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Working Paper No. 535

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Evidence, drivers and sources of distortions in the distribution of building energy ratings prior to and after energy efficient retrofitting

Matthew Collins* (ESRI, SEAI) and John Curtis (ESRI, TCD)

Abstract: Energy performance certificates provide a measure of and raise the awareness of the energy efficiency of homes. The Sustainable Energy Authority of Ireland (SEAI) operates a grant aid scheme to incentivise residential energy efficient retrofits known as the Better Energy Homes (BEH) scheme, which was implemented in 2009. Since June 2010, participating homes have been required to undertake independent Building Energy Rating (BER) assessments of the home prior to and after the completion of energy efficient works. This study analyses the distribution of pre- and post-works BERs among participant households, using a regression discontinuity design to examine the significance of discontinuities at each BER grade threshold and to estimate the number of affected BERs in our sample. We find evidence of bunching at the more efficient side of thresholds of post-works BERs, while no evidence of bunching on the more efficient side was found among pre-works BERs. We find slight evidence of bunching on the less efficient side of certain thresholds in the pre-works distribution. We estimate counter-factual distributions around each threshold to examine the number of dwellings which may have been affected by potentially incorrect assessments. We analyse whether adjustment of BER assessments is systemic and whether market forces provide an incentive to adjust assessments. We find significant evidence of the misrepresentation of Building Energy Ratings but this is not found to be systemic. We also examine potential sources of adjustment, finding discontinuities in certain parameters coinciding with the areas where bunching is found to occur.

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Keyword(s): Energy Efficiency labelling, Bunching, Regression Discontinuity design

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1. Introduction

The European Union, through the introduction of the Energy Efficiency Directive, has set a target of achieving a 20% reduction in greenhouse gas emissions and achieving energy savings of 20% by 2020 (European Union, 2012). With varying patterns of energy consumption across Europe, policies aimed at meeting 2020 targets are implemented at a national level with each state required to develop a National Energy Efficiency Action Plan (NEEAP). Ireland's third, and latest NEEAP concluded that Ireland had met 39% of its 2020 target by the end of 2012 (DCENR, 2014). With almost 40% of final energy consumption occurring in buildings, two thirds of which is used for space heating, improving the energy efficiency of the building stock provides a significant policy opportunity to help meet these targets (European Commission, 2011). This is particularly true of Ireland, where homes have the lowest level of double-glazing in northern Europe (Balaras et al., 2007) and where roughly 50% of homes in Ireland possess a Building Energy Rating (BER) between D1 and G¹, which are the lowest six grades of a 15-point scale. One such policy to help improve energy efficiency in the residential sector was the introduction of a residential energy efficiency retrofit grant scheme, now known as the Better Energy Homes (BEH) scheme. Administered by the Sustainable Energy Authority of Ireland (SEAI), the BEH scheme provides grant aid for home owners to engage in engage in retrofit activities to improve the energy efficiency of their homes.

The Energy Performance of Buildings Directive (European Union, 2002), which was transposed into Irish law in 2006 (DEHL, 2006), established a methodological framework for calculating energy performance, which has been implemented in similar manners across the EU. This framework provides for a standardised ranking of the energy performance of homes. The Irish BER was implemented using a 15-point scale ranging from A1 to G, where A1 is the most energy efficient. This rating system is discussed in more detail in section 2. As part of the BEH scheme, participant households are required to conduct independent BER assessments of their homes and submit a pre-works and post-works assessment to SEAI. As will be discussed in section 4., discontinuities appear to exist in the distribution of post-works assessments which are not present in the equivalent pre-works distribution. We implement a regression discontinuity design to examine the significance of these discontinuities.

The research issue explored in this paper is to identify whether there is potential misrepresentation of building energy ratings as evidenced by statistically significant discontinuities of the distribution of these ratings. As both pre- and post-works ratings are calculated following the completion of energy efficient retrofit works, a greater level of discontinuity of post-works ratings may indicate gaming of the system, given the benefits of an improved BER and may indicate the need for further tailoring the means by which assessments are targeted for audit.

We find that prior to the completion of energy efficient retrofit works, there is no evidence of bunching on the more efficient side of any grade thresholds and that there appears to be evidence of slight bunching on the less efficient side of the C2/C3 and D1/D2 thresholds. Significant evidence of bunching was found at most thresholds of the post-works distribution and was found to be stronger at thresholds where the letter grade changes. We estimate a counter-factual distribution of BERs surrounding each threshold and estimate that over 3% of assessments may have been adjusted to pass into more efficient grade labels. We examine drivers of the adjustment of assessments, finding no evidence of systemic drivers of adjustment. We investigate sources of adjustment, finding that the low energy lighting parameter used in BER assessments might be a commonly used tool to improve a property's rating.

The remainder of the paper is organised as follows: Section 2 provides a description of the Building Energy Rating framework. Section 3 presents earlier literature. Section 4. provides a description of the

¹Central Statistics Office (2015) Domestic Building Energy Ratings Release, December 2015, Table 15, available: http://www.cso.ie/en/releasesandpublications/er/dber/domesticbuildingenergyratingsquarter42015/

distribution of BER grades within the Better Energy Homes data. Section 5. contains a discussion of modelling and estimation issues. This is followed by the presentation and discussion of the estimation results in Section 6., while Section 7. concludes.

2. The Building Energy Rating

The Irish Building Energy Rating (BER) is an energy label pertaining to the energy efficiency of a home. Homes are assigned to an alpha-numeric grade on a 15-point scale ranging from A1 to G, with A1 being the most energy efficient. SEAI provide a guide to the BER for home owners, outlining who requires a BER and an outline of BER calculation.² A BER takes account of energy requirements for space heating, ventilation, water heating and lighting, less savings from energy generation technologies, measured in kilowatt hours $(kWh/m^2/year)$. This is based on a standardised occupancy, with living areas heated to 21°C and other rooms to 18°C (SEAI, 2013). This calculation requires assessment of a home's dimensions, orientation, insulation and space and water heating system efficiencies. BER assessment does not include the use of electrical appliances such as cookers, washing machines, etc, although pumps and fans for heating and ventilation are included. BER assessments are carried out by independent assessors who have completed an accredited training course, including national examination, and are registered with SEAI. Figure 2 shows an example BER certificate.

Qualified and registered BER assessors calculate a dwelling's rating using Dwelling Energy Assessment Procedure (DEAP) software, for which we have been provided with unique and anonymous identifiers for the assessor who has performed each assessment in the data.³ Appendix A provides a screen-shot of the DEAP software. Throughout the assessment the dwelling's estimated BER is visible to the assessor, who may also edit inputs retrospectively before final submission of the assessed BER. It is therefore relatively easy for an assessor to adjust the assessment. For the purposes of the BEH scheme, a BER assessment is carried out following completion of energy efficient retrofit works. The result of this assessment is registered as that homes BER value. The BER assessor then retrospectively discounts the parameters pertaining to the retrofit measures undertaken under the grant aid scheme to estimate what the BER would have been before retrofitting so that energy savings can be estimated. We refer to this estimation as the 'pre-works' BER.

3. Previous literature

Building energy ratings provide various market benefits, particularly the reduction of information asymmetry. With an energy efficiency rating system, agents looking to buy or rent are able to identify the energy performance of buildings which would otherwise be unknown. Provided consumers value energy efficiency, for comfort gains, monetary savings through reduced energy usage, environmental concerns or otherwise, this should lead to an increase in demand for more energy efficient homes. A body of research exists to show that this is the case in various countries, including Ireland (Hyland et al., 2013), England (Fuerst et al., 2015), Wales (Fuerst et al., 2016), Germany (Cajias and Piazolo, 2013), and the Netherlands (Brounen and Kok, 2011). BERs also provide knowledge of the energy efficiency status of a nation's building stock, which allows policy makers to identify where policy implementation may need adjustment. For example, certain categories of the building stock might require greater investment than others, or the extent to which energy efficiency improvements may be required could indicate whether grant aid or financing may be suitable policy options. For these benefits to be most effectively translated to the market, performance ratings must be accurate and dwellings appropriately labelled.

²available online: http://www.seai.ie/Your_Building/BER/Your_Guide_to_Building_Energy_Rating.pdf

 $^{^{3}}$ Not all qualified BER assessors are registered with SEAI as, in addition to qualifying as a BER assessor, one must have adequate insurance, accept the relevant code of practice, pay the required registration fee and pass the domestic BER examination every two years.



Figure 1: Example domestic BER certificate

An energy labelling system with discrete performance thresholds may give rise to perverse incentive, i.e. an incentive may also lead to unintended and undesirable outcomes. We believe bunching to be evidence of this perverse incentive, as the introduction of an incentive to improve a building's energy efficiency may have also caused an incentive to misrepresent energy efficiency ratings. Bevan and Hood (2006) define three types of perverse incentive. Ratchet effects refer to the incentive not to exceed targets in a given year if targets are based on performance during the previous year. Threshold effects refer the use of minimum performance standards which incentivise improved performance for those below the threshold but lead to stagnation of those above the threshold. Output distortions refer to distortions in economic output caused by threshold and ratchet effects. Given that the BER assessor can retrospectively adjust the final assessment, and given that the property market values energy efficiency, there is potentially a perverse incentive to marginally falsify BER assessments (i.e. adjusting the assessment in such a manner to move a rating from the less desirable side of a BER threshold to the more desirable side). If the market values energy efficiency, adjustment may allow property owners to sell or rent their home at a higher price, extracting undue rents. BER assessors are hired by home owners to conduct an assessment and, as such, assessors may be either persuaded or incentivised to give more favourable assessments. If these perverse incentive adjustments occur in a substantial number of cases we might expect to see disproportionately more bunching of BER assessments immediately on the more efficient side of the BER grade thresholds and disproportionately fewer assessments on the less efficient side of the BER grade thresholds.

Bunching analysis has been applied to various strands of literature, a summary of which is provided by Kleven (2016). Bunching analysis was originally developed in the area of tax policy and enforcement. For example Chetty et al. (2011) found significant evidence of bunching in real earnings around kink points in tax thresholds in Denmark while Bastani and Selin (2014) found no bunching of earnings in Sweden, despite the presence of kink points in the tax schedule. Larger levels of bunching were found to exist in the distribution of earnings among the self-employed, who possess greater scope for tax avoidance (Saez, 2010; Kleven and Waseem, 2013). In welfare economics, Camacho and Conover (2011) examine bunching in poverty index scores of families in Colombia at the threshold for identifying recipients eligible for a variety of social welfare programs. In labour economics, Gourio and Roys (2014) look at bunching in the distribution of the number of people employed by firms. They found that, as firms with 50 or more employees faced more stringent regulation that those with less than 50, significant bunching occurred in the distribution, with a disproportionally high number of firms employing 49 people.

In terms of energy labelling, bunching analysis has been applied to the study of the effects of energy and efficiency labelling in the car market. Sallee and Slemrod (2012) examine bunching in fuel economy ratings, including the introduction of a rebate program for energy efficient cars in Canada. They matched cars with equal specifications in the years prior to and after introduction of the rebate, using a logistic regression to model the likelihood that a car moved from the less favourable side of the threshold to the more favourable side upon introduction of the scheme. As part of an analysis of price effects of energy efficiency in the Swiss car market, Alberini et al. (2014) use a regression discontinuity design to examine bunching of prices among cars of varying efficiency labels, finding strong evidence that A-grade cars extracted a price premium. Pierce and Snyder (2012) investigate systemic manipulation of vehicle emissions testing in New York state by using a regression discontinuity design. They examine the distribution of test scores before and after a change in the test score required to pass. They find statistically significant evidence of bunching in the distribution of tests scores at the passing thresholds for five out of six emissions tests. They concluded that manipulation by testers was likely the cause, as cars could be re-tested until receiving a pass.

4. Data

Our dataset comprises all applications to the SEAI's Better Energy Homes scheme. Since June 2010 it has been mandatory for all households in receipt of grant aid to have an independent building energy rating assessment performed to assess the home's energy efficiency both before and after retrofit works were undertaken. Our dataset therefore possesses before and after BERs for successful applicants from June 2010 through to October 2015 and those who choose to undertake a pre- and post-works BER assessment prior to June 2010. This allows for comparison of the distributions of household BERs. Properties that have had more than one BER assessment over time are represented only by their latest assessments or we discarded BEH applications where a property was subsequently assessed. Of the remaining assessments, table 1 shows the number of homes in each grade band prior to and after retrofitting. We can see a clear improvement in the energy efficiency of participant homes, with reductions in the number of D, E, F and G rated homes and an increase in the number of homes in all grades from A3 to C3.

The total number of households in each grade label does not provide much insight into the shape of the distribution within each band. For this reason, we look at the pre- and post-works distributions in finer detail. Figures 2 and 3 show the distribution of pre- and post-works BERs, respectively, detailing the number of homes in each one-kWh band. The pre-works distribution appears to be reasonably smooth and is right-skewed, with more homes possessing E, F and G grades than A or B grades. There does not appear to be any visual evidence of bunching of households within any bands outside of general noise across the distribution.

The post-works distribution is much less smooth, with apparent bunching of households in many grade labels. A trend appears to exist whereby a disproportionally large number of homes appear to possess BERs

	Table 1: Distribution of BER grades									
	Pre-W	orks	Post-W	Vorks						
	Observations	Proportion	Observations	Proportion						
A1	4	0.00	0	0.00						
A2	5	0.00	4	0.00						
A3	3	0.00	38	0.03						
B1	21	0.02	292	0.26						
B2	151	0.13	2,029	1.80						
B3	1,149	1.02	9,093	8.07						
C1	4,640	4.12	16,964	15.06						
C2	9,412	8.36	21,507	19.10						
C3	$13,\!516$	12.00	$20,\!452$	18.16						
D1	20,786	18.46	18,007	15.99						
D2	18,528	16.45	12,911	11.46						
E1	$13,\!378$	11.88	5,342	4.74						
E2	$9,\!979$	8.86	2,867	2.55						
\mathbf{F}	10,938	9.71	1,964	1.74						
G	10,109	8.98	$1,\!149$	1.02						

that are marginally on the more energy efficient side of grade thresholds, while proportionally lower numbers of homes appear to possess ratings on the less efficient side. This is particularly noticeable at grades B3 to D2, which possess higher numbers of homes. Evidence of bunching at the most efficient grades is not apparent but there are very few homes with such grades. For example, only 0.26% of homes possess A or B1 grades after having energy efficiency works undertaken.

5. Methodology

5.1. Regression discontinuity design

We take a similar approach to Pierce and Snyder (2012) by using a regression discontinuity design to estimate the significance of the discontinuity at the threshold for each discrete building energy rating grade. This is done for the distribution of both pre- and post-works building energy ratings. The distribution surrounding each grade threshold is taken as a function of the bin number and a pooled polynomial regression, as described by Lee and Lemieux (2009), is modelled as follows:

$$y_{j} = \alpha + \tau . T + \Sigma_{i=1}^{p} [\beta_{i1} (X_{j} - c)^{i} + \beta_{i2} . T . (X_{j} - c)^{i}] + \epsilon$$
(1)

 X_i represents the bin number along the distribution and c represents the bin number at the grade threshold

and is used to centre the polynomials at the distribution's cut-point. Our main explanatory variable is therefore the distance from the BER grade threshold, which can be both positive or negative, with negative values occurring on the more favourable side. Our dependent variable, y_j , represents the number of households in a given bin and is measured as a proportion of all of the households in the sample. T is a dummy variable, taking a value of 1 if the bin is to the more favourable side of the threshold, indicating that it is more energy efficient. For example, when looking at the C3/D1 threshold, T will take a value of 1 if the bin is less than 225 kWh, which is the threshold. The magnitude of the discontinuity is given by the parameter τ . In order to check for robustness of our estimates, we estimate our model with varying polynomial orders and varying bin sizes.

We believe a regression discontinuity design to be an appropriate measure of bunching, as the discrete threshold appears to be the main incentive to adjust assessments, which in turn leads to bunching. We



Figure 2: Distribution of Pre-works Building Energy Ratings



Figure 3: Distribution of Post-works Building Energy Ratings

therefore make the assumption that the distributions of other independent variables are relatively smooth across the distribution of BERs. As our dependent variable measures the proportion of our total sample in a given bin, estimated parameters will be affected by scale. This means that our estimates will not provide any insight into the degree of relative bunching, i.e. the thresholds at which bunching is strongest.

After identifying where significant evidence of bunching exists, we are able to examine the extent to which BER assessments have been adjusted within our sample. We estimate the number of homes which possess adjusted BERs at each threshold where bunching is found to occur. This is done by estimating a counter-factual distribution, in addition to the fitted distribution, as is discussed in section 5.2.

5.2. Estimating a counterfactual distribution

In addition to estimating the statistical significance of bunching estimates, in order to examine more effectively the degree of bunching present in the distribution of Building Energy Ratings, we estimate the number of BER assessments which may have been adjusted. We do this by estimating a counter-factual distribution of post-works BERs. The regression used to calculate the counter-factual distribution takes the following form:

$$\hat{y}_j = \alpha + \sum_{i=1}^p \beta_i (X_j - c | X_j \notin (z_u, z_l))^i + \theta$$
(2)

where \hat{y} is the number of dwellings as a proportion of all dwellings in bin j were no bunching to occur. X_j

again represents the bin number, with c representing the bin number at the grade threshold and is used to centre the polynomials at the distribution's cut-point. z_l and z_u represents the lower and upper bounds, respectively, of the affected area, i.e. the area in which bunching occurs.

We compare this counter-factual distribution to both the observed distribution and the fitted distribution of assessed BER grades to make two estimates of the number of assessments which may have been adjusted. We do this by taking the number of assessments above the counter-factual distribution on the more favourable side of the threshold and by taking the number of assessments below the distribution on the less favourable side of the threshold. The excess above the threshold and the deficit below should be roughly equal. This is done for both the actual and fitted values of the bunched distribution for those thresholds which have been shown to possess significant evidence of bunching.

The following equations show how the estimated number of dwellings affected by adjustment are calculated. M represents an estimate of the number of dwellings affected by bunching, Y_i represents the actual number of dwellings in each bin, and y_i are the fitted values of Y_i , from equation 1. The variable \hat{y}_i represents the counter-factual value of Y_i , all measured as a proportion of the total dwellings. Equation 3 shows the number of affected dwellings, calculated using actual values on the lower side of the threshold and equation 4 shows same for the upper side. Equation 5 uses the fitted values on the lower side (from equation 2), while equation 6 uses fitted values on the upper side. If the bunching is occurring for perverse reasons, as opposed to some genuine inherent reason, we would expect that the estimates of M_{al} and M_{au} are roughly equal, and similarly for M_{fl} and M_{fu} .

$$M_{al} = \Sigma_{i=x_l}^c (Y_i - \hat{y}_i) \tag{3}$$

$$M_{au} = \sum_{i=c}^{x_u} (\hat{y}_i - Y_i) \tag{4}$$

$$M_{fl} = \sum_{i=x_l}^c (y_i - \hat{y}_i) \tag{5}$$

$$M_{fu} = \sum_{i=c}^{x_u} (\hat{y}_i - y_i) \tag{6}$$

6. Results and discussion

6.1. Significance of bunching estimates

We first estimate the significance of bunching estimates, the results of which are presented in Table 6. We choose a bin size of 0.25 kWh and a polynomial order of 3 for the purposes of this analysis. While higher order polynomials sometimes resulted in lower Akaike information criterion (AIC) for some thresholds, improvements were found to be marginal beyond orders of three in most cases. Some higher orders also led to variable omission in estimation. For details of recorded AIC statistics for each threshold and polynomial order, see Appendix B. The estimated τ statistics for these regressions of varying polynomial order were used to assess the robustness of our results, alongside those of regressions estimated using varying bin sizes.

Table 2	2: Estimated discor	ntinuities at each	n grade band
Т	hreshold	Pre-Works ¹	Post-Works ¹
Grade	$kWh/m^2/yr$	au	au
A1/A2	25	0.000075	0.0000068
A2/A3	50	-0.000111	-0.00068
A3/B1	75	-0.000213	-0.00636
B1/B2	100	0.008659	0.00541
B2/B3	125	0.007849	0.03038
B3/C1	150	-0.066623	.597***
C1/C2	175	-0.008273	1.151^{***}
C2/C3	200	3209746^{*}	1.7002^{***}
C3/D1	225	-0.103184	.915***
D1/D2	260	1706542*	.309***
D2/E1	300	-0.017400	.395***
E1/E2	340	0.087614	.125**
E2/F	380	-0.018429	0.015795
F/G	450	0.016260	$.0279^{***}$
	(*** p<0.01, **	[*] p<0.05, * p<	<0.1)

¹ Full estimation results are presented in appendix Appendix C.

Looking first at bunching estimates in our pre-works distribution, we find evidence of negative bunching, i.e. bunching on the less efficient side of the threshold, at certain grades. Statistically significant negative bunching appears to occur at C2 and D1. Bunching at C2 is found to be significant at polynomial orders of four and five, while bunching at D1 is found to be significant at orders of one, two and five. Bunching estimates at C2 and D1 are not robust to all bin sizes. Both are robust to bin sizes of $0.5 \ kWh/m^2/yr$ and bunching at D1 is also robust to bin a bin size of $1 \ kWh/m^2/yr$. Overall, this indicates that negative bunching may exist at C2 and D1. The recorded BER improvement achieved by engaging in an energy efficient retrofit for homes with a recorded pre-works BER of C2 has a mean of 27.18 kWh and standard deviation of 14. One potential explanation for pre-works negative bunching of ratings is that if a post-works BER assessment is in the same category as the pre-works assessment, i.e. the retrofit investment has not achieved a large enough improvement to change the BER grade assessment, the adjustment of the BER may occur on the less efficient pre-works BER grade. This might be caused by assessors feeling that a home owner may not be satisfied in not achieving a discrete BER improvement having made a significant investment in an energy efficient retrofit.

Evidence of positive bunching in the post-works distribution is found at all grades from B3 to G, excluding E2. All grades where evidence of bunching is found are robust to changes in bin size, as shown in Appendix E. Only estimates at C2 and C3 are robust to all polynomial orders. As shown in Appendix D, all other

significant estimates are robust to a minimum of two other polynomial orders. This provides evidence of bunching at various grade thresholds, indicating that a large number of assessments may have been unduly adjusted to place homes in more favourable BER grades.

We also examine the significance of bunching estimates across subsets of our sample. We examine homes within the Greater Dublin Area (GDA), homes outside of the GDA, houses only, apartments only, homes which have engaged in retrofits via obligated parties and homes which have engaged in retrofits privately with contractors. Obligated parties are energy distributors and retail energy sales companies that have been obliged by the state to reach certain energy targets, 20% of which must be achieved by reducing residential energy consumption. Obligated parties satisfy their statutory targets in part by achieving sufficient levels of retrofit installations, some of which are availed of by customers via the BEH scheme. There is no perverse incentive to obligated parties to misrepresent the level of BER improvement as they receive credits toward their energy savings targets based on the type of measures implemented and not energy efficiency reductions. Estimates of bunching for each of these subsets are presented in Table 3. As shown, significant evidence of bunching is found for all grades from B3 to D2 for all groups except apartments. Significant evidence for the apartments sub-group was found only at D2, although this is likely due to the reduced number of observations in this sub-group. Evidence of bunching varies in significance at less efficient grades, although evidence of bunching at F is found for all groups except those households who engaged in the BEH scheme via obligated parties and those within the GDA. As homes engaging in retrofits are much less likely to occupy these lower grades after having works done, the reduced number of homes around these thresholds make it less likely that significant evidence of bunching is identified. Overall, as evidence of bunching is found across most sub-groups of assessments, adjustment of assessments might be a systemic issue, rather than endemic to certain types of homes or applications. As further evidence of potentially systemic adjustment, Appendix F shows graphically the distribution of post-works BERs among other sub-groups of assessments.

	Table 3: Discontinuities among sub-groups of applications						
Т	hreshold	GDA only	non-GDA only	Obligated Party	Private Applications	Houses only	Apartments only
Grade	$kWh/m^2/yr$	au	au	au	au	au	au
A1/A2	25	0	9.22E-06	0.00E + 00	7.73E-06	7.01E-06	0
A2/A3	50	-0.0008512	-0.0006284	0.00143	-0.00098	-0.000708	0
A3/B1	75	0.0124666	0130882*	0.002374	-0.00757	-0.007339	0.0250873
B1/B2	100	0.0925214	-0.0256883	0.037913	0.000945	0.0028632	0.087711
B2/B3	125	0.0100122	0.0376588	-0.06881	0.044012	0.0403066	-0.2901887
B3/C1	150	$.5893741^{***}$	$.5998893^{***}$	0.384845	$.6262833^{***}$	$.5976309^{***}$	0.5807115
C1/C2	175	1.233278***	1.122481^{***}	1.293125^{***}	1.132193^{***}	1.158437^{***}	0.9316641
C2/C3	200	1.682608^{***}	1.706582^{***}	2.163202^{***}	1.636683^{***}	1.730422^{***}	0.7261539
C3/D1	225	.5525718**	1.045193^{***}	1.050458^{***}	.8970686***	$.9361588^{***}$	0.2511097
D1/D2	260	.3344321**	$.3012606^{***}$.4635002**	.2888995***	$.3227553^{***}$	-0.1025789
D2/E1	300	$.376608^{***}$.4028182***	$.3159979^*$.406902***	$.3754049^{***}$	1.058912^{**}
E1/E2	340	0.0765224	.1431748**	0.203358	.1149639*	$.1255504^{**}$	0.128533
E2/F	380	0.0242245	0.0127856	0.007314	0.01696	0.0157709	0.0165738
F/G	450	0.0187046	$.0312913^{**}$	0.00863	.0306381***	$.0274851^{***}$	0.043974
			(***	< 0.01 ** $n < 0.05 $ *	(n<0.1)		

(*** p < 0.01, ** p < 0.05, * p < 0.1)

6.2. Estimating the number of adjusted BER assessments

As discussed in section 5.2, we estimate counter-factual distributions of post-works BERs around each threshold, omitting the affected area. We choose to omit homes possessing BERs within five kWh of the threshold as we assume adjusted assessments are concentrated in these areas. The fitted values of the counter-factual distributions are compared to both the observed distribution of BERs and to the fitted values of the observed distribution to provide two estimates the number of potentially adjusted assessments. We again choose a polynomial order of 3 to estimate our counter-factual distributions.

Figures 4 and 5 graphically compare the observed and fitted distribution to the counterfactual distribution estimated for the pre- and post-works BER assessments at each grade threshold where significant evidence

of bunching was estimated. As can be seen, discontinuities exist on either side of most grade thresholds within the affected areas. The pre-works distributions presented show very little, if any, deviations of the counter-factual to the fitted distribution. Only the C2 and D1 thresholds possessed estimated evidence of bunching, as was discussed in section 6.1. This is noticeable in the fitted distributions at these grades but not so in the observed distributions at these thresholds.

Looking at the post-works distributions, the thresholds from B1 to E1 and F all show visual evidence of the variations between the fitted and counter-factual distributions. Clear spikes in the distribution are evident just to the left of the threshold, with a sharp, steep drop once the threshold is reached, before rising back toward the counter-factual distribution. These are less noticeable in the observed distributions at E1 and F grades due to sample size. As can be seen, relative to the pre-works distributions of these grades, the post-works distributions have lower samples sizes.

For each threshold where significant evidence of bunching was found, we estimate the number of adjusted assessments on either side of each threshold, with estimated values presented in Table 4. As discussed in section 5.2, M represents the estimated number of adjusted assessments, with the following notation defining how these totals were estimated. Parameter l signifies that bunching estimates are taken from the lower, i.e. the more energy efficient, side of the distribution, and u signifying the upper, or less energy efficient side. Parameter a signifies that estimates were found by comparing the actual, or observed, distribution to the counter-factual distribution and f indicates that the fitted distribution was compared to the counter-factual distribution.

The number of potentially adjusted assessments varies by method of estimation. The proportion of adjusted assessments varies between 3.1% and 4.7%, which equates to a total number of adjusted assessments between 3,531 and 5,344. The number of adjusted assessments varies across grades due to the distribution of the post-works BER sample. For example, we estimate between 23 and 43 adjusted assessments at the F/G threshold and between 1,020 and 1,503 adjusted assessments at the C3/D1 threshold. As previously discussed, very few homes in our sample remain at F and G grades following energy efficient retrofit works and, as such, there are fewer assessments that can be adjusted. Estimates on the more energy efficient side of the thresholds are larger than those on the less energy efficient side.

		Table	4: Estimate	d number of	adjusted Bl	ER assessme	nts		
Threshold		M	M_{al}		M_{fl}		au	M	fu
Grade	$kWh/m^2/yr$	%	#	%	#	%	#	%	#
B3/C1	150	0.006876	774.27	0.007308	822.91	0.004757	535.69	0.005279	594.49
C1/C2	175	0.007443	838.17	0.007746	872.28	0.006165	694.21	0.006188	696.84
C2/C3	200	0.008745	984.73	0.009444	1,063.52	0.007637	859.99	0.007963	896.65
C3/D1	225	0.01259	1,417.76	0.01335	1,503.31	0.009065	1,020.74	0.009179	1,033.68
D1/D2	260	0.003675	413.82	0.003686	415.03	0.002796	314.82	0.003106	349.76
D2/E1	300	0.005256	591.87	0.005228	588.71	0.003939	443.61	-0.00139	-156.41
E1/E2	340	0.000525	59.06	0.000476	53.59	0.000744	83.77	0.000731	82.32
F/G	450	0.000311	35.07	0.000223	25.09	0.000212	23.91	0.000305	34.37
		0.04542	$5,\!114.74$	0.04746	5,344.45	0.035315	$3,\!976.76$	0.031362	3,531.69

As a measure of relative bunching, we express the estimated number of adjusted assessments as a percentage of all assessments within 12.5 kWh of each threshold. We choose 12.5 as this is the smallest distance to the mid-point of any grade. This measure of bunching is presented in Figure 6. As can be seen, bunching appears to be strongest at thresholds corresponding to a change in letter grade, as the highest levels of relative bunching are seen at B3, C3, D2 and F. This indicates that home owners place, or are perceived by BER assessors to place a value on a more favourable energy rating for their home and in doing so, place a greater value on an improvement in a home's letter grade than is placed on an improvement in the home's

Figure 4: Actual, fitted and counter-factual distribution surrounding B- and C-grade thresholds at which significant evidence of bunching was found in the post-works BER distribution

Figure 5: Actual, fitted and counter-factual distribution surrounding D-, E- and F-grade thresholds at which significant evidence of bunching was found in the post-works BER distribution

alpha-numeric grade.

Figure 6: Relative bunching at each grade threshold

6.3. Evidence of systemic bunching

Following our analysis of the extent of bunching, we aim to identify patterns in bunching across the distribution of assessments. SEAI provide us with data, including assessor ID numbers, of every recorded BER in Ireland, provided it is the latest BER assessment of a property. This allows us to examine potential adjustment across all properties, rather than only those who had a BER assessment undertaken as part of a Better Energy Homes grant. We examine potential adjustment through variations in the number of BERs within 5 kWh of a threshold on the more efficient, and therefore more favourable, side, taken as a percentage of total assessments within 12.5 kWh of the threshold on either side. We choose a band of \pm 12.5 kWh as this is the smallest distance from a threshold to the mid-point of a grade band. We refer to this area 5 kWh to the more favourable side of each threshold as the affected area, as we believe all adjusted assessments are issued in this area, based on visual examination of the distribution of BER values.

Using the same method as in section 6.2, we estimate counterfactual distributions at each threshold where significant evidence of bunching was found, this time using the population of properties which possess BERs. Comparing the observed and counterfactual distributions at each grade, we are able to estimate the number of assessments that have been adjusted at each threshold. We chose not to use the proportion of applications as estimated in section 6.2 as the overall population of BERs is naturally more right-skewed. This is because the sample of homes who have completed retrofits is comprised of households whose energy efficiency has improved, reducing the number of E, F and G grades. We then take the proportion of home within 5kWh of the more favourable side of the threshold at each grade within each county and compare this to the proportion that should be within this 5kWh band, as per the national counterfactual distribution. The difference between these proportions is used as our measure of bunching.

We first examine whether any systemic trends across counties. We compare the percentage of applications in the affected area for each county, relative to the estimated counterfactual distribution for the country as a whole⁴. Figure 7 shows estimated levels of adjustment across regions for those grades in which significant evidence of bunching was estimated in section 6.1. Most counties exist in the middle band, with between 4.2% and 6.2% of applications estimated to be adjusted. There does not appear to be noticeable regional trends, as some counties with high levels of adjustment are situated beside counties with very low levels.

Figure 7: Bunching estimates by county (Proportion with 5kWh relative to counterfactual distribution)

We examine whether competition between assessors in an area is a driver of adjustment. Assuming that counties with a less polarised distribution of assessors are more competitive, it may be possible that in less polarised markets, assessors have greater incentive to adjust assessments as a means of generating repeat business and more business through word of mouth. We therefore calculate a gini coefficient pertaining to the polarisation of the distribution of assessors in each county's population of BERs. These gini coefficient are presented graphically in fig. 8. As can be seen, there exists a variation across counties but this variation is quite small. We test whether any correlation exists between this gini coefficient and potential adjustment

⁴This map is created using CSO administrative counties boundary file. BER data does not distinguish between South Dublin, Fingal and Dún Laoghaire-Rathdown) and, as such, data is repeated across these areas. http://www.cso.ie/en/census/census2011boundaryfiles/

Table 5: Correlations	s between	assessor	polarisatio	n and pot	tentiai adji	istment a	t each gra	ide
	B3	C1	C2	C3	D1	D2	E1	\mathbf{F}
Gini Coefficient	0.090	0.031	-0.362	0.017	-0.075	0.095	0.534	0.332
Potential adjustment:								
All Grades	0.603	0.334	0.587	0.850	0.549	0.384	0.430	0.126
B3		0.178	0.085	0.484	0.341	0.080	0.094	0.147
C1			0.039	0.176	-0.263	0.116	0.021	-0.349
C2				0.526	0.173	0.093	0.244	0.148
C3					0.456	0.118	0.270	0.095
D1						0.074	0.297	0.199
D2							0.118	-0.080
E1								0.115

at each grade, with results presented in table 5. We find that the correlation is quite variable across grades, with both positive and negative values across grades. In most cases this correlation is quite low with bunching at the E1/E2 threshold being the only grade to possess a correlation with the gini coefficient of greater than 0.5. We therefore can conclude that adjustment of assessments is not driven by competition between assessors. Furthermore, we examine whether any correlation exists between bunching at different grades across counties. Again, correlations between grades are found to be quite variable and quite low, for the most part. Were bunching to be based on other regional factors, we would expect bunching at each grade to be correlated across counties, perhaps between all grades, or just between grades where the letter grade also changes but this does not appear to be case. It is therefore unlikely that BERs in certain counties are more susceptible to adjustment than others.

In the absence of any drivers of adjustment, we also seek to examine how assessors may be manipulating applications. Some DEAP parameters could be seen as being relatively easy to adjust. Continuous measures, such as the percentage of the property which has been draught proofed, the percentage of lighting that can be classified as low energy lighting and the thickness of hot water store insulation vary from home to home and, as such, it would be difficult to identify adjusted values without an audit of the property's BER. This is particularly true of low energy lighting, as lighting can be changed at any point before or after a BER assessment. If an audit of a BER assessment were to find a lower level of low energy lighting than reported by an assessor, it would be difficult to prove that the home owner did not replace low energy lighting with less efficient alternatives following the assessment. Other categorical parameters might also be considered easy to adjust. Heating system control, response and efficiency categories also vary quite a lot across dwellings and would be difficult to identify as anomalies without a BER audit⁵.

It is difficult to identify sources of adjustment as it is not possible, without auditing, to correctly identify which homes that are within 5kWh of a threshold are those which have been adjusted, as the majority of these homes should in fact exist in this region of the distribution. We divide the distribution of BERs into bins of 5kWh and plot the proportional distribution of these parameters across all bands on either side of grade threshold where significant evidence of bunching was found. The proportion of low energy lighting in a home possesses noticeable discontinuities, as properties within 5 kWh of a threshold on the more favourable side possess higher levels of low energy lighting than those in other 5kWh bins. This is shown in fig. 9. Appendix G shows the proportional distribution for the previously mentioned categories that may be susceptible to adjustment. On visual inspection these do not appear to provide any systemic evidence of bunching across the distribution. While this does not provide enough evidence to conclude with certainty, it is likely that assessors are using low energy lighting to adjust assessments and assign more preferable grades to homes. This is an appealing parameter for assessors to adjust as it would be difficult

⁵These categories were suggested as potential sources of adjustment during discussion with SEAI which helped to inform our research.

Figure 8: Gini coefficients of assessor polarisation by county

for an auditor to prove adjustment, given that following assessment, a household is likely to have replaced some lighting fixtures over time and lighting that could previously have been considered low energy could be replaced by a less efficient alternative.

Figure 9: Proportion of Low Energy Lighting by 5kWh bin

As a means of detecting the non-compliance in BER assessments, an auditing system currently exists with penalties of differing severity. Penalties currently apply to non-compliances resulting in a net change of 5% or more of the BER, assessments where the sum of non-compliances results in a change of 10% or more of the BER and assessments where non-compliance causes a change in the BER grade of a property⁶. SEAI have to date audited a sample of 57 homes within 2kWh of grade thresholds, with low energy lighting ranking 13th by order of frequency of non-compliances among this sample, and 6th by order of frequency in all homes. Based on the findings of this research, it could be considered to increase the width of this identification band from 2kWh to 5kWh, as a sample of 57 homes is quite small and is therefore unlikely to identify any widespread sources of bunching. With regard to policy implications, this paper therefore fails to identify any other potential improvements to the auditing system in place for assessors. This is because the audited BER and for misrepresentations where the submitted BER possesses a different grade to the audited BER. While the idea of not including low energy lighting in BER calculations could be considered, this is very unlikely given that lighting represents a substantial proportion of residential energy consumption.

7. Conclusion

Residential energy efficient retrofits contribute to reducing overall energy consumption in Ireland, helping to meet the State's energy efficiency targets. Inaccurate labels caused by adjustment of building energy efficiency assessments could lead to the misrepresentation of the energy efficiency of the residential building stock. They may also lead to unmerited windfall gains to property owners if there is a label effect associated with energy efficiency ratings. A regression discontinuity methodology is used to investigate whether the adjustment of building energy ratings occurs and the extent thereof within the context of the Better Energy Homes retrofit grant scheme.

 $^{^6 \}rm More$ information on BER auditing procedures is available at <code>http://www.seai.ie/Your_Building/BER/DBER-Tech-June-20151.pdf</code>

We find only marginal evidence of downward adjustment of energy efficiency assessments in the preworks distribution but there is evidence of bunching of post-works BER ratings on the positive side of rating thresholds. Bunching in the post-works distribution is found across most sub-groups of the sample, indicating that adjustment may have been a systemic issue as opposed to being isolated to certain groups of assessments. We examine the absolute intensity of bunching, finding that between 3.1% and 4.7% of BER assessments within the Better Energy Homes grant scheme may have been adjusted downward (i.e. more efficient). We find that bunching is relatively stronger at thresholds where the letter grade changes, e.g. the C3/D1 threshold, as opposed to thresholds where the letter grade does not change, e.g. C2/C3 or D1/D2.

This research adds to the literature on evidence of perverse incentive and the literature on bunching in energy labels in the residential sector. The implications of this research are quite clear in that between 3.1–4.7% of assessments represent a significant proportion of the sample and in the interest of accuracy and consumer protection, the results of this analysis may be used to inform the auditing process. Analysis here suggests that adjustments are mostly achieved via the low energy lighting parameter. It is possible that assessors are adjusting this parameter in order to misrepresent a property's BER grade. It is also possible that assessors might advise a home owner that if they replace a certain proportion of their lighting with low energy alternatives, their BER will rise. An assessor might therefore record a higher level of low energy lighting on the promise that the recommended replacements are made. A visual lighting audit can be completed relatively easily and if the assessed level of eco-lighting is not present, an assessment is likely to have been misrepresented. While it has not been assessed within this paper the mislabelling of energy ratings potentially adds a substantial premium to property owners, which will be paid by unsuspecting customers seeking to either purchase or rent such properties.

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Appendix A. Dwelling Energy Assessment Procedure

Appendix B. Estimated akaike information criterion

Grade	Order=1	Order=2	Order=3	Order=4	Order=5
A1/A2	-3939.19	-3937.62	-3935.64	-3936.88	-3938.07
A2/A3	-3521.68	-3522.23	-3519.70	-3520.65	-3522.38
A3/B1	-3177.63	-3179.10	-3179.23	-3179.51	-3179.51
B1/B2	-2820.42	-2833.54	-2835.10	-2835.68	-2835.68
B2/B3	-2588.57	-2597.44	-2597.84	-2598.80	-2598.86
B3/C1	-2330.69	-2394.64	-2421.28	-2427.48	-2426.17
C1/C2	-2281.59	-2318.34	-2359.74	-2366.72	-2365.85
C2/C3	-2254.60	-2309.17	-2357.86	-2357.86	-2358.79
C3/D1	-2800.84	-2889.38	-2914.21	-2914.21	-2979.80
D1/D2	-4033.98	-4047.66	-4068.06	-4067.25	-4067.38
D2/E1	-4424.38	-4506.42	-4541.69	-4547.97	-4548.92
E1/E2	-4772.20	-4772.75	-4778.86	-4778.86	-4780.68
E2/F	-7166.80	-7173.89	-7174.30	-7174.30	-7172.61
F/G	-9568.67	-9571.03	-9581.27	-9583.19	-9580.87

Table B.6: Estimated Akaike information criterion for each threshold at varying polynomial orders

Appendix C. Complete estimation results

			Table	C.7: Co	omplete	e estimati	on of pre-	-works reg	gression o	liscontinu	ity design	1		
Threshold	A1/A2	A2/A3	A3/B1	B1/B2	B2/B3	B3/C1	C1/C2	C2/C3	C3/D1	D1/D2	D2/E1	E1/E2	E2/F	F/G
$kWh/m^2/yr$	25	50	75	100	125	150	175	200	225	260	300	340	380	450
Constant	-0.000007	0.000672	0.003732	-0.029875	-0.053723	-1.422059***	-3.331719***	-5.377512***	-2.05454***	8656242***	-1.075515^{***}	446071**	-0.016592	0733622**
	-0.000030	-0.000585	-0.004893	-0.031411	-0.088406	-0.256672	-0.481814	-0.709273	-0.379431	-0.180804	-0.167602	-0.156469	-0.025009	-0.022588
T	0.000001	-0.000034	-0.000130	0.000841	0.001177	$.0262482^{***}$	$.0536008^{***}$	$.0762383^{***}$	$.025503^{***}$	$.009374^{***}$.0100828***	$.003742^{**}$	0.000120	.0004547**
	-0.000003	-0.000030	-0.000174	-0.000860	-0.001969	-0.004821	-0.007825	-0.010145	-0.004751	-0.001958	-0.001586	-0.001314	-0.000182	-0.000141
(X - c)	0.000000	0.000001	0.000001	-0.000008	-0.000009	0001614^{***}	0002873^{***}	0003601***	0001054^{***}	0000338***	0000315^{***}	0000104**	0.000000	-9.38e-07**
	0.000000	0.000000	-0.000002	-0.000008	-0.000015	-0.000030	-0.000042	-0.000048	-0.000020	-0.000007	-0.000005	-0.000004	0.000000	0.000000
$(X - c)^2$	0.000000	0.000000	0.000000	0.000000	0.000000	3.31e-07***	5.13e-07***	5.67e-07***	1.45e-07***	4.05e-08***	3.27e-08***	9.72e-09**	0.000000	6.44e-10**
	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
$(X - c)^{3}$	0.000007	-0.000687	-0.006365	0.005410	0.030386	$.597123^{***}$	1.15163^{***}	1.700275^{***}	$.9155945^{***}$	$.3099874^{***}$.3959228***	.12564**	0.015795	$.02798^{***}$
	-0.000031	-0.000608	-0.005358	-0.035915	-0.035503	-0.089168	-0.147408	-0.193808	-0.113857	-0.058563	-0.051358	-0.043137	-0.008979	-0.008165
T * (X - c)	-0.000001	0.000036	0.000255	0.000005	-0.000491	0080056***	013215^{***}	0170674^{***}	0082249^{***}	00239***	0026495^{***}	0007376**	-0.000083	0001238^{***}
	-0.000003	-0.000032	-0.000202	-0.001043	-0.000570	-0.001192	-0.001689	-0.001943	-0.001008	-0.000450	-0.000343	-0.000254	-0.000047	-0.000036
$T * (X - c)^2$	0.000000	-0.000001	-0.000003	-0.000002	0.000002	.0000269***	.000038***	$.0000429^{***}$	$.0000185^{***}$	4.62e-06***	4.44e-06***	1.08e-06**	0.000000	1.37e-07***
	0.000000	-0.000001	-0.000003	-0.000010	-0.000002	-0.000004	-0.000005	-0.000005	-0.000002	-0.000001	-0.000001	0.000000	0.000000	0.000000
$T * (X - c)^3$	0.000000	0.000000	0.000000	0.000000										
	0.000000	0.000000	0.000000	0.000000										
Observations	159	159	159	159	159	159	159	159	199	259	279	279	399	519
R-squared	0.017	0.127	0.483	0.849	0.947	0.917	0.804	0.787	0.877	0.866	0.904	0.729	0.715	0.445
	Standard errors in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$)													

Table C.8: Complete estimation of post-works regression discontinuity design

Threshold	A1/A2	A2/A3	A3/B1	B1/B2	B2/B3	B3/C1	C1/C2	C2/C3	C3/D1	D1/D2	D2/E1	E1/E2	E2/F	F/G
$kWh/m^2/yr$	25	50	75	100	125	150	175	200	225	260	300	340	380	450
Constant	-0.00007360	0.00025000	0.00045160	-0.00986410	-0.02117540	.2052766*	-0.04854190	1.146138^*	0.30896310	.4440584*	0.09449250	-0.25497890	0.05087960	-0.03978430
	-0.00005530	-0.00026990	-0.00111970	-0.00774420	-0.02725320	-0.10345740	-0.27223280	-0.46746950	-0.25048190	-0.20867050	-0.24178840	-0.26938150	-0.05304710	-0.04821680
T	0.00000676	-0.00001200	-0.00001560	0.00027320	0.00048330	0039084*	0.00092340	0164162^{*}	-0.00385190	0047312*	-0.00087790	0.00214570	-0.00035470	0.00025180
	-0.00000489	-0.00001370	-0.00003980	-0.00021200	-0.00060710	-0.00194330	-0.00442100	-0.00668610	-0.00313660	-0.00225970	-0.00228730	-0.00226270	-0.00038670	-0.00030020
(X - c)	-0.00000020	0.00000019	0.0000018	-0.00000252	-0.00000370	.0000247*	-0.00000574	.0000784*	0.00001610	$.0000169^*$	0.00000276	-0.00000599	0.00000084	-0.00000053
	-0.00000014	-0.00000023	-0.00000047	-0.00000193	-0.00000450	-0.00001220	-0.00002390	-0.00003190	-0.00001310	-0.00000815	-0.00000721	-0.00000633	-0.00000094	-0.00000062
$(X - c)^{2}$	0.00000000	0.00000000	0.00000000	0.00000001	0.00000001	-5.20e-08*	0.00000001	-1.25e-07*	-0.00000002	-2.01e-08*	0.00000000	0.00000001	0.00000000	0.00000000
	0.00000000	0.00000000	0.00000000	-0.00000001	-0.00000001	-0.00000003	-0.00000004	-0.00000005	-0.00000002	-0.00000001	-0.00000001	-0.00000001	0.00000000	0.00000000
$(X - c)^{3}$	0.00007470	-0.00011060	-0.00021300	0.00865880	0.00784940	-0.06662310	-0.00827290	3209746*	-0.10318370	1706542*	-0.01740040	0.08761430	-0.01842860	0.01626030
	-0.00005530	-0.00028060	-0.00122600	-0.00885450	-0.01094470	-0.03594100	-0.08328780	-0.12773540	-0.07516320	-0.06758900	-0.07409060	-0.07426510	-0.01904450	-0.01742990
T * (X - c)	-0.00000702	0.00000079	0.00000381	-0.00023090	-0.00012640	0.00090210	0.00007970	.0032214*	0.00090310	$.0013114^{*}$	0.00011410	-0.00051780	0.00009480	-0.00007070
	-0.00000495	-0.00001490	-0.00004620	-0.00025700	-0.00017570	-0.00048060	-0.00095430	-0.00128040	-0.00066560	-0.00051900	-0.00049450	-0.00043740	-0.00009990	-0.00007750
$T * (X - c)^2$	0.00000022	0.00000011	0.00000001	0.00000203	0.00000051	-0.00000306	-0.00000019	-8.09e-06*	-0.00000198	-2.52e-06*	-0.00000019	0.00000077	-0.00000012	0.00000008
	-0.00000015	-0.00000028	-0.00000060	-0.00000253	-0.00000071	-0.00000161	-0.00000274	-0.00000321	-0.00000147	-0.00000100	-0.00000083	-0.00000064	-0.00000013	-0.00000009
$T * (X - c)^3$	0.00000000	0.00000000	0.00000000	-0.00000001										
	0.00000000	0.00000000	0.00000000	-0.00000001										
Observations	159	159	159	159	159	159	159	159	199	259	279	279	399	519
R-squared	0.085	0.062	0.051	0.307	0.829	0.909	0.870	0.773	0.364	0.686	0.681	0.620	0.751	0.805
-	Standard errors in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$)													

Appendix D. Varying polynomial order

			rable Biel	, seacheres	101 Tegrebe	nome of ta	rjing porji	ionnai ora			
T	hreshold	Orde	er=1	Ord	er=2	Ord	ler=3	Ord	ler=4	Order==5	
Grade	$kWh/m^2/yr$	τ (pre)	τ (post)	τ (pre)	τ (post)	τ (pre)	τ (post)	τ (pre)	τ (post)	τ (pre)	τ (post)
A1/A2	25	-1.67E-06	1.27E-07	-4.80E-06	3.00E-06	0.0000747	0	0.0005774	0.000228	-0.0003334	-0.0021675
A2/A3	50	-8.31E-07	8.20E-06	-0.0000453	0.0000263	-0.0001106	-0.000687	0.0004612	-0.006151	0.0056401	0.0432798
A3/B1	75	-1.60E-06	.000113***	-0.0000674	-0.0002833	-0.000213	-0.0063653	-0.0057657	-0.0184243	-0.0057657	-0.0184243
B1/B2	100	.0000515*	$.0009724^{***}$	-0.0002369	-0.0017863	0.0086588	0.0054102	0.0185618	-0.1448856	0.0185618	-0.1448856
B2/B3	125	$.0005477^{***}$.002408***	-0.0013993	0.0086942	0.0078494	0.0303856	0.0078437	0.0301106	0.2783018	-0.1277042
B3/C1	150	.0011409***	-0.0012127	0.0060943	$.1336812^{***}$	-0.0666231	$.597123^{***}$	-0.1363673	-0.2155473	-0.066201	.6013416***
C1/C2	175	1.68E-04	0025514**	0308528*	$.1733306^{***}$	-0.0082729	1.15163^{***}	-0.3227687	-0.4942966	-0.0063296	1.160392^{***}
C2/C3	200	-1.01E-03	0027212*	-0.010472	.28824***	3209746*	1.700275^{***}	3209746*	1.700275^{***}	3273348*	1.705312^{***}
C3/D1	225	0033842***	0058593***	-0.014024	.338182***	-0.1031837	$.9155945^{***}$	-0.1031837	$.9155945^{***}$	0.0861941	2.394507^{***}
D1/D2	260	0007917*	0.0002428	0343775**	.0348323**	1706542*	.3099874***	-0.1094325	0.043535	1779404^{*}	.3464827***
D2/E1	300	4.23E-04	0.0004601	0.0107158	$.0800144^{***}$	-0.0174004	.3959228***	.7450301*	-0.2378756	-0.0188702	$.3968944^{***}$
E1/E2	340	.0007381*	.0004661*	0.0185936	0.0050986	0.0876143	.12564**	0.0876143	.12564**	0.088536	.1261547**
E2/F	380	-5.76E-05	$.0005056^{***}$	-0.0033644	$.0106197^{**}$	-0.0184286	0.015795	-0.0184286	0.015795	-0.7098537	-0.017295
F/G	450	$.0007854^{***}$	$.0001787^{***}$	0.0017995	0.0022613	0.0162603	$.02798^{***}$	0.0461789	-0.0129516	0.0163203	$.0278973^{***}$
				(*:	** p<0.01, ** p	p<0.05, * p<0	0.1)				

Table D.9: τ statistics for regressions of varying polynomial order

Appendix E. Varying bin size

Т	hreshold	Bin = 0.25 kWh		Bin = 0.5 kWh		Bin = 0).75 kWh	Bin = 1 kWh		
Grade	$kWh/m^2/yr$	τ (pre)	τ (post)	τ (pre)	τ (post)	τ (pre)	τ (post)	τ (pre)	τ (post)	
A1/A2	25	0.0000747	0	0.0001374	0.000017	0.000193	0.0000188	0.0002818	4.90E-05	
A2/A3	50	-0.0001106	-0.000687	-0.0001097	-0.0014231	-0.0005337	-0.0024907	-0.0001448	-1.29E-03	
A3/B1	75	-0.000213	-0.0063653	-0.000569	-0.0144554	0.0011222	-0.0205148	-0.002191	-3.30E-02	
B1/B2	100	0.0086588	0.0054102	0.0172488	0.0185095	0.028579	0.0383001	0.0338266	6.76E-02	
B2/B3	125	0.0078494	0.0303856	0.0142284	0.0537427	0.0126744	0.0315848	0.0368301	1.07E-01	
B3/C1	150	-0.0666231	$.597123^{***}$	-0.138885	1.230673^{***}	-0.1542492	1.774392^{***}	-0.2839504	2.49091^{***}	
C1/C2	175	-0.0082729	1.15163^{***}	-0.0486383	2.32701^{***}	0.1328108	1.765952^{**}	-0.1098352	4.619151^{***}	
C2/C3	200	3209746^{*}	1.700275^{***}	5740039^{*}	3.392807^{***}	-0.6012671	3.776738^{***}	-1.05785	6.468187^{***}	
C3/D1	225	-0.1031837	$.9155945^{***}$	-0.2000646	1.829761^{***}	-0.3002313	2.710461^{***}	-0.4027853	3.615014^{***}	
D1/D2	260	1706542^{*}	$.3099874^{***}$	338941*	$.6198026^{***}$	-0.3815614	$.7412651^{***}$	6527782^{*}	1.239822^{***}	
D2/E1	300	-0.0174004	.3959228***	-0.0291379	.7737082***	-0.0279816	1.153332^{***}	0.0801394	1.514799^{***}	
E1/E2	340	0.0876143	.12564**	0.15245	$.2521776^{**}$	0.252381	.3004379*	0.2846287	$.5333505^{**}$	
E2/F	380	-0.0184286	0.015795	-0.0343782	0.0257593	-0.045651	0.035589	-0.0729491	4.63E-02	
F/G	450	0.0162603	$.02798^{***}$	0.0359747	$.0519688^{**}$	0.0490415	$.0803548^{**}$	0.0944696	$.1101886^{**}$	

Table E.10: τ statistics for regressions of varying bin size

(*** p<0.01, ** p<0.05, * p<0.1)

Appendix F. Graphical evidence of adjustment among sub-groups

Figure F.11: Post-works distributions by location

Figure F.12: Post-works distributions by year of assessment

Figure F.13: Post-works distributions by contracting type

kWh/m^2/yr

Т

300

Т

400

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600

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500

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100

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200

Figure F.14: Post-works distributions by type of dwelling

Figure F.15: Post-works distributions by version of DEAP software

Appendix G. Paramters that may be susceptible to adjustment

Figure G.17: Proportion of Heating System Response Categories by 5kWh bin

Figure G.18: Main Space Heating System Efficiency by 5kWh bin

Figure G.19: Hot Water Store Insulation Thickness by 5kWh bin

Figure G.20: % Draught Proofing by 5kWh bin

		Title/Author(s)
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