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Estimating the impact of household energy savings measures for Ireland using the BER database*

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Abstract: This paper estimates the impacts of various household energy saving measures in Ireland. The analysis develops a matrix of household energy use and types based on the Building Energy Rating (BER) system and the major dwelling and fuel-use types. It explicitly models the difference between using the BER data versus Census data. The analysis uses data from the BER, SEAI, and CSO, and other public sources. Modelling work estimated the distribution of energy ratings for the national sample of households from the BER sample, with the results indicating that the worst energy-rated households were about seven per cent underrepresented in the BER sample. The system, data, and modelled predictions were then used to perform some preliminary cost benefit analysis on energy savings measures versus costs in terms of the overall housing stock in Ireland. The results and model were used by SEAI to inform them of values and options in their energy savings policy work. Indicative results suggest that accounting for underrepresentation of the most inefficient housing units and policies aimed at the lower efficiency units may have the highest ratio of costs over benefits.

Keywords: household energy use, Building Energy Rating (BER), Ireland
JELs: Q40, Q48

1. INTRODUCTION

This article estimates the energy savings from a variety of residential upgrade retrofit 'measures' (20 measures in total) in Ireland as applied to various households with different Building Energy Rating (BER) certifications. Domestic energy use in Ireland and the EU is one of the areas where policy makers believe large and cost effective energy savings may be possible. Domestic energy use in Ireland represents about twenty five per cent of total final energy consumption (CSO 2012).[1] More widely in the EU, buildings account for forty per cent of European energy consumption (European Commission, 2004). This means that demand for lighting, heating, cooling, and hot water in homes, workplaces and leisure facilities consume more energy than either transport or industry within the EU, making buildings an ideal focus for energy policy. Energy efficiency in this area has the potential to help in reducing greenhouse gas emissions and energy costs while at the same time contributing to the security and affordability of energy supply, economic competitiveness and environmental sustainability.

The initial policy related studies available suggest domestic energy efficiency in Ireland may be one of the low-hanging fruits in GHG mitigation policy. Given that the Irish housing stock is one of the least energy efficient in Northern Europe (Ahern et al., 2013; Lapillonne et al., 2012; Brophy et al., 1999), any such changes have the potential to have a significant effect in terms of reduced energy consumption, reduced emissions, and boosting the economy.[2]

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[1] CSO, SEI01: Energy Balance by Energy Supply and Consumption, Fuel Type and Year (2012) data, accessed, Sept 2014: CSO Statbank http://www.cso.ie/px/pxeirestat/Statire/SelectVarVal/saveselections.asp

[2] We do not wish to debate the 'economic benefits' too deeply. Largely, however, fossil fuels are imported in Ireland, so ultimate expenditure on primary energy sources means cash outflows. Various aspects of expenditures, import/export, and

One initiative consistent with EU policy and focusing on buildings in Ireland is the introduction of the Building Energy Rating (BER) certification, whereby the overall efficiency of residential and commercial buildings is rated on a scale from A to G. This initiative was created as part of the Implementation of EU Energy Performance of Buildings Directive (EPBD) in 2006[3]. This was followed by subsequent energy efficiency policies such as the Low Carbon Homes Programme in 2008[4]; the Home Energy Saving Scheme in 2009[5], which was superseded by the Affordable Energy Strategy in 2011 (DCENR, 2011); and the National Energy Efficiency Action Plan 2009 – 2020 (DCENR, 2013). All new buildings, buildings for sale or sold, or rented, must have an energy rating. Ratings can be obtained at the request of the owner. Thus, older homes or residences and properties that were never sold or rented may not have a rating.

BERs are estimated by trained and registered assessors who take detailed measurements of the residence in question. Assessors measure, inter alia, the area of the rooms, the size of the windows, the thickness of the walls, the levels of insulation, details of the heating system, the number of fireplace flues, floor types and wall types. A BER typically includes 80 observations on the home. The data are entered into a standard and bespoke software tool (DEAP), which then is used to estimate the energy usage per square foot of floor space, which is mapped into the letter rating scale. The estimation is based on a standardized occupancy and usage characteristics (e.g., heating and lighting needs given weather, seasons, room temperatures, etc.).

Our paper estimates potential energy savings from a variety of residential upgrade measures and makes use of the BER data and DEAP model, and also makes use of Census data. The BER data collects observations on over 80 different housing unit characteristics and then gives a predicted energy use per square meter, which is categorized into an efficiency score—the BER rating (which is also a categorical 'expected' energy use per square meter figure).

The model is based on cross classifying housing units as 'types'; there are 20 types in total: four dwelling types (flat, terraced, semi-detached, and detached), for each of the five primary heating fuels (electricity, gas, oil, solid fuel and wood). These are specified for each of the 15 Building Energy Ratings (BER) - thus creating a 15x20 matrix with 300 possible combinations of dwelling type, fuel type and BER. The types enable us to map the BER data to 'types' that are consistent with Census data.

Predicted energy savings by type of housing unit and type of intervention were provided by SEAI and applied to the data. An econometric approach and a special Census/CSO tabulation were used to predict the national energy savings from the BER energy database savings.

The genesis of this study was work done by London Economics and Indecon Economics Consultants for SEAI as part of a wider ranging policy study and report to estimate the costs and benefits of various options for residential energy saving upgrades and financial incentives for Ireland.

2. LITERATURE REVIEW

Given the importance of energy efficiency at a policy level, there have been numerous schemes which attempt to reduce energy consumption from buildings. The literature in this area is relatively consistent with some broad themes, such as retrofits of older housing and barriers to investment, which may be the most important considerations in policy design.

Baek and Park (2012) consider the policy barriers to retrofitting existing buildings in Korea. The authors highlight issues such as a lack of awareness, financial reasons, insufficient information and the absence of regulatory systems as key barriers to improving energy performance levels relative to their European counterparts. In contrast, Arimura et al. (2008) found that, in Japan, a combination of command and control and voluntary approaches can be successful in improving the environmental performance of facilities.

Bell and Lowe (2000) considered the implications of three modernisation schemes for low rise housing in the UK in the 1990s. For all three schemes, improvements in terms of emissions were found possible at modest cost using well proven early 1980s technologies. However, given the high proportion of owner-occupied housing in the UK promoting the use of proven technologies was considered to require policies which would encourage and enable millions of individuals to make the required investment. Over a decade later, Davies and Osmani (2011) assessed

savings by business and households (and investment) would have to be evaluated in more detail to say anything more definitive on economic benefits.

[3] EC Energy Performance of Buildings Regulation 2006 (S.I. No. 666 of 2006).

[4] http://www.seai.ie/Archive1/Low_Carbon_Homes_Programme/

[5] http://www.seai.ie/hes

the main challenges for achieving Low Carbon Housing Refurbishment (LCHR) in England from an architect's standpoint. Using a combination of surveys and interviews, they found that one of the greatest challenges still faced was the high capital costs for micro-generation technologies and energy efficiency. At the same time, they identified increased government supplied low carbon programmes as a key incentive.

From an Irish perspective, Ahern et al. (2013) investigated the case for thermal retrofit measures to the existing, oil centrally heated, rural housing stock. Using data from the 2006 national census and the Irish National Survey of Housing Quality (2001-2002) they modelled the thermal effects of multiple retrofit measures. Their results found that the greatest saving potential came from retrofitting the stock of housing from pre 1979, representing 36 per cent of total savings and the proportion of the housing stock built prior to building regulations. Clinch and Healy (2000) considered domestic energy efficiency in Ireland and questioned why the market fails to ensure that society captures the associated benefits and investigates policy instruments which could correct this market failure. Similar to studies in the UK, they found that while energy-saving measures have a positive net social benefit, the cost of programmes and the unwillingness of households to finance retrofits are key barriers. A later paper by the same authors (Clinch and Healy, 2003) used a simulation model to evaluate the economic benefit of improving households' thermal comfort post-retrofit. The result found that improvements in thermal comfort accounted for ten per cent of aggregate programme benefits in the economic evaluation. Curtis et al. (2014) present a methodology to distinguish the most energy inefficient properties in Ireland. They found a much higher rate of properties fell into the "inefficient" category relative to the EPC findings (35 per cent relative to 25 per cent).

This would indicate that high capital costs and lack of individual incentives remain issues in spite of the proven nature of the efficiency and cost savings from retrofitting in the literature. Measures such as the BER are just one element to provide the needed measurement tools for an increased incentive[6] to promote energy efficiency in the housing stock, and allow for greater transparency and comparability across the housing stock as a result of implementing retrofitting measures.

3. METHODOLOGY

Since our goal is to estimate the energy savings from some generic retrofit measures, we must develop a model of the housing/dwelling stock in Ireland. The model needs to reflect the values and available data from the BER and the DEAP model, which predicts energy use, but also be able to reflect the differences from the BER database and the actual housing stock as measured by Census data.

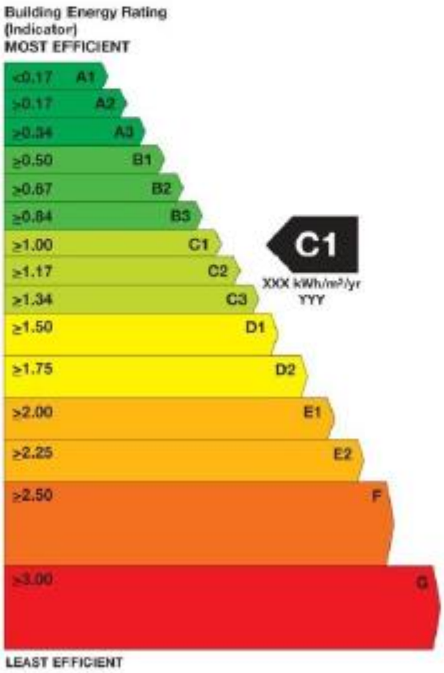
Since we did not have access to Census micro data, our approach was to cross-classify housing units by a typology that would be broadly consistent between the Census and BER methodologies. The methodology of the model thus consists of three main elements: developing the cross classification system and data calculation model as a spreadsheet; predicting the population distribution for the cross-classified system of dwelling units using an econometric model and the RAS procedure; and finally, running calculations for policy scenarios.

The first element is developing the cross classification system of housing units and then implementing the information into a spreadsheet which can be used to model and calculate costs and benefits of proposed policies. The reason for using the cross classification system is that we are interesting in summary measures that can be translated into policy prescriptions based on energy ratings. Further, we decided that obtaining CSO special tabulations of grouped data would be more straightforward that attempting to gain access to micro data.

The cross classification system is based on the 15 BERs and 20 housing unit types. The BERs are as follows, and correspond to a group/category of predicted energy use per square meter from the actual BER system. There are fifteen distinct energy ratings in BER: A1, A2, A3, B1, B2… C3, D1, D2, E, F, G, indicating a descending order of energy efficiency of the home. The BER ratings are indicators of the estimated kWh energy use per square meter of floor space per annum. The figure below gives a snapshot of the BER ratings and scale and the physical appearance of the BER certificate:

[6] The incentive from the BER is largely private, in that the owner of a property might have greater investment incentive knowing, for example, that on selling the property that the efficiency of the investment in terms of energy savings will be evident to prospective buyers.

Figure 1: BER energy ratings



Note: available online
Source: SEAI

There are twenty dwelling unit types in the model: the four types of housing units are: flat, terraced, semi-detached, and detached; and there are five primary heating fuels (electricity, gas, oil, solid fuel and wood). The housing unit types were selected as the most representative and matched types from the BER database and the CSO database. In the case of matching BER and CSO data on dwelling unit types, there are additional small categories of housing unit types, such as 'bed-sit', and types of solid fuel: e.g., coal, peat briquettes, etc. These were aggregated into 'flat' in the housing unit types, and solid fuels, in the case of primary fuel types.

Prediction

The nest step in the modelling is to predict the population of BERs for Ireland. The current BER database (2013[7]) includes about 365,000 records from households and dwelling that have received a BER rating, but there are almost 2m household dwelling units in Ireland.

It is generally believed that the BER database is not representative of households in Ireland, as households that have a BER are not selected randomly. New households and houses that have been sold or rented since 2005 all have BERs. Homeowners can voluntarily request a rating too. Some homes which have received grants or other forms of assistance for energy upgrades would also have been required to get a rating. Thus, older homes that have not changed hands or are not rented are likely to be under-represented in the BER database relative to the national population. Further, it is likely that this factor (of selection into the sample) is significantly correlated with the BER, with the expectation that such dwellings would tend to be less energy efficient.

To implement the ratings prediction, first the BER database was downloaded and input into the econometric software STATA. Preliminary regressions were run in order to study what variables available in the BER database were correlated with the energy rating and to see what similar type variables might be available from the CSO/Census.

The model selected was the ordered logit model. The ordered-logit model is a semi-categorical dependent variable econometric model. The model is appropriate for modelling dependent variables such as the BER categories, which have a clear ordering; for example, in the BER case, we know an A rating is better than a B rating, etc.

[7] Accessed in May 2013.

While the BER energy rating can actually be mapped to a numerical energy use number, our preference was to use the categories, as there is no clear pattern to the category sizes (the ranges are 25, 30, 40 kWh/m^2).

In the ordered logit model the dependent variable, y, can be represented by integer values; in our case 1-15, as there are 15 BER categories. More specifically, if the continuous variable y* has the relationship to independent variables, X, such that:

Equation 1: $$y^* = \alpha + \beta X + \varepsilon$$

But that we observe categorical variables for y, as:

$$y = \begin{Bmatrix} 1\ if\ 0 < y* \leq \chi_1 \\ 2\ if\ \chi_1 < y* \leq \chi_2 \\ 3\ if\ \chi_2 < y* \leq \chi_3 \\ \vdots \\ 15\ if\ \chi_{14} < y* \leq \chi_{15} \end{Bmatrix}$$

The equation estimated was the following, with the dependent variable y being the BER category:

Equation 2: $$\boldsymbol{y = a + b_f lnF + b_y Y + b_c i.C + b_f i.f + b_h i.h + e}$$

Where:

F is floor area

Y is year of construction
C is a set of dummy variables for County

i.f is a set of dummy variables for primary fuel type

i.h is a set of dummy variables for house type
e is the random error term

Data on unit numbers of dwelling types were obtained and cross-tabulated by: household age, household size (using room numbers[8] and average room sizes), county, fuel type, and house type from CSO/Census.

The next step was to use the model estimated in Equation 2 above and then make an out-of-sample prediction using the data obtained from the special tabulation request from the CSO/Census. The result was a predicted percentage of each type of energy rating for the national sample. The table below shows the differences in the totals between the sample and the prediction.

[8] CSO/Census data did not have data on floor area per se but does have room numbers, so the average room size from the BER database by house type was applied to estimate the house sizes in the CSO cross tab.

Table 1: BER ratings relative frequency distribution

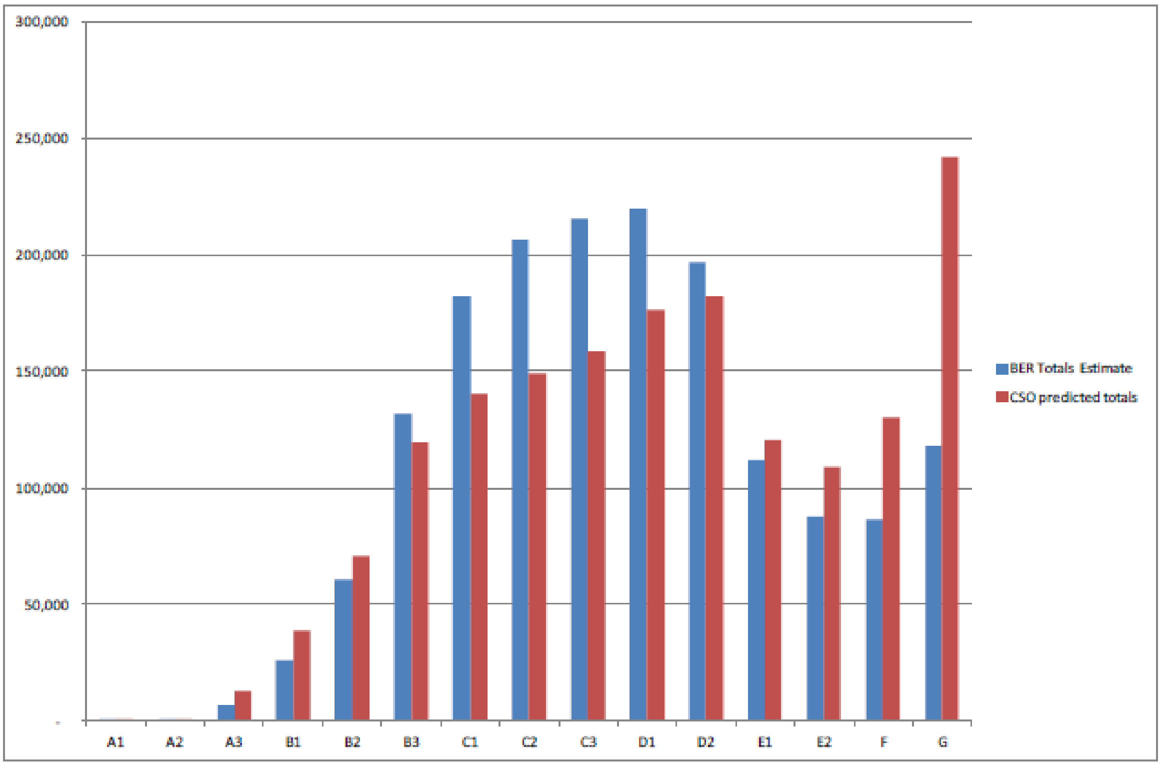
Rating	BER sample	CSO-hat national prediction
A1	0.0%	0.0%
A2	0.0%	0.0%
A3	0.4%	0.8%
B1	1.6%	2.4%
B2	3.7%	4.3%
B3	8.0%	7.3%
C1	11.0%	8.5%
C2	12.5%	9.0%
C3	13.1%	9.6%
D1	13.3%	10.7%
D2	11.9%	11.0%
E1	6.8%	7.3%
E2	5.3%	6.6%
F	5.3%	7.9%
G	7.2%	14.7%

Note: data are % of total housing units in the State
Source: Indecon/LE

Where the BER data column is the actual BER percentages (relative frequencies), and the column CSO-hat is the predicted relative frequency for the national sample.

As can be seen from the data, the BER sample and the national total relative frequencies are quite similar for some ratings, and quite different for others. The BER database seems to be under-representative with respect to the worst ratings, E-G, and especially for G, where the percentage in the national total is predicted to be about double the BER sample percentage. In contrast, the BER sample seems to be over representative of middle ratings, in the B3-D2 range, with the effect most pronounced from C1 to D1. Finally, the differences for the higher ratings, B3 and better, are predicted to be very small. The figure below gives a graphical depiction of the differences. The blue columns are the BER sample relative frequencies times the national total number of housing units from CSO, whereas the red columns are the relative frequencies derived from the predictive model times the CSO control total number of units. The large difference for the G rating is the most important finding; the number may be under-estimated by more than 100,000 units.

Figure 2: Differences in frequency of households



Note: predicted versus actual numbers
Source: Indecon/LE

AS Procedure of IPF

The final step in the prediction procedure is to 'control' the totals of the joint distribution of numbers of housing units of each type and predicted energy ratings to the CSO-Census totals (generated from the relative frequencies times the total number of units) for the four household types (Flat, House, Semi-d, Terraced), and five boiler/primary heating fuel types (electric, gas, oil, solid, wood), and to the predicted totals for the percentage of each BER category for the national totals. In this way, we predict the joint distribution of household types cross classified by rating, dwelling unit type, and primary fuel type (the 15x20 matrix). This was done using the RAS algorithm for interactive proportional fitting (IPF). A good description of the IPF method can be found in Orcutt et al (1986). Additional details on the RAS procedure are presented in the appendix.

4. DATA

Our study makes use of data from three main sources: the BER database, data from SEAI on energy savings by housing type and intervention type, and the CSO.

BER data was obtained from SEAI/the public domain database, available online upon application. These data are the energy ratings, the energy use as estimated by the DEAP model, measures of rooms, floor space, housing types, boiler and heating types, lighting, etc. Additional data take account of insulation types, year of construction, location, and even passive solar heating.

The model takes as inputs a number of key parameters. It is useful to categorize these parameters into classes:

- Energy savings measures parameters were estimated by SEAI using the DEAP model of the BER energy modelling system. These estimates are energy savings in kWh/annum/hh/m2, for each 15x20 matrix of energy ratings and household types and for each energy savings measure (e.g., wall insulation, new boiler, etc.). Thus there is an estimate of energy savings for each measure (20) for each type (300).

- The cost of the energy savings measures (annualized) data were provided by SEAI. These are the upfront costs annualized. It was assumed annual non-fuel running and maintenance costs are either zero or no different before and after a measure is implemented. In general, this data did not vary by household type (e.g., a new boiler), but was adjusted for size for some measures (e.g., wall insulation
- Market parameters and prices:
  - CO_2;
  - Electricity;
  - Gas;
  - Oil;
  - Coal/peat; and
  - Wood/other.

- Physical parameters:
  - CO_2 intensity for each fuel type;
  - Average room size by house type; and
  - The total percentage of each household type for which an energy savings measure will be available; this an estimate of the energy savings 'constraints', and a 15x20 estimate was estimated for each measure.

- Other parameters:
  - Discount rate: 5 per cent - from Department of Finance (DoF) guidelines; and
  - Comfort savings factor: 0.64 (it is assumed that only 64 per cent of potential energy savings are actually realised—the rest goes to keeping the room 'warmer').

- Number of housing units in the nation of each type (15x20) - this is the result of the prediction procedure above.
- Percentage of total housing stock for which any measure is available. This we call the constraints matrix. This is for each measure and for each of the 300 housing types, as estimate of the percentage of the national stock for which the measure would be available – so for example, the measure, upgrade to gas boiler, would not be available to those already with a gas boiler of sufficient efficiency or those not on the gas network.

The model is built to accommodate up to twenty different energy savings measures. In theory, however, more measures can be added and then just stacked down the rows in the model and added to the outputs sheet for their totals.

SEAI provided a matrix of energy savings by each of the above for implementation of energy savings measures. Thus there is an energy savings measure 'delta' for each household type for each measure of these matrices of deltas (i.e., 20x15x20). While not all the values are unique, SEAI produced these by estimation using the DEAP software used for energy ratings. The 'deltas' are thus theoretical potential energy savings, given the characteristics of the house-type, and the standard assumptions of the BER rating system and the DEAP model that is used to estimate energy use to give the rating.

SEAI have provided a measure of the estimates of the costs of each of the above measures. These were then annualized using the DoF 5 per cent discount rate and estimates of the lifetimes of each measure, with the lifetimes also provided by SEAI.

As our model is not dynamic, but there is a time element, fixed costs are amortised over the life of the supposed project and associated savings. Thus the annualised total cost benefit will give the measure of whether the total cost benefit is positive or negative. Further, the model allows energy price growth scenarios to be run and saved. The user can input a growth rate for each fuel price and then see how fuel price changes impact the values of energy saved, and how fuel price growth impacts the total energy values saved. Finally, the model allows the user to input scenarios and saves a scenario for comparison. Scenarios can be developed by allowing current energy prices to grow at a user-specified rate over a user-specified number of years.

5. RESULTS OF THE ENERGY SAVINGS FROM MEASURES MODELLING

The table below gives an example of the measures in the base case model, along with their descriptive names, and the number of households applying the measure based on the constraints estimates. All potential households have received the measure in this scenario.

Table 3: Measure names, descriptive names and units

Name	Measure Name	Measure #	Avg Energy Saved/hh (MWh)	Number Housing units upgraded 000s
R	Roof	1	1.2	940
W	Walls	2	2.1	955
F	Floor	3	1.2	1,171
WD	Windows	4	0.6	631
C	Heating controls	5	2.5	204
CB	Boiler Controls	6	4.9	1,052
L	Lighting	7	0.3	1,542
VB	Ventilation basic	8	0.4	1,474
R+W	Roof + walls	9	3.0	287
R+W+WD	etc	10	3.7	1,542
R+W+WD+CB	etc	11	7.4	1,542
R+W+WD+CB +L+VB	etc	12	8.9	1,542
R+W+WD+CB +L+VB+MVH R	Etc + heat recovery	13	10.1	1,542
R+W+WD+CB +L+VB+PV	Etc + photovoltaic	14	12.0	1,542
R+W+WD+CB +L+VB+SWH	Etc+ solar hot water	15	9.8	1,542
R+W+WD+CB +L+VB+HPUF	Etc + heat pump	16	7.9	1,542
R+W+WD+CB +L+VB+CBMB	Etc+ boiler	17	8.1	1,542
Shallow	Mix	18	2.9	1,542
Medium	Mix	19	6.1	1,188
Deep	Mix	20	9.2	630

Note: baseline scenario

Source: Indecon/LE

The next output table gives the total housing units, the total cost, the total amount of energy saved and the total amount of carbon saved. The total costs are found by multiplying the annualised costs in the model by the average lifetime from the estimates of lifetimes.

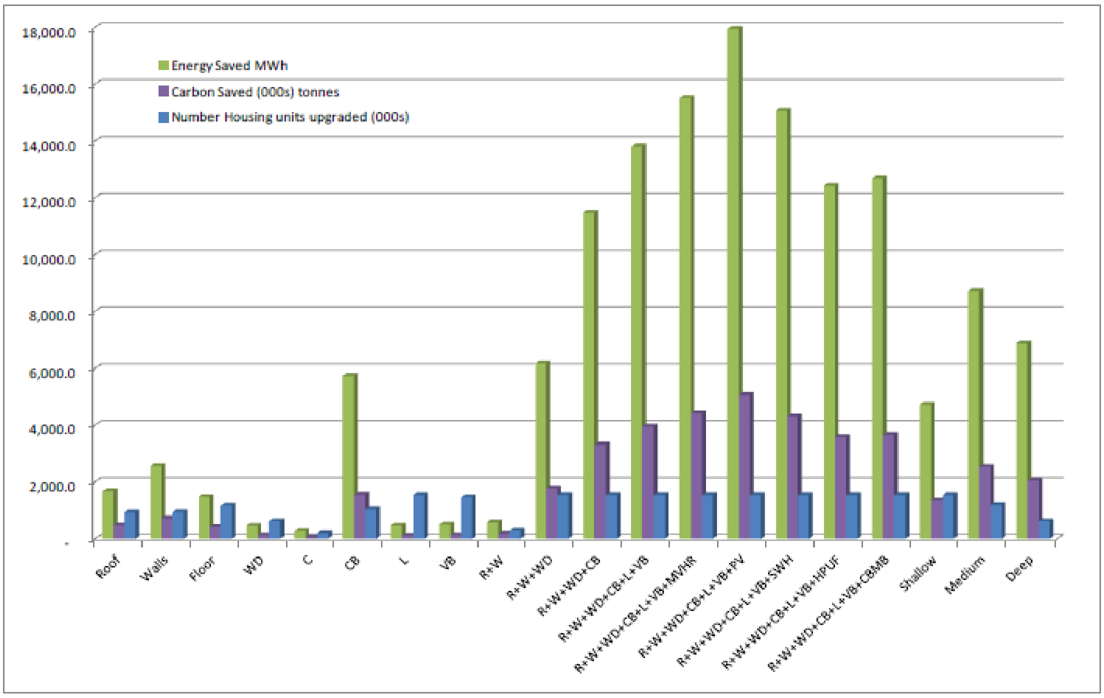
Table 4:	**Measure names, descriptive names and units**			
Name	Number Housing units upgraded (000s)	Total Cost (000s)	Energy Saved MWh	Carbon Saved (000s) tonnes
Roof	940	908,740	1,674.9	486.5
Walls	955	7,189,614	2,564.6	727.0
Floor	1,171	12,663,996	1,483.6	417.6
WD	631	5,589,193	471.3	133.0
C	204	312,132	281.7	64.5
CB	1,052	6,018,191	5,737.4	1,553.6
L	1,542	138,797	478.3	125.2
VB	1,474	672,129	510.7	137.4
R+W	287	2,059,408	598.0	183.3
R+W+WD	1,542	22,558,160	6,174.8	1,771.1
R+W+WD+CB	1,542	33,488,383	11,489.4	3,325.0
R+W+WD+CB +L+VB	1,542	37,991,717	13,805.2	3,958.4
R+W+WD+CB +L+VB+MVH R	1,542	62,528,203	15,523.6	4,416.1
R+W+WD+CB +L+VB+PV	1,542	44,524,110	17,944.1	5,069.8
R+W+WD+CB +L+VB+SWH	1,542	244,367,144	15,079.9	4,301.9
R+W+WD+CB +L+VB+HPUF	1,542	42,661,617	12,433.0	3,598.6
R+W+WD+CB +L+VB+CBMB	1,542	57,268,306	12,683.9	3,664.3
Shallow	1,542	4,956,642	4,725.4	1,361.2
Medium	1,188	11,965,084	8,726.9	2,535.8
Deep	630	12,675,701	6,877.1	2,046.6

Note: baseline scenario

Source: Indecon/LE

The figure below gives a graphical depiction of the above. The left-hand axis shows units, and can be MWh, Ktonnes, or 1000s of dwelling units.

Figure 3: Baseline scenario savings energy and CO_2



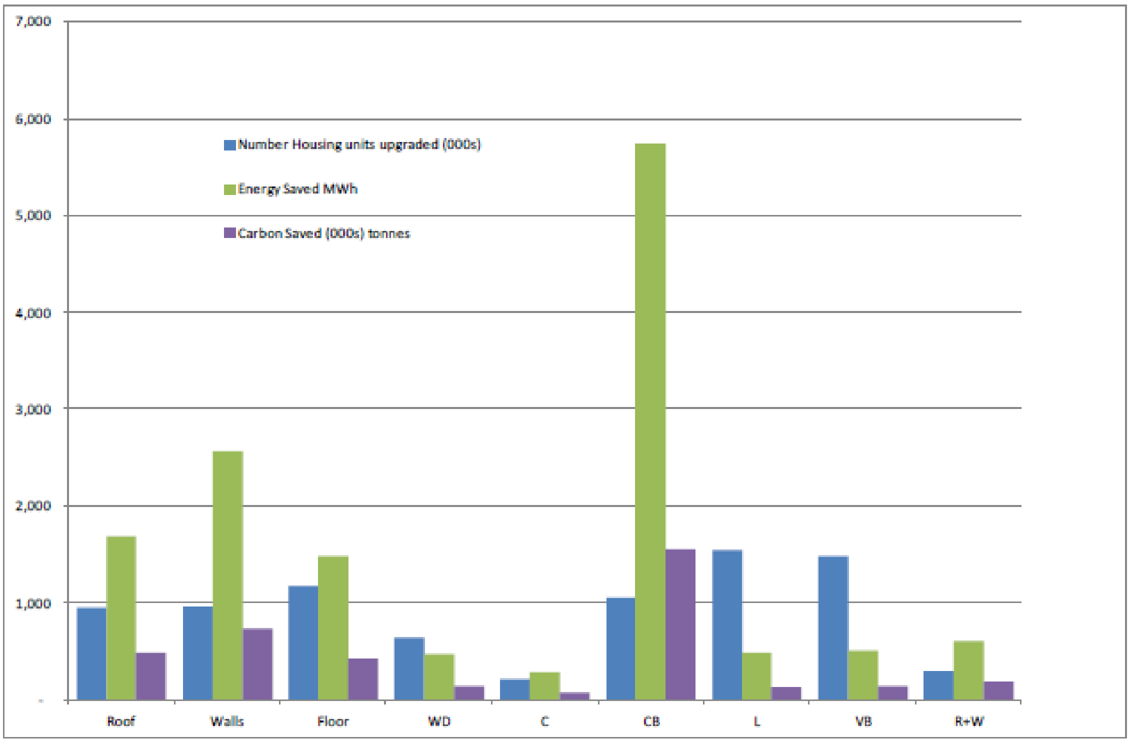
Note: Baseline scenario
Source: Indecon/LE

In general, the measures that involve a large number of measures, i.e., the combined measures have the most savings. The number of units available is constrained. It should be noted that it was not possible to estimate the joint distribution of the available measures for the multi-measure scenarios, and so the constraints from the shallow scenario (provided by SEAI) were used.

The next figure gives a more detailed breakdown of the single upgrade measures – that is, measures which do not combine measures (save roofs and walls).

It can be seen that the constraints on some of the measures, such as windows (WD) and controls (basic C), indicate that a small number of households in the state can use these measures, and thus the overall savings potential of these measures is limited.

Figure 3b: Baseline scenario savings energy and CO_2 – selected measures detail



Note: Baseline scenario
Source: Indecon/LE

The table below gives an illustration of the values of energy and carbon from the baseline scenario.

Table 5: Value of energy and carbon saved baseline scenario, and annual CBA				
Name	Value Energy Annual w/o Comfort in value	Carbon Value	Total Cost Annualised by lifetimes	CBA including Carbon and Comfort in value
Roof	122,839	18,974	36,350	174,560
Walls	191,241	28,353	239,654	87,512
Floor	112,736	16,285	506,560	-314,124
WD	35,654	5,187	186,306	-125,410
C	18,282	2,514	31,213	-133
CB	385,698	60,591	300,910	362,334
L	34,979	4,883	138,797	-79,259
VB	38,487	5,359	39,537	25,958
R+W	47,935	7,150	82,376	-327
R+W+WD	460,396	69,073	902,326	-113,884
R+W+WD+CB	893,026	129,675	1,339,535	185,493
R+W+WD+CB+L+VB	1,067,559	154,379	1,519,669	302,771
R+W+WD+CB+L+VB+MVHR	1,196,186	172,228	2,501,128	-459,859
R+W+WD+CB+L+VB+PV	1,380,389	197,721	1,780,964	573,614
R+W+WD+CB+L+VB+SWH	1,162,087	167,773	9,774,686	-7,791,152
R+W+WD+CB+L+VB+HPUF	963,519	140,347	2,133,081	-487,236
R+W+WD+CB+L+VB+CBMB	984,677	142,907	2,863,415	-1,181,950
Shallow	358,114	53,087	247,832	364,808
Medium	675,053	98,898	598,254	555,414
Deep	559,362	79,817	633,785	320,035

Note: Baseline scenario
Source: Indecon/LE

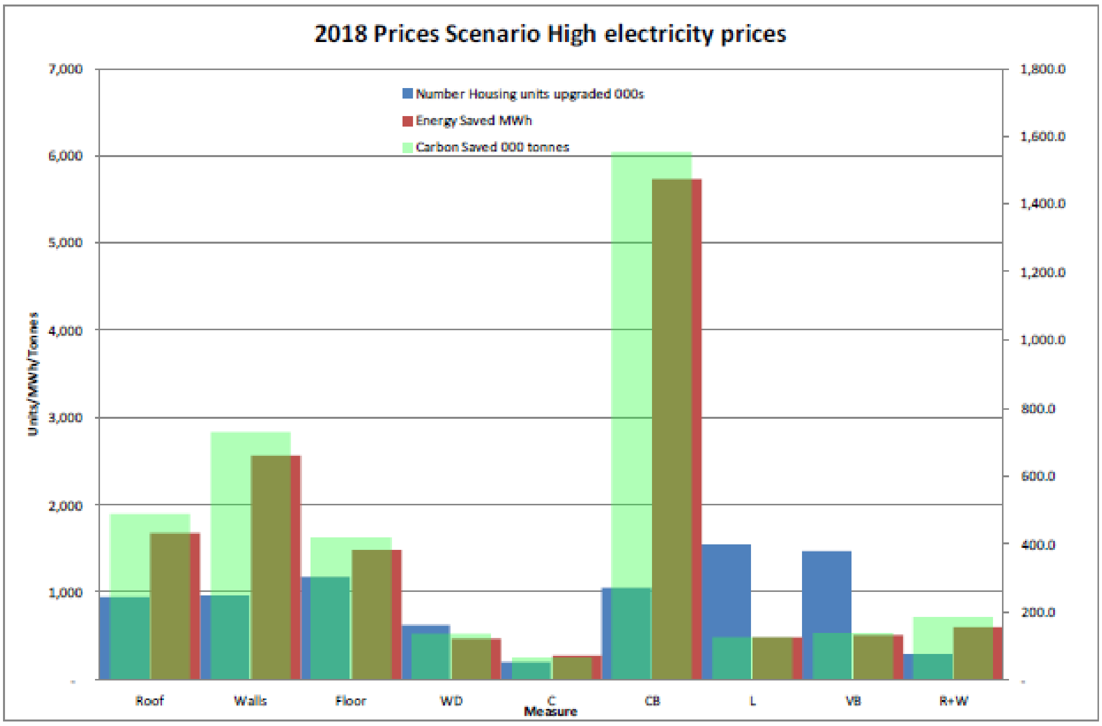
As an example of this, the previous graphic is repeated with now electricity prices growing by 12 per cent annually from 2013 to 2018, while all other prices remain constant. This is presented in the figure below. Not surprisingly, given the different scales, but that energy and carbon are due to carbon intensities, there is a high correlation between energy savings and carbon savings (given the shape of the red versus greenish-blue bars). However, the two are not perfectly correlated as the change in the energy mix due to changes in the relative prices (high electricity price growth) indicates that the weighted average carbon intensity will indeed be changing in the model when such a scenario is chosen.

The inclusion or otherwise of the 'comfort value' savings is of particular interest. This is the value of potential energy savings that is not realised as energy savings per se but taken as comfort in terms of a warmer home when a new boiler or better insulation is installed. This value was estimated by SEAI based on a sample of household data and actual gas meter readings before and after installations of upgrade measures. However, it was from an admittedly small sample (circa 500 houses over 3 years), and so these estimates should be viewed as preliminary.

Interestingly, while the combination measures make the largest savings, which might not be surprising, combination measures are less likely to be cost effective. This in part is likely to be reflective of diminishing returns. It is noteworthy that in the combined measures which used the DEAP modelling software to estimate the annual energy savings per square meter, the DEAP software does reflect diminishing returns of combined measures.

In terms of policy prescriptions, while there are some caveats and assumptions suggesting caution (e.g., various implementation and financing issues), the results suggest that some simple measures such as roof, walls, and boiler controls might be better in terms of cost effectiveness for energy savings policies. Focusing on these simple measures, one aspect is that boiler controls comes out very large, but a similar number of households could avail of other upgrades. It would appear boiler/heating controls, roof, wall, and to a lesser extent floor insulation are the more interesting upgrades to consider for future policies targeting home energy efficiency.

Figure 4: Baseline scenario savings energy and CO_2 – selected measures detail



Note: high electricity scenario, carbon saved on right hand axis
Source: Indecon/LE

6. CONCLUSIONS

This paper has presented a model and method of an application for measuring the energy and carbon savings impacts of household upgrade initiatives. The model makes use of the building energy rating system and Census data. The paper corrects BER ratings based data with population-based estimates.

A key feature of the model is to delineate housing units into 'types' which are amenable to use of BER and Census data. The typology varies by the key feature of energy use, building type (house, semi-detached, terraced, apartment), and primary fuel type (electric, gas, oil, solid, wood). Types are then used to predict the energy rating for the population versus the BER data base. The total number of each type of housing units in the State is estimated first by tabulating the distribution across the house types in the BER database. Then, using a special tabulation from CSO Census, the BER ratings data are regressed on explanatory variables such as house size, house age, county, and house type and fuel type. An out of sample prediction is made using an ordered logit model, in order to predict the national totals from the BER database. The RAS procedure of iterative proportional fitting is then used to control the percentage totals to the national total numbers of units for each type, given the predicted BERs. The result is a matrix of predicted housing unit numbers that is cross classified by 15 BERs, four housing types and five primary fuel types (electricity, gas, oil, coal-solid, wood), or 300 types in total.

The SEAI energy team then used the DEAP BER model to produce energy savings 'deltas' for each housing type, for a variety of upgrade measures (e.g., floor insulation, window upgrade, roof insulation, lighting upgrade, etc.) in terms of predicted kWh-saved/annum/m-squared. Thus where possible, the savings varied by each of the 300 house types for each measure. SEAI also provided estimates of costs and lifetimes of the upgrade measures. The model allows input of prices of energy saved. The result is an estimate of various costs and benefits of upgrade measures, with a flexible model which can be updated over time.

A few key results also emerge from our work. First, empirical estimates of the population distribution of energy ratings are provided. We estimate that the BER percentage of the worst houses (G rating) could underestimate the population percentage by about half (from about 7% to 14%).

Upgrading the worst houses first therefore has some of the better cost benefit outcomes regardless of measure, and updating the estimates of the BER to include under-represented older inefficient houses is an important aspect of consideration of future energy policy. As noted in Curtis et al (2014), there is a substantially greater likelihood that the elderly or families in rental properties will live in less efficient properties.

While the CBA results may be subject to further more refined research, our results indicate simple measures such as exterior insulation (walls and roof), and boiler controls, aimed at the more energy inefficient housing units represent the most promising areas for positive returns from any policies aimed at encouraging housing energy efficient upgrades.

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APPENDIX 1: DESCRIPTION OF THE RAS PROCEDURE

The IPF method is essentially a method to estimate the 'joint' frequency[9] distribution when the 'marginal' distributions are known. For the problem at hand, we have the percentage of Households with each Building

[9] The relative frequency is equally possible.

Energy Rating from the ordered-logit predictions (econometric model), and we have the Census special tabulation of the percentage of households with each type of boiler and type of building, so the procedure estimates the energy ratings across the boiler types and house types for the national totals.

The matrix of elements in our household joint frequency distribution is a 15x20 matrix (15 energy ratings x (5 house types x 4 fuel types). Thus we can think of the matrix M0, with elements m(i,j) 0, i=1…15, and j=1…20.

We can think of the 'true' matrix of totals as X, and the elements as x(i,j). Then the totals or marginal distribution for the energy ratings as, x(i) and the marginal distribution for house-types x fuel-types, x(j), where:

Equation 3: $$\boldsymbol{x}_i = \sum_{j=1}^{20} x_{ij}$$

And

Equation 4: $$\boldsymbol{x}_j = \sum_{i=1}^{15} x_{ij}$$

The matrix $\mathbf{M^0}$, is changed with each iteration, by the following; first the rows are controlled (proportionally adjusted) to the known totals, for each element, i, j.:

Equation 5: $$m_{ij}^1 = m_{ij}^0 \frac{\boldsymbol{x}_i}{\boldsymbol{m}_i^0} = m_{ij}^0 \frac{\sum_{j=1}^{20} x_{ij}}{\sum_{j=1}^{20} m_{ij}^0}$$

Then the columns are controlled to equal the known totals, with the updated matrix, M^1:

Equation 6: $$m_{ij}^2 = m_{ij}^1 \frac{\boldsymbol{x}_j}{\boldsymbol{m}_j^1} = m_{ij}^1 \frac{\sum_{i=1}^{15} x_{ij}}{\sum_{i=1}^{15} m_{ij}^1}$$

The process is repeated until some convergence criterion is satisfied. The resulting estimates are maximum likelihood (ML).

APPENDIX 2: ECONOMETRIC MODELLING RESULTS AND DETAILS

This annex presents the results from the econometric modelling used to predict the percentages of house-units with each different energy type. The foundation of the modelling is an ordered logit model, for each of the 15 energy ratings, based on the BER data, and observations that can be matched to Census Special Tabulation data. The regression outputs are in the table below.

```
Ordered logistic regression                       Number of obs   =     358091
                                                  LR chi2(34)     =  279783.58
                                                  Prob > chi2     =     0.0000
Log likelihood = -714058.49                       Pseudo R2       =     0.1638

------------------------------------------------------------------------------
   energyrating_indx |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------------+--------------------------------------------------------
     lnfloorarea_tot |  -2.212055    .0095537  -231.54   0.000     -2.23078    -2.19333
year_of_construction |  -.0419914    .0001375  -305.33   0.000     -.042261   -.0417219
                     |
             cnt_idx |
                  2  |   -.333786    .0351563    -9.49   0.000    -.4026911   -.2648809
                  3  |  -.2026354    .0292452    -6.93   0.000    -.2599548   -.1453159
                  4  |  -.4853783    .0259322   -18.72   0.000    -.5362044   -.4345522
                  5  |  -.3838137     .030188   -12.71   0.000    -.4429812   -.3246463
                  6  |   .1662916    .0254364     6.54   0.000      .116437    .2161461
                  7  |  -.0991183    .0269932    -3.67   0.000    -.1520241   -.0462125
                  8  |  -.6012802    .0290606   -20.69   0.000    -.6582379   -.5443224
                  9  |   .0260065    .0289664     0.90   0.369    -.0307667    .0827797
                 10  |  -.0771179    .0328476    -2.35   0.019    -.1414981   -.0127377
                 11  |  -.3642378    .0335604   -10.85   0.000     -.430015   -.2984606
                 12  |  -.3162097    .0450251    -7.02   0.000    -.4044572   -.2279621
                 13  |  -.2064488    .0275754    -7.49   0.000    -.2604955   -.1524021
                 14  |  -.3580134    .0414032    -8.65   0.000    -.4391622   -.2768645
                 15  |  -.3716538    .0308558   -12.04   0.000    -.4321301   -.3111775
                 16  |  -.2020561    .0300954    -6.71   0.000     -.261042   -.1430701
                 17  |  -.1739766    .0300494    -5.79   0.000    -.2328723   -.1150809
                 18  |  -.4896508    .0379478   -12.90   0.000    -.5640271   -.4152746
                 19  |   -.238174    .0355242    -6.70   0.000       -.3078   -.1685479
                 20  |   -.153883    .0371151    -4.15   0.000    -.2266272   -.0811388
                 21  |  -.3005768    .0327145    -9.19   0.000    -.3646961   -.2364574
                 22  |  -.2971441    .0290735   -10.22   0.000    -.3541271   -.2401611
                 23  |   -.313183    .0301277   -10.40   0.000    -.3722322   -.2541339
                 24  |  -.3222712    .0334737    -9.63   0.000    -.3878784    -.256664
                 25  |  -.2111874    .0294939    -7.16   0.000    -.2689944   -.1533804
                 26  |   .1015654    .0299897     3.39   0.001     .0427867    .1603441
                     |
       fuel_type5_idx |
                  2  |  -3.111977    .0118347  -262.95   0.000    -3.135172   -3.088781
                  3  |  -2.646818    .0127737  -207.21   0.000    -2.671854   -2.621782
                  4  |  -.0752912    .0200183    -3.76   0.000    -.1145262   -.0360561
                  5  |   -3.52085     .057268   -61.48   0.000    -3.633093   -3.408607
                     |
      house_type4_idx |
                  2  |   2.601803    .0134192   193.89   0.000     2.575501    2.628104
                  3  |   2.146896    .0116226   184.72   0.000     2.124116    2.169675
                  4  |   1.252379    .0113649   110.20   0.000     1.230105    1.274654
------------------------------------------------------------------------------
```

Where the variables are log of floor area, year of construction, county as an index, fuel type primary fuel type index, and house type index. As can be seen from the data, the major explanatory variables of interest, floor area, year of construction, fuel type and house type are all significant. The floor area is an expected negative sign, as there are scale efficiencies and the ratings are increasing by usage per square meter. Similar, older houses, indicate larger usage, larger rating index number and so the sign is as expected. The fuel types are harder to interpret, as the negative correlation would have to do with a correlation with other efficiency factors, and perhaps usage (e.g., coal for older homes).

The next step is then to predict the energy rating using the Census data which is special tabbed to include house ages and house types, fuel types, and rooms (converted to floor area) for the full Census population. The results and a tabulation of the predictions is found below.

Variable	Obs	Mean	Std. Dev.	Min	Max
p1	65520	0.0000332	0.000103	1.90E-10	0.0015573
p2	65520	0.0003086	0.0009544	1.78E-09	0.0143121
p3	65520	0.0076092	0.0217169	4.75E-08	0.272664
p4	65520	0.023566	0.0534141	1.94E-07	0.3777089
p5	65520	0.04273	0.0721983	5.60E-07	0.2899406
p6	65520	0.0725856	0.0720999	1.80E-06	0.2860517
p7	65520	0.085161	0.0850377	4.38E-06	0.2416944
p8	65520	0.0901683	0.0752156	9.66E-06	0.2136567
p9	65520	0.096148	0.0715524	0.0000219	0.206685
p10	65520	0.1068334	0.0760282	0.0000563	0.2213103
p11	65520	0.110459	0.0815071	0.0001535	0.2362448
p12	65520	0.0731307	0.060154	0.0002466	0.1727321
p13	65520	0.0658784	0.0608768	0.0001243	0.1758248
p14	65520	0.0787572	0.0852428	0.0000779	0.2557008
p15	65520	0.1466317	0.0957529	0.0000422	0.9971166

A comparison of the out-of-sample predictions, above, can be made to the within-sample predictions, which are found below.

Variable	Obs	Mean	Std. dev	Min	Max
p1	359,033	0.0000	0.0000	0.0000	0.0073
p2	359,033	0.0002	0.0004	0.0000	0.0636
p3	359,033	0.0039	0.0081	0.0000	0.5866
p4	359,033	0.0147	0.0248	0.0000	0.3786
p5	359,033	0.0350	0.0472	0.0000	0.2900
p6	359,033	0.0781	0.0800	0.0000	0.2861
p7	359,033	0.1102	0.0835	0.0000	0.2417
p8	359,033	0.1255	0.0727	0.0000	0.2137
p9	359,033	0.1318	0.0648	0.0000	0.2067
p10	359,033	0.1344	0.0684	0.0000	0.2213
p11	359,033	0.1194	0.0756	0.0000	0.2362
p12	359,033	0.0668	0.0546	0.0000	0.1727
p13	359,033	0.0518	0.0525	0.0000	0.1758
p14	359,033	0.0522	0.0683	0.0000	0.2557
p15	359,033	0.0760	0.0772	0.0000	1.0000

Ascertaining the validity of one versus the other is difficult. It is noteworthy, though, that the simple confidence intervals using the predicted proportions would contain the predicted value (e.g., the 14.7% would be in the confidence interval for the in-sample prediction of 7.6%). Nonetheless we have used these proportions as our best point estimate of the sample and out-of-sample predictions, but the indications are that additional future work in the area would be welcome.

FIRST VOTE OF THANKS PROPOSED BY SHEONA GILSENAN, CENTRAL STATISTICS OFFICE

I'd like to welcome the work in this paper by Mr Swinand and Ms O'Mahoney which combines multiple data sources and uses predictive models with industry estimates to produce a solid policy recommendation. This is an excellent example of the ability of data to influence policy making. Over the last number of years the availability of the BER dataset has allowed a large amount of new research including work on combining the BER dataset with other data sources such as deprivation indices to research fuel poverty, property sales ads to assess the effect of the BER rating on property prices, household budget data to look at expenditure on energy as just some of the examples.

This type of research will need to continue in the future with the increased demands for answers to comply with new regulatory requirements in the environmental area. In my response I would like to review the presented paper and highlight some of the new developments in the dataset that will be of interest for future research.

The paper presented explains the background to the history and development of the BER along with a detailed description of the process of collecting BER data It then discusses some of the limitations of the BER dataset for the purposes of using it for policy formulation.

These include that

1. The BER estimate itself is based on standard assumptions on consumption.
   There is no adjustment the calculation of energy consumption based for example on
   - Occupancy
   - Tenure
   - Location
2. Secondly that the dwelling in the BER dataset are not representative of the national stock, it is assumed that the stock of energy inefficient dwellings is underrepresented in the dataset and it needs to be adjusted to represent the national stock for policy formulation.

In relation the second point, this lies at the heart of the analysis and the authors use the results of the CSO Census 2011 to estimate the national number of dwellings by BER rating. The number of poorer rated dwellings (E, F and G Ratings) is thus increased from 25% of dwellings in the BER dataset to an estimated 35% in the analysis dataset. This estimate matches that of the paper "Using census and administrative records to identify the location and occupancy type of energy inefficient residential properties"[1]

Also in support of this estimate is the study on "Price Effect of Building Energy Ratings in the Dublin Residential Market " which estimated that E F and G ratings were approximately 35% , based on properties advertised for sale on the DAFT website in Dublin[2]

Using the presented model to predict BER ratings for the national stock, the estimate of the lowest rated ("G") dwellings more than doubled from 7.2% to 14.7%. When looking at how to target energy saving policy initiatives a good estimate of this category is crucial.

In the CSO we have been publishing a quarterly release based on the BER dataset supplied by the SEAI since Quarter 1 2014. In our release we also perform a basic reweighting using census totals, with banded year of construction, location and dwelling type. This differs from the model in the level of detail on location and also excludes heating. When compared to these predicted figures the CSO reweighted data appears to still have an underestimate. This will need to be examined in more detail in the future and this model will prove useful in this regard and I appreciate this opportunity to explore further some of the details of the model with some questions.

[1] Using census and administrative records to identify the location and occupancy type of energy inefficient residential properties: John Curtis,, Niamh Devitt, Adele Whelan

[2] Price Effect of Building Energy Ratings in the Dublin Residential Market: Sarah Stanley, Ronan C. Lyons and Sean Lyons

What is the prevalence of BER exempt dwellings in the national stock and did you make any adjustments for them?

Did you explore banding the periods of construction with respect to changes in regulation, as an explanatory variable model, together rather than just using year of construction as a continuous variable?

Can I ask, when you used counties in the predictive model, was this just at a basic county level, Dublin county Offaly etc. or did you look at subdividing for example Cork city , Cork County etc.? Based on our reweighting using CSO data there appears to be very different representation even on areas within Dublin, (high coverage of Dublin1 for example with lower coverage of neighbouring Dublin 3). Did you examine the importance and use of urban / rural splits as an explanatory variable in your model? As an aside, it would be useful to have the actual counties and reference county named in the model output rather than county 1 -26.

Finally were there any variables that would you ideally like to add to the model that may not have been available to you at the time of the analysis, what are they?

The CSO will look further into methods of reweighting for this dataset using available data, this will be also be aided by the upcoming Census in April that will allow an update of the weights.

With regard to the model schema, in light of the changes in commodity prices since the creation of the model it seems a welcome initiative to allow inputs such as changing prices for example in oil etc. This creates a powerful policy tool. Developments in additional data sources may allow improvements in the model in terms of estimates of consumption, for example meter data which could be directly linked to the BER data available.

Since the paper has been produced there has been continuing development of the BER dataset to allow further research and analysis. By the end of 2015 there were just under 600 thousand records, compared to 350 thousand at the time of this analysis. The proportion of each BER category in the dataset are largely unchanged .

Despite almost 600,000 assessments the awareness in the general population of the Building Energy Rating status of their dwelling is surprisingly low. In a recent survey of households carried out by the CSO just over 250,000 households were aware that a BER assessment had been carried out on their dwelling. This disparity between the actual number of assessments and the awareness of their BER rating seemed more acute in non-owner occupier households. Since 2012 the BER dataset has included a reason for the BER assessment taking place, which shows that more than half the assessments are carried out for the purposes of rent or sale. The survey respondent may not have been responsible for commissioning the BER assessment which may explain this disparity.

In the last year, we have received Eircodes attached to BER records which should improve the analysis potential of the BER dataset and build on existing work using small areas. At the moment we have coverage of approximately 57% of the total dataset with an Eircode. On a regional level, rural areas have less coverage, for example Dublin city has 72% of its records attached to an Eircode while Roscommon county has just 32%. However, we also see a disparity in areas within Dublin; with coverage running from 80% in some postal divisions to just over 56% in others areas in Dublin. So the issue of identifying local areas for policy initiatives is not just a rural one .

The provision of Eircodes will allow better matching of data with census and other household surveys. This could contribute to further exploration of some of the socio economic factors influencing energy consumption such as occupancy, age profiles, family status etc. Additionally the CSO has requested data from utility companies at a household level. The provision of actual consumption data for energy by utility companies should allow the updating of standard consumption estimates and provide improved estimates for energy savings. As the energy use accounted for by the BER is estimated to be approximately 70% of total household energy use, this additional data will also allow a fuller picture of energy consumption by households in Ireland.

As previously mentioned, the upcoming census should also update the picture of the current building stock and reflect some of the changes in energy consumption over the last few years; for example changes of primary heating systems from oil to wood burning and upgrading of existing housing stock through initiatives such as SEAI Better Energy Homes etc..In addition in the next year the CSO hopes to publish a regular release using the data from non-domestic BER assessments to further the picture of energy consumption in Ireland.

This is a brief overview of some of the developments in the pipeline that could be utilised in future research however we would encourage you to discuss what developments in data would be useful to you in this area. In conclusion, I’d like to congratulate you on your work and thank you for your presentation.

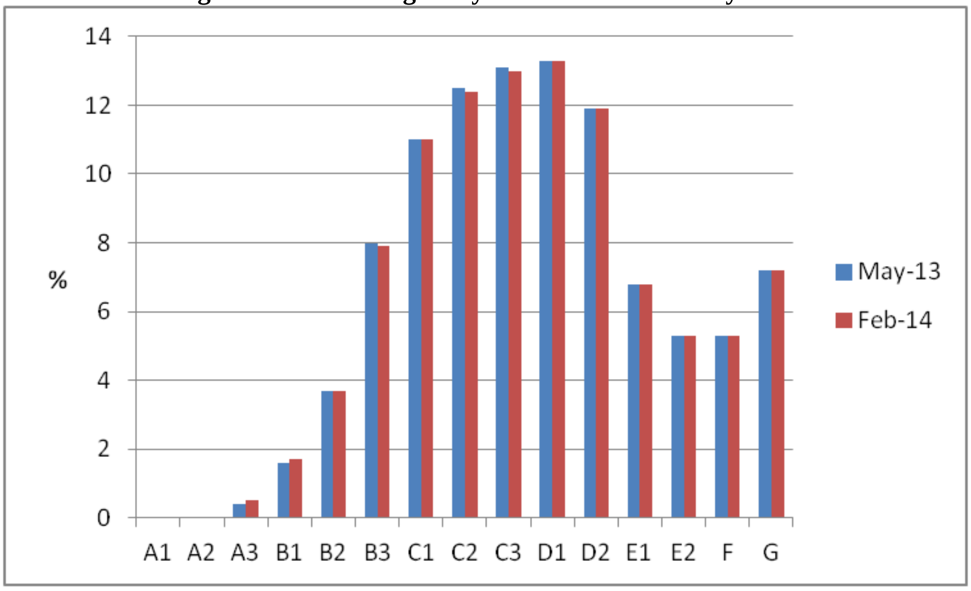
SECOND VOTE OF THANKS PROPOSED BY JOHN CURTIS, ESRI

Mr Chairman, ladies and gentlemen, I am grateful for the opportunity to second the vote of thanks to Gregory Swinand and Amy O'Mahoney. The BER dataset is a valuable resource for examining the issue of residential energy efficiency and I welcome this paper as a very useful contribution to the policy space that is tackling this issue. I propose starting by comparing the paper with some of my own work and conclude with some specific comments on the detail of the paper.

One of the three elements or methodological steps within the paper was predicting the population or housing stock distribution of BER ratings. This is something that I have undertaken, with two colleagues, and it is useful to compare the results.[1]

The authors cite our working paper draft, which has been since published, and will be familiar with what I'm about to present. We too used the BER database but in our case related to the database in February 2014, 9 months later and with 410,000 records compared to 365,000 in May 2013. While we didn't employ an ordered logit we also estimated BER as a function of household characteristics that were also contained in the population census dataset. Given our different models, it is not possible to compare parameter estimates. But our choice of explanatory variables differs slightly – we didn't use a county dummy, which was an option nor did we use floor area, which isn't a variable included in the census dataset and therefore requires further inference in the analysis. But we can compare the projection of national household stock of BER ratings. First, as Figure 1 illustrates thought the BER database has 12% more records in February 2014 there proportionate breakdown on BER ratings did not change.

Figure 1: BER ratings May 2013 versus February 2014



Our second comparison is to compare Swinand & O'Mahoney's results from Table 1 with our estimates, which are presented in Figure 2. As our analysis was aggregated to letter scale the results have be adjusted accordingly. The results are substantially different. Which is better? There isn't a obvious answer to that question. However, we know from our analysis that our model only had 47% within sample prediction accuracy. Which isn't very reliable, and particularly so if policy decisions riding on it. But false-positives and false-negative mostly cancel each other out and the aggregate result is possibly not far from reality.

[1] Curtis et al. (2015)

Figure 2: Comparison of BER projections

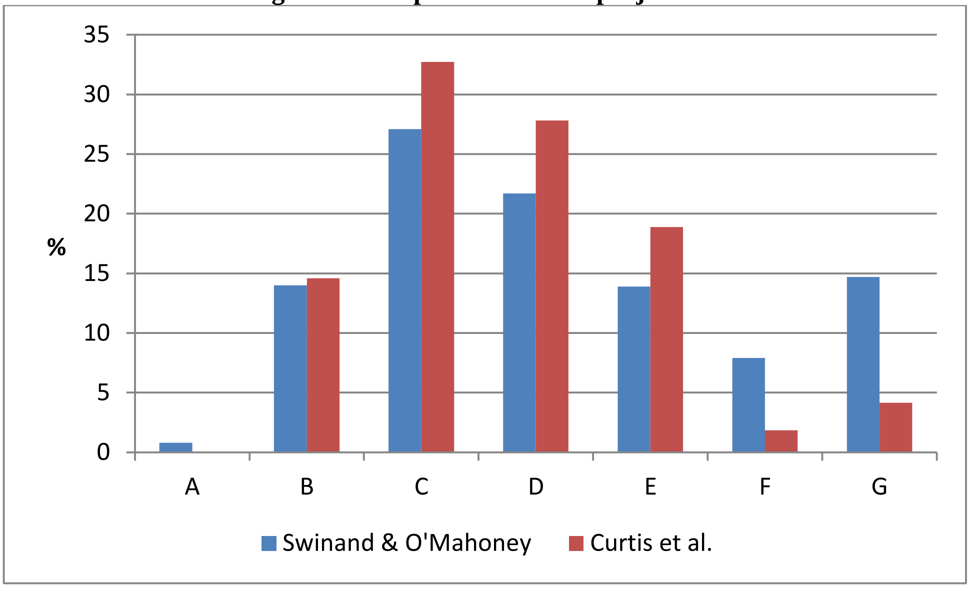
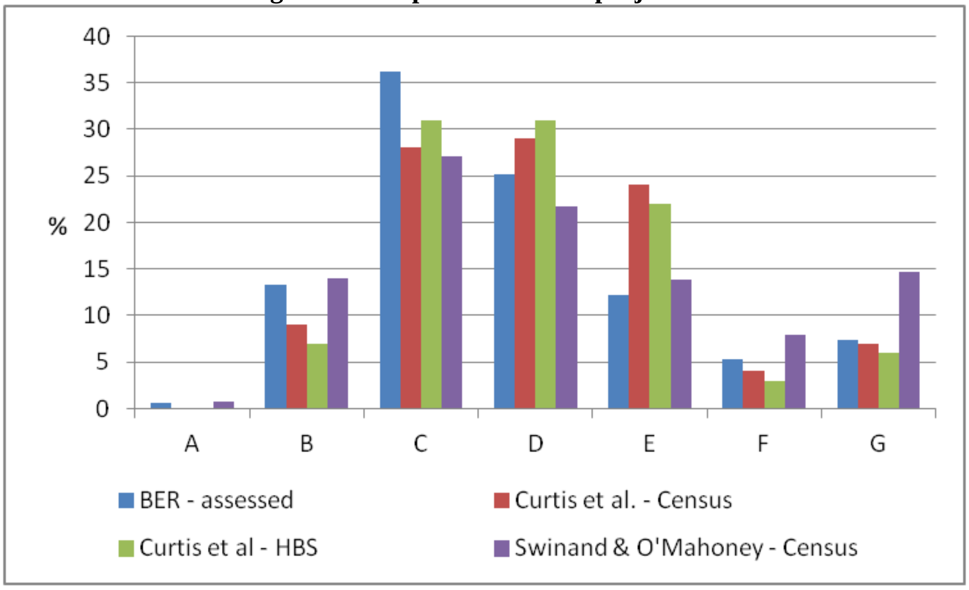


Figure 3 provides four separate projections of BERs across the housing stock, with the additional projection based on a similar analysis projected onto the CSO's HBS dataset. The conclusion I draw from this is that there is considerable uncertainty across the estimator methodologies employed. For our own paper's analysis we proceeded with a just two energy efficiency categories: high (BER letters A, B, C & D) and low (E, F & G). Our within-sample prediction accuracy in that instance increased from 47% to 82%

Figure 3: Comparison of BER projections



While we focused on just two types of dwelling (energy efficient versus energy inefficient)[2] Swinand & O'Mahoney's projection methodology extended to cover property types: 15 BER scales across 4 dwelling types and 5 primary fuels – a total of 300 archetypes! On the basis of our own separate analysis I feel that the level of forecast error inherent in such analysis is extremely high. Notwithstanding this I think the paper merited a discussion of how the projection results compared with other estimates, including the paper by Ahern et al (2013) cited in the paper.

I found the analysis undertaken in the rest of the paper to be very interesting and take it at face value. However, I did find myself confused at various points and possibly I have misinterpreted the discussion of the results

[2] Our analysis was identifying where energy inefficient houses were located and what socio-demographic groups lived in energy inefficient houses

including tables 4 and 5. I would have benefited from some further explanation of the calculations and analysis. Some of my confusion surrounded the following:

- As an example, in table 4 940,000 housing units (potentially could) upgrade their roof (measure #1) and 955,000 housing units upgrade their walls (measure #2) but only 287,000 upgrade their roof and wall combined (measure #9). These figures don't stack up. While the table rows may be independent, they lack some credibility. Is the number of housing units across measures additive? The sum of the housing units considered in the shallow, medium and deep retrofits totals 3.36 million. Some clarity on how these housing unit numbers were derived would be useful. As a further example the sum of properties subjected to shallow, medium and deep retrofits is way in excess of the residential housing stock so when these types of numbers are used later to calculate total costs and benefits they are not relevant to the reality on the ground.
- I presume that the 'Total Cost' in table 4 are discounted costs, as all the capital costs of retro fits would occur in the initial period. Compare measure #8 (VB) with measure #9 (R+W). Energy savings are roughly similar at circa 5-600MWh. Capital costs are €672 million for #8 versus €2 billion under #9. Even allowing for different energy prices and allowing for the primary energy prices in electricity, we would expect that #8 is orders of magnitude better value. What I am confused with here is how these figures relate to those in table 5. It's not clear to me what the figures in Table 5 really mean, especially the 'total cost annualised by lifetimes'. And furthermore, if many of the deeper retrofit type measures within measures #3-17 have a negative CBA how does measure #20 'deep' have a positive CBA?

One final point I have relates to the scenario analysis towards the end, in particular the 12% per annum electricity price increase (other energy prices constant). I believe that such an increase is possibly unrealistically high – that's almost a doubling of electricity prices in 6 years. Furthermore, while electricity prices have a regulatory component (as well as a fuel component), it is unlikely that electricity prices would change that dramatically with other fuel prices constant. But my main point about this scenario analysis is that the result of this price increase scenario does not reflect any behavioural change, as there is no behavioural function built into the model. And given my point earlier the scenario appears somewhat constructed.

Notwithstanding, any issues I have raised I enjoyed the paper very much and congratulate the authors for their analysis.

References

Curtis, John; Devitt, Niamh and Whelan, Adele. (2015) Using census and administrative records to identify the location and occupancy type of energy inefficient residential properties, Sustainable Cities and Society 18, 56–65, http://dx.doi.org/10.1016/j.scs.2015.06.001

DISCUSSION

Noel O'Gorman: I am surprised at the very high energy savings associated, in Tables 3 & 4, with 'Boiler Controls - its 4.9 MWh accounting for over half the total saving associated with the full package of conventional measures. He noted that "Heating Controls" also seemed to make a relatively large contribution. I wonder whether these two measures might, in some way, be serving as a proxy for a shift to intrinsically more efficient energy sources e. g. electricity to gas?

John FitzGerald: The results shown in a Table displayed at the meeting looked very strange. The total cost of possible energy efficiency measures over future years was shown as €38bn whereas the yearly saving from this was estimated at 4 million tonnes of carbon dioxide. Assuming the life of the efficiency improvements was 40 years, before discounting this would translate into a cost per tonne of carbon dioxide avoided of around €9500. This seems completely unrealistic. If correct it would mean that this was an extremely expensive way to reduce emissions – something which other studies have contradicted.

Niall Farrell: In relation to the validation of the results of the Iterative Proportional Fitting (IPF) procedure. When this methodology is employed in the literature, the results are often validated both internally and to external benchmarks. It would be interesting for the reader to see an internal validation showing the degree of convergence of the IPF procedure and also a validation of the output to an external data source.

Gerard Keogh: The BER system classifies dwellings according to energy rating classes A-G. Dwellings in the BER are also classified according to several other variables such as dwelling type, age of dwelling, county etc. The paper identifies an over/under representation of dwellings classified in the BER relative to corresponding

Census marginal aggregates. To make state level extrapolations/estimates of dwellings in energy rating classes the authors sensibly propose adjusting marginal totals in the BER to agree with corresponding Census aggregates using a multinomial logit model. This procedure results in a redistribution of dwellings within BER energy rating classes A-G that, it is believed, better estimates BER at the state level.

The accuracy of the resulting BER estimates depends on the multinomial logit model. Where representation is poorest (class G) the authors show their procedure increases the percentage of dwellings from 7% to 14%, meanwhile the Census marginals seemed to suggest this share could be much higher. Of course the accuracy of the estimates also depends on the level of agreement that exists between marginal BER aggregates and corresponding marginal Census aggregates. While the authors are stuck with the marginal aggregates they can choose how they combine them in the multinomial logit model. It strikes me that the authors may have plumbed for the default saturated model, unfortunately this will reproduce the BER distribution at the saturated level of interaction but with Census aggregates and typically this will result in relatively modest adjustments to the non-marginal quantities in the multinomial logit model, the energy rating classes A-G in this case. This I believe is a likely explanation for the modest change in the representation of energy rating Group G. In light of this I am interested to know whether the authors have explored alternative models and what policy insight this may have provided.

Noel Cahill: I understand that the energy savings presented are based on modelling. What research has been undertaken on actual energy savings? I understand from earlier comments that more data will be becoming available that will facilitate research on this.

Gerry Brady: There are around 40,000 dwellings with more than one BER rating. A comparison of the oldest and the most recent ratings for these dwellings is given in Table 14 of the CSO quarterly Domestic BER release and shows the impact of home improvements in terms of improved BER ratings. CSO Environment staff will discuss with Census colleagues whether a more detailed classification of household types could be introduced for the 2021 Census of Population e.g. mid-floor apartments and mid-terrace houses. The CSO BER release shows an estimate of 9% of dwellings have a G energy rating after the BER data for 2009-2015 were weighted to national level.