Quantitative evaluation of deep retrofitted social housing using metered gas data

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Abstract

Research into home energy retrofit is important because most existing homes will operate in 2050. A lack of funding or incentives often prevents home energy retrofit, particularly of social housing. This study analysed retrofitted Irish social housing and their gas meter data, including pre-payment meters that require regular "top-ups" purchased from shops. The data comprised records from 100 retrofit and control group homes throughout 2013–2015.

A novel evaluation of retrofitted rented homes processed meter data into multiple metrics. Gas consumption is computed per house and weather correction is incorporated, enabling statistical testing of the retrofit. A "difference in difference" technique compared the retrofit and control groups. Gas consumptions of the most popular building type are plotted as distribution curves before and after retrofit. Subsequently the energy use intensity (kWh/m^2/year) is computed per home; leading to calculation of the prebound effect. In social housing, prebound effect quantifies energy underconsumption due to self-rationing.

Retrofit significantly reduced gas consumption, and reduced its variance among homes. A small positive skewness in the statistical distribution of home gas consumption prevented characterisation as a normal distribution. The prebound effect is high, but alleviated by the retrofit. Finally, retrofit extended average pre-payment intervals.

Table 1
Nomenclature used in this paper, prebound and rebound meanings from Galvin and Sunikka-Blank [24].

Symbol, acronym or term	Meaning
β_{dd}	difference in difference
BER	Building Energy Rating
EU	European Union
EPC	Energy Performance Certificate
EUI	energy use intensity [kWh/m^2/year]
$\bar{G}$	mean average gas consumption of homes
HDD	heating degree days
kWh	kilowatt-hours
kWh/m^2/year	kilowatt-hours per square metre per year
P_{act}	Actual prebound effect
P_{pred}	Predicted prebound effect
p-value	The smallest level of significance at which the null hypothesis can be rejected. Lower values indicate results of greater significance.
Prebound effect	A measure of the shortfall in actual energy consumption as a proportion of theoretical, calculated consumption.
Rebound effect	A measure of the proportion of an energy efficiency increase used to increase the level of energy services, rather than decrease the level of energy consumption.
σ	Standard deviation

1. Introduction

Energy use in residential and commercial buildings accounts for 40% of EU total secondary energy consumption and greenhouse gas (GHG) emissions [16]. In 2014, the Irish housing sector consumed 23.4% of secondary energy, according to Sustainable Energy Authority of Ireland [50]. The proportion of secondary energy allocated to homes is even higher at 30% when pooled over eight European countries [32]. Furthermore, most existing housing will still operate in 2050 [46]. The long lifespan of homes and their considerable proportion of GHG emissions highlight the role of home energy retrofit. Home energy retrofits are not uniform however, varying in depth and evaluation.

Deep retrofits tend to be described rather than defined. Gupta et al. [27] characterise deep retrofit as multiple measures; fabric, ventilation, heating, lighting and micro-generation that improve energy performance by 65–95%. Filippidou et al. [21] identify deep retrofit in Dutch social housing as a combination of measures, adoption of innovative heat pumps or μCHP and improvement to the entire building fabric. Improving the entire building fabric provides a consistent building envelope. [21] conclude that common “maintenance measures” of improved boiler efficiency or replacement glazing will not achieve Dutch energy performance targets. One or two maintenance measures constitute "shallow" retrofit.

Scaling up deep building retrofit is recommended internationally [15, 38, 37]. Large-scale shallow retrofit predominates in Dutch social housing, however, Filippidou et al. [21] recommend deep retrofit. Gupta et al. [26] propose community led retrofit; possibly combined with an area-based approach supported by local government [15]. Fylan et al. [22] report that local councils or housing associations could maximise retrofit return by scaling up to "area-by-area" while simultaneously treating each dwelling as a whole-house.

The Irish energy agency (SEAI) has launched a domestic retrofit programme, and one of the main aims is "development toward large-scale deployment" [51]. Scaling from building to city levels suffers from a research gap [2]. Koch et al. [33] argue for *neighbourhood* retrofit. Differentiating a *district* as an administrative boundary, the neighbourhood defines a group of buildings both spatially and socially. Galster [23] describes neighbourhoods as bundling attributes including structural characteristics of buildings and infrastructure. A shared infrastructure and similar building structure facilitate the delivery of home energy retrofit at neighbourhood level.

Similarity of building structure includes similarity in thermal envelope. This assumption underpins neighbourhood retrofit proposals by Koch et al. [33]. Their proposals predict that a standard building type exemplifies the average energy use in a neighbourhood of similar homes. They conclude that the energy use of a neighbourhood's homes is expressed as a statistical distribution around a calculated average of a specific building type. Existing research already identifies the building types influencing energy demand. In their review of building stock retrofit in Germany, McKenna et al. [38] forecast that single family houses will account for approximately two thirds of heat demand until 2050. Single family homes dominate heat demand due to their large average area and higher specific heat demand. Having identified a building type, its associated statistical distribution of heat demand would increase prediction accuracy at neighbourhood scale compared to individual homes.

A literature review finds a dearth of empirical plots that illustrate heat demand variation by homes in the same neighbourhood. One exception is an analysis of 41 German houses; providing distribution plots to illustrate energy demand variation among a neighbourhood of passive houses [20].

Social housing facilitates large-scale retrofit, due to a single owner and frequent energy underperformance. The retrofits potentially support social policies by reducing hardship upon low income dwellers. Furthermore, social homes are less likely to be retrofitted by dwellers when compared to owner occupied homes. A drawback is the prebound effect where energy savings are not achieved due to underheating before retrofit [54]. More recently, Galvin and Sunikka-Blank [24] find that a prebound effect combined with low income indicates fuel poverty. They recommend further research to understand the motivations and practices of affected households. A study of social housing in a tower block estimated 40% prebound effect [55]. The study concluded that typical energy modelling is unrepresentative of social housing and retrofit of social housing may not achieve

CO_2 reduction targets. On the other hand, retrofit makes social impacts in thermal comfort, occupant well-being and health.

The overarching aim of this work is to quantitatively evaluate the effectiveness of large-scale retrofit when applied to rented social housing. The novelty herein derives from: i) the retrofit of rented homes as opposed to self-selecting households; ii) customised processing of empirical metered data to produce multiple quantitative metrics and iii) comparison of the treatment group to itself in a prior year and a concurrent control group.

Instead of focusing on individual buildings, individual households or individual retrofit measures this study uses a set of interlinked criteria to capture the effects of scaled retrofit. These criteria measure energy effects to the owner, utility provider and importantly the dwellers. This is achieved through interlinked objectives. First, quantify annual gas consumption by every house, and test the differences after retrofit for statistical significance. Second, select the most popular type of home and plot their distribution of gas consumption before and after retrofit. The plot tests for a statistical distribution function of gas energy demand by buildings of the same type, as proposed by Koch et al. [33]. Third, quantify the prebound effect across all houses based on metered gas consumption. The fourth objective focuses on the homes that pre-pay their supplier for networked gas. Pre-pay meters reduce risk and transaction costs to suppliers, but increase transaction costs upon households [43, 56]. This last objective measures the intervals between gas pre-payments, before and after retrofit.

This quantitative study develops as follows; the background in Section 2 expands on the motivation and evaluation of home energy retrofit, followed by a methodology in Section 3 of quantitative techniques. Subsequently, the calculated results are presented in Section 4, completed by conclusions, limitations and further work in Section 5.

2. Background

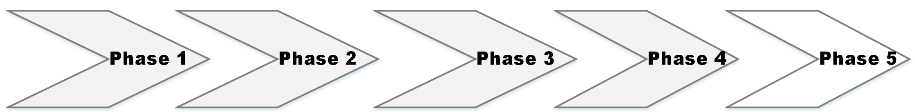
In this study the social housing landlord retrofitted homes to improve comfort and lower energy bills [44]. At the scale of national building stock, retrofit motivation stems from the low rate of annual building renovation; 1-1.5% in Denmark [37], “only” 1% in Britain [28] and in Germany 1% but targeting 2%. McKenna et al. [38] consider the German target rate of 2% rate as ambitious and define renovation rate as the fraction of total living area renovated per year, including supply and demand side measures. Most current buildings will remain in 2050 [46]. Haines and Mitchell [28] estimate that 75% of British dwellings will exist in 2050.

The need for household energy retrofit is more acute in Ireland. According to EPA [18] assessment: “the average Irish household uses just under 50 kWh daily, comprising 13 kWh electricity”. By this metric, Irish homes are the second worst performing in Europe, after Finland. SEAI [46] discusses the energy underperformance of Irish homes in its Residential Roadmap to 2050.

This report outlines scenarios to reduce the 2010 average household energy consumption of 22,500 kWh/year by 60–65% by 2050.

Years later, CRU [11] estimates a lower average energy use by Irish homes at 15,200 kWh/year; split into 11,000 kWh/year gas and 4,200 kWh/year electricity. Nevertheless, the Residential Roadmap assumes the realisation of energy savings by at least one million home retrofits.

Ma et al. [35] address the difficulty in realising retrofit energy savings with a detailed retrofit methodology. They identify five key phases in a complete retrofit programme (Fig. 1). The study presented in this paper executes phase five: "validation and verification".



Project setup and pre-retrofit survey	Energy auditing and performance assessment	Identification of retrofit options	Site implementation and commissioning	Validation and Verification
• Define scope of work • Set project targets • Determine available resources • Pre-retrofit survey	• Energy auditing • Select key performance indicators • Building performance assessment & diagnostics	• Energy saving estimation • Economic analysis • Risk assessment • Prioritise retrofit options	• Site implementation • Test and commissioning (T&C)	• Post measurement and verification (M&V) • Post occupancy survey

Fig. 1. Key phases of building retrofit, completed by validation and verification [35].

Various metrics exist to evaluate building retrofits. Gupta et al. [27] recommend absolute metrics of energy consumption or GHG emissions. Metrics of one-off reductions in energy or GHG emissions ignore long-term building operation. For example, a New Zealand community intervention to retrofit home insulation results in 13% reduction in metered energy compared to the control group [30].

One mandatory building certification is relevant to this study, due to its application by European law. Energy Performance Certificates (EPCs) exist due to the Directive on Energy Performance of Buildings by the European Union. Their purpose is a market tool; creating demand for energy efficiency in buildings [3]. Home EPCs such as the Irish Building Energy Rating (BER) are calculated from modelled, not metered data as discussed in Section 2.1.

2.1. BER: energy performance certification of residential buildings

SEAI [52] have administered the Building Energy Rating (BER) of Irish homes since 2007. A BER certification estimates the primary energy for home energy services: heating, lighting, pumps and fans. This certificate excludes appliances such as cookers, fridges and washing machines. Being a metric of primary energy, BER comprises all "source" energy including production and distribution losses. The energy consumption during a year is divided by home floorspace, expressing a result in kWh/m^2/year. The same building performance metric appears internationally. The United States Energy Star [17] programme terms it "energy use intensity" (EUI). An identical mathematical division by floorspace produces the other BER metric of CO_2 emissions. The two BER metrics are:

- Primary energy value: kWh/m^2/year
- CO_2 emissions indicator: kgCO_2/m^2/year

BER certificates are modelled estimates of home energy performance in terms of primary energy EUI. The certification comprises 15 discrete bands where lower EUI indicates superior home energy performance. Bands ranges from low energy intensity A1, through to high energy intensity G (Fig. 2).

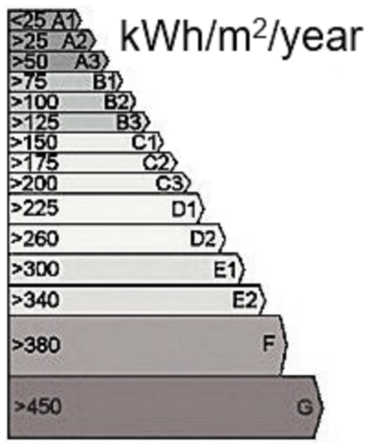


Fig. 2. Discrete BER bands of primary energy use intensity [7].

The average BER certification is band D of 225–300 kWh/m^2/year [46]. Dennehy et al. [13] report a lower average home consumption calculated from energy balances; equating to BER band 150–175 kWh/m^2/year.

BER certifications calculate primary energy by converting a model of secondary energy use. This model, called Dwelling Energy Assessment Procedure (DEAP), executes energy conversions by primary energy factors. The primary energy factor for gas is 1.1, and the 2017 revision for electricity is 2.08 [49].

The assumptions inherent in DEAP are based on building age, standard occupancy and minimum thermal comfort levels. Further drawbacks exist in BER's intended purpose as market information. An analysis of BER ratings from the SEAI Better Energy Homes scheme reveal bunched ratings post-retrofit [9]. The discrete nature of BER bands provides a perverse incentive known as the threshold effect. "Threshold effects refer to the use of minimum performance standards which incentivise improved performance for those below the threshold but lead to stagnation of those above the threshold".

2.2. Reduced energy savings due to prebound effect

The underconsumption of building energy compared to its rated energy performance quantifies the prebound effect. This prebound effect is often caused by occupant self-rationing of energy and increases in homes of inferior energy ratings - the type of homes more likely to be rented. O'Sullivan et al. [42] find that pre-pay metering increases information feedback to consumers, accompanied by risks of self-disconnection and heat self-rationing. They quote examples of self-rationing as prioritising other energy services (such as refrigeration and lighting) instead of heating. The prebound effect is the reverse of the well known "rebound ", the reduction in predicted energy efficiency gains due to increased user demand.

Sorrell et al. [53] exemplify the rebound effect by "temperature take back" in buildings after energy retrofit. Temperature take back occurs where occupants prefer a warmer internal temperature instead of maximum energy and financial savings. Hamilton et al. [29] refer to the reduction in potential energy savings as "comfort taking". The evidence from their research is that lower income households are less likely to realise energy savings compared to higher-income households.

This study computes both energy savings and the prebound effect from metered gas data of rented homes. The results presented in this paper compare the actual prebound effect to predictions defined in Section 3.4, originating from Loga et al. [34].

3. Methodology

This study analyses the gas meter data of rented social housing owned by Respond! Housing Association, hereinafter "Respond!". The purpose is to evaluate home energy retrofits completed in 2014 after Respond! received funding from the SEAI Better Energy Communities scheme [48]. The meter data extends across three calendar years 2013–2015 (Fig. 3).

Respond! selected the retrofit homes. Unlike many home retrofits the households are neither self-selecting nor constrained by household funding. Twenty-four housing estates in over a dozen towns and cities across the Irish Republic benefited from the retrofit programme [44]. The total of 100 gas metered households that permitted access to gas meter data are located in seven housing estates. This total of 100 homes splits evenly into 50 retrofitted group and 50 control group.

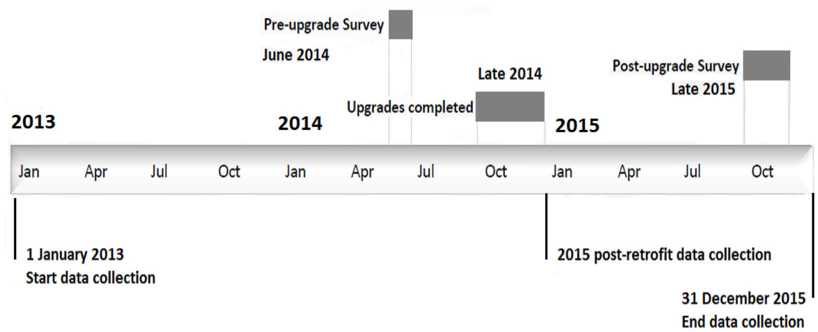


Fig. 3. Retrofit programme timeline. Data collected throughout the calendar years before and after retrofit year 2014 [10].

Data access requests were made during household surveys, permitting this study to access gas meter data from the beginning of 2013 to year end 2015. The household surveys are not considered in this study. Analysis of the household surveys appears in an ESRI working paper [10]. The available data enables statistical tests of the differences in per home gas consumption by data processing (Fig. 4). Post-retrofit gas consumption during 2015 is weather corrected for comparison to 2013 pre-retrofit gas consumption (Section 3.5).

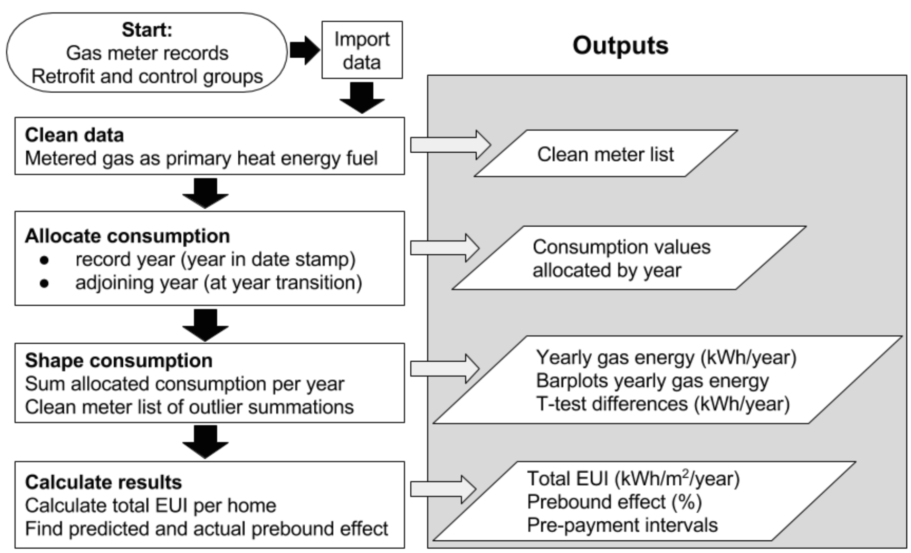


Fig. 4. Overall method of data cleaning, allocation, shaping and results calculation.

3.1. Retrofit Measures

Deep home retrofit delivers a combination of retrofit measures. Six individual measures to upgrade homes of this study are:

- Gas boiler upgrade
- Heat boiler replacement by gas boiler
- Heating controls
- Lighting replacement
- Window and door replacement
- Cavity wall insulation

The first three measures improve the heat generation and its control, while the last two measures improve the building fabric. A "Heat boiler" replaces a back boiler located behind a fire with a new gas boiler. Compact fluorescent lighting (CFL) replaces the existing lighting. Other measures from the retrofit programme are absent from the studied homes: attic insulation and external wall insulation. Data cleaning removes houses below the aforementioned gas consumption threshold and reduces the studied retrofits to 49. Their retrofits are delivered in four combinations of measures (Table 2).

Table 2
Six retrofit measures in a total of four combinations, all include fabric upgrades to windows, doors and walls.

Gas boiler	Heat boiler	Heating controls	CFL lights	Windows and doors	Cavity wall	Total homes
-	✓	-	✓	✓	✓	21
✓	-	-	✓	✓	✓	16
✓	-	✓	✓	✓	✓	11
-	-	-	✓	✓	✓	1

3.2. Processing meter data

Due to the timing of waiver signatures, the quantity of available gas meter data differs across the three years. Imported data from the available meters enters a process beginning with data cleaning. The clean data step ensures valid comparisons of gas consumptions by selecting meters that supply the primary heat energy fuel to the home (Fig. 4). In order to be considered a home's main source of heat energy, the gas meters consume a minimum threshold of 1,500 kWh during 2013. The threshold is 10% of reported non-electric energy per home in 2011 [13]. The clean data step outputs a list of meters that supply the main heat energy during years 2013–2015.

Metered gas consumptions are allocated, shaped and input to calculations of energy use intensity and prebound effect. Automation of the data processing is performed by R statistical software and its “lubridate” library developed by Grolemund and Wickham [25].

The “Allocate” consumption step apportions a consumption to its year of recording and an adjoining year where applicable. Most gas consumption records are apportioned completely to the year recorded, except those closest to adjoining years. This step outputs gas energy allocations in kWh to year of recording, the previous year and the following or “latter” year using defined equations (Appendix A.1).

The “Shape consumption” step sums the gas allocations into the three calendar years 2013, 2014 and 2015, using defined equations (Appendix A.2). Meters failing the aforementioned minimum consumption threshold are removed. This step outputs total gas consumption per home, per calendar year in kWh/year. After weather correction, the yearly gas consumption by each home during 2013 and 2015 are compared. Boxplots display the pattern of gas consumption by the retrofit and control groups pre-retrofit 2013 and post-retrofit 2015. Barplots illustrate the yearly gas consumption differences between the same homes during the same years.

3.3. Statistical tests on gas consumption results

A paired t-test was used to test the hypothesis of reduced home gas consumption after retrofit. The t-test is “paired” because it compares the 2013 and 2015 consumption paired by each home. The Engineering Statistics Handbook describes how a t-test determines if two population means are equal [40]. If the measured means of gas consumption before and after retrofit are different with statistical significance, the retrofit most likely reduced gas consumption. As mentioned in Table 1, a lower p-value corresponds to more significant hypothesis result. The p-value is the probability of observing the difference in means in a retrofit sample, without a difference in means existing in a population of all retrofitted homes. In other words, it is the probability that the null hypothesis is true. A null hypothesis states that the retrofit had no impact on the mean gas consumption.

This statistical test was applied to the gas consumption results grouped by retrofit and control; then the sub-categories of post-pay and pre-pay meter types. Note that the control group comprises similar homes owned by Respond! during the same years 2013–2015.

Another technique that directly compares results between the retrofit and control groups, is “difference in difference”. Difference in difference incorporates other factors impacting gas consumption by directly comparing the retrofit group to a concurrent control group. Potential factors are extreme weather events or pricing; the latter is discussed in results (Section 4.1).

Both the retrofit and control groups have two averages of 2013 and 2015 home gas consumption ($\bar{G}_{2013}$, $\bar{G}_{2015}$). Difference in difference technique computes four averages in total. Therefore each group has their own change in averages between 2013 to 2015. The parameter β_{dd} is the difference between the each group’s change in averages from 2013 to 2015 (Eq. 1). Adan and Fuerst [1] and

Scheer et al. [45] employ the difference in difference technique and interpret its result as the reduction due to retrofit.

$$\beta_{dd} = (\bar{G}_{2013} - \bar{G}_{2015})_{retrofit} - (\bar{G}_{2013} - \bar{G}_{2015})_{control} \qquad [kWh/year] \qquad (1)$$

The most common building type in the retrofit group is a semi-detached, two storey, single family home. Statistical distributions of gas consumption are plotted for these similar buildings to allow comparison. These distributions are the only plots based on the single most popular home type. All other plots include the remaining home types. The reduction in average gas consumption and its variance between 2013 and 2015 are computed.

3.4. Calculation of prebound effect and pre-payment intervals

The final step calculates two result: the prebound effect and pre-payment intervals. The prebound effect described in Section 2.2, is a proportion of the BER. As mentioned in Section 2.1, the BER is a metric of primary energy.

Metered domestic gas consumed is secondary or "site" energy. The conversion from secondary to primary energy relies on parameters in the DEAP procedure. The procedure includes lights, pumps and a gas primary energy factor of 1.1. DEAP variables complete the home EUI calculation of Eq. 2: lighting 9.3 kWh/m^2/year, central heating pump 130 kWh/year and gas boiler flue fan 45 kWh/year [47].

$$EUI = 9.3 + \frac{(gas\ energy \times 1.1) + 130 + 45}{floor\ area} \qquad [kWh/m^2/year] \qquad (2)$$

The actual prebound effect (P$_{act}$), found with Eq. 3, is a function of the EUI and the BER. As as dimensionless proportion it may be expressed in %.

$$P_{act} = 100 \times \left(1 - \frac{EUI}{BER}\right) \qquad [\%] \qquad (3)$$

The BER determines a predicted prebound (P$_{pred}$) using Eq. 4 developed by Sunikka-Blank and Galvin [54] from a model based on German homes by Loga et al. [34]. This study presented here quantifies the BER variable as the lower threshold of the BER band; for example a B1 band converts to a 75 kWh/m^2/year (Fig. 2). Selection of a lower BER moderates the prebound results.

$$P_{pred} = 100 \times \left(1.2 - \frac{1.3}{(1 + \frac{BER}{500})}\right) \qquad [\%] \qquad (4)$$

Finally, one indicator of transaction costs due to pre-pay meters is the prepayment intervals. The subset of pre-pay meters in retrofitted homes is identified for years 2013 and 2015. The pre-payment intervals amongst the retrofit group are converted into days by R statistical software and categorised.

3.5. Weather correction and comparison of gas consumption

Although outside temperature differences are implicit when comparing retrofit and control groups, it is good practice to quantify weather differences by heating degree days (HDD). The Chartered Institution of Building Services Engineers describe HDD degree days as a tool to analyse weather related energy consumption in buildings [8].

Degree days quantify the difference between the outdoor temperature and a reference temperature over a specified period. CIBSE recommends daily summation of positive hourly temperature differences from a 15.5°C base temperature. Dividing the summation by 24, converts the hourly degree difference into degree days. This study inputs hourly temperature data from Met Éireann, into a standard weather correction defined in Eq. 5 [36].

$$Weather\ correction\ factor\ (post\text{-}retrofit) = \frac{\sum (HDD\ pre\text{-}retrofit)}{\sum (HDD\ post\text{-}retrofit)} \quad (5)$$

After weather correction, the 2015 gas consumption per home is compared to 2013. The first test compares the differences in gas consumption, per individual home, before and after retrofit. This paired t-test, treats the 2013 and 2015 gas consumption of each home as an individual pair. As mentioned, the number of retrofitted homes with available metered data increases during 2015. The larger set of 2015 gas consumptions cannot all be paired with 2013 gas consumptions, but are plotted as a statistical distribution (Section 4.4).

4. Results and discussion

The timing of data waivers reduced the meter data during 2013. Data cleaning subsequently removed eight homes that fail the minimum gas consumption threshold, as discussed in Section 3.2. Seven homes fail the threshold during 2013, as does one home during 2015.

As a result, the study analysed 20 retrofit group and 25 control group meters that provide paired meter data throughout 2013–2015. The number of retrofit group meters increases to 49 by 2015, the final year of the study. The retrofit 20 meters from 2013 are a subset of the 49 meters available in 2015 (Table 3).

Table 3
Gas meters with available data after data cleaning.

Year	Retrofit	Control	Total
2013	20	25	45
2015	49	37	88

A few of the same meters indicated fuel switching after retrofit. During 2013–2015, eight gas meters exchanged from post-pay to pre-pay. No meters reverse exchanged from pre-pay to post-pay. Pre-payments constitute the majority of meter records due to their shorter intervals (Section 4.6). This study measures pre-payment intervals between non-zero payments, excluding the 8% of zero value pre-payments.

The weather correction factor is applied to comparisons of gas consumption between 2013 and 2015 (Section 3.5). Gas consumption in 2015 is scaled up due to the slightly warmer outdoor air temperature during that year. Heating degree days reduced from 2000 during 2013 to 1937 during 2015; causing a weather correction factor of 1.03 (Eq.5). Having secured a cleaned list of meters and the weather correction factor, the following four objectives are calculated:

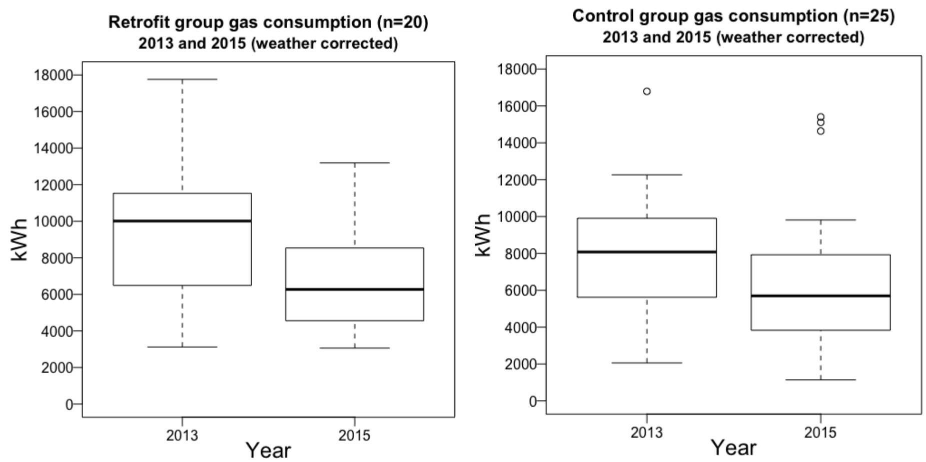
1. Quantify and test for differences in annual gas consumption per home
2. Plot the density of gas consumption by semi-detached home type
3. Quantify the prebound effect
4. Illustrate the measured intervals between pre-payments

Household sizes range from one to eight but a majority are of two or three persons. Household composition and occupant behaviour are, however, not analysed separately. One reason is the small sample sizes of most household types. Another reason is that household variables have limited accuracy in identifying homes with cold indoor temperature [31], unless extended to a persona-based approach [28].

In this study, household and other user variables manifest in the variation of the distribution density of gas consumption (Fig. 8). This variation reduces after retrofit, illustrating a reduced influence of user-specific variables.

4.1. Yearly gas consumption per home

The annual gas consumption of all homes during 2013 and 2015 was computed and weather corrected. The results, including outliers, are split into boxplots and are all used in this study's analysis. Fig. 5a summarises the gas consumption of the retrofit group in 2013 and 2015. Between the two years, the retrofit group medians reduced from 10,011 to 6,271 kWh; while standard deviations (σ) reduced from 3,952 to 2,678 kWh. Fig. 5b summarises the control group gas consumption over the same two years. The control group reduces its median gas consumption from 8,078 to 5,696 kWh and σ from 3,243 to 3,955 kWh.



(a) Retrofit group (b) Control group

Fig. 5. Gas consumption by group during 2013 and 2015 (weather corrected)

Annual gas consumption is dis-aggregated to illustrate yearly gas consumption per anonymous home (Fig. 6, Fig. 7). Of the 20 retrofitted homes, 16 (80%) reduced gas consumption during the post-retrofit year 2015. Of the four increases in gas consumption after retrofit, the three largest are reported by the minority pre-pay meter type (Fig. 6; indices 14, 18 and 20), index 11 refers to a post-pay meter. Hence, these three pre-pay meters indicate possible self-rationing during 2013 and high post-retrofit rebound effect. Fuel switching may also be a factor. Three post-pay meters report large system overestimates during the post-retrofit heating season (Fig. 6; indices 4, 17, 19). Such overestimates add independent evidence of reduced gas consumption.

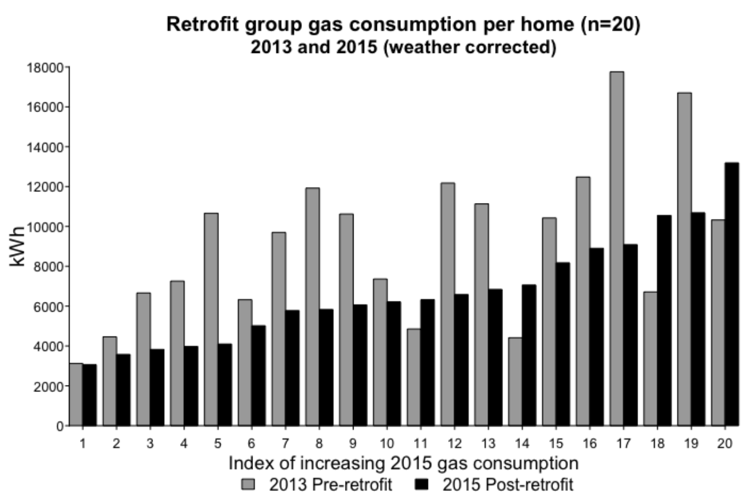


Fig. 6. Retrofit group gas consumption: 2013 and 2015 (weather corrected).

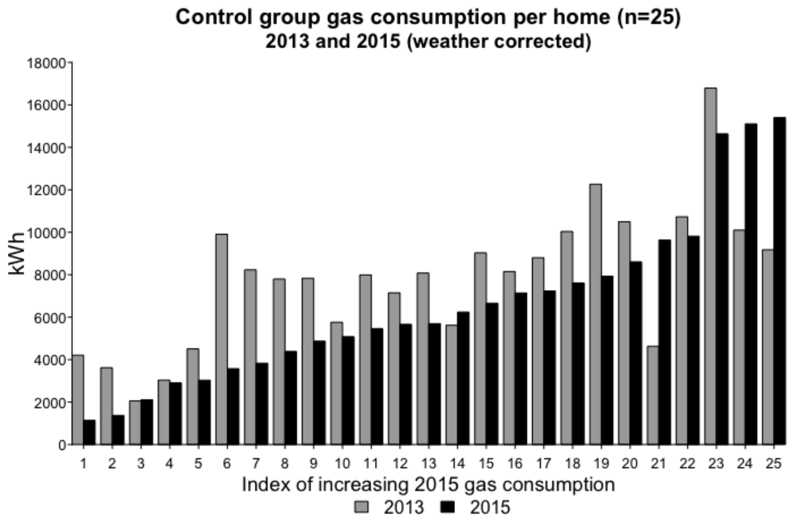


Fig. 7. Control group gas consumption: 2013 and 2015 (weather corrected).

Turning to the control group, its annual gas consumption during 2013 and 2015 appears in Fig. 7. Of the 25 homes, a majority of 21 (84%) reduced gas consumption between 2013 and 2015. Two of the four meters that increase gas consumption are pre-pay (Fig. 7; indices 21 and 24). Similar to the retrofit group, these two control group pre-pay meters indicate self-rationing during 2013.

Note that two control group meters exchanged from post-pay to pre-pay after the 2012–2013 heating season (Fig. 7; indices 5 and 6). They report the largest and third largest absolute reductions in gas consumption. The change to pre-pay metering may have contributed to their reductions.

According to Ireland's CSO, residential consumption of networked gas was 6.7% higher in 2013 than 2015; 7,752 GWh and 7,262 GWh respectively [12]. Hence, a reduction in gas consumption by the control group is expected between the same years. Since the aforementioned weather correction provides insufficient scaling up of 2015 gas consumption, gas price is the likely alternative cause. During 2013 annual gas prices were 3% lower at €0.0653/kWh compared to €0.0673/kWh during 2015 [19]. Moreover the lowest residential consumption of networked gas between 2011–2016 occurred in 2014, coinciding with peak annual prices to households of €0.0681/kWh. These summary comparisons evince a negative correlation of annual residential gas consumption with annual gas price, potentially explaining the differences in gas consumption after weather correction (Fig. 7).

4.2. Tests for differences in mean gas consumption per home

The difference in mean gas consumption between 2013 and 2015 were investigated using the paired t-test (Section 3.3). The retrofit and control groups were tested for difference in mean consumption between 2013 and 2015, followed by their sub-categorises of pre-pay and post-pay meter types (Table 4).

Considering the available retrofit group (n=20), their difference between mean gas consumption of 2013 and 2015 is 2,512 kWh with p-value=0.004. The low p-value equates to a highly significant t-test result, despite dweller "comfort taking" of energy savings (Section 2.2).

Turning to the control group, its mean difference between 2013 to 2015 is 1,235 kWh, less than half that of the retrofit group. Control group p-value=0.045 or 4.5%; less significant than the retrofit group. Nevertheless, a significance under 5% indicates a difference within the control group between 2013 and 2015 gas consumption caused by factors other than retrofit, for example pricing (Section 4.1).

Reviewing p-values in Table 4, the most significant differences appear in the post-pay metered homes. A contributory reason for the difference is the larger average floorspace of post-pay metered homes. Other reasons linked to the meters themselves may be higher self-rationing by pre-pay households during 2013, coupled with higher metering accuracy due to shorter pre-payment intervals. Post-pay meter records recur every 63 days, but weekly pre-payment intervals are the most common (Section 4.6).

Table 4
Paired t-test of the same meters yearly gas consumption during 2013 and 2015 (weather corrected).

Group	Meter type	Pair size (n)	Mean differences 2013–2015 (kWh)	p-value*
retrofit	all	20	2512	0.004
retrofit	post-pay	9	3709	0.006
retrofit	pre-pay	11	1532	0.185
control	all	25	1235	0.045
control	post-pay	17	1376	0.026
control	pre-pay	8	934	0.541

*Statistical significance of difference in mean gas consumption from 0 kWh.

4.3. Difference in difference and cost saving estimates

The difference in difference (β_{dd}) is calculated by substituting mean difference values from Table 4 into Eq. 6. As mentioned in Section 3.2 it is interpreted as the reduction in gas consumption due to retrofit.

$$\beta_{dd} = (\bar{G}_{2013} - \bar{G}_{2015})_{retrofit} - (\bar{G}_{2013} - \bar{G}_{2015})_{control} \quad (6)$$

$$\beta_{dd} = 2512 - 1235 = 1277 \qquad [kWh] \quad (7)$$

The mean difference in gas consumption by 20 retrofitted homes between 2013 and 2015 is 2,512 kWh. Without a control group the 2,512 kWh average difference appears large; equating to over 27% of the 2013 mean consumption

9,253 kWh. The 25 control group homes, owned by Respond! in Ireland, provided a reference to the retrofit group. Control group homes simultaneously reduced mean gas consumption by 1,235 kWh, almost half of the retrofit group mean reduction. Such a high ratio of control to retrofit reductions was unexpected after the application of weather correction to 2015 metered data (Section 3.5).

The difference in difference test resulted in a p-value of 9.7%. Thereby, the null hypothesis of no difference between the retrofit group differences and the control group differences is rejected at 10% significance, but not at 5% significance. Given the relatively small sample size, further analysis should be conducted. Finally, the mean difference between the retrofit and control groups is 1,277 kWh (95% confidence interval: -675 to 3,228). This mean difference of 1,277 kWh represents 13.8% of the retrofitted homes 2013 mean of 9,253 kWh.

A typical cost saving per home is estimated from the difference in difference of gas consumption at 1,277 kWh and representative tariff €0.06/kWh [4]. In the context of the social costs of cold homes, the energy saving converts to €77.62 or 13% of the €585 yearly Fuel Allowance provided by Government [14]. The largest home gas saving of 8,676 kWh due to retrofit converts to €521, still below the €585 allowance. Cost savings from reduced gas consumption will not offset the Fuel Allowance, partially due to the relatively low cost of utility supplied gas.

4.4. Distribution of gas consumption by semi-detached home type

As mentioned, Koch et al. [33] propose expression of neighbourhood energy use as a statistical "distribution function around a mean value". The mean value corresponds to "a specific calculation of a building type". In this study one building type predominates. The semi-detached, two storey building type accounts for 42 of the available 49 retrofitted homes; complemented by three apartments, three bungalows and a single terraced house.

Three distributions of metered gas consumption are superimposed for comparison (Fig. 8). The distribution comparisons are plotted using smoothing methods in R [5]. Smoothing parameters are selected as "asymptotically optimal for the normal distribution" and rely on kernel techniques [6]. Each distribution represents a sample density of structurally similar semi-detached houses. The two n=16 plots are the same homes before and after retrofit, years 2013 and 2015 respectively. The n=42 plot is a superset, containing the 16 homes of the other two plots after retrofit.

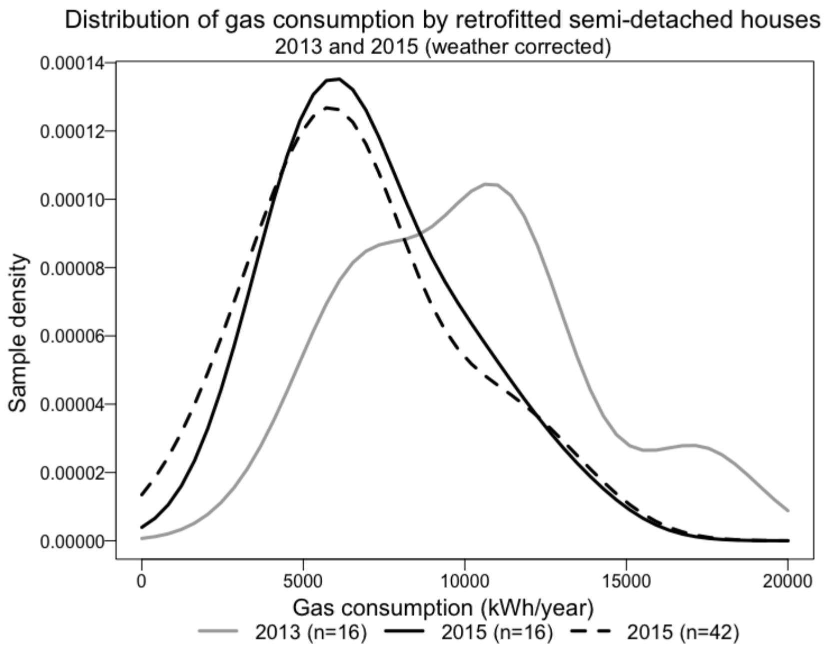


Fig. 8. Distribution of 2013 and 2015 (weather corrected) gas consumption by semi-detached houses.

The solid irregular grey line distributes the gas consumption of 16 semi-detached homes during 2013 before retrofit (Fig. 8). The 16 consumption values are a subset of the 20 values available for all retrofit homes (Fig. 6). Subset mean is 10,137 kWh/year, peaking at 17,760 kWh/year during 2013. As a result, this asymmetric distribution plateaus around 18,000 kWh/year and with high variance (σ=3,678).

After retrofit, a solid black line distributes the same 16 homes with improved symmetry and reduced variance (σ=2,688). Finally, the broken line of 42 retrofit homes during 2015 includes the previous 16 homes and further enhances the post-retrofit distribution (Fig. 8). The increased set of 42 semi-detached homes reduces the mean from 7,105 (n=16) to 6,718 kWh/year (n=42), but increases variance (σ=3,019). As expected, the n=42 distribution converges its mean and median, 6,718 kWh/year and 6,232 kWh/year respectively.

Taking the 2013 mean gas consumption of 10,137 kWh/year, the same 16 houses reduce that mean by 30%. When compared to the larger set of 42 retrofitted homes, the reduction in mean gas consumption increases to 34%. The percentage reductions in mean gas consumption exceeds that of the distribution variance. The 2013 standard deviation of 3,678 kWh/year reduces by only 18% to 3,019 kWh/year during 2015 (n=42).

The positive skewness of both 2015 statistical distributions prevent classification as a symmetric normal distribution. From the distribution curves, it can be seen that high gas consumers persist after retrofit. The n=16 2015 consumption peak of 13,188 kWh/year is followed by 10,685 kWh/year. The n=42 consumption adds one higher value of 13,915 kWh/year, forming five values above 11,000 kWh/year. This cluster of values exceeding 11,000 kWh/year disrupts the smooth distribution curve, but are not boxplot outliers (Fig. 5a).

Considering the other extreme, the 2015 (n=42) consumption contains two values near the minimum threshold of primary heat fuel - 1,500 kWh/year (Section 3.2). The smoothed distribution extrapolates these low values to a sample density greater than 0.00001 for homes consuming no gas at all. Such a high sample density at low gas consumption levels is an exaggeration due to plot smoothing. Practical occurrences would be due to combinations of non-occupancy, alternative primary heat fuel and self-rationing (Section 4.5).

4.5. Prebound effect

The prebound effect is described and its formulae defined in Sections 2.2 and 3.4. The actual prebound effect (P_{act}) mostly exceeds that predicted by a German model (P_{pred}), across both retrofit and control groups (Figs. 9 & 10).

Amongst the retrofit group, the 2013 P_{act} mean is 42.5% (n=19). During 2013, only two retrofit group homes overconsume energy compared to their BER certification, producing negative 2013 P_{act} points (Fig. 9). During 2015, four retrofitted homes display negative P_{act}. Prebound measures the unused proportion of the modelled energy certification, thus negative prebound identify energy use exceeding the same energy certification. High prebound values indicate that dweller comfort would benefit from the planned home retrofit.

Retrofit alleviates the prebound effect as expected; reducing the 2015 P_{act} mean to 36.6% (n=36). Overall prebound reduction after retrofit is illustrated by curves fitted to 2013 and 2015 prebound values (Fig. 9; 2013 P_{act}, 2015 P_{act}). The fitted curves are computed by a non-linear least squares function, and extend over different BER bands due to retrofit upgrades.

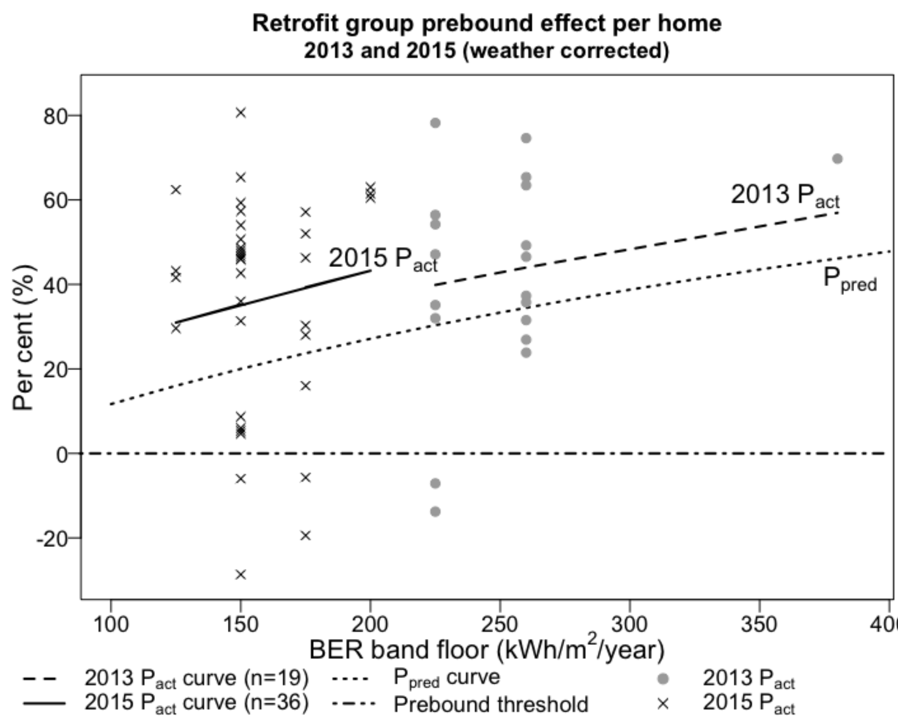


Fig. 9. Retrofit group prebound effect 2013 and 2015, reduced by retrofit but consistently above predictions for German homes [34].

Turning to the control group, the 2013 P_{act} mean of 44.1% (n=25) marginally exceeds the 42.5% mean of the retrofit group during the same year. One cause may be the superior average BER compared to the retrofit group. Control group P_{act} values increase slightly in 2015 to a mean of 49.7%, as illustrated by the fitted curves (Fig. 10). Likely causes of increased prebound during 2015 are the aforementioned lower degree days and higher gas tariffs. Reviewing both the retrofit and control plots, the P_{act} fitted curves increase with band of BER certification as expected.

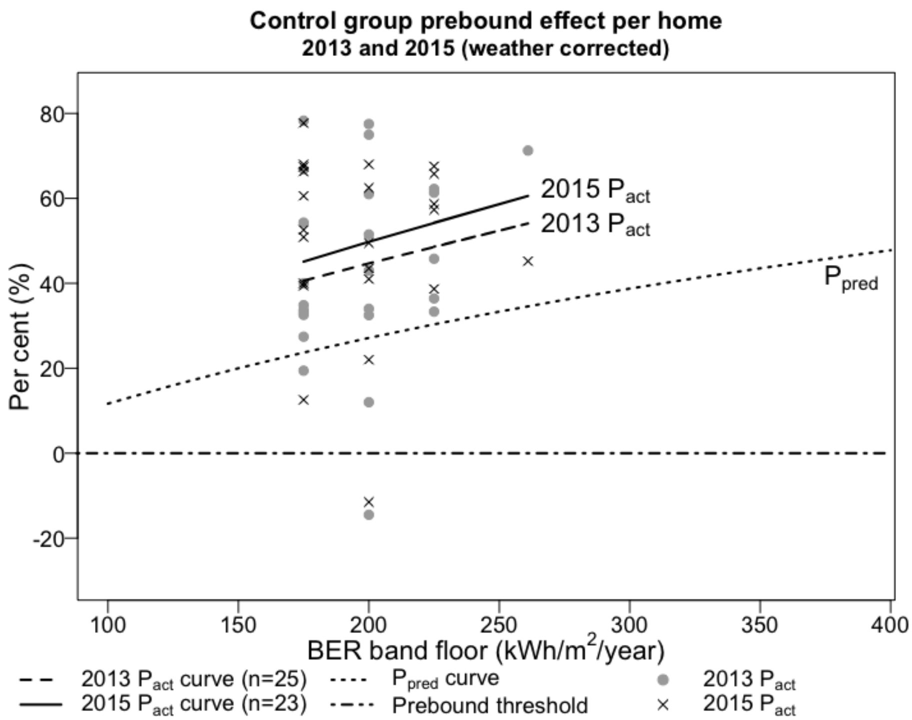


Fig. 10. Control group prebound effect 2013 and 2015, increasing in 2015 and consistently above prediction for German homes [34].

After conversion of the dimensionless prebound effect to EUI (kWh/m^2/year), the 2013 retrofit group (n=19) displays greater absolute prebound than the 2013 control group (n=25). Where prebound is expressed in EUI, the 2013 retrofit group mean of 110 kWh/m^2/year exceeds the 88 kWh/m^2/year of the control group. The 2015 retrofit group reduces its mean absolute prebound to 58 kWh/m^2/year (n=36), substantially under the 2015 control group mean of 98 kWh/m^2/year (n=23). In summary, retrofit alleviates the prebound effect to below that of the control group when expressed in EUI and proportion (%).

4.6. Prepay meter payment intervals

Pre-payment intervals demonstrate patterns of consumer transactions and potentially their budgeting. O'Sullivan et al. [41] define interval categories but rely on self-reported results at household scale. This study adopts the same interval categories; but measures empirical results of each non-zero pre-payment.

To allow comparison, available meters must operate as pre-pay throughout 2013–2015. This constraint reduces the group sizes to 10 retrofit and 6 control meters. During 2013, control group average fewer pre-payments; approximately 30 per meter but of greater average energy (>200 kWh). In contrast, the retrofit group average 44 repayments per meter of smaller average energy (150 kWh). In 2015, average pre-payments per year by the retrofit group reduce by 13%

to 38 per meter. The quantity of control group pre-payments remains steady (Fig. 11).

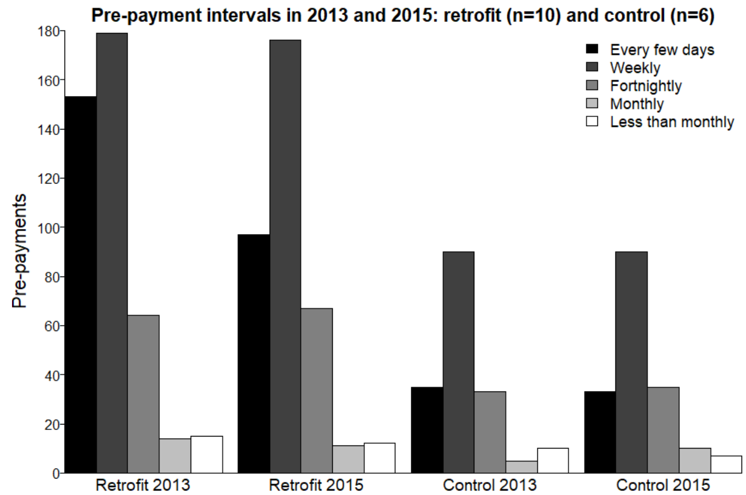


Fig. 11. Pre-payment intervals of a the same retrofit and control groups during 2013 and 2015. The retrofit group shifts a proportion of payments occurring every few days to weekly.

The number of pre-payments occurring every few days by the retrofit meters reduces by 37% from 153 to 97 (Fig. 11). Simultaneously, the weekly interval increases its proportion of retrofit meter pre-payments to almost half at 47.7%.

Control group pre-payments in the same interval category remain steady at 35 and 33. The 2015 control group resembles the proportion of pre-payments in O'Sullivan et al. [41]: 18% every few days, 52% weekly, 22% fortnightly, 6% monthly and 2% less than once monthly.

The data indicates that retrofit increases the interval between pre-payments, mainly those payments previously occurring every few days. A by-product of home retrofit for pre-payment households appears to be reduced transactions and inconvenience upon dwellers.

5. Conclusions and future work

Analysis of the available meter data illustrates that deep retrofit has the potential to significantly reduce gas consumption by social housing in Ireland. The deep retrofits, selected by the social housing owner, upgrade homes traditionally prone to the prebound effect. This study finds a 13.8% mean reduction in gas consumption by the difference in difference technique. By this metric, the study concurs with 13.3% reduction in Britain [1] and 13% in New Zealand [30]. As expected, this study finding of 13.8% gas reduction is below the 21% average reduction by 444 self-selected households analysed by Scheer et al. [45].

This study of social housing also contrasts with those higher income, self-selected, households in operation after retrofit. The mean gas consumption by

42 semi-detached social housing after retrofit is 6,718 kWh/year (Section 4.4). Irish self-selected homes more than double the social housing mean gas consumption with a mean of 14,124 kWh/year persisting after their retrofit [45]. In environmental terms, the associated GHG reductions are far short of the 80% targeted by a British retrofit programme [27].

Differences in the weather corrected gas consumption between 2013 and 2015 were seen in both the retrofit and control groups, but the mean differences were higher in the retrofit group. The deep retrofits of home fabric, gas boilers and their controllers are effective without complicated energy storage or local energy generation. On the other hand, this study of rented social housing found that the bulk of the gas consumption remains after retrofit, albeit from an already low baseline before retrofit.

Homes of the same structural type reduce their mean and variance in gas consumption. The reduced variance reshapes the statistical distribution of gas consumption towards a normal but somewhat skewed curve. High measures of prebound effect are calculated in the retrofit and control group. Retrofit reduces the prebound effect as expected. Reduced prebound effect in low income households is welcome because it reduces the risk of self-rationing.

This study is prevented by data unavailability from executing a paired t-test on all retrofit homes between 2013 and 2015. Two other limitations with the gas meter records appeared during the analysis. First, estimated final consumptions at the end of 2015 would be more accurate with the first meter readings of 2016 (Appendix A.1.2). Second, any self-disconnections are obscured by the reporting of meter payments without visibility of possible meter zero balances.

Comparing meter types, the pre-pay meters display the biggest difference in statistical p-values between retrofit group (0.185) and control group (0.541). This means that the difference in retrofitted pre-pay metered homes is much more unlikely to be caused by chance, compared to its pre-pay meter control group. Pre-pay metered households generally minimise gas consumption due to information feedback and the transaction costs of pre-payments.

In terms of absolute energy savings the post-pay households are assisted by their larger floorspaces and report larger energy savings. A sole focus on absolute energy savings could lead to selection of only post-pay homes as recipients of limited retrofit resources. The authors do not recommend home retrofit selection by a single home characteristic to achieve a sole evaluation metric. One observed reason is the dynamic nature of a the home characteristic of pre-pay metering. Eight meters exchanged from post-payment to pre-payment meter type, with no reports of reverse meter exchanges. In literature Hutchinson et al. [31] describe how property and household characteristics provide only limited prediction potential of energy efficiency in homes due to occupant choices. The occupants making the choices will also change from time to time.

The authors recommend the neighbourhood and community retrofit approach to economically deliver multiple objectives of home retrofit. As mentioned, the multiple objectives are energy savings, reduction of variance in neighbourhood energy consumption, reduced prebound linked to self rationing and finally reduced transaction costs for occupants.

The first objective of energy savings has been evaluated already. Any concomitant savings in operational costs depend on occupant schedules, current and future energy tariffs. Retrofitting an existing gas heated rented home returns small cost savings (Section 4.3). Current gas tariffs limit operational cost savings to a fraction of the State provided Fuel Allowance. Small operational cost savings postpone payback periods into the distant future and impact the aims of other home retrofit programmes. Reviewing Retrofit for the Future, Gupta et al. [27] refer to the "Golden Rule" that retrofit is repaid by energy savings but unintentionally restricts GHG reductions. A longer view is that natural gas fuel is finite and reduced home heat demand facilitates any future electrification of heat.

The second objective plotted the statistical distribution curves of the 2013 and 2015 gas consumption by the retrofit group. Two 2015 plots illustrate reduced mean and variance of the gas consumed by structurally similar homes. This reduced variance in gas consumption by type of home is predicted in literature and referred to as increased homogeneity [33]. Despite the increased homogeneity, a skewness in the statistical distribution by approximately 10% of the retrofitted homes prevents its characterisation as a symmetric Normal distribution. Skewness of the distribution manifests in its mean values exceeding the median.

Translated into practice, a small proportion of high gas consumers persist in these socially rented homes after retrofit. The gas consumption of 11,000 kWh/year to identify skewed observations in the study's rented social housing, is in fact average home gas consumption [11]. Therefore one may accept the minority of high heat demand in the rented social housing, especially as the population ages and proportion of retirees increases. Assuming the users are educated and their home heat controls work, further progress to GHG reduction may require an energy systems approach. An neighbourhood of increased homogeneous energy demand is a step towards transforming a neighbourhood into a distributed energy system argued by Koch et al. [33].

The third objective found that the prebound effect impacts both retrofit and control groups, despite the latter having superior energy ratings. During 2013, the mean P_{act} of both groups are consistent with the 40% estimate in a British study of tower block social housing [55]. The prebound effect of both groups exceeds the 30% predicted prebound in German homes [54, 34]. Thus best fit curves of prebound values follow the shape, but not the magnitude of the predicted prebound - increasing prebound with inferior BER bands. These BER bands are based on a reasonable heating schedule. (Specifically, BER assumes 8 hours daily of required internal temperature [47].) Despite these efforts at accurate BER banding, the observed increases in prebound with BER band hinders social housing retrofit. The largest shortfalls in retrofit savings caused by prebound occur with inferior BERs, common in social housing.

The control group has a higher *percentage* of prebound in 2013 than the retrofit group. Possible explanations are the control group self-rationed heating or used their higher performing homes to reduce gas consumption by a greater proportion than the retrofit group. In terms of *absolute* prebound in kWh/m^2/year, the retrofit group exceeds the control group as expected. Fortunately, retrofit alleviates P$_{act}$, as illustrated in retrofit group during 2015 (Fig. 9). In contrast, the control group increases P$_{act}$ across all BER bands during 2015 (Fig. 10). The consistent P$_{act}$ increase by the control group indicates correlation with warmer weather and higher gas prices during 2015.

Solid fuel use may marginally contribute to the prebound effect in certain homes. Self-reported estimates of solid fuel consumption are discussed in a working paper [10]. These estimates of solid fuel reduce after retrofit. Whilst beneficial, partial fuel switching to gas after retrofit are unquantifiable, thus not evaluated in this study. Homes that relied on solid fuel for primary heat fuel are removed from this study by initial data cleaning (Fig. 4).

One final unappreciated benefit of retrofit is reduced pre-payment frequency and transaction costs on pre-pay households. In 2015, a portion of treatment pre-payments shifts from every few days to weekly. The total quantity of prepayments reduces after retrofit, although the median prepayment in kWh remains steady. This is a rare example of reducing dweller transaction costs, as opposed to alleviating supplier transaction costs.

5.1. Future work

Fuel switching and use of alternative solid fuel, deserve further analysis. Ideally their contribution to the calculated prebound effect could be quantified. Fuel switching to gas, while not a stated goal of home energy retrofit, addresses three drawbacks of solid fuel: i) higher GHG emissions per unit energy, ii) air pollution and iii) fuel transportation costs. Measuring the success of fuel switching requires temperature sensors to confirm occupant comfort is maintained.

The use of external wall insulation at a few homes mainly in one estate is notable. A larger sample of external wall insulation could allow an energy performance analysis to compare external and cavity wall insulation.

The 2015 distribution of gas consumption displays a sizeable variance, even after retrofit (Fig. 8). It could be more accurate to define neighbourhood gas demand by multiple distributions representing distinct heating schedules. The schedules would reflect the heating needs of retired persons and those who work or study outside the home.

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Appendix A. Appendix

Appendix A.1. Allocation of metered consumption by calendar year

The allocation stage apportions a metered consumption to its year of reading, and if at a year transition, to the adjoining year. The first and last consumption values of an individual meter differ from those at year transitions. The interval to the neighbouring reading is unknown, requiring estimated allocations to the year of reading. Techniques and worked examples of consumption allocation appear for meter first records (Appendix A.1.1), meter last records (Appendix A.1.2) and records at year transitions (Appendix A.1.3).

Appendix A.1.1. Allocation of gas consumption from meter first records

The technique distinguishes between post-pay and pre-pay meter records. In both meter types, year to date (YTD) is the number of *completed* days into the year. A post-pay meter is assumed to record consumption bimonthly, every 63 days. Hence, the allocation of the first consumption record is the proportion of its YTD divided by 63 (Eq. A.1)

$$\textit{Post-pay } 1^{st} \textit{ allocation} = \frac{YTD}{63} \times 1^{st} \textit{ meter record} \tag{A.1}$$

Pre-pay meters exclude the period from the start of the year to the first reading. An estimate is made by scaling up the pre-pay consumption to include the time interval from the year start to the first record. The extended period sums the YTD *and* the interval between the first and second non-zero records. The assumption is that the average consumption between the first and second readings equals that of the YTD interval.

$$\textit{Pre-pay } 1^{st} \textit{ allocation} = \left(1 + \frac{YTD}{interval}\right) \times 1^{st} \textit{ meter record} \tag{A.2}$$

Worked examples of consumption allocations from a meter first records appear in Table A.5. Each example of a post-pay and pre-pay meter display the consumption allocations from the initial three records of each meter.

Table A.5
Worked examples of first records allocation: post-and pre-pay meters.

Type	Record date	YTD days	Interval days	Consumption kWh	Record year allocation kWh
post-pay	2013-02-04	34	63	100	54
	2013-04-04	-	-	100	100
	2013-06-04	-	-	100	100
pre-pay	2013-01-05	4	11	100	136
	2013-01-16	-	-	100	100
	2013-01-25	-	-	100	100

Appendix A.1.2. Allocation of gas consumption from meter final records

The techniques to estimate final consumptions again distinguish between post-pay and pre-pay meters. The final meter records coincide with public holidays during heating season, increasing the variation in daily consumption rate. As a result, pre-pay meter final consumptions are estimated by two equations, each of which applies depending on the number of remaining days (Eqs. A.4, A.5).

The post-pay meters lack consumption allocation for the number of remaining days in the year (Yrem) after the final record. The consumption value equals the last consumption record scaled up by Yrem, as a proportion of the last record interval. The record interval is the number of days between the final and penultimate records of an individual meter. It is assumed that the most recent average of daily consumption continues during Yrem.

$$Post\text{-}pay\ final\ allocation = \left(1 + \frac{Yrem}{interval}\right) \times final\ record \tag{A.3}$$

The final pre-pay record allocates consumption to the year end, without the date of the next pre-payment. Where Yrem is small, a similar allocation method as post-pay is applied. It is assumed that the recent average of daily consumption continues during Yrem. As this is pre-pay, the penultimate consumption value is scaled by the Yrem as a proportion of the last known record interval. Such a scaled value of allocation cannot exceed the final reading, thus a 80% figure acts a upper boundary.

$$Pre\text{-}pay\ final\ allocation\ (Yrem \leqslant 5) = \\ min\left(\frac{Yrem}{interval} \times penultimate\ record,\ OR\ 0.8 \times final\ record\right) \tag{A.4}$$

Where the Yrem is larger, the last pre-payment is allocated by estimating its probable meter interval. The YTD of the first pre-payment in the final year offers an estimated number of days in the unobserved year (YTD$_{est}$) until the next reading. The proportion of consumption allocated to the final year is Yrem divided by the sum of Yrem and YTD$_{est}$.

$$Pre\text{-}pay\, final\, allocation\, (Yrem > 5) = \\ \frac{Yrem}{(Yrem + YTD_{est})} \times final\, record \tag{A.5}$$

Worked examples of consumption allocations of meter final readings appear in Table A.6. The post-pay and two pre-pay examples display the final three records of each meter.

Table A.6
Worked examples of final records allocation: post-and pre-pay meters.

Type	Date	Yrem days	Est. interval days	Reading kWh	Read year allocation kWh
post-pay	2015-11-25	-	-	100	100
	2015-12-03	-	-	100	0
	2015-12-10	15	22	100	247
pre-pay	2015-12-21	-	-	100	100
	2015-12-24	-	-	100	100
	2015-12-30	2	6	100	33
pre-pay	2015-12-04	-	-	100	100
	2015-12-16	-	-	100	100
	2015-12-22	10	11	100	91*

* The first 2015 meter reading on 2015-01-02, makes YTD$_{est}$ = 1 and estimated interval = 11.

Appendix A.1.3. Consumption allocation over year transitions

The nature of post-pay and pre-pay meters require different calculations at year transitions. The post-pay meters require a consumption allocation of the *first record of the latter year* across both years; the record (latter) year and the prior year. Initially the interval between the first meter record of the year and the last meter record of the prior year is calculated. The record year allocation is proportional to the YTD divided by the record interval (Eq. A.6). The allocation to the prior year is proportional to the record interval minus the YTD (Eq. A.7).

$$Post\text{-}pay\ record\ year\ allocation = \frac{YTD}{interval} \times year\ 1^{st}\ record \tag{A.6}$$

$$Post\text{-}pay\ prior\ year\ allocation = \left(1 - \frac{YTD}{interval}\right) \times year\ 1^{st}\ record \tag{A.7}$$

Pre-pay meters require an allocation of their *last record of prior year* across the prior year and the subsequent latter year. After the record interval is computed, the prior year allocation is proportional to the year remaining (Yrem) divided by the record interval. The latter year allocation is proportional to the reading interval minus the Yrem. The interval of records demarcating the year transition, and Yrem are computed in days. Consumption allocations over year transitions appear in Table A.7. As expected, the small sample of pre-pay meter readings are more frequent and report smaller consumption values than post-pay readings.

$$Pre\text{-}pay\ record\ year\ allocation = \frac{Yrem}{interval} \times year\ last\ record \tag{A.8}$$

$$Pre\text{-}pay\ latter\ year\ allocation = \left(1 - \frac{Yrem}{interval}\right) \times year\ last\ record \tag{A.9}$$

Table A.7
Worked examples of year transition allocations: post and pre-pay meters.

Type	Date	YTD days	Yrem days	Interval days	Reading kWh	Yearly allocation kWh		
						Read	Prior	Latter
post-pay	2014-12-09	-	-	-	100	100	0	0
post-pay	2015-02-09	39	-	62	100	63	37	0
post-pay	2015-04-13	-	-	-	100	100	0	0
pre-pay	2014-12-11	-	-	-	100	100	0	0
pre-pay	2014-12-23	-	9	13	100	69	0	31
pre-pay	2015-01-05	-	-	-	100	100	0	0

Appendix A.2. Shaping of consumption data

The allocation of metered consumption to its recorded year, and where applicable to the prior and latter years is complete. The next step is summation, or shaping, allocations into calendar years. Most allocations belong to same year they are recorded. As discussed, allocations at year transition include the prior or latter year. The middle year 2014, reports allocations from both is adjoining years. It receives 2013 latter year allocations, and the prior year allocations from 2015 (Eq. A.11). Summation equations use abbreviations of cons (consumption), yr (year) and rec (recorded).

$$2013\ cons = \sum 2013\, rec.\, yr + \sum 2014\, prior.\, yr \tag{A.10}$$

$$2014\ cons = \sum 2013\, latter.\, yr + \sum 2014\, rec.\, yr + \sum 2015\, prior.\, yr \tag{A.11}$$

$$2015\ cons = \sum 2014\, latter.\, yr + \sum 2015\, rec.\, yr \tag{A.12}$$