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Daire McCoy and Raphaela Kotsch

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# Quantifying the distributional impact of energy efficiency measures

Daire McCoy*, Raphaela Andrea Kotsch†

February 14, 2020

**Abstract**

The distributional impact of the low-carbon transition is an increasingly important topic both for academics and policymakers. Quantifying where the costs and benefits fall can provide greater insight into the equity and cost-effectiveness of government policies, and improve our understanding of household investment decisions. This paper provides new evidence on the distribution of returns from energy efficiency measures both over time and across household-type. A range of econometric techniques are applied to a database of over four million households over an eight year period to quantify heterogeneity, persistence and how these factors impact the relative cost-effectiveness of measures. Results suggest that more deprived households experience lower energy savings, the difference persists over time, and that significantly heterogeneity may be present across levels of deprivation and income deciles that can not be explained by differences in baseline consumption. Measures have been largely cost-effective but savings are much lower than previous policy evaluations using ex-ante estimates would suggest.

**Keywords:** Energy efficiency; Distributional impact of policy; Panel data econometrics

**JEL codes:** C23; D12; Q40; Q48

*McCoy (corresponding author): Grantham Research Institute, London School of Economics and Political Science, Houghton Street, London, U.K. WC2A 2AE, Economic and Social Research Institute, Sir John Rogerson's Quay, Dublin, Ireland, d.m.mccoy@lse.ac.uk. This work makes use of data from the National Energy Efficiency framework Database (NEED) UK. We are grateful for financial support for this research from the European Investment Bank, EIBURS grant scheme. Project title: "Policies to finance energy efficiency: an applied welfare assessment". We thank Antoine Dechezleprtre, Francois Cohen, Louis-Gaetan Giraudet and Karsten Neuhoff for securing this funding. This research has also been supported by the Grantham Research Institute and the ESRC Centre for Climate Change Economics and Policy under Grant No. ES/K006576/1. We thank seminar participants at AIEE (2017), FSR Annual Climate Conference (2017), IEB International Academic Symposium (2018), UKNEE enevecon (2018), LSE, Grantham Research Institute PDE Workshop (2018), Montpellier Energy Workshop (2018), EAERE World Congress (2018) and BIEE (2018) for comments. The authors are extremely grateful to Arlan Brucal and Roger Fouquet for useful discussions and for providing comments on an earlier draft. We would also like to thank Kenneth Gillingham, Meredith Fowlie and Matt Kotchen for useful discussions. All remaining errors are our own.

†University of Zurich, Affolternstrasse 56, 8050 Zurich, Switzerland

# 1 Introduction

Residential buildings account for around 30 percent of the United Kingdom's energy consumption and constitute the third largest sector by emissions (BEIS, 2018). With the introduction of recent legislation to achieve net zero emissions by 2050 (UK Climate Change Act, 2019), major steps to reduce emissions occurring in homes will be necessary. Energy efficiency measures will play an increasing role in achieving these reduction targets. In addition to the challenge of the decarbonisation of the domestic energy sector, more than 10 percent of the UK's population still lives in fuel poverty today (BEIS, 2019). For this reason, energy efficiency programmes to date have typically pursued two objectives simultaneously: reducing emissions and combating fuel poverty.

Yet, policy evaluations often do not take into account the distributional impacts of energy efficiency measures and tend to be based on energy saving estimates from ex-ante engineering models. Previous studies have shown that the engineering estimates of energy savings can be more than three times what is actually realised and the upfront investment costs can be up to twice the actual savings (Allcott and Greenstone, 2017; Fowlie et al., 2018).

We build on this research tackling the question of how much savings energy efficiency measures actually deliver, a question that is more difficult to answer than it may appear. In contrast to previous research, we further evaluate how these savings are distributed, both across households and over time. Providing answers to these questions is important both for understanding why households appear to under-invest in energy efficiency measures relative to what is socially or even privately optimal, the so-called "energy-efficiency gap"[1] and evaluations of policies aimed at encouraging adoption of energy efficiency measures. Overstated returns make private investments seem more attractive, and makes policies appear more cost-effective than they actually are. This issue is exacerbated by the fact that many policy evaluations rely on ex-ante engineering estimates of savings, rather than observed outcomes.

Evaluations of energy efficiency improvements tend to take a short time-scale, usually a window of a couple of years on either side of the intervention in order to assess the magnitude of savings. This is despite the fact that time-scale has proven an important factor when examining the impact of building energy codes on energy consumption (Kotchen, 2017), and on the effect of behavioural interventions to reduce energy consumption (Allcott and Rogers, 2014). The impact of energy efficiency measures could vary over time for various reasons. Specific factors related to usage patterns in any particular period may bias results both before and after, while

[1]The reluctance of some consumers to make energy saving investments that offer them seemingly positive net-present value (NPV) returns has been widely studied. For example see Hausman (1979); Blumstein et al. (1980); Jaffe and Stavins (1994); Golove and Eto (1996); Allcott and Greenstone (2012). However, there has been much debate on the size of this gap and the relative contribution of market failures, behavioural anomalies or model and measurement error. A recent paper by Gerarden et al. (2015) argues that the energy efficiency gap may not be as large as expected and that unobserved costs, overstated savings from adoption, consumer heterogeneity, inappropriate discount rates and uncertainty may all contribute to the low adoption rate not being as "paradoxical as it first appears. A related literature focuses on supply side market failures, imperfect competition and suboptimal rate of innovation. See for example Goldberg (1998); Cohen et al. (2017); Brucal et al. (2017)

poor installation quality or degradation in the installed equipment may affect the results post-installation. Variation over time could affect the accuracy of measurement, the attractiveness of the investment, or the cost-effectiveness of a government scheme.

Additionally, it has been shown that rebound effects can exhibit significant heterogeneity across income groups (Aydin et al., 2017)[2]. Understanding the way in which cross-sectional and temporal variation interact is crucial to developing a complete picture of the distributional impact of energy efficiency policies and measures. This research extends the above literature by examining both the heterogeneity and persistence of savings associated with installing widely-used energy efficiency measures. In order to conduct this analysis we exploit an extremely large database of home energy efficiency upgrades and metered energy consumption[3], covering over four million households and a period of eight years. By combining statistical matching and a range of panel econometric estimators we control for unobserved heterogeneity and selection into various government schemes which funded the upgrades. Another novel feature of this analysis is that our database covers the universe of households entering into energy efficiency schemes administered by energy suppliers in the UK, thus reducing the potential for "site-selection bias" as identified by Allcott (2015).

The data allows us to examine the variation in performance depending on when measures were installed, how they perform over time, how this varies by dwelling and socioeconomic characteristics, and ultimately how this affects the cost-effectiveness of measures for different household types. Results indicate significant cross-sectional and temporal variation in energy savings. In particular, the results demonstrate that energy savings are lower for more deprived households. Using predicted income data, heterogeneity becomes even more pronounced showing extremely low savings in the lowest decile and significant differences between the lowest deciles. Quantile regression analysis suggests that differential baseline energy consumption does explain some of the difference between socioeconomic groups, but not all. We also present suggestive evidence that savings diminish over time for loft insulation and heating system replacements. The measures are generally still NPV positive, and compare favourably with the cost-effectiveness of other initiatives, but the returns are much lower than expected.

It is important to state that more deprived households may trade-off energy savings with increased internal temperatures resulting in increased well-being or health benefits. For this reason we cannot make claims about total welfare gains and how they are distributed. However, the results do raise concerns over distributional factors given how the costs of policies are subsequently levied on households.

The rest of the paper is organised as follows; Section 2 provides the context in which this analysis takes place;

[2]Other recent work has demonstrated the way in which energy efficiency incentives are distributed across income groups (Jacobsen, 2019).

[3]The National Energy Efficiency Framework Database (NEED). Further details available at: https://www.gov.uk/government/collections/national-energy-efficiency-data-need-framework

Section 4 the data; Section 3 describes the methodological approach employed and considerations undertaken; Section 5 outlines the results; Section 6 provides the results of robustness checks and sensitivity analysis; Section 7 provides a concluding discussion.

## 2 Background

The Supplier Obligation (SO), first introduced to the UK in 1994, has become the principal policy instrument for implementing energy efficiency improvements in the domestic sector in the UK (Rosenow, 2012). The Supplier Obligations are an example of a "Tradable White-Certificate" (TWC) scheme. These are regulatory mechanisms, employing a market-based approach to deliver energy savings. Theoretically, they can be considered a hybrid subsidy-tax instrument, in which suppliers provide subsidies for energy efficiency upgrades that are then recovered through increased energy prices (Giraudet et al., 2012), having parallels with traditional demand-side management (DSM) programmes in that companies are required to invest in projects that ultimately reduce demand for their product (Sorrell et al., 2009b).

As outlined in Bertoldi and Rezessy (2008) and Giraudet et al. (2012), SOs have three main features: an obligation is placed on energy companies to achieve a quantified target of energy savings; savings are based on standardised ex-ante calculations; the obligations can be traded with other obligated parties. This flexibility ideally allows suppliers to choose the most cost-effective way to reach their target. Suppliers bear the cost of installations in the first instance, costs are then passed through to their entire population of customers through increases in energy prices (Chawla et al., 2013)[4] . Clearly, this may have distributional consequences if certain segments of the population are less likely to avail of the schemes. To alleviate this concern, targets were imposed regarding the proportion of savings to be achieved from lower income groups.

The former Department of Energy and Climate Change (DECC)[5], sets the savings targets which are then enforced by the energy regulator, the Office of Gas and Electricity Markets (Ofgem). Ofgem sets and administers individual savings targets for each energy supplier. Energy suppliers have various options to achieve their targets such as contracting installers, subsidising energy efficiency products, cooperating with local authorities, delivery agents or supermarkets, or directly working with their customers (Rosenow, 2012).

[4]Other recent work has examined this question in a US context(Burger et al., 2020).
[5]now Department for Business, Energy and Industrial Strategy (BEIS)

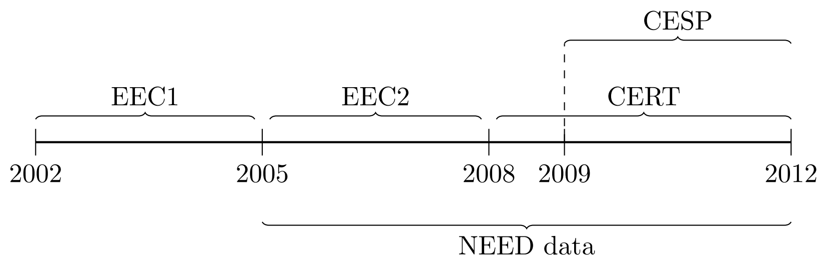


Figure 1: Time-span of selected UK Energy Efficiency Programmes from 2002-2012. NEED data used in this research is from 2005-2012

Figure 1 gives an overview of SOs from 2002-2012. The first Energy Efficiency Commitment (EEC1) ran from 2002 to 2005, followed by EEC2 in 2005. In 2008, EEC2 was replaced by the Carbon Emissions Reduction Target (CERT) which ran until 2012. In 2009, the Community Energy Saving Programme (CESP) was introduced in parallel with CERT. While the main architecture of SOs did not change, the savings targets and the costs of the delivering the programmes increased over time. Rosenow (2012) provides a comprehensive overview of the main changes in each scheme from 1994 - 2012 with regards to the target, the costs, social equity implications and other changes in design. The main change concerned the target size, increasing substantially in lifetime savings from 2.7 to 494 terawatt hours (TWh) between 1994 and 2012 (Rosenow, 2012).

From 2002, all programmes included a target for disadvantaged households and fuel poverty increasingly came to the fore. Eventually, CESP only allowed projects to be carried out in specific low income areas of Britain, the lowest 10-15% of areas ranked in Income Domain of the Indices of Multiple Deprivation (Hough and Page, 2015). Thus, CESP was only available in certain geographical regions. Furthermore, CESP introduced a new bonus structure that incentivised the installation of multiple measures in a single dwelling and the treatment of as many dwellings as possible in the same area (Duffy, 2013). Table 1 summarises the key features of the schemes under consideration.

A key feature of all previous evaluations of the above policies is that the energy savings achieved were based on model ex-ante estimates and not actual ex-post data. Engineering model estimates tend to overstate actual savings significantly, as they are derived from lab-based estimates and factors such as occupancy and behaviour are typically not considered. This would lead to concern over the accuracy of measurement regarding both the energy savings achieved and the cost-effectiveness of various policies in delivering savings.

Table 1: Overview of Supplier Obligations

| | ECC1 | ECC2 | CERT | CESP |
|---|---|---|---|---|
| *Target* | 62 TWh | 130 TWh | 494 TWh | 19.25 Mt CO2 |
| Annual costs (millions) | 167 | 400 | 1,158 | unknown |
| % savings in priority group | 50% | 50% | 40% | 10-15% most deprived areas |
| | | | | |
| *Total measures installed* | | | | |
| Cavity wall insulation | 791,524 | 1,760,828 | 2,568,870 | 3,000 |
| Loft insulations | 754,741 | 1,780,302 | 3,897,324 | 23,503 |
| Replacement heating system | 366,488 | 2,018,812 | 31,986 | 42,898 |
| | | | | |
| *Total estimated energy saving by measure* | | | | |
| Insulation | 56% | 75% | 66.20% | - |
| Heating | 9% | 8% | 8.20% | - |
| Lighting | 24% | 12% | 17.30% | - |
| Appliances | 11% | 5% | 5.90% | - |
| Other | - | - | 2.40% | - |

**Notes**: Information on estimated total costs, energy savings and primary measures installed through selected UK energy efficiency programmes from 2005-2012. This table does not provide a comprehensive account of each policy, rather a mapping of measures installed through each policy and data included in NEED. Savings presented are estimated based on engineering models. Estimated savings by measure presents the contribution of each measure to total savings for each policy. Source: Adapted from information presented in Lees (2006, 2008); Rosenow (2012); Duffy (2013); Ofgem (2013)

# 3 Methods

## 3.1 Empirical framework

Lancastrian Demand Theory suggests that households do not derive utility from consumption of a good but from the characteristics of the good and its combination with other goods (Lancaster, 1966). In this particular case, households derive benefits from their consumption of energy services and not units of energy per se. Energy services can be considered as a final good produced by the combination of energy inputs and capital equipment. The services produced include lighting, space heating, water heating. The capital equipment includes heating systems and insulation. These are intermediate goods in the production of thermal comfort or other measures of household satisfaction (Quigley and Rubinfeld, 1989).

The benefit a household derives from an improvement in the capital equipment can be realised through either a reduction in energy units required to maintain the previous level of energy service or through increased consumption of energy services, due to a reduction in their effective price. The latter effect is sometimes referred to as the "rebound effect" and has been widely studied.[6]

[6]Empirical estimates of the size of this effect vary considerably. See Sorrell et al. (2009a) for an overview. Increased energy service consumption could result in a range of other benefits to households and has been described as the multiple benefits of energy efficiency (Ryan and Campbell, 2012)

As outlined by Nordhaus (1996); Hunt and Ryan (2015); Fouquet (2018) amongst others, not accounting for energy services in any empirical framework may result in model mis-specification and biased estimates. However, energy services can be difficult to observe. To account for this Hunt and Ryan (2015) suggest adding additional terms to the empirical framework in order to account for unobserved energy efficiency. These include adding exogenous time trends, information on past energy prices and the components of past energy prices - all of which help to account for any underlying changes in unobserved energy efficiency. Taking this on board, we propose a reduced-form framework with a rich set of fixed-effects which account for both exogenous improvements in energy efficiency and changes in energy prices without explicitly modelling these factors. In addition, by examining heterogeneity in energy savings for different household types following installation of similar capital equipment, we can implicity observe changes in energy services derived by different households.

## 3.2 The baseline model

Energy consumption is determined by a range of factors such as temperature, characteristics of the dwelling and its inhabitants, and energy prices. We estimate the following baseline panel specification:

$$ln(y_{it}) = \alpha_i + \gamma_t + \rho_{rt} + \delta D_{ijt} + \epsilon_{it} \tag{1}$$

Where $y_{it}$ denotes consumption of either electricity or natural gas (both in kWhs) by household $i$ in year $t$, $\alpha_i$ is a household fixed-effect, $\gamma_t$ is a year fixed-effect which controls for unobserved factors which vary at an annual level such as broader macroeconomic conditions and weather patterns, $\rho_{rt}$ is a year-by-region fixed effect to control for factors which vary at a sub-national level, such as more localised economic shocks and weather patterns, $D_{ijt}$ is the treatment dummy denoting measure $j$ in household $i$ at year $t$. The key parameter of interest is $\delta$ the Average Treatment Effect on the Treated (ATT).

The model is estimated as a fixed effects panel specification controlling for unobserved time-invariant household characteristics which might affect energy consumption. Over the course of the analysis, a variety of extensions to the above are estimated, to account for interactions between upgrades and household socioeconomic characteristics, and to examine the performance of upgrades over time. Models are primarily estimated for gas consumption, but electricity consumption is also considered. Standard errors are clustered at the region level in all specifications[7].

[7] Abadie et al. (2017) suggest clustering standard errors at the level of treatment assignment unless one is estimating a fixed-effects regression, in which case clustering is necessary at the level of the fixed effect if there is heterogeneity in treatment effects. This is true in our case and we cluster at the region level. However, this results in a small number of clusters (10). To account for the low number of clusters we run a Wild Bootstrap estimation with 5000 replications and Webb weights as per Roodman et al. (2019) and Webb (2013). Comparing results, the confidence intervals of our estimates are extremely stable for bootstrapped standard errors and cluster robust standard errors at the region level. Given our extremely large sample size, bootstrapping is very computationally intensive. For this reason we perform it as a robustness check and present results in the Supplementary Material.

### 3.3 Event study analysis

Building on our baseline model the next step is to examine how upgrades perform over longer periods of time, a key novelty of this research. In order to do this we perform a series of Event-Study analyses. In all estimations we include a matched control group of households. We run our baseline specification however we initialise our treatment indicator at 0 for the year of upgrade with all previous years $(-n, ..., -1)$ and all subsequent years $(+1, ..., +n)$. Applying this methodology allows us to stack all observations in order to exploit the full sample of pre- and post-upgrade years[8]. This affords us a number of benefits: (i) It allows us to assess whether pre-treatment trends are similar and that the parallel-path assumption holds; (ii) It allows us to rule out the possibility of any treatment-effect over time resulting from specific factors in any given year (although we also include year fixed effects); (iii) It allows us to estimate the size of the initial treatment-effect, then decompose it over time.

### 3.4 Quantile regression

In order to more deeply explore heterogeneity we next estimate a series of quantile regression models. Standard linear regression enable an analysis of the relationship between regressors and outcome based on the conditional mean function $E(y/x)$. Quantile regression allows an analysis of this relationship at different points in the conditional distribution of $y$, allowing for a potentially richer characterisation of the data.

Undertaking this analysis is important to further understand the relationship between varying levels of baseline energy consumption, the socioeconomic characteristics of the households and the resultant energy saving from installing measures. For example, it might be the case that savings are related more to baseline consumption levels than to the socioeconomic characteristics of the household. The quantile regression estimator for quantile p minimises the following objective function:

$$Q(\beta_p) = \sum_{i:Y_{it} \geq X'_{it}}^{N} p|Y_{it} - X'_{it}\beta_p| + \sum_{Y_{it} < X'_{it}}^{N} (1-p)|Y_{it} - X'_{it}\beta| \tag{2}$$

where $0 < p < 1$. In this analysis quantile regressions are estimated at $20^{th}$ percentile of the annual gas consumption distribution, resulting in $p = 0.1, 0.2, ...0.9$.

### 3.5 Pre-processing data using statistical matching

Prior to undertaking analysis we pre-process the data using statistical matching. There is strong evidence that the presence of unobserved heterogeneity leads to inaccurate econometric estimates in a fixed-effects OLS setting

[8] We are very grateful to one of our Referees for making this suggestion

(Ferraro and Miranda, 2017; Gibbons et al., 2014). Self-selection bias occurs as households voluntarily decide to apply upgrades in their homes or take part in government funded schemes, potentially causing the treatment and control group to differ systematically in aspects that both affect their likelihood of taking part in energy efficiency programs, and their energy consumption, causing the failure of the conditional mean independence assumption (Wooldridge, 2010). Unobserved heterogeneity between households means that households respond differently to common shocks. For instance, increasing energy prices might lead to different behaviour of low and high income households. One strategy to overcome this threat and to obtain consistent and unbiased estimators is to apply a matching technique (Wooldridge, 2010). Recent research has shown that by combining statistical matching with Differences-In-Differences estimation (DID), the accuracy of evaluations can approach that achieved by a randomised-controlled trial (RCT) (Ferraro and Miranda, 2017). We should note that (Chabé-Ferret, 2017) caution about the use of Difference-In-Differences with conditioning on pre-treatment outcomes when the Parallel Trend Assumption (PTA) fails. In our case the Event-Study analysis in Section 5.4 demonstrates that pre-treatment energy consumption trends in upgrade and control group are very similar, and the PTA does not fail.

Coarsened-exact matching (CEM) is a non-parametric statistical procedure which improves the estimation of causal effects by reducing imbalance in observed variables between treatment and control groups (Iacus et al., 2008; Blackwell et al., 2009). Iacus et al. (2012) compare CEM with a range of other matching methods using Monte Carlo simulations and conclude that CEM has superior performance in terms of the bias and variance of the ATT. Alberini and Towe (2015) use a similar approach in an analysis of home energy audits in the state of Maryland.

Our extremely large sample size allows a high level of precision in matching. A high degree of balance is achieved across variables used in matching and variables not used in matching as measured by the standardised differences, variance ratios and most importantly, the pre-treatment trends. Detailed information on the procedures used, the degree of balance obtained and comparison with other matching methods can be found in the online Appendix to this article.

# 4 Data

## 4.1 The National Energy Efficiency Database framework

The primary dataset used for analysis is National Energy Efficiency Database framework (NEED). This dataset contains dwelling-level data on four million households, over an eight-year period. Information comes from a range of sources including meter point electricity and gas consumption data[9], Valuation Office Agency (VOA) property attribute data, the Homes Energy Efficiency Database (HEED) containing data on energy efficiency measures installed, and modelled data provided by Experian on household characteristics. An overview of data types and sources is provided in Table 2.

Table 2: Data sources combined in NEED

| Type of variable | Source |
|---|---|
| Energy efficiency measures | HEED/Ofgem/DECC |
| Energy consumption | Energy Supplier |
| Property attributes | VOA |
| Household characteristics | Experian |

Note: Description of data sources included in NEED database

The NEED database includes measures installed through EEC2, CERT and CESP schemes. These schemes were by far the most prevalent mechanism for delivering energy savings in residential dwellings in the UK over this period. The database does not include an exhaustive list of measures installed as part of the various schemes, appliances and lighting also featured but are not included. However, as Table 1 demonstrates, insulation and heating comprised the vast majority of estimated energy savings across various schemes over this period. In total over two million measures were installed over the period within our sample.

All insulation installations in our dataset were funded through government schemes. Heating upgrades were funded through both public and private means. In the early part of the sample (pre-2007) boiler installations were likely to have been funded through government schemes, however government support for replacement boilers was withdrawn during EEC2, as a combination of previous support schemes and new building regulations in 2005 had already delivered a significant penetration of new condensing boilers. Therefore the boiler data we report on is a combination of publicly and privately funded investments. As specified in the 2005 Building Regulations, all replacement boilers were required to be condensing gas or oil and have a minimum efficiency rating of 86 percent.

## 4.2 The English Housing Survey (EHS)

One limitation of the NEED dataset is that household income data is not made available to academic researchers. We attempt to over come this limitation by supplementing the NEED dataset with the English Housing Survey (EHS). The EHS is a cross-sectional survey, which reports information on socio-economic characteristics, includ-

[9] According to the NEED methodology meter readings are obtained from the existing administrative systems of the energy companies and provided by the data aggregators. Gas data are weather corrected by the aggregators.

ing income, and dwelling information of households at two-year intervals. Several common variables in the EHS and NEED allow to us predict EHS Basic income (annual net household income (HRP + Partner) including savings) for the households in NEED for different periods from 2005 to 2012. The income prediction model uses LASSO methods for feature selection and we run a number of sensitivity checks. The Appendix includes a detailed explanation of the income prediction process. Given that income is predicted rather than observed, this does not form the core of our analysis. However, it provides a useful comparison for our analysis using the area-level Index of Multiple Deprivation (IMD).

### 4.3 Descriptive statistics

Descriptive statistics for all variables used in the analysis are presented in Table 3. Due to space considerations, further detail on all variables contained within the dataset is provided in Table A1 in the online Appendix. This includes an overview of the information used in constructing the area-level IMD groupings.

Table 3: Selected summary statistics

| **Variable** | **Type** | **Mean** | **Std. Dev.** | **Min** | **Max** |
|---|---|---|---|---|---|
| Gas consumption | continuous | 16951 | 7839 | 0 | 50000 |
| Electricity consumption | continuous | 3975 | 2243 | 100 | 25000 |
| Total energy | continuous | 20925 | 9047 | 550 | 75000 |
| log(Gas) | continuous | 9.625 | 0.503 | 6.215 | 10.820 |
| log(Electricity) | continuous | 8.147 | 0.536 | 4.605 | 10.127 |
| log(Total energy) | continuous | 9.853 | 0.453 | 6.310 | 11.225 |
| Year cavity wall | binary | 0.147 | 0.354 | 0 | 1 |
| Year loft insulation | binary | 0.115 | 0.319 | 0 | 1 |
| Year new boiler | binary | 0.153 | 0.360 | 0 | 1 |
| Region | categorical | 5.649 | 2.619 | 1 | 10 |
| Year | categorical | 2008.5 | 2.291 | 2005 | 2012 |
| Fuel type | binary | 0.991 | 0.096 | 0 | 1 |
| Property age | categorical | 3.132 | 1.577 | 1 | 6 |
| Property type | categorical | 3.067 | 1.614 | 1 | 6 |
| IMD group | categorical | 3.126 | 1.433 | 1 | 5 |
| Electricity price | continuous | 0.121 | 0.014 | 0.094 | 0.138 |
| Gas price | continuous | 0.035 | 0.006 | 0.024 | 0.044 |
| Predicted income | continuous | 26975 | 8912 | 3438 | 62591 |
| Income quintile | categorical | 3.248 | 1.408 | 1 | 5 |
| Income decile | categorical | 6.019 | 2.857 | 1 | 10 |

Note: Summary statistics for variables used in regressions and additional calculations.

N=5,502,936 ; n=687,925; t=8

Figure 2 depicts annual uptakes of energy efficiency measures by IMD group. In all years, the largest number of loft insulation installations and heating system replacements were done by the most deprived households (IMD group 1). In the years 2005 to 2007, this is also true for cavity wall insulations but from 2008 on the number of installations increased with the income level of households. However, logistic regressions (see Appendix) show that controlling for region and dwelling characteristics, the odds of up-taking cavity wall insulations are still higher for the most deprived households then for better-off households. This also holds true for loft insulation installations and heating system replacements. This pattern reflects the prioritisation of disadvantaged households as prescribed by the SO.

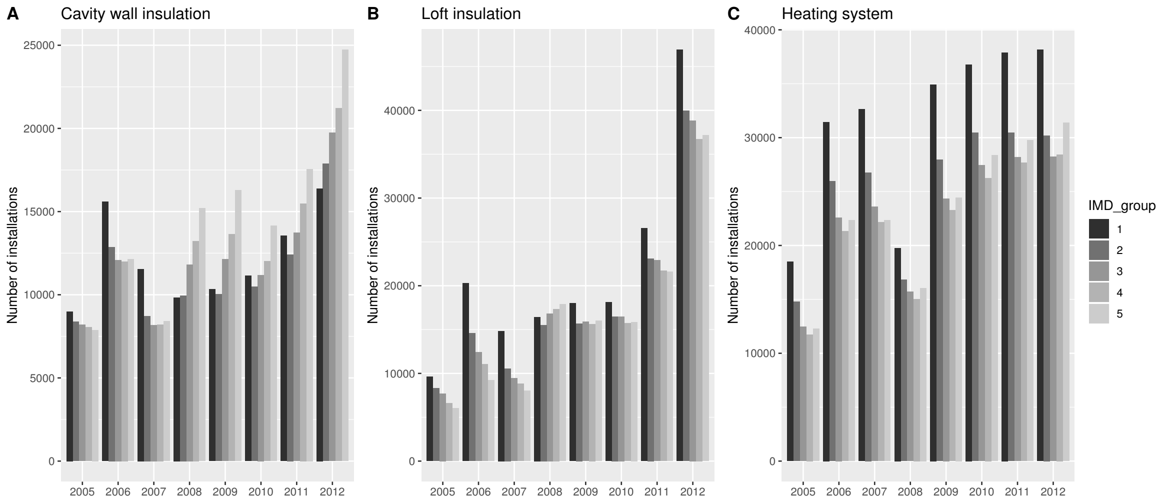


Figure 2: Number of installations by IMD group and year. Unweighted sample.

Table 4 presents a correlation matrix of IMD group and predicted income within our final sample used in the analysis. We compare IMD group with a continuous measure of income along with income quintile and decile. We collapse our continuous income measure into quintiles in order to make a direct comparison with IMD group in our analysis. A further categorisation into deciles allows us to extend our analysis of variation. We observe a reasonably high correlation and a highly statistically significant relationship between all measures of income and IMD group.

Table 4: Correlation of predicted income and IMD group

| | IMD group | Income | Income quintile | Income decile |
|---|---|---|---|---|
| IMD group | 1 | | | |
| Income | 0.5785* | 1 | | |
| Income quintile | 0.6262* | 0.8808* | 1 | |
| Income decile | 0.6373* | 0.9099* | 0.9843* | 1 |

Note: single asterisks statistical significance at the 0.1% level

# 5 Results

All reported results are estimates of the average treatment effect on the treated (ATT) and can be interpreted as percentage energy savings, unless otherwise stated. Multiple upgrade and control groups are created for the entire period of analysis and for each individual year. This allows us to calculate the average effect and to examine trends over time. Analysis is restricted to households with electricity consumption between 100 and 25,000 kWh, and gas consumption between 3000 and 50,000 kWh. Outliers are excluded to minimise risk of inclusion of invalid consumption readings or non-domestic properties[10]. Following this we create dummy variables to indicate if household energy (either electricity or gas) changed by more than 50, 60 or 70 percent in any given year. These dummy variables are then used in sensitivity analysis to control for any large changes which might haver been the result of unobserved changes in occupancy. For comparison purposes we also calculate the energy savings in kWh for electricity and total energy (Table D1 in the online Appendix). As these measures primarily impact heating and natural gas is by far the main fuel used for heating the focus of our analysis will be on a subset of dwellings using natural gas for heating. Additional results from a range of sensitivity checks and applying different data trimming are presented in Table E1 in the online Appendix and discussed in Section 6.

## 5.1 Central estimates

The central estimates from our main specification are presented in Table 5. Results show that the energy savings over time are quite consistent for each measure, regardless of when the installation took place. Annual gas savings for cavity wall insulation range from 9.4 - 11.1 percent, loft insulation 2.6 - 3.9 percent, and replacement heating systems 8 - 10.1 percent. These results are consistent with Adan and Fuerst (2015) and Hamilton et al. (2016) who perform similar analysis on this dataset and other related data.

[10] Properties above this threshold for either gas or electricity are likely to be non-domestic users. Properties below are likely to include dwellings that only use gas for non-heating purposes. Properties below the threshold for electricity are likely to be dwellings in which electricity supplies are not being used or are new builds and not yet occupied. In total restricting the sample in this way removes about four percent of the sample. This restriction is applied as part of BEIS Validation and quality assurance. Available here: https://www.gov.uk/government/publications/domestic-national-energy-efficiency-data-framework-need-methodology. A similar restriction is also applied by Adan and Fuerst (2015).

Table 5: The effect of energy efficiency upgrades on energy consumption

| | (1) Full sample | (2) 2006 upgrades | (3) 2007 upgrades | (4) 2008 upgrades | (5) 2009 upgrades | (6) 2010 upgrades | (7) 2011 upgrades |
|---|---|---|---|---|---|---|---|
| Cavity wall insulation | -0.094*** | -0.097*** | -0.111*** | -0.099*** | -0.098*** | -0.097*** | -0.101*** |
| | (0.001) | (0.002) | (0.003) | (0.002) | (0.002) | (0.002) | (0.002) |
| Loft insulation | -0.030*** | -0.026*** | -0.031*** | -0.028*** | -0.027*** | -0.039*** | -0.035*** |
| | (0.001) | (0.003) | (0.003) | (0.002) | (0.002) | (0.002) | (0.002) |
| Replacement boiler | -0.092*** | -0.080*** | -0.093*** | -0.087*** | -0.102*** | -0.109*** | -0.099*** |
| | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Household fixed effects | Y | Y | Y | Y | Y | Y | Y |
| Year fixed effects | Y | Y | Y | Y | Y | Y | Y |
| Year*region fixed effects | Y | Y | Y | Y | Y | Y | Y |
| Observations | 5502936 | 617022 | 545627 | 564756 | 730447 | 746573 | 871379 |
| Number of households | 687925 | 77128 | 68203 | 70595 | 91306 | 93322 | 108922 |
| R squared | 0.349 | 0.327 | 0.353 | 0.370 | 0.369 | 0.386 | 0.367 |

**Notes**: This table reports coefficient estimates and standard errors from eight separate regressions. The dependent variable in all regressions is the logarithm of annual gas consumption in kilowatt hours. Column(1) "All" denotes efficiency upgrades occurring at any time during the sample period. Columns (2-7) relate to upgrades occurring only in the relevant year. Each individual year denotes upgrades occurring solely in that year. For each upgrade group a matched control group is created using coarsened-exact matching. The sample includes metered energy consumption records from 2005 to 2012. Standard errors are clustered at the region level. Triple asterisks denote statistical significance at the 1% level; double asterisks at the 1% level; single asterisks at the 10% level.

## 5.2 Heterogeneity by level of deprivation

The next set of results, presented in Figure 3, show the interaction of the treatment variable with the variable indicating the socioeconomic characteristics (deprivation level) of the area in which the household resides. Energy savings are much greater for those households living in more affluent areas (IMD = 5), compared to those in less affluent areas (IMD = 1). This is true for all upgrade types. Combining all measures, the annual savings range from approximately 15 percent for those in the lowest IMD category to approximately 25 percent for those in the highest. This result raises concerns over distributional issues as the costs of these policies were likely applied as a flat-rate tariff on energy bills (Chawla et al., 2013). If savings are concentrated in the higher income groups, this suggest a further loading of policy costs onto those least able to afford it. Particularly as a flat-rate charge is already regressive, disproportionately affecting those on lower incomes.

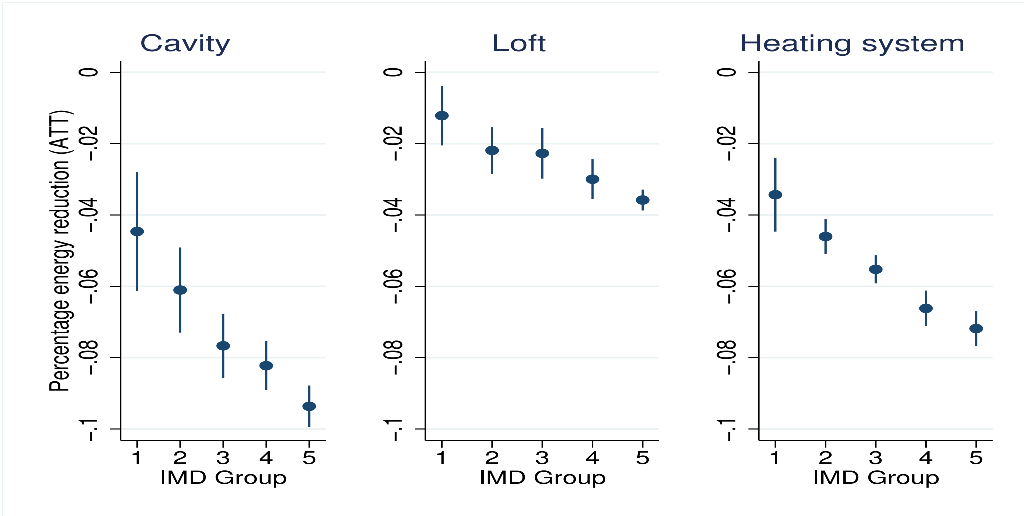


Figure 3: Average Treatment effect on the Treated (ATT) for each IMD group. ATT is percentage reduction in energy consumption following installation of energy efficiency measure.

### 5.3 Heterogeneity by predicted household income level

Since IMD is a composite indicator for several socioeconomic characteristics, the use of the predicted income enriches our analysis with more specific information on the relationship between energy consumption and income. We interact income category with the treatment for both income quintile and decile. The results presented in Figure 4 show a broadly similar pattern with those of IMD group. Energy savings are smallest for the lowest quintile and largest for the highest quintile. Interestingly, the heterogeneity in energy savings is even more pronounced for predicted income as the difference in ATT between the lowest and the highest income quantile are larger than between the lowest and highest IMD group.

Performing the same analysis with income deciles provides an even more fine-grained picture of the disparity in energy saving between income groups. Variations that are masked within quantiles and IMD groups become apparent. The results depicted in Figure 5 suggest that the difference in ATT are largest at both ends of the distribution. Thus, households in the first decile have significantly smaller energy savings than for households in the second decile regarding cavity and heating system measures and households with the highest incomes in the 10th-decile have higher energy savings than high-income households in the ninth decile.

As our income variable is predicted rather than observed we treat these results with a degree of caution, and will use IMD group for subsequent socioeconomic categorisation. However, by undertaking a comparison with IMD we provide a degree of assurance that the use of IMD is valid as a socioeconomic indicator. If anything IMD group represents a lower bound on the degree of variation that exists in the population.

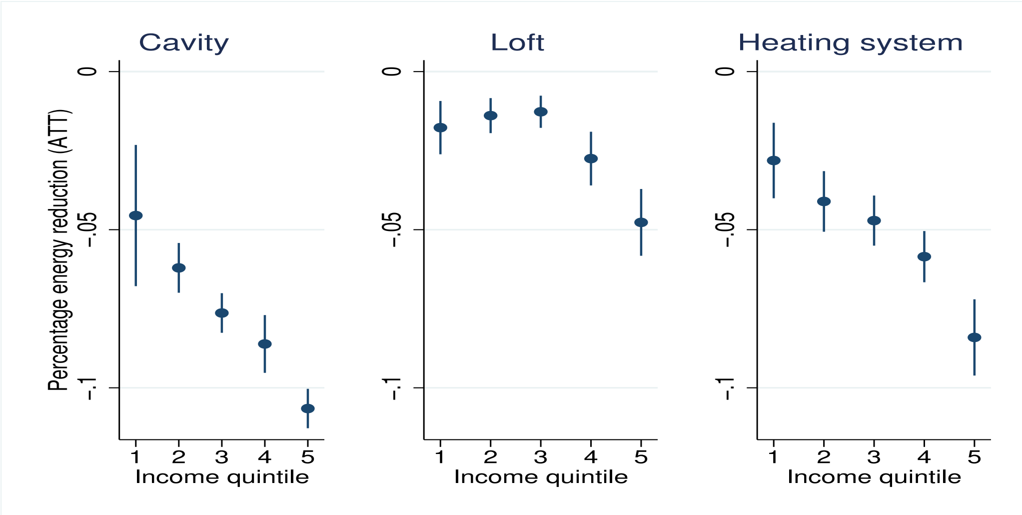


Figure 4: Average Treatment effect on the Treated (ATT) for each income quintile. ATT is percentage reduction in energy consumption following installation of energy efficiency measure.

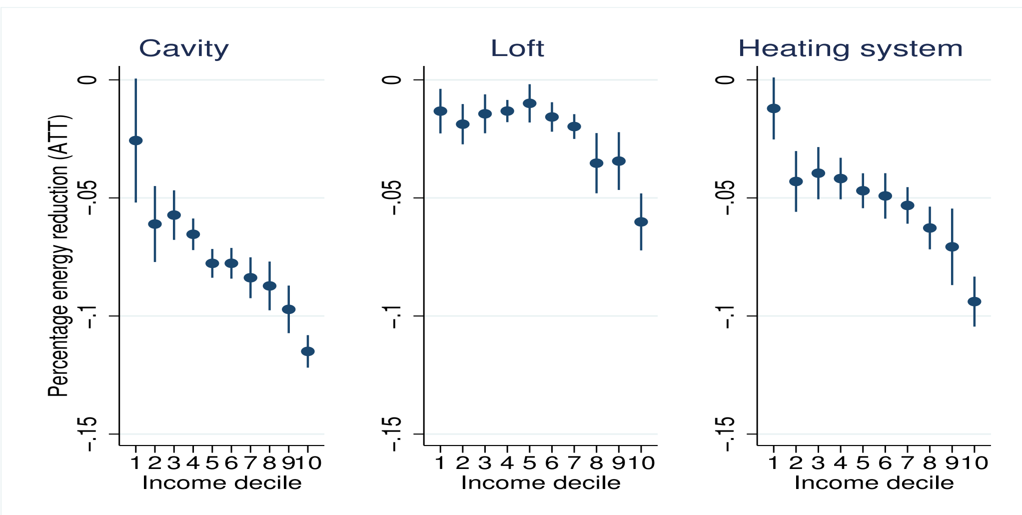


Figure 5: Average Treatment effect on the Treated (ATT) for each income decile. ATT is percentage reduction in energy consumption following installation of energy efficiency measure.

### 5.4 Event Study analysis

Building on the above analysis we now apply an Event Study methodology. The use of this method allows for a comprehensive assessment of the treatment effect over time for all years. All Event Study figures display the percentage difference in energy consumption between upgrade and control group for all periods. Given that the time of treatment varies across the sample, we can extend our analysis to six periods pre- and six periods post-upgrade.

Figure 6 presents results of installing any measure for all households, decomposed by IMD group. Across all IMD groups pre-treatment trends are very similar, and not statistically different from zero in almost all cases[11]. The full savings resulting from any measure are realised by year plus 1. This is due to a slight mismatch in the calendar year for energy consumption and installation of measures, rather than any delayed impact[12]. For this reason we consider the treatment period to be between $(-1 \leq t \leq t+1)$. The magnitude of the treatment effect is lowest for IMD group 1 and savings increase with increasing affluence, in line with our previous results. The observe difference by IMD group persists over time. In the online Appendix we provide more detailed information on the breakdown of savings over time by measure. The savings for cavity wall insulation are again lower for more deprived groups and savings appear quite persistent over time for all groups. A similar pattern is observed for loft insulation, however for IMD group 1 the savings are statistically close to zero. The confidence interval on the estimate actually includes zero in later years pointing towards an erosion of savings, but this is also potentially due to lower number of observations in later periods. For heating system upgrades, again savings are lower for more deprived households. For all groups savings appear to erode over time. However when performing this sample split, the pre-treatment trend shows some evidence of an increase also, suggesting that other factors may also be influencing the post-treatment trend. All of these results are presented graphically in the online Appendix.

[11] For IMD group 1 the difference is marginally different from zero in early periods but is of low magnitude.
[12] The gas consumption year is October-September. See Appendix for further information

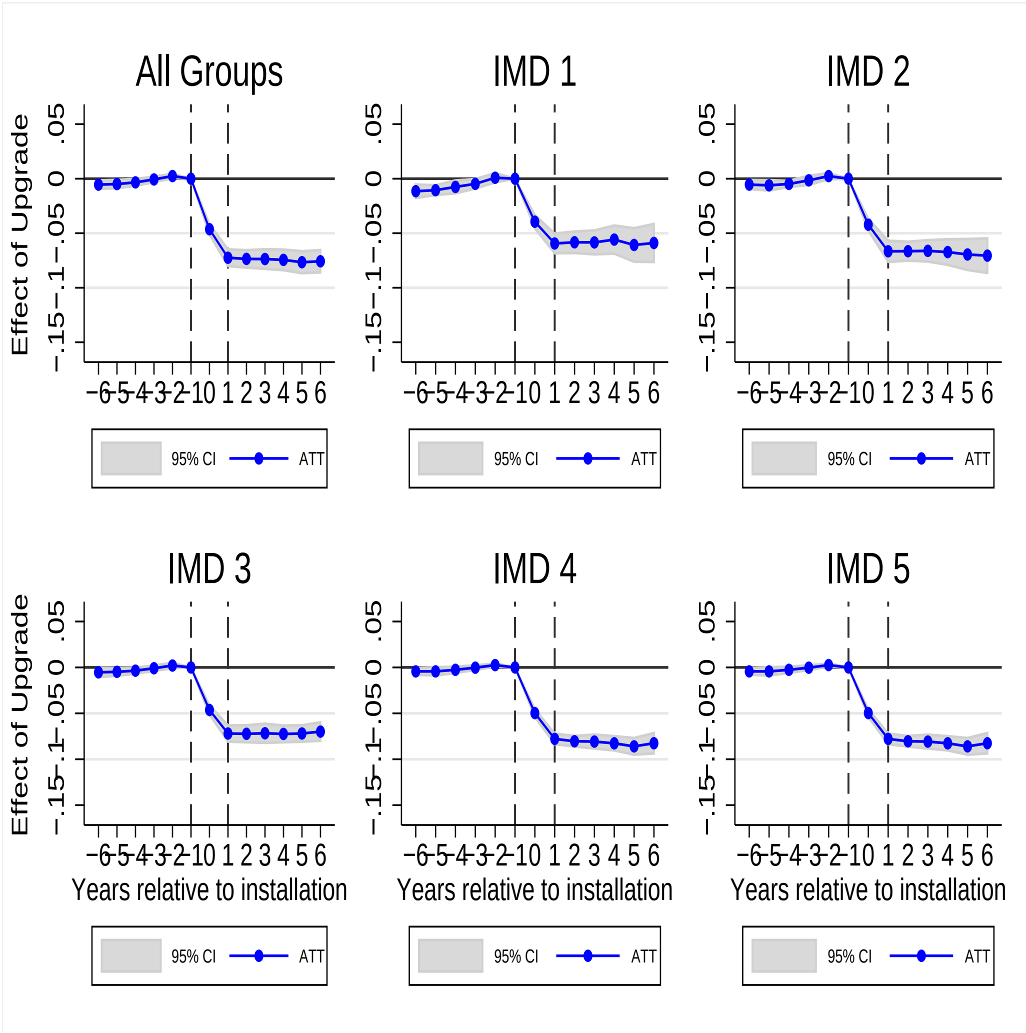


Figure 6: Composite measure: Event Study analysis of percentage savings for all households and by IMD group. Upgrade occurs during period $-1 \leq t \leq +1$

### 5.5 Quantile regression analysis

We next run a series of quantile regressions to further tease-out the heterogenous effects across the distribution of the dependent variable. We first estimate a quantile regression for the entire sample across all years, following this we estimate separate models for each IMD group. Results in kWh are presented in Figure 7. A number of interesting findings emerge.

Firstly, as one might expect, households at the higher percentiles of energy consumption save more energy after installing measures. This relationship is broadly linear across all measures and IMD groups. Secondly, savings from cavity wall insulation are largely comparable to that of boiler replacement across all quantiles and groups[13]. Savings from both of these measures exceed savings from loft insulation. Thirdly, while the patterns

[13]However, replacing a heating system costs considerably more than installing cavity wall insulation. See Section I of the Appendix

are largely comparable across IMD groups, as per previous results the level of savings are lower for the more deprived groups. In fact, savings are close to zero at the lower end of the energy consumption distribution for the lowest IMD groups. These results suggest that level of deprivation and baseline consumption are both contributing factors in determining the level of savings.

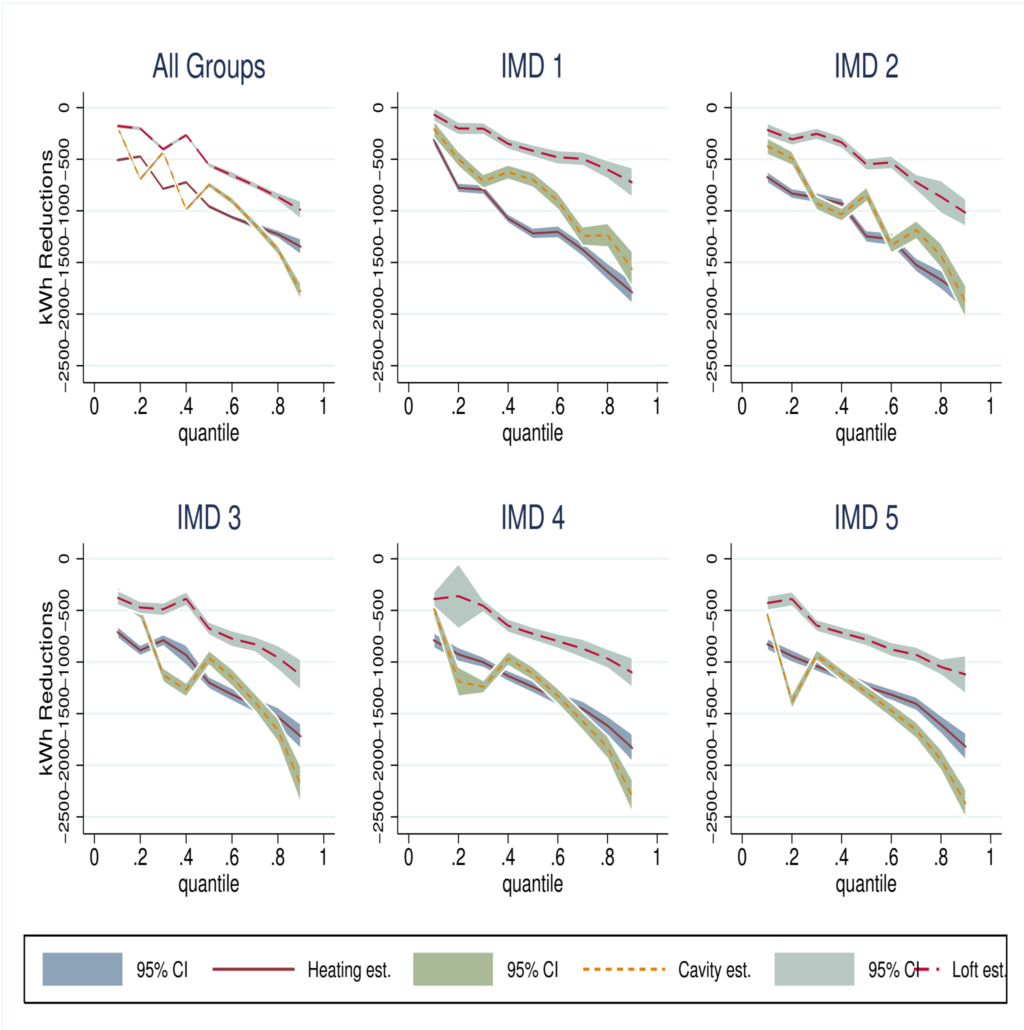


Figure 7: Quantile regression results estimated for 10 quantiles of the dependent variable. Estimation performed for all groups together and for each IMD group separately. The grey/red line denotes loft insulation; green/yellow cavity wall insulation and blue/red boiler upgrade.

## 5.6 Cost-effectiveness and Net Present Value calculations

Taking our estimates of the estimated energy savings for different households we can develop more realistic assessments of the cost-effectiveness of measures than had been previously calculated. While much of the measures observed in our sample are funded by utilities, funding for heating system upgrades finished in 2007.

From that point onwards they have been privately funded by households. The rest of the measures were funded by utilities, although households did make a small contribution[14].

We acknowledge that the following set of results do not fully describe the incentives faced by households or utilities in our sample. But in the spirit of Fowlie et al. (2018) we would argue that it is still informative to investigate the return on investment, despite the fact that suppliers funded the majority of these measures. During our sample period, other schemes such as the Warm Front funded very similar upgrades and were fully publicly funded. In addition, many households who would consider making these investments are not eligible for support and are faced with the type of investment decisions we examine.

A number of published academic and policy papers provide cost-estimates. The estimates we present in Panel A of Table 6 are based on a range of previous studies, outlined in more detail in Tables I1, I2 and I3 in the online Appendix. The costs we present are the costs incurred by the energy companies in installing each measure. These may understate the actual costs in some cases, and can thus be considered a lower bound. For example, the cost for replacement heating system used (£200) for past policy evaluations is the assumed additional cost of installing a high efficiency system, over and above a typical lower-efficiency system. We consider this estimate to be a lower bound. The Energy Savings Trust estimate the costs of boiler replacements to range from £700 to £6,000 (EST, 2013). On average the installation of condensing boiler costs around £2,400 per dwelling. In a 2015 review Frontier Economics assumed that the fixed cost of for gas-fired condensing boilers lie between £2,200-3,000 (Economics, 2015). For the purposes of comparison we consider the upper bound for a replacement heating system installation to have been £2000 in 2006.

The internal rate of return (IRR) on a project is the discount rate (r) that yields a net-present value of zero, or the discount rate at which the average value of avoided discounted future energy costs equals the upfront investment cost. Formally, this can be calculated using the below formula:

$$NPV = \sum_{t=1}^{T} \frac{C_t}{(1+r)^t} - C_0 \tag{3}$$

Where $T$ is the estimated lifespan of the measure, $C_t$ are the avoided energy costs in year $t$, $C_0$ is the upfront investment cost and $r$ is the IRR which we solve for. The IRR is calculated based on the econometric estimates we observe, for varying estimated lifespans of measures and assuming constant future energy prices.

Panel B of Table 6 presents estimated IRRs for each measure, calculating the IRR for 10, 20 and 30 years. Our preferred estimated lifespan is 10 years for replacement heating system and 30 years for both types of insulation. Assuming a lifespan of 30 years or more, cavity wall insulation is an attractive investment yielding a

[14] Based on Lees 2008 suppliers bore 80-93 percent of the costs for cavity wall insulation in the Priority (low-income) groups and 50-65 percent of the costs for all other households.

return of 16 percent. Loft insulation is less attractive yielding 6 percent. Whether to invest in a heating system depends greatly on whether one uses the estimated policy cost or private cost.

The next set of results, presented in Panel C, Table 6 takes the preferred estimated lifespan and presents IRR estimates for each measure and each IMD group, along with the sample average for comparison purposes. A considerable degree of variation exists around the sample average, with households living in more deprived areas experiencing much lower returns than those in more affluent areas.

To broaden the perspective somewhat we also consider two other measures of cost-effectiveness: the cost per tonne of CO2 removed and the cost per kWh of energy saved. These are calculated at the sample average and allow a comparison of the overall cost of these policies with other similar initiatives. The estimated cost per kWh of energy saved is calculated by summing up the annual estimated savings over the expected lifetime of the measure. To calculate the cost per tonne of CO2 removed, we convert our kWh estimates based on the estimated CO2 produced in consuming one kWh of gas and electricity based on DEFRA/DECC greenhouse gas conversion factors. These are reported in Table 6, detailed information on the underlying assumptions is presented in Section I in the online Appendix.

Cavity wall insulation is the most cost-effective measure, followed by loft insulation and replacement heating systems. Relative to the estimated social cost of carbon and natural gas prices, insulation and the lower estimate for replacement heating systems seem relatively cost effective. However, at the upper bound of replacement heating system cost it does not represent an attractive investment.

Converting the cost per kWh saved in 2000 GBP to 2015 USD it is possible to compare the cost of these interventions with a wide range of other initiatives, such as behavioural programmes, building code changes, subsidies and information provision. These are based on a recent review paper by Gillingham et al. (2018). Table K1 in the online Appendix demonstrates that these measures, and in particular cavity wall insulation, compare quite favourably with most other initiatives.

Table 6: Cost-effectiveness of each measure

| | **Cavity wall insulation** | **Loft insulation** | **Replacement boiler (policy cost)** | **Replacement boiler (private cost)** |
|---|---|---|---|---|
| Panel A: Cost assumptions (GBP) | | | | |
| Estimated average cost of installation | 350 | 285 | 200 | 2000 |
| Panel B: Internal Rate of Return (IRR) over a range of product lifetime assumptions | | | | |
| IRR 10 | 7% | -8% | 17% | -24% |
| IRR 20 | 15% | 4% | 23% | -7% |
| IRR 30 | 16% | 6% | 23% | -2% |
| Panel C: Internal Rate of Return (IRR) over all IMD groups | | | | |
| Sample Average | 16% | 6% | 17% | -24% |
| IMD1 | 11% | 5% | 12% | -26% |
| IMD2 | 14% | 5% | 14% | -25% |
| IMD3 | 16% | 5% | 17% | -24% |
| IMD4 | 17% | 7% | 20% | -23% |
| IMD5 | 18% | 9% | 22% | -22% |
| Panel D: Cost-effectiveness | | | | |
| GBP per tonne of CO2 removed | 36 | 90 | 60 | 600 |
| GBP per kWh saved | 0.0072 | 0.0171 | 0.0141 | 0.1412 |

# 6 Sensitivity analysis and robustness

This section presents the results of a range of sensitivity analyses and robustness tests. All results are presented in Sections D, G and H of the online Appendices. The aim is to present information on the stability of the results across a range of sample splits and alternative specifications.

Considering Table G1, Column 1 presents results when the entire sample is included without using a matched control group. This is useful as it provides quantification of the degree of bias that might exist should selection not be controlled for. The coefficients for both type of insulation remain consistent with our central estimates, however heating system replacement is considerably lower. Column 2 performs the same estimation including only dwellings in which natural gas is the primary source of cental heating. This reduces the sample size slightly and results in a slight improvement in model fit (as measured by $R^2$), and an increase in size of the coefficient on replacement heating system. Columns 3 and 4 repeat this analysis however we now introduce a matched control group in both cases. Column 5 presents results using a matched control group, where natural gas is the primary source of central heating. However, in this specification we also include electricity consumption as an explanatory variable. This is likely endogenous as households could substitute between both types of heating, and should be treated with caution. However, this variable contains much information about household behaviour, appliance usage and occupancy that is otherwise omitted in our estimations, and is interesting to consider for that reason - particularly if it has an effect on our main results. Inclusion of this variable does not affect our central estimates giving us confidence in their accuracy.

Taking the sample used to estimate Column 4 results (matched upgrade and control group, primary heating is gas), we now estimate a number of additional specifications in which we exclude households with large annual changes in energy consumption. This is to control for any large changes that might be as a result of changes in occupancy. Column's (6-8) present these results in which we exclude dwellings with any annual changes in either gas or electricity greater than ±50, 40 and 30 percent respectively of the previous year's consumption. When this sensitivity check is included, sample size drops significantly and model fit improves considerably ($R^2 = 0.398$). The coefficients on both insulation measures do not change much, but the effect of heating system replacement increases. The results in column's (6-8) are otherwise consistent with each other and for this reason we favour Column 8 as the preferred specification as this maximises sample size while also accounting for potential unobserved occupancy changes. Finally, in Column 9 we again include electricity consumption as an explanatory variable and results remain largely unchanged.

Table D1 provides a comparison of our preferred estimates using Coarsened-Exact Matching with results generated using both Nearest Neighbour and Kernel Matching techniques. The results are stable across all matching procedures. Table H1 details of standard errors calculated using alternative clustering methods.

# 7 Discussion and conclusions

The aim of this research was to explore the distributional impacts of energy efficiency measures. Variation in energy savings was quantified across a range of domains, by measure, over time, by household type and how this variation impacts the financial rate of return. In order to comprehensively and robustly explore heterogeneity we apply Statistical matching, panel econometric estimators, Quantile regression and an Event-Study analysis to an extremely large database of energy efficiency measures and metered consumption. The database includes a representative sample from the universe of households entering into energy efficiency schemes administered by energy suppliers in the UK, mitigating site-selection bias.

Our results indicate that cavity wall insulation and heating system replacement (installation of a condensing gas boiler) result in an energy saving of about 10 percent of annual consumption, while loft insulation results in approximately a three percent reduction. These savings are consistent regardless of when the measures were installed over the sample period. Households living in more deprived areas observe less savings (both in absolute and percentage terms) than those in more affluent areas. This result is true for all measures examined. Our composite measure of deprivation may also be masking significant heterogeneity, extremely low savings are observed in the lowest decile when savings are decomposed by predicted income. Quantile regression analysis suggests that differential baseline energy consumption does explain some of the difference between socioeconomic groups, but not all. Differences between groups persist over time, and we also present suggestive evidence that savings diminish over time for loft insulation and heating system replacements. This is an interesting avenue for future research.

The results of this analysis provide both academic and policy insights. Our academic contribution is to more comprehensively explore heterogeneity in savings from installing energy efficiency measures, allowing us to better quantify their cost-effectiveness. As far as we are aware this is the first paper to examine longer run effects and how they vary by levels of household deprivation. This adds to a growing literature examining longer run effects of building energy codes (Kotchen, 2017) and information stimuli (Allcott and Rogers, 2014).

Better estimation of the financial return on investment provides insight for both policy design and policy evaluation. Pay-as-you-save financing mechanisms are becoming increasingly popular for energy efficiency. For example, the Green Deal was a recent policy initiative in the UK (2011-2015) which provided households with loans in order to finance energy efficiency measures at interest rates of approximately eight percent. This was widely considered to have been a spectacular failure. The National Audit Office conducted an independent audit of the Green Deal scheme, finding that during its lifespan the scheme only funded one percent of energy efficient measures installed nationally. It also found that the scheme saved negligible amounts of CO2 and that households did not see the loans as an attractive proposition. Concerns were raised prior to the Green Deal policy that it would not have sufficient appeal for householders. These relate to a range of factors, including uncertainty regarding energy savings, limited financial appeal, and limited awareness of the scheme (Dowson et al., 2012). A key factor in limiting its appeal were the high rates of interest charged on loans (Rosenow and Eyre, 2016). Given the results we observe, it is clear that this rate is not sufficiently low to provide incentives for many households to partake in this scheme. In particular, low income households would actually lose money by making these improvements unless energy prices rise significantly. Market-based interventions will only work for certain segments of the population and policy needs to take this into account.

A question one might ask is why lower income households experience lower rates of return? A body of literature on the rebound effect identifies changes in energy service consumption that might reduce the expected savings (Sorrell et al., 2009a). It has also been shown that significant heterogeneity in the rebound effect is determined by household income and wealth (Aydin et al., 2017)[15]. A naive assessment might suggest that environmental policy is more effective when focused on better-off households. However, this is true only in the narrow sense that upgrades to such households will be more effective at reducing energy use and carbon emissions. Total welfare gains from upgrades may well be greater for upgrades to low income households, particularly if lower income households trade-off lower energy savings with increased internal temperatures and this results in improved well-being and even health outcomes. Evidence suggests this might be the case with regard to health

[15]This has also been shown in an inter-temporal sense by Fouquet (2018)

(Wilkinson et al., 2009; Hamilton et al., 2015) and poverty alleviation (Hills, 2012; Watson and Maitre, 2015).

The benefits of energy efficiency investments need to be re-considered with a greater focus on the non-financial benefits, from both a public and private perspective. At a societal level this means a greater focus on carbon emissions reduction, as opposed to cost-savings. In particular for low-income households, where much policy is directed, a greater focus on quantifying other welfare benefits and including them in cost-benefit calculations is essential.

# References

Abadie, A., Athey, S., Imbens, G. W., and Wooldridge, J. (2017). When should you adjust standard errors for clustering? Technical report, National Bureau of Economic Research.

Adan, H. and Fuerst, F. (2015). Do energy efficiency measures really reduce household energy consumption? a difference-in-difference analysis. *Energy Efficiency*, 9(5):1207–1219.

Alberini, A. and Towe, C. (2015). Information v. energy efficiency incentives: Evidence from residential electricity consumption in Maryland. *Energy Economics*, 52:S30–S40.

Allcott, H. (2015). Site selection bias in program evaluation. *The Quarterly Journal of Economics*, 130(3):1117–1165.

Allcott, H. and Greenstone, M. (2012). Is there an energy efficiency gap? *Journal of Economic Perspectives*, 26(1):3–28.

Allcott, H. and Greenstone, M. (2017). Measuring the welfare effects of residential energy efficiency programs. Technical report, National Bureau of Economic Research.

Allcott, H. and Rogers, T. (2014). The short-run and long-run effects of behavioral interventions: Experimental evidence from energy conservation. *American Economic Review*, 104(10):3003–3037.

Aydin, E., Kok, N., and Brounen, D. (2017). Energy efficiency and household behavior: the rebound effect in the residential sector. *The RAND Journal of Economics*, 48(3):749–782.

BEIS (2018). Energy consumption by final user (energy supplied basis), 1970 to 2018 (digest of uk energy statistics dukes 1.1.5-2. *Department for Business Energy and Industrial Strategy, UK.*

BEIS (2019). Annual fuel poverty statistics in england. *Department for Business Energy and Industrial Strategy, UK.*

Bertoldi, P. and Rezessy, S. (2008). Tradable white certificate schemes: fundamental concepts. *Energy Efficiency*, 1(4):237–255.

Blackwell, M., Iacus, S. M., King, G., and Porro, G. (2009). CEM: Coarsened Exact Matching in Stata. *The Stata Journal*, 9(4):524–546.

Blumstein, C., Krieg, B., Schipper, L., and York, C. (1980). Overcoming social and institutional barriers to energy conservation. *Energy*, 5(4):355–371.

Brucal, A., Roberts, M., et al. (2017). Do energy efficiency standards hurt consumers? Evidence from household appliance sales. Technical report, Grantham Research Institute on Climate Change and the Environment.

Burger, S. P., Knittel, C. R., Pérez-Arriaga, I. J., Schneider, I., and Vom Scheidt, F. (2020). The efficiency and distributional effects of alternative residential electricity rate designs. *The Energy Journal*, 41(1).

Chabé-Ferret, S. (2017). Should we combine difference in differences with conditioning on pre-treatment outcomes?

Chawla, M., Pollitt, M. G., et al. (2013). Energy-efficiency and environmental policies & income supplements in the uk: evolution and distributional impacts on domestic energy bills. *Economics of Energy & Environmental Policy*, 2(1).

Cohen, F., Glachant, M., and Söderberg, M. (2017). Consumer myopia, imperfect competition and the energy efficiency gap: Evidence from the UK refrigerator market. *European Economic Review*, 93:1–23.

Dowson, M., Poole, A., Harrison, D., and Susman, G. (2012). Domestic uk retrofit challenge: Barriers, incentives and current performance leading into the green deal. *Energy Policy*, 50:294–305.

Duffy, A. (2013). The final report of the community energy saving programme (cesp) 2009-2012. *Ofgem, UK.*

Economics, F. (2015). Energy efficiency: an infrastructure priority. *London: Frontier Economics. http://www.frontier-economics. com/documents/2015/09/energy-efficiency-infrastructurepriority. pdf.*

EST (2013). Review of potential for carbon savings from residential energy efficiency. *Final report for The Committee on Climate Change., Cambridge.*

Ferraro, P. J. and Miranda, J. J. (2017). Panel data designs and estimators as substitutes for randomized controlled trials in the evaluation of public programs. *Journal of the Association of Environmental and Resource Economists*, 4(1):281–317.

Fouquet, R. (2018). Consumer surplus from energy transitions. *The Energy Journal*, 39(3).

Fowlie, M., Greenstone, M., and Wolfram, C. (2018). Do energy efficiency investments deliver? evidence from the Weatherization Assistance Program. *The Quarterly Journal of Economics*, 133(3):1597–1644.

Gerarden, T., Newell, R. G., and Stavins, R. N. (2015). Deconstructing the energy-efficiency gap: conceptual frameworks and evidence. *The American Economic Review*, 105(5):183–186.

Gibbons, C. E., Urbancic, M. B., Anderson, M., Auerbach, A., Andrews, R., Bitler, M., Bohn, H., Buchinsky, M., Bugni, F., Cameron, C., Dobkin, C., Khan, S., Kasy, M., Kline, P., Kodrzycki, Y., Lozano, F., Masten, M., Maurel, A., Miller, D., Montoy, J. C., Moretti, E., Oaxaca, R., Raphael, S., Rosen, A., Shapiro, J., and Sekhon, J. (2014). Broken or fixed effects? NBER Working Paper No. 20342. *NBER Working Paper No. 20342*.

Gillingham, K., Keyes, A., and Palmer, K. (2018). Advances in evaluating energy efficiency policies and programs. *Annual Review of Resource Economics*, (0).

Giraudet, L.-G., Bodineau, L., and Finon, D. (2012). The costs and benefits of white certificates schemes. *Energy Efficiency*, 5(2):179–199.

Goldberg, P. K. (1998). The effects of the corporate average fuel efficiency standards in the us. *The Journal of Industrial Economics*, 46(1):1–33.

Golove, W. H. and Eto, J. H. (1996). Market barriers to energy efficiency: a critical reappraisal of the rationale for public policies to promote energy efficiency. *LBL-38059. Berkeley, CA: Lawrence Berkeley National Laboratory.*

Hamilton, I., Milner, J., Chalabi, Z., Das, P., Jones, B., Shrubsole, C., Davies, M., and Wilkinson, P. (2015). Health effects of home energy efficiency interventions in england: a modelling study. *BMJ Open*, 5(4):e007298–e007298.

Hamilton, I. G., Summerfield, A. J., Shipworth, D., Steadman, J. P., Oreszczyn, T., and Lowe, R. J. (2016). Energy efficiency uptake and energy savings in english houses: A cohort study. *Energy and Buildings*, 118:259–276.

Hausman, J. A. (1979). Individual discount rates and the purchase and utilization of energy-using durables. *Bell Journal of Economics*, 10(1):33–54.

Hills, J. (2012). Getting the measure of fuel poverty: Final report of the fuel poverty review.

Hough, D. and Page, R. (2015). Eco, the energy company obligation. *Briefing Paper: Number CBP*, 6814:1–32.

Hunt, L. C. and Ryan, D. L. (2015). Economic modelling of energy services: Rectifying misspecified energy demand functions. *Energy Economics*, 50:273–285.

Iacus, S. M., King, G., and Porro, G. (2008). Matching for causal inference without balance checking.

Iacus, S. M., King, G., and Porro, G. (2012). Causal inference without balance checking: Coarsened Exact Matching. *Political Analysis*, 20(1):1–24.

Jacobsen, G. D. (2019). An examination of how energy efficiency incentives are distributed across income groups. *The Energy Journal*, 40(6).

Jaffe, A. B. and Stavins, R. N. (1994). The energy paradox and the diffusion of conservation technology. *Resource and Energy Economics*, 16(2):91–122.

Kotchen, M. J. (2017). Longer-run evidence on whether building energy codes reduce residential energy consumption. *Journal of the Association of Environmental and Resource Economists*, 4(1):135–153.

Lancaster, K. J. (1966). A new approach to consumer theory. *Journal of Political Economy*, 74(2):132–157.

Lees, E. (2006). Evaluation of the energy efficiency commitment 2002-05. *DEFRA, Wantage (Oxfordshire).*

Lees, E. (2008). Evaluation of the energy efficiency commitment 2005-08. *DEFRA, Wantage (Oxfordshire).*

Nordhaus, W. D. (1996). Do real-output and real-wage measures capture reality? the history of lighting suggests not. In *The Economics of New Goods*, pages 27–70. University of Chicago Press.

Ofgem (2013). The final report of the Community Energy Saving Programme (CESP) 2009-2012. *Ofgem.*

Quigley, J. M. and Rubinfeld, D. L. (1989). Unobservables in consumer choice: residential energy and the demand for comfort. *The Review of Economics and Statistics*, pages 416–425.

Roodman, D., Nielsen, M. Ø., MacKinnon, J. G., and Webb, M. D. (2019). Fast and wild: Bootstrap inference in stata using boottest. *The Stata Journal*, 19(1):4–60.

Rosenow, J. (2012). Energy savings obligations in the uka history of change. *Energy Policy*, 49:373–382.

Rosenow, J. and Eyre, N. (2016). A post mortem of the green deal: Austerity, energy efficiency, and failure in british energy policy. *Energy Research & Social Science*, 21:141–144.

Ryan, L. and Campbell, N. (2012). Spreading the net: the multiple benefits of energy efficiency improvements.

Sorrell, S., Dimitropoulos, J., and Sommerville, M. (2009a). Empirical estimates of the direct rebound effect: A review. *Energy Policy*, 37(4):1356–1371.

Sorrell, S., Harrison, D., Radov, D., Klevnas, P., and Foss, A. (2009b). White certificate schemes: Economic analysis and interactions with the eu ets. *Energy Policy*, 37(1):29–42.

UK Climate Change Act (2019). Climate change act 2008 (2050 target amendment) order 2019.

Watson, D. and Maitre, B. (2015). Is fuel poverty in ireland a distinct type of deprivation? *The Economic and Social Review*, 46(2, Summer):267–291.

Webb, M. D. (2013). Reworking wild bootstrap based inference for clustered errors. Technical report, Queen's Economics Department Working Paper.

Wilkinson, P., Smith, K. R., Davies, M., Adair, H., Armstrong, B. G., Barrett, M., Bruce, N., Haines, A., Hamilton, I., Oreszczyn, T., et al. (2009). Public health benefits of strategies to reduce greenhouse-gas emissions: household energy. *The Lancet*, 374(9705):1917–1929.

Wooldridge, J. (2010). *Econometric analysis of cross section and panel data.* MIT Press, Cambridge, Mass., 2nd ed. edition.

# Quantifying the distributional impact of energy efficiency measures: Online Appendix

Daire McCoy[*], Raphaela Andrea Kotsch[†]

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[*]McCoy (corresponding author): Grantham Research Institute, London School of Economics and Political Science, Houghton Street, London, U.K. WC2A 2AE, Economic and Social Research Institute, Sir John Rogerson's Quay, Dublin, Ireland, d.m.mccoy@lse.ac.uk. This work makes use of data from the National Energy Efficiency framework Database (NEED) UK. We are grateful for financial support for this research from the European Investment Bank, EIBURS grant scheme. Project title: "Policies to finance energy efficiency: an applied welfare assessment". We thank Antoine Dechezleprtre, Francois Cohen, Louis-Gaetan Giraudet and Karsten Neuhoff for securing this funding. This research has also been supported by the Grantham Research Institute and the ESRC Centre for Climate Change Economics and Policy under Grant No. ES/K006576/1. We thank seminar participants at AIEE (2017), FSR Annual Climate Conference (2017), IEB International Academic Symposium (2018), UKNEE enevecon (2018), LSE, Grantham Research Institute PDE Workshop (2018), Montpellier Energy Workshop (2018), EAERE World Congress (2018) and BIEE (2018) for comments. The authors are extremely grateful to Arlan Brucal and Roger Fouquet for useful discussions and for providing comments on an earlier draft. We would also like to thank Kenneth Gillingham, Meredith Fowlie and Matt Kotchen for useful discussions. All remaining errors are our own.

[†]University of Zurich, Affolternstrasse 56, 8050 Zurich, Switzerland

# 1 Appendix

## 1.1 Overview of NEED dataset

Table A1: Description of variables in NEED

| Variable | Description |
|---|---|
| HH_ID | Household identifier. A unique value for each record. Created specifically for these datasets. |
| REGION | Region code - formally Government Office Region. See ONS website for more details: http://www.ons.gov.uk/ons/guide-method/geography/beginner-s-guide/administrative/england/government-office-regions/index.html. |
| IMD_ENG | English Index of multiple deprivation 2010. Households are allocated to five groups (quintiles) based on the deprivation rank of the 2001 Lower Layer Super Output Area (LSOA) they are located in. Households in the 20 per cent most deprived LSOAs are in the bottom quintile (1) and households in the 20 per cent least deprived LSOAs are in the top quintile (5). |
| IMD_WALES | Welsh Index of multiple deprivation 2011. Households are allocated to one of five bands based on the deprivation rank of the LSOA (2001) they are located in. 1, most deprived, 5 least deprived. |
| FP_ENG | EUL only. Fuel Poverty Indicator for England. Households are allocated to one of five bands based on the estimate of the proportion of households in fuel poverty in the LSOA (2001) they are located in. Uses the 2011 estimates of fuel poverty low income high cost definition. |
| EPC_INS_DATE | EUL Only. Provides information on the date of the EPC inspection (based on lodgement date). |
| GconsYEAR | Weather corrected annual gas consumption. Based on meter point data from Xoserve and independent gas transporters. Readings relate to October to September each year (e.g. 2012 consumption is October 2011 to September 2012). See here for more information on this source: https://www.gov.uk/government/publications/regional-energy-data-guidance-note. |
| GconsYEARValid | Flag indicates records with valid consumption and households off the gas network. |
| EconsYEAR | Annual electricity consumption in kWh - values relate to end January to end January each year (e.g. 2012 consumption is end January 2012 to end January 2013). See here for more information on this source: https://www.gov.uk/government/publications/regional-energy-data-guidance-note. |
| EconsYEARValid | Valid electricity consumption (between 100 and 25,000 inclusive) |
| E7Flag2012 | Shows whether the electricity meter is an E7 (profile 2) meter - this does not necessarily mean the household has an E7 tariff, some households will have an E7 meter without an E7 tariff. |
| MAIN_HEAT_FUEL | Main fuel used to heat the property, based on information from Energy Performance Certificate |
| PROP_AGE | Banded year of construction based on EPC data. |
| PROP_TYPE | Type of property (based on combination of EPC built form and property type). |
| FLOOR_AREA_BAND | Banded floor area based on EPC (m2). |
| EE_BAND | Energy Efficiency Band Based on EPC (A and B grouped). |
| LOFT_DEPTH | Amount of loft insulation as assessed by EPC (all properties with loft insulation recorded as installed through a Government scheme are assigned 2 irrespective of EPC information). No information could occur where the information is missing from the EPC or where the property does not have a loft. |
| WALL_CONS | Wall construction as recorded on EPC. |
| CWI | Cavity wall insulation installed through Government schemes. This includes measures recorded as installed on HEED, including, Energy Efficiency Commitment, Community Energy Savings Programme and Carbon Emissions Reduction Target. |
| CWI_YEAR | Year of CWI installation |
| LI | Loft insulation installed through Government schemes. This includes measures recorded as installed on HEED, including, Energy Efficiency Commitment, Community Energy Savings Programme and Carbon Emissions Reduction Target. |
| LI_YEAR | Year of LI installation |
| BOILER | This includes boilers installed through Government schemes, and those registered by CORGI (up to 2009) and Gas Safe (2009 onwards). |
| BOILER_YEAR | Year of Boiler installation |
| WEIGHT | EUL Only. Weighting based on Region, property age, property type and floor area band. Summing all weights gives (approximate) total number of households in England and Wales 2011. |

## B Socioeconomic information

The NEED dataset comprises information on household characteristics modelled by Experian and matched with indicators based on the geographic location of the property (DECC, 2016).[1] For reasons of data protection, the dataset was anonymised and household-level information on variables such as income and tenure-type are not available. However, the dataset does include two composite indicators of the socio-economic background of the households.

1. *Index of multiple deprivation* (IMD)

   NEED contains two variables describing IMDs: IMD 2010 for England and IMD 2011 for Wales. Both indicators classify Lower Layer Super Output Areas (LSOAs) according to a quintile ranking that is based on eight different domains that are incorporated using a weighting scheme. The first quintile (IMD=1) indicates the most deprived areas. Table B1 shows the composition of domains that are incorporated in the indicators and their weight in percent.

2. *Fuel poverty indicator* (FP)

   Combining data from the English Housing Survey and Census data, the fuel poverty indicator indicates if households are fuel poor based on the households' income and energy requirements, as well as on fuel prices (BEIS, 2013).

Table B1: Composition of IMD in %

| | England 2010 | Wales 2011 |
|---|---|---|
| Income | 22.5 | 23.5 |
| Employment | 22.5 | 23.5 |
| Health | 13.5 | 14 |
| Education | 13.5 | 14 |
| Access/barriers to services | 9.3 | 10 |
| Living environment/ housing | 9.3 | 5 |
| Physical environment | 0 | 5 |
| Crime [Wales: Community Safety] | 9.3 | 5 |

Note: Composition of domains and weights in percent of indicators comprising Index of multiple deprivation.

Source: Payne and Abel (2012); ONS (2011)

[1] Experian is a commercial organisation which produces modelled data of household characteristics at address level. These are derived from a range of sources including Census outputs and Experian's consumer survey.

Table B2: Logistic regressions

| | (1) **Upgrade** | | (2) **Cavity** | | (3) **Loft** | | (4) **Boiler** | |
|---|---|---|---|---|---|---|---|---|
| 2005 Gas | 1.000*** | (0.000) | 1.000*** | (0.000) | 1.000*** | (0.000) | 1.000*** | (0.000) |
| 2005 Electricity | 1.000*** | (0.000) | 1.000*** | (0.000) | 1.000*** | (0.000) | 1.000*** | (0.000) |
| *Cavity wall* | | | | | | | | |
| Other | 0.609*** | (0.001) | 0.0803*** | (0.000) | 0.900*** | (0.002) | 0.965*** | (0.002) |
| East Midlands | 1.340*** | (0.003) | 1.218*** | (0.004) | 1.705*** | (0.005) | 1.058*** | (0.003) |
| East of London | 1.023*** | (0.002) | 0.991** | (0.003) | 1.207*** | (0.003) | 0.949*** | (0.002) |
| London | 0.857*** | (0.002) | 0.744*** | (0.003) | 0.807*** | (0.002) | 0.859*** | (0.002) |
| North East | 1.651*** | (0.005) | 1.821*** | (0.006) | 2.011*** | (0.006) | 0.999 | (0.003) |
| North West | 1.356*** | (0.003) | 1.613*** | (0.004) | 1.749*** | (0.004) | 0.869*** | (0.002) |
| *South East* | | | | | | | | |
| South West | 1.185*** | (0.003) | 1.224*** | (0.004) | 1.371*** | (0.004) | 0.997 | (0.002) |
| Wales | 1.233*** | (0.003) | 1.312*** | (0.005) | 1.847*** | (0.006) | 0.791*** | (0.002) |
| West Midlands | 1.217*** | (0.003) | 1.288*** | (0.004) | 1.473*** | (0.004) | 0.948*** | (0.002) |
| Yorkshire and The Humber | 1.355*** | (0.003) | 1.347*** | (0.004) | 1.644*** | (0.004) | 1.039*** | (0.002) |
| Detached house | 1.096*** | (0.002) | 1.078*** | (0.003) | 1.155*** | (0.003) | 1.025*** | (0.002) |
| *Semi-detached house* | | | | | | | | |
| End terrace house | 0.908*** | (0.002) | 0.846*** | (0.002) | 0.949*** | (0.002) | 1.000 | (0.002) |
| Mid terrace house | 0.802*** | (0.001) | 0.672*** | (0.002) | 0.875*** | (0.002) | 0.949*** | (0.002) |
| Bungalow | 1.377*** | (0.003) | 1.042*** | (0.002) | 1.440*** | (0.003) | 1.252*** | (0.003) |
| Flat (inc. maisonette) | 0.528*** | (0.001) | 0.495*** | (0.002) | 0.233*** | (0.001) | 0.943*** | (0.003) |
| *Before 1930* | | | | | | | | |
| 1930-1949 | 1.277*** | (0.002) | 1.692*** | (0.005) | 1.272*** | (0.003) | 1.136*** | (0.002) |
| 1950-1966 | 1.477*** | (0.003) | 2.058*** | (0.006) | 1.265*** | (0.003) | 1.212*** | (0.003) |
| 1967-1982 | 1.338*** | (0.003) | 1.920*** | (0.006) | 1.289*** | (0.003) | 1.116*** | (0.002) |
| 1983-1995 | 0.835*** | (0.002) | 0.861*** | (0.003) | 0.966*** | (0.003) | 0.995 | (0.003) |
| 1996 onwards | 0.301*** | (0.001) | 0.406*** | (0.002) | 0.247*** | (0.001) | 0.459*** | (0.002) |
| IMD group 1 | 1.419*** | (0.003) | 1.278*** | (0.003) | 1.401*** | (0.003) | 1.214*** | (0.002) |
| IMD group 2 | 1.169*** | (0.002) | 1.166*** | (0.003) | 1.236*** | (0.003) | 1.010*** | (0.002) |
| IMD group 3 | 1.073*** | (0.002) | 1.099*** | (0.002) | 1.134*** | (0.002) | 0.972*** | (0.002) |
| IMD group 4 | 1.014*** | (0.002) | 1.034*** | (0.002) | 1.038*** | (0.002) | 0.971*** | (0.002) |
| *IMD group 5* | | | | | | | | |
| *Gas* | | | | | | | | |
| Other | 0.976*** | (0.004) | 1.234*** | (0.008) | 1.224*** | (0.007) | 0.831*** | (0.004) |
| 1 to 50 m2 | 0.976*** | (0.003) | 0.836*** | (0.003) | 0.768*** | (0.003) | 1.075*** | (0.003) |
| *51-100 m2* | | | | | | | | |
| 101-150 m2 | 0.938*** | (0.001) | 0.879*** | (0.002) | 0.958*** | (0.002) | 0.969*** | (0.001) |
| Over 151 m2 | 0.867*** | (0.002) | 0.630*** | (0.002) | 0.836*** | (0.003) | 1.049*** | (0.003) |
| Observations | 2527182 | | 2527182 | | 2527182 | | 2527182 | |
| Pseudo R-squared | 0.063 | | 0.184 | | 0.068 | | 0.011 | |

**Notes**: This table reports odds ratio/ coefficient estimates and standard errors from four separate regressions. Columns (1) to (4) report odds ratio from logit regressions. The dependent variable in column (1) indicates whether a dwelling had an efficiency upgrades occurring at any time during the sample period. In every regression in columns (2), (3) and (4), the dependent variable indicate a different type of upgrade. The standard errors are given in brackets. The reference group of dummy variables is printed in italic.

# C Predicting income

In the first stage of the prediction process, we estimate income using the EHS data. The dependent variable in our model is the EHS Basic income, which provides information on annual net household income (HRP + Partner) including savings for 75,361 households. We consider to included all variables that are available in NEED and that could explain income in the estimation model and transform these variables such that the categories of the variables correspond to the NEED variables. See tables C1, C2 and C3 for the transformation of the variables property type, property age and region. EHS does not provide information for households in Wales and region of residence was not reported in the first wave 2005-2006. IMD is given in deciles for each wave. We merge the IMD groups in EHS such that they correspond to the quantiles in NEED. The floor area band is continuous in the EHS, we thus group the variable in the same band with as the NEED data.

Table C1: Government regions

| Govern. Region | NEED | EHS | EHS frequency |
|---|---|---|---|
| E12000001 | North East | North East | 2,670 |
| E12000002 | North West | North West | 6,577 |
| E12000003 | Yorkshire and The Humber | Yorkshire and The Humber | 5,324 |
| E12000004 | East Midlands | East Midlands | 4,047 |
| E12000005 | West Midlands | West Midlands | 4,440 |
| E12000006 | East of England | East | 4,848 |
| E12000007 | London | London | 6,093 |
| E12000008 | South East | South East | 6,919 |
| E12000009 | South West | South West | 4,665 |
| W99999999 | Wales | Missing | 0 |

Table C2: Property age

| NEED | EHS | Frequency EHS |
|---|---|---|
| before 1930 | 1850 to 1899 | 6,600 |
| before 1930 | 1900 to 1918 | 5,957 |
| before 1930 | 1919 to 1944 | 12,911 |
| 1930-1949 | 1945 to 1964 | 17,971 |
| 1950-1966 | 1965 to 1974 | 12,224 |
| 1967-1982 | 1975 to 1980 | 5,724 |
| 1967-1982 | 1981 to 1990 | 6,727 |
| 1983-1995 | post 1990 | 7,904 |
| after 1996 | pre 1850 | 2,336 |

Table C3: Property type

| NEED | EHS | Frequency EHS |
|---|---|---|
| end terrace | end terrace | 8,043 |
| mid terrace | mid terrace | 15,015 |
| semi detached | semi detached | 19,698 |
| detached | detached | 10,359 |
| bungalow | bungalow | 7,434 |
| flat | converted flat | 2,754 |
| flat | purpose built flat, low rise | 13,289 |
| flat | purpose built flat, high rise | 1,762 |

From the pre-selected variables, we choose the features to be included in the estimation model based on standard linear regression by stepwise selection process choosing features with the lowest p-values, as well as Lasso method for feature selection. The LASSO method is standardised method to determine the right set of features. The LASSO estimator solves an optimisation problem that minimises the sum of squared errors with an upper bound of the sum of the absolute values of the model parameters, thus penalising the inclusion of redundant and irrelevant features and thus avoiding overfitting. The LASSO estimator selects all variables and thus does not partial-out any of our pre-selected variables. It further reveals that floor area is the most important variable in the model (see figure 1). Applying a 5-fold cross-validation shows that the lowest cross-validation mean square error can be obtained with the inclusion of all variables (eight features) (See figure 2). The range of the lambda that optimises the mean-square error and penalises overfitting lies between eight and five model features with an upper bound at five. Since most coefficients are significant, we decide to include all our variables in the model.

Figure 1: Glmnet for the basic model

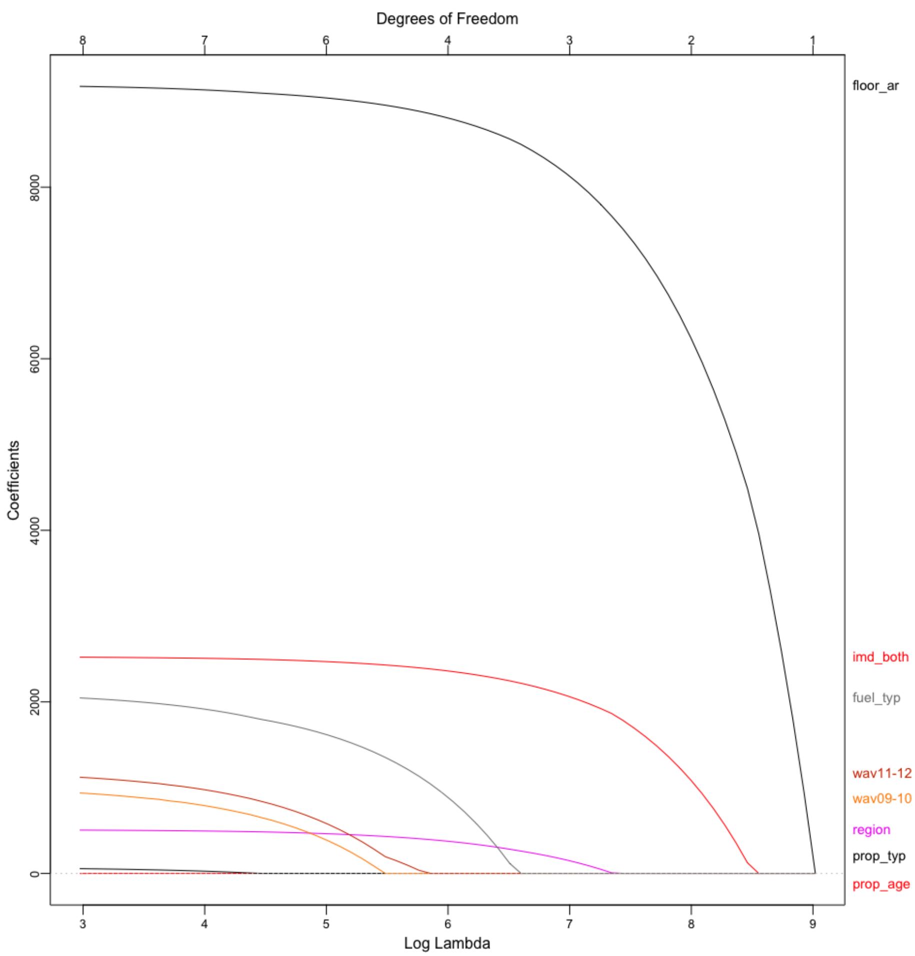
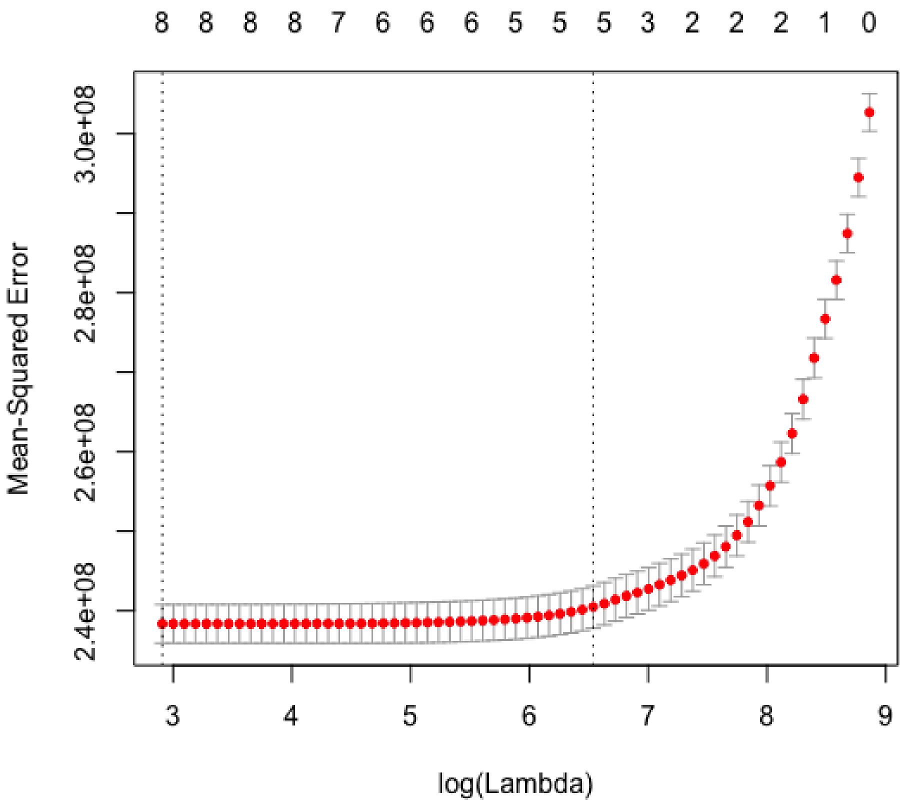


Figure 2: 5-fold cross-validation




In the final model, we include the variables IMD group, region, an indicator for the main heating fuel, as well as dwelling characteristics such as property type, property age and floor area and estimate with dwelling weights to ensure representability of our results. Most variables are highly significant with a p-value at 0.01 (See table **??**). We estimate a separate model for the period 2005-2006, since region was not reported in the 2005/2006 EHS survey. Including interactions in the model, does not increase the predictive power of the model (see adjusted R-square of model 2 in table **??**) but enormously increases the computational costs of predicting income in NEED. This is so because the coefficient matrix we obtain in the first step inflates for every variable we add in the model. Multiplication of matrices in the second step then becomes increasingly complex and consumes a lot of computational power.

In a second step, we use the coefficients from the first stage to predict income in NEED.

Table C4: First stage: Estimation model

| | Annual net household income | | |
|---|---|---|---|
| | (1) Basic model | (2) With interactions | (3) Basic model for 2005-2006 |
| *IMD group 1* | | | |
| IMD group 2 | 2,796.644*** (279.734) | 2,770.539*** (279.804) | 2,624.671*** (454.017) |
| IMD group 3 | 5,289.021*** (287.551) | 5,291.229*** (287.489) | 5,130.349*** (467.529) |
| IMD group 4 | 7,427.007*** (292.931) | 7,409.695*** (292.897) | 6,080.672*** (476.019) |
| IMD group 5 | 10,648.520*** (309.355) | 10,560.590*** (309.853) | 8,961.979*** (493.569) |
| *1-50 m2* | | | |
| 51-100 m2 | 4,036.371*** (322.444) | 3,646.616*** (556.121) | 4,127.138*** (542.831) |
| 101-150 m2 | 10,874.310*** (391.415) | 8,506.496*** (783.703) | 10,767.440*** (651.143) |
| Over 151 m2 | 22,352.340*** (473.674) | 19,818.060*** (822.730) | 25,869.620*** (795.843) |
| *North East* | | | |
| North West | 557.708 (446.241) | 547.668 (446.157) | |
| Yorkshire and The Humber | 358.595 (465.801) | 364.322 (465.718) | |
| East Midlands | −108.940 (481.903) | −88.658 (481.843) | |
| East Midlands | 859.607* (465.957) | 874.109* (465.888) | |
| East of England | 2,235.437*** (467.484) | 2,276.779*** (467.567) | |
| London | 9,392.044*** (457.411) | 9,405.638*** (457.349) | |
| South East | 3,763.329*** (444.634) | 3,771.052*** (444.561) | |
| South West | 175.792 (470.415) | 229.325 (470.466) | |
| *Before 1930* | | | |
| 1930-1949 | −2,239.046*** (299.586) | −2,347.805*** (300.414) | −2,720.271*** (480.367) |
| 1950-1966 | −4,355.881*** (291.591) | −4,447.088*** (292.174) | −4,974.613*** (473.609) |
| 1967-1982 | −3,448.846*** (284.707) | −3,556.549*** (285.567) | −3,666.762*** (459.227) |
| 1983-1995 | −1,978.010*** (368.180) | −2,129.114*** (369.603) | −2,028.518*** (610.119) |
| After 1996 | 956.453*** (321.266) | 801.340** (322.932) | −4.798 (571.549) |
| *End terrace house* | | | |
| Mid terrace house | −367.296 (343.774) | −384.567 (343.722) | 1,339.147** (564.087) |
| Semi detached house | 1,960.954*** (329.205) | 1,972.677*** (329.148) | 2,024.877*** (541.306) |
| Detached house | 4,576.612*** (388.216) | 4,660.368*** (388.545) | 4,091.597*** (646.439) |
| Bungalow | −3,482.680*** (409.284) | −3,385.405*** (410.300) | −2,120.809*** (676.932) |
| Flat | −2,237.751*** (374.749) | −2,346.431*** (375.511) | 408.501 (621.779) |
| Period 09-10 | 1,010.673*** (212.320) | 1,009.994*** (212.275) | |
| Period 11-12 | 1,203.948*** (211.793) | 1,206.842*** (211.748) | |
| 51-100 m2 * Gas fired system | | 729.085 (645.868) | |
| 101-150 m2 * Gas fired system | | 2,912.586*** (846.116) | |
| Over 151 m2 * Gas fired system | | 3,300.171*** (890.828) | |
| Gas fired system | 2,076.278*** (259.358) | 838.314 (547.178) | 2,648.456*** (421.372) |
| Constant | 11,385.180*** (649.024) | 12,329.070*** (721.926) | 11,062.750*** (864.028) |
| Observations | 43,839 | 43,839 | 15,648 |
| $R^2$ | 0.236 | 0.236 | 0.216 |
| Adjusted $R^2$ | 0.235 | 0.236 | 0.215 |
| Residual Std. Error | 693,191.300 (df = 43810) | 693,039.000 (df = 43807) | 653,324.300 (df = 15629) |
| F Statistic | 482.922*** (df = 28; 43810) | 437.097*** (df = 31; 43807) | 238.987*** (df = 18; 15629) |

Note: The table reports coefficient estimates and standard errors from three regressions using alternative model specification. The dependent variable in all regressions is the annual net household income. Column (1) reports the results from the basic model that includes EHS data from 2007 to 2012. Column (2) includes interaction terms, Column (3) uses EHS data for the years 2005 and 2006 for which the region variable is not available.

## D Matching

### D.1 Coarsened-Exact Matching procedure

The CEM procedure initially coarsens continuous variables into discrete bins, each with their own "Bin Signature" or strata. Households are then exactly matched to another household in the same strata. The algorithm works by selecting strata that make treated and control groups balanced with respect to $X$. This can be performed for multiple variables. Weights are produced in which unmatched observations receive a weight of zero. Matched units receive a weight of one if they belong to the treatment group and a weight of $\frac{m_C}{m_T}\frac{m_T^s}{m_C^s}$ if they belong to the control group. This is formally described by Iacus et al. (2012) as:

$$w_i = \begin{cases} 1 & i \in T^s \\ \frac{m_C}{m_T}\frac{m_T^s}{m_C^s} & i \in C^s \end{cases} \tag{1}$$

Where $w_i$ is the calculated weight for $observation_i$, $(T^s, C^s)$ the treated and control units in stratum $s$, $(m_T, m_C)$ the total number of treated and control units and $(m_T^s, m_C^s)$ the number of treated and control units in stratum $s$. The trade-off with CEM is choosing between the bin width or number of strata and proportion of disgarded unmatched observations. Overly narrow bin widths result a large number of strata, making matching more difficult and resulting in more unmatched observations. Overly wide bin widths result in a low number of strata, making matching easier but observations may not be sufficiently similar. This is more of a problem when working with small sample sizes.

In this case we are concerned with matching the group that received the energy efficiency upgrades with the group that did not. Covariates on which the matching is performed should be predictors of household energy consumption and simultaneously impact the uptake of energy efficiency upgrades. The IMD of the area in which the household resides, provides information on the household's socioeconomic environment, an important predictor of energy consumption and energy efficiency uptakes (Hamilton et al., 2014). Dwelling characteristics, such as the period in which the dwelling was built has an important impact on residential energy consumption (Brounen et al., 2012; Harold et al., 2015). Regional differences in weather patterns will also affect fuel consumption. In addition, Alberini and Towe (2015) provide evidence that matching solely based on dwelling or household characteristics is not sufficient and can be optimised if past energy usage is also included. Taking into consideration all these factors, matching is performed on the following variables: property age, fuel-type, energy consumption in the pre-treatment years, location of dwelling and the IMD of the area in which the household resides. By performing matching on energy consumption in prior years, we can account for unobservable household and property characteristics that might vary over time, such as the household size, composition and appliance usage. The large sample size allows us to perform 1:1 matching in which each treatment household is matched with a similar control household.

### D.2 Assessing the quality of matching

The quality of the matching process depends on the similarity in the distribution of covariates between treated and matched control group. This is commonly assessed by comparing the standardised difference and variance ratio of the variables in both groups, before and after matching (Caliendo and Kopeinig, 2005). The standardised difference is the difference in sample means in the treated and control group, divided by the corresponding sample variances. Formally:

$$d = \frac{\overline{\mathrm{x}}_{treatment} - \overline{\mathrm{x}}_{control}}{\sqrt{\frac{s^2_{treatment} + s^2_{control}}{2}}} \tag{2}$$

It allows for a comparison of balance which is independent of the sample size and measurement unit (Austin, 2009). The smaller the difference, the better, and it is recommended that this ratio should not exceed 10 percent (Austin, 2009). The variance ratio measures the ratio of the mean variance in the treated and control group for each covariate. Formally:

$$F = \frac{s^2_{treatment}}{s^2_{control}} \tag{3}$$

This should be close to unity (Austin, 2009; Ferraro and Miranda, 2017). A significant divergence from this indicates that the matching model is misspecified. Further methods of balance diagnostic include assessing the magnitude of the difference between treatment and matched control group covariates using tests for statistical significance. However, the use of the t-test for balance testing is criticised for several reasons under which the most problematic is the dependence on the sample size. For instance, randomly discarding control units will always increase the balance, falsely indicating a better balance (Imai et al., 2008).

Table D1: Unmatched sample

| Unmatched sample | | Treated | | | Control | | | Balance | |
|---|---|---|---|---|---|---|---|---|---|
| | Variable | Mean | Variance | Skewness | Mean | Variance | Skewness | Std-diff | Var-ratio |
| Variables used in matching | prop_age | 2.96 | 1.98 | 0.16 | 3.00 | 3.00 | 0.31 | -0.03 | 0.66 |
| | imd_both | 2.85 | 2.11 | 0.15 | 2.96 | 2.01 | 0.05 | -0.08 | 1.05 |
| | region | 5.34 | 7.33 | 0.03 | 5.81 | 6.31 | -0.29 | -0.18 | 1.16 |
| | fuel_type | 0.98 | 0.02 | -7.43 | 0.98 | 0.02 | -6.33 | 0.04 | 0.74 |
| | Gcons2005 | 18124 | 78900000 | 0.65 | 17394 | 86200000 | 0.73 | 0.08 | 0.92 |
| Variables not used in matching | prop_type | 3.33 | 2.63 | 0.22 | 3.56 | 2.92 | 0.08 | -0.14 | 0.90 |
| | floor_area | 2.20 | 0.40 | 0.89 | 2.20 | 0.46 | 0.77 | -0.01 | 0.86 |
| | loft_depth | 2.03 | 0.28 | 0.04 | 2.08 | 0.53 | -0.13 | -0.08 | 0.52 |
| | wall_cons | 0.73 | 0.20 | -1.02 | 0.59 | 0.24 | -0.36 | 0.29 | 0.82 |
| | FP_ENG | 2.95 | 1.97 | 0.06 | 2.89 | 2.12 | 0.10 | 0.04 | 0.93 |
| | Econs2005 | 3903 | 7653561.00 | 2.16 | 3998.54 | 8374713 | 2.14 | -0.03 | 0.91 |

Note: Comparison of means, standard deviations and skewness of variables in both Treatment and Control groups prior to CEM. Comparison provided of variables used in matching procedure and variables not used in matching procedure.

Table D2: Matched sample all years

| All years matched sample | | Treated | | | Control | | | Balance | |
|---|---|---|---|---|---|---|---|---|---|
| | Variable | Mean | Variance | Skewness | Mean | Variance | Skewness | Std-diff | Var-ratio |
| Variables used in matching | prop_age | 2.91 | 2.32 | 0.24 | 2.91 | 2.31 | 0.24 | 0.00 | 1.00 |
| | imd_both | 2.92 | 2.07 | 0.09 | 2.92 | 2.07 | 0.09 | 0.00 | 1.00 |
| | region | 5.62 | 6.83 | -0.15 | 5.62 | 6.82 | -0.15 | 0.00 | 1.00 |
| | fuel_type | 0.98 | 0.02 | -7.45 | 0.98 | 0.02 | -7.47 | 0.00 | 1.01 |
| | Gcons2005 | 18020 | 84200000 | 0.67 | 18017 | 84300000 | 0.67 | 0.00 | 1.00 |
| Variables not used in matching | prop_type | 3.36 | 2.68 | 0.19 | 3.48 | 2.87 | 0.14 | -0.07 | 0.93 |
| | floor_area | 2.21 | 0.42 | 0.86 | 2.21 | 0.45 | 0.80 | 0.00 | 0.93 |
| | loft_depth | 2.04 | 0.30 | 0.03 | 2.05 | 0.52 | -0.08 | -0.02 | 0.57 |
| | wall_cons | 0.67 | 0.22 | -0.71 | 0.63 | 0.23 | -0.52 | 0.09 | 0.95 |
| | FP_ENG | 2.95 | 2.04 | 0.06 | 2.96 | 2.09 | 0.05 | -0.01 | 0.98 |
| | Econs2005 | 3945.89 | 7999389.00 | 2.15 | 4028.94 | 8182317.00 | 2.09 | -0.03 | 0.98 |

Note: Comparison of means, standard deviations and skewness of variables in both Treatment and Control groups after CEM performed. Comparison provided of variables used in matching procedure and variables not used in matching procedure.

Table D3: Percentage of observations matched

| Dwellings receiving upgrades | Count |
|---|---|
| Full database | 1,869,372 |
| 2005 or unknown upgrade date | 416,994 |
| Remaining sample | 1,452,378 |
| Matched sample | 1,286,419 |
| Unmatched | 165,959 |
| Matched as a percentage of eligible | 89% |

Note: Information on proportion of observations included in final matched sample.

Table D4: Results under different matching procedures

| | (1) CEM Matching | (2) Nearest neighbour matching | (3) Kernel matching |
|---|---|---|---|
| Cavity wall insulation | -0.094*** | -0.094*** | -0.096*** |
| | (0.001) | (0.002) | (0.003) |
| Loft insulation | -0.030*** | -0.029*** | -0.031*** |
| | (0.001) | (0.003) | (0.003) |
| Replacement boiler | -0.092*** | -0.093*** | -0.097*** |
| | (0.001) | (0.002) | (0.002) |
| Control variables | Y | Y | Y |
| Household fixed effects | Y | Y | Y |
| Year fixed effects | Y | Y | Y |
| Year*region fixed effects | Y | Y | Y |
| Observations | 5,502,936 | 3,341,747 | 3,263,178 |
| Number of households | 687,925 | 417,751 | 407,928 |
| R squared | 0.349 | 0.363 | 0.411 |

**Notes**: This table reports coefficient estimates and standard errors from three regressions using alternative matching procedures. The dependent variable in all regressions is the logarithm of annual gas consumption in kilowatt hours. Column(1) reports the results from the preferred CEM procedure, Column (2) from Nearest Neighbour matching and Column (3) reports results from a Kernel matching procedure. Triple asterisks denote statistical significance at the 1% level; Double asterisks at the 1% level; single asterisks at the 10% level.

## E Results in kWh

Table E1: Results in units of energy saved (kWh)

| | (1) Gas | (2) Elec | (3) Tot Energy |
|---|---|---|---|
| Cavity wall insulation | -1254.909*** | -23.002 | -1277.911*** |
| | (41.989) | -14.009 | (46.216) |
| Loft insulation | -375.539*** | -8.901 | -384.440*** |
| | (36.250) | -11.268 | (39.533) |
| Replacement boiler | -1229.965*** | -98.273*** | -1328.238*** |
| | (32.918) | -10.796 | (35.722) |
| Control variables | Y | Y | Y |
| Household fixed effects | Y | Y | Y |
| Year fixed effects | Y | Y | Y |
| Year*region fixed effects | Y | Y | Y |
| Observations | 549072 | 549072 | 549072 |
| Number of households | 68,634 | 68634 | 68634 |
| R squared | 0.337 | 0.092 | 0.357 |

**Notes**: This table reports coefficient estimates and standard errors from three separate regressions. The dependent variable in all regressions is annual energy consumption. Column(1) is Gas, (2) Electricity and (3) Total Energy. For each upgrade group a matched control group is created using coarsened-exact matching. The sample includes billing records from 2005 to 2012. Standard errors are clustered at the household level. Triple asterisks denote statistical significance at the 1% level; Double asterisks at the 1% level; single asterisks at the 10% level.

## F Event-Study results by measure

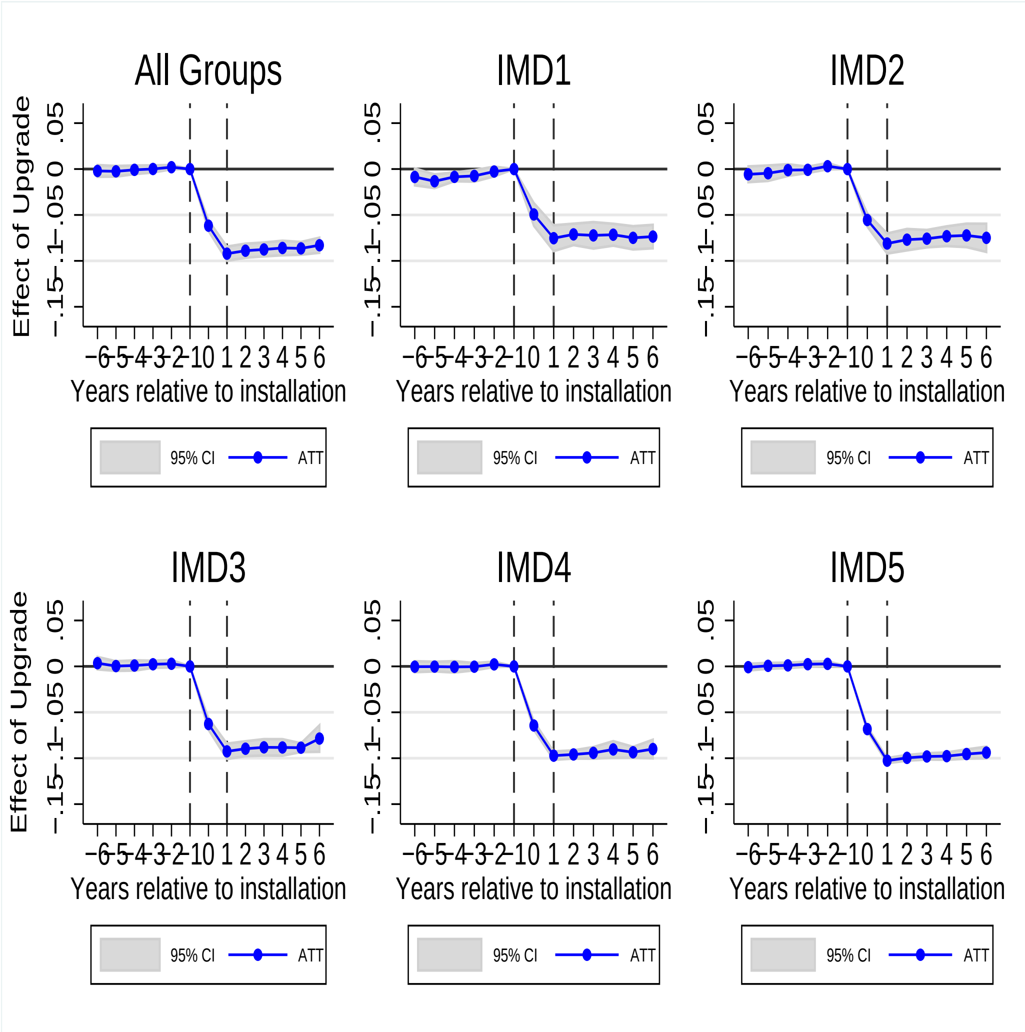



Figure 3: Cavity-wall insulation: Event-study analysis of percentage savings for all households and by IMD Group. Upgrade occurs during period $-1 \leq t \leq +1$

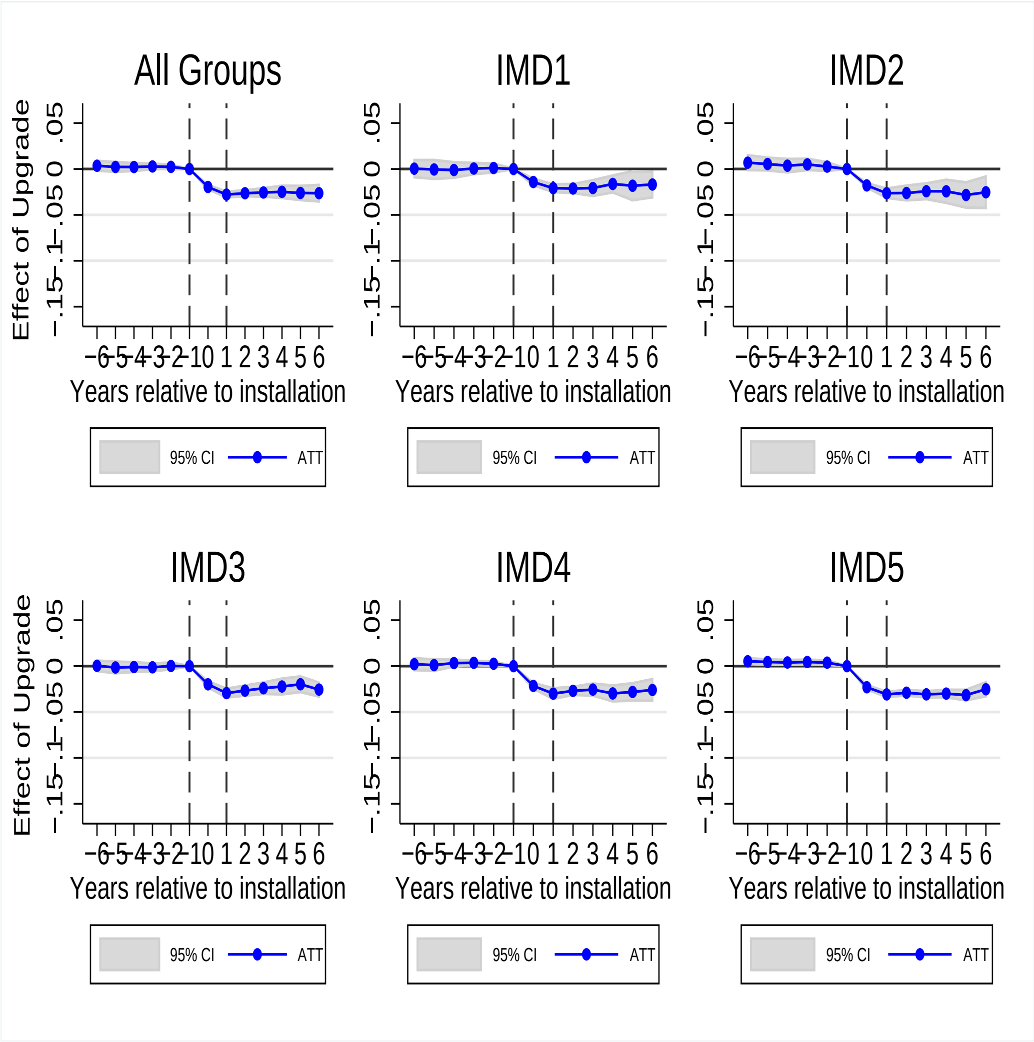



Figure 4: Loft insulation: Event-study analysis of percentage savings for all households and by IMD Group. Upgrade occurs during period $-1 \leq t \leq +1$

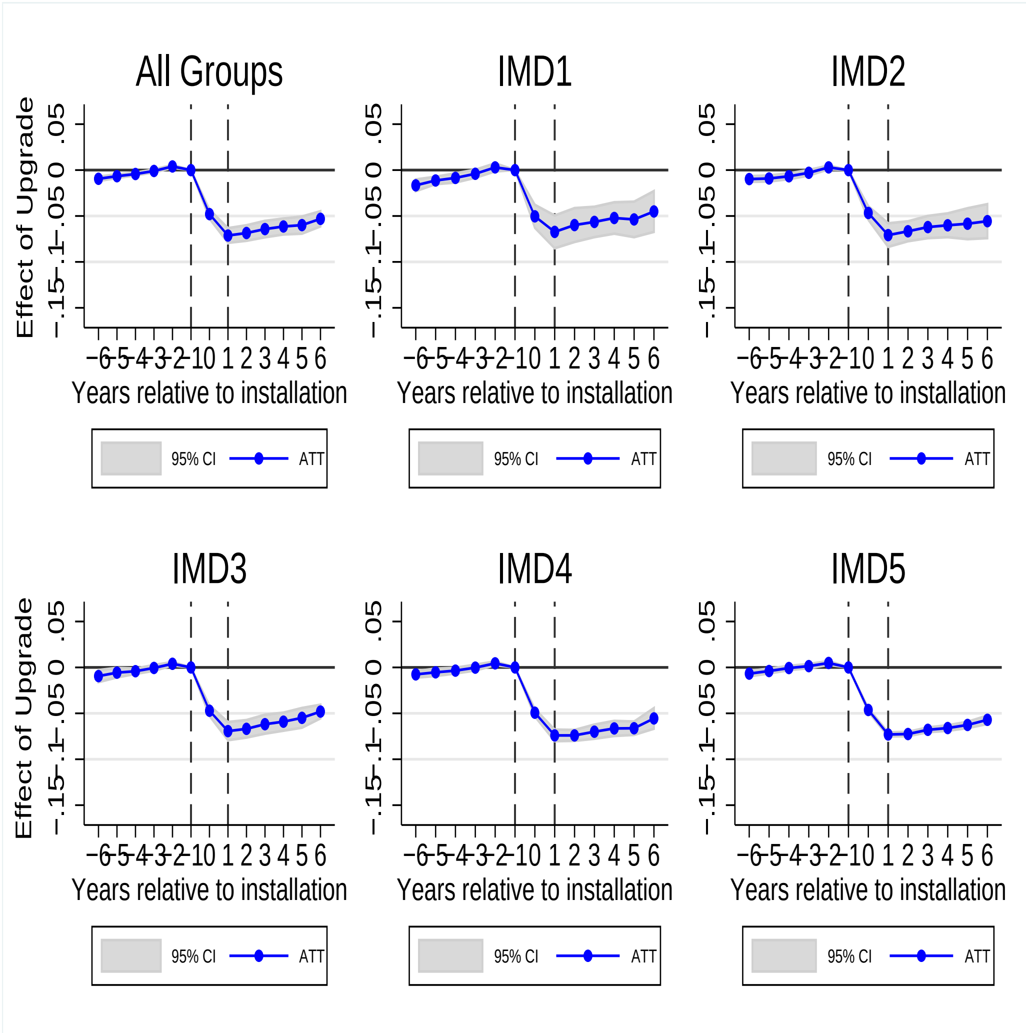



Figure 5: Heating system replacement: Event-study analysis of percentage savings for all households and by IMD Group. Upgrade occurs during period $-1 \leq t \leq +1$

# G Results from alternative specifications

Table G1: Results from alternative specifications

| | (1) Full sample | (2) Only gas | (3) Matched sample | (4) Only gas and matched | (5) Only gas, matched and elec | (6) 50 drop | (7) 60 drop | (8) 70 drop | (9) 70 drop, elec |
|---|---|---|---|---|---|---|---|---|---|
| Cavity wall insulation | -0.092*** | -0.092*** | -0.083*** | -0.084*** | -0.083*** | -0.095*** | -0.096*** | -0.094*** | -0.092*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Loft insulation | -0.025*** | -0.026*** | -0.018*** | -0.019*** | -0.020*** | -0.029*** | -0.030*** | -0.030*** | -0.029*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Replacement boiler | -0.055*** | -0.062*** | -0.038*** | -0.045*** | -0.049*** | -0.090*** | -0.092*** | -0.092*** | -0.091*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| | | | | | 0.179*** | | | | 0.138*** |
| | | | | | (0.000) | | | | (0.001) |
| Control variables | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Household fixed effects | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Year fixed effects | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Year*region fixed effects | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Observations | 20,180,976 | 19,886,106 | 14,090,155 | 13,912,535 | 13,912,535 | 3,516,155 | 4,530,404 | 5,502,936 | 5,502,936 |
| Number of households | 2,527,073 | 2,489,345 | 1,764,246 | 1,741,574 | 1,741,574 | 439,545 | 566,339 | 687,925 | 687,925 |
| Number of households | 0.115 | 0.118 | 0.115 | 0.118 | 0.168 | 0.398 | 0.375 | 0.349 | 0.369 |

**Notes**: This table reports coefficient estimates and standard errors from nine separate regressions. The dependent variable in all regressions is the logarithm of annual gas consumption in kilowatt hours. For each upgrade group a matched control group is created using coarsened-exact matching. The sample includes billing records from 2005 to 2012. Standard errors are clustered at the household level. Triple asterisks denote statistical significance at the 1% level; Double asterisks at the 1% level; single asterisks at the 10% level.

# H Bootstrapping standard errors

Table H1: Comparison of standard error clustering for main model

| | Point Estimate | [95% Conf. | Interval] |
|---|---|---|---|
| *Panel A: Standard errors clustered at the individual level* | | | |
| Cavity wall insulation | -0.09442 | -0.0960 | -0.0928 |
| Loft insulation | -0.02969 | -0.0311 | -0.0282 |
| Replacement boiler | -0.09227 | -0.0936 | -0.0909 |
| *Panel B: Standard errors clustered at the region level* | | | |
| Cavity wall insulation | -0.09442 | -0.1035 | -0.0853 |
| Loft insulation | -0.02969 | -0.0333 | -0.0261 |
| Replacement boiler | -0.09227 | -0.1007 | -0.0839 |
| *Panel C: Standard errors clustered at the region level. Wild bootstrap with 5000 replications* | | | |
| Cavity wall insulation | -0.09442 | -0.1029 | -0.0848 |
| Loft insulation | -0.02969 | -0.0332 | -0.0258 |
| Replacement boiler | -0.09227 | -0.1008 | -0.0836 |
| *Panel D: Standard errors clustered at the region level. Wild bootstrap with 500 replications* | | | |
| Cavity wall insulation | -0.09442 | -0.1031 | -0.0837 |
| Loft insulation | -0.02969 | -0.0335 | -0.0258 |
| Replacement boiler | -0.09227 | -0.1010 | -0.0833 |

# I Cost assumptions

Table I1: Sources of cost assumptions

| | Low | High |
|---|---|---|
| Cavity wall (pre 1976) | 300 | 325 |
| Cavity wall (post 1976) | 300 | 325 |
| Loft 300mm (currently none) | 138 | 273 |
| Loft 300mm (currently 100mm) | 86 | 211 |
| Loft 300mm (currently 200mm) | 35 | 170 |
| Condensing boiler | 100 | 300 |

Source: Shorrock et al. (2005)

Note: All costs in GBP

Table I2: Sources of cost assumptions

| | EESOP1 (1994) | EESOP2 | EESOP3 | EEC1 (2005) |
|---|---|---|---|---|
| Cavity wall insulation | 223 | 219 | 261 | 261 |
| Condensing boiler | 450 | 270 | 165 | 114 |

Source: Lees (2006)

Note: All costs in GBP

Table I3: Sources of cost assumptions

| | Defra EEC1 | Defra EEC2 | Defra CERT | Lees 2005 | Lees 2008 |
|---|---|---|---|---|---|
| Cavity wall insulation | 268 | 313 | 380 | 274 | 350 |
| Loft insulation (top up) | 213 | 260 | 286 | 217 | 275 |
| Loft insulation (virgin) | 213 | 260 | 286 | 252 | 295 |
| A and B boiler | 145 | | | 120 | |
| A and B boiler and heating control | 217 | | | 190 | |
| All boilers | | | 50 | | 45 |

Source: Lees (2006, 2008)

Note: All costs in GBP

# J Carbon saving assumptions

Table J1: Assumptions for CO2 saving calculation

| | (1) Cavity wall insulation | | (2) Loft insulation | | (3) Replacement heating system | |
|---|---|---|---|---|---|---|
| | **Gas** | **Elec** | **Gas** | **Elec** | **Gas** | **Elec** |
| kg CO2 per (kWh) | 0.18 | 0.52 | 0.18 | 0.52 | 0.18 | 0.52 |
| Total annual saving (kWh) | 1551.46 | 67.51 | 546.22 | 10.74 | 1363.85 | 52.29 |
| Total annual saving (kgCO2) | 284.85 | 35.42 | 100.29 | 5.63 | 250.40 | 27.43 |
| Lifespan | 30 | 30 | 30 | 30 | 12 | 12 |
| Total lifetime savings (kgCO2) | 8545.41 | 1062.54 | 3008.56 | 168.99 | 3004.82 | 329.16 |

**Notes**: Source: Based on DEFRA/DECC Greenhouse gas conversion factors 2011. Available at https://www.gov.uk/government/publications/2011-guidelines-to-defra-decc-s-greenhouse-gas-conversion-factors-for-company-reporting-methodology-paper-for-emission-factors

# K Comparison of cost-effectiveness

Table K1: Comparison of cost-effectiveness

| Intervention type | Reference | Evaluation type | Relevant subset | Percent reduction in energy usage | Engineering estimates of percent reduction in energy usage | Cost effectiveness (cents per kWh saved, 2015 USD) |
|---|---|---|---|---|---|---|
| Behavioral programs | Allcott (2011) | RCT | NA | 2 | | 3.6 |
| | Allcott and Rogers (2014) | RCT | One-shot intervention | | | 4.4 |
| | | | Two-year intervention | | | 1.1 to 1.8 |
| | | | Four-year intervention | | | 1.2 to 1.8 |
| | Ayres et al. (2013) | RCT | Sacramento, California | 2 | | 5.5 |
| | | | Puget Sound, Washington | 1.2 | | 2 |
| Building codes | Novan et al. (2017) | RD analysis | NA | 1.3 | 20 | 24.4 |
| Efficient equipment or energy savings subsidy | Alberini and Towe (2015) | Matching | NA | 5.3 | | 3.9 |
| | Alberini et al. (2014) | DID | Rebate of $1,000 or more | 0 | | |
| | | | Rebate of $450 | 5.5 | | 47.9 |
| | | | Rebate of $300 | 6.2 | | 28.2 |
| | Burlig et al. (2017) | Machine learning | NA | 2.9 to 4.5 | 11.6 to 18 | |
| | Davis et al. (2014) | DID regression | Refrigerators | 8 | | 27.2 |
| | | | Air conditioners | plus 1.7 | | 4.5 |
| Information provision | Alberini and Towe (2015) | Matching | | 5.5 | | |
| Supplier Obligation (TWC) | McCoy & Kotsch (2018) | Matching, FE regression | Cavity wall insulation | 9.4 | 20.0 | 1.54 to 2.31 |
| | | | Loft insulation | 3 | 5.2 | 3.65 to 5.47 |
| | | | Replacement heating system | 9.2 | 24.9 | 3.02 to 30.19 |
| Previous estimate of UK Supplier obligation (Lees, 2008)) | | | | | | 1.92 |

Note: Adapted from Gillingham et al. (2018)

## References


Alberini, A. and Towe, C. (2015). Information v. energy efficiency incentives: Evidence from residential electricity consumption in Maryland. *Energy Economics*, 52:S30–S40.

Alberini, A., Towe, C., and Gans, W. (2014). Energy efficiency incentives: Do they work for heating and cooling equipment? evidence from Maryland homeowners. *The Energy Journal*.

Allcott, H. (2011). Social norms and energy conservation. *Journal of Public Economics*, 95(9-10):1082–1095.

Allcott, H. and Rogers, T. (2014). The short-run and long-run effects of behavioral interventions: Experimental evidence from energy conservation. *American Economic Review*, 104(10):3003–3037.

Austin, P. C. (2009). Balance diagnostics for comparing the distribution of baseline covariates between treatment groups in propensity-score matched samples. *Statistics in Medicine*, 28(25):3083–3107.

Ayres, I., Raseman, S., and Shih, A. (2013). Evidence from two large field experiments that peer comparison feedback can reduce residential energy usage. *The Journal of Law, Economics, and Organization*, 29(5):992–1022.

BEIS (2013). Fuel poverty statistics.

Brounen, D., Kok, N., and Quigley, J. M. (2012). Residential energy use and conservation: Economics and demographics. *European Economic Review*, 56(5):931–945.

Burlig, F., Knittel, C., Rapson, D., Reguant, M., and Wolfram, C. (2017). Machine learning from schools about energy efficiency. Technical report, National Bureau of Economic Research.

Caliendo, M. and Kopeinig, S. (2005). Some Practical Guidance for the Implementation of Propensity Score Matching. *Journal of Economic Surveys (2008)*, 22(1):31–72.

Davis, L. W., Fuchs, A., and Gertler, P. (2014). Cash for coolers: evaluating a large-scale appliance replacement program in mexico. *American Economic Journal: Economic Policy*, 6(4):207–38.

DECC (2016). Domestic NEED: Methodology Note. Technical report.

Ferraro, P. J. and Miranda, J. J. (2017). Panel data designs and estimators as substitutes for randomized controlled trials in the evaluation of public programs. *Journal of the Association of Environmental and Resource Economists*, 4(1):281–317.

Gillingham, K., Keyes, A., and Palmer, K. (2018). Advances in evaluating energy efficiency policies and programs. *Annual Review of Resource Economics*, (0).

Hamilton, I. G., Shipworth, D., Summerfield, A. J., Steadman, P., Oreszczyn, T., and Lowe, R. (2014). Uptake of energy efficiency interventions in english dwellings. *Building Research & Information*, 42(3):255–275.

Harold, J., Lyons, S., and Cullinan, J. (2015). The determinants of residential gas demand in Ireland. *Energy Economics*, 51:475–483.

Iacus, S. M., King, G., and Porro, G. (2012). Causal inference without balance checking: Coarsened Exact Matching. *Political Analysis*, 20(1):1–24.

Imai, K., King, G., and Stuart, E. A. (2008). Misunderstandings between experimentalists and observationalists about causal inference. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 171(2):481–502.

Lees, E. (2006). Evaluation of the energy efficiency commitment 2002-05. *DEFRA, Wantage (Oxfordshire).*

Lees, E. (2008). Evaluation of the energy efficiency commitment 2005-08. *DEFRA, Wantage (Oxfordshire).*

Novan, K., Smith, A., and Zhou, T. (2017). Residential building codes do save energy: Evidence from hourly smart-meter data. *UC Davis.*

ONS (2011). Office of National Statistics. Technical Report: Welsh Index of Multiple Deprivation 2011. Technical report.

Payne, R. and Abel, G. (2012). UK indices of multiple deprivation - a way to make comparisons across constituent countries easier. *Health Statistics Quarterly, ONS*, 53:22–38.

Shorrock, L., Henderson, J., and Utley, J. (2005). Reducing carbon emissions from the uk housing stock. *BRE Report BR480.*