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Assessing the effectiveness of energy efficiency measures in the residential sector gas consumption through dynamic treatment effects: Evidence from England and Wales

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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 29.5% in the UK (IEA, 2020a). Using a staggered differences-in-differences approach with dynamic treatment effects, we analyse changes in residential gas consumption five years before and after the adoption of energy efficiency measures. The analysis includes energy efficiency interventions involving the installation of new heating-related insulation equipment—i.e., of loft insulation and cavity walls, supported by 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 the extent to which gas consumption changes are dependent on household characteristics and variations in weather conditions. 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 the retrofitting of cavity wall insulation measures and after two years following the installation of loft insulation. The disappearance of energy savings in the longer run could be explained by the energy performance gap, the rebound effect and/or by concurrent residential construction projects and renovations associated with increases in energy consumption. Notably, for households in deprived areas, the installation of these efficiency measures does not deliver energy savings. These results confirm the existence of effects that reduce the energy savings from the adoption of these efficiency technologies over time and indicates that, for some groups, these net savings do not seem to materialize.

1. Introduction

Improving energy efficiency (EE) in the residential sector is key to address multiple energy-related challenges. According to the IEA (2020b), increasing EE in buildings is important because many energy-efficient products and services can cost-effectively 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 73% of the TFC in buildings (UNEP, 2020).

In 2018, residential buildings in the UK were responsible for about 29.5% of the country's final energy consumption, with 37,991 Ktoe,[1] making the sector the second largest in terms of energy consumption after the transportation sector (IEA, 2020a). Not surprisingly, there is a long history of research studying the drivers and factors affecting UK energy demand –mostly price elasticity studies for gas and (mainly) electricity consumption- relying on different types of ex-post data (See Cuce, 2016; Fouquet, 2014; Chitnis et al., 2020; Asche et al., 2008;

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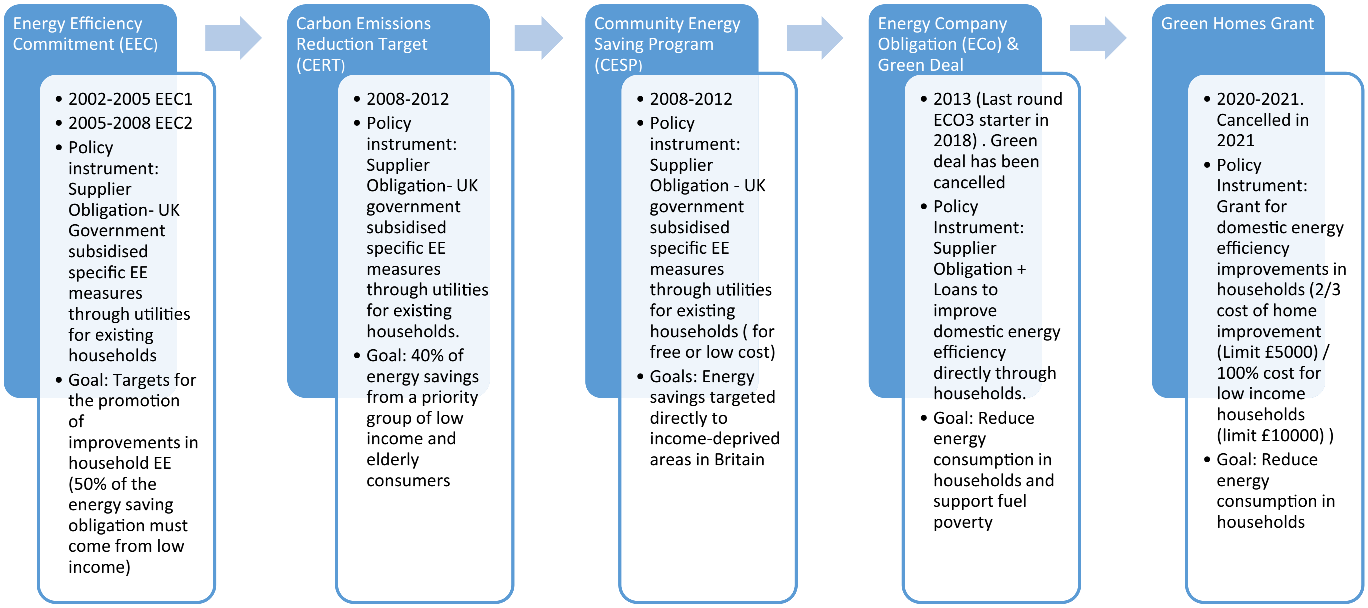

Fig. 1. Timeline of main residential building EE policies in the UK between 2002 and 2021. (In addition to the schemes shown in Fig. 1, the UK Government has set up non-EE focused heating and housing benefits that may influence both the energy consumption and expenditure of households. First, the Labour 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.)
Source: Own elaboration with information from OFGEM.

Serletis et al., 2011; among others).

Some analysis indicates that energy efficiency has already contributed to reducing UK energy consumption (Jenkins, 2019). For example, according to a report from DECC (2012), while UK domestic energy use increased by 22% from 1970 to 2007, if new insulation or more efficient heating technologies had not been installed during that time period, this increase would have been more than double. But as noted by the DECC (2012) report, much more work on energy efficiency (as well as in other areas) is needed to meet the UK's climate and EE targets, reduce energy bills, and fight fuel poverty (ICL, 2019). The important role of EE in residential buildings can be observed in policy efforts since 2002 to boost efficiency either through targets or through economic and financial mechanisms as summarized in Fig. 1. However, these policies have come and gone, and there is a sense that policy makers are not achieving the results expected from the implementation of energy saving policies in buildings.[2]

Recent estimates suggest that 12 million dwellings will need to be retrofitted with energy efficiency technical improvements like insulation in the next 30 years, if the UK wants to meet its net zero target by 2050 (IPPR, 2020). However, while the UK government has put in place several policies to promote the adoption of EE technical measures, research has been inconclusive regarding the effectiveness of such policies in terms of their impact on the adoption of retrofitting measures and/or on achieving significant energy savings. A potential reason for that is the possible rebound effects associated with the behaviour of occupants (Aydin et al., 2018; Galassi and Madlener, 2018; Sorrell et al., 2018). Research about the size and drivers of the well-known energy performance gap and of rebound effects, — increases in energy consumption due to behavioural changes induced by the lower energy costs—, either indirect or direct, resulting from different EE measures in the residential sector, is vast. However, studies estimating the direct rebound effects of the adoption of particular efficiency measures affecting heating are rare and, in most cases, they only use a relatively short-term before and after comparison without a control group and/or without controlling for confounding variables (see Sorrell, 2007 for a review). Gillingham et al. (2016) also point to the fact that there is more evidence on the nature of the rebound effects for gasoline used for transport and for electricity than for natural gas or oil for residential heating purposes. Crucially, Gillingham et al. (2016) and other work do not consider or estimate the extent to which the installation of different EE measures may yield different effects on heating consumption. In this study, we focus on improving our understanding of the impact of the installation of two specific (and important) efficiency measures on residential gas energy consumption.

We shed light on the extent to which technical energy efficiency improvements —specifically, the installation of loft insulation and cavity walls— are associated with changes in residential gas consumption. Focussing on gas consumption is especially important in the context of the UK where 85% of households use gas as their main heating source and where there are large social, institutional and financial barriers to the adoption of low carbon heating technologies like heat-pumps (Thornton, 2022). We consider the adoption of loft insulation and cavity walls as they have been consistently the focus of all energy efficiency schemes in the UK over the past two decades. This paper analyses the dynamic effect of the installation of such efficiency measures to determine whether such measures resulted in changes in gas

[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 million meters of the Smart Metering Programme aimed by the end of 2020 (DBEIS, 2019). The Green Deal was cancelled after only 1% of expected households benefitted from the loans of the programme (National Audit Office, 2016). Also, in March 2021, the UK Government cancelled its last programme, the Green Homes Grant, only after 6 months from inception in September 2020.

consumption in the long run, i.e. up to five years after the adoption of an energy efficiency measure.

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 listed in Fig. 1 during that period, namely: the Energy Efficiency Commitment (EEC), the Carbon Emissions Reduction Target (CERT), the Community Energy Savings Programme (CESP) and the Green Deal. This paper contributes to the literature in three ways. First, to the best of our knowledge, this is the first study analysing gas consumption patterns in the UK at the micro level for a large panel of households of more than 50,000 dwellings and over a period of 12 years, thus involving 700,000 observations. This was made possible by data that were made available by the National Energy Efficiency Dataset (NEED). Recent synthetic academic work notes that there is little evidence (in the UK or beyond) on the impact of policies for the installation of residential efficiency measures on heating use in buildings (Gillingham et al., 2016; Eyre and Baruah, 2015).

Second, we apply a staggered differences-in-differences (DiD) methodology considering dynamic treatment effects for the first time to understand the impact of the EE installations on gas consumption over time, i.e., five years before and after the adoption of an EE technical measure, at a household level. To the best of our knowledge this methodology, which allows us to construct a relatively robust counterfactual, has not been used to study efficiency measures in the UK. We control for the following characteristics at the household level: dwelling size, the age of the dwelling and the type of dwelling and the vulnerability of the households, which we approximate by using the index of multiple deprivation (See section 3 for further details). We also take into consideration the region in which the dwelling is located by introducing regional differences[3] in gas prices and in weather conditions. This allows us to briefly discuss potential impacts on the intensive margin i.e. on gas consumption; and on the extensive margin i.e. on the adoption on EE measures.

Third, we segment our sample to allow us to understand the role played by other house renovations made alongside energy efficiency improvements and the vulnerability of the households to derive policy implications.

Overall, the results obtained have important implications for the design of policies to help improve EE in residential buildings and thus help deliver the UK net zero targets. Given that more than 80% of dwellings in the UK use gas as the main source of heating, policies to reduce gas consumption in households and improve efficiency are important complements to other key efforts, most notably heating electrification.

The rest of the paper is structured as follows. In the next section, we review the literature and outline the research hypotheses. Section 3 introduces our model and methods. Results are summarized and discussed in section 4 and robustness checks are presented in section 5. Finally, section 6 concludes with some policy implications, limitations and future research directions.

2. Literature review and research hypotheses

The reduction of energy use and consequently of GHG emissions in households, in particular CO_2 emissions that represent around 97% of total GHG emissions in the residential sector, can be achieved using three main strategies that are not mutually exclusive: the adoption of technical solutions to improve EE, the replacement of energy carriers, and behavioural changes that result in energy savings (Trotta, 2018). This paper focusses on analysing the impact of two important technical efficiency measures at the household level. Although there are behavioural aspects directly related to choices regarding the adoption of EE measures (Barr et al., 2005; Trotta, 2018), we focus here on the impact of the adoption of these measures over time on gas consumption as mediated by behaviour and not on what preferences lead to the adoption of the technical measures.

2.1. The impact of efficiency improvements on energy consumption: the energy efficiency gap, the rebound effect and expected energy savings

Improving EE in the residential sector is key to addressing energy-related challenges. The International Energy Agency (IEA) estimates that a range of public policies can reduce energy consumption in residential buildings globally by 30–80% while increasing energy security and improving welfare conditions (IEA, 2017). However, this estimate is based on an ex-ante engineering-based model that makes important assumptions regarding the impact of new policies without considering systemic or behavioural aspects. While there is a consensus regarding the need to put in place additional public policies to reduce energy consumption in residential buildings in countries such as the UK (Eyre et al., 2018), there is less agreement about the level of effectiveness of different interventions (Kerr et al., 2017). Indeed, while improving energy efficiency in the building sector is believed to be one of the most cost-effective ways to improve energy security and reduce the environmental damages from the current energy system (IEA, 2016), energy consumption in households is not decreasing (Gram-Hanssen, 2015; Gram-Hanssen and Georg, 2018). In addition, some EE interventions could perpetuate the use of natural gas in the residential sector for heating in that they may, for example, delay electrification, and this may also result in some increases in methane emissions, another important GHG (Slorach and Stamford, 2021; Field and Derwent, 2021).

One of the reasons explaining why gas consumption in households is not decreasing in most places is the well-known building energy performance gap (EPG) (see Zou et al., 2018 for a review). While there are two main definitions of the energy performance gap, the one relevant to the analysis presented in this paper is the one that defines the energy performance gap as the difference (or gap) found between the predicted building energy performance in ex-ante evaluations –i.e. the potential simulated energy savings-, and the actual ex-post performance of a building (Zou et al., 2018). In the context then of energy retrofits in households, the aforementioned energy performance gap can be divided in two. First, a pre-bound effect defined as the difference between the simulated theoretical consumption of a building and the actual energy use before an energy efficiency retrofitting measure is installed. Second, a rebound effect after an energy efficiency retrofitting measure has been adopted (Mahdavi et al., 2021).

The energy performance gap, therefore, is understood as the deviation in energy use from the expected (or forecasted) change in demand at the design stage. Based on a review of 144 papers on the energy performance gap for both residential and non-residential buildings, Mahdavi et al. (2021) calculated that for residential buildings, the mean energy performance gap is about 30% (±51%). The review seems to confirm occupant-related factors as important causes of the EPG. On a recent analysis using data for Ireland, Coyne and Denny (2021) calculated that, excluding potential rebound effects that can arise after a retrofit, dwellings that have been assigned high Energy Performance Certificates (EPCs) based on a set of observable characteristics, display, on average, an energy consumption that is higher than their expected consumption based on their EPC. The literature suggests a great variability, however, depending on the quality of the thermal performance of the building (e.g. Cozza et al., 2020 for a case study on Switzerland) and/or the occupants' socio-economic background, income, lifestyle or environmental attitudes, among others (See section 2.2 and van den Brom et al., 2018; Sunikka-Blank and Galvin, 2012, Dall'O et al., 2012 for Italy among others).

Regarding the rebound effect i.e. the energy performance gap

[3] These England Regions were formerly known as Government Office Regions. We include: South East, London, North West, East of England, West Midlands, South West, Yorkshire and the Humber, East Midland and North East plus Wales.

observed after an EE retrofit; there are increasing concerns about the effectiveness of energy efficiency retrofits in terms of their ability to realize the expected energy savings (Galvin, 2014). Several recent papers have estimated, ex-ante, the impact of household EE technical improvements on energy consumption using different techniques. These include 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), scenario analysis (Chitnis et al., 2014; Chitnis et al., 2013; Druckman et al., 2011) and input-output models (Thomas and Azevedo, 2013; Freire-Gonzalez et al., 2017). One of the most recent contributions on the potential of energy savings in the residential sector in the UK has been Rosenow et al. (2018), who forecast the lifetime energy savings associated to different levels of deployment of energy efficiency technologies up to 2035. The Rosenow et al. (2018) study is an example of the wide range of ex ante assessments in the literature.

While there is significant ex-post research on the factors determining the adoption of different types of energy efficiency measures in residential buildings across different countries (Achtnicht and Madlener, 2014; Bergman and Foxon, 2020; De Vries et al., 2020; Ebrahimigharehbaghi et al., 2019; Lang and Lanz, 2021; among others); ex-post research on the impact of the adoption of EE measures on energy consumption is relatively scarce, with a few notable exceptions (namely: Trotta, 2018; Elsharkawy and Rutherford, 2018; Adan and Fuerst, 2016; Webber et al., 2015; Fowlie et al., 2018). The ex post analysis of the impact of EE measures in households is particularly timely in the UK, given the perceived policy failures in the residential EE space in the UK (See, e.g. Kjaerbye et al., 2011; Sovacool et al., 2017; DBEIS, 2016; National Audit Office, 2016).

Understanding the extent to which the expected energy savings in households after the adoption of EE measures are realized—the combination of the prebound and rebound effects—is paramount given that around 80% of the housing stock that the UK will have in 2045 already exists and will need to be subject to energy retrofits (Gibb, 2022). Authors like Allcott (2017), Allcott and Greenstone (2017) for the U.S. and Gerarden et al. (2017) have identified the existence of an energy efficiency gap between ex-ante engineering forecasts and the actual energy savings after the adoption of EE measures. Based on a laboratory field experiment in Australia, Dorner (2019) argues that residential energy efficiency technological improvements 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 related to a change in the pro-environmental behaviour of individuals, i.e., there could be a decrease in environmental efforts after the adoption of a technological energy efficiency measure. That said, there is no conclusive large scale, on the ground evidence detailing the extent to which the differences between expected energy savings from EE measures and realized savings may depend on contextual social factors, e.g., vulnerability or consumer resistance (Sovacool et al., 2017), or may be associated to rebound effects of policy-induced improvements (Gillingham et al., 2016; Brockway et al., 2017; Sorrell et al., 2018) among other relevant policy questions.

In the last few years, some ex-post evaluation studies using data on residential energy consumption over time have tried to shed light on the role and magnitude of the rebound effects, i.e. the reduction in expected savings from the installation of EE technologies because of behavioural or other systemic responses.

Using ex-post information about the Kirklees Warm Zone (KWZ)[4] scheme in UK homes between 2007 and 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 had been greater than predicted in part because performance gaps and rebound effects had been lower than the ones initially assumed by the Buildings Research Establishment and by the Savings Trust.[5] The same authors point to the mediating role of demographic characteristics and find that rebound effects in all households in Kirklees 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). It is important to note that the EE improvements were subsidized and free for everyone and that there is no record of adopters combining the insulation with other house projects.

In a US context, Fowlie et al. (2018) evaluated with a randomized experiment and quasi-experimental techniques the U.S.' Weatherization Assistance Program (WAP) using a sample of 30,000 low-income households from Michigan. The programme provided on average, approximately $5150 worth efficiency improvements (including loft and wall insulation) per household. The authors concluded that the costs of adoption of the energy efficiency measures were twice the actual savings and that therefore the WAP energy efficiency investments were not delivering on their goals.

Davis et al. (2020) conducted a field experiment in Mexico to assess the impact of energy efficiency upgrades in new dwellings (specifically insulation and passive cooling systems) on electricity use and thermal comfort over a 16-month period after the retrofit. 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 consumption, contrasting with the ex-ante engineering estimates that predicted electricity consumption reductions of 26%.

Finally, using a version of the dataset used in this paper covering an earlier time period, Adan and Fuerst (2016) applied a traditional diff- in –diff econometric model to analyse variation in energy consumption before and after the installation of cavity wall insulation, loft insulation or the installation of a new boiler in the period from 2008 to 2012. The authors analyse energy efficiency improvements for a treatment group of households who installed some energy efficiency measure in 2011 relying on the funding made available through the CERT and/or CESP policies. The authors find statistically significant energy savings one year after the adoption of the energy efficiency improvement despite other factors like the rebound effect. However, the study does not control for mediating effects of changes associated to, for example, other home improvements unrelated to energy efficiency technical measures, nor does it consider the extent to which the energy savings that they observed one year after installation may not continue over time.

So, what happens in the long-term? Research indicates that consumers would need to both adopt new technology and adapt their behaviour to reduce residential energy consumption (Aydin et al., 2017; Aydin et al., 2018). According to Galassi and Madlener (2018), for a sample of 3161 individuals in Germany, changes in occupants' behaviour could reduce the energy efficiency impact of the retrofit. These authors find that retrofitting residential dwellings may result in better insulation and therefore in higher room temperatures (Psomas et al., 2016). In that situation, occupants may change their behaviour (they may adapt) and open the windows when it is too warm. These types of effects might explain why energy saving policies in buildings are often not leading to the expected results. Rau et al. (2020) used a before-after experimental research and online survey to test the impact of retrofitting on twenty households in Ireland in 2015. The authors conclude that

[4] 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 coordinated by the Kirklees Council. The scheme included and energy audit and free loft and cavity wall insulation to all households in the metropolitan area.

[5] The results indicate that while predictive models from the Buildings Research Establishment, from 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 measures adopted under KWZ respectively; the KWZ, following the predictive models methodology, realized 76% and 62% respectively on average.

heating-related energy efficiency retrofits[6] generated a reduction in gas consumption in 17 out of the 20 surveyed households of 23% on average. However, the experimental research does not include a control group, there may be self-selection bias, and the effect is only measured one year after retrofitting which does not allow the authors to estimate the long-term effects of the adopted energy efficiency measures.

2.2. The role of other mediating factors: renovations and vulnerability of the households

In addition to being subject 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 (Jack et al., 2011) —. On average, Jack et al. (2011) estimate that, across all building and extension types in the UK, extensions result in a 16% increase in energy consumption. The combination of an old housing stock, the rebound effect, and the possible correlation between the implementation of EE measures and other building work, which may lead to increase energy use, might when taken together, result in no reductions in gas consumption at the household level. When these renovations (e.g. adding an extension, renovation of bathrooms, adding new rooms…) take place, the adoption of an energy efficiency measure may be considered as part of the wider renovation primarily aimed at improving the physical well-being of the families (Judson and Maller, 2014). Research considering the impact of renovations on heating energy consumption is scant. Sandu and Petchey (2009), however, found that in Australian households, despite an increase from 33% to 59% between 2005 and 2008 in the proportion of households using energy efficient lighting, the lighting energy demand per household increased at the aggregate level. This may be the effect of a greater use of halogen lamps after renovations, increases in the amount of lighting used (e.g., more locations and/or new devices), and/or a change in how occupants used electricity. For the UK, Hand et al. (2007) using interviews with UK households also points to the fact that spatial changes and extensions tend to be associated with the acquisition of new devices that may contribute to an increase in energy consumption both gas and electricity.

One aspect that has not been generally considered by the literature is the extent to which the cost of specific EE improvements is a possible driver of subsequent energy consumption patterns i.e. the fact that households may adapt their energy consumption behaviours depending on the theoretical payback period of the EE investment. Authors like Gillingham et al. (2016), Greening et al. (2000) and Turner (2009) among others have highlighted this as an area for future research. For example, differences in the size of the upfront cost, the level of retrofit schemes or the expected payback period may have important impacts on subsequent energy consumption in households. Indeed, according to simulation exercises facilitated by technicians and installers, the payback time at the household level for a cavity wall installation, for example, vary between 3 and 4 years, on average.[7] It is possible that households that made those investments would adapt their energy consumption behaviours during the first few years after the installation to accelerate the amortization period. If this is the case, households that spend more money upfront on the adoption of EE measures may experience smaller rebound effects in their energy consumption—they may be more likely to reduce heating consumption. Tovar (2012) using data from England and Bye et al. (2018) using data from Norway are two studies that have considered this hypothesis.

Tovar (2012) used the English Household Condition Survey including data from 2003 to 2007 to make projections of expected costs and savings. His ex-ante modelling study estimated that the adoption of low cost measures such as the ones analysed in this paper, i.e. cavity and loft insulation, would bring cost savings to households over a five-year time period because of the expected overall reductions in annual energy consumption.

In turn, rebound effects may be higher for those receiving external financing (since they do not have costs to recover) and those belonging to low-income percentiles which spend a higher fraction of their income on energy consumption. More specifically, the literature indicates that we may expect differences in the energy consumption of households after adopting a particular measure for households with different income levels, mainly due to price sensitivity. The sensitivity of rebound effects to income or consumption groups has been widely studied in the literature (Belaïd et al., 2020; Gillingham et al., 2016; Kulmer and Seebauer, 2019; McCoy and Kotsch, 2021; among others). 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) conduct ex ante modelling of the rebound effect of six heating and lighting EE measures in households in terms of GHG emission reductions. Using the Community Domestic Energy Model the authors conclude that rebound effects are likely to be modest (0–32%).

Understanding ex-post energy consumption responses to EE technical improvements in different types of households (vulnerable vs. high income, for instance) is important for policy making as most of the energy efficiency programmes have focused on vulnerable households and it is those households that may experience the largest rebound effects given the ex-ante evidence available.

2.3. Research hypotheses

We propose the following hypotheses related to the relationship between the installation of loft insulation and cavity walls and the evolution of household energy consumption:

H1. The installation of EE technical improvements in households generates statistically significant reductions in the amount of gas consumed by dwellings in the **short-term** (a year after installation) when compared to similar dwellings that have not adopted them.

H2. Any reduction in gas consumption in UK households after the installation of an EE technical improvement will not be sustained **in the longer term** (over 2–5 years) due to mediating factors unrelated to the energy savings potential of the measure adopted, e.g. behaviour and purchases of residents.

H3. Households installing EE technical improvements **alongside other renovations** in dwellings do not experience a significant reduction in gas consumption in the short or medium-term.

H4. For the two EE measures investigated, **vulnerable households** installing EE technical measures exhibit a higher rebound effect that results in no reduction (in the short- or medium-term) to their gas consumption.

In summary, Hypothesis 1 and 2 focus on the timing of any energy saving effect, Hypothesis 3 on differences between households depending on whether or not additional home renovations took place, and Hypothesis 4 probes whether there are differences in the rebound effect based on household income.

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

[6] Energy efficiency retrofit in this group of community dwellings included pumped cavity wall insulation, attic insulation, double-glazed uPVC-framed windows, uPVC-framed front door, uPVC-framed back patio doors and heating system and controls (Rau et al., 2020).

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

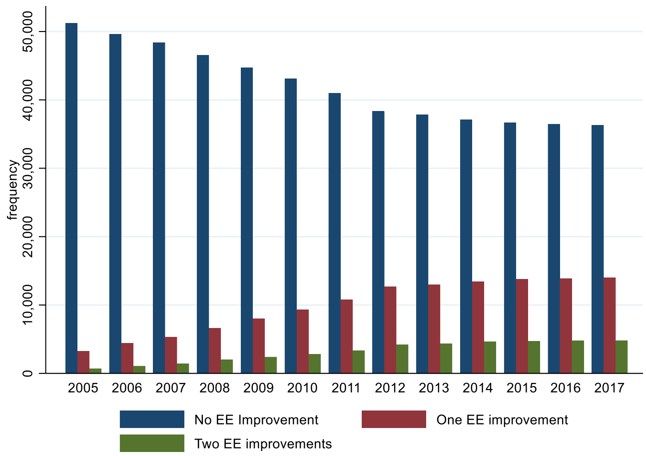

Fig. 2. Number of households in the sample broken down by the adoption of EE measures.
Note: The blue bar denotes dwellings that have not adopted any EE improvement, the red bar one improvement i.e., either cavity wall or loft insulation, and the green bar denotes households that have implemented both improvements.
Source: Own elaboration with NEED data 2019.

form of a panel of households and includes annual 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[8] to facilitate a better understanding of energy use and energy efficiency in Great Britain. For the purpose of this research, we will focus on its data 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 household attributes and characteristics to deliver a representative sample of the housing stock in the England and Wales. The EE measures installed were (at least partly) supported by National EE support schemes i.e., EEC, CERT, CESP, and the Green Deal Communities. The technical measures covered in a panel form in this paper are loft insulation and cavity wall installation. We focus on gas consumption as 85% of the dwellings in the UK as of 2018 relied on central gas heating systems (Ministry of Housing, Communities and Local Governments, 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 UK Department of Business, Energy and Industrial Strategy (DBEIS). In order to analyse the impact of the installation of EE improvements in the energy consumption of households, we 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[9] or the characteristics of the building itself, in addition to changes in energy prices, may play a role in the gas consumption pattern in the residential sector.

Fig. 2 shows the number of households that have adopted different types of energy efficiency measures i.e., cavity wall and/or loft insulation, in the period of analysis.

Table 1 shows the descriptive statistics for the dependent and control variables used in this research for the group of households in the treatment group, which we define as the group of households that had at least one EE measure implemented in some year between 2005 and 2017, and for the households in the control group, which are the households that did not implement any of the two EE improvements considered during the period of analysis. We discuss potential heterogeneity concerns and selection biases in section 5.

This table presents 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 any sample segmentation by type of energy efficiency measure. A more detailed descriptive statistics table of the variables, the units of measurement, the sources of data and expected relations with the dependent variable is provided in table A1 in the Supplementary Information (SI). Details of a Wilcoxon rank-sum test for medians for non-continuous variables[10] can be found in table A2 in the SI.

3.2. Methods

The main goal of this paper is to study the impact, if any, of the installation of EE technical improvements to reduce gas consumption in households. For most quasi-experimental applications of Differences in Differences (DiD) approaches, the method comprises two groups i.e. treatment and control groups; and two periods i.e., before and after the intervention -in this case, the installation of the improvement-. With this identification, we would be able to calculate the average treatment effect on the treated, assuming the common trends assumption holds (Goodman-Bacon, 2021).

In this paper the installation of EE measures differs in the time in that different households carried out the EE improvements over the course of the 12 years covered by the panel data. In this situation, the aforementioned canonical approach for a DiD methodology is not appropriate to show the effect of the event on the outcome variable because the EE improvements are implemented at particular points in time that vary depending on the household. After the EE installation, each dwelling will remain in the treatment group since it is rare for cavity walls and loft insulation to be removed shortly after installation. Taking this into consideration, we identify and estimate the effect of the treatment using a generalization of the DiD approach with multiple time periods to account for variations in the treatment timing and for the parallel trends assumption after controlling for possible confounding covariates, through a staggered differences in differences methodology. This approach allows us to evaluate the effect observed when certain units in a panel receive a treatment at different moments in time (Borusyak et al., 2021). For the purpose of this paper we will define the treatment as the adoption of one EE technical measure.

Cerulli and Ventura (2019) developed an estimation procedure to apply to the case of binary time-varying treatment with pre- and post-intervention periods. We use their method to analyse the differences in the gas consumption of households up to five years before and after the adoption of EE improvements. With this approach, we cannot only analyse the effect of the EE improvements but also if we observe anticipatory or delay effects in gas consumption.

To start with, we consider the installation of an EE measure whether loft insulation or cavity wall[11] (a binary treatment indicator) for household i at time t:

[8] DECC became part of the UK Department of Business, Energy, Innovation and Skills—BEIS—in 2016.

[9] Unfortunately, the NEED data does not provide information about the size of the household measured as the number of people living in the household i.e. occupancy. We use here therefore the size of the dwelling measured as the surface in squared metres as a proxy given that these two variables, when available, tend to be highly correlated (Henderson, 2008; Hopkin et al., 2019).

[10] This test is used to check whether two samples are likely to derive from the same population.

[11] We also consider households that have adopted the two types of energy efficiency installations vs. those who did install none, and/or one. This analysis is included in Table A5 in the SI.

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

	Units	Treated		Non-treated		Difference
		Mean	Median	Mean	Median	Mean
Age Dwelling	Dwelling age band 1 to 4 1 = Pre 1930 2 = 1930–1972 3 = 1973–1999 4 = 2000 or later	2.079	2	2.21	2	−0.131***
Property type	Property type 1 = Flat 2 = Semi detached 3 = Detached 4 = Mid terrace 5 = End terrace 6 = Bungalow	3.31	3	2.899	3	0.411***
IMD band	Index of multiple deprivation quintiles 1 = Highest Deprivation To 5 = Lowest Deprivation	2.92	3	3.012	3	−0.092***
Surface area	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	2.368	2	2.289	2	0.079***
Conservatory	1 = Yes 0 = No	0.047	0	0.04	0	0.007***
Annual gas consumption	kWh/yr	14,107.85	13,100	15,632.01	14,300	1524.163***
Annual electricity consumption	kWh/yr	3958.486	3200	4720.746	3700	762.260 ***
HDD	Difference between a reference temperature (T*) (15.5 °C) and the average daily temperatures (Ta) $HDD = \sum_{i=1}^{n} \max(0; T^* - Ta)$	2776.998	2760.2	2692.238	2663.79	−84.760***
Gas Price	Cents/KWh	4.182	4.287	3.752	3.816	−0.430***
Electricity price	Cents/KWh	14.300	14.919	13.111	13.325	−1.189***
Number of households		**35,422**		**18,930**		

* Significant at the 90% confidence level. **Significant at the 95% confidence level. ***Significant at the 99% confidence level.

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

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 becomes 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).

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

Where y_{it} is the annual energy consumption i.e., gas consumption in KWh (the 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 time-varying household related variables, i.e. gas price paid by the household normalised by the region in which the dwelling is located and the heating degree days of the region, 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. With this approach we consider the same household as a treatment unit in certain years and as controls in others (Gonçalves et al., 2020).

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, 2021). 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. Like in any DiD analysis, this approach does not completely exclude a possible role for selection bias. In other words, although we include important control variables, the DiD method still has inherent limitations in terms of its ability to control for other unobservable household characteristics that may be correlated to the treatment. Having said that, although in this case the treatment takes place at various points in time and therefore, the possibility of bias from individual events is reduced; we also implement a propensity score matching approach as a robustness check, as shown in the section 4.3 and in the SI.

Second, we consider dynamic treatment effects. We use an extension of the DiD estimator by including five leads and lags of the treatment as regressors 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 adopt Cerulli and Ventura (2019) approach, which allows us to analyse simultaneously the average treatment effect (ATE) together with the pre- and post-treatment effects.

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

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. The next stage will be testing the significance 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

Table 2
Baseline results (staggered DiD with covariates).

	(1)	(2)	(3)	(4)	(5)	(6)
	Fe			OLS		
Gas Consumption	Any	Loft	Cavity	Any	Loft	Cavity
EE (t-5)	−0.0015	0.0034	0.0105	0.07890***	0.0252***	0.0967***
	(0.0221)	(0.0506)	(0.0239)	(0.0193)	(0.0310)	(0.0200)
EE (t-4)	−0.0036	−0.0006	0.0022	−0.0194	0.0141	−0.0317
	(0.0151)	(0.0206)	(0.0166)	(0.0192)	(0.0305)	(0.0194)
EE (t-3)	0.0101	0.0053	0.0205	−0.0006	0.0108	0.0067
	(0.0133)	(0.0189)	(0.0126)	(0.0145)	(0.0207)	(0.0149)
EE (t-2)	−0.0136	−0.0146	−0.0130	−0.0155	−0.0127	−0.0141
	(0.0118)	(0.0149)	(0.0123)	(0.0140)	(0.0183)	(0.0151)
EE (t-1)	−0.0028	0.0017	−0.0138	−0.0107	−0.0125	−0.0061
	(0.0070)	(0.0076)	(0.0091)	(0.0083)	(0.0090)	(0.0111)
EE (t)	−0.0462***	−0.0348***	−0.0776***	−0.0460***	−0.0402***	−0.0691***
	(0.0050)	(0.0056)	(0.0064)	(0.0060)	(0.0065)	(0.0082)
EE (t + 1)	−0.0239***	−0.0145**	−0.0371***	−0.0222***	−0.0181**	−0.0269***
	(0.0053)	(0.0062)	(0.0072)	(0.0067)	(0.0078)	(0.0090)
EE (t + 2)	0.0030	0.0031	0.0099	−0.0045	−0.0088*	−0.0012
	(0.0049)	(0.0060)	(0.0060)	(0.0068)	(0.0083)	(0.0089)
EE (t + 3)	0.0050	0.0048	0.0118*	−0.0145**	−0.0143	−0.0114
	(0.0049)	(0.0062)	(0.0062)	(0.0065)	(0.0079)	(0.0084)
EE (t + 4)	0.0107*	0.0099	0.0120*	0.0010	0.0091	−0.0092***
	(0.0055)	(0.0068)	(0.0066)	(0.0073)	(0.0089)	(0.0089)
EE (t + 5)	0.0097	0.0114	0.0219***	0.0032	0.0057	0.0131
	(0.0069)	(0.0089)	(0.0081)	(0.0084)	(0.0111)	(0.0101)
Time-variant controls						
Lhdd	0.1910***	0.1914***	0.1907***	0.1164***	0.1093***	0.1138***
	(0.0061)	(0.0061)	(0.0061)	(0.0123)	(0.0123)	(0.0122)
Lgasprice	−0.2744***	−0.2867***	−0.2832***	−0.2189***	−0.2349***	−0.2365***
	(0.0115)	(0.0108)	(0.0107)	(0.0117)	(0.0116)	(0.0114)
Time-invariant controls	No	No	No	Yes	Yes	Yes
Intercept	8.3173***	8.3190***	8.3250***	8.1015***	8.1766***	8.1766***
	(0.0535)	(0.0541)	(0.0525)	(0.1046)	(0.1047)	(0.1047)
Test parallel trend 1	Yes	Yes	Yes	No	No	No
Test parallel trend 2	No	Yes	Yes	No	Yes	Yes
Observations	127,384	127,384	127,384	127,384	127,384	127,384
F test	F(13,43,100) = 186.88 (0.0000)	F(13,43,100) = 180.78 (0.0000)	F(13,43,100) = 196.23 (0.0000)	F(24, 43,100) = 833.93 (0.0000)	F(24, 43,100) = 827.93 (0.0000)	F(24, 43,100) = 834.38 (0.0000)
R-Squared	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.

heterogeneity by exposure time. We aim to capture a pre-installation period and a post-installation period of 5 years allowing us to detect whether the impact of the treatment changes over time.

In order to infer a causal interpretation we need to test that: i) the conditional parallel trends are valid, which is needed to be able to assume that, in the absence of treatment, similar households would follow similar energy consumption trends; ii) there has not been an anticipation of the treatment, implying that households have not adjusted their gas consumption proactively prior to the to the installation of the measure; and iii) there has not been selective treatment timing (no causal effect on the outcome, with respect to an early versus a later adoption) (Goodman-Bacon, 2021). The violation of these assumptions would imply that caution must be exercised while interpreting the results. We test those assumption and therefore whether households introducing a technical energy efficiency measure differ from the non-treated households (H1) by checking that the coefficients of $EEM_{i,t-k}$ are not significant. Test results on the parallel trend assumption can be found in the tables in the result section. Also, a summary of the parallel trend tests associated to the main regressions performed in section 4.1 and 4.2 can be found in table A4 in the SI. If the coefficient is statistically insignificant, we can assume that both groups followed the same trend.[12]

Regarding the third assumption, recently some authors have highlighted the existence of potential biases when using Differences-in-Differences estimators with homogeneous treatment effects in non-canonical applications of these quasi-experimental design as they assume that the treatment effect is constant, between groups and overtime (de Chaisemartin and D'Haultfoeuill, 2020; de Chaisemartin and d'Haultfoeuille, 2021; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021; Roth et al., 2022; Goodman-Bacon, 2021). With the dynamic model that we use in this paper we are already testing lags in the effects of EE measurement and treatment heterogeneity by exposure to time. In addition, we apply a diagnostics tool for two-ways fixed

[12] The parallel trend assumptions are tested through a time-trend approach based on two types of tests. One, whether all the leads' coefficients (β + s's) are jointly equal to zero, i.e. the parallel trend assumption holds and/or, second, through dropping lags and leads and augmenting Eq. (2) with a time-trend variable t and its interaction with the treatment variable. If the interaction term is statistically significant, the parallel trend assumption can be rejected (Cerulli and Ventura, 2019).

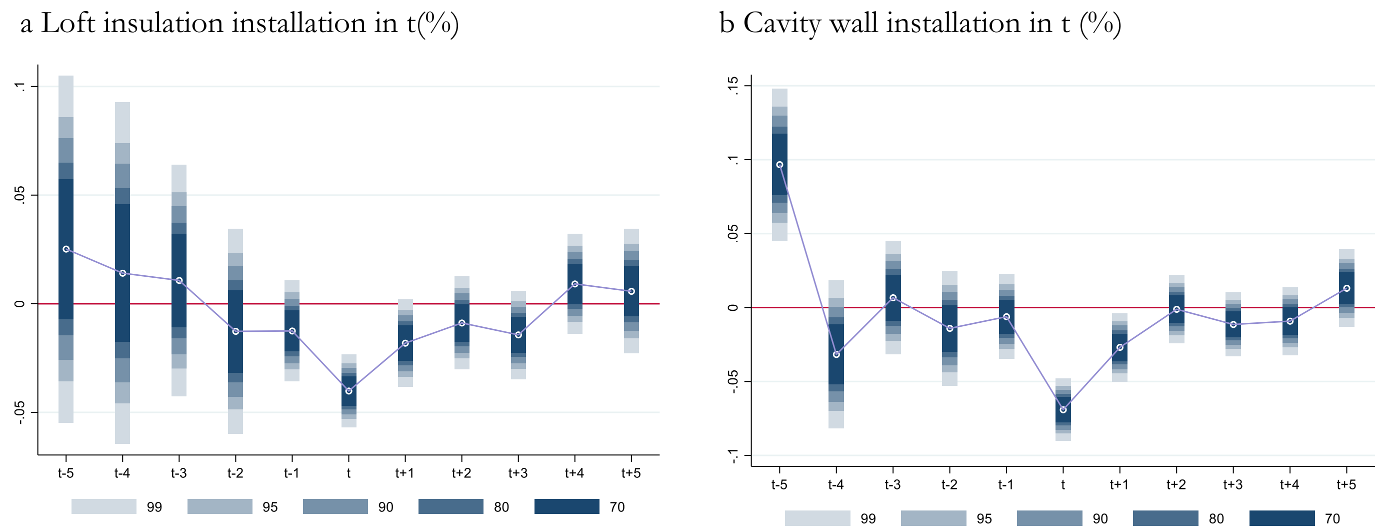

Fig. 3. Graph of the pre- and post-treatment pattern for the relation between household adoption on an EE measure and gas consumption.
a. Loft insulation installation in t (%). b. Cavity wall installation in t (%).
Outcome variable: Ln gas consumption / Treatment variable: Loft insulation or Cavity wall / X variables: Ln Heating degree days, Ln gas price / Time-invariant controls: surface area (sqm), index of multiple deprivation band, property type, age of the dwelling.
Note: The vertical axis shows the variation in gas consumption (percentage change). The blue bars represent the confidence intervals. The horizontal axis measures the effect five years before and after the adoption.

effects staggered models to test for the presence or absence of heterogeneous effects (Goodman-Bacon, 2021). This analysis is included in Fig. A2 in the SI. The Goodman-Bacon decomposition diagnostic plot confirms that most of weight and differences found between households in the sample come from households that are never treated vs. those treated at some point in the sample (~75% of the total weight) and differences between households treated at different points in time represent a smaller proportion (~15%). Due to this, we consider that our dynamic staggered Diff-in-Diff approach is robust. As an additional robustness check, we include regression results using different segmentations of the sample in section 4.2 and in the SI.

Both Eqs. (1) and (2) are estimated using fixed effects and ordinary least squares with the inclusion of covariates. We report the results using robust clustered standard errors with clusters defined at the household level.

4. Results

4.1. Impact of adoption of EE measures on gas consumption

Table 2 shows results from Eq. (2) where we consider a staggered DiD with dynamic treatment effects. We perform conditional estimations and test specifications under a set of control variables and fixed effects. 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. Our preferred model (see columns 4–6 in Table 2) includes the covariates as we see differences on those variables between control and treatment group (see Table 1). The baseline results of the estimation from the staggered DiD can be seen in Table A3 in the SI. Table A3 includes the results on the effect of an EE installation (in year t) in the period before and after the installation of the energy efficiency measure by estimating Eq. (1).

Columns (1) to (6) in Table 2 report the estimations for the staggered diff-in-diff approach with dynamic effects (see Eq. (2)).[13] Table 2 includes both results derived from a fixed effect model with time and household fixed effects and also an OLS model with covariates. The columns (1), (2) and (3) of Table 2 depict the results from the dynamic staggered DiD approach 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 household fixed effects are introduced in those estimations. Columns (4), (5) and (6) show the relationship between economic, weather and building characteristics and changes in gas consumption i.e., we introduce the 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. We will focus the discussion on the latter given the significant differences in those variables between control and treatment groups. The results in columns (4), (5) and (6) confirm, in line with literature, that energy efficiency technical improvements in households reduce energy consumption on those households undertaking such measures in the short term (Hypothesis 1). While we cannot translate this result into an estimate of the rebound effect, given that we do not have an assessment of the ex-ante expected energy savings of the improvements for each household, we see that the rebound effect does not completely erase the gains of the technical improvement, at least one to two years after the introduction.

However, a new, challenging and policy relevant result emerges in our ex-post analysis: energy efficiency effects resulting from the installation of technical measures are not long-lasting and energy efficiency

[13] Due to the characteristics of the NEED, we cannot know the month in which the EE measure has been installed by the households in the sample. To overcome a possible limitation associated to households in the sample having adopted an EE measure later in the year, an additional robustness check has been included in the SI considering as the year of treatment t + 1 instead of t for our preferred model with covariates (See Table A6 and Fig. A4 in the SI). The results are robust to this additional test.

gains disappear around one to four years after the treatment.

The results indicate that cavity wall retrofits are more effective at reducing gas consumption than loft insulations after the installation of the EE measure (Table 2 column 6). Cavity wall insulation generates, for our preferred model with covariates (6), 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 lasts up to four more years. For the second period after treatment, the observed reduction in gas consumption 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 prior to the installation, suggesting that behavioural interventions are as needed in addition to technical ones if the goal is to get long-lasting energy efficiency gains. Loft insulation (Table 2 column 5) seems to be half as effective as cavity wall installation, leading to reductions on gas consumption around 4%. Unlike cavity wall reforms, loft insulation effects on gas reduction only last for one to two years after the installation of the technical energy efficiency measure with a reduction of 1.8% and 0.9% respectively.

In terms of the effectiveness of the different measures, results are aligned with Adan and Fuerst (2016), who conclude that one year after the treatment, cavity walls are the most effective technical measures in reducing gas and energy consumption. Fig. 3a and b represent the dynamic treatment effects for the OLS model with covariates for both, loft (3a) and cavity wall installations (3b). One reason for this could be technology decay. One of the known barriers to the implementation of energy efficiency measures in the building sector, particularly in the UK, is the lack of skills and expertise for energy professionals and technicians (Kangas et al., 2017; Bagaini et al., 2020). For example, loft insulation installed under the roof could, if not properly installed, lead to a lack of ventilation between insulation and timbers generating damp, humidity and a faster decay. However, given the size of the sample, it seems more plausible that the differences in energy savings per family are due to aspects associated to occupant behaviour, especially after controlling for important covariates. Therefore, there seems to be a need for additional behavioural changes to realize the full saving potential of the adoption of EE improvements.

We note that most of our control variables are statistically 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. Regarding the latter variable i.e., HDD, our data does not allow us to disentangle the month in which the EE measure has been installed. However, previous studies on energy demand in households have determined that the higher the amount of HDD, the higher the energy consumption per household (e.g., Meier and Rehdanz, 2017 for the UK, Romero-Jordán et al., 2014 for Spain). While a seasonality analysis is not possible for data reasons, the HDD variable is positive and statistically significant and it is likely to go some way towards addressing the possible impact of seasonality. The results for HDD might be a sign of the existence of an 'intensive' margin effect—namely, that households may be more inclined to turn up the thermostat higher during a particularly cold winter after a retrofit. We include a segmentation of the sample per region to disentangle this possible intensive margin effect in the SI (See table A7 and Fig. A5).

In addition, a household's probability of adopting energy efficiency retrofits may also increase after a particularly cold winter, something that we refer to as an 'extensive' margin effect. We can disentangle this effect by analysing if households in different regions with different climates (proxied by their temperature profiles) in the UK are more or less prone to adopting an EE measure. Table A8 in the SI includes a panel probit estimation of the probability of adopting an EE measure as a function of the region in which the household is located, the characteristics of the households and the number of HDDs to separate the contributions of the extensive margin. We find evidence of an extensive margin and the probability of adopting an EE measure is higher when the households have experienced particularly cold temperatures the year before (see Table A8 and Fig. A6).

An important observation arises from Fig. 3. The installation of loft insulation and, importantly, of cavity walls seems to result in a more stable pattern in gas consumption in the years after the installation of an energy efficiency measure. This result in itself suggests an important positive outcome derived from energy efficiency retrofitting as upgrades act as factors reducing the volatility of energy demand. This is particularly relevant in the context of the current energy crisis as the value of reducing the volatility around gas consumption is clear.

We also consider the extent to which fuel switching from gas to electricity may be a factor in our results. This could be important because one of the suggestions made by many analysts regarding how the UK Government could navigate this energy crisis and the increase in gas prices for households is fuel switching. At the moment, only around 5% of UK households use electricity as a heating source (Ministry of Housing, Communities and Local Governments, 2021). In order to detect potential fuel switching behaviour during the period of analysis as a result of, for example, increases in gas prices, we have added three additional regressions in the SI mirroring the baseline results to control for possible omitted variable bias from electricity prices. The first set of additional analysis includes the cross-price elasticity of electricity together with the gas-price elasticity (See table A9). The second set jointly controls for the cross-price elasticity of electricity and the electricity consumption together with gas-price elasticity (Table A10). Given that the National Energy Efficiency Database (NEED) provides a variable indicating whether the property uses gas as its main heating fuel or not, the third additional robustness check involves running the baseline regressions for those households that do not use gas as their main heating source (Table A11). During the period of analysis included in this paper, gas prices were relatively low during most of the period under consideration, and the barriers associated to the lack of interest and undervaluing of energy efficiency in the building sector are higher in the UK than in other European countries (Bagaini et al., 2020). Fuel switching therefore was not happening to a significant extent in the UK between 2005 and 2017 and we did not detect clear differences –increases- in the consumption of electricity in those households with gas as a result of fuel switching (See Table A11, A12 and brief explanation in the SI).

As previously noted, the reliability of the causal inferences of the effects in a staggered diff-in-diff approach with dynamic effects depends on confirming non-anticipatory effects of the treatment (Gonçalves et al., 2020). Anticipatory effects are not observed for the dynamic model with covariates.[14] While the results for any type of installation, do not comply with the parallel trend assumption and therefore, causal inferences derived from those estimations should be considered carefully, when we restrict by type of EE measure, the parallel trend assumption cannot be rejected by using a time-trend significant test (Cerulli and Ventura, 2019). For our preferred estimations, i.e. OLS staggered diff-in-diff with dynamic treatment effects controlling for covariates (Columns 4 to 6 in Table 2), anticipatory effects cannot be detected and the parallel trend assumption cannot be rejected, indicating that the conditions for applying DiD are met.

The analysis performed with 5 leads and 5 lags reduces the sample size to a set of households that can be followed within the dataset specifically on those numbers of years. Considering the dataset runs from 2005 to 2017, this analysis allows us to explore the variation in energy consumption mostly in households that have adopted energy efficiency measures between 2010 and 2012, i.e. under the CERT and the CESP Government programmes. In order to expand the results to include some of the households under the ECO and Green Deal programme, we run a

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

Table 3
Staggered DiD gas consumption with segmentation of sample by conservatory.

	Any EE improvement		Loft Insulation		Cavity wall	
	(7)	(8)	(9)	(10)	(11)	(12)
Gas Consumption	Conservatory	No conservatory	Conservatory	No conservatory	Conservatory	No conservatory
EE (t-5)	0.1380***	0.0752***	0.1529*	0.0166	0.0584	0.0984***
	(0.0552)	(0.0200)	(0.0763)	(0.0325)	(0.0610)	(0.0209)
EE (t-4)	−0.1858***	−0.0111	−0.1501	0.0245	−0.1095	−0.0282
	(0.0702)	(0.0198)	(0.0988)	(0.0318)	(0.0700)	(0.0202)
EE (t-3)	0.1023	−0.0052	0.1173	0.0062	0.0672	0.0036
	(0.0690)	(0.0149)	(0.1000)	(0.0211)	(0.0606)	(0.0153)
EE (t-2)	−0.0855	−0.0121	−0.1670**	−0.0060	−0.0154	−0.0138
	(0.0525)	(0.0144)	(0.0784)	(0.0188)	(0.0563)	(0.0156)
EE (t-1)	0.0396	−0.0130***	0.0310	−0.0146	0.0313	−0.0077
	(0.0324)	(0.0085)	(0.0366)	(0.0093)	(0.0362)	(0.0114)
EE (t)	−0.0457**	−0.0460***	−0.0514**	−0.0395***	−0.0526*	−0.0699***
	(0.0202)	(0.0062)	(0.0223)	(0.0067)	(0.0292)	(0.0085)
EE (t + 1)	0.0008	−0.0235***	0.0214	−0.0202**	−0.0258	−0.0272***
	(0.0250)	(0.0069)	(0.0294)	(0.0081)	(0.0348)	(0.0093)
EE (t + 2)	−0.0099	−0.0041	−0.0009	−0.0092	−0.0375	0.0010
	(0.0243)	(0.0070)	(0.0302)	(0.0090)	(0.0323)	(0.0092)
EE (t + 3)	−0.0050	−0.0149**	0.0224	−0.0160*	−0.0146	−0.0113
	(0.0200)	(0.0068)	(0.0278)	(0.0082)	(0.0239)	(0.0088)
EE (t + 4)	−0.0440	0.0033	−0.0871**	0.0140	−0.0220	−0.0086
	(0.0267)	(0.0075)	(0.0348)	(0.0092)	(0.0309)	(0.0092)
EE (t + 5)	0.0180	0.0024	0.0466	0.0039	0.0374	0.0117
	(0.0341)	(0.0087)	(0.0473)	(0.0114)	(0.0396)	(0.0104)
Time-variant controls						
Lhdd	0.1445***	0.1166***	0.1370***	0.1095***	0.1417***	0.1140***
	(0.0473)	(0.0126)	(0.0474)	(0.0126)	(0.0468)	(0.0126)
Lgasprice	−0.1419***	−0.2225***	−0.1600***	−0.2386***	−0.1511***	−0.2402***
	(0.0426)	(0.0121)	(0.0429)	(0.0120)	(0.0412)	(0.0118)
Time-invariant controls	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	7.6444***	8.1023***	7.7261***	8.1772	7.6607***	8.1448***
	(0.4157)	(0.1077)	(0.4166)	(0.1079)	(0.4105)	(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	5766	121,618	5766	121,618	5766	121,618
F test	F(24, 1943) = 33.23 (0.0000)	F(24, 41,156) = 789.69 (0.0000)	F(24, 1943) = 33.35 (0.0000)	F(24, 41,156) = 784.14 (0.0000)	F(24, 1943) = 33.19 (0.0000)	F(24, 41,156) = 789.83 (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.

sensitivity analysis with combinations of periods from 2 lags (2 years before the installation of the EE measure) to 5 leads (5 years after the installation of the EE measure). Results are summarized in Table A13 in the SI. The effects of the implementation of both technical improvements simultaneously (the simultaneous installation of cavity walls and loft insulations) when compared to those households in which none of them has been installed are also included in the SI. The additional effect of a subsequent energy efficiency installation when compared to households that have installed in the past already one measure can be found in the SI (Table A5 and Fig. A3).

Results derived from Table 2 allow us to confirm our first hypothesis, H1. Results support the idea that the installation of EE technical improvements in households generates significant reductions in the amount of gas consumed by dwellings when compared to those that have not adopted them. The results also support H2. We find that the reduction in household gas consumption in the UK after the installation of an EE technical improvement does not last 3–5 years after the installation. 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 types of installations. As mentioned in section 2, on average, the payback time for a cavity wall installation may oscillate between 3 and 4 years after the installation. For loft insulation, the payback period tends to be slightly lower at around 1.5–3 years. This result suggests the value of exploring aspects related to behavioural economics and consumer psychology in future work.

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 the time, and as stated in the literature review, EE measures are implemented alongside other home improvements such as extensions which are very popular in the UK. In those cases, the possible correlation between EE measure implementation and other building work which may lead to increased energy use, might result in no reduction in energy consumption at the household level on those households.

Table 3 shows a segmentation of the sample breaking down the gas consumption reduction effects of EE installations in those households

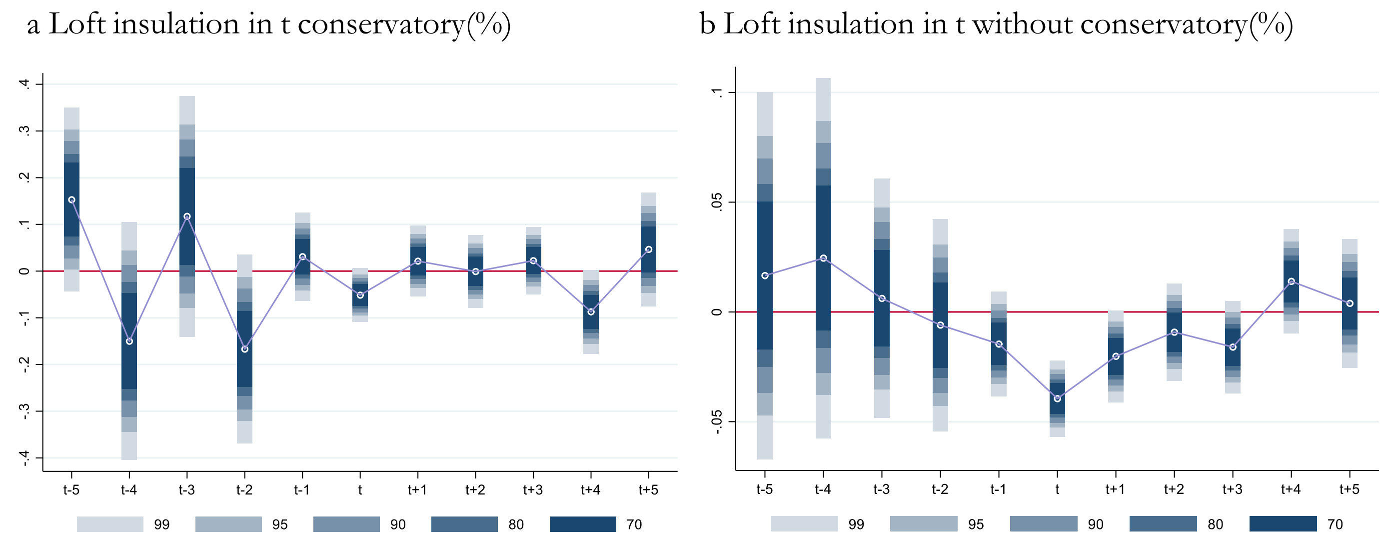

Fig. 4. Graph of the pre- and post-treatment pattern for the relation between household adoption on loft insulation and gas consumption in households with conservatory vs. non conservatory.
a. Loft insulation in t conservatory (%). b. Loft insulation in t without conservatory (%).
Outcome variable: Ln gas consumption / Treatment variable: Loft insulation / X variables: Ln Heating degree days, Ln gas price / Time-invariant controls: surface area (sqm), index of multiple deprivation band, property type, age of the dwelling.
Note: The vertical axis shows the variation in gas consumption (percentage change). The blue bars represent the confidence intervals. The horizontal axis measures the effect five years before and after the adoption.

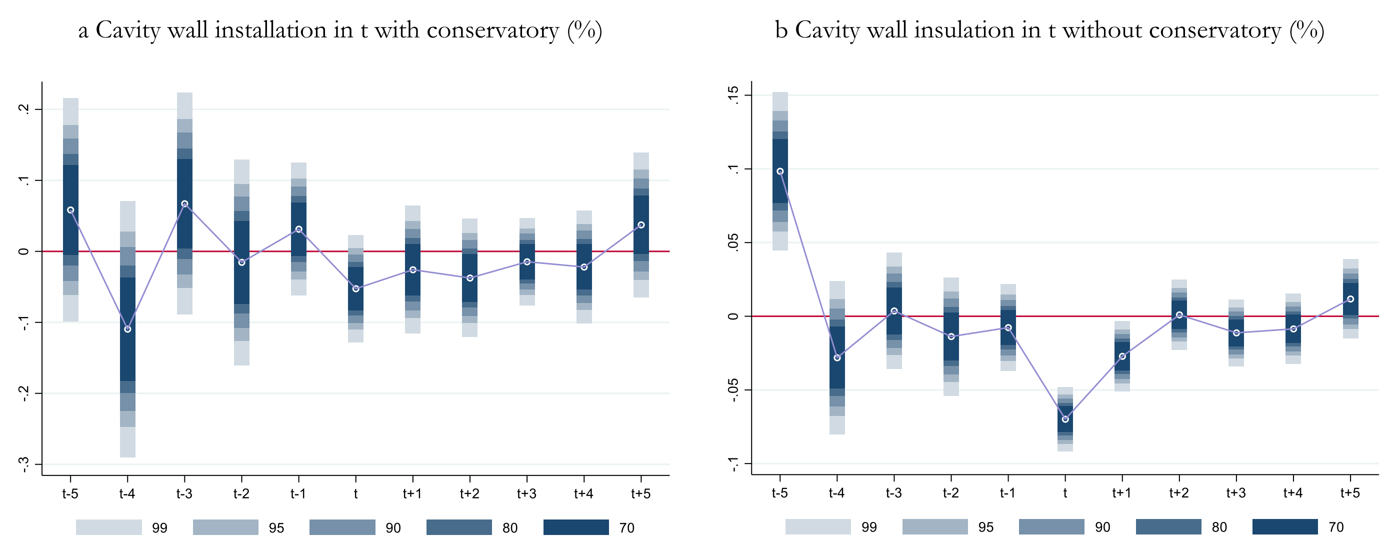

Fig. 5. Pre- and post-treatment changes in gas consumption for households adopting cavity walls in households with conservatory vs. non conservatory.
a. Cavity wall in t with conservatory (%). b. Cavity wall in t without conservatory (%).
Outcome variable: Ln gas consumption / Treatment variable: Cavity wall / X variables: Ln Heating degree days, Ln gas price / Time-invariant controls: surface area (sqm), index of multiple deprivation band, property type, age of the dwelling.
Note: The vertical axis shows the variation in gas consumption (percentage change). The blue bars represent the confidence intervals. The horizontal axis measures the effect five years before and after the adoption.

with conservatories and those without conservatories.[15]

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

H3 tested the hypothesis that households installing EE technical improvements alongside other renovations in dwellings may not experience significant gas consumption reductions. 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 can be built to high efficiency specifications, it is possible that the increase in space to be heated is at least partly

[15] While not perfect, we use the existence of a conservatory as a proxy of having proceeded with renovations involving an extension, of some nature, of the usable surface of the dwelling.

Table 4
Staggered DiD of gas consumption with segmentation of the sample by bands of the index of deprivation.

Any EE improvement					
	(13)	(14)	(15)	(16)	(17)
Gas Consumption	IMD1	IMD2	IMD3	IMD4	IMD5
EE (t-5)	0.1049**	0.0735	0.0965**	0.0452***	0.0823**
	(0.0453)	(0.0478)	(0.0490)	(0.0397)	(0.0346)
EE (t-4)	−0.0701	−0.0012	−0.0114	0.0047	−0.0207
	(0.0459)	(0.0474)	(0.0454)	(0.0393)	(0.0328)
EE (t-3)	0.0431	0.0051	−0.0473	−0.0205	−0.0159
	(0.0357)	(0.0294)	(0.0305)	(0.0288)	(0.0297)
EE (t-2)	0.0102	−0.0358	−0.0038	−0.0032	−0.0331
	(0.0263)	(0.0332)	(0.0339)	(0.0316)	(0.0316)
EE (t-1)	−0.0210***	−0.0043	−0.0159***	5.96E-05	0.0006
	(0.0182)	(0.0200)	(0.0194)	(0.0177)	(0.0165)
EE (t)	−0.0304**	−0.0353**	−0.0552***	−0.0566***	−0.0503***
	(0.0153)	(0.0142)	(0.0144)	(0.0125)	(0.0104)
EE (t + 1)	−0.0371**	−0.0093	−0.0205	−0.0154***	−0.0277**
	(0.0172)	(0.0163)	(0.0155)	(0.0142)	(0.0118)
EE (t + 2)	−0.0273	0.0009	0.0229	−0.0128	−0.0033
	(0.0186)	(0.0164)	(0.0158)	(0.0140)	(0.0116)
EE (t + 3)	−0.0397**	−0.0211	−0.0083	−0.0057	−0.0047
	(0.0195)	(0.0161)	(0.0146)	(0.0125)	(0.0105)
EE (t + 4)	0.0343***	−0.0005	−0.0056	−0.0220	−0.0110***
	(0.0195)	(0.0166)	(0.0162)	(0.0167)	(0.0121)
EE (t + 5)	0.0362*	0.0187	−0.0327*	−0.0119	−0.0233
	(0.0200)	(0.0185)	(0.0199)	(0.0194)	(0.0158)
Time-variant controls					
Lhdd	0.0065	0.1196***	0.1168***	0.1699***	0.1660***
	(0.0313)	(0.0287)	(0.0279)	(0.0257)	(0.0223)
Lgasprice	−0.4000***	−0.2237***	−0.2164***	−0.1565***	−0.1134***
	(0.0310)	(0.0281)	(0.02703)	(0.0233)	(0.0209)
Time-invariant controls	Yes	Yes	Yes	Yes	Yes
Intercept	9.1501***	8.1336***	8.1874***	7.7863***	7.7123***
	(0.2675)	(0.2448)	(0.2381)	(0.2187)	(0.1899)
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.

responsible for lower gas consumption reductions for those households that implement EE measures alongside an extension.

For any EE measure installed, we see more or less the same reduction on gas consumption in the first year (~4.6% reduction) for households that implement them without a conservatory. However, the effect for those households with conservatories disappears almost immediately after the first year. We see positive energy efficiency gains associated with the installation of loft insulation or cavity walls for those dwellings with no conservatories but, as in the general case, the energy efficiency gains tend to disappear over time suggesting there may be behavioural aspects determining energy use. Due to data limitations it is out of the scope of this paper, to determine what those reasons are.

Interestingly, in Fig. 4 we see that, for loft insulation installations in dwellings with a conservatory, the pattern of consumption in the years before the installation is pretty unstable when compared to the households without conservatories. This can be explained by the fact that different weather conditions affect those dwellings with conservatories to a greater extent. For those households 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, the reduction in gas consumption after a loft insulation installation happens only the first year after the adoption (−5.1%). There are positive energy efficiency gains for those without conservatories but, just like when we analysed the sample without the conservatory/no-conservatory distinction, the energy efficiency gains tend to disappear over time suggesting there may be behavioural aspects that we are not able to measure. This suggests the possible value of further efforts in education or informational campaigns in the long-run. For the case of households installing loft insulation, what stands out from Fig. 3 is that, even if the reductions are not long-lasting, the installation of the EE measures seems to stabilise the pattern of gas consumption in the households. On top of that, the reduction in gas consumption is bigger than in those households without conservatory (−5.1% vs. -3.9%) a year after installation (time t) but it does not last as long as the reductions in households without a conservatory. We find that, when compared to cavity walls (Fig. 5), loft insulations are more effective for those households with conservatory vs. those without which one may expect given that cavity walls cannot be installed in glass walls, which are used in many conservatories.[16]

For the case of cavity wall installations, the effect of those installations in 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 3 and Fig. 5). However, as we have seen for the whole sample (Table 2 and Fig. 3), the effect in this case disappears in two years corresponding approximately with the payback time of an installation.

One interesting fact for analysis is the variation of electricity

[16] Certain types of conservatories might still have a non-glass roof that allows to use loft insulation.

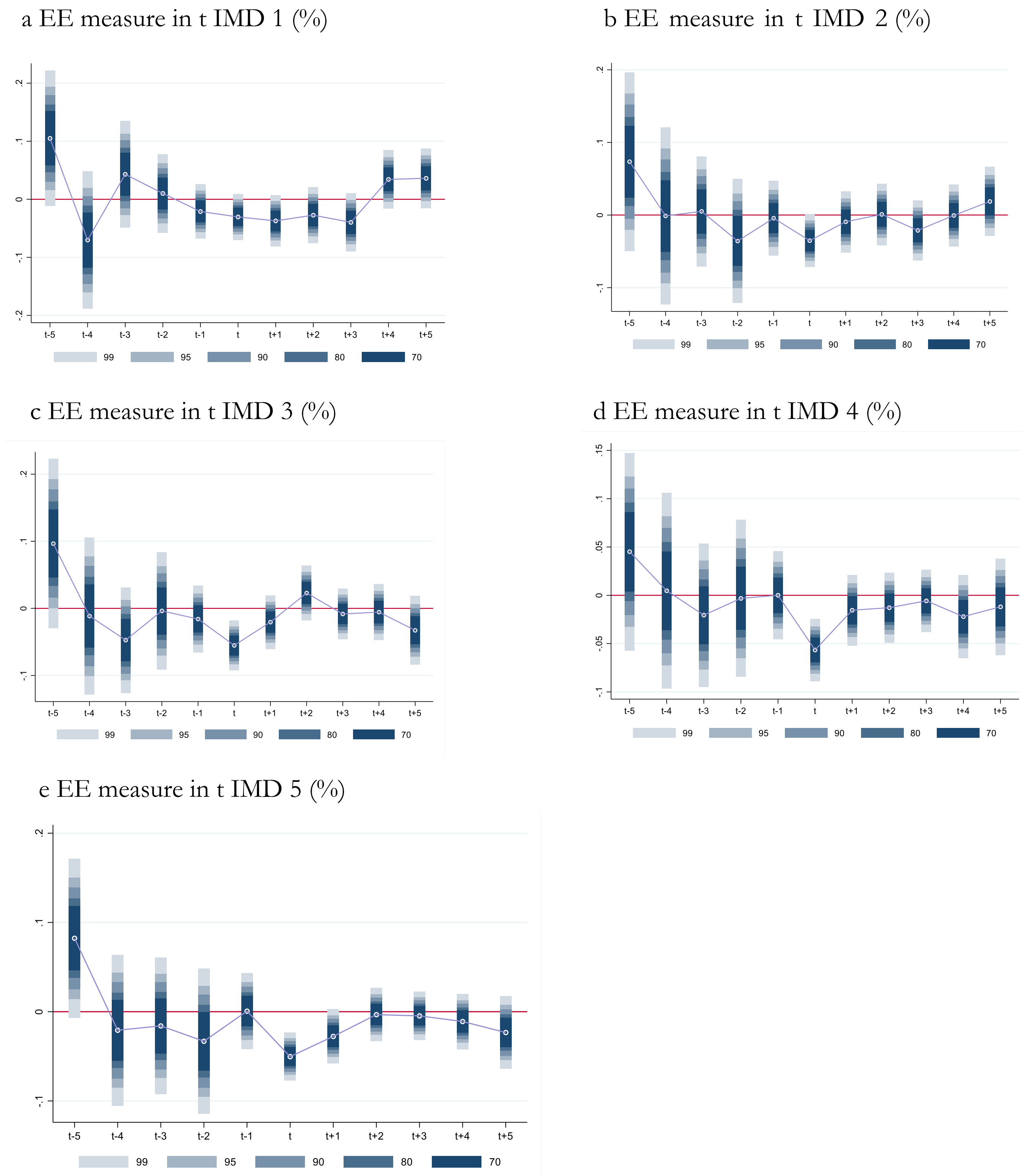

Fig. 6. Pre- and post-treatment patterns of the relationship between household adoption of any type of EE measure and gas consumption in households belonging to different deprivation areas.
a. EE measure in t IMD 1 (%). b. EE measure in t IMD 2 (%).
c. EE measure in t IMD 3 (%). d. EE measure in t IMD 4 (%).
e. EE measure in t IMD 5 (%).
Outcome variable: Ln gas consumption / Treatment variable: Loft insulation or Cavity wall / X variables: Ln Heating degree days, Ln gas price / Time-invariant controls: surface area (sqm), index of multiple deprivation band, property type, age of the dwelling.
Note: IMD1 is the category with the highest deprivation and IMD5 with the lowest. The vertical axis shows the variation in gas consumption (percentage change). The blue rectangles represent the confidence intervals. The horizontal axis measures the treatment effect five years before and after the adoption.

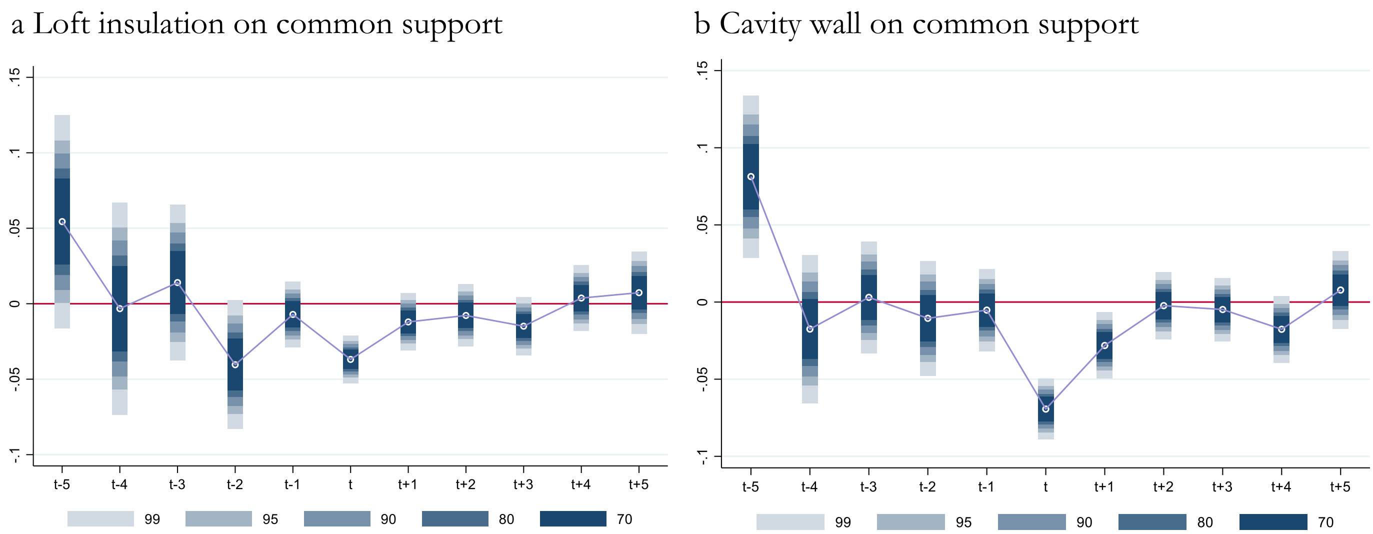

Fig. 7. Pre- and post-treatment patterns of the relationship between household adoption on loft insulation / cavity walls and gas consumption on common support. a. Loft insulation on common support. b. Cavity wall on common support.
Outcome variable: Ln gas consumption / Treatment variable: Loft insulation or Cavity wall / X variables: Ln Heating degree days and Ln gas price.
Note: The vertical axis shows the variation in gas consumption (percentage change). The blue rectangles represent the confidence intervals. The horizontal axis measures the treatment effect five years before and after the adoption.

consumption, instead of gas, in those households that, having gas as a main source, have conservatories. This is important because after an EE renovation, many of those conservatories might be heated with electric devices. We could expect that, if fuel switching is happening in those households with conservatories and gas as the main source, they would reduce electricity consumption after an EE renovation –if any- to a lesser extent than those households not using gas as their main heating source. Unfortunately, the available data does not allow us to test for fuel switching given that we cannot disentangle the amount of electricity used only for heating purposes; so we leave this venue open for future research.

In sum, results partially supports hypothesis 3 in that households performing other type of renovations alongside EE technical improvements will not experience the same level of statistically significant gas consumption reductions when compared to those installing only EE technical improvements.

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 especially 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 4 we see that those households in more deprived areas experience half of the gas consumption reductions in percentage terms of 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. This is probably because those households already consume little energy and display a higher energy price elasticity than their wealthier peers.

Controlling by gas prices, weather conditions and household characteristics, those households 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 energy efficiency technical measures adopted (see Table A14 in the SI).

However, an important result is that the most deprived households can expect statistically significant increases in the energy consumption four and five years after the EE installation. These increases would completely offset the initial consumption reductions during the year of installation reaching increases in gas consumption of around 3.6%.

These results in Table 4 confirm that, generally, the demand of those households in more deprived areas mostly covers basic needs, and therefore the installation of new energy efficiency improvements does not, on average, generate a decrease in the energy consumption. It may however result in a higher flexibility to adjust to prices and therefore it makes it possible for people to not just meet their basic needs but to also reduce 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 makes gas demand more flexible 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. 6 shows the pre- and post-treatment pattern of the relationship between household adoption of any type of EE measure and gas consumption in households belonging to different deprivation areas.[17] We find that for the higher deprivation areas (IMD1 and IMD2) after 4 or 5 years the energy savings have most likely disappeared and they increase their gas consumption.

5. Robustness checks

5.1. Propensity Score Matching (PSM) and common support of household

Selection biases may occur if there are non-random factors affecting the decision of a household to adopt an energy efficiency measure. The

[17] Because results are consistent across energy efficiency technical measures 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
Staggered DiD for gas consumption on common support area after PSM.

	(18)	(19)	(20)
Gas Consumption	Any	Loft	Cavity
EE (t-5)	0.0885***	0.0544**	0.0813***
	(0.0181)	(0.0274)	(0.0204)
EE (t-4)	−0.0247	−0.0032	−0.0175
	(0.0176)	(0.0273)	(0.0186)
EE (t-3)	0.0002	0.0140	0.0030
	(0.0138)	(0.0201)	(0.0141)
EE (t-2)	−0.0277**	−0.0404**	−0.0105
	(0.0131)	(0.0166)	(0.0144)
EE (t-1)	−0.0061	−0.0071	−0.0052
	(0.0078)	(0.0084)	(0.0103)
EE (t)	−0.0454***	−0.0369***	−0.0693***
	(0.0056)	(0.0061)	(0.0077)
EE (t + 1)	−0.0201	−0.0121*	−0.0281***
	(0.0062)	(0.0073)	(0.0083)
EE (t + 2)	−0.0045	−0.0078	−0.0023
	(0.0065)	(0.0080)	(0.0085)
EE (t + 3)	−0.0106*	−0.0149**	−0.0048
	(0.0061)	(0.0075)	(0.0079)
EE (t + 4)	−0.0057	0.0038	−0.0176**
	(0.0068)	(0.0085)	(0.0084)
EE (t + 5)	−0.0015	0.0073	0.0078
	(0.0081)	(0.0106)	(0.0098)
Time-variant controls			
Lhdd	0.1331***	0.1254***	0.1331***
	(0.0118)	(0.0119)	(0.0118)
Lgasprice	−0.2084***	−0.2276***	−0.2257***
	(0.0110)	(0.0110)	(0.0108)
Time-invariant controls	Yes	Yes	Yes
Intercept	8.0646***	8.1466***	8.0884***
	(0.1009)	(0.1016)	(0.1006)
Test parallel trend 1	No	No	No
Test parallel trend 2	No	Yes	Yes
Number of observations	114,145	113,671	113,927
F test	F(24, 39,151) = 722.23 (0.0000)	F(24, 38,977) = 705.61 (0.0000)	F(24, 39,076) = 717.89 (0.0000)
R-squared	0.2711	0.2675	0.2700

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.

use of propensity score matching can help us mitigate selection biases issues related to observable variables in the sample (Tucker, 2011). As an additional robustness check, we run the baseline regression on a common support sample of households similar to the ones that adopted the EE measures in terms of pre-treatment observed characteristics. We use the same covariates included in regressions (4), (5) and (6) in Table 2, i.e., type of property, age of the dwelling, index of multiple deprivation band, size (sqm); in addition, we match households according to the region in which they are located. In order to do this we estimate the propensity score, i.e. the probability of installing an EE measure, with a probit regression (See Table A15 in the SI). To do so we use a k-nearest neighbour matching algorithm (See Table A16 in the SI). We then restrict the sample to a common support area based on the calculated propensity scores (Fig. A7 SI). Lastly, we estimate Eq. (2). See SI for further details on the estimation process.

After the application of PSM the differences between treated and control households in terms of the covariates is significantly reduced (See Fig. A8 in the SI). The results in section 4.1 are consistent with those in Fig. 7 below: we find similar effects around 3.7% reduction and 6.9% for loft and cavity wall respectively in t that half on t + 1 following the installation of the EE measure (see Table 5 and Fig. 7).

5.2. Placebo test

In order to further rule out identification issues, we include an additional robustness check: a falsification test. Mirroring the strategy followed by other authors like Cai et al. (2016), or La Ferrara et al. (2012), we run a placebo test (falsification) test, by randomly assigning the adoption of an EE measure to a group of households different from the ones in the treated group in our analysis. Our estimations include 18,930 household that have received some kind of treatment. We first randomly select a group of households from the whole sample and we consider them as treated units having installed at least an EE measure. Then we generate a random false year of installation between 2005 and 2017 for the falsely treated households. With this, we re-estimate our baseline model using the placebo-false energy efficiency installation variable. The randomization process should ensure that the placebo treatment variable has no effect on gas consumption and therefore that there are no significant omitted variable biases. If the false treatment was significant, this would be a signal of misspecification problems in our estimation strategy. We store the estimates and repeat the exercise 500 times. Fig. 8 shows the cumulative distribution function and density of the estimated coefficients on the installation of any type of energy efficiency installation. Figs. A10 and A11 in the SI shows the cumulative distribution function and density of the estimated coefficients on the installation of loft insulation and cavity walls respectively. The distribution of the estimated coefficient on the placebo energy efficiency installation is centered around zero as expected, and our baseline estimation clearly lies outside the range of coefficients estimated in the simulation exercise. The results shown in the aforementioned figures and summarized in Table 6 enhance the confidence that the findings of our analysis are not spurious.

5.3. Heterogeneous effects: assessing energy savings inequality using percentile shares

In section 4.2.2, we found that the impact of the adoption of the two EE technical measures under consideration varies considerably depending on the level of deprivation of the areas in which households are located (see Table 4). The variation found in that analysis let us confirm heterogeneous effects. The smaller reduction on energy consumption seen on the poorest segments of the population, proxied by the quintile levels 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 households installing a technical energy efficiency measure vs. those in the control group. We analyse outcomes for ten distribution groups (deciles) in absolute (Table 7) and relative terms (See Table A18 and Figs. A11 in the SI).

Percentile analysis has been widely used in inequality research to study the distribution of income and wealth, see e.g., Piketty (2014), Anand and Segal (2015), and Milanovic (2012), among others. The assessment of percentile shares allows us, in this case, to separate households into groups according of gas consumption and 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 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 when compared to those that have not

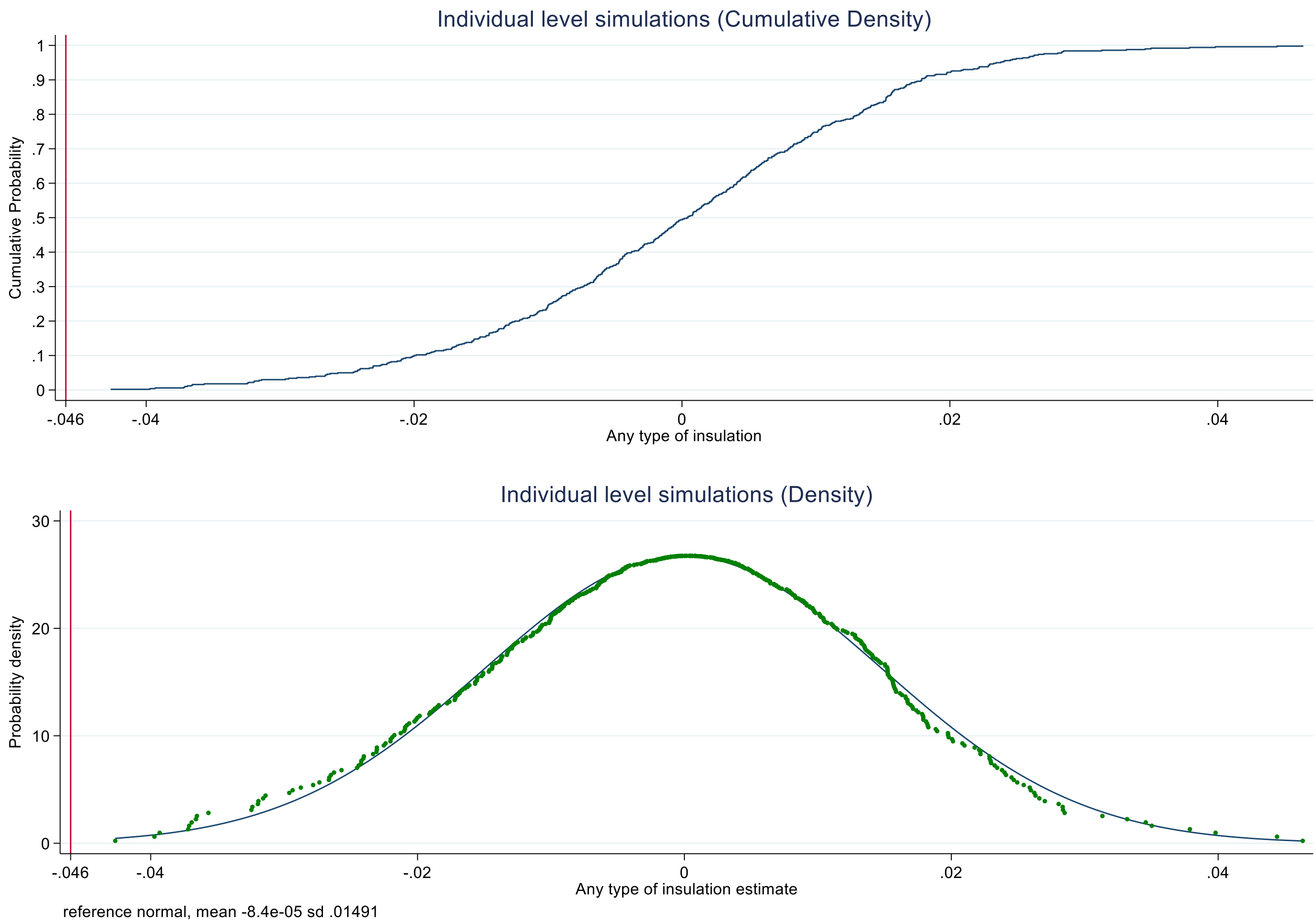

Fig. 8. Placebo regressions for any type of insulation – distribution of estimated coefficients. Note: Cumulative distribution function (top panel) and density (bottom panel) of the estimated coefficients from 500 simulations using false date and treatment of an energy efficiency installation.

adopted such measures.[18] 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 (See Table 7).

Expressing the results in average levels of gas consumptions, Table 7 shows that the bottom two deciles i.e., the bottom 20%, of the gas consumption distribution increase their gas consumption after the installation of an EE technical measure. Only from the third decile we start seeing significant gas consumption reductions in absolute terms. Results are consistent across technical measures (See Fig. 9a and b). The differences in Fig. 9 reflect the overall variation in the gas consumption by percentile group. Another interesting result to explore is if those differences impact the distributional shape of gas consumption in relative terms. Due to of space reasons those results are included in Table A19. Results in this subsection are important as they highlight that for those bottom two decile groups, the EE technical measures are not being effective in terms of reducing consumption. As previously mentioned, most UK EE policy instruments have targeted vulnerable households. However, those dwellings do not reduce their consumption but instead increase their energy use. This is not necessarily a bad outcome if the policy schemes are aimed at reducing fuel poverty in low-income households. Notwithstanding, to the extent that reducing energy consumption and consequently greenhouse gas emissions is at least one of several goals, those policies are not effective at delivering on all their missions. From a policy perspective, this result calls for mission-oriented energy policy measures distinguishing between groups.

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. (2021), this result indicates 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 in vulnerable households. However, considering other outcomes like the distributional effects of the policy instruments, subsidizing EE measures may improve inequality indicators by reducing the energy consumption differences between different types of households and pushing people in deprived areas out of the dangers of fuel poverty.

6. 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 prerequisite for the formulation of accurate, effective and cost-effective energy policies. While the vast majority of literature has studied the energy performance gap and the rebound effects from an ex-

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

Table 6
Placebo regressions.

	(21)	(22)	(23)
Gas Consumption	Any	Loft	Cavity
EE (t-5)	−0.0059	−0.0023	−0.0075
	(0.0091)	(0.0065)	(0.0091)
EE (t-4)	0.0047	0.0060	0.0048
	(0.0087)	(0.0062)	(0.0087)
EE (t-3)	0.0043	−0.0092	0.0044
	(0.0084)	(0.0061)	(0.0085)
EE (t-2)	−0.0010	−0.0084	−0.0001
	(0.0089)	(0.0063)	(0.0090)
EE (t-1)	−0.0093	0.0055	−0.0086
	(0.0090)	(0.0062)	(0.0091)
EE (t)	0.0018	0.0051	0.0038
	(0.0089)	(0.0062)	(0.0089)
EE (t + 1)	−0.0091	0.0026	−0.0098
	(0.0085)	(0.0075)	(0.0086)
EE (t + 2)	0.0037	0.0074	0.0013
	(0.0087)	(0.0140)	(0.0088)
EE (t + 3)	−0.0040	−0.0202	−0.0024
	(0.0087)	(0.0522)	(0.0087)
EE (t + 4)	0.0105	−0.0336	0.0080
	(0.0090)	(0.0559)	(0.0090)
EE (t + 5)	0.0015	0.0004	0.0029
	(0.0095)	(0.0713)	(0.0095)
Time-variant controls			
Lhdd	0.1027***	0.1023***	0.1027***
	(0.0122)	(0.0122)	(0.0122)
Lgasprice	−0.2636***	−0.2642***	−0.2635***
	(0.0113)	(0.0121)	(0.0113)
Time-invariant controls	Yes	Yes	Yes
Intercept	8.2663***	8.2697***	8.2665***
	(0.1041)	(0.1047)	(0.1041)
Test parallel trend 1	Yes	Yes	Yes
Number of observations	127,384	127,384	127,384
F test	F(24, 43,100) = 823.56	F(24, 43,100) = 823.13	F(24, 43,100) = 823.58
	(0.0000)	(0.0000)	(0.0000)
R-squared	0.2791	0.2791	0.2791

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.

ante perspective, studies using actual consumption data are few. To the best of our knowledge, this paper is the first one analysing longer-term effects of up to 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 a Staggered DiD analysis with micro-level data on a representative sample of more than 50,000 households in England and Wales.

The results show that the adoption of EE measures in households leads to a decrease in the demand of gas consumption right after the adoption. However, the energy savings generated from the installation of those technical measures i.e., loft insulation and cavity walls, do not long-last. Energy savings disappear two to four years after the adoption for cavity wall installations. The reduced gas consumption from loft insulation 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 reductions in gas consumption on the poorest segments of the population, proxied by the quintiles level of the index of multiple deprivations by area, shows the importance of considering the heterogeneous impacts of policies and further investigating the mechanisms that prevent those households from realizing energy savings after the adoption of EE measures. Dwellings in deprived areas are more likely to receive full support for the costs of the energy efficiency improvement. Romero-Jordán et al. (2016) suggest that public policy should not inhibit price signals but instead provide rent transfer-oriented policies, such as annual payments or grants to vulnerable households. However, the policies in Fig. 1 reflect this and our analysis suggest that the reduction on energy consumption have not materialized in low income households.

We found, however, that the introduction of EE technical improvements seems to procure a more stable pattern in gas consumption in the years following implementation. This result in itself suggests an important positive outcome derived from energy efficiency retrofitting as upgrades act as mediating factors for volatility in energy demand. Also, 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

Table 7
Effect of the installation of EE measures on percentile shares of the gas consumption and differences in percentile shares between treated and control households (annual KWh of gas consumption).

	Loft			Cavity			Any		
	Control	Treatment	Diff	Control	Treatment	Diff	Control	Treatment	Diff
0-10th	3858.90	4314.05	455.15***	3863.17	4272.35	409.18***	3819.84	4247.23	427.40***
	(26.2260)	(52.3743)	(57.2987)	(27.0865)	(54.4260)	(59.4836)	(28.1287)	(43.1172)	(49.7865)
10th -20th	7285.92	7455.95	170.03***	7289.35	7437.06	147.71**	7267.87	7433.95	166.08***
	(32.5524)	(52.2542)	(59.8228)	(31.5641)	(56.8968)	(63.6662)	(34.6382)	(44.6636)	(54.4237)
20th -30th	9507.89	9272.95	−234.94***	9507.41	9287.18	−220.23***	9535.95	9302.12	−233.84***
	(32.4978)	(55.3686)	(62.1525)	(32.5981)	(53.6781)	(61.2836)	(34.4509)	(42.1033)	(52.1424)
30th -40th	11,396.03	10,852.87	−543.16***	11,416.16	10,823.94	−592.22***	11,483.56	10,880.60	−602.95***
	(33.0195)	(55.6245)	(62.3111)	(33.2160)	(56.6769)	(63.9709)	(36.9807)	(44.5149)	(55.1288)
40th -50th	13,200.86	12,369.29	−831.57***	13,253.46	12,255.59	−997.86***	13,354.96	12,371.01	−983.97***
	(34.8456)	(58.8539)	(65.6321)	(37.1026)	(55.5768)	(64.7691)	(39.1177)	(46.9530)	(57.8849)
50th -60th	15,094.39	13,915.21	−1179.19***	15,178.81	13,698.71	−1480.10***	15,325.46	13,887.73	−1437.73***
	(38.9596)	(63.5720)	(71.1690)	(39.3776)	(60.0412)	(69.3806)	(43.4407)	(50.5955)	(62.7482)
60th -70th	17,248.75	15,645.59	−1603.16***	17,363.76	15,316.30	−2047.46***	17,549.17	15,581.35	−1967.82***
	(42.7966)	(72.5706)	(80.1396)	(45.1207)	(65.3666)	(76.4156)	(47.2311)	(54.7184)	(67.5747)
70th -80th	19,859.15	17,776.19	−2082.96***	20,002.96	17,282.49	−2720.47***	20,212.64	17,674.90	−2537.74***
	(51.5342)	(86.0011)	(94.8654)	(49.0403)	(79.4199)	(89.6438)	(56.0563)	(68.3850)	(82.1535)
80th -90th	23,612.02	20,982.95	−2629.07***	23,828.16	20,164.21	−3663.95***	24,066.70	20,773.87	−3292.82***
	(65.3558)	(120.1097)	(129.1477)	(67.2652)	(97.5387)	(113.336)	(68.9474)	(87.1330)	(102.6858)
90th -100th	33,056.36	29,413.12	−3643.24***	33,328.13	27,535.34	−5792.79***	33,619.65	28,846.26	−4773.39***
	(101.4566)	(202.2680)	(213.6883)	(105.5670)	(189.2132)	(208.7648)	(107.4288)	(157.6647)	(176.9825)

Notes: * Significant at the 90% confidence level. **Significant at the 95% confidence level. ***Significant at the 99% confidence level.

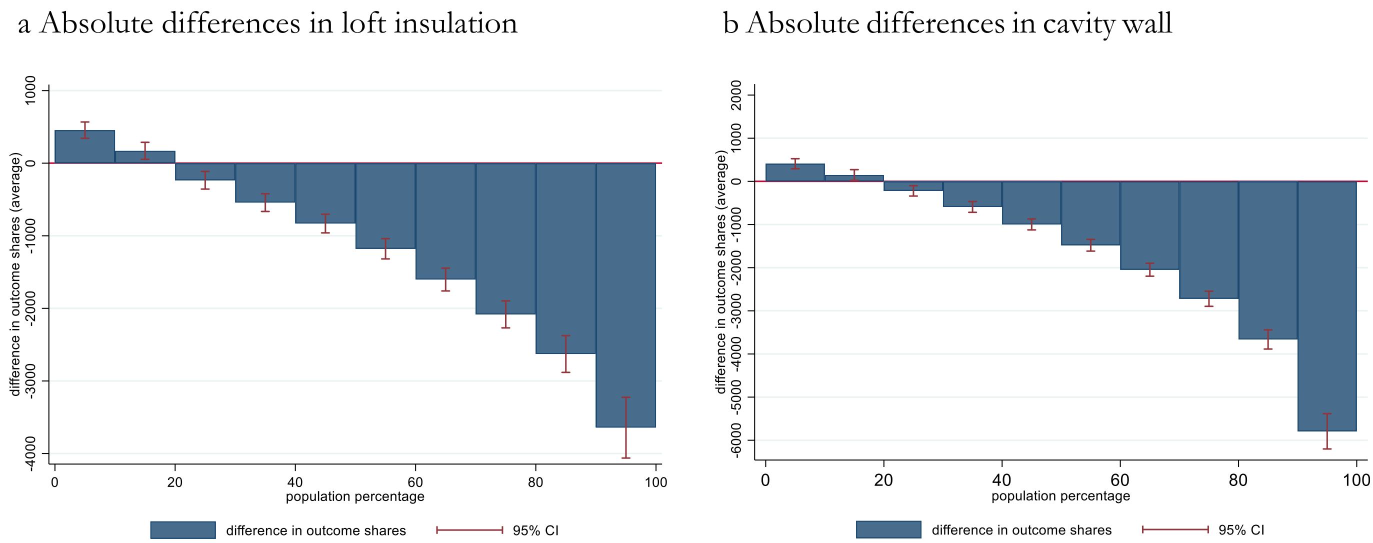

Fig. 9. Percentile histogram (average annual differences in gas consumption in KWh).
a. Absolute differences in loft insulation. b. Absolute differences in cavity wall.

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 longer-term effects that could be connected to technology decay and/or aspects related to occupant behaviour. We suggest that the implementation of energy efficiency schemes consisting of a mix of regulatory instruments (tighter standards for newly constructed dwellings and for renovations), financial incentives (grants, loans or subsidies), and soft instruments influencing behaviour is more likely to result in longer term reductions in gas consumption. 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, those households in the lowest quintiles of the IMD are likely to represent households with low-income levels, low education attainment and that are more likely to be hit by unemployment. Our results indicate 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 as the other groups. 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, the energy efficiency schemes are not effective in this segment of the population in terms of delivering energy savings. This result is relevant for the design of measures targeting different groups and policy goals e.g., reduction of fuel poverty vs. energy efficiency savings. Third, 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. The UK with a 62.7% share of gas in final energy consumption in the residential sector, has the second largest share in Europe after The Netherlands (70.9%) (EUROSTAT, 2017). These figures reinforce the idea that targeted policies may be needed, specifically, for the reduction of gas consumption. These findings regarding the specific challenges by income group and type of residence may also be important when thinking about designing new policies focusing on household heat electrification. Cultural and behavioural aspects need to be considered in the design of the policy schemes. This will be essential given the reluctance of citizens to shift to electric heating if the UK wants to get a net zero carbon economy by 2050.

While technical measures result in some savings 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 financial and regulatory energy efficiency policy instruments with soft instruments to promote the behavioural changes needed to realize the full saving potential of the adoption of EE improvements. From a policy perspective, this result underlines the need to establish more tailored energy policies adapted to a wider set of household characteristics.

Given that technical energy efficiency improvements are not sufficient to generate energy saving, additional initiatives are needed. 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 –similar to the *No stamp duty on zero carbon homes policy in the UK* (HMRC, 2016)-. 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. Successful examples can be found in schemes like the Pay-as-you-save (PAYS) in which using a tariff, the utility puts a fixed charge on the customer's monthly bill smaller than the estimated savings expected by the adoption of the energy efficiency measure. This provides the final users an immediate and sustained economic savings (Lin, 2018). These types of policies would be equally relevant in a context in which the measures taken by households were oriented towards the electrification of heating in residential buildings e.g., adoption and/or substitution of gas boilers by electric heat pumps. While these are just some ideas, further research is needed to disentangle the reasons behind the lack fully. It is essential to understand what the actual nature of reasons is, since they could be related to social challenges e.g., vulnerable households, behavioural challenges e.g., lack of information or incentives, or (more likely) both.

Data statement

Data were made available by the National Energy Efficiency Dataset (NEED). Access to the dataset can be found here. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/857035/anon_set_50k_2019.csv Data was complemented with information from Eurostat and DBEIS. Stata codes will be made available though Mendeley data server with doi: 10.17632/z3ffct4gfj.1 Peñasco et al. (2021), "Assessing the effectiveness of energy efficiency measures in the residential sector gas consumption through dynamic treatment effects: Evidence from England and Wales", Mendeley Data, V1, doi: 10.17632/z3ffct4gfj.1.

CRediT authorship contribution statement

Cristina Peñasco: Conceptualization, Methodology, Investigation, Visualization, Writing – original draft. **Laura Díaz Anadón:** Conceptualization, Methodology, Validation, Writing – review & editing.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2022.106435.

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