Energy efficiency measures in the residential sector: Implementing mechanisms for successful low-carbon transitions in households

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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, 19% of the total final energy consumption in the OECD countries in 2016, reaching one of the highest percentages of Europe in the UK, with 29% of total final energy consumption (IEA, 2016). We analyse changes in residential energy consumption before and after the adoption of energy efficiency measures, which include both household and policy-driven upgrades in England between 2012-2014 using data on 12,000 households from the English Housing Survey (EHS). We control for, among other factors, energy prices, and estimate the extent to which energy consumption changes are dependent on household income levels and up-front investments costs for the efficiency measures. We determine the extent to which higher cost EE investments are associated with larger changes in energy consumption for households, controlling for differences in building characteristics and occupant incomes. We include nine EE measures according to their type (e.g., from loft insulation to the replacement of central heating boilers) and their upfront cost, and we consider the possibility that households in different parts of the income distribution may experience different changes in energy consumption using quantile regressions. Our results indicate that the adoption of EE measures is not associated with significant reductions in household residential energy consumption one year after their implementation. Given that changes in climate conditions are unlikely to account for increased energy consumption in 2014, this negative result could be explained by either the rebound effect and/or by concurrent residential projects that can increase energy consumption. This effect is even higher for households in the 10-20 percentile. While the results do not show associated reductions in energy use, they do indicate that households have a more price-elastic energy demand after the adoption of EE measures. This may suggest that there may be energy demand reduction benefits that cannot be captured within the timeframe used in the study and that may only be realized in times of more volatile energy prices.

Keywords: Energy efficiency, Energy consumer-domestic, Energy Economics, Energy Policy

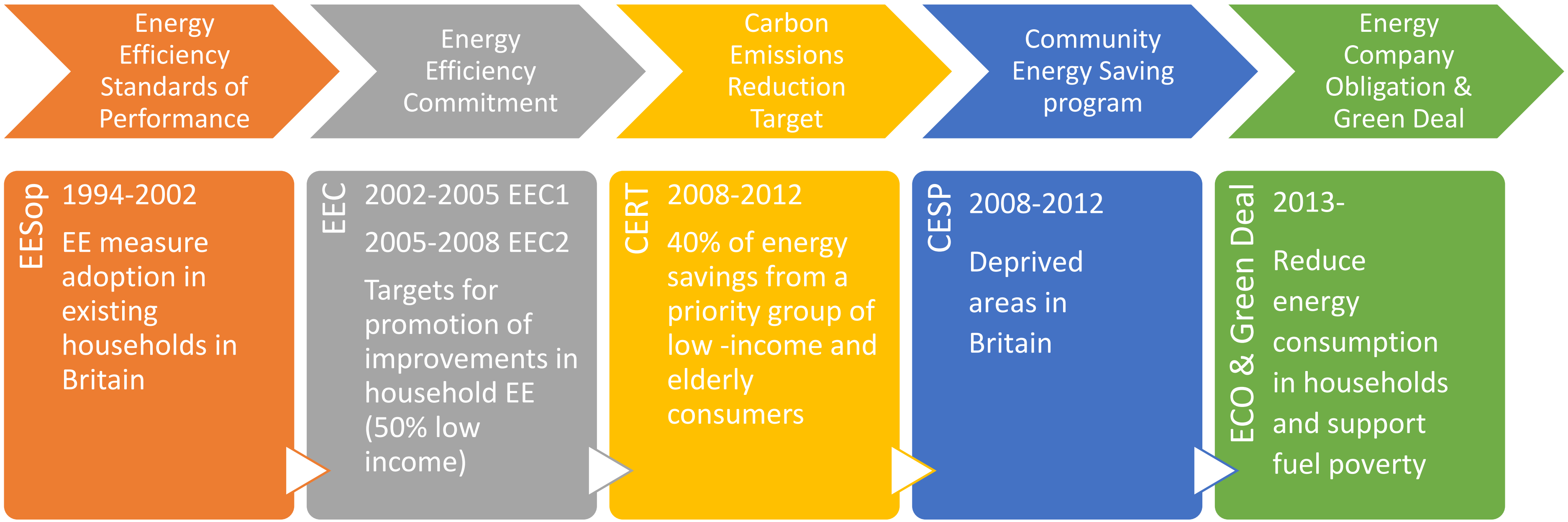
1. Introduction

Improving energy efficiency (EE) in the residential sector is key to address energy-related challenges. According to the IEA (2016a), increasing EE in buildings represents one of the most cost-effective ways to improve energy security and reduce the environmental damages from the current energy system. The buildings sector is responsible for a third of the global total final energy consumption (TFC). Moreover, residential buildings account for 74% of the TFC in buildings (IEA, 2016b). Many studies have highlighted the important role that public policy can play to reduce energy consumption in residential buildings (Geller et al. 2006).

In 2016, households in the UK were responsible for about 29% of the country's final energy consumption being the second sector in terms of energy consumption after the transport of passengers (annual report 2018 EE directive UK). The UK household energy use increased by

22% from 1970 to 2007, however if new insulation or efficient heating technologies had not been installed during that time period, this increase would have been more than double (DECC, 2012). Reducing energy demand through greater efficiency can help the UK meets its climate and EE targets, reduce energy bills and fight fuel poverty among other benefits (ICL, 2016). Energy costs have increased on average from 3.10% in 2005 to 4% in 2015 as a percentage of the total annual household expenditure in UK households. These figures are even more significant for households in the lowest 10% income group: these households went from spending 5.80% of annual expenditures in 2005 in energy to 8.40% in 2015. In order to meet its climate and EE targets and reduce the energy consumption the UK government has put in place several EE related policies since the mid 1990s, as summarized in Fig. 1.

Fig. 1. Timeline of EE policies in the UK between 1994-2018



Source: Own elaboration with information from OFGEM

Additionally to the schemes shown in Fig.1, the U.K. Government has set up heating and housing benefits that may influence both the energy consumption and expenditure of households[1].

This paper sheds light on the extent to which energy efficiency measures (or improvements) of different upfront costs are associated by changes in residential energy consumption. It also assesses the degree of sensitivity of household energy consumption to changes in energy prices and household income with the objective of understanding how to design policies to reduce residential energy use in a cost-effective and affordable manner. With this goal in mind, we address the following three aspects.

First, we analyse the patterns of energy consumption in English households between 2012 and 2014. We control, at a micro level, for the following socioeconomic characteristics of households: household size, whether or not the household includes children, the age of the dwelling, and whether the dwelling is located in a rural vs. an urban area. We also account for the vulnerability of the households, which we approximate by using the following policy variables: whether or not the household receives a winter fuel payment (for electricity consumption), whether or not it is part of the CERT priority group, and whether or not the dwelling is eligible for a Warm Front Grant (See section 4 for further details).

Second, we analyse the relationship between the adoption of a set of nine EE measures (which we also classify by the level of upfront investment cost) on electricity and gas consumption on those dwellings controlling for the same set of socio-economic and policy variables.

And third, we calculate the welfare change for different income groups with the adoption of the particular EE measures. It is important to note that the first two of these questions were highlighted by a recent literature review by Reid et al. (2015) as key areas that deserved attention. As Advani et al. (2013) and McInnes (2017), among others show, the third question regarding the distributional impact of environmental or other policies has risen to the policy agenda around the world.

Hence, the overall objectives of this paper are:

- Determining the relationship between different EE measures adopted by households on household primary energy use, i.e. gas and electricity consumption (Kwh/year), one year after their adoption.
- Determining the extent to which energy prices and household income changes mediate the relationship between EE measures and reductions in household energy consumption.
- Determining the welfare effects related to the adoption of lower and higher cost EE measures across different groups. The analysis focuses on the cost and benefits after one year of the adoption of the EE measures. Therefore, this is a preliminary result that must be used carefully.

In the remainder of this paper we review the literature, present our data and methodology, our results, and conclude with a discussion of policy implications and future research.

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

2. Literature review and research hypotheses

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

Recently several papers have aimed to estimate the impact of household EE investments on future energy consumption using different techniques including general equilibrium models (Lecca et al., 2014; Bye et al., 2018; Figus et al., 2017), microeconomic demand systems (Tovar and Wolfing, 2018) and input-output models (Freire-Gonzalez et al., 2017). In this sense, there is a wide range of ex ante assessments in the literature.

With a few notable exceptions (Trotta, 2018; Elsharkawy and Rutherford, 2018; Webber et al., 2015), we have found that there is a gap in the literature in terms of ex-post evaluation of the changes in residential energy consumption that follow the implementation of different EE measures. The evaluation of actual energy savings in England (and the UK more broadly) and the factors that may influence residential energy consumption or the impact of different EE measures, is timely, particularly given the perceived policy failures in the residential EE space[2] (See, e.g. Kjaerbye et al., 2011; Sovacool et al., 2017; DBEIS, 2016). While there is significant research on the factors determining the adoption of energy efficiency measures (e.g., Ramos et al., 2016; Miller et al., 2014; Trotta, 2018 among others) research has found that there is no conclusive evidence detailing the extent to which differences between expected energy savings from EE measures and realized ones may be related to social challenges, e.g. vulnerability or consumer resistance (Sovacool et al., 2017), or may be caused by rebound effects of policy-induced improvements (Gillingham et al., 2016; Brockway et al., 2017) among other reasons.

Some studies using data on actual changes in energy consumption have tried to shed light on the role of the rebound effects, i.e. the reduction in expected savings from new technologies and/or the adoption of EE measures because of behavioural or other systemic responses (Gillingham, 2016). In a recent study using ex post information about the Kirklees Warm Zone (KWZ)[3] scheme in UK homes between 2007-2010 using micro level data on 49,000 households, Webber et al. (2015) found that the impact of the scheme in energy savings in households have been greater than predicted in part because performance gaps and rebound effects have been lower than the once initially assumed by Buildings Research Establishment and by the Savings Trust[4]. However, Webber et al (2015) highlight that rebound effects are much bigger in low-income areas (realized savings of around 53% and 49% of expected savings) than in high-income areas (around 90% and 70% of expected savings). In any case, it must be highlighted that the KWZ scheme offered free energy assessments, and free loft and cavity wall insulation to all households in Kirklees, when feasible. Therefore, the absent of upfront costs may be the reason why rebound effects are lower than expected.

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[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).

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

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

Webber et al's findings are consistent with Sorrell (2007), which suggests, from a review of more than 500 studies and reports, that losses in energy savings for EE measures in dwellings regarding heating, when compared to energy savings projected by standard engineering models, are about 30%. Other studies suggest a smaller magnitude for the rebound effect, varying from 5% to 15%, measured as the difference between projected and realized savings that can be attributed to increased consumption through indirect effects (Chitnis et al., 2013). Therefore, the existence of rebound effects, may undermine the reduction in energy consumption when it comes to analysing individual EE measures.

In addition to the rebound effect, in practice, many EE measures are implemented alongside other home improvements that may have associated increases in energy consumption, such as extensions, which are popular in the UK. The combination of an old housing stock, the rebound effect, and the possible correlation between EE measure implementation and other building work which may lead to increase energy use might, when taken together, result in no reduction in energy consumption at the household level. Judson et al. (2014, p: 63) states that renovation "involves an element of upgrading to improve performance to meet new conditions or standard, but may also involve the introduction of new elements for partial demolition to remove parts that are unsafe functionally redundant, have maintenance problems, outdated or limit a viable use". In an ethnographic study for Australia, Judson and Maller. (2014) find that renovation practices are related to social practices to create and maintain living standards. It is when these renovations (e.g. add extension, renovation of bathrooms, added new rooms…) take place when energy efficiency measure adoptions are considered as part of the renovation to improve the physical well-being of the families. For the UK, Hand et al. (2007) using interviews with UK households, relates spatial changes to the acquisition of new technologies and goods. Sandu and Petchey (2009) for Australia conclude that despite an increase from 33% to 59% between 2005-2008 in the proportion of households using energy saving lights, the energy demand on lighting increased. This may be the effect of a greater use of halogen lamps after renovations related to increases in the size of the dwellings.

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

H1. There are increases in the amount of electricity and gas consumed by households that have adopted at least one EE measure vs. those households that have not adopted them within a twelve month time period after the adoption of such measure.

Research about the size and drivers of rebound effects to different EE measures (See Sorrell, 2007 for a review) in the residential sector is vast. However, one aspect that has not been previously considered has been the extent to which the cost of specific EE improvements is a possible driver of subsequent energy consumption patterns (Gillingham et al., 2013; Greening et al., 2000; Turner, 2009; among many others). For example, differences in the cost and extent of retrofit schemes may have important impacts on subsequent energy consumption in households. The benefits from reduced energy bills over the years may compensate the economic upfront costs of the investment (Chapman et al., 2009; Tovar, 2012). Chapman et al. (2009) using a cluster randomized trial of retrofitting insulation in 1350 houses in low-income areas in New Zealand conclude that the value of the money of improving dwelling quality by retrofitting insulation is positive. However, this results is calculated over a 30 year horizon considering benefits from reduce healthcare needs, days off school or work, energy savings and CO_2 savings.

Tovar (2012), using the English Household Condition Survey from 2003 to 2007 and projections of costs and savings, finds that the adoption of low cost measures such as cavity and loft insulation may bring savings to households over a five year time period because of overall reductions in annual energy consumption. However, Tovar do not use upfront costs of the investment but a categorical variable to measure different levels of investments. Taking into account the cost of investment in EE adoption when trying to estimate whether there is a relationship between a particular EE measure and household energy consumption is not common in the literature (Gillingham, 2016). One exception is Bye et al. (2018). Bye et al (2018) analyse the effect of EE policies in Norwegian households and include the upfront costs of different EE measures at the household level. However, this research relies on an ex ante computable general equilibrium model, and not in actual energy consumption data over time at the household level. They conclude that EE policies may increase carbon emissions the whole economy although they may lead to electricity use reductions in the household sector. They assume, theoretically, that EE measures with higher costs lead to greater energy savings (greater reductions in household energy consumption).

To the best of the authors knowledge, previous research has not tried to estimate the relationship between upfront investment costs made by households when adopting different EE measures and subsequent changes in residential energy consumption. Following the theoretical work of Bye et al. (2018), we account for the investment costs faced by households adopting EE measures when trying to estimate what factors may mediate the impact of different measures on reductions in energy consumption.

In addition to the size of upfront EE measure costs, the literature indicates that we may also expect differences in the energy consumption of households after adopting a particular measure for different income levels, mainly due to price sensitivity. For example, previous studies have observed higher rebound effects in low-income households for improvements in heating technologies (Milne and Boardman, 2000). Chitnis et al. (2014) study the rebound effect of six heating and lighting EE measures in households in terms of GHG emission reductions. The authors, using information coming from the Community Domestic Energy Model conclude that rebound effects are modest (0-32%). However this is an ex-ante assessment which relies on information based on an engineering model of the English housing stock. Besides, measures undertaken by low-income households are related to larger rebound effects. For relatively costly EE measures and for low-income households, the capital cost significantly offset the energy cost savings. Measures that are subsidised or affect highly taxed energy commodities may be less effective as well (Chitnis et al. 2014). We may expect therefore that those households that have spent more upfront money on the adoption of EE measures will experience smaller rebound effects in their energy consumption, partly because we presume they will be high-income households. However, rebound effects may be higher for those receiving external support and those belonging to low-income percentiles. We account for this with a policy proxy variable for vulnerability.

We thus include two more hypothesis to test:

H2. The higher the cost of the adoption of EE measures, the smaller the energy consumption increase, i.e. smaller rebound effects regardless the income.

H3. For all the EE measures investigated, low income households and vulnerable households receiving external economic support, will experience higher rebound effects, i.e. higher energy consumption increases.

We now turn to the distribution of energy price elasticities to EE improvements across different household income levels. The evaluation of demand response and welfare effects across different income groups is important given the poor efficiency of housing stock in many lead economies such a UK (UKERC, 2017a; Alcott and Greenstone, 2017). Energy services can be considered basic goods and as such we may expect that income elastic of demand varies between 0 and 1 (Tovar, 2012; Jamasb and Meier, 2010). There is a particular need to better understand how EE policy affects welfare in low-income households (UKERC, 2017b; Figus et al. 2017, Tovar, 2012). To the best of our knowledge, previous research has not analysed the effect of the adoption of specific EE measures, such as cavity, loft insulation and/or upgrades to boilers on the energy consumption and welfare, measured as a loss in purchase power, i.e. income of the household, along different income deciles. We expect that the welfare of the poorest segment of the population will be more affected by higher upfront costs in the adoption of these retrofit efficiency measures. Therefore:

H4. The adoption of EE measures has a more negative impact on the welfare of the poorest households than on the medium and high-income households measured by income loss with higher cost measures resulting in lower welfare in the short term (after one year).

3. Methodology

In this research, we use a Cobb-Douglas model to estimate household energy demand (which we estimate separately for gas and electricity since different EE measures may affect distinct energy sources differently).

$$E_i = \frac{\beta_1 Y_i^{\beta_2} H_r^{\beta_4} \sum D_{ji}^{\beta j}}{p_r^{\beta_3}} \tag{1}$$

where E is energy consumption of households[5] measured in kWh year, β_1 is the constant term, Y_i represents the annual household income, p_r is an index that captures average changes in energy prices, i.e. gas and electricity prices, in the 9 Government office regions in England, H_r are the number of annual heating degree days of the region where the household is located, D refers to a set of j variables which capture the heterogeneity of households with respect to energy consumption. Subscripts i, and r refer to households and the regions, respectively.

A first set of control variables captures the socioeconomic characteristics of households: household size, households with children, the age of the dwellings[6] and if the dwelling is located in a rural vs. an urban area. A second group of variables captures the vulnerability of the households in terms of energy consumption: if the household receives a winter fuel payment (for electricity consumption), if it is part of the CERT priority group and if the dwelling is eligible for a Warm Front Grant. This variable acts a control of whether the breadwinner is older than 65 too. Finally, when modelling energy consumption in those dwellings that have adopted at least one EE measure in the last 12 months, we use a variable that determines the investment costs of the adopted measures. This variable is particularly important in order to analyse the impact of upfront cost on subsequent changes in energy consumption and the effects of different EE measures in different income groups.

[5] We will analyse electricity and gas consumption separately. We will consider gas used for space heating, water heating and cooking. Electricity consumption will correspond to space heating, water heating, cooking, and lights and appliances. Other fuels are not considered as on average gas and electricity consumption represent 96% of the total energy used of the households in the sample. Cooling degree days have been included but they are not significant in any of the regression so they have been excluded from the analysis.

[6] Dwellings built before 1919, from 1919 to 1944, from 1945 to 1964, from 1965 to 1980, from 1981 to 1990 or after 1990.

Taking logarithms, parameters β2 and β3 can be interpreted as price and income elasticities of energy demand. The use of quantile regression, proposed by Koenker and Bassett (1978), offers a more comprehensive picture of the determinants of gas and electricity consumption across the conditional distribution of the dependent variables:

$$LE_i = L\beta_{\theta 1} + \beta_{\theta 2}LY_i - \beta_{\theta 3}Lp_r + \beta_{\theta 4}LH_r + [\beta_{\theta 5}LI_i] + \Sigma\beta_{\theta j}d_{ji} + Le_{\theta i} \quad (2)$$

For 0<θ<1, with Quantile$_\theta$ (y/x)= x_i β_θ where y is the dependent variable and x is the set of covariates, with quantile θ being the conditional distribution in the θ quantiles. In the quantile regression, the estimation of the parameters $\widehat{\beta_{\theta i}}$ is obtained by minimizing the asymmetric weighted sum of absolute deviations.

$$\min_{\beta \epsilon R^k}\{ \textstyle\sum_{i:\ln E_i \geq \beta X_i} \theta \mid \ln E_i \ - \beta_\theta X_i| + \sum_{i:\ln E_i < \beta X_i} (1-\theta) \mid \ln E_i \ - \beta_\theta X_i|\} \quad (3)$$

The $\beta_{\theta j}$ parameters can be interpreted as the impact of the respective variable on the demand for energy in quantile θ. Therefore, we can identify whether or not the reaction of households to changes in prices, income and EE investments remains stable across the distribution of energy consumption for both gas and electricity during the years for which data is available.

In order to analyse the impact of the upfront costs of the adoption of different types of EE measures on the welfare of the households, measured as the gains or losses on available income, we will based our analysis on the Equivalent Variation (EV) concept proposed by Hicks which is defined as

$$EV = f(x^0, v^1) - f(x^1, v^1) = G_f^1 - G \quad (5)$$

where superindexes 0 and 1 indicate, respectively, the initial and final values (before and after the adoption of EE measures) of the variables under analysis, i.e. EE investment costs, potential energy saving costs after the adoption of the measures and potential emissions reductions after the adoption of the measures, x are the variables under evaluation, v is the indirect utility function, G is the initial rent (income) and Gf is the final rent (income) defined as

$$G_f^1 = f(X_0, V^1(X, G)) \quad (6)$$

4. **Data**

The analysis relies on the microdata from the English Housing Survey (EHS) 2013-2014, which includes information between April 2012 and March 2014. We have used this specific set because it is the last year in which variables regarding actual energy consumption and EE measures are included together.

The EHS collects annual information about people's housing conditions and EE of housing in England. This survey provides rich information, as perceived by household occupants, on energy consumption, energy expenditures, notional CO_2 emission levels, the economic structure of the household, the income and the location of households among other variables. The electricity and gas price indexes are provided by ONS (2016)[7]. The survey offers data at the household level about around 12,200 households on a repeated cross-sectional way[8].

[7] These indexes have been weighted by the consumer price index (CPI) of each English region (North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East, London, South East, South West)

[8] For methodological information see DECC(2015) and DCLG (2017).

The survey also includes data about energy efficiency measures that the household could undertake, as per the Energy Performance Certificate (EPC), as well as energy efficiency measures that were implemented. The EPC has its origin in the European Energy Performance of Buildings Directive, implemented in 2007. Under this directive, all households in the EU are required to obtain an Energy Performance Certificate (EPC) before they are sold or let. Among other things, the EPC Scheme makes recommendations regarding a range of lower and higher cost energy efficiency upgrade measures, including heating, insulation and other building features. As previously mentioned, the data for each of the households in the survey includes a set of recommended measures and the total investment cost of installing the recommended measures, as well as the measures that were actually adopted by the household. In order to calculate the cost of the EE measures to the household, we have broken down the total cost of the EE improvements recommended and extracted the cost that was estimated for the measure that was implemented in the first snapshot (2012-2013)[9].

The EE measures considered in this paper are divided following the EPC classification in two groups: low cost measures (upfront costs under £500) and high cost measures (upfront cost greater than £500). Table A1. in the supplementary information details the specific measures that fall into the two categories.

We complemented the analysis with information coming from Eurostat (Table 1). Descriptive statistics are provided in table A2 on the SI.

Table 1. Description of variables, sources of data and expected relationship with the dependent variable.

Variable	Definition	Data Source	Expected relation
Total electricity consumption by household	Total amount of electricity used for electric space heating, electric water heating, electric cooking and for lights and appliances (kWh/yr)	EHS- UK data service	Dependent variable
Total gas consumption by household	Total amount of gas used for gas space heating, gas water heating and gas cooking (kWh/yr)	EHS- UK data service	Dependent variable
Income	Household annual income (£)	EHS- UK data service	(+)
Electricity price	Electricity Price index (2012/2013) weighted by the CPI in each region.	ONS	(-)
Gas price	Gas price index (2012/2013) weighted by the CPI in each region	ONS	(-)
Household size	Number of members of the household	EHS- UK data service	(+)
Children	Dummy: presence of any dependent children in the household	EHS- UK data service	(+)
Urban	Dummy: whether the household is located in urban areas (>10,000 inhabitants)	EHS- UK data service	(+)
Age	Dwelling age Pre 1919 1919-44 1945-64 1965-80 1981-90 Post 1990	EHS- UK data service	(-)

[9] The EHS also estimates a measure of CO2 emission reduction and fuel costs after any recommended improvements have been installed. Using these notional estimates we have calculated the pre and post level of emissions and fuel costs to see the effect of the actual measures adopted on the annual income of each household.

Heating degree days[10]	Difference between a reference temperature (T*) (18ºC) and the average daily temperatures (Ta) by region $$\mathrm{HDD} = \sum_{i=1}^{n} \max(0;\ T^* - Ta)$$	EUROSTAT	(+)
Winter Payment	Dummy: whether the household receives income from Winter Fuel Payment (WFP) programme (only for electricity regression)	EHS-UK data service	(-)
CERTPriority	Dummy: whether the household is considered as a priority household in the CERT scheme. The Priority Group are vulnerable and low-income households, including those in receipt of eligible benefits and pensioners over the age of 70.	EHS-UK data service	(-)
Warm Front Grant	Dummy: whether the household is eligible for Warm Front grant (based upon criteria prior to April 2011)	EHS-UK data service	(+)
EE investment costs	Modelled total cost of installing all of the specified EE measures. Costs are inflated annually to current prices (£).	EHS-UK data service	(+)

Source: own elaboration

Since our first hypothesis is to determine the extent to households adopting at least one EE measure are associated with an increase in energy consumption when compared to those that did not, we first conduct a descriptive analysis of the dataset that we built using ANOVA[11]. Our null hypothesis (H_0), under H1 is that households that have adopted at least one EE measure have increased their energy consumption when compared to the previous 12 months. . Without controlling for additional variables and using ANOVA, we find that there are no statistically significant increases (or decreases) in electricity consumption. Results regarding gas consumption show, at the 99% confidence level, that households which adopted EE measures had higher gas consumption when compared to those that did not (Table 2).

Table 2. ANOVA electricity and gas consumption and expenditure by EE measure adoption

EE adoption	Electricity consumption (kWh/yr)	Electricity expenditure (£ /y)	Gas consumption (kWh/yr)	Gas expenditure (£/ yr)
Not adopted	4157.422* (2925.576) 8,389 Obs	562.645 (308.229) 8,389 Obs	13314.455 (8435.472) 8,389 Obs	625.390 (354.619) 8,389 Obs
EE measure adopted	4144.58 (2570.618) 3,619 Obs	569.8143 (283.131) 3,619 Obs	13940.719 (8142.084) 3,619 Obs	648.142 (338.361) 3,619 Obs
Total	4153.553 (2823.2) 12,008 Obs	564.806 (300.892) 12,008 Obs	13503.2 (8352.743) 12,008 Obs	632.247 (349.940) 12,008 Obs

* Mean (Std. Dev)

Source: own elaboration with data from EHS

Therefore, this preliminary descriptive analysis opens a venue to explore the differences in energy consumption of both types of households (with EE measures vs. without) and strongly suggests the existence of rebound effects and/or additional building projects reducing (or negating) the energy savings that could be derived by the EE measures.

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

[11] ANOVA is a classic method to compare and to examine the differences in the mean values of a metric dependent variable associated with the effect of one or more controlled categorical independent variables (See Malhotra and Dash (2015), Smalheiser (2017) or Weisberg (2005), among others, for a detailed explanation of the methodology).

5. Results

Table 3 shows the results of the estimation of eq. 2 for those households that have not introduced any EE measure (the full tables with all deciles can be found in the SI Tables A3 and A4). Table 4 provides the results for those households that had introduced at least one efficiency measure. These tables show the relationship between economic, weather, and building characteristics and changes in consumption. The information in these tables allow to reinforce results for H1 and to test H2 and H3. The price and income elasticities estimated for electricity and gas consumption are shown in Fig. 2 and Fig. 3. Additionally the elasticity of the changes in energy consumption in a 12 month timeframe to the level investment costs is also provided in Fig. 3.

Table 3. Results of the quantile regression for those households without EE measure adoption

Electricity consumption | EE measure=0	10		30		50		70		90	
LIncome	0.055***	(0.006)	0.059***	(0.005)	0.057***	(0.006)	0.056***	(0.009)	-0.082***	(0.018)
LSize	0.521***	(0.008)	0.486***	(0.007)	0.476***	(0.007)	0.431***	(0.011)	0.029	(0.032)
LElecprice	-0.161**	(0.072)	-0.166**	(0.082)	-0.248***	(0.084)	-0.303***	(0.105)	-1.388***	(0.442)
LHdd	0.342***	(0.049)	0.289***	(0.066)	0.34***	(0.062)	0.129**	(0.056)	-1.689***	(0.313)
Urban	-0.031***	(0.009)	-0.062***	(0.007)	-0.097***	(0.011)	-0.123***	(0.012)	-0.333***	(0.069)
Children	0.006	(0.009)	0.006	(0.005)	0	(0.007)	-0.009	(0.012)	0.002	(0.048)
LAge	-0.018***	(0.004)	-0.018***	(0.004)	-0.023***	(0.007)	-0.016**	(0.008)	0.038	(0.034)
Winter	0.021**	(0.010)	0.062***	(0.007)	0.064***	(0.008)	0.05***	(0.011)	-0.017	(0.037)
CERT	-0.014	(0.011)	-0.021**	(0.008)	-0.022**	(0.010)	-0.019	(0.014)	-0.045	(0.038)
Warm	0.048***	(0.010)	0.041***	(0.008)	0.033**	(0.013)	0.039***	(0.014)	0.12**	(0.054)
Intercept	4.999***	(0.648)	5.587***	(0.842)	5.757***	(0.813)	7.895***	(0.782)	29.963***	(3.827)
Observations: 8307										
Gas consumption | EE measure=0	10		30		50		70		90	
LIncome	0.106***	(0.017)	0.100***	(0.010)	0.105***	(0.006)	0.117***	(0.010)	0.096***	(0.012)
LSize	0.309***	(0.015)	0.277***	(0.013)	0.273***	(0.012)	0.267***	(0.018)	0.295***	(0.022)
LGasprice	-1.136***	(0.216)	-0.951***	(0.154)	-0.924***	(0.146)	-1.011***	(0.127)	-1.020***	(0.201)
LHdd	0.899***	(0.143)	0.666***	(0.094)	0.497***	(0.116)	0.338***	(0.095)	0.231*	(0.133)
Urban	-0.091***	(0.020)	-0.08***	(0.014)	-0.076***	(0.016)	-0.067***	(0.015)	-0.092***	(0.019)
Children	-0.038**	(0.017)	-0.013	(0.013)	-0.008	(0.012)	-0.01	(0.016)	-0.021	(0.024)
LAge	-0.315***	(0.014)	-0.332***	(0.010)	-0.323***	(0.011)	-0.32***	(0.012)	-0.314***	(0.012)
Winter	0.068***	(0.018)	0.085***	(0.011)	0.117***	(0.015)	0.107***	(0.017)	0.141***	(0.019)
CERT	0.023	(0.017)	-0.015	(0.011)	-0.054***	(0.010)	-0.052***	(0.012)	-0.101***	(0.021)
Warm	---	---	---	---	---	---	---	---	---	---
Intercept	6.552***	(1.838)	7.875***	(1.407)	9.232***	(1.398)	10.977***	(1.137)	12.363***	(1.830)
Observations: 7304										

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

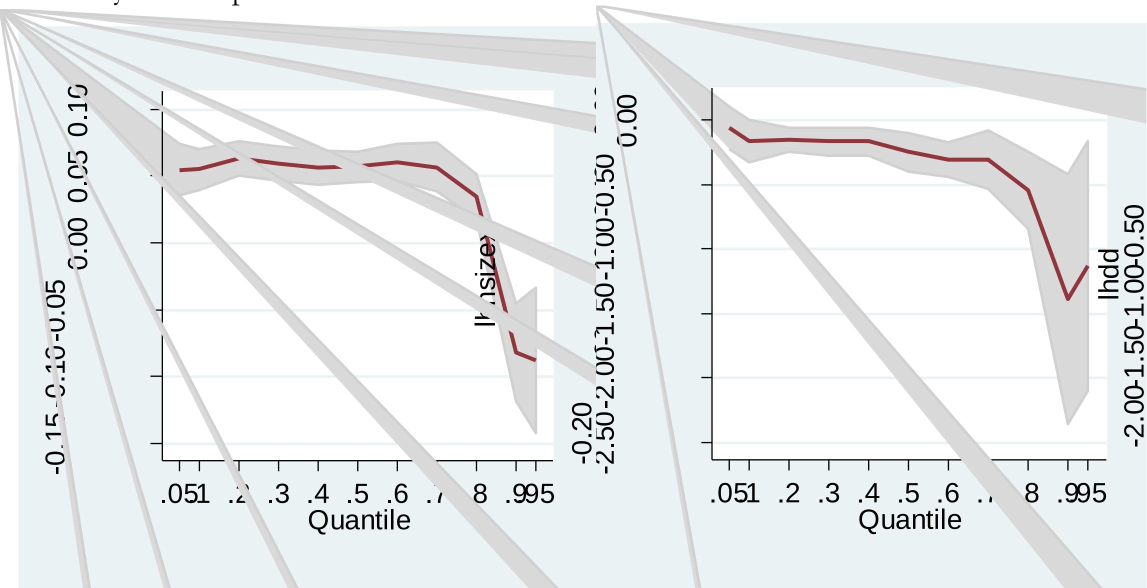
Table 4. Results of the quantile regression for those household with at least one EE measure adoption in the last 12 months.

Electricity consumption | EE measure=1	10		30		50		70		90	
Lincome	0.056***	(0.013)	0.054***	(0.011)	0.055***	(0.007)	0.049***	(0.009)	-0.019	(0.033)
Lsize	0.51***	(0.015)	0.481***	(0.015)	0.467***	(0.012)	0.443***	(0.022)	0.175*	(0.096)
Lelectprice	-0.207	(0.140)	-0.205*	(0.108)	-0.207*	(0.107)	-0.406***	(0.124)	-0.056	(0.479)
Linvcost	0.007	(0.006)	0.010**	(0.005)	0.017***	(0.004)	0.007	(0.007)	-0.038**	(0.018)
LHdd	0.231**	(0.093)	0.368***	(0.088)	0.397***	(0.085)	0.201***	(0.107)	-1.659***	(0.521)
Urban	-0.048**	(0.020)	-0.098***	(0.014)	-0.112***	(0.010)	-0.13***	(0.018)	-0.423***	(0.101)
Children	0.009	(0.013)	-0.004	(0.015)	-0.004	(0.018)	-0.005	(0.028)	0.04	(0.084)
LAGe	-0.025**	(0.011)	-0.025***	(0.007)	-0.033***	(0.006)	-0.018	(0.013)	0.082**	(0.039)
Winter	0.048**	(0.019)	0.059**	(0.014)	0.05***	(0.016)	0.064***	(0.021)	-0.074	(0.073)
CERT	-0.054***	(0.013)	-0.035**	(0.014)	-0.024*	(0.014)	-0.028***	(0.016)	0.062	(0.060)
Warm	0.054***	(0.016)	0.031*	(0.016)	0.005	(0.016)	0.014	(0.029)	-0.01	(0.092
Incercept	6.13*	(1.382)	5.223***	(1.088)	5.071***	(1.060)	7.849***	(1.303)	22.775***	(5.586)
Observations: 3,071										
Gas consumption | EE measure=1	10		30		50		70		90	
Lincome	0.112***	(0.017)	0.131***	(0.018)	0.099***	(0.014)	0.095***	(0.014)	0.073***	(0.017)
Lsize	0.223***	(0.031)	0.221***	(0.024)	0.241***	(0.024)	0.234***	(0.021)	0.246***	(0.036)
LGasprice	-1.234***	(0.208)	-1.528***	(0.156)	-0.999***	(0.141)	-1.283***	(0.185)	-1.103***	(0.178)
Linvcost	0.082***	(0.010)	0.066***	(0.009)	0.062***	(0.008)	0.062***	(0.007)	0.060***	(0.009)
LHdd	0.249	(0.159)	0.044	(0.171)	0.034	(0.130)	-0.109	(0.131)	-0.102	(0.224)
Urban	-0.059*	(0.031)	-0.044*	(0.025)	-0.085***	(0.031)	-0.1***	(0.022)	-0.096***	(0.028)
Children	0.006	(0.032)	-0.01	(0.018)	-0.002	(0.025)	0.009	(0.023)	0.007	(0.034)
LAGe	-0.268***	(0.017)	-0.271***	(0.017)	-0.289***	(0.011)	-0.304***	(0.011)	-0.327***	(0.019)
Winter	0.077***	(0.029)	0.072***	(0.024)	0.093***	(0.026)	0.100***	(0.024)	0.131***	(0.032)
CERT	-0.058***	(0.019)	-0.032	(0.020)	-0.074***	(0.019)	-0.098***	(0.018)	-0.103***	(0.029)
Warm	---	---	---	---	---	---	---	---	---	---
Incercept	11.785***	(1.948)	14.959***	(1.808)	13.023***	(1.584)	15.773***	(1.690)	15.319***	(2.325)
Observations: 2,721										

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

Fig. 2. Price and income elasticities without EE measures

Electricity consumption



Gas consumption

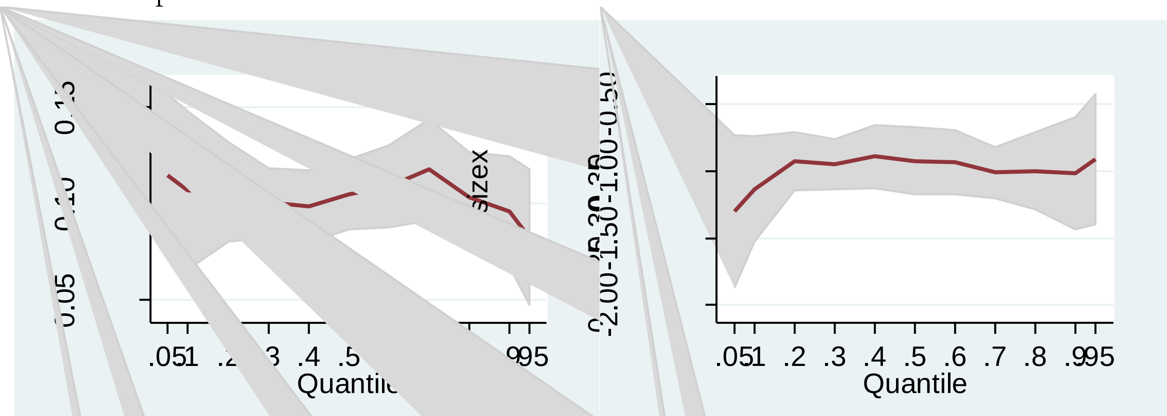
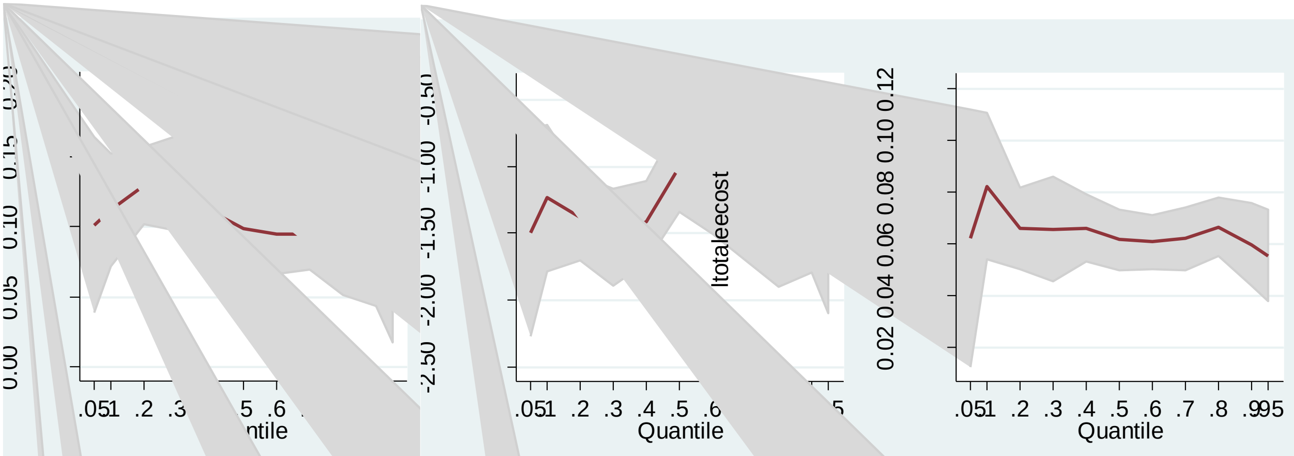
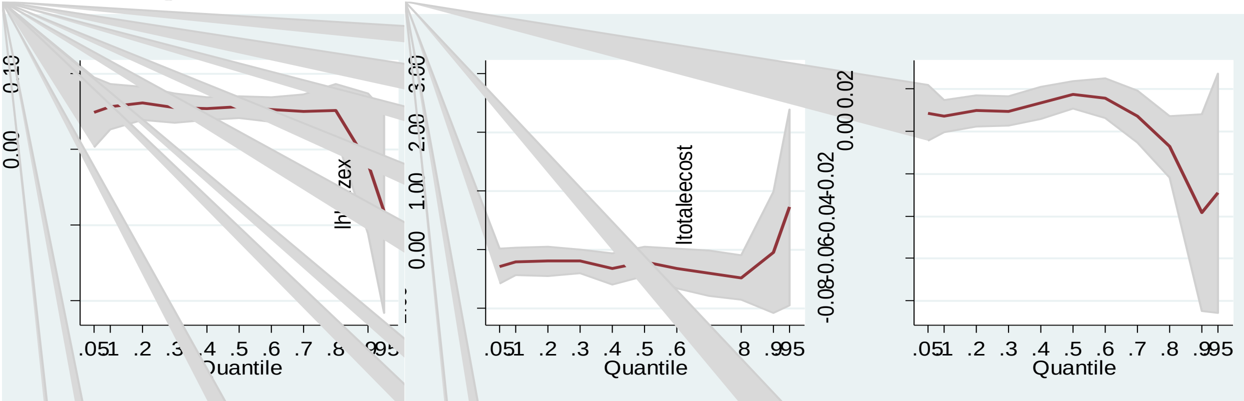


Fig. 3. Price, income and investment cost elasticities with EE measures

Electricity Consumption



Gas Consumption



Source: Own elaboration

The estimated coefficients have the sign expected (as in Table 1), except for the dummy measuring urban location, and are statistically significant for most of the deciles. Household size, the presence of children, the fact that the breadwinner is older than 65[12], and the number of HDD have a statistically significant positive impact on both gas and electricity consumption.

While electricity price elasticities show an upward pattern: the higher the income deciles the higher the price elasticity i.e. from a minimum (in absolute value) to a maximum (in absolute value) [13], the pattern for gas price elasticities starts relatively high (low in absolute value) at low income levels, go down for medium-low income levels and increase again (in absolute values) for high income households. In this sense, higher income households show similar price gas elasticities than the poorest households. These results suggest that the poorest and the richest segments of the population are more insensitive to gas price variations than medium-income households. Indeed, poor households have a limited pathway to reduce gas demand when prices increase, since this demand mostly covers basic needs. This is consistent with research on Spanish households, which has shown using quantile regression that households with very high income levels are insensitive to gas price because energy costs do not represent an important fraction of their consumption (Romero-Jordan et al., 2016).

The results on the relationship between the price and energy demand show that while electricity prices elasticities stay more or less stable independently of the introduction of EE measures in households, gas consumption is more responsive to changes in prices when the household has introduced at least one EE measure, especially for the middle-income quartiles (30–80). This is consistent with the notion that in many cases EE measures are implemented alongside with other building improvements which may result in increases in energy consumption, in particular due to the increase of space to be heated by gas (See literature review section). For instance, the price elasticity of demand for quantile 40 increase (in absolute terms) from −0.89 to −1.41. In contrast, the change was modest for both extremes of the distribution (-1.14 vs. -1.23 for the first decile and -1.0 vs. -1.1 for the last decile). This may be due to the fact that most of the EE measures considered in this paper are related to heating issues and not to lighting or appliances energy use.

The shape of the gas price elasticity values along quantiles is similar in the households with and without EE measures in the last 12 months. However, elasticities after the introduction of EE measures are higher in absolute terms than the ones in those households without EE measures. This result is very interesting because it suggests that the adoption of EE technologies in

[12] This variable is proxied with the dummy related to the existence of the Winter Fuel Payment.
[13] There are no large differences in electricity price elasticities between income deciles.

households make more flexible the energy demand, mainly the gas demand, perhaps mediated by the fact that EE measures may be done simultaneously with other building projects.

As shown in Table 3 and 4, income elasticities remain constant in both dimensions, i.e. there are no significant differences neither among income deciles nor between households with and without EE measures adoption. Therefore the adoption of EE measures does not seem to be associated with a more responsive energy demand to income but to price changes (mainly to gas prices). The highest differences between price elasticities in those households with and without EE measures are found for middle-income deciles, e.g. -0.17 vs. -0.33 for electricity price elasticity in the 5th decile or -0.95 vs. -1.53 and -0.89 vs. -1.14 for the 3rd and the 4th decile for gas price elasticities respectively in households with and without EE measures adopted in the last year. As an example, if gas prices increase by 1%, and you are in decile 40, if the household has adopted an EE measure the consumption will reduce by 0.87% and if you did not adopted such measure the consumption will reduce by 1.12%. In line with the literature (Romero-Jordan et al., 2016), households in middle-income segments may react to changes in prices because energy is not a basic good but cover also other needs and still represents a non-negligible share of the total housing expenditures.

H3 tested the idea that the investment costs of the adopted EE measures may affect the subsequent energy consumption of the households. For both sources of energy, i.e. gas and electricity, we found that the higher the investment costs, the higher the energy demand the year after the EE measure was adopted. It is worth mentioning, once again, that the effect on gas consumption is higher than the effect on electricity consumption. In fact, the investment costs were only associated with statistically significant changes (increases) in electricity consumption for middle-income deciles, i.e. 2nd to 6th. Just like in the testing of H2, it is possible that higher EE measure costs are more likely to be incurred. This outcome reinforces the preliminary result obtained in the ANOVA and confirms H1: households that have adopted EE measures have, controlling for a wide range of factors, an energy consumption a year after the adoption that is higher than those households that did not. This result confirm as well our H2.

To test H3, we look at the differences between high cost EE measures and low cost EE measures (See tables A5 and A6 in the SI). The results are robust with the analysis of energy demand in the dwellings that have adopted EE measures whatever type, i.e. regardless of which of the two categories of EE measures had been adopted, consumption increases compared to no EE measure adoption. However, contrary to expectations, low cost EE measures make households more responsive to changes in electricity and gas prices. The same happens when focussing the attention on the cost of the adopted measures. Except for the case of electricity in the highest deciles in those households that only adopted low cost EE measures and in which higher investment costs implies lower electricity consumption, generally households adopting low cost measures will tend to show a higher energy demand that those adopting high cost EE measures[14]. This result reinforces the outcome supporting H2.

In contrast to the findings by Milne and Boardman (2000) we do not find that investment costs affect differently household gas consumption by income groups. Regarding electricity, we find that only households in the last decile would decrease their electricity consumption when they spend more money, i.e. they have higher upfront costs, in EE measures. These results do not allow to confirm our H3. It is worth noting that households belonging to the CERT priority group, i.e. very vulnerable households, present a negative relationship with consumption of both in gas and in electricity, above all in the middle-income deciles, so they tend to be associated with reductions in energy use.

[14] Although in both cases, i.e. households with low cost measures vs. households with high cost measures there are positive relationships.

As mentioned in the methodology we use an adaptation of the Equivalent variation to calculate the distribution of the welfare losses/gains per income deciles of those households that have adopted EE measures. Table 5 summarizes the results. Column 2 shows the results in terms of average income per decile, the average cost of the investment is provided in column 3. Investment costs ranges from 635£ for the first decile to 899£ for the highest. However, when these costs are related to household income levels, the impact of the investment on the income of the household is completely regressive representing a much greater percentage of the total income of the household for the poorest ones (9.84%) than for the richest (1.6%). We find that, in relative terms, the welfare loss is much greater for the poorest households. Besides, this relative loss would not be compensated with the hypothetical cost savings[15]. Although hypothetical expected cost savings are progressive, they only represents a 1% of the total income for the poorest households. Therefore, in order to redeem the cost of the investment households will need an average of 9 years. This may be one of the barriers that prevent more households of the adoption of EE measures (Watson et al., 2006; Webber et al., 2015). Then, as proposed in Hypothesis 4, the welfare losses are a decreasing function of income.

Table 5. Impact of investments costs, costs savings and emission savings on the welfare of households when adopting any type of EE measure (3,095 obs)

Decile (Income)	Avg. household income (£/year)	Avg. cost of the investment[16] (£)	Relative welfare loss in year of investment (%)	Avg. energy cost savings after the adoption (£/year)	Relative welfare gain in year of investment (%)	Avg. emissions savings (Tonnes/year)
1	6451.615	634.5822	9.836021	70.31552	1.08989	1.176461
2	12489.02	599.2147	4.797932	70.05089	0.5609	1.083808
3	13591.29	583.0007	4.289517	68.74215	0.505781	1.063971
4	16173.44	529.6382	3.274741	67.46479	0.417133	0.994129
5	18939.34	655.2395	3.459674	75.89708	0.400738	1.13854
6	21899.04	686.8541	3.136458	76.14276	0.347699	1.209455
7	25852.43	718.6981	2.780002	76.64641	0.296477	1.213558
8	29255.56	815.1652	2.78636	81.64604	0.279079	1.356655
9	35881.51	737.3325	2.054909	82.55576	0.230079	1.218339
10	56212.26	899.1536	1.599568	83.3833	0.148337	1.430365
Total	23351.64	681.4223	2.918092	75.00188	0.321185	1.183279

As a robustness check, we have done the same calculations trying to find out which is the best strategy for households in order to minimize the impact of those measures in their budget and take the maximum benefit. When comparing those households that had only adopted low cost EE measures (Table 6) vs. those ones that had adopted high cost EE measures (Table 7), the relative welfare loss is comparatively smaller for households adopting low cost investments in every decile but in the highest one where the loss for low cost measures is 1.56% vs. 1.47 for high cost measures. For the poorest households the impact is incredibly high with an impact of 7.82% on the total income when installing low cost EE measures vs. 12.48% when installing high cost ones. Besides, the relative welfare gain is smaller for all deciles when installing high cost energy efficiency.

[15] Our results have shown that the households, during the first year after the adoption of an EE measure, do not experience energy savings. As we may not be counting for future energy savings, the average energy cost savings after the adoption shown in Tables 5 to 7 represents an ex-ante calculation provided by the English Housing Survey of the notional energy saving costs after the adoption of EE measures.

[16] Unfortunately we do not have information about which method the head of the household used to pay for the energy efficiency update, e.g. bank loan, public loan, cash, private loan etc.

Therefore, households may be more willing to adopt low cost efficiency measures which will prevent them of suffering higher welfare losses[17].

Table 6. Impact of investments costs, costs savings and emission savings on the welfare of households when adopting only low cost EE measures (1200 obs)

Decile (Income)	Avg. household income (£/year)	Avg. cost of the investment (£)	Relative welfare loss in year of investment (%)	Avg. energy cost savings (£/year)	Relative welfare gain in year of investment (%)	Avg. emissions savings (Tonnes/year)
1	6602.607	516.1561	7.817459	70.39098	1.066109	0.898607
2	13619.32	570.857	4.191524	74.751	0.54886	0.941636
3	13727.18	573.4757	4.177666	74.37984	0.541844	0.94814
4	16025.24	460.4466	2.873259	66.48218	0.414859	0.853028
5	18424.16	634.6967	3.444915	76.27841	0.414013	0.975044
6	21798.09	621.2176	2.849872	80.30351	0.368397	0.98855
7	25254.17	720.0608	2.851255	81.58431	0.323053	1.029817
8	29660.62	690.3124	2.32737	86.212	0.290661	1.06488
9	35908.45	780.4883	2.173551	89.91562	0.250402	1.106071
10	53689.24	842.1384	1.568542	89.10121	0.165957	1.112804
Total	22928.58	633.7721	2.764114	78.54881	0.34258	0.9872

Table 7. Impact of investments costs, costs savings and emission savings on the welfare of households when adopting only high cost EE measures (1194)

Decile (Income)	Avg. household income (£/year)	Avg. cost of the investment (£)	Relative welfare loss in year of investment (%)	Avg. energy cost savings (£/year)	Relative welfare gain in year of investment (%)	Avg. emissions savings (Tonnes/year)
1	5945.29	742.0882	12.48195	52.62438	0.885144	1.229375
2	11906.86	607.0706	5.098494	54.69848	0.459386	0.98864
3	13314.37	494.9043	3.717069	48.06066	0.360968	0.912647
4	16417.1	563.5644	3.432789	52.00554	0.316777	0.918261
5	18892.37	605.6348	3.205711	53.20843	0.28164	0.97899
6	21497.08	715.3939	3.327865	55.61109	0.258691	1.179182
7	26419.55	708.2935	2.680945	59.016	0.22338	1.134929
8	27634.06	797.0382	2.88426	58.72242	0.2125	1.198817
9	35747.05	678.0189	1.896713	57.03712	0.159558	1.055405
10	57531.7	846.7521	1.471801	61.48973	0.10688	1.350385
Total	23602.44	671.1485	2.843556	55.17363	0.233762	

6. Discussion and conclusions

This paper has analysed the responsiveness of household energy demand for electricity and gas and the welfare effects related to adoption of EE measures in the period 2012-2014.

The results show that the adoption of EE measures in households lead to an increase in the demand of both commodities. However, it must be highlighted that the introduction of these measures make households more responsive to changes in energy prices. This represents a positive

[17] This result is not taking into account the emissions savings that would be generally higher when installing high cost energy efficiency measures.

outcome as EE measures may be acting as tools for the flexibility of the energy demand in the residential sector.

Attention must be paid to the fact that the impact of the adoption of these measures in the welfare of the households varies considerably for different deciles on annual income. The particularly negative impact on the poorest segment of the population may provide a rationale to focus the attention on the barriers that may prevent those households to engage in EE measures adoption. There are high up-front costs and stigmatization issues that should be taking into account when designing policies for promoting EE in dwellings. Indeed, results allow to conclude that the adoption of low cost EE measures implies lower up-front cost and higher energy cost savings than high cost EE measures. To mitigate the negative impact of the adoption of EE measures on vulnerable households calls for targeted-oriented energy policy measures distinguishing between income groups. In this sense, firstly, although it is true that the reduction in CO2 emissions is higher when the households adopt high cost EE measures, policies that prioritize the adoption of low cost EE measures in low-income households may be a way to improve both distributional impacts and EE issues all at once. Secondly, Romero et al. (2016) suggest that in order to mitigate negative distributive impacts, public policy should not inhibit the energy price signal but to provide rent transfers oriented policies, such an annual payments or grants to vulnerable households. However, British policy has been using this approach for years without the expected results. The analysis in this paper suggests that neither the Warm Front Grant nor the Winter Fuel Payment generates decreases in the consumption of energy. Although those programmes are not directly oriented towards the reduction of energy consumption but to support and reduce fuel poverty in those more vulnerable households, we would expect a reduction in the energy use of those targeted dwellings. The existence of rebound effects may be eroding the outcomes of the policies. Regarding specifically those programmes oriented towards increasing energy efficiency, being a CERT priority households decreases energy consumption, however, the programme does not help to reduce the distributional impacts of the adoption of EE measures in households. Although it is not analysed in this paper, the retrofit policy of the Green Deal failed to persuade large numbers of households to participate in the adoption of EE measures (Harvey, 2013; Webber et al., 2015).

In this paper, we have analysed how investment EE costs can increase energy consumption. We assume this is a signal of rebound effects in energy consumption mainly regarding gas consumption. Therefore, this paper represents one more step in understanding EE measures adoption in households and dwelling energy consumption behaviour.

However, there are limitations that suggest avenues for further research. First, the analysis of welfare gains and losses uses notional modelled variables from the EHS for energy cost savings, investment costs and CO2 emissions reductions. The availability of actual data would represent a boost in understanding the outcomes of the adoption of EE measures in the residential sector. Second, we have focused exclusively on households outcomes. A more accurate picture of the EE context in the England would require to consider all the actors involved. Third, although the theoretical framework can be extrapolated to the UK geography, the quantitative analysis is focused on the English context because of data availability. Fourth, although there have been some advances in literature, behavioural aspects behind the existence of rebound effects need to be investigated more in depth. Finally, although the quintile analysis used in this paper allows to overcome some of the disadvantages of pooled regression, the availability of balance panel data will allow to see patterns of change and use other quasi experimental techniques to analyse the effects of the EE policy in the UK and elsewhere.

Supplementary information

Table A1. Type of EE measures considered and number of households adopting them

Low cost EE measures		
Loft	Have you [or your landlord/freeholder] put in loft insulation / extra loft insulation in the last 12 months to this property 1,363 households	EHS- UK data service
Cavity wall	Put in cavity wall insulation in the last 12 months in the property 563 households	EHS- UK data service
Cylinder	Installed or upgrade hot water cylinder insulation in the last 12 months in the property 426 households	EHS- UK data service
High cost EE measures		
Cylinder thermostat	Installed/ upgrade a how hater cylinder thermostat in the last 12 months in the property 300 households	EHS- UK data service
Heating controls	Upgrade central heating controls [Put new thermostatic radiator valve, replace central heating thermostat, replace central heating time clock / programmer] in the last 12 months in the property 1,366 households	EHS- UK data service
Biomass systems	Install a manual feed biomass boiler or wood pellet stove in the last 12 months in the property 74 households	EHS- UK data service
Boiler	Upgrade or replace central heating boiler in the last 12 months in the property 2,368 households	EHS- UK data service
Storage radiators	Upgrade or replace existing storage radiators in the last 12 months in the property 128 households	EHS- UK data service
Warm air system	Upgrade or replace warm-air heating units in the last 12 months in the property 25 households	EHS- UK data service

Source: Own elaboration with information coming from EHS guidelines

Table A2. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Total electricity consumption	12,008	4153.553	2823.2	-2524.58	40970.84
Total gas consumption	12,008	13503.2	8352.743	0	87408.91
Income	12,008	21135.02	15940.56	0	100000
Household size	12,008	2.374001	1.321525	1	10
Electricity price	12,498	118.3645	5.399507	110.6941	130.5696
Gas price	12,498	128.1231	5.909113	119.7405	141.4148
HDD	12,498	2966.481	169.148	2721.79	3375.54

Urban	12,498	0.823332	0.381403	0	1
0 (no)	2,208				
1 (yes)	10,290				
Children	12,498	0.31061	0.462762	0	1
0 (no)	8,616				
1 (yes)	2,882				
Age dwelling	12,498	3.329253	1.569548	1	6
Pre 1919	1,990				
1919-1944	1,903				
1945-1964	3,053				
1965-1980	2,800				
1981-1990	1,058				
Post 1990	1,694				
Winter Payment	12,498	0.363818	0.481117	0	1
0 (no)	7,951				
1 (yes)	4,547				
CERTpriority	12,008	0.541223	0.498319	0	1
0 (no)	5,509				
1 (yes)	6,499				
Warm Fuel	12,008	0.126832	0.332799	0	1
0 (no)	10,485				
1 (yes)	1,523				
EE measured adopted	12,498	0.289566	0.453579	0	1
0 (no)	8,879				
1 (yes)	3,619				
Upfront cost adopted EE measure	4,778	873.3145	729.1543	16.07	6681.005

Source: own elaboration with data from EHS

Table A3. Results of the quantile regression for those households without any EE measure adopted in the last 12 months

Electricity consumption | EE measure=0	10		20		30		40		50		60		70		80		90	
LIncome	0.055***	(0.006)	0.063***	(0.006)	0.059***	(0.005)	0.056***	(0.006)	0.057***	(0.006)	0.060***	(0.007)	0.056***	(0.009)	0.035***	(0.008)	-0.082***	(0.018)
LSize	0.521***	(0.008)	0.496***	(0.010)	0.486***	(0.007)	0.483***	(0.008)	0.476***	(0.007)	0.458***	(0.009)	0.431***	(0.011)	0.384***	(0.014)	0.029	(0.032)
LElecprice	-0.161**	(0.072)	-0.155***	(0.059)	-0.166**	(0.082)	-0.167**	(0.068)	-0.248***	(0.084)	-0.309***	(0.084)	-0.303***	(0.105)	-0.548***	(0.164)	-1.388***	(0.442)
LHdd	0.342***	(0.049)	0.322***	(0.062)	0.289***	(0.066)	0.333***	(0.062)	0.34***	(0.062)	0.279***	(0.042)	0.129**	(0.056)	-0.227**	(0.113)	-1.689***	(0.313)
Urban	-0.031***	(0.009)	-0.041***	(0.009)	-0.062***	(0.007)	-0.074***	(0.011)	-0.097***	(0.011)	-0.121***	(0.010)	-0.123***	(0.012)	-0.166***	(0.028)	-0.333***	(0.069)
Children	0.006	(0.009)	0.01	(0.008)	0.006	(0.005)	0.003	(0.006)	0	(0.007)	-0.005	(0.008)	-0.009	(0.012)	-0.024	(0.017)	0.002	(0.048)
LAge	-0.018***	(0.004)	-0.02***	(0.006)	-0.018***	(0.004)	-0.017***	(0.006)	-0.023***	(0.007)	-0.021***	(0.008)	-0.016**	(0.008)	-0.011	(0.013)	0.038	(0.034)
Winter	0.021**	(0.010)	0.035***	(0.009)	0.062***	(0.007)	0.067***	(0.009)	0.064***	(0.008)	0.051***	(0.011)	0.05***	(0.011)	0.037**	(0.017)	-0.017	(0.037)
CERT	-0.014	(0.011)	-0.011	(0.009)	-0.021**	(0.008)	-0.024***	(0.008)	-0.022**	(0.010)	-0.019	(0.012)	-0.019	(0.014)	-0.034**	(0.016)	-0.045	(0.038)
Warm	0.048***	(0.010)	0.045***	(0.011)	0.041***	(0.008)	0.035***	(0.008)	0.033**	(0.013)	0.038***	(0.011)	0.039***	(0.014)	0.064***	(0.017)	0.12**	(0.054)
Intercept	4.999***	(0.648)	5.151***	(0.700)	5.587***	(0.842)	5.339***	(0.723)	5.757***	(0.813)	6.602***	(0.650)	7.895***	(0.782)	12.321***	(1.210)	29.963***	(3.827)
Observations: 8307																		

Gas consumption | EE measure=0	10		20		30		40		50		60		70		80		90	
LIncome	0.106***	(0.017)	0.106***	(0.015)	0.100***	(0.010)	0.098***	(0.008)	0.105***	(0.006)	0.109***	(0.008)	0.117***	(0.010)	0.103***	(0.009)	0.096***	(0.012)
LSize	0.309***	(0.015)	0.271***	(0.016)	0.277***	(0.013)	0.281***	(0.014)	0.273***	(0.012)	0.27***	(0.013)	0.267***	(0.018)	0.288***	(0.012)	0.295***	(0.022)
LGasprice	-1.136***	(0.216)	-0.928***	(0.151)	-0.951***	(0.154)	-0.893***	(0.133)	-0.924***	(0.146)	-0.935***	(0.126)	-1.011***	(0.127)	-0.999***	(0.129)	-1.020***	(0.201)
LHdd	0.899***	(0.143)	0.822***	(0.112)	0.666***	(0.094)	0.571***	(0.122)	0.497***	(0.116)	0.399***	(0.100)	0.338***	(0.095)	0.149	(0.114)	0.231*	(0.133)
Urban	-0.091***	(0.020)	-0.095***	(0.014)	-0.08***	(0.014)	-0.075***	(0.014)	-0.076***	(0.016)	-0.068***	(0.014)	-0.067***	(0.015)	-0.066***	(0.014)	-0.092***	(0.019)
Children	-0.038**	(0.017)	-0.03**	(0.012)	-0.013	(0.013)	-0.016	(0.016)	-0.008	(0.012)	-0.009	(0.016)	-0.01	(0.016)	-0.031	(0.019)	-0.021	(0.024)
LAge	-0.315***	(0.014)	-0.319***	(0.011)	-0.332***	(0.010)	-0.326***	(0.011)	-0.323***	(0.011)	-0.317***	(0.011)	-0.32***	(0.012)	-0.319***	(0.015)	-0.314***	(0.012)
Winter	0.068***	(0.018)	0.068***	(0.012)	0.085***	(0.011)	0.109***	(0.016)	0.117***	(0.015)	0.111***	(0.017)	0.107***	(0.017)	0.107***	(0.018)	0.141***	(0.019)
CERT	0.023	(0.017)	0.003	(0.014)	-0.015	(0.011)	-0.047***	(0.013)	-0.054***	(0.010)	-0.056***	(0.012)	-0.052***	(0.012)	-0.07***	(0.016)	-0.101***	(0.021)
Warm	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---
Intercept	6.552***	(1.838)	6.36***	(1.391)	7.875***	(1.407)	8.467***	(1.500)	9.232***	(1.398)	10.105***	(1.286)	10.977***	(1.137)	12.679***	(1.367)	12.363***	(1.830)
Observations: 7304																		

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

Table A4. Results of the quantile regression for those households with at least one EE measure adopted in the last 12 months

Electricity consumption | EE measure=1	10		20		30		40		50		60		70		80		90	
Lincome	0.056***	(0.013)	0.06***	(0.012)	0.054***	(0.011)	0.053***	(0.008)	0.055***	(0.007)	0.052***	(0.007)	0.049***	(0.009)	0.051***	(0.016)	-0.019	(0.033)
Lsize	0.51***	(0.015)	0.48***	(0.016)	0.481***	(0.015)	0.474***	(0.014)	0.467***	(0.012)	0.452***	(0.013)	0.443***	(0.022)	0.394***	(0.031)	0.175*	(0.096)
Lelectprice	-0.207	(0.140)	-0.203*	(0.121)	-0.205*	(0.108)	-0.331***	(0.114)	-0.207*	(0.107)	-0.331***	(0.128)	-0.406***	(0.124)	-0.483***	(0.185)	-0.056	(0.479)
Linvcost	0.007	(0.006)	0.010*	(0.005)	0.010**	(0.005)	0.014***	(0.005)	0.017***	(0.004)	0.016***	(0.005)	0.007	(0.007)	-0.007	(0.007)	-0.038**	(0.018)
LHdd	0.231**	(0.093)	0.255***	(0.081)	0.368***	(0.088)	0.359***	(0.095)	0.397***	(0.085)	0.325***	(0.105)	0.201***	(0.107)	-0.103	(0.248)	-1.659***	(0.521)
Urban	-0.048**	(0.020)	-0.081***	(0.013)	-0.098***	(0.014)	-0.106***	(0.011)	-0.112***	(0.010)	-0.108***	(0.012)	-0.13***	(0.018)	-0.215***	(0.050)	-0.423***	(0.101)
Children	0.009	(0.013)	0.011	(0.012)	-0.004	(0.015)	-0.003	(0.016)	-0.004	(0.018)	-0.007	(0.018)	-0.005	(0.028)	-0.001	(0.039)	0.04	(0.084)
LAGe	-0.025**	(0.011)	-0.027***	(0.007)	-0.025***	(0.007)	-0.028***	(0.008)	-0.033***	(0.006)	-0.028***	(0.009)	-0.018	(0.013)	0.006	(0.020)	0.082**	(0.039)
Winter	0.048**	(0.019)	0.061***	(0.012)	0.059**	(0.014)	0.046***	(0.014)	0.05***	(0.016)	0.051***	(0.017)	0.064***	(0.021)	0.031	(0.029)	-0.074	(0.073)
CERT	-0.054***	(0.013)	-0.043***	(0.013)	-0.035**	(0.014)	-0.032**	(0.015)	-0.024*	(0.014)	-0.030**	(0.015)	-0.028***	(0.016)	-0.018	(0.020)	0.062	(0.060)
Warm	0.054***	(0.016)	0.043***	(0.013)	0.031*	(0.016)	0.016	(0.017)	0.005	(0.016)	0.018	(0.025)	0.014	(0.029)	0.025	(0.042)	-0.01	(0.092
Incercept	6.13*	(1.382)	5.981***	(1.093)	5.223***	(1.088)	5.953***	(1.093)	5.071***	(1.060)	6.344***	(1.306)	7.849***	(1.303)	10.909***	(2.440)	22.775***	(5.586)
Observations: 3,071																		

Gas consumption | EE measure=1	10		20		30		40		50		60		70		80		90	
Lincome	0.112***	(0.017)	0.129***	(0.016)	0.131***	(0.018)	0.112***	(0.017)	0.099***	(0.014)	0.094***	(0.011)	0.095***	(0.014)	0.087***	(0.015)	0.073***	(0.017)
Lsize	0.223***	(0.031)	0.209***	(0.022)	0.221***	(0.024)	0.237***	(0.025)	0.241***	(0.024)	0.243***	(0.022)	0.234***	(0.021)	0.239***	(0.021)	0.246***	(0.036)
LGasprice	-1.234***	(0.208)	-1.384***	(0.150)	-1.528***	(0.156)	-1.412***	(0.116)	-0.999***	(0.141)	-1.196***	(0.139)	-1.283***	(0.185)	-1.511***	(0.187)	-1.103***	(0.178)
Linvcost	0.082***	(0.010)	0.066***	(0.008)	0.066***	(0.009)	0.066***	(0.008)	0.062***	(0.008)	0.061***	(0.007)	0.062***	(0.007)	0.066***	(0.006)	0.060***	(0.009)
LHdd	0.249	(0.159)	0.116	(0.137)	0.044	(0.171)	-0.023	(0.128)	0.034	(0.130)	-0.005	(0.128)	-0.109	(0.131)	-0.23	(0.172)	-0.102	(0.224)
Urban	-0.059*	(0.031)	-0.054**	(0.023)	-0.044*	(0.025)	-0.063**	(0.024)	-0.085***	(0.031)	-0.09***	(0.023)	-0.1***	(0.022)	-0.097***	(0.022)	-0.096***	(0.028)
Children	0.006	(0.032)	-0.013	(0.017)	-0.01	(0.018)	-0.003	(0.023)	-0.002	(0.025)	0.012	(0.018)	0.009	(0.023)	0.008	(0.023)	0.007	(0.034)
LAGe	-0.268***	(0.017)	-0.26***	(0.014)	-0.271***	(0.017)	-0.283***	(0.013)	-0.289***	(0.011)	-0.289***	(0.012)	-0.304***	(0.011)	-0.314***	(0.015)	-0.327***	(0.019)
Winter	0.077***	(0.029)	0.06***	(0.020)	0.072***	(0.024)	0.09***	(0.021)	0.093***	(0.026)	0.104***	(0.023)	0.100***	(0.024)	0.122***	(0.025)	0.131***	(0.032)
CERT	-0.058***	(0.019)	-0.048***	(0.013)	-0.032	(0.020)	-0.058***	(0.017)	-0.074***	(0.019)	-0.082***	(0.013)	-0.098***	(0.018)	-0.109***	(0.019)	-0.103***	(0.029)
Warm	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---
Incercept	11.785***	(1.948)	13.627***	(1.668)	14.959***	(1.808)	15.222***	(1.422)	13.023***	(1.584)	14.411***	(1.588)	15.773***	(1.690)	17.992***	(2.025)	15.319***	(2.325)
Observations: 2,721																		

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

Table A5. Results of the quantile regression for those households with at least one low cost EE measure adoption in the last 12 months.

Electricity consumption | EE low cost measure=1 & EE high cost measure==0	10		20		30		40		50		60		70		80		90	
Lincome	0.034	0.021	0.055***	0.021	0.034*	0.018	0.051***	0.014	0.047***	0.015	0.038**	0.016	0.048***	0.014	0.047**	0.019	0.120***	0.029
Lsize	0.481***	0.028	0.463***	0.023	0.470***	0.028	0.447***	0.017	0.451***	0.02	0.466***	0.018	0.461***	0.03	0.431***	0.049	0.186**	0.088
Lelectprice	-0.279*	0.15	-0.277	0.174	-0.360***	0.132	-0.327**	0.133	-0.379*	0.199	-0.510**	0.246	-0.774***	0.282	-0.672	0.436	-0.339	0.837
Linvcost	0.019*	0.011	0.011	0.007	0.018*	0.01	0.015*	0.008	0.017**	0.007	0.015*	0.009	-0.002	0.014	-0.043**	0.02	-0.139***	0.029
LHdd	0.323*	0.176	0.193	0.193	-0.01	0.152	0.123	0.183	0.204	0.195	0.038	0.162	-0.015	0.201	-0.457	0.323	-1.514***	0.516
Urban	-0.016	0.033	-0.046*	0.025	-0.067***	0.026	-0.075***	0.023	-0.085***	0.02	-0.098***	0.027	-0.122***	0.027	-0.223***	0.066	-0.57***	0.167
Children	0.024	0.022	0.015	0.023	0.001	0.019	0.01	0.018	0.033	0.026	0.02	0.03	0.022	0.04	0.033	0.057	0.137*	0.081
LAGe	-0.014	0.014	-0.008	0.016	-0.009	0.017	-0.021	0.014	-0.022*	0.012	-0.014	0.016	0	0.016	0.006	0.023	0.044	0.06
Winter	0.043	0.027	0.057**	0.023	0.055**	0.022	0.035**	0.017	0.05**	0.02	0.038	0.023	0.025	0.03	0.017	0.043	-0.035	0.08
CERT	-0.072***	0.028	-0.072***	0.026	-0.06**	0.024	-0.048**	0.023	-0.046**	0.022	-0.039*	0.02	-0.031*	0.019	-0.03	0.028	0.038	0.059
Warm	0.072***	0.026	0.089***	0.027	0.065***	0.028	0.049**	0.023	0.012	0.019	0.004	0.021	0.015	0.031	-0.007	0.048	0.079	0.117
Intercept	5.869***	1.915	6.841***	2.18	9.101***	1.62	7.829***	1.771	7.492***	2.275	9.596***	2.137	11.359***	2.742	14.872***	4.021	22.316***	7.068
Observations:1190																		

Gas consumption | EE low cost measure=1 & EE high cost measure==0	10		20		30		40		50		60		70		80		90	
Lincome	0.119***	0.036	0.115***	0.035	0.078***	0.028	0.056**	0.027	0.067**	0.029	0.049	0.036	0.040	0.034	0.036	0.023	0.055***	0.018
Lsize	0.167***	0.046	0.199***	0.04	0.222***	0.04	0.246***	0.041	0.231***	0.034	0.238***	0.042	0.214***	0.042	0.26***	0.035	0.273***	0.048
Lelectprice	-1.718***	0.55	-1.692***	0.401	-1.814***	0.374	-1.370***	0.323	-1.249***	0.334	-1.163***	0.236	-1.129***	0.366	-1.420***	0.406	-1.116***	0.409
Linvcost	0.110***	0.025	0.093***	0.018	0.093***	0.017	0.090***	0.017	0.089***	0.015	0.080***	0.012	0.084***	0.013	0.079***	0.019	0.066***	0.023
LHdd	-0.209	0.307	-0.224	0.264	-0.116	0.258	0.075	0.189	0.144	0.162	0.165	0.202	0.109	0.323	-0.261	0.392	-0.557	0.412
Urban	-0.088*	0.047	-0.085***	0.033	-0.09***	0.033	-0.071**	0.032	-0.058	0.037	-0.081**	0.038	-0.064	0.045	-0.063	0.05	-0.084*	0.045
Children	0.006	0.062	-0.017	0.052	0.007	0.048	0.018	0.04	0.033	0.04	0.045	0.04	0.055	0.042	0.012	0.042	0.035	0.05
LAGe	-0.265***	0.034	-0.275***	0.028	-0.297***	0.029	-0.299***	0.025	-0.301***	0.025	-0.295***	0.026	-0.314***	0.029	-0.329***	0.035	-0.339***	0.036
Winter	0.063	0.042	0.063*	0.034	0.072**	0.035	0.081**	0.037	0.087***	0.033	0.108***	0.031	0.098***	0.036	0.083*	0.046	0.12*	0.063
CERT	-0.05	0.04	-0.035	0.025	-0.052**	0.026	-0.076**	0.033	-0.074***	0.029	-0.078***	0.027	-0.118***	0.033	-0.08*	0.042	-0.043	0.044
Warm	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---
Intercept	17.651***	3.673	17.895***	3.639	18.084***	2.983	14.682***	2.186	13.514***	2.192	13.232***	2.505	13.701***	4.04	18.23***	4.621	19.136***	4.664
Observations: 1056																		

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

Table A6 Results of the quantile regression for those households with at least one high cost EE measure adoption in the last 12 months.

Electricity consumption | EE low cost measure=0 & EE high cost measure==1

	10		20		30		40		50		60		70		80		90	
Lincome	0.060***	0.014	0.071***	0.012	0.057***	0.014	0.045**	0.018	0.056***	0.02	0.053***	0.02	0.055***	0.02	0.062*	0.035	-0.048	0.049
Lsize	0.541***	0.022	0.526***	0.02	0.52***	0.022	0.518***	0.021	0.485***	0.024	0.446***	0.024	0.431***	0.038	0.36***	0.078	0.022	0.157
Lelectprice	-0.143	0.225	-0.300	0.245	-0.265	0.268	-0.452**	0.218	-0.248	0.186	-0.386*	0.206	-0.432	0.304	-0.659*	0.35	-0.513	1.027
Linvcost	-0.002	0.008	0.009	0.007	0.007	0.007	0.011*	0.006	0.018***	0.007	0.016*	0.009	0.005	0.009	0.007	0.018	0.027	0.039
LHdd	0.184	0.152	0.202	0.222	0.375**	0.18	0.427***	0.166	0.482***	0.185	0.392**	0.166	0.269	0.227	-0.028	0.388	-2.169***	0.84
Urban	-0.081***	0.031	-0.101***	0.022	-0.109***	0.016	-0.114***	0.02	-0.12***	0.018	-0.091***	0.023	-0.133***	0.034	-0.195**	0.089	-0.365***	0.129
Children	0.004	0.021	0.004	0.024	-0.019	0.02	-0.029	0.022	-0.026	0.022	-0.011	0.027	0.003	0.035	0.002	0.042	0.11	0.152
LAGe	-0.044**	0.019	-0.037***	0.011	-0.03**	0.013	-0.041***	0.012	-0.043***	0.014	-0.041**	0.019	-0.025	0.023	0.001	0.041	0.042	0.068
Winter	0.043**	0.02	0.068***	0.026	0.067***	0.019	0.062***	0.023	0.051**	0.025	0.067***	0.019	0.09***	0.025	0.041	0.044	-0.086	0.093
CERT	-0.035**	0.014	-0.037*	0.019	-0.04**	0.016	-0.041**	0.02	-0.029	0.021	-0.057**	0.029	-0.048	0.038	-0.018	0.051	-0.04	0.096
Warm	0.021	0.022	0.015	0.033	0.009	0.028	0.011	0.026	0.013	0.03	0.029	0.033	0.021	0.052	0.017	0.071	0.159	0.166
Intercept	6.238***	2.279	6.762**	2.736	5.432**	2.562	6.091***	2.175	4.603**	2.186	6.082***	2.041	7.427**	3.012	10.994***	3.91	29.166***	9.964

Observations: 1184

Gas consumption | EE low cost measure=0 & EE high cost measure==1

	10		20		30		40		50		60		70		80		90	
Lincome	0.126***	0.043	0.145***	0.032	0.19***	0.039	0.163***	0.03	0.140***	0.026	0.131***	0.017	0.136***	0.024	0.123***	0.031	0.079**	0.033
Lsize	0.274***	0.071	0.232***	0.038	0.223***	0.053	0.211***	0.048	0.254***	0.038	0.249***	0.027	0.226***	0.051	0.272***	0.05	0.242***	0.063
Lelectprice	-1.028***	0.364	-1.099***	0.269	-1.441***	0.381	-1.271***	0.38	-0.946**	0.399	-0.992***	0.351	-1.152***	0.429	-1.358***	0.464	-1.250***	0.422
Linvcost	0.084***	0.016	0.071***	0.012	0.065***	0.013	0.072***	0.011	0.069***	0.013	0.067***	0.011	0.065***	0.012	0.057***	0.015	0.069***	0.017
LHdd	0.718*	0.377	0.528***	0.144	0.244	0.256	0.354	0.218	0.22	0.224	0.109	0.237	-0.195	0.326	-0.09	0.387	-0.043	0.279
Urban	-0.062	0.053	-0.053	0.038	-0.065	0.042	-0.073***	0.025	-0.05*	0.027	-0.074***	0.026	-0.075**	0.031	-0.062***	0.024	-0.13***	0.05
Children	-0.074	0.062	-0.051	0.043	-0.031	0.051	-0.024	0.044	-0.057	0.043	-0.068*	0.036	-0.067*	0.037	-0.096**	0.042	-0.09	0.057
LAGe	-0.324***	0.034	-0.268***	0.028	-0.274***	0.027	-0.259***	0.031	-0.282***	0.028	-0.283***	0.021	-0.29***	0.024	-0.29***	0.029	-0.328***	0.039
Winter	0.062	0.066	0.064**	0.031	0.08**	0.038	0.063	0.043	0.103***	0.038	0.099***	0.032	0.104***	0.035	0.094**	0.041	0.085	0.054
CERT	-0.017	0.049	-0.024	0.038	0.01	0.035	-0.035	0.029	-0.068**	0.034	-0.089***	0.024	-0.113***	0.02	-0.12***	0.034	-0.131***	0.042
Warm	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---
Intercept	6.935*	4.024	8.751***	1.98	12.368***	3.367	10.994***	3.16	10.797***	3.401	12.118***	3.342	15.403***	4.106	15.807***	4.887	15.566***	3.404

Observations: 1031

Notes: Robust standard errors in parentheses. * Significant at the 90% confidence level. **Significant at the 95% confidence level. ***Significant at the 99% confidence leve

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