Assessing the effectiveness of energy efficiency measures in the residential sector through dynamic treatment effects: Evidence for heating in the United Kingdom

Cristina Peñasco[†] and Laura Diaz-Anadon[‡]
[†] Department of Politics and International Studies / C-EENRG [University of Cambridge]
[‡] Department of Land Economy / C-EENRG [University of Cambridge]

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Abstract
Improving energy efficiency (EE) is vital to ensure a sustainable, affordable, and secure energy system. The residential sector represents, on average, 18.6% of the total final energy consumption in the OECD countries in 2018, reaching one of the highest percentages of Europe in the UK, with 29.5% of total final energy consumption (IEA, 2020). Using a staggered differences-in-differences approach with dynamic treatment effects, we analyse changes in residential gas consumption before and after the adoption of energy efficiency measures in an event study design. The analysis includes households' technical energy efficiency interventions for heating subjected to energy efficiency programmes in England and Wales between 2005 and 2017 using a panel of 55,154 households from the National Energy Efficiency Data-Framework (NEED). We control for, among other factors, energy prices, and estimate the extent to which gas consumption changes are dependent on household characteristics and variations in weather conditions. We comprise two energy efficiency technological interventions i.e. loft insulation and cavity wall. Our results indicate that the adoption of EE measures is associated with significant reductions in household residential gas consumption one year after their implementation. However, the effect does not last in the long run and energy savings disappear four years after retrofitting for cavity wall insulation measures and after two years for loft insulations. This negative result could be explained by either the rebound effect and/or by concurrent residential projects and renovations that can increase energy consumption. For households in deprived areas the installation of technological interventions does not deliver energy savings. These results confirm the existence of backfire effects and the magnitude of energy efficiency rebounds show potential to completely offset any energy savings for certain groups.

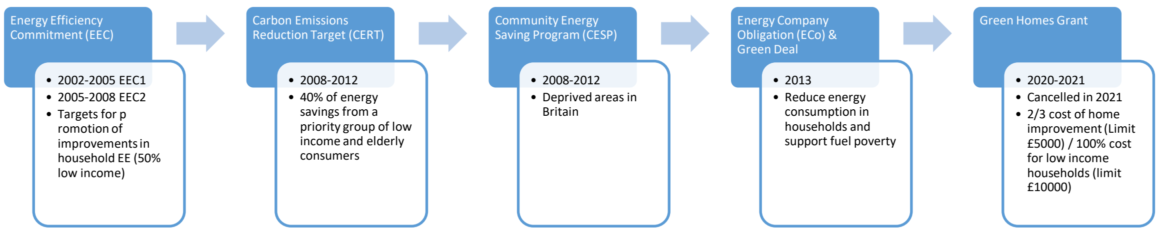
Keywords: Energy efficiency, households, residential energy consumption, gas consumption, heating, staggered diff-in-diff, generalised diff-in-diff, event study, energy policy

1. Introduction

Improving energy efficiency (EE) in the residential sector is key to address energy-related challenges. According to the IEA (2016a), increasing EE in buildings represents one of the most cost-effective ways to improve energy security and reduce the environmental damages from the current energy system. The buildings sector is responsible for a third of the global total final energy consumption (TFC). Moreover, residential buildings account for 74% of the TFC in buildings (IEA, 2016b).

In 2018, households in the UK were responsible for about 29.5% of the country's final energy consumption being the second sector in terms of energy consumption after the transport of passengers (IEA, 2020). According to DECC (2012), the UK household energy use increased by 22% from 1970 to 2007, however if new insulation or efficient heating technologies had not been installed during that time period, this increase would have been more than double. More and more it is assumed that reducing energy demand through greater efficiency can help the UK meets its climate and EE targets, reduce energy bills and fight fuel poverty among other benefits (ICL, 2019). In order to meet its climate and EE targets and reduce the energy consumption, the UK government has put in place several EE related policies, as summarized in Fig. 1. However, policy makers are not achieving the results expected from the implementation of energy saving policies in buildings.

Fig. 1. Timeline of EE policies in the UK between 2002-2021



Source: Own elaboration with information from OFGEM

In addition to the schemes shown in Fig.1, the U.K. Government has set up heating and housing benefits that may influence both the energy consumption and expenditure of households[1]. The focus of those policies has been mostly vulnerable households. According to IPPR (2020), 12M dwellings will need to be retrofitted with energy efficiency technical improvements like insulations, in the next 30 years, if the UK wants to meet its net zero target by 2050. However, while the UK keeps investing in policies to promote the adoption of EE technical measures, research is inconclusive about the effectiveness of such instruments to support the adoption of retrofitting measures or to transform 100% of saving potential mostly due to the impact of rebound effects associated to occupants behaviours (Aydin et al, 2018; Galassi and Madlener, 2018; Sorrell et al., 2018).

The aim of this paper is to shed light on the extent to which technical energy efficiency improvements, specifically the installation of loft insulation and cavity walls, are associated by changes in residential gas consumption. More importantly, this paper analyses the dynamic effects of the installation of such measures and the lasting effect of the gas consumption reductions. It

[1] First, the Labour Government established the Winter Fuel Payment in 1997. This program was designed specifically to support people over 65 in paying heating bills. The scheme provides an annual tax-free payment of £100 to £300 to the beneficiary. The Warm Home discount scheme was established by the Warm Home discount regulation in 2011. Its main aim was to fight fuel poverty in Britain. Under this scheme, households on risk of fuel poverty are allowed to receive an electricity bill rebate of £140 year. Both schemes are still ongoing.

also assesses the degree of sensitivity of household gas consumption to changes in gas prices with the objective of understanding how to design policies to reduce residential energy use in a cost-effective and affordable manner. With this goal in mind, this paper contributes to the current literature in three ways.

First, we analyse the patterns of gas consumption in English and Welsh households between 2005 and 2017 in those households subjected to any of the energy efficiency programmes adopted by the UK Government during the aforementioned period of time. Those programmes are the Energy Efficiency Commitment (EEC), Carbon Emissions Reduction Target (CERT), Community Energy Savings Programme (CESP) and the Green Deal. To the best of our knowledge, this is the first study analysing the gas consumption patterns in the UK at the micro level for a large panel of households of more than 50,000 dwellings and 700,000 observations. Data were extracted from the National Energy Efficiency Dataset (NEED). The specific consideration of energy use for heating will be a valuable contribution, since recent debates argue the importance of decarbonising the heating sector to comply with the net zero targets (Kavvadias et al., 2019) and that there is little evidence on the impact of policies on heating use in buildings (Gillingham et al. 2016, Eyre and Baruah, 2015). Second, we apply a novel approach based on a staggered differences-in-differences (DiD) methodology considering dynamic treatment effects. To the best of the authors' knowledge, this is the first study aiming at disentangling the long-lasting effects of EE technical improvements in residential buildings with observational and ex-post data, through an event study. Our goal is analysing the lasting gas consumption reduction effects, if any, after the installation of two EE technical measures. We control, at a micro level, for the following characteristics of households: dwelling size, the age of the dwelling and the type of dwelling. We take into consideration the region in which the dwelling is located by introducing regional differences in gas prices and in weather conditions. We also account for the vulnerability of the households, which we approximate by using the index of multiple deprivation (See section 3 for further details). Third, we segment our sample to understand the role played by other renovations delivered alongside energy efficiency improvements, the main type of energy used and the vulnerability of the households to derive policy implications that may help the UK to comply with its climate and energy targets.

The results of this paper will shed light into the reasons for the possible biases between projections and actual performance of policies to improve our understanding of decision-making behaviour within households, relevant for reducing energy consumption in residential buildings. Improvements in this regard will provide a better prediction of the outcome of different policy instruments and thereby support the progress of the transition of the energy system.

The paper is structured as follows. In the next section we review the literature and outline the research hypothesis. Section 3 introduces our model and methods. Results are summarized and discussed in section 4. Finally, section 5 concludes with some policy implications, limitations and future research lines.

2. Literature review and research hypotheses

The reduction of energy use and CO2 related emissions in households can be achieved using two main strategies: the adoption of technical solutions to improve EE and behavioural changes that result in energy savings (Trotta, 2018). For the purpose of this paper we will focus on analysing the impact of a set of EE technical solutions at the household level, although there are behavioural aspects directly related to the choices about the adoption of EE measures (Barr et al., 2005, Trotta, 2018).

Recently several papers have aimed to estimate the impact of household EE technical improvement on energy consumption using different techniques including general equilibrium models (Lecca et al., 2014; Bye et al., 2018; Figus et al., 2017; (Wei and Liu, 2017; Kulmer and Seebauer, 2019), microeconomic demand systems (Tovar and Wolfing, 2018) and input-output models (Thomas and Azevedo, 2013; Freire-González, Font Vivanco and Puig-Ventosa, 2017). One of the last contributions regarding the potential of energy savings in the household sector in the UK has been Rosenow et al. (2018) who estimate the lifetime energy savings associated to different levels of deployment of energy efficiency technologies up to 2035. In this sense, there is a wide range of ex ante assessments in the literature.

With a few notable exceptions (Trotta, 2018; Elsharkawy and Rutherford, 2018; Adan and Fuerst, 2016; Webber et al., 2015), we have found that there is a gap in the literature in terms of ex-post evaluations of the changes in residential energy consumption that follow the implementation of different EE technical improvements. The evaluation of actual energy savings in the UK and the factors that may influence residential energy consumption or the impact of different EE technical measures, is timely, particularly given the perceived policy failures in the residential EE space[2] (See, e.g. Kjaerbye et al., 2011; Sovacool et al., 2017; DBEIS, 2016). While there is significant research on the factors determining the adoption of energy efficiency measures (e.g., Ramos et al., 2016; Miller et al., 2014; Trotta, 2018 among others) research has found that there is no conclusive evidence detailing the extent to which differences between expected energy savings from EE measures and realized ones may be related to social challenges, e.g. vulnerability or consumer resistance (Sovacool et al., 2017), or may be caused by rebound effects of policy-induced improvements (Gillingham et al., 2016; Brockway et al., 2017) among other reasons. Dorner (2019) concludes that energy efficiency technological improvements while essential for reducing environmental damage from consumption, may see their benefits partially offset by the existence of direct rebound effects when the consumer responds to resource efficiency by consuming more energy. The partial offset could be due to changes in occupants' behaviour as well. Research about the size and drivers of rebound effects to different EE measures (See Sorrell, 2007 for a review) in the residential sector is vast.

Some studies using data on actual changes in energy consumption have tried to shed light on the role of the rebound effects, i.e. the reduction in expected savings from new technologies and/or the adoption of EE measures because of behavioural or other systemic responses (Gillingham et al., 2016). In a recent study using ex post information about the Kirklees Warm Zone (KWZ)[3] scheme in UK homes between 2007-2010 using micro level data on 49,000 households, Webber et al. (2015) found that the impact of the scheme in energy savings in households have been greater than predicted in part because performance gaps and rebound effects have been lower than the ones initially assumed by Buildings Research Establishment and

[2] For example, the UK's Smart Meter Implementation Program, projected that every household and small businesses across Great Britain would have installed a smart meter by 2020. The average household was expected to reduce their electricity and gas bill by £11 in 2020 and by £47 in 2030 (DBEIS, 2016). However, only 7.14% of the target number had been installed by late 2016, which makes it hard for the projected savings to be realized (Sovacool et al., 2017). By March 2019 13.19 domestic and 1.15 non-domestic smart and advanced meters had been installed in the UK far away from the goal of 50 millions meters of the Smart Metering Programme aimed by the end of 2020 (DBEIS, 2019). Also the UK Government cancelled in March 2021 its last programme the Green Homes Grant only after 6 months from inception in September 2020.

[3] The KWZ is one of the largest retrofit energy efficiency programmes completed in the UK up to date and it took place from 2007 to 2010 coordinate by the Kirklees Council.

by the Savings Trust[4]. However, Webber et al (2015) highlight that rebound effects are much larger in low-income areas (realized savings of around 53% and 49% of expected savings) than in high-income areas (around 90% and 70% of expected savings). In any case, it must be highlighted that the KWZ scheme offered free energy assessments, and free loft and cavity wall insulation to all households in Kirklees, when feasible. Therefore, the absence of upfront costs may be the reason why rebound effects are lower than expected. However, literature is inconclusive regarding this effect. According to Liang et al., (2018) for residential buildings energy consumption in Phoenix, for households receiving an energy retrofit equivalent to 100% of the cost of the installation, energy efficiency savings are null.

For Mexico, Davis et al. (2020) used a quasi experimental sample of new dwellings to calculate the impact of energy efficiency upgrades, specifically insulation, on electricity use and thermal comfort. With a sample of around 500 households (229 vs. 238 homes in the treatment and control groups respectively), the authors found no effect on electricity reduction which contrasted with the engineering estimates that predicted electricity consumption reductions of 26%.

Webber et al's findings are consistent with Sorrell (2007), which suggests, from a review of more than 500 studies and reports, that losses in energy savings for EE measures in dwellings regarding heating, when compared to energy savings projected by standard engineering models, are about 30%. Other studies suggest a smaller magnitude for the rebound effect, varying from 5% to 15%, measured as the difference between projected and realized savings that can be attributed to increased consumption through indirect effects (Chitnis et al., 2014). Lately, studies like Wei and Lio (2017) using computer general equilibrium models found rebound effects in the household sector of around 61%, globally. Therefore, the existence of rebound effects, may undermine the reduction in energy consumption when it comes to analysing individual EE measures.

Using a former version of the dataset used in this paper, Adan and Fuerst (2016) applied a traditional diff- in –diff econometric model to analyse data from 2008 to 2012. The authors analyse the effectiveness of CERT and/or CESP policies on energy efficiency improvements for a treatment group of households who installed some energy efficiency measure in 2011. The authors conclude that energy saving happens one year after the adoption of the energy efficiency improvement despite other factors like the rebound effect. However, the authors do not control for mediating effects of changes associated to, for example, other home improvements non related to energy efficiency technical measures.

But what does it happen in the long-term? Behavioural factors are important, as consumers need to adopt and adapt to achieve residential energy savings (Aydin et al. 2017; Aydin et al., 2018). According to Galassi and Madlener (2018) for a sample of 3,161 individuals in Germany, the change in occupants' behaviour may risk the energy efficiency potentials of the retrofit. These authors state that retrofitting residential dwellings, may result in a higher room temperature (Psomas et al. 2016). In that context, occupants may change their behaviours to adapt to the new comfort, e.g. they could open the windows when it is too warm. This might explain why energy saving policies in building are not leading to desired results. For a before-after experimental research with twenty households in Ireland in 2015, Rau et al. (2020) concluded that government programmes aimed at retrofitting households should not only focus

[4] The results indicate that while predictive models from the Buildings Research Establishment for the UK Committee on Climate Energy and from the Saving Trust for the UK DEFRA, assumed 44% and 50% energy savings of the total full technical potential of the measured adopted under KWZ respectively; the KWZ, following the predictive models methodology, realized 76% and 62% respectively on average.

on technical changes but on re-shaping citizens behaviours and practices if governments want to see lasting reductions in energy use. Policy makers need to consider changes in energy consumption behaviour at the individual level when they implement energy saving policies. Therefore, understanding the anticipatory and long-lasting effects of energy efficiency measures is essential in informing future policy.

Accordingly, we propose the following hypotheses related to the potential reduction in household energy consumption:

H1. The installation of EE technical improvements in households is not enough to generate significant reductions in the amount of gas consumed by dwellings vs. those that have not adopted them.

H2. The gas consumption reduction, of households in the UK after the installation of an EE technical improvement, if any, does not last in time due to factors unrelated to the effectiveness of the technical measured taken.

In addition to the rebound effects, in practice, many EE measures are implemented alongside other home improvements that may have associated increases in energy consumption, such as extensions, which are popular in the UK. The combination of an old housing stock, the rebound effect, and the possible correlation between EE measure implementation and other building work which may lead to increase energy use might, when taken together, result in no reduction in energy consumption at the household level. Judson et al. (2014, p: 63) states that renovation "involves an element of upgrading to improve performance to meet new conditions or standard, but may also involve the introduction of new elements for partial demolition to remove parts that are unsafe, functionally redundant, have maintenance problems, outdated or limit a viable use". In an ethnographic study for Australia, Judson and Maller (2014) find that renovation practices are related to social practices to create and maintain living standards. It is when these renovations (e.g. add extension, renovation of bathrooms, added new rooms…) take place, when energy efficiency measure adoptions are considered as part of the renovation to improve the physical well-being of the families. For the UK, Hand et al. (2007) using interviews with UK households, relates spatial changes to the acquisition of new technologies and goods.

One aspect that has not been previously considered by the literature has been the extent to which the cost of specific EE improvements is a possible driver of subsequent energy consumption patterns (Gillingham et al., 2013; Greening et al., 2000; Turner, 2009; among many others). For example, differences in the cost, the extent of retrofit schemes or the payback period may have important impacts on subsequent energy consumption in households. The benefits from reduced energy bills over the years may compensate the economic upfront costs of the investment (Chapman et al., 2009; Tovar, 2012). Chapman et al. (2009) using a cluster randomized trial of retrofitting insulation in 1350 houses in low-income areas in New Zealand conclude that the value of the money of improving dwelling quality by retrofitting insulation is positive. However, this result is calculated over a 30 year horizon considering benefits from reduce healthcare needs, days off school or work, energy savings and CO2 savings.

Tovar (2012), using the English Household Condition Survey from 2003 to 2007 and projections of costs and savings, finds that the adoption of low cost measures such as cavity and loft insulation may bring savings to households over a five year time period because of overall reductions in annual energy consumption. Indeed, according to current ex-ante calculations of the payback time for e.g. cavity wall installation, a household should amortize the cost of the installation on 3-4 year time, on average[5].

In addition to the size of upfront EE measure costs, the literature indicates that we may also expect differences in the energy consumption of households after adopting a particular measure for different income levels, mainly due to price sensitivity. For example, previous studies have observed higher rebound effects in low-income households for improvements in heating technologies (Milne and Boardman, 2000). Chitnis et al. (2014) study the rebound effect of six heating and lighting EE measures in households in terms of GHG emission reductions. The authors, using information coming from the Community Domestic Energy Model conclude that rebound effects are modest (0-32%). Sensitivity of rebound effects to income or consumption groups have been something widely studied in literature (Belaid et al. 2020; Gillingham et al, 2016; Kulmer and Seebauer, 2019; among others). Understanding energy consumption response to EE technical improvement in different types of households (vulnerable vs. rich) is essential for policy making as most of the energy efficiency programmes have focused on vulnerable households whose energy efficiency rebounds are expected to be higher than from other groups. EE technical improvements that are subsidised or affect highly taxed energy commodities may be less effective as well (Chitnis et al. 2014). We may expect therefore that those households that have spent more upfront money on the adoption of EE measures will experience smaller rebound effects in their energy consumption. However, rebound effects may be higher for those receiving external support and those belonging to low-income percentiles.

We thus include two more hypotheses to test:

H3. Households installing EE technical improvements alongside other renovations in dwellings do not experience significant gas consumption reductions.

H4. For all the EE measures investigated, vulnerable households installing EE technical measures do not reduce their gas consumption.

3. Material and methods

3.1. Data

The analysis included in this paper relies on the microdata from the National Energy Efficiency Data-Framework (NEED) which takes the form of a panel of households and includes information from 2005 to 2017. Our dataset includes a total of 717,002 observations corresponding to than 55,154 households. This data framework was set up by the Department of Climate Change (DECC) of the UK Government to facilitate a better understanding of energy use and energy efficiency in Great Britain. For the purpose of this research, we will focus on residential buildings.

The NEED collects annual information about energy consumption, i.e. gas and electricity, together with information on energy efficiency measures installed in dwellings, and some property and households attributes and characteristics to deliver a representative sample of the housing stock in the UK. The representative sample includes information on English and Welsh

[5] Data extracted from https://www.cavitech-uk.com/cavity-wall-insulation/

households. The EE measures installed corresponds to EE improvements carried out under National EE support schemes, i.e. EEC, CERT, CESP, and the Green Deal Communities. The measures covered in a panel form in this paper are loft insulation and cavity wall installation. We will focus on gas consumption as 85% of the dwellings in the UK by 2018 relied on gas central heating systems (Ministry of Housing, Communities and Local Government, 2019)

We complement the dataset with a measure of weather conditions, approximated by the heating degree days variable coming from Eurostat, and the average annual domestic unitary cost of gas by region provided by the ONS and the Department of Business, Energy and Industrial Strategy (DBEIS) of the UK government. In order to analyse the impact of the installation of EE improvements in the energy consumption of households, we must include controls for confounding variables that may have an effect on the outcome variables. It is probable that the age and size of the dwelling or the characteristics of the building itself, in addition to changes in energy prices, may play a role in the pattern we see on gas consumption in the residential sector. Figure 1a and 1b show the number of households that have adopted some type of energy efficiency measure, i.e. cavity wall and/or loft insulation, in the period of analysis.

Fig. 1. Number of households adopting an EE measure by year

Fig. 1.a. Adoption of at least one EE measure

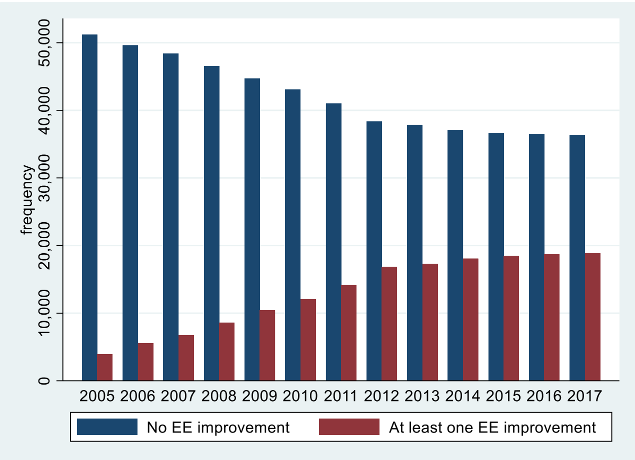
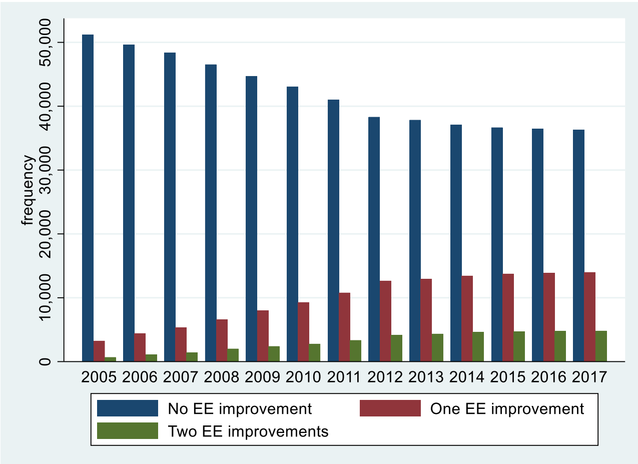


Fig. 1.b. Adoption of one and two EE measures



Source: Own elaboration with NEED data 2019.

Table 1 depicts the descriptive statistics for the dependent and control variables used in this research for the group of households in the treatment group that have at least one EE measure implemented in some year from 2005 to 2017 and for the households in the control group.

This table present the average of the variables as well as the results of a two-sample test for equal means. This table has been constructed without the establishment of sample selections. A detail description of the variables, sources of data and expected relations with the dependent variable is provided in table A1 on the Appendix.

Table 1. Descriptive statistics for variables in the control and treatment groups

Variable	Control	Treatment	Mean diff
Annual gas consumption	15197.94	15209.17	-11.22428
IMD_band	3.011998	2.919651	0.0923468***

Floorsq	2.289425	2.367987	-0.0785627***
Gas price	3.860649	3.848542	0.0121063***
HDD	2683.393	2766.559	-83.16544***
Age dwelling	2.210124	2.07887	0.1312541***
Property type	2.899018	3.31046	-0.411442***
Conservatory	0.039636	0.0472795	-0.0076431***
Number of HH	**35,422**	**18,930**	

3.2. Methods

The main goal of this paper is to study the impact, if any, of the installation of EE technical improvements in gas consumption in households. For most of quasi-experimental applications of Differences in Differences (DiD) approaches, the method comprises two groups, i.e. treatment and control group, with two different periods, i.e. before and after. With this identification, we would be able to calculate the average treatment effect on the treated, under a common trend assumption (Goodman-Bacon, 2018).

In this paper the installation of EE measures differs in time, i.e. households carried out the EE improvements in different years. Then, the aforementioned canonical approach for a DiD methodology is not valid. EE improvements are implemented at a particular point in time, that varies depending on the household at hand, and each dwelling will remain expose to this treatment, i.e. the EE improvement, at all times afterwards. Taking this into consideration, we will identify and estimate the effect of the treatment using a generalization of the DiD approach with multiple time periods, variations in the treatment timing and the parallel trend assumption holding after controlling for possible confounding covariates. Cerulli and Ventura (2019) have developed an estimation methodology to the case of binary time-varying treatment with pre and post intervention periods. We will use their development to analyse the differences in the gas consumption of households 5 years before and after the implementation of EE improvements. With this approach, we can not only analyse the effect of the EE improvements but also if they have some anticipatory or delay effects.

To start with, we will consider a binary treatment indicator, i.e. the installation of an EE measure whether loft insulation or cavity wall, for household i at time t:

$$EEM_{it} = \begin{cases} 1\ if\ household\ i\ is\ treated\ at\ time\ t \\ 0\ otherwise \end{cases}$$

For a regular generalised DiD, we would only allow for treatment effect heterogeneity, in terms of the observed covariates and time, i.e. every household become treated ($EEM_{it} = 1$) at the time when the first EE measure is installed, and that time varies across households. In the first application, we do not consider dynamic treatment effects allowing the possibility of having some effect before and after the period of intervention (1).

$$\ln(y_{it}) = \alpha + \beta EEM_{it} + \gamma X_{it} + \theta_i + \mu_t + \varepsilon_{it} \qquad (1)$$

Where y_{it} is the annual energy consumption, i.e. gas consumption in KWh (outcome variable), i denotes the household and t the year. EEM_{it} represents our variable of interest that identifies the introduction of a specific energy efficiency measure, whether loft insulation or cavity wall, in the analysed households. The variable of interest is set to one in the year of the installation in household i and in all the following years. X_{it} is a vector of household characteristics, θ_i are the households fixed effects while, μ_t is a time fixed effect to control for shocks that are common to all households. According to Goncalves et al. (2020) with this approach we will consider the same household as a treatment unit in certain years and as controls in others.

With this staggered DiD methodology we overcome one of the main limitations of a canonical two-way fixed effects model with a binary post-treatment variable. With a staggered DiD approach we avoid the bias generated with an estimator that represents the weighted average of all possible two-group and two-period DiD in case the effect changes overtime (Goodman-Bacon, 2018). However, a more generalised DiD methodology is not exempted of limitations related to controlling characteristics of the households that may vary along time and for some non-observable factors fixed over time. This can generate endogeneity problems. We address this issue including control variables. A propensity score matching approach will be use as a robustness test too.

Second, we will consider dynamic treatment effects. We will use an extension of the DiD by including five leads and lags of the treatment as regressors, in an event study design, to estimate the average dynamic effect of discrete shocks on non-transient treatments. This second quasi-experimental exercise allows us to analyse the extent and duration of the effectiveness of the implementation of EE measures in reducing energy consumption in the residential sector. For this purpose, we will adopt Cerulli and Ventura (2019) approach that allows to analyse simultaneously the average treatment effect (ATE) together with the pre and post-treatment effects.

$$\ln(Y_{it}) = \alpha + \sum_{j=1}^{J} \beta_{pre,j} EEM_{i,t+j} + \sum_{k=0}^{K} \beta_k EEM_{i,t-k} + \gamma X_{it} + \theta_i + \mu_t + \varepsilon_{it} \tag{2}$$

where $EEM_{i,t-k}$ are year–specific indicators that denote whether a specific household i in year $t-k$ has installed one EE improvement; and $t+j$ will indicate if a household i will have EE improvements implemented in j years in future periods. In event studies, the next stage will be testing the significant of those coefficients $\beta_{pre,j}$ to understand if there are pre-existing trends in the outcome variables of interests. The introduction of β_k will also allow for testing lags in the effects of EE measurement and treatment heterogeneity by exposure time. We aim at capturing a pre-installation period and a post-installation period of 5 years. With this analysis, we allow the impact of the treatment to change over time.

In order to infer a causal interpretation, we will need to test first i) conditional parallel trends are valid, implying that in the absence of treatment, similar households would follow similar energy consumption trends; ii) no anticipation of the treatment, implying that households have no prior knowledge concerning the probability of the implementation of EE measures over time and hence, do not respond proactively prior to the to the installation of the measure; and iii) no selective treatment timing, and no causal effect on the outcome, with respect to an early versus a later adoption (Goodman-Bacon, 2018). The violation of these assumptions implies that caution must be exercised, while interpreting the results.

We test that households introducing a technical energy efficiency measure do not differ from the non-treated households by checking that the coefficients of EEMi,t-k are not significant. If the coefficient is statistically non-significant, we can assume that both groups followed the same trend.

Both equations are estimated using fixed effects and ordinary least squares with the inclusion of covariates. We report robust clustered standard errors with clusters defined at the household level.

4. Results

4.1. General results of the staggered DiD

Table 3 shows the baseline results of the estimation from the staggered DiD. First, Table 3 includes the results on the effect of an EE installation in the period before and after the installation of the energy efficiency measure by estimating Eq. (1). Second, it also shows results from Eq. (2) where we consider an event study with dynamic treatment effects. We perform conditional estimations and test specifications under a set of control variables and fixed effects. Our prefer estimation includes the covariates as we see differences on those variables between control and treatment group.

We test different specifications. For all of our estimations we control for the unitary price of gas and the temperature conditions proxied by the number of heating degree days, both standardized by region. The columns (1), (2) and (3) of Table 3 depicts the results from generalized staggered DiD when we consider the installation of any type of EE technical measure, a loft installation or a cavity wall installation in year t, respectively. Time and households fixed effects are introduced in those estimations. The columns (4), (5) and (6) show the relationship between economic, weather and building characteristics and changes in gas consumption, i.e. we introduce specific covariates to control for the characteristics of the dwelling in the sample, specifically the age of the building, the type of property, the size of the property and the economic characteristics of the areas in which the households are situated as a proxy of the income levels of the household. The coefficient of the EE installation (EEMit) is statistically significant across these estimations confirming that the introduction of an EE improvement generates a decrease in the gas consumption of the households analysed. Given the power of the estimations, the analysis of the results will focus on the models considering the set of households' covariates to control for the typology of dwellings among control and treatment groups. The coefficients accompany the introduction of an EE improvement varies between -0.061 (reduction of 6.1%) for the installation of loft insulations to -0.113 (reduction in gas consumption of around 11.3%) for cavity walls installations. We conclude therefore, that the installation of cavity walls almost doubles the energy saved, i.e. gas, in comparison to loft insulation installations. Columns (7) to (12) in Table 3 reports the estimations for a staggered diff-in-diff approach with dynamic effects, i.e. an event study, including as regressors five treatment leads and lags. Like in the generalised model, while Table 3 includes both results derived from a fixed effect model with time and household fixed effects and also and OLS model with covariates, we will focus the analysis on the latter given the power of the estimations. The results in columns (10), (11) and (12) confirm, in line with literature, that energy efficiency technical improvements in households are effective in reducing energy consumption on those households undertaking such measures. However, a new, challenging and policy relevant result derived from our ex-post analysis, i.e. energy efficiency effects derived from the installation of technical measures are not long-lasting and energy efficiency gains dissolve around one to four years after the treatment. The reliability of the causal inferences of the effects in a staggered diff-in-diff approach with dynamic effects, i.e. in an event study, depend on confirming non anticipatory effects of the treatment (Goncalves et al. 2020). Anticipatory effects are not observed for the dynamic model with covariates[6]. While the results for any type of installation, do not comply with the parallel trend assumption and therefore, causal inferences

[6] Anticipatory effects are only observed for the uncontrolled general model without covariates and with fixed effects (See table A2 in the appendix). However, these models do not comply with the parallel trend assumption and therefore, causal inferences derived from those estimations should be considered carefully.

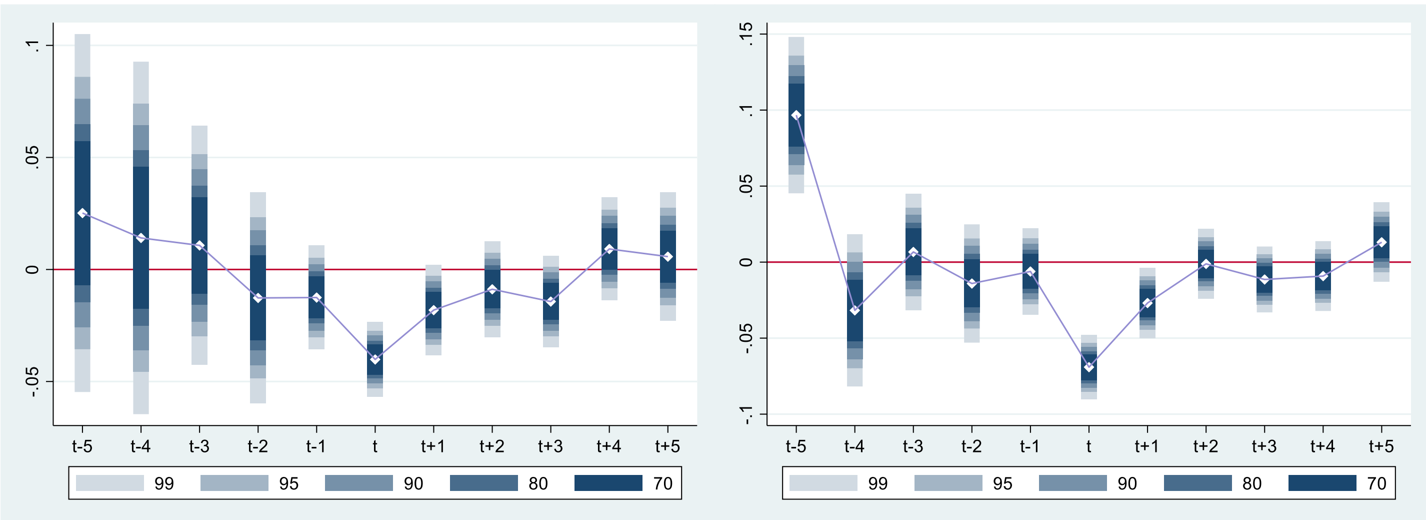
derived from those estimations should be considered carefully, when we restrict by type of EE measure, the parallel trend assumption cannot be rejecting by using a time-trend significant test (Cerulli and Ventura, 2019). For our prefer estimation, i.e. ols staggered diff-in-diff with dynamic treatment effects controlling for covariates, anticipatory effect cannot be detected.

The results affirming that cavity wall retrofits are more effective than loft insulations in the reduction of gas consumption after the installation of the EE measure are confirmed. Cavity wall insulation generates, for our prefer model with covariates (12), an observed reduction on gas in the range of approximately a 6.9% in comparison with the pre-treatment period. The effect shows a decreasing pattern and the effective reduction in consumption only last up to four more years. For the second period after treatment, the observed gas reduction oscillates around 2.7%. After four periods, when the reduction of gas consumption is only of 0.9%, the gas consumption returns to the levels previous to the installation, suggesting that behavioural interventions are as needed as technical ones if our goal is to get long-lasting energy efficiency gains. Loft insulation seems to be half effective than cavity wall installation with reductions on gas consumption around 4%. Unlike cavity wall reforms, loft insulation effects on gas reduction only lasts for one to two periods after the installation of the technical energy efficiency measure with a reduction of 1.8% and 0.9% respectively. In terms the effectiveness of the different measures, results are aligned with Alan and Fuerst (2016) who concludes that one year after the treatment, cavity walls are the most effective technical measures in reducing gas and energy consumption. Figs. 2a and 2b represents the dynamic treatment effects for the OLS model with covariates for both, loft (2a) and cavity wall installations (2b).

We note that most of our control variables are significant. Irrespective of the estimation, the size of the dwelling, the age of the household, the type of property, and the number of HDD have a statistically significant positive impact on gas consumption.

Fig. 2. Graph of the pre- and posttreatment pattern for the relation between household adoption on an EE measure and gas consumption

Fig. 2.a Loft insulation installation in t (%) Fig. 2.b. Cavity wall installation in t (%)



Note: The vertical axe shows the variation in gas consumption and the horizontal axe measures the effect five periods before and after the adoption.

Table 3. Baseline results (staggered DiD and event study with covariates)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Fe			Re			fe			OLS		
Gas Consumption	Any	Loft	Cavity	Any	Loft	cavity	Any	loft	cavity	Any	Loft	cavity
EE (t-5)							-0.00152 (0.022133)	0.003428 (0.050578)	0.010499 (0.023925)	0.078901*** (0.019252)	0.025189*** (0.031006)	0.096682*** (0.019965)
EE (t-4)							-0.00357 (0.015068)	-0.00063 (0.02063)	0.002151 (0.016626)	-0.01941 (0.01915)	0.014087 (0.030532)	-0.03172 (0.01944)
EE (t-3)							0.01007 (0.013288)	0.005273 (0.018913)	0.020536 (0.012628)	-0.0006 (0.014527)	0.01075 (0.020697)	0.006685 (0.014861)
EE (t-2)							-0.0136 (0.0118)	-0.01459 (0.014905)	-0.01296 (0.012322)	-0.01552 (0.013981)	-0.0127 (0.018293)	-0.01407 (0.015103)
EE (t-1)							-0.00276 (0.007033)	0.001747 (0.007575)	-0.01377 (0.009066)	-0.01067 (0.008267)	-0.01251 (0.009012)	-0.00614 (0.011053)
EE (t)	-0.08965*** (0.00340)	-0.0646323*** (0.00340)	-0.1272409*** (0.0041628)	-0.0824492*** (0.0030985)	-0.0606172*** (0.00366)	-0.1130519*** (0.0037056)	-0.04623*** (0.005049)	-0.03479*** (0.005584)	-0.0776*** (0.00636)	-0.04595*** (0.006023)	-0.04015*** (0.006496)	-0.06908*** (0.008199)
EE (t+1)							-0.02394*** (0.005335)	-0.01445** (0.006182)	-0.03708*** (0.0072)	-0.02222*** (0.006664)	-0.01812** (0.007819)	-0.0269*** (0.008974)
EE (t+2)							0.003046 (0.00489)	0.003075 (0.005973)	0.009893 (0.006044)	-0.00451 (0.006762)	-0.00883* (0.008283)	-0.00115 (0.008911)
EE (t+3)							0.004966 (0.004948)	0.0048 (0.006186)	0.011785* (0.006154)	-0.01451** (0.00651)	-0.01431 (0.007891)	-0.01141 (0.008407)
EE (t+4)							0.010703* (0.005547)	0.009929 (0.006777)	0.01198* (0.00664)	0.000956 (0.007279)	0.009148 (0.008924)	-0.00917*** (0.008917)
EE (t+5)							0.009687 (0.006868)	0.01137 (0.008878)	0.021942*** (0.008085)	0.003184 (0.008435)	0.005745 (0.011101)	0.013078 (0.010124)
Property (b. flat)												
Semi-detached				0.3258089*** (0.0086371)	0.3158619*** (0.008628)	0.3254022*** (0.0086336)				0.316473*** (0.010082)	0.312769*** (0.010035)	0.314963*** (0.010045)
Detached				0.4545535*** (0.0104009)	0.4454943** (0.0104013)	0.452671*** (0.0103932)				0.44391*** (0.012004)	0.441032*** (0.011984)	0.442153*** (0.011956)
Mid terrace				0.1172932*** (0.0089883)	0.1144334*** (0.008989)	0.1123343*** (0.0089858)				0.124822*** (0.010343)	0.124535*** (0.010353)	0.123165*** (0.010309)
End terrace				0.2410193*** (0.0097486)	0.2351446*** (0.0097438)	0.237953*** (0.0097488)				0.241048*** (0.011361)	0.239496*** (0.011353)	0.239073*** (0.011333)
Bungalow				0.3535801*** (0.0097887)	0.3413872*** (0.0097656)	0.3501212*** (0.0097799)				0.335594*** (0.011345)	0.329867*** (0.01131)	0.331673*** (0.011254)
Age				-0.1171919***	-0.1167755***	-0.1147207***				-0.10608***	-0.10604***	-0.1052***

				(0.0024644)	(0.0024611)	(0.0024634)				(0.002922)	(0.002928)	(0.002919)
Floorsq				0.2619469*** (0.0035153)	0.2638888*** (0.0035164)	0.2609907*** (0.0035167)				0.262168*** (0.003946)	0.262868*** (0.003946)	0.261978*** (0.003947)
Lhdd	0.091598*** (0.005331)	0.0952048*** (0.0053378)	0.0917961*** (0.0053368)	0.0853239*** (0.0052551)	0.0865043*** (0.005259)	0.085954*** (0.0052576)	0.190998*** (0.006115)	0.191403*** (0.006113)	0.190667*** (0.006074)	0.116445*** (0.01225)	0.109273*** (0.012268)	0.113818*** (0.012193)
Lgasprice	- 0.4663369*** (0.003631)	- 0.4839359*** (0.0035566)	-0.4736774*** (0.0035256)	-0.4673936*** (0.0035785)	-0.4830868*** (0.0035203)	-0.4750794*** (0.0034855)	-0.27443*** (0.011457)	-0.28672*** (0.010801)	-0.2832*** (0.010696)	-0.21889*** (0.011693)	-0.23488*** (0.011639)	-0.23652*** (0.011383)
IMD_band												
2				0.0527954*** (0.0066434)	0.0550842*** (0.0066314)	0.0540308*** (0.0066491)				0.05537*** (0.00759)	0.05607*** (0.007589)	0.056015*** (0.007587)
3				0.0650486*** (0.0067132)	0.0690328*** (0.0067016)	0.0666349*** (0.0067154)				0.07056*** (0.007681)	0.072064*** (0.007676)	0.071361*** (0.007668)
4				0.0970451*** (0.0066493)	0.100879*** (0.0066407)	0.0995178*** (0.0066534)				0.101908*** (0.007568)	0.103389*** (0.007565)	0.103409*** (0.007547)
5				0.1220217*** (0.0066374)	0.1260263*** (0.006628)	0.1244333*** (0.006639)				0.124355*** (0.007575)	0.125931*** (0.007569)	0.125693*** (0.007558)
Intercept	9.386564*** (0.041953)	9.367799*** (0.041999)	9.392373*** (0.0419652)	8.726659*** (0.0426411)	8.724739*** (0.0426669)	8.726773*** (0.0426363)	8.317287*** (0.053533)	8.318963*** (0.054062)	8.324997*** (0.052495)	8.101498*** (0.104573)	8.176551*** (0.104745)	8.176551*** (0.104745)
Test parallel trend 1							Yes	Yes	Yes	No	No	No
Test parallel trend 2							No	Yes	Yes	No	Yes	Yes
Number of observations	555,570	555,570	555,570	555,570	555,570	555,570	127,384	127,384	127,384	127,384	127,384	127,384
F test	F(3,46145) = 7581.95 Prob > F = 0.0000	F(3,46145) = 7426.95 Prob > F = 0.0000	F(3,46145) = 7782.34 Prob > F = 0.0000	Wald chi2(14) = 48357.05 Prob > chi2 = 0.0000	Wald chi2(14) = 47839.75 Prob > chi2 = 0.0000	Wald chi2(14) = 48846.87 Prob > chi2 = 0.0000	F(13,43100) = 186.88 Prob > F = 0.0000	F(13,43100) = 180.78 Prob > F = 0.0000	F(13,43100) = 196.23 Prob > F = 0.0000	F(24, 43100) = 833.93 Prob > F = 0.0000	F(24, 43100) = 827.93 Prob > F = 0.0000	F(24, 43100) = 834.38 Prob > F = 0.0000
R-Squared	0.0360	0.0369	0.0364	0.2945	0.2942	0.2938	0.0019	0.0024	0.0029	0.2809	0.2800	0.2808

Notes: Clustered standard errors in parentheses by household. * Significant at the 90% confidence level. **Significant at the 95% confidence level. ***Significant at the 99% confidence level.

Results derived from Table 3, allow to reject our first hypotheses H1. Results support the idea that the installation of EE technical improvements in households generate significant reductions in the amount of gas consumed by dwellings vs. those that have not adopted them. However, we can support H2, as results show that the gas consumption reduction, of households in the UK after the installation of an EE technical improvement does not last in time. Interestingly, the period by which the EE installations generate gas consumption reductions (2 to 4 years depending on the type of EE technical measure) approximately coincides with the payback time for those type of installations. As mentioned in section 2, on average, the payback time for a cavity wall installation may vary oscillate between 3 to 4 years after the installation. For loft insulation the payback period tends to be slightly lower at around 1.5-3 years. This result open venues to explore aspects related to behavioural economics and consumer psychology that are out of the scope of this paper.

4.2. Segmentation of the sample

4.2.1. Conservatory vs. Non conservatory

Besides gas unitary prices per region and weather conditions, we have controlled for time-invariant household characteristics. The coefficient of the EE installation captures then the total effect of the adoption of an EE technical measure in a household on their gas consumption. However, most of times, and as stated in the literature review, EE measures are implemented alongside other home improvements like extensions which are very popular in the UK. In that sense, the possible correlation between EE measure implementation and other building work which may lead to increase energy use might result in no reduction in energy consumption at the household level on those households.

Table 4 shows a segmentation of the sample breaking down the gas reduction effects of EE installations in those households with conservatories and those without conservatories.

Analysing this result is of special importance for the UK where conservatories reminds one of the most popular modifications to a property. In 2011, almost 20% of households in England had conservatories and around 80% of them have some type of heating (DECC, 2013). Half of those are connected to central heating systems though, approximately the other haft, use electric heaters. The market for conservatory and glazed extensions increased by 3% in 2018 (AMA Research, 2018).

H3 tested the idea that the Households installing EE technical improvements alongside other renovations in dwellings do not experience significant gas consumption reductions. In a UK context, testing this hypothesis has clear implications from a policy efficiency point of view. We found that those dwellings with conservatories, i.e. those that have carried out extensions of a building with more than 50% of its wall surface glazed experienced less long-lasting effects than those without conservatories. While modern conservatories are made to be as energy efficient as possible, it seems that those households with a conservatory installation are not subjected to any energy consumption reduction derived from the installation of EE technical measures in the form of loft insulations, cavity walls in the medium-run. For any measured installed, we see more or less the same reduction on gas consumption in the first year (~4.6% reduction) however, the effect for those households with conservatories disappear almost immediately. We see positive energy efficiency gains associated to the installation of loft insulation or cavity walls, for those dwellings with non-conservatories but, as in the general case, the energy efficiency gains tend to dissolve with time suggesting there may be behavioural aspects that we are not considering and therefore suggesting further efforts in education or informational campaigns in the long-run (Table 4).

Table 4. Event study gas consumption with segmentation of the sample by conservatory

	Any EE improvement		Loft Insulation		Cavity wall	
Gas Consumption	Conservatory	No conservatory	conservatory	Non conservatory	conservatory	No conservatory
EE (t-5)	0.137986*** (0.055225)	0.075204*** (0.02003)	0.152881* (0.076267)	0.016583 (0.032478)	0.058376 (0.060981)	0.098434*** (0.020856)
EE (t-4)	-0.1858*** (0.070231)	-0.01108 (0.019807)	-0.15013 (0.098809)	0.024536 (0.031839)	-0.10947 (0.07004)	-0.02815 (0.020188)
EE (t-3)	0.102252 (0.06895)	-0.0052 (0.014855)	0.117324 (0.099976)	0.006173 (0.021142)	0.067224 (0.060643)	0.003626 (0.015298)
EE (t-2)	-0.08551 (0.052473)	-0.01208 (0.014419)	-0.16701** (0.078427)	-0.00597 (0.018752)	-0.01537 (0.056271)	-0.01376 (0.015591)
EE (t-1)	0.039626 (0.032376)	-0.01301*** (0.008523)	0.03096 (0.036616)	-0.01461 (0.009277)	0.031281 (0.036208)	-0.00768 (0.011443)
EE (t)	-0.04566** (0.020169)	-0.04596*** (0.006248)	-0.05137** (0.022351)	-0.03948*** (0.006734)	-0.05255* (0.029235)	-0.06986*** (0.008488)
EE (t+1)	0.000773 (0.025037)	-0.02353*** (0.006894)	0.021431 (0.0294)	-0.0202** (0.008093)	-0.02582 (0.034833)	-0.02718*** (0.009267)
EE (t+2)	-0.00988 (0.024308)	-0.00414 (0.007013)	-0.00087 (0.03024)	-0.00919 (0.008586)	-0.03747 (0.032315)	0.00098 (0.009238)
EE (t+3)	-0.00501 (0.019953)	-0.01485** (0.006778)	0.022393 (0.027836)	-0.01599* (0.008177)	-0.01457 (0.02388)	-0.01125 (0.008774)
EE (t+4)	-0.04402 (0.026733)	0.003349 (0.007525)	-0.08712** (0.034761)	0.013952 (0.009199)	-0.022 (0.030866)	-0.00855 (0.009241)
EE (t+5)	0.017957 (0.034079)	0.002398 (0.00869)	0.046558 (0.047295)	0.003928 (0.011397)	0.037391 (0.039605)	0.011749 (0.010449)
Property (b. flat)						
Semi-detached	0.602243*** (0.123616)	0.312013*** (0.010198)	0.596478*** (0.123333)	0.308313*** (0.010149)	0.605442*** (0.121536)	0.31053*** (0.010162)
Detached	0.745882*** (0.125608)	0.438423*** (0.012233)	0.741083*** (0.125364)	0.435514*** (0.012213)	0.747502*** (0.123594)	0.43681*** (0.012185)
Mid terrace	0.360029*** (0.125944)	0.12264*** (0.010438)	0.358508*** (0.125736)	0.122318*** (0.010449)	0.362168*** (0.124017)	0.121087*** (0.010403)
End terrace	0.566475*** (0.127206)	0.235563*** (0.011499)	0.563043*** (0.126958)	0.233971*** (0.011491)	0.569599*** (0.125224)	0.233661*** (0.01147)
Bungalow	0.61112*** (0.124407)	0.330476*** (0.011599)	0.602276*** (0.124065)	0.324861*** (0.011565)	0.612346*** (0.12222)	0.326626*** (0.011503)
Age	-0.11433*** (0.013151)	-0.10554*** (0.002994)	-0.11521*** (0.013181)	-0.10547*** (0.003)	-0.11193*** (0.013129)	-0.1047*** (0.002991)
Floorsq	0.222474*** (0.015399)	0.263948*** (0.004075)	0.224003*** (0.015417)	0.264604*** (0.004075)	0.222678*** (0.015348)	0.263753*** (0.004077)
Lhdd	0.144473*** (0.047271)	0.116611*** (0.012616)	0.137011*** (0.04736)	0.109513*** (0.012634)	0.141742*** (0.046789)	0.113967*** (0.012559)
Lgasprice	-0.14185*** (0.042628)	-0.22245*** (0.012083)	-0.15985*** (0.042855)	-0.2386*** (0.012025)	-0.15112*** (0.041176)	-0.24022*** (0.011767)
IMD_band						
2	0.083737* (0.045927)	0.054046*** (0.007714)	0.085504* (0.045903)	0.054694*** (0.007713)	0.088962* (0.045814)	0.054606*** (0.007711)
3	0.054739 (0.045232)	0.070861*** (0.007827)	0.053072 (0.045188)	0.072378*** (0.007821)	0.059364 (0.045247)	0.071621*** (0.007814)
4	0.087806** (0.044158)	0.102219*** (0.00772)	0.08534* (0.04419)	0.103729*** (0.007715)	0.097011** (0.043976)	0.103545*** (0.0077)
5	0.129115*** (0.042924)	0.123468*** (0.007748)	0.127792*** (0.042899)	0.12512*** (0.007742)	0.137477*** (0.042825)	0.124621*** (0.007732)
Intercept	7.644361*** (0.4157)	8.102342*** (0.107733)	7.726107*** (0.4165975)	8.177182 (0.107899)	7.660668*** (0.4104581)	8.144825*** (0.1072719)

Test parallel trend 1	NO	NO	YES	NO	YES	NO
Test parallel trend 2	YES	NO	NO	YES	YES	YES
Number of observations	5,766	121,618	5,766	121,618	5,766	121,618
Treated						
Control						
F test	F(24, 1943) = 33.23 Prob > F = 0.0000	F(24, 41156) = 789.69 Prob > F = 0.0000	F(24, 1943) = 33.35 Prob > F = 0.0000	F(24, 41156) = 784.14 Prob > F = 0.0000	F(24, 1943) = 33.19 Prob > F = 0.0000	F(24, 41156) = 789.83 Prob > F = 0.0000
R-squared	0.2637	0.2785	0.2628	0.2775	0.2640	0.2784

Notes: Clustered standard errors in parentheses by household. * Significant at the 90% confidence level. **Significant at the 95% confidence level. ***Significant at the 99% confidence level.

Fig. 3. Graph of the pre- and posttreatment pattern for the relation between household adoption on loft insulation and gas consumption in households with conservatory vs. non conservatory

Fig. 3.a Loft insulation in t with conservatory

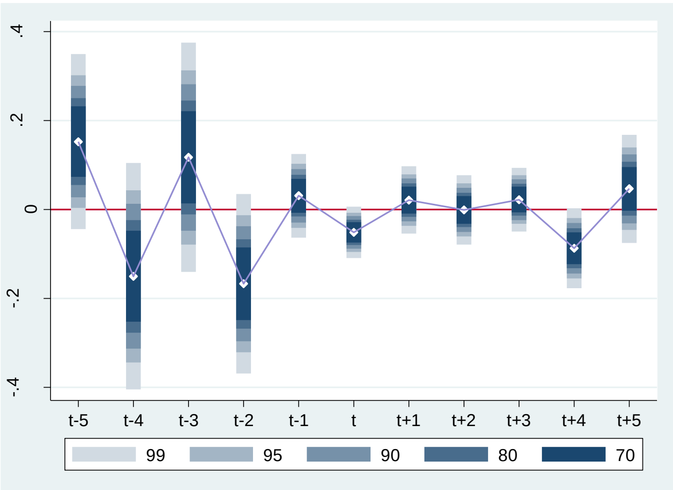
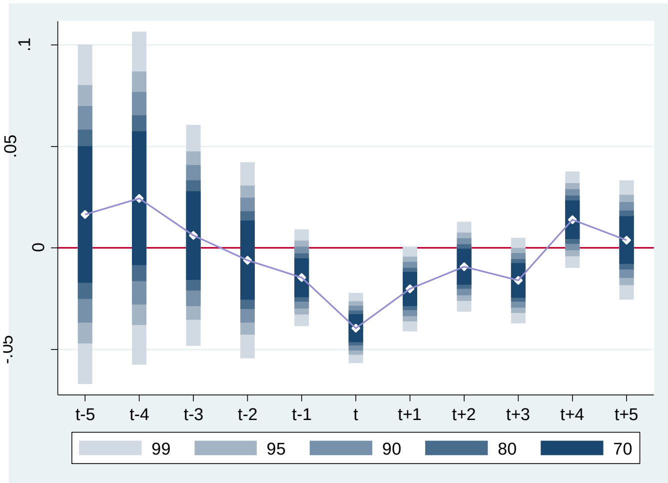


Fig. 3.b. Loft insulation in t without conservatory



Note: The vertical axe shows the variation in gas consumption and the horizontal axe measures the effect five periods before and after the adoption.

Interestingly, in Fig. 3 for loft insulation installations, we can see that the pattern of consumption in the years before the installation is pretty unstable and unpredictable. This can be due to the impact of weather conditions that may affects those dwellings with conservatories to a greater extent. Indeed, for those household with conservatories the size of the weather control variable is larger than for those households without conservatories (0.14 vs. 0.11 for households with conservatory and without conservatory respectively). In those dwellings with conservatories, i.e. with extensions of some nature, the reduction in gas consumption happens only the first year after the adoption (-5.1%). However, we see anticipatory effects prior to the installation of the EE measure. Anticipatory effects can appear due to disruptions cause by building works (DECC, 2012). If there is also uncertainty about the energy saving gains, renters or owners may be considering to undertake an energy efficiency reform for a long period of time before they decide to do it and in parallel they may be already adjusting their behaviour before the treatment. However, as mention the existence of anticipatory effects should be analysed cautiously. For the case of loft insulation, what it stands is that, even if the reductions are not long-lasting, the installation of the EE measures seem to stabilise the pattern of gas consumption in the households adopting loft insulation. We see, as in line with the general results, positive energy efficiency gains for those with non-conservatories but as in the general case the energy efficiency gains tend to dissolve with time suggesting there may be behavioural aspects that we are not considering and therefore suggesting further efforts in education or informational campaigns in the long-run.

Fig. 4. Graph of the pre- and posttreatment pattern for the relation between household adoption of cavity walls and gas consumption in households with conservatory vs. non conservatory

Fig. 4.a Cavity wall in t with conservatory

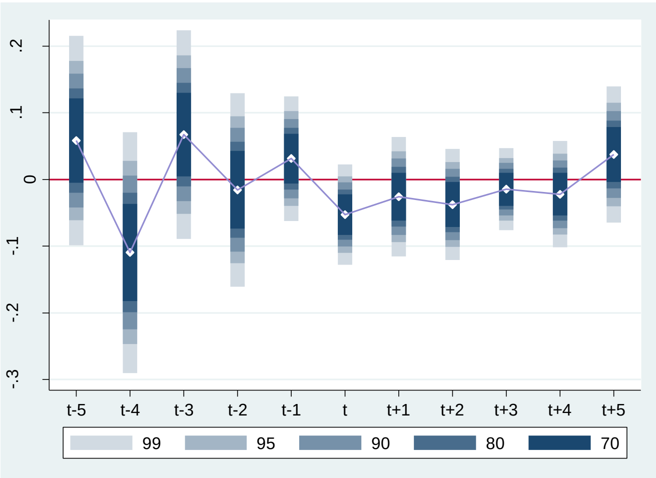
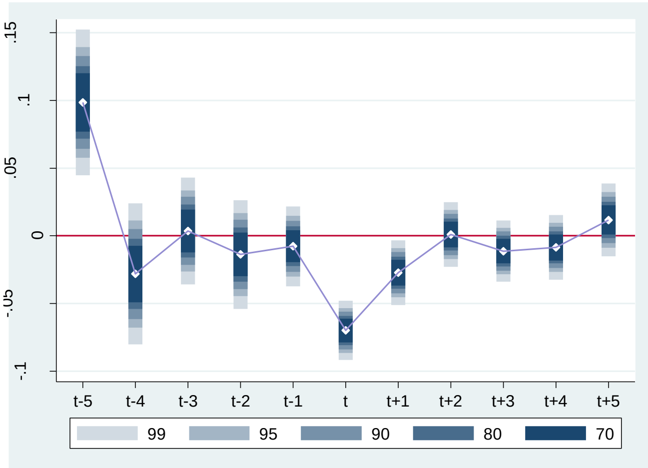


Fig. 4.b. Cavity wall in t without conservatory



Note: The vertical axe shows the variation in gas consumption and the horizontal axe measures the effect five periods before and after the adoption.

With cavity walls, the effect is the similar to that with loft insulation. For the case of cavity wall installations, we do not see anticipatory effects like in the case of loft insulation. However, it stands clearly that the effect of those installations in the gas consumption is smaller in households with conservatories (~5% only in the first year after the installation), than in those dwellings without conservatories (~7% one year after the installation plus additional reductions in gas consumption of around 3% during the second year) (See Table 4 and Fig. 4). However, as we have seen for the whole sample, the effect in this case disappear in two years. This seems to correspond approximately with the payback time of an installation.

Therefore, our results support partially hypothesis 3 and households performing other type of renovations along side EE technical improvements will not experiment the same level of statistically significant gas consumption reductions than those installing only EE technical improvments like loft insulation and cavity walls.

4.2.2. By bands of the index of deprivation

Energy efficiency policy instruments in the UK have traditionally focused on improving energy efficiency in all households but specifically in low-income households (EEC1, EEC2 programmes and CERT) and in households in deprived areas in Britain (CESP).

However, looking at the results derived from Table 5 we see that those households in more deprived areas experience half of the gas consumption reductions that their peers in the richer areas of the country. When we segment the sample by deprivation index, in those areas in which the deprivation is the highest, the installation of such measures generates the lowest reduction in gas consumption that is statistically significant. Probably because those households already consume little energy. They present a higher energy price elasticity than their richer peers.

Controlling by gas prices, weather conditions and household characteristics, those household installing EE measures in more deprived areas will experience statistically significant gas consumption reductions of around 3% during the first and second year after installation of the technical measure. Similar households in less deprived areas can expect reductions in gas consumption of around 5.6%. Results are consistent across technologies.

However, an important result to highlight is that those most deprived households can expect statistically significant increases in the energy consumption four and five years after the adoption. These increases would completely offset the initial consumption reduction reaching increases in gas consumption of around 3.6%.

These results confirm that generally the demand of those households in more deprived areas mostly covers basic needs, and therefore the installation of a new energy efficiency improvement does not generate a decrease in the energy consumption but may produce a higher flexibility to adjust to prices and therefore it facilitates that they cover, after the installation of an EE measure, not only their basic needs pushing these households out of fuel poverty. For households on less deprived areas, the installation of energy efficiency measures represents a way to reduce consumption, at least during the first year, which makes them less sensitive to changes in gas prices. This result is very interesting because it suggests that the adoption of EE technologies in households make more flexible the gas demand in deprived areas. The pattern for gas price elasticities starts relatively high for deprived areas, and it goes down steadily for medium deprived areas and for low deprived areas. These results suggest that the poorest segments of the population are more sensitive to gas price variations than medium-income households when they have installed an energy efficiency improvement.

Fig. 5. shows of the pre- and posttreatment pattern for the relation between household adoption of any type of EE measure and gas consumption in households belonging to different deprivation areas[7].

[7] Because results are consistent across technologies and because of space reasons, the graphs by loft insulation and cavity walls installations are not included. The graphs are available from the authors upon request.

Table 5. Event study gas consumption with segmentation of the sample by bands of the index of deprivation

Any EE improvement					
Gas Consumption	IMD1	IMD2	IMD3	IMD4	IMD5
EE (t-5)	0.104888** (0.045317)	0.073526 (0.047775)	0.096476** (0.048994)	0.045173*** (0.039691)	0.082285** (0.034648)
EE (t-4)	-0.07011 (0.045921)	-0.00117 (0.047352)	-0.01143 (0.045415)	0.004739 (0.039333)	-0.02077 (0.032825)
EE (t-3)	0.04311 (0.035689)	0.005078 (0.02942)	-0.04727 (0.030493)	-0.0205 (0.02879)	-0.01593 (0.029727)
EE (t-2)	0.010178 (0.026287)	-0.03584 (0.033175)	-0.0038 (0.033881)	-0.00319 (0.03157)	-0.03311 (0.031623)
EE (t-1)	-0.02102*** (0.018212)	-0.00432 (0.019978)	-0.0159*** (0.019369)	5.96E-05 (0.01766)	0.000624 (0.016518)
EE (t)	-0.03037** (0.015339)	-0.03527** (0.01417)	-0.05518*** (0.014354)	-0.05659*** (0.012482)	-0.05032*** (0.010402)
EE (t+1)	-0.03713** (0.017172)	-0.00925 (0.016306)	-0.02045 (0.015488)	-0.01543*** (0.014183)	-0.02767** (0.011816)
EE (t+2)	-0.02733 (0.018614)	0.00093 (0.01642)	0.022871 (0.015848)	-0.01281 (0.014042)	-0.0033 (0.011569)
EE (t+3)	-0.03968** (0.019461)	-0.02112 (0.016092)	-0.00833 (0.014626)	-0.00573 (0.01249)	-0.00467 (0.010501)
EE (t+4)	0.034252*** (0.019532)	-0.00054 (0.016579)	-0.00557 (0.016196)	-0.02204 (0.01667)	-0.01099*** (0.012092)
EE (t+5)	0.036228* (0.019973)	0.018728 (0.018523)	-0.03269* (0.019896)	-0.0119 (0.019354)	-0.02329 (0.015765)
Property (b. flat)					
Semi-detached	0.366016*** (0.020684)	0.322966*** (0.021498)	0.310277*** (0.023049)	0.272832*** (0.025191)	0.28952*** (0.027667)
Detached	0.527116*** (0.038584)	0.469321*** (0.030942)	0.445573*** (0.028423)	0.393371*** (0.027658)	0.415424*** (0.028724)
Mid terrace	0.214736*** (0.020291)	0.140855*** (0.021656)	0.104395*** (0.023532)	0.039662 (0.027033)	0.074791** (0.030094)
End terrace	0.294056*** (0.022604)	0.262022*** (0.023981)	0.207159*** (0.026633)	0.206631*** (0.027758)	0.214631*** (0.031001)
Bungalow	0.304276*** (0.026956)	0.309076*** (0.025646)	0.312317*** (0.02599)	0.307085*** (0.026653)	0.357726*** (0.029237)
Age	-0.07581*** (0.007231)	-0.09636*** (0.006931)	-0.10043*** (0.006733)	-0.12855*** (0.006073)	-0.12553*** (0.005735)
floorsq	0.240978*** (0.011136)	0.24748*** (0.010127)	0.255326*** (0.009317)	0.265311*** (0.007961)	0.281199*** (0.006855)
Lhdd	0.006509 (0.031345)	0.119589*** (0.02867)	0.116824*** (0.02791)	0.169945*** (0.025723)	0.165989*** (0.022249)
Lgasprice	-0.39952*** (0.030971)	-0.22371*** (0.028133)	-0.21644*** (0.027026)	-0.15648*** (0.023332)	-0.11341*** (0.020923)
Intercept	9.150103*** (0.267518)	8.133561*** (0.244839)	8.187405*** (0.238094)	7.786324*** (0.218678)	7.712297*** (0.189923)
Test parallel trend 1	NO	Yes	YES	YES	YES
Test parallel trend 2	YES	YES	YES	YES	YES
Number of observations	26,187	25,348	24,087	24,620	27,142
F test	F(20, 8950) = 123.18 (0.0000)	F(20, 8570) = 130.22 (0.0000)	F(20, 8139) = 152.97 (0.0000)	F(20,8292) = 185.59 (0.0000)	F(20, 9145) = 259.83 (0.0000)
R-squared	0.1843	0.2118	0.2448	0.2842	0.3336

Notes: Clustered standard errors in parentheses by household. * Significant at the 90% confidence level. **Significant at the 95% confidence level. ***Significant at the 99% confidence level.

Table 5 (cont). Event study gas consumption with segmentation of the sample by bands of the index of deprivation

	Loft insulation					Cavity wall				
Gas Consumption	IMD1	IMD2	IMD3	IMD4	IMD5	IMD1	IMD2	IMD3	IMD4	IMD5
EE (t-5)	0.060137 (0.076312)	0.034992 (0.06587)	0.03303 (0.071671)	-0.04736 (0.071893)	0.042958 (0.05764)	0.128524*** (0.047212)	0.095988** (0.045368)	0.065235 (0.055407)	0.087341** (0.038985)	0.091779** (0.037337)
EE (t-4)	-0.069 (0.073726)	0.030027 (0.062561)	0.058445 (0.07408)	0.080029 (0.064082)	0.011471 (0.056314)	-0.06484 (0.042965)	-0.03634 (0.052968)	0.004769 (0.046084)	-0.02178 (0.040578)	-0.03617 (0.03473)
EE (t-3)	0.065416 (0.045908)	0.027757 (0.037977)	-0.02737 (0.041978)	-0.08016* (0.042087)	-0.01193 (0.045856)	0.030355 (0.036437)	-0.00538 (0.03227)	-0.01776 (0.032738)	0.009787 (0.029715)	0.004624 (0.029385)
EE (t-2)	0.010335 (0.029352)	-0.04406 (0.041146)	-0.03883 (0.049502)	0.058887 (0.048948)	-0.02458 (0.046828)	0.005657 (0.033676)	-0.01757 (0.037449)	0.008425 (0.033522)	-0.00845 (0.030351)	-0.04809 (0.030463)
EE (t-1)	-0.00995 (0.019169)	-0.0191 (0.021382)	-0.011 (0.021801)	0.00203 (0.019134)	-0.01548 (0.017252)	-0.01003 (0.026439)	0.020561 (0.027676)	-0.03576 (0.026266)	-0.01377 (0.022919)	0.01862 (0.020518)
EE (t)	-0.02629* (0.015692)	-0.02986** (0.014554)	-0.05493*** (0.015194)	-0.04501*** (0.014364)	-0.04221*** (0.011513)	-0.04798** (0.023663)	-0.05553*** (0.020455)	-0.06804*** (0.020543)	-0.09033*** (0.013951)	-0.07465*** (0.013972)
EE (t+1)	-0.02887 (0.018647)	-0.03154* (0.018555)	-0.00914 (0.018542)	-0.00342 (0.017441)	-0.01795 (0.013959)	-0.0678*** (0.026014)	0.014334 (0.022793)	-0.02785 (0.021512)	-0.02176 (0.017837)	-0.02853* (0.015381)
EE (t+2)	-0.02739 (0.020235)	0.005629 (0.020378)	-7.9E-05 (0.01944)	-0.01464 (0.017769)	-0.00197 (0.014783)	-0.0141 (0.031158)	-0.01394 (0.019147)	0.034905* (0.020956)	-0.00823 (0.018445)	-0.00451 (0.014121)
EE (t+3)	-0.03788* (0.020887)	-0.01655 (0.019367)	-0.00647 (0.017107)	0.000088 (0.016054)	-0.00932 (0.013892)	-0.03807 (0.029408)	-0.02742 (0.021167)	0.004499 (0.018595)	-0.00667 (0.01515)	-0.00486 (0.013719)
EE (t+4)	0.051899** (0.021664)	0.009183 (0.019612)	4.55E-05 (0.020465)	-0.02849 (0.020955)	-0.00557 (0.016018)	0.023905 (0.027174)	-0.02566 (0.021964)	-0.03072 (0.019667)	-0.02519 (0.018249)	0.001355 (0.014659)
EE (t+5)	0.006944 (0.024392)	0.041174* (0.02345)	-0.02069 (0.026261)	-0.00547 (0.026239)	-0.01153 (0.022268)	0.056766** (0.025815)	0.03211 (0.024148)	-0.02169 (0.023662)	0.003025 (0.021892)	-0.03455* (0.01804)
Property (b. flat)										
Semi-detached	0.365998*** (0.020691)	0.322495*** (0.021318)	0.305958*** (0.022879)	0.263044*** (0.025073)	0.279698*** (0.027579)	0.367919*** (0.020567)	0.323788*** (0.021388)	0.308508*** (0.023041)	0.26971*** (0.025158)	0.287682*** (0.02763)
Detached	0.526586*** (0.038712)	0.470569*** (0.030919)	0.442932*** (0.028345)	0.383812*** (0.027552)	0.406159*** (0.028654)	0.530024*** (0.038496)	0.470219*** (0.03089)	0.443127*** (0.028384)	0.390061*** (0.027564)	0.412853*** (0.028678)
Mid terrace	0.215054*** (0.020392)	0.140629*** (0.021666)	0.104301*** (0.023522)	0.037176 (0.027033)	0.073068*** (0.030075)	0.217711*** (0.020191)	0.14185*** (0.021565)	0.102177*** (0.023447)	0.037514 (0.026991)	0.071567** (0.030074)
End terrace	0.294535*** (0.022667)	0.261961*** (0.023915)	0.205484*** (0.026592)	0.203376 (0.02778)	0.209625** (0.03098)	0.296725*** (0.022464)	0.262248*** (0.02391)	0.204636*** (0.026571)	0.204203*** (0.027747)	0.21146*** (0.030979)
Bungalow	0.303466*** (0.027044)	0.307661*** (0.025579)	0.306007*** (0.025766)	0.292538*** (0.026534)	0.343936*** (0.029096)	0.306241*** (0.026966)	0.308937*** (0.025475)	0.306685*** (0.025769)	0.300799*** (0.026392)	0.350823*** (0.029134)
Age	-0.07573*** (0.007257)	-0.09623*** (0.00695)	-0.10056*** (0.006746)	-0.12805*** (0.006074)	-0.1242*** (0.005734)	-0.07665*** (0.007248)	-0.09648** (0.006943)	-0.09874*** (0.006716)	-0.12731*** (0.006066)	-0.12401*** (0.005726)
floorsq	0.241283***	0.247724***	0.256323***	0.26693***	0.282963***	0.240761***	0.247346***	0.254903***	0.265599***	0.281157***

	(0.011146)	(0.010116)	(0.009311)	(0.007952)	(0.006864)	(0.01113)	(0.010129)	(0.00934)	(0.007957)	(0.006858)
Lhdd	0.002719 (0.031393)	0.117916*** (0.028736)	0.109382*** (0.027881)	0.161273*** (0.025775)	0.151808*** (0.022351)	0.004193 (0.031293)	0.119747*** (0.028431)	0.112792*** (0.027753)	0.164683*** (0.025617)	0.165232*** (0.022037)
Lgasprice	-0.40655*** (0.031167)	-0.23013*** (0.027939)	-0.23313*** (0.026909)	-0.1822*** (0.02307)	-0.13886*** (0.020572)	-0.41751*** (0.030188)	-0.23624 (0.027273)	-0.23708*** (0.02625)	-0.17282*** (0.022858)	-0.13006*** (0.020152)
Intercept	9.19181*** (0.26791)	8.156013*** (0.245338)	8.265744*** (0.238106)	7.885482*** (0.219002)	7.851157*** (0.190401)	9.196328*** (0.26713)	8.150707 (0.242645)	8.243291*** (0.236594)	7.844684*** (0.218002)	7.735382*** (0.188357)
Test parallel trend 1	NO	Yes	YES	YES	YES	NO	Yes	yes	NO	yes
Test parallel trend 2	YES	YEs	YES	YES	YES	YES	YES	NO	YES	YES
Number of observations	26,187	25,348	24,087	24,620	27,142	26,187	25,348	24,087	24,620	27,142
F test	F(20,8950) = 121.89 Prob > F = 0.0000	F(20, 8570) = 130.37 Prob > F = 0.0000	F(20, 8139) = 151.37 Prob > F = 0.0000	F(20, 8292) = 183.91 Prob > F = 0.0000	F(20, 9145) = 256.35 Prob > F = 0.0000	F(20, 8950) = 121.46 Prob > F = 0.0000	F(20, 8570) = 130.64 Prob > F = 0.0000	F(20, 8139) = 152.59 Prob > F = 0.0000	F(20, 8292) = 186.62 Prob > F = 0.0000	F(20, 9145) = 258.00 Prob > F = 0.0000
R-squared	0.1833	0.2117	0.2437	0.2818	0.3307	0.1840	0.2117	0.2444	0.2843	0.3332

Notes: Clustered standard errors in parentheses by household. * Significant at the 90% confidence level. **Significant at the 95% confidence level. ***Significant at the 99% confidence level.

Fig. 5. Graph of the pre- and posttreatment pattern for the relation between household adoption of any type of EE measure and gas consumption in households belonging to different deprivation areas

Fig. 5.a EE measure in t IMD 1

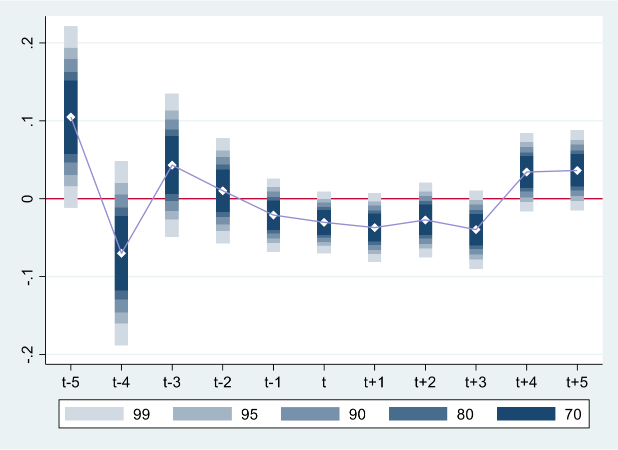


Fig. 5.b. EE measure in t IMD 2

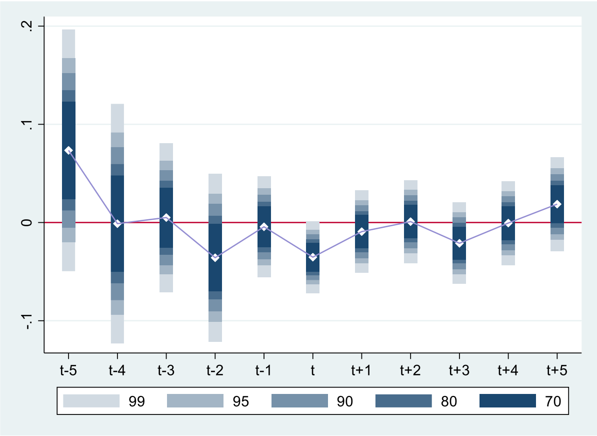


Fig. 5.c. EE measure in t IMD 3

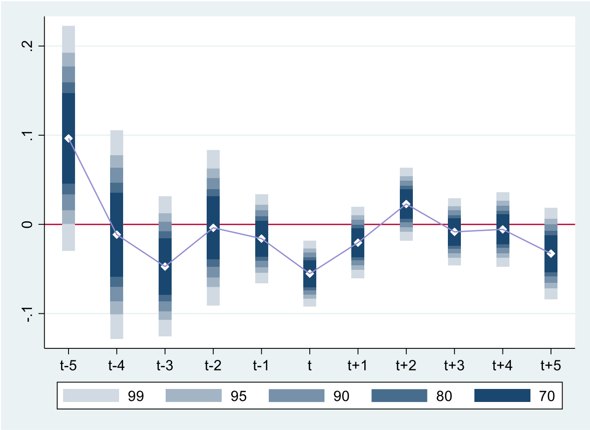


Fig. 5.d. EE measure in t IMD 4

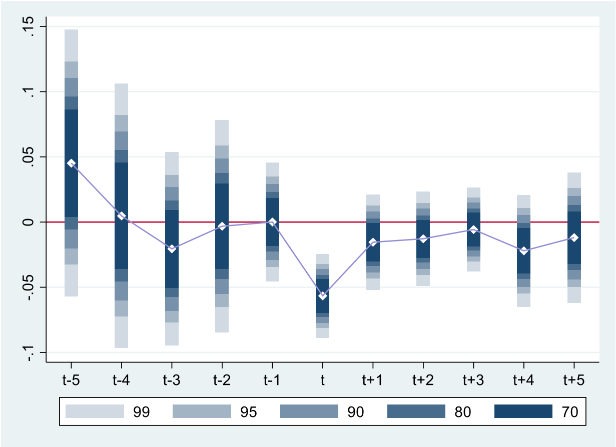
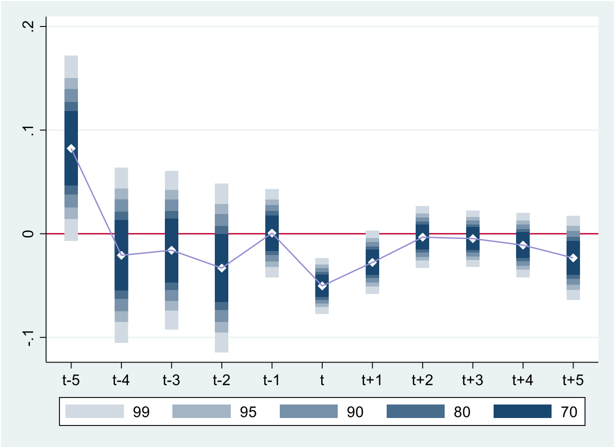


Fig. 5.e. EE measure in t IMD 5



4.3. Assessing energy savings inequality using percentile shares

Attention must be paid to the fact that the impact of the adoption of these measures varies considerably depending on the level of deprivation of the areas in which households are located. The particular lower effect on the poorest segment of the population, proxied by the quintiles level of the index of multiple deprivations by area, may provide a rationale to focus the attention on the barriers that may prevent those households to get potential energy savings derived from the adoption of EE measures. In order to further explore results to test our fourth hypothesis, we will analyse the gas consumption distribution using percentile shares. We present estimates of the distribution of gas consumption for those household installing a technical energy efficiency measure vs. those in the control group. We analyse outcomes for ten distribution groups (deciles) in absolute and relative terms.

Percentile analysis has been widely used in inequality research to study the distribution of income and wealth e.g. Piketty (2014), Anand and Segal (2015), Milanovic (2012); among others. The assessment of percentile shares allows us, in this case, to quantify the proportion of total gas consumption from 2005 to 2017 that will go to our defined groups in terms of their absolute and relative rank in the gas consumption distribution.

We use the analysis developed by Jann (2016) to estimate the differences in the gas consumption distribution between households that have adopted an EE measure vs. those that have not adopted such measures[8]. The percentile shares represent on average, how much of the total gas consumption each member in the percentile group gets in relation to the overall average.

Expressing the results in average levels of gas consumptions, Table 6 shows that the bottom two deciles, i.e. the bottom 20%, of the gas consumption distribution increases their gas consumption after the installation of an EE technical measure. Only from the 3rd decile we start seeing significant gas consumption reductions in absolute terms. Results are consistent across technical measures (See Fig. 6.a and 6.b). This result is important as it highlights that for those decile groups, the EE technical measures are not being effective. As aforementioned, most of the UK EE policy instruments have targeted vulnerable households. However, those dwellings do not reduce their consumption but increases their use of energy. This is not necessarily a bad outcome if the support governmental schemes aim at reducing fuel poverty of more deprived families. Notwithstanding, if the whole goal is the reduction of energy consumption and subsequently to get emission reductions, those policies are not effective. From a policy perspective this result calls for targeted-oriented energy policy measures distinguishing between income groups.

Table 6. Effect of the installation of EE measures on percentile shares of the gas consumption and differences in percentile shares (KWh of gas consumption)

	Loft			Cavity			Any		
	Control	Treatment	Diff	Control	Treatment	Diff	Control	Treatment	Diff
0-10th	3858.903 (26.22598)	4314.048 (52.3743)	455.1448*** (57.2987)	3863.168 (27.08654)	4272.35 (54.42598)	409.1816*** (59.48355)	3819.838 (28.12869)	4247.234 (43.11721)	427.3966*** (49.7865)
10th - 20th	7285.916 (32.55242)	7455.953 (52.25415)	170.0366*** (59.8228)	7289.353 (31.56407)	7437.055 (56.89682)	147.7025** (63.66623)	7267.873 (34.63819)	7433.949 (44.66356)	166.0758*** (54.42373)
20th - 30th	9507.888 (32.49776)	9272.951 (55.36857)	-234.937*** (62.15246)	9507.413 (32.59808)	9287.181 (53.67811)	-220.232*** (61.28363)	9535.953 (34.45088)	9302.117 (42.10333)	-233.836*** (52.14244)

[8] Estimates of percentile shares might be affected by biases related to the size of the samples specially at the top of the distribution (Jann, 2016). Give the size of our global sample, i.e. more than 500,000 observations, we do not expect biases on these estimations.

30th - 40th	11396.03 (33.01949)	10852.87 (55.62445)	-543.159*** (62.31111)	11416.16 (33.216)	10823.94 (56.67687)	-592.216*** (63.97088)	11483.56 (36.98072)	10880.6 (44.51494)	-602.954*** (55.12877)
40th - 50th	13200.86 (34.84558)	12369.29 (58.85388)	-831.572*** (65.63209)	13253.46 (37.10263)	12255.59 (55.57684)	-997.863*** (64.76913)	13354.96 (39.11769)	12371.01 (46.95304)	-983.946*** (57.88486)
50th - 60th	15094.39 (38.95957)	13915.21 (63.57199)	-1179.19*** (71.16899)	15178.81 (39.37763)	13698.71 (60.0412)	-1480.1*** (69.38056)	15325.46 (43.44072)	13887.73 (50.59552)	-1437.73*** (62.74815)
60th - 70th	17248.75 (42.79659)	15645.59 (72.57064)	-1603.16*** (80.13956)	17363.76 (45.12074)	15316.3 (65.36657)	-2047.46*** (76.41558)	17549.17 (47.23109)	15581.35 (54.71836)	-1967.82*** (67.5747)
70th - 80th	19859.15 (51.53422)	17776.19 (86.00114)	-2082.96*** (94.86539)	20002.96 (49.04029)	17282.49 (79.41987)	-2720.47*** (89.64377)	20212.64 (56.05633)	17674.9 (68.38496)	-2537.74*** (82.15345)
80th - 90th	23612.02 (65.3558)	20982.95 (120.1097)	-2629.07*** (129.1477)	23828.16 (67.26516)	20164.21 (97.53871)	-3663.95*** (113.3356)	24066.7 (68.94744)	20773.87 (87.13304)	-3292.82*** (102.6858)
90th - 100th	33056.36 (101.4566)	29413.12 (202.268)	-3643.24*** (213.6883)	33328.13 (105.567)	27535.34 (189.2132)	-5792.79*** (208.7648)	33619.65 (107.4288)	28846.26 (157.6647)	-4773.39*** (176.9825)

Notes: Clustered standard errors in parentheses by household. * Significant at the 90% confidence level. **Significant at the 95% confidence level. ***Significant at the 99% confidence level.

Fig. 6. Percentile histogram (average differences in gas consumption in KWh)

Fig 6.a. Absolute differences in loft insulation

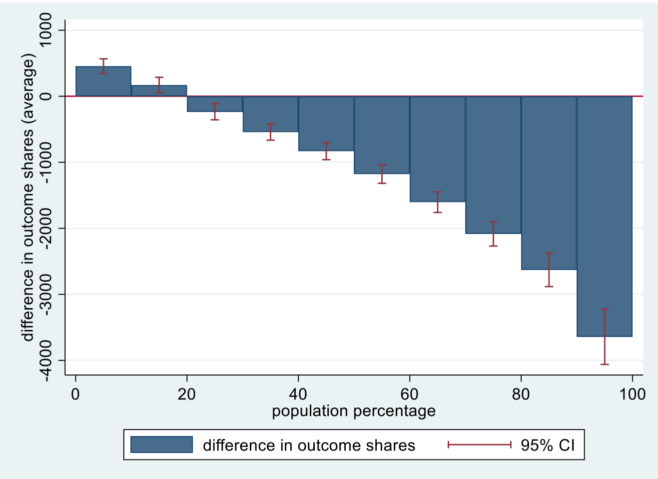
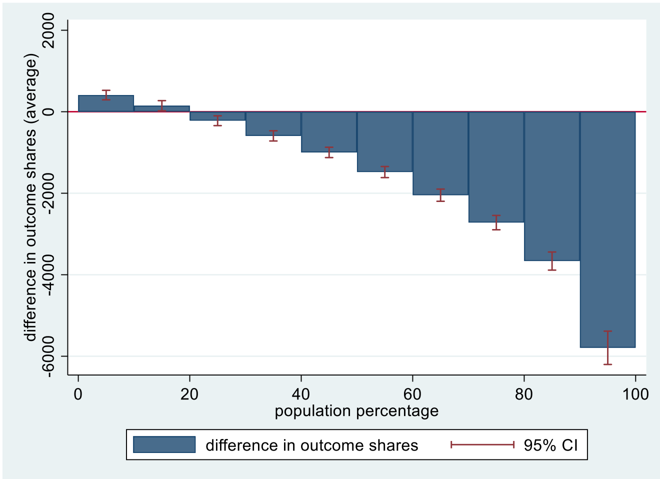


Fig.6.b Absolute differences in cavity wall



The differences in Fig. 6 reflex the overall variation in the gas consumption by percentile group. However, an interesting result to explore is if those differences impact the distributional shape of gas consumption in relative terms. Those results are included in Table 7.

From the results in Table 7, we see that the top 60% reduces their gas consumption when they adopt an energy efficiency measure, however, the bottom 50% increases their energy consumption after adopting an energy efficiency measure in relative terms towards the total gas consumption. From a welfare perspective and in order to fight fuel poverty, we can conclude that the installation of EE measures reduces the inequalities in energy consumptions between percentile groups. The installation of EE measures, at least in the short term, reduces differences between groups to access to energy services, e.g. gas in this specific case. This is a positive results in terms of policy goals as it seems EE measures may act as a mean to change the unequal distribution of energy consumption within a country. This is considered essential in order to get a fair and equitable transitions to low carbon economies (Oswald et al. 2020)

Table 7. Effect of the installation of EE measures on percentile shares of the gas consumption (differences in percentile shares)

	Loft			Cavity			Any		
	Control	Treatment	Diff	Control	Treatment	Diff	Control	Treatment	Diff
0-10th	0.250383 (0.00153)	0.30381 (0.003338)	0.0523428*** (0.0036)	0.249186 (0.001571)	0.309427 (0.003537)	0.06024*** (0.003797)	0.244492 (0.001619)	0.301224 (0.002754)	0.056733*** (0.003099)
10th - 20th	0.472742 (0.001663)	0.525074 (0.002936)	0.052332*** (0.0033)	0.470186 (0.0016)	0.538631 (0.003205)	0.068446*** (0.00352)	0.465186 (0.001745)	0.527234 (0.002489)	0.062048*** (0.002937)
20th - 30th	0.616914 (0.001451)	0.653033 (0.002778)	0.036120*** (0.0030)	0.613257 (0.001452)	0.672627 (0.002674)	0.05937*** (0.002983)	0.610357 (0.001518)	0.659729 (0.002101)	0.049373*** (0.00249)
30th - 40th	0.739424 (0.001298)	0.764296 (0.002531)	0.024872*** (0.0027)	0.736377 (0.001306)	0.783928 (0.00252)	0.047551*** (0.002781)	0.735015 (0.001435)	0.771679 (0.002002)	0.036665*** (0.002355)
40th - 50th	0.85653 (0.001216)	0.871088 (0.002428)	0.014558*** (0.0026)	0.854889 (0.001288)	0.887616 (0.00225)	0.032727*** (0.002533)	0.854795 (0.00134)	0.877383 (0.001906)	0.022588*** (0.002222)
50th - 60th	0.979391 (0.001226)	0.979957 (0.002397)	0.00057 (0.0026)	0.97908 (0.001233)	0.992134 (0.00224)	0.013055*** (0.002501)	0.980919 (0.001342)	0.984952 (0.001877)	0.004034* (0.002203)
60th - 70th	1.119174 (0.001256)	1.101816 (0.002516)	-0.01736*** (0.0027)	1.120016 (0.001306)	1.109288 (0.002346)	-0.01073*** (0.002631)	1.123249 (0.00136)	1.105068 (0.001926)	-0.01818*** (0.002259)
70th - 80th	1.288549 (0.001519)	1.25186 (0.002908)	-0.03669*** (0.0032)	1.290253 (0.001451)	1.251691 (0.002792)	-0.03856*** (0.003081)	1.293727 (0.001642)	1.253548 (0.002335)	-0.04018*** (0.002733)
80th - 90th	1.532052 (0.002217)	1.477692 (0.004503)	-0.05436*** (0.0048)	1.53699 (0.002236)	1.4604 (0.00381)	-0.07659*** (0.004297)	1.540409 (0.002337)	1.473335 (0.003292)	-0.06707*** (0.003831)
90th - 100th	2.144842 (0.004728)	2.071373 (0.010108)	-0.07347*** (0.0107)	2.149767 (0.004826)	1.994257 (0.009857)	-0.15551*** (0.010634)	2.151853 (0.004975)	2.045848 (0.007985)	-0.106*** (0.008841)

Notes: Clustered standard errors in parentheses by household. * Significant at the 90% confidence level. **Significant at the 95% confidence level. ***Significant at the 99% confidence level.

Fig. 7. Percentile density histogram

Fig 7.a. Relative differences in loft insulation

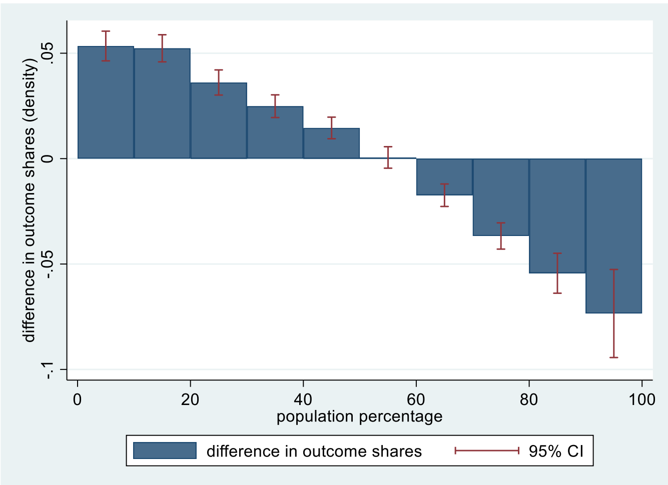
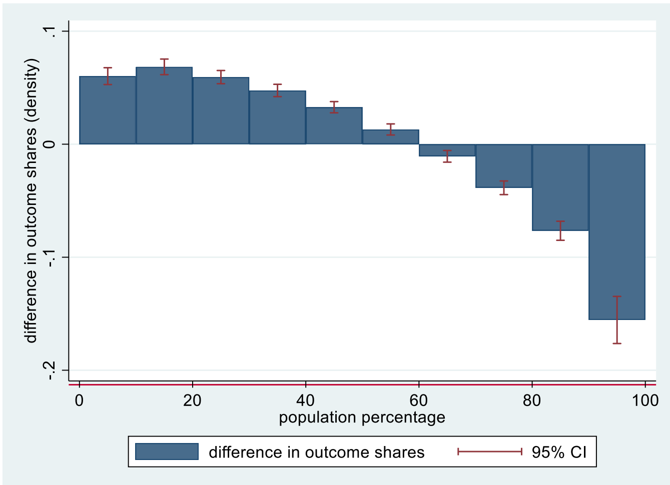


Fig. 7.b Relative differences in cavity wall



Given these results, we cannot reject our fourth hypothesis. All in all, results confirm that for the two EE measures investigated, vulnerable households do not reduce their gas consumption after installing an EE technical measure. Using the framework developed by Peñasco et al. (2020), this result implies that the main goal pursued by governments with the promotion and subsidization of the installation of this type of energy measures is not achieved in vulnerable households, i.e. the policies have been not effective from an environmental point of view. However, considering other outcomes like distributional effects of the policy instruments, EE measures subsidization may improve inequality indicators reducing the differences between different types of households and pushing people in deprived areas out of the dangers of fuel poverty.

4.4. Propensity Score Matching (PSM)

5. Discussion and conclusions

This paper has analysed the responsiveness of household energy demand, specifically gas consumption, in England and Wales to the adoption of EE technical improvements during the period 2005-2017.

Understanding the patterns of energy consumption in residential buildings and if energy efficiency technical measures generate the expected energy savings modelled before the adoption of such measures, is a requisite for the formulation of accurate, effective and cost-effective energy policies. While the vast majority of literature has studied rebound effects from an ex-ante perspective, studies using actual consumption data are few. To the best of our knowledge, this paper is the first one analysing long-lasting effects, i.e. during five years after the installation, of the adoption of energy efficiency technical improvements.

Our study employs robust quasi-experimental estimation methods taking the form of an event-study with micro-level data, for a representative sample of more than 50,000 households in England and Wales.

The results show that the adoption of EE measures in households lead to a decrease in the demand of gas consumption right after the adoption. However, the energy gains generated from the installation of those technical measures, i.e. loft insulation and cavity walls, do not long-last. Energy savings dissolve two to four years after the adoption for cavity wall installations. Loft insulation effect only lasts one to two years. Attention must be paid to the fact that the impact of the adoption of these measures varies considerably depending on the level of deprivation of the areas in which households are located and the existence of conservatories in the households.

The particular lack of effect on the poorest segments of the population, proxied by the quintiles level of the index of multiple deprivations by area, may provide a rationale to focus the attention on the barriers that may prevent those households to get potential energy savings derived from the adoption of EE measures.

According to Ling et al. (2018), those households in which upfront costs of the investments are completely funded by Government energy efficiency schemes, do not experience energy gains. This result aligns with our conclusion that households in more deprived areas do not get the expected energy savings. Usually those dwellings on deprived areas will more likely receive full support for the costs of the energy efficiency improvement. Romero et al. (2016) suggest that in order to mitigate negative distributive impacts, public policy should not inhibit the price signals but to provide rent transfers oriented policies, such an annual payments or grants to vulnerable households. However, British policy has been using this approach for years without the expected results. Our result on the differences among quintiles of the index for multiple deprivation confirms previous literature on rebound effects and consumer group variations (Belaid et al., 2020).

However, it must be highlighted that the introduction of EE technical improvements measures makes households on deprived areas more responsive to changes in energy prices. This represents a positive outcome as EE measures may be acting as tools for the flexibility of the energy demand in the residential sector. They also reduce inequalities between groups of consumers allowing households at the bottom of the gas consumption distribution to increase their gas consumption in absolute and relative terms regarding their peers at the top of the distribution. This result implies positive impacts of EE measures in reducing fuel poverty in deprived areas of the UK geography.

Several implications derive from this research. First, our paper shows that energy efficiency gains derived from the technical installation of energy efficiency measures are only effective in the short-term. Further research is therefore needed in understanding the reasons behind the lack of long-lasting effects. We hypothesize that the implementation of energy efficiency schemes consisting of a mix of regulatory instruments, i.e. tighter standards for newly constructed dwellings and for renovations, financial incentives, i.e. grant, loans or subsidies, and soft instruments is needed. Soft instruments influencing behaviour might be key to get long-term efficiency gains. Second, energy efficiency gains vary widely among households located in areas with different levels of deprivation. Considering the domains of the Index of Multiple Deprivation (IMD) of the UK Government, we assume that those households in the lowest quintile of the IMD represent households with low-income levels, low education attainment and that are more likely to be hit by unemployment. Our results determine that households in the first and second quintile of the IMD do not experience the same levels of energy efficiency gains after the installation of technical efficiency improvements. This conclusion is reinforced by the result obtained with the analysis of percentile shares of the total gas consumption distribution where we see that the bottom 20% of the distribution increases their gas consumption after the installation of EE measures. While energy efficiency policies therefore may be having a positive impact on reducing fuel poverty, e.g. those households become more sensitive to changes in energy prices and they reduces the inequality gap with their peers at the top of the distribution; the energy efficiency schemes are not effective in this segment of the population and they do not get the expected energy savings. This result is relevant for the design of measures that may need to be targeted differently depending on the group and the intended objective, e.g. reduction of fuel poverty vs. energy efficiency savings. Finally, our results highlight the specific difficulties of the British housing stock associated to the very high natural gas penetration and the traditional existence of conservatories in households that may be counteracting the positive effects of the energy efficiency technical improvements. UK with a 62.7%, is the second country in Europe, after The Netherlands (70.9%) with the highest share of gas in the final energy consumption in the residential sector (Eurostat, 2017). These figures reinforce the idea that targeted policies may be needed, specifically, for the reduction of gas consumption and, even the electrification of the residential sector. Cultural and behavioural aspects need to be considered in the design of the policy schemes if the UK wants to get a net zero carbon economy by 2050.

While technical measures are effective in the short-term, it seems that in order to get long-term effects additional policy support would be needed. Our results call for the urgent need to fully incorporate human behaviour into ex-ante modelling of energy use and to complement energy efficiency policies oriented to support the adoption of measures from a financial point of view with soft instruments that allow to integrate behaviours into the new ambience of households with EE improvements. From a policy perspective, this result underline the need to establish more tailored energy policies adapted to the individual characteristics of the households.

As we conclude that technical energy efficiency improvements are not enough to promote energy gains, several options remind open for UK households. First, energy reduction targets could be established for households instead of for energy companies. Energy reduction targets per household may be associated to waivers in the energy bills in the long run. Those households complying with their energy targets can qualify for receiving those waivers. A similar approach can be taken by linking energy prices (tariffs), to the compliance with certain reduction targets by household, i.e. the household would pay a lower tariffs if they manage to reach their reduction targets. For those households in deprived areas, assistance measures to reduce barriers of those households may be needed. In this sense, the role of local governments can be essential as they have a better knowledge of the necessities and barriers faced by local communities. While these are just some ideas, further research is needed to disentangle the reasons behind the disparities in projected energy savings in households and the actual ex-post gains. Understanding what the actual nature of those factors are and if they are related to social challenges, e.g. vulnerable households; and behavioural challenges, e.g. lack of information or incentives is needed.

Appendix

Table A1. Description of variables, sources of data and expected relationship with the dependent variable.

Variable	Definition	Data Source	Expected relation
Total gas consumption by household	Rounded amount of gas used for gas space heating, gas water heating and gas cooking (kWh/yr) provided by energy suppliers through meter readings	NEED	Dependent variable
IMD band	Index of multiple deprivation quintiles, i.e. 1 to 5 (2015 information) 1 = Highest Deprivation To 5= Lowest Deprivation	NEED	(+)
Gas price	Average annual domestic standard gas average unit costs per UK region (cents/KWh)	BEIS	(-)
Household size	Floor area band 1 to 5 1= Under 50 sqm 2= 51 to 100 sqm 3= 101 to 150 sqm 4= 151 to 200 sqm 5= over 200 sqm	NEED	(+)
Property type	Property type 1= Flat 2= Semi detached 3= Detached 4= Mid terrace 5= End terrace 6= Bungalow	NEED	(?)
Age	Dwelling age band 1 to 4 1= Pre 1930 2= 1930-1972 3= 1973-1999 4= 2000 or later	NEED	(-)
Heating degree days[9]	Difference between a reference temperature (T*) (18ºC) and the average daily temperatures (Ta) by region $\mathrm{HDD} = \sum_{i=1}^{n} \max(0;\ T^{*} - \mathrm{Ta})$	EUROSTAT	(+)

[9] Cooling degree days are not included in the analysis because of collinearity problems.

Conservatory	Dummy variable indicating if the property has a conservatory 1= Yes 0= No	NEED	(+)

Source: own elaboration

Table A2. Event study gas

	Any EE improvement		Loft insulation		Cavity wall	
Gas Consumption	ols	fe	ols	fe	ols	fe
EE (t-5)	0.1122637*** (0.020106)	-0.05469** (0.021533)	0.08755*** (0.033914)	-0.04141 (0.05037)	0.115201*** (0.023827)	-0.03731 (0.023868)
EE (t-4)	-0.0389234 (0.018812)	-0.04657*** (0.012773)	-0.01571 (0.033290)	-0.04433** (0.020578)	-0.05085* (0.022689)	-0.03222* (0.016548)
EE (t-3)	-0.021311 (0.013786)	-0.03132*** (0.011591)	-0.02842 (0.021103)	-0.03783** (0.018827)	-0.01624 (0.016412)	-0.02562** (0.012619)
EE (t-2)	0.031061* (0.014193)	-0.04207*** (0.010692)	0.042055* (0.020025)	-0.0433*** (0.014849)	0.022081 (0.016733)	-0.03931*** (0.012281)
EE (t-1)	-0.0023925 (0.008635)	-0.05683*** (0.006658)	-0.01088 (0.009542)	-0.05198*** (0.007461)	0.000844 (0.012207)	-0.06261*** (0.009003)
EE (t)	-0.0425552*** (0.006277)	-0.0711*** (0.004777)	-0.04065*** (0.006821)	-0.06357*** (0.005514)	-0.06565*** (0.009135)	-0.10949*** (0.006311)
EE (t+1)	-0.0007902 (0.007318)	-0.0568*** (0.00503)	0.004192 (0.008736)	-0.05047*** (0.006107)	-0.00419 (0.010203)	-0.07278*** (0.007158)
EE (t+2)	0.0063326 (0.007551)	-0.03352*** (0.004759)	0.004942 (0.009164)	-0.0332*** (0.005916)	0.020741 (0.009933)	-0.02719*** (0.005998)
EE (t+3)	-0.0199885* (0.007237)	-0.03169*** (0.004836)	-0.02472* (0.008599)	-0.03504*** (0.006111)	-0.0175 (0.009316)	-0.02628*** (0.006083)
EE (t+4)	-0.0120465 (0.008147)	-0.01779*** (0.005461)	-0.00781 (0.009913)	-0.01778*** (0.006722)	-0.0172 (0.009994)	-0.01769*** (0.006599)
EE (t+5)	-0.0420835*** (0.009385)	-0.03883*** (0.006748)	-0.02805** (0.012164)	-0.03863*** (0.008788)	-0.0395*** (0.011333)	-0.02773*** (0.008015)
Intercept	9.425039*** (0.003648)	9.578557*** (0.011269)	9.427356*** (0.003191)	9.517457*** (0.014377)	9.435453*** (0.003177)	9.522981*** (0.007886)
Test parallel trend 1	NO	NO	NO	NO	NO	NO
Test parallel trend 2	NO	NO	NO	NO	NO	NO
Number of observations	127,384	127,384	127,384	127,384	127,384	127,384
Treated						
Control						
F test	F(11, 127372) = 30.84 Prob > F = 0.0000	F(11,43100) = 71.38 Prob > F = 0.0000	F(11, 127372) = 17.36 Prob > F = 0.0000	F(11,43100) = 42.69 Prob > F = 0.0000	F(11, 127372) = 20.30 Prob > F = 0.0000	F(11,43100) = 61.38 Prob > F = 0.0000

Notes: Robust standard errors in parentheses. * Significant at the 90% confidence level. **Significant at the 95% confidence level. ***Significant at the 99% confidence level. Clustered standard errors for FE models

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