: Figure provide stylized illustration of the three empirical approaches that are used in various forms throughout the paper. Hollow circles represent residential properties that exist. Filled circles are properties for which EPC certificates are available. Treatment properties are indicated with red. Control group circles are indicated with green color.

Figure A4: Visualization of bomb damage map classification and information extraction for instrumental variables exercise

Panel A: Raw image

Panel B: Classified image with stray pixels

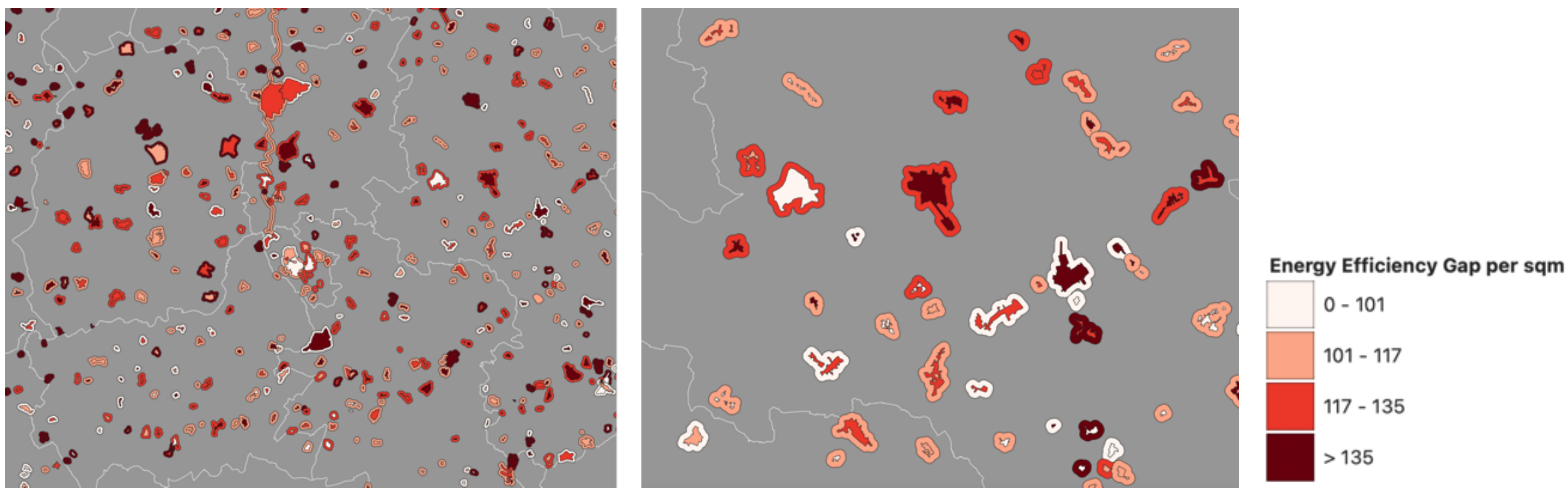


Panel C: Final image after kernel smoothing

Notes: Figure displays the processing steps of the raw image to classified final image to extract bomb damage information into a format that can be used econometrically. This leverages a random forest classifier that has been trained to pick up the color coding of the map. The result of that application is shown in Panel A, Panel B and Panel C. In Panel C the image from Panel B is reprocessed with a kernel smoothing technique to get rid of stray pixels. The underlying map data is the The London County Council Bomb Damage Maps: 1939-1945. The map is digitally available via the Layers of London project: `https://www.layersoflondon.org/map/overlays/bomb-damage-1945`.

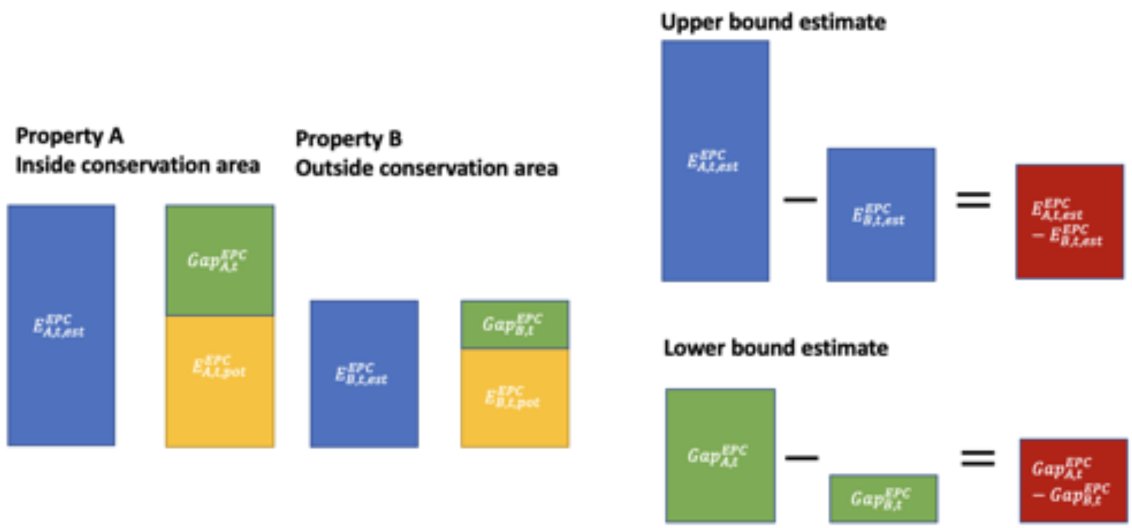
Figure A5: Illustration of energy efficiency gap as measured comparing energy efficiency inside- and outside conservation area boundary with 250 m bandwidth

Panel A: Coarse *Panel B:* Zoom in



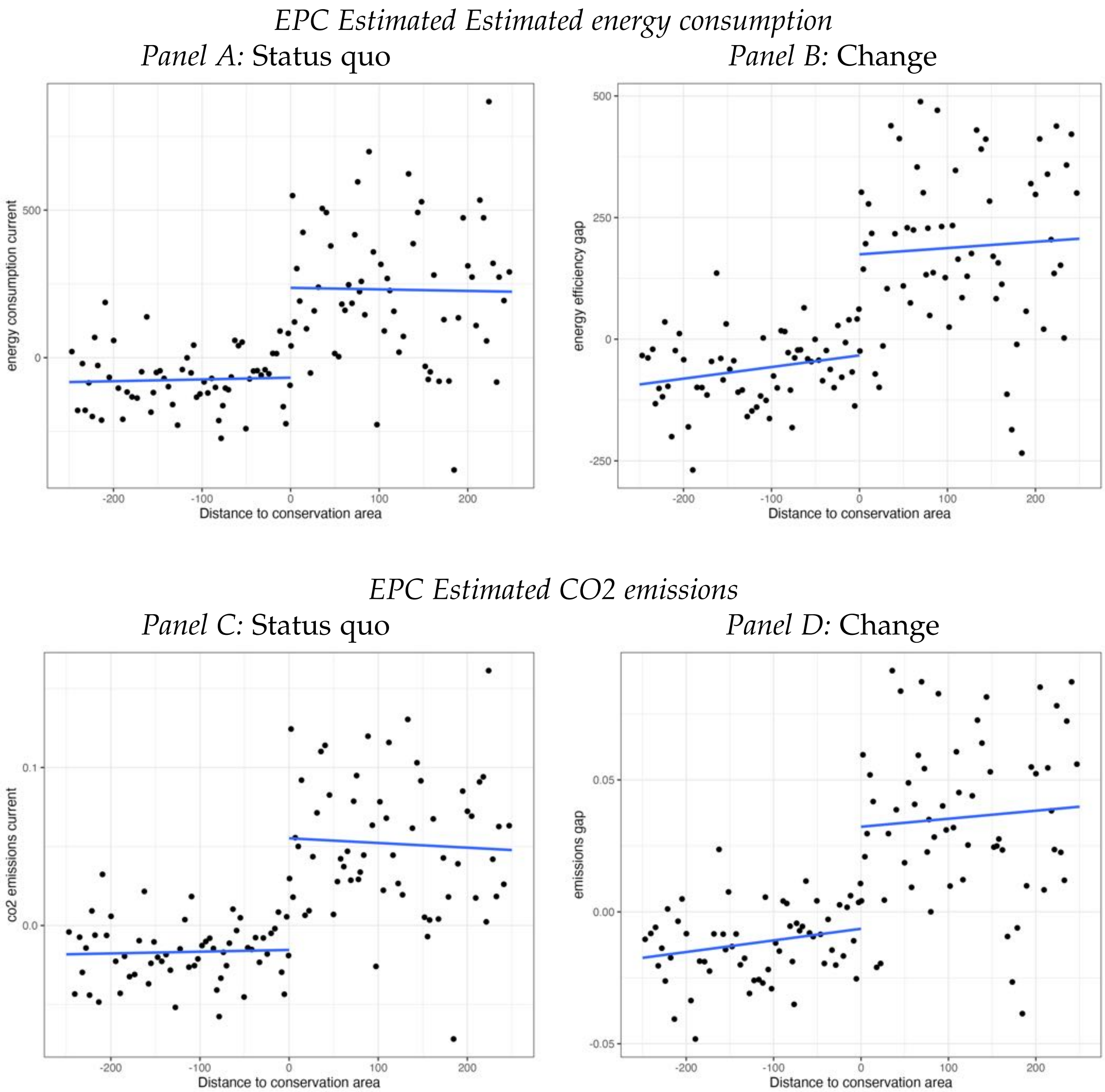
Notes: Map illustrates the regression around a conservation area boundary. Around each conservation area a 250 buffer polygon is drawn. For each property inside- and outside the conservation area, if it falls into the buffer of the nearest conservation area, I compute the energy efficiency gap in terms of kWh per square meter. The average is calculated and plotted across five groups. The pattern that emerges is that properties inside conservation areas, on average have a worse energy efficiency vis-a-vis properties outside. This design is further refined across a set of empirical exercises.

Figure A6: Illustration of the estimated differences of the energy efficiency gap derived from EPC data



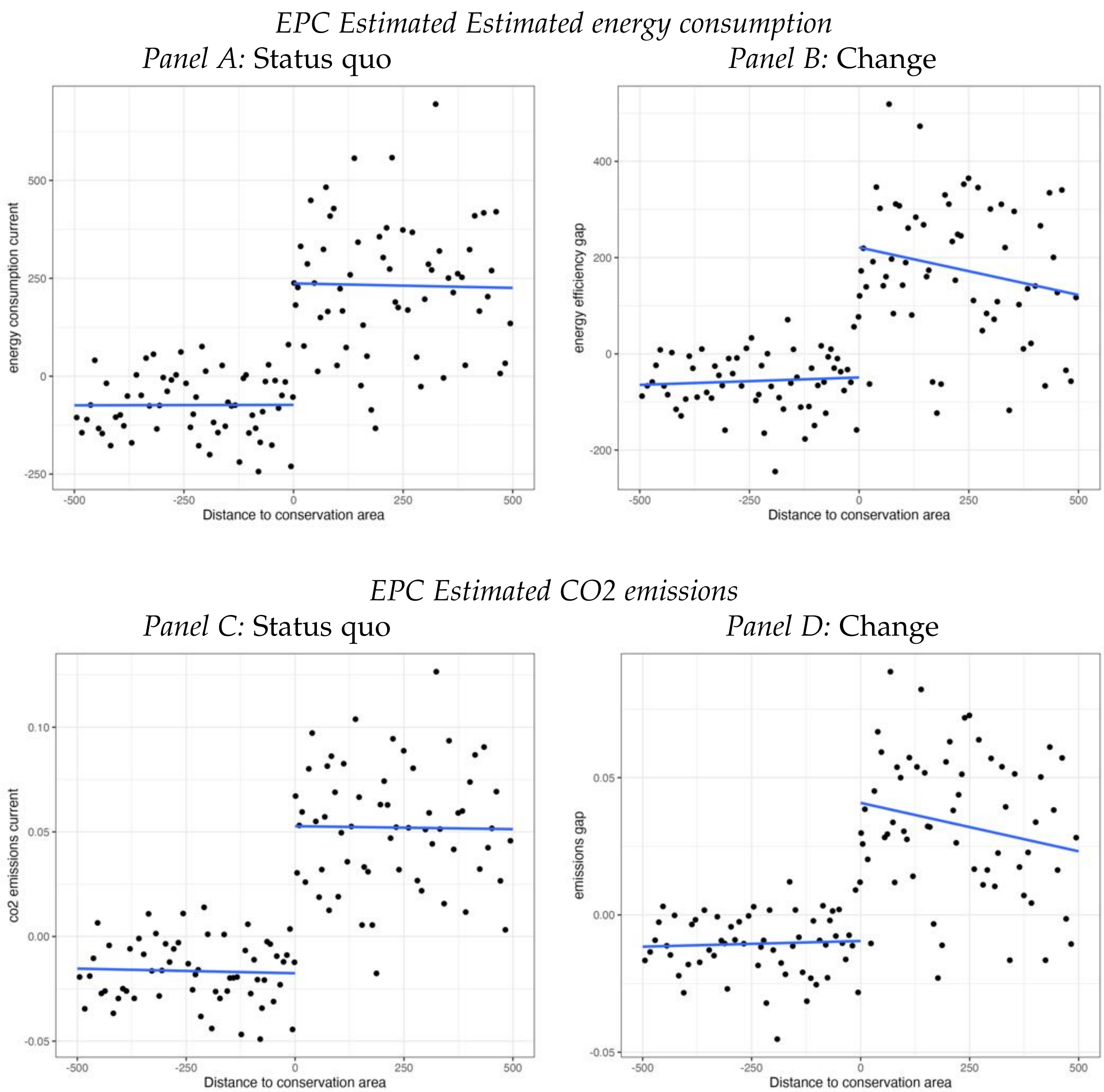
Notes: Figure provide stylized illustration of the estimated differences in the energy efficiency gap between properties inside- and outside conservation areas. The upper bound estimate of the energy efficieny gap is based on the difference in the estimated current energy consumption between a property inside- and outside a conservation area, while the lower bound is based on the difference in the gap between estimated- and potential energy efficiency.

Figure A7: Visualization of Regression Continuity Design Within 250m of Conservation Area Boundaries



Notes: Figure provides a visual representation of the estimation results presented from Appendix Table A3 column (4). The estimating sample includes properties that lie within 250m of a conservation area. Properties with a positive distance are *inside* a conservation area while properties outside have a negative signed distance.

Figure A8: Visualization of Regression Continuity Design Within 500m of Conservation Area Boundaries

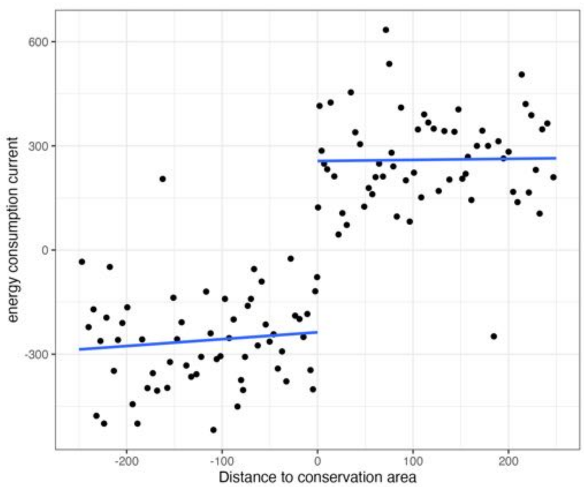


Notes: Figure provides a visual representation of the estimation results presented from Appendix Table 2 column (4). The estimating sample includes properties that lie within 500m of a conservation area. Properties with a positive distance are *inside* a conservation area while properties outside have a negative signed distance.

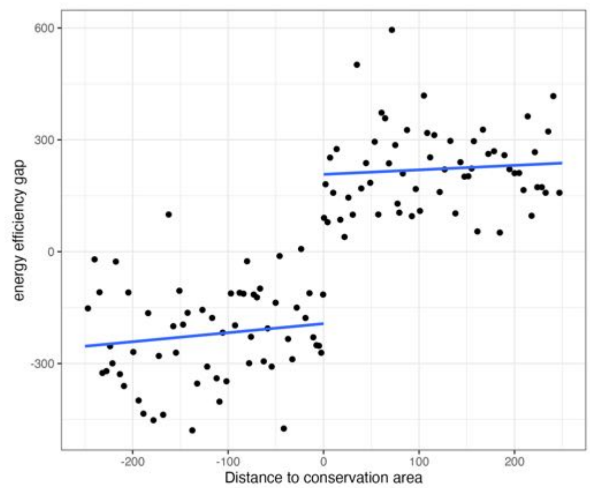
Figure A9: Visualization of Matched Regression Continuity Design Within 250m of of Conservation Area Boundaries

EPC Estimated Estimated energy consumption

Panel A: Status quo

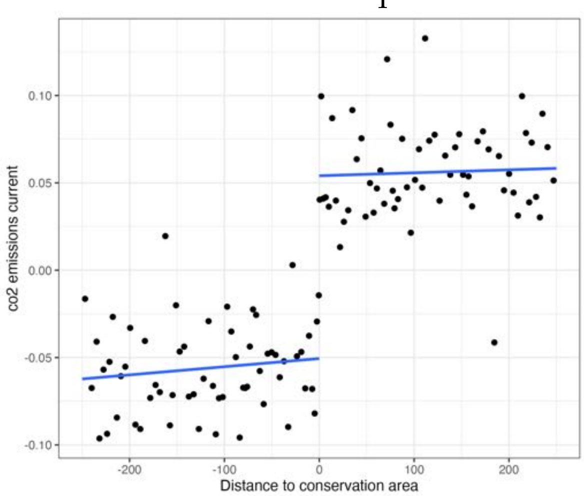


Panel B: Change

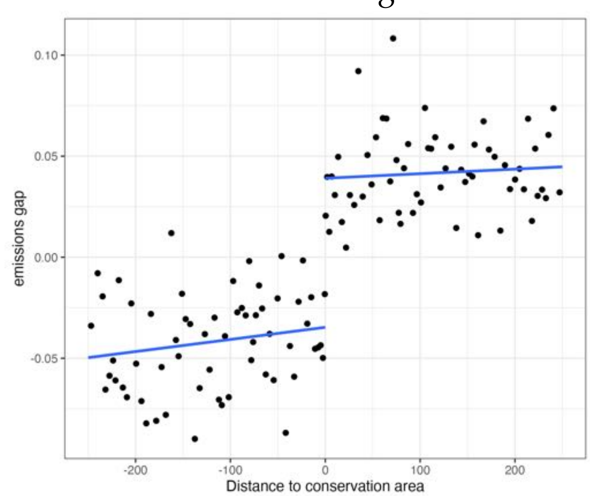


EPC Estimated CO2 emissions

Panel C: Status quo



Panel D: Change

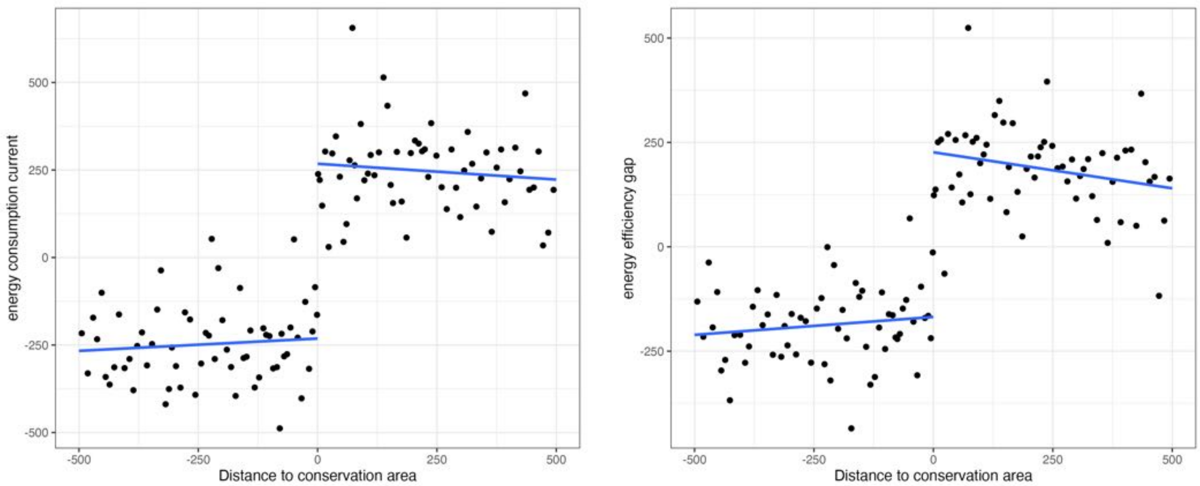


Notes: Figure provides a visual representation of the estimation results presented from Appendix Table 3 column (4). The estimating sample includes properties that lie within 250m of a conservation area. Properties with a positive distance are *inside* a conservation area while properties outside have a negative signed distance.

Figure A10: Visualization of Matched Regression Continuity Design Within 500m of Conservation Area Boundaries

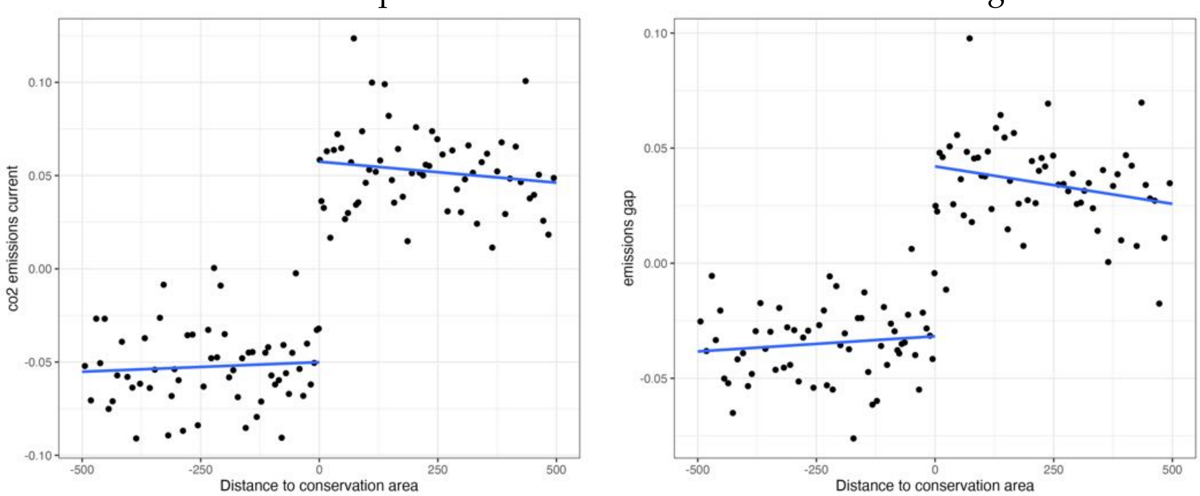
EPC Estimated Estimated energy consumption

Panel A: Status quo *Panel B:* Change



EPC Estimated CO2 emissions

Panel C: Status quo *Panel D:* Change

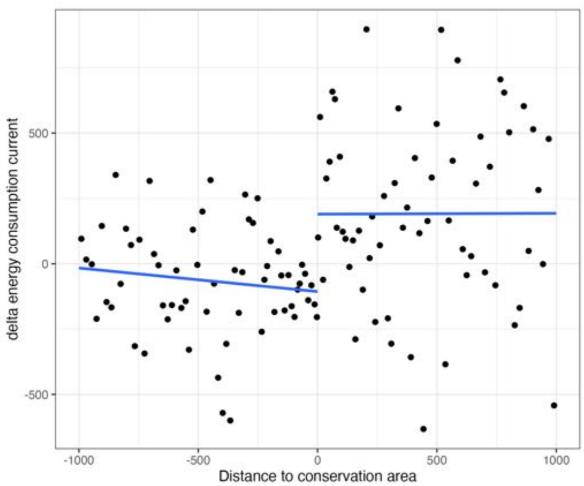


Notes: Figure provides a visual representation of the estimation results presented from Appendix Table 3 column (4). The estimating sample includes properties that lie within 500m of a conservation area. Properties with a positive distance are *inside* a conservation area while properties outside have a negative signed distance.

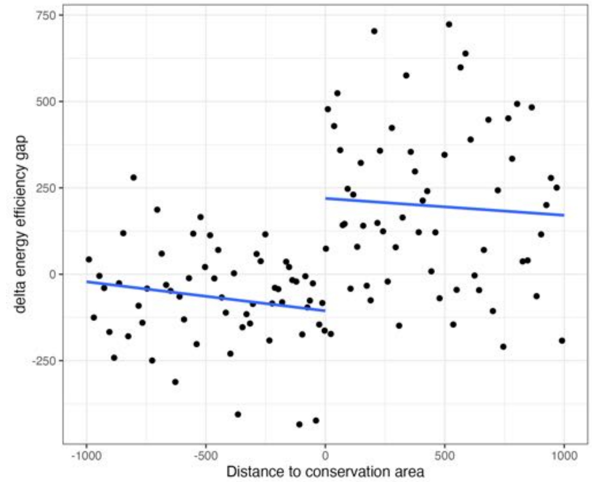
Figure A11: Studying *within-property changes* in estimated energy consumption: visualization of Regression Continuity Design Around Conservation Area Boundaries

Δ *EPC Estimated Energy*

Panel A: Energy consumption

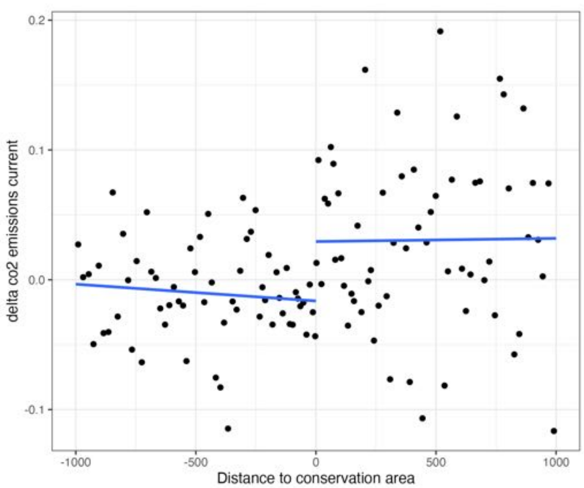


Panel B: Energy efficiency gap

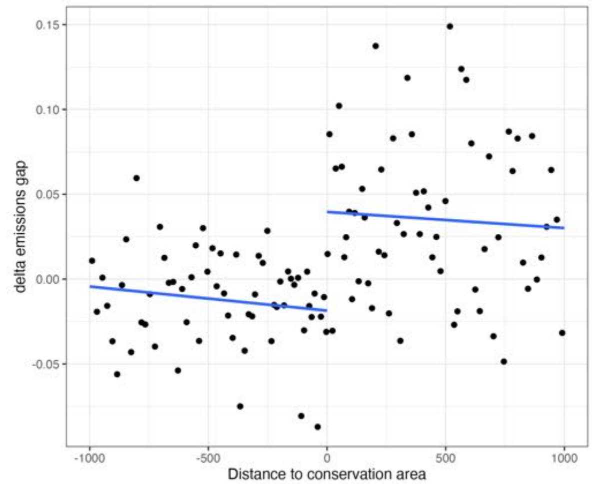


Δ *EPC Estimated CO2 Emissions*

Panel C: Emissions

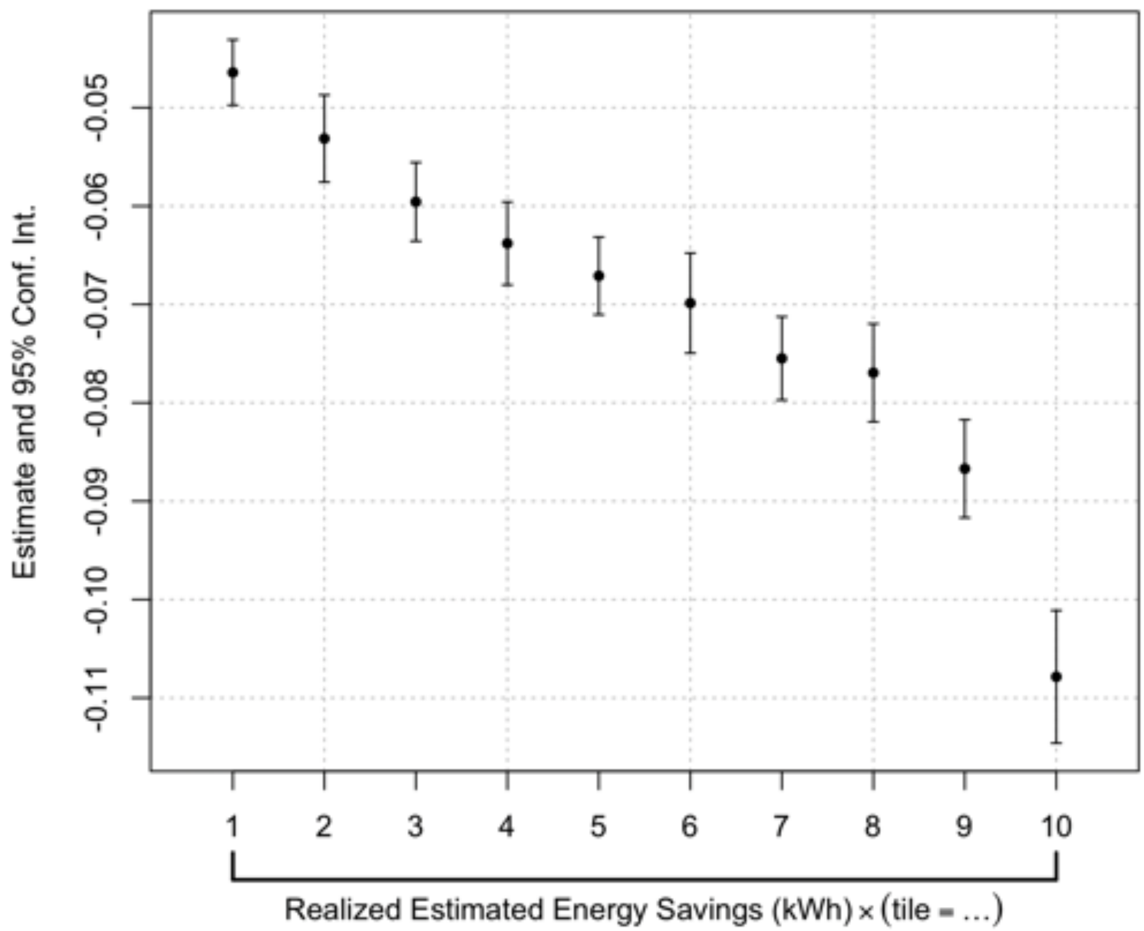


Panel D: Emissions gap



Notes: Figure provides a visual representation of the estimation results presented from Appendix Table A5 column (4). The estimating sample includes properties that lie within 1000m of a conservation area. Properties with a positive distance are *inside* a conservation area while properties outside have a negative signed distance.

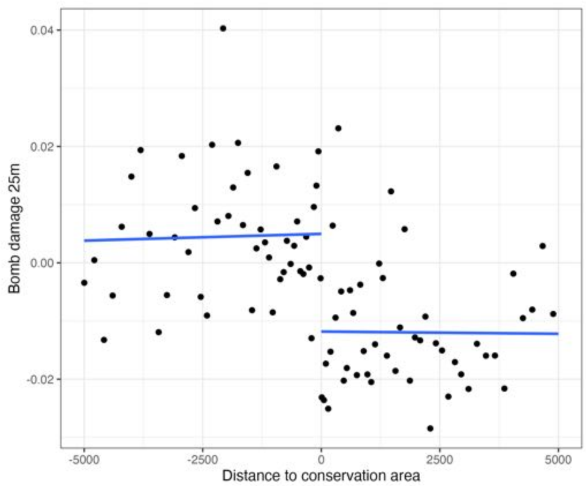
Figure A12: Noisy measures of retrofit activity owing to non-complete data coverage in the EPC records is inducing a downward bias in the estimates of the retrofit-proxy measure and energy consumption relationship



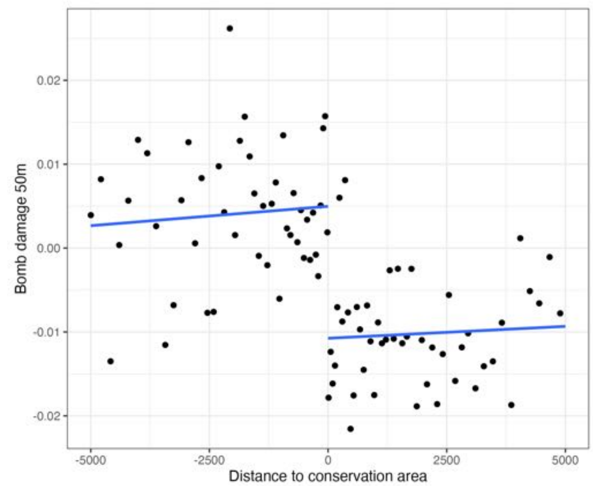
Notes: Figure plots a regression result studying the relationship between actual energy consumption measured as the mean postcode level natural gas consumption in 2019 and the estimated energy savings owing to retrofit measures that has been identified based on properties in said postcode that have multiple EPC certificates. Only 16% of the properties in my estimating sample have at least two EPC certificates implying that this measure is a noisy proxy for retrofit activity in a whole postcode. This should produce attenuation bias. The purpose of this regression is to show that the point estimate appears indeed downward biased by showing that in postcodes where the data coverage for the EPC is stronger, the estimated effect size is larger. The coefficients plotted capture an interaction effect between an indicator capturing whether a postcode is in the 1, ... 10th decile of the empirical distribution capturing the share of residential properties inside a postcode area for which there are at least two EPC certificates for which a change in the estimated energy consumption can be constructed. This is interacted with the estimate of the average change in estimated energy consumption that is estimated based on that sample in a postcode. The regression also controls for all controls included in column (1) of Table 11. 95% percentile confidence bands obtained from clustering standard errors at the district level are indicated.

Figure A13: Distribution of World War II bomb damage around conservation area boundaries in London

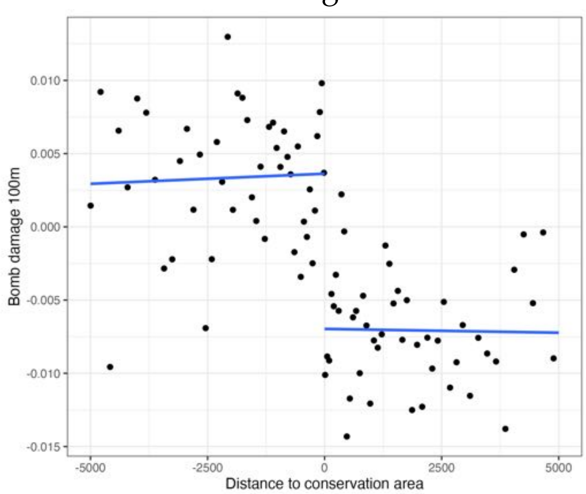
Panel A: Bomb damage within 25 m



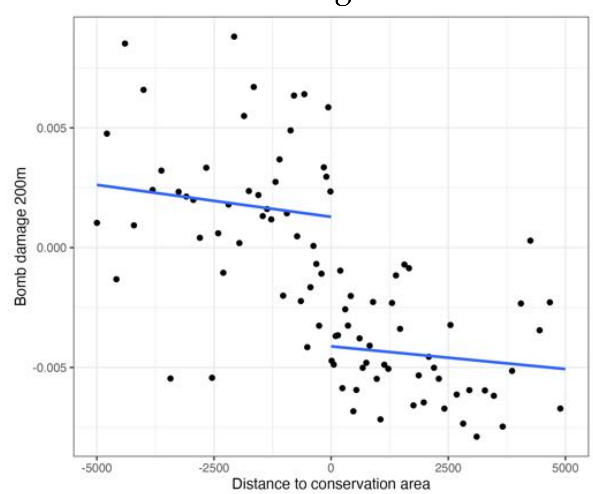
Panel B: Bomb damage within 50 m



Panel C: Bomb damage within 100 m



Panel D: Bomb damage within 200m



Notes: Figure provides a visual display of the variation in the WWII bomb damage intensity distribution around conservation area boundaries across conservation areas in London. We note that there is notably less WWII bomb damage, on average, around present day properties inside conservation areas compared to outside conservation areas. All properties fall within the built up area boundaries for which bomb damage data is available.

Table A1: Studying energy consumption and the energy efficiency gap in conservation areas

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: EPC Estimated Energy consumption (kWh)						
Inside Conservation Area	537.4***	667.5***	727.5***	684.2***	751.8***	682.8***
	(55.88)	(49.77)	(44.64)	(40.07)	(46.26)	(42.00)
Dependent variable mean	22,508.2	22,508.2	22,508.2	22,508.2	23,933.9	24,129.7
R^2	0.68636	0.70858	0.71854	0.71980	0.70823	0.72963
Observations	10,412,448	10,412,448	10,412,448	10,412,448	6,674,611	3,328,164
Panel B: EPC Estimated Energy efficiency gap (kWh)						
Inside Conservation Area	79.83**	209.5***	201.4***	181.6***	327.9***	373.5***
	(37.31)	(31.52)	(30.56)	(29.18)	(34.92)	(32.09)
Dependent variable mean	10,284.9	10,284.9	10,284.9	10,284.9	11,053.2	10,766.5
R^2	0.52163	0.54606	0.55916	0.56028	0.52892	0.55850
Observations	10,412,448	10,412,448	10,412,448	10,412,448	6,674,611	3,328,164
Panel C: EPC Estimated CO2 emissions (tonnes CO2)						
Inside Conservation Area	0.0961***	0.1328***	0.1451***	0.1343***	0.1508***	0.1406***
	(0.0098)	(0.0093)	(0.0086)	(0.0078)	(0.0092)	(0.0085)
Dependent variable mean	4.0965	4.0965	4.0965	4.0965	4.3478	4.3624
R^2	0.69831	0.72114	0.73035	0.73169	0.71479	0.72834
Observations	10,412,448	10,412,448	10,412,448	10,412,448	6,674,611	3,328,164
Panel D: EPC Estimated CO2 emissions gap (tonnes CO2)						
Inside Conservation Area	0.0087	0.0407***	0.0398***	0.0356***	0.0642***	0.0719***
	(0.0072)	(0.0057)	(0.0056)	(0.0053)	(0.0065)	(0.0059)
Dependent variable mean	1.8538	1.8538	1.8538	1.8538	1.9849	1.9279
R^2	0.53189	0.55931	0.57164	0.57268	0.53949	0.56322
Observations	10,412,448	10,412,448	10,412,448	10,412,448	6,674,611	3,328,164
Regression specification:						
Continuous Property Characteristics	X	X	X	X	X	X
Categorical Property Characteristics	Additive	Interactive	Interactive	Interactive	Interactive	Interactive
Census Tract FE			X	X	X	X
District x Council Tax Band FE				X	X	X
Property Value					X	X
Nearest Conservation Area FE						X

Notes: Table presents results from a border regression discontinuity design. Each observation refers to a unique property. The dependent variable measured at the property level is indicated in the panel heading from A-D. The regressions control for increasingly more demanding sets of control variables as we move across the columns. Not all control variables are available at the property level for all properties resulting in the sample size to shrink. Continuous property characteristics include the number of habitable rooms and the floor area in square meters. Categorical property characteristics include the property age, the property type, the built form, the tenure and the main heating fuel and whether the property is (in a) listed building. The features are included either additively or in interactive fashion. Census tracts refer to output areas which are statistical geographies with, on average, 100 households. Council tax bands refer to the level of local taxation for local public goods that are levied following tax bands based on property values. The underlying tax burden is specific to the council. Property values refer to the most recent price that was paid for a property as per HMRC's Price Paid dataset. In addition to the log value of the price paid in pounds the regression also controls for the year of the transaction as a fixed effect. Lastly, the fixed effect of the nearest conservation area is included. 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: Studying energy consumption and the energy efficiency gap *between properties within 1000m of a conservation area border*

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: EPC Estimated Energy consumption (kWh)						
Inside Conservation Area	436.8***	429.3***	771.2***	733.0***	820.2***	824.2***
	(80.73)	(63.15)	(59.84)	(57.27)	(66.97)	(69.13)
Dependent variable mean	22,555.2	22,555.2	22,555.2	22,555.2	24,187.2	24,187.2
R^2	0.68954	0.71336	0.75331	0.75516	0.75429	0.75590
Observations	1,269,227	1,269,227	1,269,227	1,269,227	804,630	804,630
Panel B: EPC Estimated Energy efficiency gap (kWh)						
Inside Conservation Area	370.8***	320.2***	356.8***	343.4***	448.5***	454.6***
	(39.67)	(35.53)	(38.74)	(37.62)	(49.20)	(50.21)
Dependent variable mean	9,810.4	9,810.4	9,810.4	9,810.4	10,696.0	10,696.0
R^2	0.53049	0.55684	0.60257	0.60462	0.59669	0.59942
Observations	1,269,227	1,269,227	1,269,227	1,269,227	804,630	804,630
Panel C: EPC Estimated CO2 emissions						
Inside Conservation Area	0.0921***	0.0954***	0.1594***	0.1483***	0.1694***	0.1700***
	(0.0147)	(0.0117)	(0.0116)	(0.0112)	(0.0126)	(0.0131)
Dependent variable mean	4.0778	4.0778	4.0778	4.0778	4.3774	4.3774
R^2	0.69163	0.71552	0.75473	0.75678	0.75201	0.75375
Observations	1,269,227	1,269,227	1,269,227	1,269,227	804,630	804,630
Panel D: EPC Estimated CO2 emissions gap (tonnes CO2)						
Inside Conservation Area	0.0657***	0.0597***	0.0691***	0.0657***	0.0877***	0.0887***
	(0.0070)	(0.0065)	(0.0072)	(0.0070)	(0.0091)	(0.0092)
Dependent variable mean	1.7605	1.7605	1.7605	1.7605	1.9171	1.9171
R^2	0.53536	0.56348	0.60843	0.61047	0.60134	0.60432
Observations	1,269,227	1,269,227	1,269,227	1,269,227	804,630	804,630
Regression specification:						
Continuous Property Characteristics	X	X	X	X	X	X
Categorical Property Characteristics	Additive	Interactive	Interactive	Interactive	Interactive	Interactive
Census Tract FE			X	X	X	X
District x Council Tax Band FE				X	X	X
Property Value					X	X
Nearest Conservation Area FE						X

Notes: Table presents results from a border regression discontinuity design. Each observation refers to a unique property. The dependent variable measured at the property level is indicated in the panel heading from A-D. The regressions control for increasingly more demanding sets of control variables as we move across the columns. Not all control variables are available at the property level for all properties resulting in the sample size to shrink. Continuous property characteristics include the number of habitable rooms and the floor area in square meters. Categorical property characteristics include the property age, the property type, the built form, the tenure and the main heating fuel and whether the property is (in a) listed building. The features are included either additively or in interactive fashion. Census tracts refer to output areas which are statistical geographies with, on average, 100 households. Council tax bands refer to the level of local taxation for local public goods that are levied following tax bands based on property values. The underlying tax burden is specific to the council. Property values refer to the most recent price that was paid for a property as per HMRC's Price Paid dataset. In addition to the log value of the price paid in pounds the regression also controls for the year of the transaction as a fixed effect. Lastly, the fixed effect of the nearest conservation area is included. 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: Studying energy consumption and the energy efficiency gap *between properties within 250m of a conservation area border*

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: EPC Estimated Energy consumption (kWh)						
Inside Conservation Area	419.5***	432.5***	806.3***	787.0***	805.8***	814.8***
	(92.06)	(74.30)	(88.86)	(87.87)	(97.46)	(103.0)
Dependent variable mean	22,553.1	22,553.1	22,553.1	22,553.1	24,167.6	24,167.6
R^2	0.69090	0.71697	0.78601	0.78894	0.79938	0.80283
Observations	414,016	414,016	414,016	414,016	262,788	262,788
Panel B: EPC Estimated Energy efficiency gap (kWh)						
Inside Conservation Area	404.2***	365.0***	426.2***	439.9***	523.6***	525.0***
	(48.36)	(43.09)	(66.71)	(66.61)	(81.67)	(84.87)
Dependent variable mean	9,815.5	9,815.5	9,815.5	9,815.5	10,683.3	10,683.3
R^2	0.53202	0.56107	0.65472	0.65852	0.67020	0.67558
Observations	414,016	414,016	414,016	414,016	262,788	262,788
Panel C: EPC Estimated CO2 emissions						
Inside Conservation Area	0.0887***	0.0969***	0.1691***	0.1613***	0.1745***	0.1755***
	(0.0166)	(0.0137)	(0.0179)	(0.0177)	(0.0197)	(0.0205)
Dependent variable mean	4.0777	4.0777	4.0777	4.0777	4.3743	4.3743
R^2	0.69220	0.71826	0.78645	0.78964	0.79640	0.79987
Observations	414,016	414,016	414,016	414,016	262,788	262,788
Panel D: EPC Estimated CO2 emissions gap (tonnes CO2)						
Inside Conservation Area	0.0726***	0.0692***	0.0858***	0.0874***	0.1069***	0.1072***
	(0.0086)	(0.0078)	(0.0127)	(0.0127)	(0.0155)	(0.0160)
Dependent variable mean	1.7616	1.7616	1.7616	1.7616	1.9151	1.9151
R^2	0.53720	0.56917	0.66172	0.66560	0.67689	0.68258
Observations	414,016	414,016	414,016	414,016	262,788	262,788
Regression specification:						
Certificate Year FE	X	X	X	X	X	X
Continuous Property Characteristics	X	X	X	X	X	X
Categorical Property Characteristics	Additive	Interactive	Interactive	Interactive	Interactive	Interactive
Census Tract FE			X	X	X	X
District x Council Tax Band FE				X	X	X
Property Value					X	X
Nearest Conservation Area FE						X

Notes: Table presents results from a border regression discontinuity design. Each observation refers to a unique property. The dependent variable measured at the property level is indicated in the panel heading from A-D. The regressions control for increasingly more demanding sets of control variables as we move across the columns. Not all control variables are available at the property level for all properties resulting in the sample size to shrink. Continuous property characteristics include the number of habitable rooms and the floor area in square meters. Categorical property characteristics include the property age, the property type, the built form, the tenure and the main heating fuel and whether the property is (in a) listed building. The features are included either additively or in interactive fashion. Census tracts refer to output areas which are statistical geographies with, on average, 100 households. Council tax bands refer to the level of local taxation for local public goods that are levied following tax bands based on property values. The underlying tax burden is specific to the council. Property values refer to the most recent price that was paid for a property as per HMRC's Price Paid dataset. In addition to the log value of the price paid in pounds the regression also controls for the year of the transaction as a fixed effect. Lastly, the fixed effect of the nearest conservation area is included. 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: Full sample analysis studying *within-property changes* in energy consumption and the energy efficiency gap in conservation areas

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: EPC Estimated Δ Energy consumption (kWh)						
Inside Conservation Area	533.8***	558.4***	644.5***	629.9***	686.6***	651.9***
	(73.13)	(67.08)	(72.90)	(69.51)	(72.43)	(73.84)
Dependent variable mean	-3,754.4	-3,754.4	-3,754.4	-3,754.4	-2,580.1	-2,635.1
R^2	0.52098	0.52921	0.55140	0.55236	0.55854	0.57460
Observations	2,977,510	2,977,510	2,977,510	2,977,510	1,918,591	1,001,888
Panel B: EPC Estimated Δ Energy efficiency gap (kWh)						
Inside Conservation Area	199.4***	244.7***	225.4***	215.0***	323.4***	347.1***
	(44.80)	(41.44)	(46.12)	(45.21)	(53.02)	(54.86)
Dependent variable mean	1,881.8	1,881.8	1,881.8	1,881.8	2,809.5	2,118.3
R^2	0.49289	0.50199	0.52729	0.52828	0.53008	0.54959
Observations	4,061,608	4,061,608	4,061,608	4,061,608	2,573,588	996,327
Panel C: EPC Estimated Δ CO2 emissions						
Inside Conservation Area	0.0848***	0.0966***	0.1094***	0.1068***	0.1251***	0.1225***
	(0.0124)	(0.0120)	(0.0131)	(0.0126)	(0.0131)	(0.0132)
Dependent variable mean	-0.59304	-0.59304	-0.59304	-0.59304	-0.38389	-0.44110
R^2	0.54727	0.55564	0.57629	0.57717	0.58123	0.59103
Observations	2,977,510	2,977,510	2,977,510	2,977,510	1,918,591	1,001,888
Panel D: EPC Estimated Δ CO2 emissions gap (tonnes CO2)						
Inside Conservation Area	0.0318***	0.0449***	0.0418***	0.0395***	0.0608***	0.0623***
	(0.0081)	(0.0074)	(0.0086)	(0.0085)	(0.0101)	(0.0104)
Dependent variable mean	0.32142	0.32142	0.32142	0.32142	0.48303	0.34606
R^2	0.49945	0.50908	0.53344	0.53438	0.53558	0.55021
Observations	4,061,608	4,061,608	4,061,608	4,061,608	2,573,588	996,327
Regression specification:						
Certificate Year	X	X	X	X	X	X
Continuous Property Characteristics	X	X	X	X	X	X
Categorical Property Characteristics	Additive	Interactive	Interactive	Interactive	Interactive	Interactive
Census Tract FE			X	X	X	X
District x Council Tax Band FE				X	X	X
Property Value					X	X
Nearest Conservation Area FE						X

Notes: Table presents results from a border regression discontinuity design. Each observation refers to a unique property. The regressions are not adjusted for weights. The dependent variable measured at the property level is indicated in the panel heading from A-D. The regressions control for increasingly more demanding sets of control variables as we move across the columns. Not all control variables are available at the property level for all properties resulting in the sample size to shrink. Continuous property characteristics include the number of habitable rooms and the floor area in square meters. Categorical property characteristics include the property age, the property type, the built form, the tenure and the main heating fuel and whether the property is (in a) listed building. The features are included either additively or in interactive fashion. Census tracts refer to output areas which are statistical geographies with, on average, 100 households. Council tax bands refer to the level of local taxation for local public goods that are levied following tax bands based on property values. The underlying tax burden is specific to the council. Property values refer to the most recent price that was paid for a property as per HMRC's Price Paid dataset. In addition to the log value of the price paid in pounds the regression also controls for the year of the transaction as a fixed effect. Lastly, the fixed effect of the nearest conservation area is included. 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: Studying *within-property changes* in energy consumption and the energy efficiency gap *between properties within 1000m of a conservation area border*

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: EPC Estimated Δ Energy consumption (kWh)						
Inside Conservation Area	394.5***	386.5***	816.3***	797.6***	998.2***	1,025.7***
	(118.9)	(96.83)	(138.8)	(138.7)	(164.7)	(172.0)
Dependent variable mean	-3,862.0	-3,862.0	-3,862.0	-3,862.0	-2,593.0	-2,593.0
R^2	0.51612	0.52889	0.62038	0.62343	0.65497	0.65999
Observations	383,476	383,476	383,476	383,476	243,980	243,980
Panel B: EPC Estimated Δ Energy efficiency gap						
Inside Conservation Area	430.4***	335.6***	413.3***	410.4***	567.7***	556.7***
	(64.01)	(58.51)	(90.45)	(89.86)	(110.1)	(115.8)
Dependent variable mean	1,128.8	1,128.8	1,128.8	1,128.8	2,004.8	2,004.8
R^2	0.48531	0.49879	0.59646	0.59979	0.63454	0.64012
Observations	377,988	377,988	377,988	377,988	240,753	240,753
Panel C: EPC Estimated Δ CO2 emissions (tons)						
Inside Conservation Area	0.0670***	0.0698***	0.1469***	0.1423***	0.1963***	0.2007***
	(0.0210)	(0.0173)	(0.0254)	(0.0256)	(0.0313)	(0.0331)
Dependent variable mean	-0.67254	-0.67254	-0.67254	-0.67254	-0.43483	-0.43483
R^2	0.53582	0.54795	0.63398	0.63688	0.66754	0.67234
Observations	383,476	383,476	383,476	383,476	243,980	243,980
Panel D: EPC Estimated Δ CO2 emissions gap (tons)						
Inside Conservation Area	0.0747***	0.0601***	0.0754***	0.0739***	0.1020***	0.0976***
	(0.0112)	(0.0105)	(0.0169)	(0.0168)	(0.0205)	(0.0213)
Dependent variable mean	0.17149	0.17149	0.17149	0.17149	0.32612	0.32612
R^2	0.48765	0.50097	0.59703	0.60027	0.63510	0.64074
Observations	377,988	377,988	377,988	377,988	240,753	240,753
Regression specification:						
Continuous Property Characteristics	X	X	X	X	X	X
Categorical Property Characteristics	Additive	Interactive	Interactive	Interactive	Interactive	Interactive
Census Tract FE			X	X	X	X
District x Council Tax Band FE				X	X	X
Property Value					X	X
Nearest Conservation Area FE						X

Notes: Table presents results from a border regression discontinuity design. Each observation refers to a unique property that has seen at least two EPC certificates. The dependent variable measures the changes in the property level energy efficiency measure between the most recent EPC certificate and the first EPC certificate that was issued for this property. The measure name is indicated in the panel heading from A-D. The regressions control for increasingly more demanding sets of control variables as we move across the columns. Not all control variables are available at the property level for all properties resulting in the sample size to shrink. Continuous property characteristics include the number of habitable rooms and the floor area in square meters. Categorical property characteristics include the property age, the property type, the built form, the tenure and the main heating fuel and whether the property is (in a) listed building. The features are included either additively or in interactive fashion. Census tracts refer to output areas which are statistical geographies with, on average, 100 households. Council tax bands refer to the level of local taxation for local public goods that are levied following tax bands based on property values. The underlying tax burden is specific to the council. Property values refer to the most recent price that was paid for a property as per HMRC's Price Paid dataset. In addition to the log value of the price paid in pounds the regression also controls for the year of the transaction as a fixed effect. Lastly, the fixed effect of the nearest conservation area is included. 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: Studying *within-property changes* in energy consumption and the energy efficiency gap *between properties within 250m of a conservation area border*

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: EPC Estimated Δ Energy consumption (kWh)						
Inside Conservation Area	377.6**	411.8***	816.9***	732.8**	783.3**	810.2**
	(154.5)	(131.2)	(286.3)	(294.7)	(327.8)	(345.0)
Dependent variable mean	-3,846.9	-3,846.9	-3,846.9	-3,846.9	-2,595.3	-2,595.3
R^2	0.51650	0.53370	0.71355	0.72092	0.76899	0.77855
Observations	125,429	125,429	125,429	125,429	80,043	80,043
Panel B: EPC Estimated Δ Energy efficiency gap						
Inside Conservation Area	485.9***	409.9***	514.0**	547.0***	743.2***	698.8***
	(78.21)	(74.00)	(200.3)	(208.2)	(214.9)	(235.2)
Dependent variable mean	1,104.2	1,104.2	1,104.2	1,104.2	1,931.1	1,931.1
R^2	0.48613	0.50435	0.70005	0.70776	0.75838	0.76844
Observations	123,347	123,347	123,347	123,347	78,862	78,862
Panel C: EPC Estimated Δ CO2 emissions						
Inside Conservation Area	0.0636**	0.0723***	0.1442**	0.1302**	0.1604**	0.1500**
	(0.0285)	(0.0246)	(0.0561)	(0.0585)	(0.0648)	(0.0673)
Dependent variable mean	-0.67144	-0.67144	-0.67144	-0.67144	-0.43668	-0.43668
R^2	0.53564	0.55220	0.72334	0.73046	0.77806	0.78698
Observations	125,429	125,429	125,429	125,429	80,043	80,043
Panel D: EPC Estimated Δ CO2 emissions gap						
Inside Conservation Area	0.0839***	0.0721***	0.0988***	0.1040***	0.1458***	0.1365***
	(0.0140)	(0.0138)	(0.0374)	(0.0393)	(0.0412)	(0.0439)
Dependent variable mean	0.16611	0.16611	0.16611	0.16611	0.31283	0.31283
R^2	0.48919	0.50714	0.70082	0.70834	0.76021	0.77018
Observations	123,347	123,347	123,347	123,347	78,862	78,862
Regression specification:						
Certificate Year FE	X	X	X	X	X	X
Continuous Property Characteristics	X	X	X	X	X	X
Categorical Property Characteristics	Additive	Interactive	Interactive	Interactive	Interactive	Interactive
Census Tract FE			X	X	X	X
District x Council Tax Band FE				X	X	X
Property Value					X	X
Nearest Conservation Area FE						X

Notes: Table presents results from a border regression discontinuity design. Each observation refers to a unique property that has seen at least two EPC certificates. The dependent variable measures the changes in the property level energy efficiency measure between the most recent EPC certificate and the first EPC certificate that was issued for this property. The measure name is indicated in the panel heading from A-D. The regressions control for increasingly more demanding sets of control variables as we move across the columns. Not all control variables are available at the property level for all properties resulting in the sample size to shrink. Continuous property characteristics include the number of habitable rooms and the floor area in square meters. Categorical property characteristics include the property age, the property type, the built form, the tenure and the main heating fuel and whether the property is (in a) listed building. The features are included either additively or in interactive fashion. Census tracts refer to output areas which are statistical geographies with, on average, 100 households. Council tax bands refer to the level of local taxation for local public goods that are levied following tax bands based on property values. The underlying tax burden is specific to the council. Property values refer to the most recent price that was paid for a property as per HMRC's Price Paid dataset. In addition to the log value of the price paid in pounds the regression also controls for the year of the transaction as a fixed effect. Lastly, the fixed effect of the nearest conservation area is included. 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: Studying *within-property changes* in energy consumption and the energy efficiency gap in conservation areas: exploiting quasi-exogenous variation in conservation area status due to historic WW2 bomb damage

	(1)	(2)	(3)	(4)	(5)
Panel A: EPC Estimated Δ Energy consumption (kWh)					
Inside Conservation Area	867.2	905.9	1,099.9	1,919.6	3,609.8
	(1,587.3)	(1,557.1)	(1,704.8)	(2,620.5)	(2,587.4)
Dependent variable mean	-4,543.4	-4,543.4	-4,813.5	-5,261.5	-5,223.1
F-test (1st stage), Inside Conservation Area	434.78	433.44	265.79	164.04	172.93
R^2	0.39572	0.40386	0.44313	0.47726	0.48694
Panel B: EPC Estimated Δ Energy efficiency gap					
Inside Conservation Area	2,498.7**	2,378.9**	1,484.1	2,725.9	2,843.4
	(1,226.6)	(1,181.3)	(1,308.0)	(2,165.0)	(1,954.9)
Dependent variable mean	2,343.1	2,343.1	2,463.7	2,684.3	2,767.4
F-test (1st stage), Inside Conservation Area	434.78	433.44	265.79	164.04	172.93
R^2	0.30108	0.31297	0.34482	0.40473	0.41753
Panel C: EPC Estimated Δ CO2 emissions (tons)					
Inside Conservation Area	0.7495	0.7771	0.7683	0.2167	0.5117
	(0.5099)	(0.5230)	(0.7977)	(0.5091)	(0.5184)
Dependent variable mean	-0.77612	-0.77612	-0.83662	-0.90281	-0.89753
F-test (1st stage), Inside Conservation Area	434.78	433.44	265.79	164.04	172.93
R^2	0.05637	0.05776	0.04727	0.44414	0.45368
Panel D: EPC Estimated Δ CO2 emissions gap					
Inside Conservation Area	0.5377**	0.5227**	0.3587	0.4429	0.4679
	(0.2456)	(0.2463)	(0.3004)	(0.3946)	(0.3687)
Dependent variable mean	0.41243	0.41243	0.42992	0.47263	0.48747
F-test (1st stage), Inside Conservation Area	434.78	433.44	265.79	164.04	172.93
R^2	0.19396	0.20193	0.20681	0.39052	0.40227
Observations	113,881	113,881	81,491	53,085	50,022
Instrumental variable:	World War II bomb damage within 50m of property				
Additional control variables:					
Certificate Year	X	X	X	X	X
Continuous Property Characteristics	X	X	X	X	X
Categorical Property Characteristics	Additive	Interactive	Interactive	Interactive	Interactive
District x Council Tax Band FE			X	X	X
Property Value				X	X
Nearest Conservation Area FE					X

Notes: Table presents results from an instrumental variables regression. A unit of observation is an EPC for a property that is located inside the historic county of London for which WWII bomb damage data is available. Each observation refers to a unique property that has seen at least two EPC certificates. The dependent variable measures the changes in the property level energy efficiency measure between the most recent EPC certificate and the first EPC certificate that was issued for this property. The measure name is indicated in the panel heading from A-D. The sample has been subsetted to only include properties that have been constructed *prior to World War II* and that survived the World War II bombings of London. The treatment of whether a property is located inside a *conservation area* is instrumented for by the bomb damage *within 50 m radius around a present day property*. This captures the fact that conservation area status requires a minimum density of properties with *character*, which is less likely if there has been notable war destruction in the vicinity. The regressions control for increasingly more demanding sets of control variables as we move across the columns. Not all control variables are available at the property level for all properties resulting in the sample size to shrink. Continuous property characteristics include the number of habitable rooms and the floor area in square meters. Categorical property characteristics include the property age, the property type, the built form, the tenure and the main heating fuel and whether the property is (in a) listed building. The features are included either additively or in interactive fashion. Council tax bands refer to the level of local taxation for local public goods that are levied following tax bands based on property values. The underlying tax burden is specific to the council. Property values refer to the most recent price that was paid for a property as per HMRC's Price Paid dataset. In addition to the log value of the price paid in pounds the regression also controls for the year of the transaction as a fixed effect. Lastly, the fixed effect of the nearest conservation area is included. 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: Studying postcode-level electricity consumption in conservation areas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Mean Electricity Gas consumption (kWh)									
Inside Conservation Area	103.9***	26.71	54.86***	-3.851	-50.56*	27.21***	-8.389	-46.75	-113.7***
	(29.28)	(28.88)	(1×10^{-5})	(23.05)	(27.25)	(1×10^{-5})	(22.89)	(31.30)	(1×10^{-5})
Dependent variable mean	3,719.1	3,719.1	3,719.1	3,719.1	3,719.1	3,719.1	3,719.1	3,719.1	3,719.1
R^2	0.31714	0.61326	0.94978	0.37979	0.70057	-7.8787	0.38997	0.74394	0.99453
Observations	553,512	553,512	553,512	553,512	553,512	553,512	553,486	553,486	553,486
Panel B: Median Electricity consumption (kWh)									
Inside Conservation Area	50.85**	-21.09	-14.55***	-37.84**	-85.03***	-49.63***	-34.04*	-72.25***	-158.5***
	(23.85)	(23.54)	(1×10^{-5})	(18.64)	(21.83)	(1×10^{-5})	(18.27)	(23.69)	(1×10^{-5})
Dependent variable mean	3,166.7	3,166.7	3,166.7	3,166.7	3,166.7	3,166.7	3,166.7	3,166.7	3,166.7
R^2	0.28244	0.59507	0.94080	0.33979	0.68281	-7.66×10^{23}	0.34882	0.72755	0.99519
Observations	553,512	553,512	553,512	553,512	553,512	553,512	553,486	553,486	553,486
Panel C: log(Total Electricity consumption (kWh))									
Inside Conservation Area	-0.0159**	-0.0214***	0.0097***	-0.0220***	-0.0291***	-0.0122***	-0.0296***	-0.0383***	-0.0941***
	(0.0073)	(0.0074)	(1×10^{-5})	(0.0069)	(0.0085)	(1×10^{-5})	(0.0070)	(0.0102)	(1×10^{-5})
Dependent variable mean	11.081	11.081	11.081	11.081	11.081	11.081	11.081	11.081	11.081
R^2	0.64761	0.78739	-1.28×10^{27}	0.65485	0.81970	-4.67×10^{27}	0.66135	0.84475	-29.951
Observations	553,512	553,512	553,512	553,512	553,512	553,512	553,486	553,486	553,486
Regression specification:									
Property Characteristics	X	X	X	X	X	X	X	X	X
Council Tax Band		X	X		X	X		X	X
Price Per Sqm Moments			X			X			X
Characteristics interacted with ...	Local Authority District (330 units)			MSOA (7200 units)			LSOA (32000 units)		

Notes: Table presents results from a regression. Each observation refers to a postcode by year observation for which natural gas energy consumption data is available. The data provides the mean, median and total electricity consumption in a postcode for 2013, 2015-2019 provided there are at least five meter readings available within a postcode. The dependent variable is either the mean (panel A), the median (panel B) or the log of total electricity consumption (panel C). Across the columns we add successively more demanding empirical specifications. The property characteristics capture the share of properties in the EPC data by property age, the property type, the built form, the tenure and the main heating fuel. Council tax band refers to the share of properties in the EPC data by their respective council tax band. The price per square meter moments is the mean, 10th, 25th, 50th, 75th and 90th percentile of the price paid per square meter for properties in the EPC data that have been matched to the price paid data. The features are interacted with local authority fixed-effects (columns 1-3), MSOA fixed effects (columns 4-6) or LSOA fixed effects (columns 7-9). This allows for the effect of these measures on the energy consumption to vary by location. 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: Impact of conservation area status on retrofit measures as proxied through data for which there are multiple EPC certificates per property: analysis at the postcode level weighted

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
			change in % rated as poor or very poor					*change in % with retrofit recommendation for*				*Photovoltaic*	
	kWh	CO2	Roof	Wall	Heat	Water	Windows	Roof	Wall	Boiler	Window	Rec	Inst
Panel A: LAD													
Inside Conservation Area	1,572.0***	0.1736***	0.0193***	0.1840***	0.0491***	0.0406***	0.1738***	-0.0098**	0.1156***	-0.0828***	0.1354***	-0.1955***	-0.0367***
	(187.7)	(0.0454)	(0.0045)	(0.0094)	(0.0047)	(0.0046)	(0.0066)	(0.0043)	(0.0085)	(0.0043)	(0.0064)	(0.0136)	(0.0025)
Dependent variable mean	-1,178.4	-0.05240	-0.00913	-0.04250	-0.06846	-0.07408	-0.10686	0.07879	0.16067	-0.08615	-0.00208	0.30088	0.06271
R^2	0.05046	0.06437	0.02981	0.06946	0.02675	0.03221	0.06754	0.01255	0.05450	0.02026	0.05126	0.12129	0.04060
Observations	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297
Panel B: MSOA													
Inside Conservation Area	1,101.5***	0.0907***	0.0217***	0.1618***	0.0342***	0.0254***	0.1490***	-0.0011	0.1071***	-0.0616***	0.1181***	-0.1300***	-0.0339***
	(134.2)	(0.0289)	(0.0039)	(0.0079)	(0.0034)	(0.0034)	(0.0051)	(0.0034)	(0.0070)	(0.0040)	(0.0050)	(0.0089)	(0.0021)
Dependent variable mean	-1,178.4	-0.05240	-0.00913	-0.04250	-0.06846	-0.07408	-0.10686	0.07879	0.16067	-0.08615	-0.00208	0.30088	0.06271
R^2	0.12733	0.16041	0.06401	0.14124	0.07513	0.08366	0.09506	0.03885	0.12260	0.05051	0.08252	0.19556	0.08259
Observations	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297
Panel C: LSOA													
Inside Conservation Area	1,145.3***	0.1052***	0.0262***	0.1595***	0.0228***	0.0123***	0.1377***	0.0037	0.1105***	-0.0491***	0.1102***	-0.0859***	-0.0340***
	(121.9)	(0.0261)	(0.0038)	(0.0079)	(0.0032)	(0.0034)	(0.0047)	(0.0034)	(0.0070)	(0.0042)	(0.0045)	(0.0078)	(0.0022)
Dependent variable mean	-1,178.4	-0.05240	-0.00913	-0.04250	-0.06846	-0.07408	-0.10686	0.07879	0.16067	-0.08615	-0.00208	0.30088	0.06271
R^2	0.20165	0.23939	0.11787	0.21672	0.14476	0.15175	0.14298	0.08933	0.19770	0.10377	0.13736	0.27728	0.14198
Observations	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297
Panel D: OA													
Inside Conservation Area	1,158.5***	0.1353***	0.0307***	0.1674***	0.0165***	0.0061	0.1296***	0.0109***	0.1206***	-0.0405***	0.1036***	-0.0609***	-0.0318***
	(123.2)	(0.0234)	(0.0040)	(0.0080)	(0.0036)	(0.0041)	(0.0052)	(0.0037)	(0.0073)	(0.0043)	(0.0047)	(0.0067)	(0.0020)
Dependent variable mean	-1,178.4	-0.05240	-0.00913	-0.04250	-0.06846	-0.07408	-0.10686	0.07879	0.16067	-0.08615	-0.00208	0.30088	0.06271
R^2	0.38728	0.42255	0.29400	0.40406	0.33983	0.34362	0.31496	0.26644	0.38881	0.28508	0.31496	0.47121	0.32099
Observations	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297

Notes: Table presents results from a regression. Each observation refers to a postcode in 2019. The dependent variables move across the columns and capture the changes in the dependent variable as measured through the EPC certificate data aggregated at the postcode level. The underlying sample of EPC certificates is those studied in Table 5 covering the population of properties for which we have at least two EPC certificates. We construct the changes within property over time across the certificates as a way to proxy retrofit measures. The data in this table is weighted by the % of properties in the postcode that is covered in this sample. The regressions control for different sets of fixed effects moving across panels. Panel A include district FE, Panel B includes MSOA FE, Panel C includes LSOA fixed effects while Panel D includes Output Area fixed effects. Columns (1) and (2) measure the changes in the EPC estimated energy- and CO2 consumption of the properties across certificates within a postcode. Columns (3) - (7) measures the share of properties in the sample with multiple EPCs that has seen a change in the evaluation whether their respective roof, walls,... and windows are considered poor or very poor from an energy efficiency standpoint. Columns (8) - (11) studies the change in the share of properties that has recommendations to improve their roof, walls,...windows. A negative number here indicates that retrofit changes may have been done resulting in fewer recommendations of such measures. Column (12) and (13) focus specifically on PV recommendations and installations Standard errors provided in parentheses are clustered at the district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.

Table A10: Impact of conservation area status on retrofit measures as proxied through data for which there are multiple EPC certificates per property: analysis at the postcode level unweighted

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
			change in % rated as poor or very poor					*change in % with retrofit recommendation for*				*Photovoltaic*	
	kWh	CO2	Roof	Wall	Heat	Water	Windows	Roof	Wall	Boiler	Window	Rec	Inst
Panel A: LAD													
Inside Conservation Area	2,224.9***	0.3272***	0.0273***	0.2076***	0.0516***	0.0469***	0.1843***	-0.0032	0.1347***	-0.0862***	0.1453***	-0.1999***	-0.0376***
	(167.8)	(0.0413)	(0.0038)	(0.0094)	(0.0037)	(0.0038)	(0.0061)	(0.0037)	(0.0080)	(0.0039)	(0.0060)	(0.0123)	(0.0023)
Dependent variable mean	-1,178.4	-0.05240	-0.00913	-0.04250	-0.06846	-0.07408	-0.10686	0.07879	0.16067	-0.08615	-0.00208	0.30088	0.06271
R^2	0.03550	0.04608	0.01999	0.06353	0.02231	0.02645	0.05084	0.00716	0.04489	0.01569	0.03882	0.09691	0.02880
Observations	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297
Panel B: MSOA													
Inside Conservation Area	1,596.8***	0.2043***	0.0299***	0.1861***	0.0372***	0.0330***	0.1600***	0.0060*	0.1265***	-0.0654***	0.1280***	-0.1418***	-0.0354***
	(126.2)	(0.0272)	(0.0035)	(0.0081)	(0.0028)	(0.0031)	(0.0052)	(0.0031)	(0.0068)	(0.0036)	(0.0051)	(0.0080)	(0.0020)
Dependent variable mean	-1,178.4	-0.05240	-0.00913	-0.04250	-0.06846	-0.07408	-0.10686	0.07879	0.16067	-0.08615	-0.00208	0.30088	0.06271
R^2	0.09885	0.12499	0.04270	0.11953	0.05602	0.06354	0.07065	0.02519	0.09582	0.03564	0.05998	0.15276	0.05690
Observations	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297
Panel C: LSOA													
Inside Conservation Area	1,572.9***	0.2012***	0.0324***	0.1808***	0.0250***	0.0182***	0.1472***	0.0099***	0.1277***	-0.0534***	0.1191***	-0.0990***	-0.0348***
	(117.6)	(0.0250)	(0.0034)	(0.0077)	(0.0028)	(0.0030)	(0.0047)	(0.0031)	(0.0068)	(0.0035)	(0.0046)	(0.0067)	(0.0020)
Dependent variable mean	-1,178.4	-0.05240	-0.00913	-0.04250	-0.06846	-0.07408	-0.10686	0.07879	0.16067	-0.08615	-0.00208	0.30088	0.06271
R^2	0.16131	0.19178	0.08427	0.18028	0.10618	0.11344	0.10844	0.06435	0.15443	0.07541	0.10096	0.21596	0.10146
Observations	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297
Panel D: OA													
Inside Conservation Area	1,423.7***	0.1956***	0.0339***	0.1822***	0.0171***	0.0096***	0.1331***	0.0145***	0.1333***	-0.0438***	0.1075***	-0.0697***	-0.0323***
	(113.6)	(0.0218)	(0.0038)	(0.0072)	(0.0032)	(0.0036)	(0.0051)	(0.0034)	(0.0066)	(0.0037)	(0.0048)	(0.0056)	(0.0019)
Dependent variable mean	-1,178.4	-0.05240	-0.00913	-0.04250	-0.06846	-0.07408	-0.10686	0.07879	0.16067	-0.08615	-0.00208	0.30088	0.06271
R^2	0.32773	0.35588	0.24428	0.34588	0.26997	0.27590	0.26152	0.22316	0.32376	0.23537	0.25780	0.38861	0.25855
Observations	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297	671,297

Notes: Table presents results from a regression. Each observation refers to a postcode in 2019. The dependent variables move across the columns and capture the changes in the dependent variable as measured through the EPC certificate data aggregated at the postcode level. The underlying sample of EPC certificates is those studied in Table 5 covering the population of properties for which we have at least two EPC certificates. We construct the changes within property over time across the certificates as a way to proxy retrofit measures. The data in this table is unweighted. The regressions control for different sets of fixed effects moving across panels. Panel A include district FE, Panel B includes MSOA FE, Panel C includes LSOA fixed effects while Panel D includes Output Area fixed effects. Columns (1) and (2) measure the changes in the EPC estimated energy- and CO2 consumption of the properties across certificates within a postcode. Columns (3) - (7) measures the share of properties in the sample with multiple EPCs that has seen a change in the evaluation whether their respective roof, walls,... and windows are considered poor or very poor from an energy efficiency standpoint. Columns (8) - (11) studies the change in the share of properties that has recommendations to improve their roof, walls,...windows. A negative number here indicates that retrofit changes may have been done resulting in fewer recommendations of such measures. Column (12) and (13) focus specifically on PV recommendations and installations Standard errors provided in parentheses are clustered at the district level with stars indicating *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A11: Impact of conservation area status on retrofit measures as proxied through data for which there are multiple EPC certificates per property: analysis at the postcode level including postcodes that are within 2000 m of a conservation area

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
			change in % rated as poor or very poor					*change in % with retrofit recommendation for*				*Photovoltaic*	
	kWh	CO2	Roof	Wall	Heat	Water	Windows	Roof	Wall	Boiler	Window	Rec	Inst
Panel A: LAD													
Inside Conservation Area	2,051.1***	0.3618***	0.0144***	0.1581***	0.0515***	0.0495***	0.1694***	-0.0022	0.0996***	-0.0527***	0.1352***	-0.1435***	-0.0259***
	(196.3)	(0.0421)	(0.0052)	(0.0102)	(0.0042)	(0.0051)	(0.0065)	(0.0049)	(0.0094)	(0.0046)	(0.0066)	(0.0130)	(0.0019)
Dependent variable mean	-1,086.0	-0.11350	-0.00170	0.01655	-0.05865	-0.07592	-0.06408	0.06728	0.19529	-0.13044	0.02717	0.19767	0.04788
R^2	0.06470	0.07047	0.03497	0.07494	0.02540	0.02660	0.10598	0.01630	0.05689	0.02132	0.08358	0.15535	0.03685
Observations	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974
Panel B: MSOA													
Inside Conservation Area	1,770.2***	0.2855***	0.0246***	0.1674***	0.0413***	0.0349***	0.1566***	0.0053	0.1128***	-0.0475***	0.1250***	-0.1196***	-0.0293***
	(165.7)	(0.0338)	(0.0048)	(0.0099)	(0.0042)	(0.0054)	(0.0059)	(0.0044)	(0.0084)	(0.0051)	(0.0061)	(0.0103)	(0.0022)
Dependent variable mean	-1,086.0	-0.11350	-0.00170	0.01655	-0.05865	-0.07592	-0.06408	0.06728	0.19529	-0.13044	0.02717	0.19767	0.04788
R^2	0.15821	0.18136	0.09485	0.16474	0.10930	0.10905	0.16194	0.07173	0.14558	0.07894	0.14083	0.26122	0.11124
Observations	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974
Panel C: LSOA													
Inside Conservation Area	1,942.0***	0.3110***	0.0316***	0.1819***	0.0311***	0.0208***	0.1528***	0.0098**	0.1244***	-0.0415***	0.1219***	-0.0880***	-0.0302***
	(166.3)	(0.0331)	(0.0046)	(0.0100)	(0.0042)	(0.0054)	(0.0056)	(0.0045)	(0.0086)	(0.0052)	(0.0058)	(0.0096)	(0.0024)
Dependent variable mean	-1,086.0	-0.11350	-0.00170	0.01655	-0.05865	-0.07592	-0.06408	0.06728	0.19529	-0.13044	0.02717	0.19767	0.04788
R^2	0.27743	0.30395	0.20400	0.28394	0.24063	0.23148	0.26196	0.17403	0.26593	0.18834	0.24617	0.38246	0.22506
Observations	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974
Panel D: OA													
Inside Conservation Area	1,772.9***	0.2931***	0.0386***	0.1866***	0.0229***	0.0108	0.1369***	0.0127**	0.1323***	-0.0290***	0.1106***	-0.0741***	-0.0289***
	(198.2)	(0.0388)	(0.0062)	(0.0102)	(0.0051)	(0.0066)	(0.0068)	(0.0062)	(0.0097)	(0.0072)	(0.0068)	(0.0091)	(0.0030)
Dependent variable mean	-1,086.0	-0.11350	-0.00170	0.01655	-0.05865	-0.07592	-0.06408	0.06728	0.19529	-0.13044	0.02717	0.19767	0.04788
R^2	0.55985	0.57910	0.49412	0.57224	0.53745	0.52848	0.53135	0.47223	0.55841	0.48221	0.52151	0.64582	0.52040
Observations	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974

Notes: Table presents results from a regression. Each observation refers to a postcode in 2019 that lies within 2000 m of the nearest conservation area boundary. The dependent variables move across the columns and capture the changes in the dependent variable as measured through the EPC certificate data aggregated at the postcode level. The underlying sample of EPC certificates is those studied in Table 5 covering the population of properties for which we have at least two EPC certificates. We construct the changes within property over time across the certificates as a way to proxy retrofit measures. The data in this table is unweighted. The regressions control for different sets of fixed effects moving across panels. Panel A include district FE, Panel B includes MSOA FE, Panel C includes LSOA fixed effects while Panel D includes Output Area fixed effects. Columns (1) and (2) measure the changes in the EPC estimated energy- and CO2 consumption of the properties across certificates within a postcode. Columns (3) - (7) measures the share of properties in the sample with multiple EPCs that has seen a change in the evaluation whether their respective roof, walls,... and windows are considered poor or very poor from an energy efficiency standpoint. Columns (8) - (11) studies the change in the share of properties that has recommendations to improve their roof, walls,...windows. A negative number here indicates that retrofit changes may have been done resulting in fewer recommendations of such measures. Column (12) and (13) focus specifically on PV recommendations and installations 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 A12: Impact of conservation area status on retrofit measures as proxied through data for which there are multiple EPC certificates per property: analysis at the postcode level including postcodes that are within 2000 m of a conservation area (unweighted)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
			change in % rated as poor or very poor					*change in % with retrofit recommendation for*				*Photovoltaic*	
	kWh	CO2	Roof	Wall	Heat	Water	Windows	Roof	Wall	Boiler	Window	Rec	Inst
Panel A: LAD													
Inside Conservation Area	2,431.3***	0.4522***	0.0189***	0.1798***	0.0572***	0.0582***	0.1798***	0.0035	0.1166***	-0.0590***	0.1438***	-0.1590***	-0.0280***
	(172.9)	(0.0383)	(0.0043)	(0.0103)	(0.0038)	(0.0047)	(0.0061)	(0.0040)	(0.0088)	(0.0042)	(0.0062)	(0.0114)	(0.0020)
Dependent variable mean	-1,086.0	-0.11350	-0.00170	0.01655	-0.05865	-0.07592	-0.06408	0.06728	0.19529	-0.13044	0.02717	0.19767	0.04788
R^2	0.04931	0.05422	0.02422	0.06986	0.02062	0.02250	0.08526	0.01040	0.04783	0.01778	0.06739	0.13662	0.02876
Observations	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974
Panel B: MSOA													
Inside Conservation Area	2,053.7***	0.3506***	0.0272***	0.1877***	0.0457***	0.0435***	0.1667***	0.0095**	0.1286***	-0.0543***	0.1332***	-0.1370***	-0.0313***
	(148.1)	(0.0301)	(0.0041)	(0.0098)	(0.0038)	(0.0045)	(0.0057)	(0.0038)	(0.0081)	(0.0047)	(0.0058)	(0.0090)	(0.0022)
Dependent variable mean	-1,086.0	-0.11350	-0.00170	0.01655	-0.05865	-0.07592	-0.06408	0.06728	0.19529	-0.13044	0.02717	0.19767	0.04788
R^2	0.12770	0.14572	0.07019	0.14196	0.07969	0.08234	0.13065	0.05310	0.11717	0.06180	0.11290	0.22241	0.08344
Observations	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974
Panel C: LSOA													
Inside Conservation Area	2,181.9***	0.3640***	0.0337***	0.1999***	0.0352***	0.0297***	0.1599***	0.0147***	0.1395***	-0.0497***	0.1290***	-0.1064***	-0.0319***
	(139.9)	(0.0278)	(0.0042)	(0.0096)	(0.0039)	(0.0043)	(0.0055)	(0.0040)	(0.0083)	(0.0048)	(0.0055)	(0.0082)	(0.0023)
Dependent variable mean	-1,086.0	-0.11350	-0.00170	0.01655	-0.05865	-0.07592	-0.06408	0.06728	0.19529	-0.13044	0.02717	0.19767	0.04788
R^2	0.23397	0.25486	0.16221	0.24284	0.18328	0.18233	0.21511	0.14152	0.21852	0.15308	0.20112	0.32546	0.17867
Observations	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974
Panel D: OA													
Inside Conservation Area	1,919.2***	0.3198***	0.0355***	0.1981***	0.0272***	0.0162***	0.1399***	0.0142**	0.1395***	-0.0377***	0.1137***	-0.0829***	-0.0302***
	(175.7)	(0.0349)	(0.0063)	(0.0095)	(0.0048)	(0.0057)	(0.0062)	(0.0057)	(0.0091)	(0.0066)	(0.0061)	(0.0076)	(0.0029)
Dependent variable mean	-1,086.0	-0.11350	-0.00170	0.01655	-0.05865	-0.07592	-0.06408	0.06728	0.19529	-0.13044	0.02717	0.19767	0.04788
R^2	0.51381	0.52899	0.45261	0.52377	0.47294	0.47116	0.48660	0.43549	0.50509	0.44237	0.47450	0.58854	0.47109
Observations	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974	122,974

Notes: Table presents results from a regression. Each observation refers to a postcode in 2019 that lies within 2000 m of the nearest conservation area boundary. The dependent variables move across the columns and capture the changes in the dependent variable as measured through the EPC certificate data aggregated at the postcode level. The underlying sample of EPC certificates is those studied in Table 5 covering the population of properties for which we have at least two EPC certificates. We construct the changes within property over time across the certificates as a way to proxy retrofit measures. The data in this table is unweighted. The regressions control for different sets of fixed effects moving across panels. Panel A include district FE, Panel B includes MSOA FE, Panel C includes LSOA fixed effects while Panel D includes Output Area fixed effects. Columns (1) and (2) measure the changes in the EPC estimated energy- and CO2 consumption of the properties across certificates within a postcode. Columns (3) - (7) measures the share of properties in the sample with multiple EPCs that has seen a change in the evaluation whether their respective roof, walls,... and windows are considered poor or very poor from an energy efficiency standpoint. Columns (8) - (11) studies the change in the share of properties that has recommendations to improve their roof, walls,...windows. A negative number here indicates that retrofit changes may have been done resulting in fewer recommendations of such measures. Column (12) and (13) focus specifically on PV recommendations and installations 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 A13: Impact of conservation area status on retrofit measures as proxied through data for which there are multiple EPC certificates per property: analysis at the postcode level on sample of matched pairs of postcodes that lie either inside- or outside a conservation area

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
			change in % rated as poor or very poor					*change in % with retrofit recommendation for*				*Photovoltaic*	
	kWh	CO2	Roof	Wall	Heat	Water	Windows	Roof	Wall	Boiler	Window	Rec	Inst
Panel A: Property characteristics													
Inside Conservation Area	2,584.8***	0.4885***	0.0098	0.0469***	0.0101	0.0128	0.0590***	-0.0054	0.0284**	-0.0381***	0.0347***	0.0225**	-0.0056
	(376.1)	(0.0786)	(0.0094)	(0.0144)	(0.0069)	(0.0084)	(0.0071)	(0.0097)	(0.0115)	(0.0115)	(0.0072)	(0.0110)	(0.0045)
Dependent variable mean	-48.718	0.18401	-0.03001	-0.08496	-0.06647	-0.07190	-0.10663	0.06849	0.12564	-0.09467	-0.00376	0.33961	0.06284
R^2	0.69732	0.70095	0.69245	0.69975	0.70076	0.69494	0.70334	0.69327	0.70011	0.68851	0.69964	0.70883	0.68713
Observations	30,641	30,641	30,641	30,641	30,641	30,641	30,641	30,641	30,641	30,641	30,641	30,641	30,641
Panel B: Property characteristics and council tax													
Inside Conservation Area	1,858.0***	0.3400***	0.0037	0.0234*	0.0219***	0.0232***	0.0428***	-0.0068	0.0097	-0.0297***	0.0335***	0.0168	-0.0119***
	(328.3)	(0.0625)	(0.0092)	(0.0124)	(0.0066)	(0.0089)	(0.0078)	(0.0089)	(0.0125)	(0.0107)	(0.0067)	(0.0117)	(0.0045)
Dependent variable mean	-61.854	0.17768	-0.02600	-0.06091	-0.06584	-0.06870	-0.10807	0.06961	0.14534	-0.10078	-0.00894	0.32435	0.06203
R^2	0.69747	0.70201	0.69830	0.69922	0.68960	0.69218	0.68200	0.69688	0.69235	0.69293	0.67802	0.70344	0.69340
Observations	30,924	30,924	30,924	30,924	30,924	30,924	30,924	30,924	30,924	30,924	30,924	30,924	30,924
Panel C: Property characteristics, council tax and price-paid data													
Inside Conservation Area	1,851.9***	0.3092***	0.0124*	0.0394***	0.0068	0.0099	0.0418***	-0.0010	0.0161	-0.0468***	0.0244***	0.0167*	-0.0114***
	(304.5)	(0.0588)	(0.0074)	(0.0100)	(0.0062)	(0.0079)	(0.0062)	(0.0073)	(0.0105)	(0.0083)	(0.0053)	(0.0100)	(0.0034)
Dependent variable mean	-214.32	0.13759	-0.02355	-0.05770	-0.06200	-0.06580	-0.11033	0.06974	0.14847	-0.10016	-0.01195	0.30791	0.05959
R^2	0.64811	0.64690	0.64536	0.65280	0.63974	0.64288	0.63970	0.63717	0.64684	0.64205	0.63382	0.66223	0.65459
Observations	32,290	32,290	32,290	32,290	32,290	32,290	32,290	32,290	32,290	32,290	32,290	32,290	32,290

Notes: Table presents results from a regression. Each observation refers to a postcode in 2019 that lies inside a conservation area that has been matched to a postcode that lies outside a conservation areas. The set of features on which matched pairs are constructed on varies across the Panels. Panel A matches on the share of properties by construction age, main heating fuel, the property type, the built form along with the floor area and the number of habitable rooms. Panel B adds the shares of properties by council tax band. Panel C adds the shares of properties by the 10, 25, median, 75 and 90th percentile of the price paid per square meter for properties that have been sold and are included in the price paid data by HMRC. The dependent variables move across the columns and capture the changes in the dependent variable as measured through the EPC certificate data aggregated at the postcode level. The underlying sample of EPC certificates is those studied in Table 5 covering the population of properties for which we have at least two EPC certificates. We construct the changes within property over time across the certificates as a way to proxy retrofit measures. The data in this table is unweighted. The regressions control for district fixed effects and matched pair identifier. Only matched pairs whose propensity score difference is less than the 25th percentile of the distribution of propensity score differences are included in the sample. Columns (1) and (2) measure the changes in the EPC estimated energy- and CO2 consumption of the properties across certificates within a postcode. Columns (3) - (7) measures the share of properties in the sample with multiple EPCs that has seen a change in the evaluation whether their respective roof, walls,... and windows are considered poor or very poor from an energy efficiency standpoint. Columns (8) - (11) studies the change in the share of properties that has recommendations to improve their roof, walls,...windows. A negative number here indicates that retrofit changes may have been done resulting in fewer recommendations of such measures. Column (12) and (13) focus specifically on PV recommendations and installations 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 A14: Impact of property-level retrofit on energy consumption in postcodes: border regression discontinuity design leveraging data from postcodes that lie in- and outside conservation areas

	(1)	(2)	(3)	(4)	(5)	(6)
	Measuring retrofit uptake with the estimated change in EPC certificate stated ...					
	energy consumption (kWh)			*CO2 savings (t CO2)*		
Panel A: Mean Natural Gas consumption (kWh)						
Realized Estimated Energy Efficiency Savings (kWh)	-0.0661***	-0.0412***	-0.0392***			
	(0.0014)	(0.0014)	(0.0014)			
Realized Estimated Energy Efficiency Savings (CO2)				-327.1***	-202.7***	-193.3***
				(10.05)	(8.746)	(8.729)
Dependent variable mean	13,858.1	13,858.1	14,050.8	13,858.1	13,858.1	14,050.8
R^2	0.61087	0.69585	0.70642	0.60920	0.69517	0.70582
Observations	772,070	772,070	730,599	772,070	772,070	730,599
Panel B: Median Natural Gas consumption (kWh)						
Realized Estimated Energy Efficiency Savings (kWh)	-0.0637***	-0.0400***	-0.0383***			
	(0.0015)	(0.0015)	(0.0015)			
Realized Estimated Energy Efficiency Savings (CO2)				-315.5***	-196.9***	-189.0***
				(10.27)	(9.008)	(9.049)
Dependent variable mean	13,063.4	13,063.4	13,264.1	13,063.4	13,063.4	13,264.1
R^2	0.60929	0.68896	0.69726	0.60773	0.68833	0.69668
Observations	772,070	772,070	730,599	772,070	772,070	730,599

Notes: Table presents results from a regression studying to what extent measured changes in the energy efficiency of properties are correlated with lower energy consumption to document retrofitting effectiveness. The dependent variable is the mean or median of natural gas consumption of properties within a postcode in 2019 in Panel A and B. The estimating sample includes all postcodes for which energy consumption data is available. Table 5 documents, at the property-level, that properties in conservation areas have less retrofit measures carried out. This analysis is replicated at the postcode level and is shown in Appendix Table A9. Retrofitting is measured by comparing the difference in the estimated energy consumption (in kWh) in columns (1) - (3) or the estimated CO2 emissions in columns (4) - (6) for properties in a postcode that have at least two EPC certificates. EPC certificates are typically valid for 10 years implying this provides a long difference. . Weighted results are presented in Table 11. Only matched pairs whose propensity score difference is less than the 25% percentile of the propensity score are being retained in the estimation. 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 A15: Impact of property-level retrofit on energy consumption in postcodes: border regression discontinuity design leveraging data from postcodes whose property centroids lie within 2000m of a conservation area

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Measuring retrofit uptake with the estimated change in EPC certificate stated ...							
	energy consumption (kWh)				*CO2 savings (t CO2)*			
Panel A: Mean Natural Gas consumption (kWh)								
Realized Estimated Energy Savings (kWh)	-0.0594***	-0.0547***	-0.0512***	-0.0456***				
	(0.0021)	(0.0020)	(0.0021)	(0.0029)				
Realized Estimated Energy Savings (CO2)					-297.3***	-275.0***	-256.9***	-228.8***
					(11.36)	(10.82)	(10.93)	(15.84)
Dependent variable mean	14,441.0	14,441.0	14,441.0	14,441.0	14,441.0	14,441.0	14,441.0	14,441.0
R^2	0.64933	0.68394	0.72935	0.84888	0.64828	0.68316	0.72873	0.84858
Observations	104,344	104,344	104,344	104,344	104,344	104,344	104,344	104,344
Panel B: Median Natural Gas consumption (kWh)								
Realized Estimated Energy Savings (kWh)	-0.0580***	-0.0536***	-0.0497***	-0.0445***				
	(0.0023)	(0.0022)	(0.0022)	(0.0030)				
Realized Estimated Energy Savings (CO2)					-290.3***	-269.2***	-249.8***	-223.7***
					(12.04)	(11.59)	(11.82)	(16.34)
Dependent variable mean	13,469.8	13,469.8	13,469.8	13,469.8	13,469.8	13,469.8	13,469.8	13,469.8
R^2	0.64300	0.67649	0.72225	0.84464	0.64199	0.67573	0.72168	0.84437
Observations	104,344	104,344	104,344	104,344	104,344	104,344	104,344	104,344
Regressions Control for:								
Fixed Effect	LAD	MSOA	LSOA	OA	LAD	MSOA	LSOA	OA
Baseline EPC measures	X	X	X	X	X	X	X	X

Notes: Table presents results from a regression studying to what extent measured changes in the energy efficiency of properties are correlated with lower energy consumption to document retrofitting effectiveness. The dependent variable is the mean or median of natural gas consumption of properties within a postcode in 2019 in Panel A and B. The estimating sample includes postcodes whose centroid lies within 2000m of a conservation area. Table 6 and Appendix Tables A5 and **??** documents, at the property-level, that properties in conservation areas have less retrofit measures carried out. This analysis is replicated at the postcode level and is shown in Appendix Table A11. Retrofitting is measured by comparing the difference in the estimated energy consumption (in kWh) in columns (1) - (3) or the estimated CO2 emissions in columns (4) - (6) for properties in a postcode that have at least two EPC certificates. EPC certificates are typically valid for 10 years implying this provides a long difference. Weighted results are presented in Table A11. Only matched pairs whose propensity score difference is less than the 25% percentile of the propensity score are being retained in the estimation. 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 A16: Impact of property-level retrofit on energy consumption in postcodes: empirical design leveraging matched pairs of postcodes that lie in- and outside conservation areas

	(1)	(2)	(3)	(4)	(5)	(6)
	Measuring retrofit uptake with the estimated change in EPC certificate stated ...					
	energy consumption (kWh)			*CO2 savings (t CO2)*		
Panel A: Mean Natural Gas consumption (kWh)						
Realized Estimated Energy Savings (kWh)	-0.0803***	-0.0688***	-0.0738***			
	(0.0083)	(0.0076)	(0.0063)			
Realized Estimated Energy Savings (CO2)				-369.0***	-347.0***	-357.2***
				(42.43)	(38.49)	(33.76)
Dependent variable mean			14,937.0			14,937.0
R^2	0.90009	0.90777	0.89263	0.89907	0.90744	0.89190
Observations	24,527	24,327	25,781	24,527	24,327	25,781
Panel B: Median Natural Gas consumption (kWh)						
Realized Estimated Energy Savings (kWh)	-0.0815***	-0.0658***	-0.0741***			
	(0.0088)	(0.0075)	(0.0063)			
Realized Estimated Energy Savings (CO2)				-375.0***	-327.8***	-360.5***
				(44.98)	(38.87)	(33.11)
Dependent variable mean			14,077.2			14,077.2
R^2	0.89632	0.90516	0.89100	0.89523	0.90478	0.89029
Observations	24,527	24,327	25,781	24,527	24,327	25,781
Additional controls:						
Matched Pair x Year FE	X	X	X	X	X	X
Matching Characteristics	X	X	X	X	X	X
Matching variables:						
Property Characteristics	X	X	X	X	X	X
Council Tax Band		X	X		X	X
Price Per Sqm Moments			X			X

Notes: Table presents results from a regression studying to what extent measured changes in the energy efficiency of properties are correlated with lower energy consumption to document retrofitting effectiveness. The dependent variable is the mean or median of natural gas consumption of properties within a postcode in 2019 in Panel A and B. Matched pairs consist of postcodes that are similar in terms of their make-up of the physical housing stock, the council tax bands and the underlying empirical moments of the house prices. The set of matched pairs considered is the same as used in Table 10. Table 7 documents, at the property-level, that properties in conservation areas have less retrofit measures carried out. This analysis is replicated at the postcode level and is shown in Appendix Table A13. Retrofitting is measured by comparing the difference in the estimated energy consumption (in kWh) in columns (1) - (3) or the estimated CO2 emissions in columns (4) - (6) for properties in a postcode that have at least two EPC certificates. EPC certificates are typically valid for 10 years implying this provides a long difference. Weighted results are presented in Appendix Table 13. Only matched pairs whose propensity score difference is less than the 25% percentile of the propensity score are being retained in the estimation. 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 A17: Impact of World War II destruction on whether a present day property is located inside a conservation areas

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable = 1 if a present day property is inside a conservation area					
Panel A:						
Bombing destruction < 25m	-0.1943***	-0.1745***	-0.1173***	-0.1599***	-0.1565***	-0.0618***
	(0.0396)	(0.0312)	(0.0236)	(0.0393)	(0.0368)	(0.0138)
Dependent variable mean	0.28491	0.28491	0.28491	0.28491	0.28491	0.28491
R^2	0.34277	0.52792	0.75769	0.23965	0.34786	0.96806
Observations	1,061,026	1,061,026	1,061,026	1,061,026	1,061,026	1,061,026
Panel B:						
Bombing destruction < 50 m	-0.3324***	-0.3086***	-0.2357***	-0.2721***	-0.2746***	-0.1658***
	(0.0641)	(0.0532)	(0.0409)	(0.0643)	(0.0617)	(0.0300)
Dependent variable mean	0.28491	0.28491	0.28491	0.28491	0.28491	0.28491
R^2	0.34438	0.52899	0.75811	0.24066	0.34885	0.96812
Observations	1,061,026	1,061,026	1,061,026	1,061,026	1,061,026	1,061,026
Area FE Type	Census geography			Postcode		
	MSOA	LSOA	OA	District	Sector	Full

Notes: The dependent variable is a binary indicator indicating whether a present day property is based inside a conservation area. The independent variable measures, at the property level, the extent of wartime destruction within a radius of 25 or 50 meter radius of the present day property. The focus is on the roughly 1 million records of properties that are physically located within the boundaries of the War Destruction map held by Layers of London and the City of London. Across panels fixed effects are made more granular to zoom in on specific sub-geographies to account for the fact that German bombers may have targeted specific areas. Yet, due to low level of precision of areal bombardment at the time, within areas, the actual location of bomb damage is conditionally random. Standard errors provided in parentheses are clustered at the postcode district level with stars indicating *** p <0.01, ** p <0.05, and * p <0.1.