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Benchmarking and Tracking Domestic Gas and Electricity Consumption at the Local Authority Level

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Abstract:

Government, local authority and industry initiatives to improve the energy efficiency of housing stocks are central to national and international commitments to reduce carbon dioxide emissions. To be effective, initiatives need to target homes which, given their location, size, fuel type and occupancy, use more energy than expected. This paper illustrates how energy efficiency benchmarks can be developed that account for these factors and highlights the shortcomings of relying on simple energy consumption statistics. The study uses existing data (with national coverage) and the measured electricity and gas consumption of groups consisting of, on average, 500-700 households to benchmark and track domestic gas and electricity consumption across England. Multiple regression models, which account for 65% of the variation in domestic gas consumption and 73% of domestic electricity variation, are used to derive the benchmarks. The actual gas and electricity consumption of each group of homes is compared against the derived benchmark and an energy efficiency index presented. The approach enables changes in energy efficiency to be tracked temporally, for example to assess the effectiveness of government, local authority or industry initiatives. National and city-scale patterns of energy efficiency are also discussed.

Keywords: Domestic Electricity Consumption; Domestic Gas Consumption; Benchmarking; England; Local Authorities

1. Introduction

In 2008, as part of a wider international commitment to reduce carbon dioxide emission (CO_2), the UK Government set a target to reduce CO_2 emissions by 80% relative to 1990 levels by 2050 (HM Government 2008). This target fits with a wider European Union (EU) identification of improving energy efficiency measures in buildings as a key action to achieve reductions in European-wide CO_2 emissions. This is perhaps best exemplified by the recast Energy Performance of Buildings (EPBD) directive (European Council Directive 2010/31/EU) that promotes 'nearly zero' energy building, i.e. a building with a very high energy performance for all new building construction (Commission of the European Union 2010). Although this does not specifically target existing buildings, the recast directive states that European member states are expected to develop policies – using instruments such as target setting – to stimulate the transformation of buildings via refurbishment into very low energy buildings (Commission of the European Union 2010). This paper explores the latter in relation to the domestic sector in the UK, which, despite accounting for almost 25% of national carbon emissions and 30% of total final energy use (Utley and Shorrock 2008; Kannan and Strachan 2009), has historically not received anywhere near the same attention in terms of regulations and resources through UK legislature to tackle carbon emissions when compared to industrial and commercial sectors (Scott et al. 2014).

Recent years have seen signs that the increasing evidence base surrounding the environmental impact of the UK's housing stock on of carbon emissions is raising awareness for the need to implement residential energy and CO_2 reduction policies (Marchard et al. 2015). The UK has incorporated new build directives into national legislation, for example, regarding the construction of new housing in the Building Regulations Part L (Raslan 2012). Nonetheless, existing housing is forecasted to account for 70% of the UK's 2050 housing stock and while there exists significant potential to reduce domestic energy demand by improving the thermal efficiency of the existing housing stock and introducing energy efficient electrical appliances (Firth and Lomas 2009), there is a clear need for tools to benchmark and track energy consumption in the domestic sector to measure progress against carbon targets.

1.1 Current Policy Approaches

In January 2013 the UK Government replaced a raft of previous domestic sector energy efficiency policies – including the Carbon Emissions Reduction Target (CERT), Community Energy Saving Programme (CESP), and Warm Front (see Mallaburn and Eyre, 2014 for a comprehensive review) – with the Green Deal and Energy Company Obligation (ECO) schemes. One of the key developments of the 2013 policies was the focus on stimulating an energy efficiency refurbishment market: under the Green Deal households are to cover the upfront costs of energy efficiency improvements to their house through a loan which is secured on the property and paid back through savings to energy bills (HM Government 2011; Department of Energy and Climate Change [DECC] 2011a; Dowson et al. 2012), while the ECO scheme obliges larger energy companies to deliver energy efficiency measures to vulnerable consumer groups and hard-to-treat properties, primarily to tackle fuel poverty[1] (DECC 2011b; DECC 2013a). Although the general methods used to tackle fuel poverty and reduce energy consumption may be broadly similar – such as the interventions provided

[1] Fuel poverty is defined in the UK as the situation when a household spends more than 10% of its income on fuel. However, the 2011 Hills Review has redefined this concept in England so that households are in fuel poverty if their fuel bills are above the national median and their remaining income is below the official poverty line (see DECC 2013b).

under the Green Deal and ECO schemes – the impact on carbon emissions may vary depending on the value households place on increased warmth (Scott et al. 2014; Marchand et al. 2015). In this paper, the focus is on policies to reduce energy consumption, such as the Green Deal, as part of efforts to reduce CO_2 emissions.

1.2 Identifying Energy (In)Efficiency

The Green Deal consultation emphasises the role of Local Authorities in promoting energy efficiency schemes, in part, due to the perceived trust they have from their residents (Institute of Gas Engineers and Managers [IGEM] 2011, DECC 2012), their unique position in communities as an organisation that can act as both a partner or direct provider of Green Deal schemes (DECC 2013a), their local knowledge which should enable them to better identify areas best suited for Green Deal measures, and their role in the active promotion of such schemes (DECC 2011b, Bale et al. 2012). That said, previous research on local energy efficiency schemes highlights the need for appropriate data and evidence. For example, Hamilton et al. (2013 p464) state that:

> ‘the successful delivery and uptake of energy efficiency measures in order to achieve the goal of reducing greenhouse gas emissions … requires that policies are developed from an empirical foundation built on high quality data.’

There are signs that the UK Government is now taking steps to produce the ‘high quality data’ needed to provide this empirical foundation. Beginning with the year 2008, DECC

(2013b) now publish annual sub-national gas and electricity consumption data at Lower Super Output Area (LSOA)[2] with the stated aim to:

> 'Enable councils and others to monitor and target small areas for further interventions as part of their local energy strategies, and enhance the implementation of energy efficiency programmes and thus reduce carbon dioxide emissions' (DECC 2013a p2).

DECC re-affirm their commitment to assisting Local Authorities in energy efficiency strategies, adding (2013a p12): 'the most significant use of the sub-national consumption data is by Local Authorities and devolved administrations for targeting and monitoring a range of carbon reduction and efficiency policies'.

Annual data releases allow for the monitoring of progress in terms of reductions in energy consumption but may not necessarily identify suitable target areas for energy efficiency programs. This is because the absolute energy demand alone does not always indicate the potential energy reductions from improving the energy efficiency of the housing stock. For example, areas with larger houses and colder weather will typically have a higher energy demand and the challenge is to identify areas of higher than average household demand after considering factors independent of the level of energy efficiency in the housing stock.

Previous research to identify predictors of energy demand identifies house size, income and weather as key predictors of energy consumption. Baker and Rylatt's (2007) study of 148 houses across Leicester and Sheffield showed that the number of bedrooms accounted for almost 35% in the variation in household gas and electricity consumption. A similar study of 36 low energy houses in Milton Keynes revealed that the top 30% of households by income

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[2] LSOAs are census output areas of 500-700 households and based loosely on homogenous tenure and house types. LSOA boundaries align to those of Local Authorities (ONS 2013).

used more energy than the remaining 70% of households combined (Summerfield et al. 2010a). Furthermore, Summerfield et al. (2010b) observed that a 1°C increase in external air temperature leads to an approximate 5% decrease in energy demand. Taking these factors together, DECC's National Energy Efficiency Data-Framework (NEED) study of 4 million individual households revealed that average number of rooms, household income, tenure type, and type of dwelling were the most important factors influencing the level of consumption at the individual level (DECC 2011c). Added to this, the most common fuel for space heating in UK housing is natural gas, but 4.3 million homes (approximately 17% of the housing stock) are not connected to the gas grid (Boardman 2010). This has implications for understanding consumption of non-gas fuels in these properties, although at present the only reliable data is available for those houses with electric heating. These studies present a range of potential variables influencing energy demand independent on the energy efficiency of the housing stock. The challenge is to identify potential inefficiency in the housing stock (as well as over-consumption) after accounting for the variation in physical, social, economic and climatic factors.

1.3 The Need for a Benchmarking Approach

Rather than using raw energy consumption figures, a better way to indicate the potential to reduce energy demand would be to use an appropriate benchmark figure against which the actual demand could be compared. Luque-Martinez and Muñoz (2005 p414) describe benchmarking as a method of 'identifying, learning and implementing the most effective practices and capacities from other cities in order for one's own city to improve its actions'. In their review of sub-national energy policy in the UK, Keirstead and Schulz (2010 p4877) state:

> ‘Ideally, one would like to be able to state with confidence that one city is ‘better’ than another owing to its policies, rather than simply benefitting from a benign climate, unique economic structure or other fortuitous circumstances.’

Normalising energy consumption to take into consideration these ‘fortuitous circumstances’ would enable Local Authorities to benchmark energy consumption within their areas and monitor the success of energy efficiency reduction schemes in reducing energy consumption relative to this benchmarking figure. Keirstead (2013) provides a comprehensive review of benchmarking mechanisms that could be applied to measuring the energy efficiency of the housing stock at Local Authority level. Many of these techniques would require specialist computational inputs, such as: Total Factor Productivity (TFP), where there is a need to apply an indicator of productivity so that forecasting mechanisms can be applied to historical data (Jamasb and Pollit 2000); Data Envelopment Analysis (DEA), whereby computational analysis based on a number of factors unique to each area of study is required (Jamasb and Pollit 2000; Keirstead 2013); or, Frontier approaches that require large samples of bottom up data (Jamasb and Pollit 2000). The computational requirements for these benchmarks would likely deter Local Authorities from developing energy efficiency monitoring strategies.

Alternative ways of identifying areas of inefficient housing would be to examine the energy efficiency measures installed in dwellings, for example, as recorded in the Home Energy Efficiency Database (HEED), or energy performance certificates (EPC), which includes information on the physical characteristics of the houses. The problem is HEED only covers 50% of the housing stock at present and EPC data is only required for houses sold or rented since 2008 (Watts et al. 2011, DECC 2012). Importantly EPCs are based on a prediction of likely energy demand, normalised to standard occupancy, and so often reflect actual energy demand very poorly: the so-called performance-prediction gap. The use of EPCs and HEED also add to the administrative burden of Local Authorities, and to the contractor firms delivering energy efficiency schemes, because they require intensive data collection and analysis.

1.4 Contribution of the Research

The aim of this paper is to demonstrate a new method for benchmarking domestic energy consumption that accounted for factors outside of the control of domestic energy policy tools, utilising widely available national energy statistics. The method should be designed in order to assist policymakers in identifying areas that may benefit from energy efficiency measures while removing the need to collect large databases of energy performance certificates and installed measures – meaning this information is available at low cost to Local Authorities. These benchmarks should normalise the data so that 'the direction and range of each metric is comparable' (Keirstead 2013 p576). To achieve this, the paper seeks to establish answers to the following questions:

- Independent of the energy efficiency performance of the housing stock what are the driving factors that impact on energy consumption in the domestic sector within Local Authority boundaries?
- How can the energy consumption occurring with Local Authority boundaries be assessed objectively given that the size of existing houses, the income of the occupants, the weather and level of gas grid connectivity is largely beyond Local Authority control?
- How do the benchmark results relate to areas of known energy efficiency in the housing stock?

The paper is structured as follows. Section 2 outlines the materials and methods used, introduces the datasets analysed, and explains the methodological approach that produces Energy Consumption Indices (ECI). Section 3 presents the results from the study and the validation of the ECIs. The implications of this research is discussed in Section 4, before finally, Section 5 examines the policy implications and next research steps.

2. Method

Secondary data to describe gas and electricity fuel consumption and the key explanatory variables were sourced, as shown in Table 1. These data were readily available and had been used in previous UK Government research, most notably in the NEED report (DECC 2011c; 2013c). Statistical models were constructed to predict gas consumption, and to predict electricity consumption, from the explanatory variables. The fuel consumption data was then compared with these benchmarks to create Energy Consumption Indices (ECIs). Attempts were made to verify the results, explore how they changed from year to year, and rank the Local Authorities based on the performance of the housing within their boundaries. To demonstrate the method, all of the work described here was carried out for England only.

2.1 Fuel Consumption Data

Gas and electricity consumption data for 2010 were used as the dependent variables in the statistical modelling. They were obtained from the open access, sub-national, gas and electricity statistical releases published annually by DECC (2013a). These data are aggregated at the level of LSOAs, which are loosely based on homogenous tenure and house types (ONS 2013). There are 32,482 LSOAs in England each containing between 400 and

1200 homes, the average being between 500-700 homes (ONS 2013). As a result rural LSOAs cover a much larger geographical area than urban LSOAs.

The gas consumption data were supplied to DECC by Xoserve, a private company responsible for collating gas consumption in the UK national gas network (DECC 2013a). Electricity consumption data were supplied to DECC directly from energy suppliers. The consumption figures are based on the metered data (or estimated consumption where meter readings are unavailable) used for customer billing. To date, the sub-national domestic gas and electricity consumption data have been published at LSOA level for the years 2008-2011, with a commitment to annual releases following an 18 month lag (DECC 2013a). The work described in this paper was carried out before the release of the 2011 dataset.

For the year 2010 the mean domestic gas and electricity consumption was calculated for each LSOA from the total fuel demand and the number of meters for that fuel. Total electricity consumption was calculated by summing 'economy7' and 'ordinary' domestic data[3]. The published LSOA gas consumption data are weather corrected to an average base year of a 17-year average for 1988-2004 to distinguish changes in gas consumption levels from annual variations in the weather (National Grid 2012; DECC 2013a). This influenced the choice of weather variable as discussed in Section 2.2. LSOAs with no connection to the national gas grid were not included in the gas model, and were not recorded in the DECC gas consumption statistics. In the published LSOA gas consumption data those LSOAs with fewer than 6 (but more than 1) gas meters are merged with neighbouring LSOAs to avoid disclosure of the demand for individual homes (DECC 2013a). In these cases, the average gas

[3] Economy 7 is a two period tariff structure comprising premium cost daytime (7am-midnight) and lower-cost night-time (midnight-7am) electricity designed to encourage off-peak demand and support the use of night-time storage heating.

consumption was assigned to all of the merged LSOAs. It is acknowledged that this presents a challenge to Local Authorities with 'merged' LSOAs within their boundaries but this affects 0.3% of total domestic gas consumption in England, and covered 1.7% of LSOAs.

Descriptive statistics were calculated to examine how domestic energy consumption varies across England at LSOA level. Skew and kurtosis values were calculated and examined, and square root transformations applied to bring the distributions of these consumption figures closer to a normal distribution.

2.2 Explanatory Variables

Explanatory variables were sourced to represent variations in house size, household income, external air temperatures, and primary heating fuels (see Table 1). Data on the physical size of houses, even at LSOA level, were not readily available and so, in keeping with other studies (see Baker and Rylatt 2007, DECC 2013d), the average number of rooms per house from the 2001 Census was used to approximate house size. Although house type and tenure have been shown to be strongly correlated with the size of house (DECC 2013c), tenure and house types were included from the 2001 Census to confirm this. Whereas most variables are based on measurement, it should be noted that the Experian median household income data is modelled from household credit surveys.

Table. 1 Data Sources Used in Study

The gas consumption statistics are weather corrected temporarily, using a ‘composite weather variable’ (CWV) accounting for temperature and wind speed to a ‘base year’ of a 17-year average of 1988-2004 to enable year-on-year comparisons of gas consumption independent of weather effects (DECC 2010c, National Grid 2012). However, this variable does not account for spatial variation in external air temperature for different LSOAs. Therefore spatially weighted average annual heating degree days[4] were calculated using GIS for each LSOA in England using data obtained from the MET Office’s UKCP09 directive for the years 1988 to 2004 at 5 x 5 km grid squares (MET Office 2013) assigned to the relevant LSOAs sourced from the UK Borders facility at Edinburgh University (EDINA 2013). This time period matches the averaged year used for the weather correction of the gas consumption data (National Grid 2012; DECC 2013a).

2.3 Statistical modelling

Multiple linear regression was selected as the method most appropriate for evaluating long-term trends and benefits from simple inputs and outputs, where the dependent variable is related to various independent variables (Swan and Ugursal 2009, Ren et al. 2012; Aydin 2014) – as is the case in domestic gas and electricity consumption. Regression analysis is also held up as a suitable method for providing results in a format that are relatively simple to interpret for non-statistical audiences, for example Local Authority Officers (Bianco et al.

[4] Heating Degree Days are a function of the length of time the external air temperature is below a specified base temperature, and how far below the base temperature the air temperature is, giving a linear relationship between temperatures below the base temperature and heating energy demands of buildings. 15.5°C is the standard base temperature for domestic properties in the UK (Chartered Institute of Building Service Engineers 2006).

2009; Aranda et al. 2014). The use of a regression model is a compromise between the simplicity of the evaluation method and the accuracy of the result without requiring a significant amount of input data (Aranda et al. 2014). Tso and Yau's (2007) study comparing regression analysis, decision tree, and neural networks for predicting electricity consumption found the difference in error between the three methods was minimal. Howard et al (2012) use this as justification that multiple linear regression is a valid method for predicting electricity consumption of urban building energy use in New York City to determine cost-effectiveness and policies for implementing energy efficiency and renewable energy programmes. Multiple linear regression therefore has the advantage of being simple to interpret and more widely-understood than more complex technqiues such as decision tree and neural network methods.

Multiple linear regression models for gas consumption and electricity consumption were generated using the stepwise entry method in SPSS (IBM, Version 19). Each of the explanatory variables (average number of rooms, median household income, heating degree days, and ratio of gas to electricity meters) had correlation coefficient of $|r|>0.25$ against the dependent variables and were therefore included. To ensure the independence assumption of multiple regression was not violated (see Moore et al. 2009) thus avoiding the problem of multicollinearity, the correlation between any two pairs of independent variables in the models was checked. When this exceeded $|r|>0.7$, the variable that produced the strongest change in R^2 in the stepwise entry process was retained. This process was repeated until no pairs of independent variables included in the model were correlated where $|r|>0.7$. Finally, to remove redundant variables in the model, only those variables that produced a change in R^2 of greater than 0.1 were included. This is because the number of LSOAs modelled exceeded 30000 (n=32482) and therefore greatly increased the chances of spurious results being highlighted as statistically significant (Miles and Shelvin 2001).

The gas and electricity consumption predicted by the two models for each LSOA was used as the ‘benchmark consumption’ for that LSOA. ECIs were then calculated for every LSOA by dividing the recorded consumption figures (in the sub-national consumption data) by the benchmark consumption, and then multiplying by 100. This resulted in a scale where a score of 100 indicated that the average consumption for the relevant fuel in the LSOA was the same as the benchmark predicted by the model. This process is shown in Figure 1. A score above 100 indicated that households in that LSOA were consuming more of that fuel, on average, than expected (potential inefficiency), while a score lower than 100 indicated less than expected (potential efficiency). The ECIs also indicate the scale of potential inefficiency. A gas ECI of 120 indicates the LSOA is consuming 20% more gas than would be expected.

(Equation 1. Calculation of the Energy Consumption Index)

$$ECI = \frac{Regression\ Predicted\ Consumption}{Recorded\ Consumption} \times 100$$

These ECIs provide Local Authorities with an evidence base for targeting their efforts in areas that will make the biggest impact in reducing domestic energy consumption. It is important to note that the model deals with aggregated data and therefore it is not possible to infer the relative energy consumption performances of individual households from the LSOA score (avoiding the ecological fallacy – see Gelman et al. 2001). The benchmarks and ECIs indicate to the model the relative energy consumption levels of householders on average within each LSOA. There is still a need for local knowledge and specific data to assess the specific individual energy uses at a household level. Nevertheless, the model provides indication for where Local Authority resources and efforts might be most appropriate targeted in order to encourage uptake of households to energy efficiency measures.

To demonstrate the practical applications for policymakers, maps of Local Authority areas with LSOA boundaries were overlaid with colour coded results, in a GIS, so that their geographical location and spatial variation could be visualised as an aid to interpretation. Leicester and Milton Keynes were chosen as case studies for this visualisation. Leicester was chosen as it is a typical urban area, comprising houses constructed over more than 100 years, and was the focus of the 4M[5] project that funded this study (Lomas et al. 2010). Milton Keynes was expected to offer a contrasting result given its 'New Town' status as detailed in Section 2.4, and was used in previous academic studies (e.g. Summerfield et al. 2010a).

2.4 Case Studies

Verifying the results was complicated by the absence of readily available data on the level of insulation in properties or the proliferation of electrical appliances. Therefore, case studies of areas known to contain houses of relatively energy efficient construction were used. This verification is based on the hypothesis that Local Authorities containing 'planned' settlements as part of the 1945-1975 'New Town Movement' (see Fothergill et al. 1983, Department of Communities and Local Government [DCLG] 2006) would have a more efficient housing stock, and therefore a higher proportion of LSOAs with gas ECIs of less than 100. This is because these settlements contain less of the pre-1919 housing that is the least energy efficient. This was tested statistically using a t-test to compare New Town Local

[5] The 4M Project, Measurement, Modelling, Mapping and Management, 4M: An Evidence Based Methodology for Understanding and Shrinking the Urban Carbon Footprint was a research project funded by the Engineering and Physical Sciences Research Council under the Sustainable Urban Environments programme. The City of Leicester served as the case study region, incorporating carbon emissions from domestic and non-domestic buildings, as well as transport carbon emissions and carbon sequestration.

Authorities with what have been termed here ‘Pre-Existing’. While this may be adequate for gas consumption, there was not a similar way to test the model results for electricity consumption.

2.5 Exploring Changes over Time

ECIs can be calculated each year, using the most up-to-date data that are available. In this way the benchmarks will change each year to reflect the average performance of the housing stock, and the new ECIs will then demonstrate the relative performance of housing in each LSOA against these benchmarks. If the method is to be used for tracking the performance of areas of housing temporally, it is important that the model produces relatively stable benchmarks and ECIs and ensure that the results are not spurious for a single year. If the results indicated dramatic swings in the performance of areas it would undermine any confidence in the method. ECIs were therefore calculated for an additional two years of data: 2008 and 2009. This was done by repeating the regression analysis for these years and updating the consumption data and median household income variable. As with the 2010 data, gas and electricity consumption were sourced from the sub-national energy statistics, and updated income data were sourced from Experian (as shown in Table 1). The ECIs for each of these three years were then compared to identify any LSOAs where large changes occurred.

2.6 Ranking Local Authorities

The 2010 ECI results were used to rank Local Authorities by the proportion of LSOAs with ECIs of greater than 100. This is more appropriate than ranking Local Authorities by the mean ECI values, as the proportion ranking highlights those Local Authorities with the greatest number of LSOAs that would benefit from energy efficiency interventions. This enables Local Authorities to compare the energy efficiency of their housing stock against other councils, and enable the Central Government to evaluate energy efficiency levels of Local Authorities across the country.

A map indicating the performance of Local Authorities in England was produced. The results for the Leicestershire/Derbyshire/Nottinghamshire areas of the East Midlands region of England were compared in this paper as they include the 4M city of Leicester and offer an interesting regional perspective by which comparisons could be made.

3. Results

3.1 Distribution of Domestic Fuel Consumption in England

There is considerable variation in domestic per meter gas and electricity consumption across LSOAs in England, as shown in Figures 2 and 3. This is particularly true for electricity consumption, which exhibits a long tail above the mean. The gas consumption figures show LSOAs with gas consumption of double the mean, while the tail of the electricity distribution extends to 4 times the mean. A square root transformation was applied to both gas and electricity consumption. Descriptive statistics are given in Table 2. The resulting distributions (from visual shape, skew values, and kurtosis values) were a closer approximation to a normal distribution and therefore suitable for multiple linear regression.

Fig.2 Distribution of Untransformed Per Meter Gas Consumption

Fig.3 Distribution of Untransformed Per Meter Electricity Consumption

Table. 2 Descriptive Statistics of Gas and Electricity Consumption Statistics

3.2 Explanatory Variables

The correlations between the dependent variables and the explanatory variables are shown in Table 3. This shows that the average number of rooms and the median household income have the strongest relationship with square root per meter gas consumption (r=0.727 and r=0.667 respectively). These variables are also the strongest for square root electricity consumption (r=0.596 and r=0.638 respectively), whilst the ratio of gas to electricity meters variable also has a strong inverse relationship with per meter electricity consumption (r=-0.628). These results are all expected given the reports in the academic literature and focus in policy documents. Incidentally, heating degree days has a relatively weak correlation with per meter gas consumption (r=0.220). While this lack of correlation with gas consumption may seem surprising, previous studies (e.g. Summerfield et al. (2010b) focused on changes to annual heating demands in a single location rather than on the regional variations explored here. The variables where explanatory variables had strong correlations (|r| > 0.7) with each other are shown in bold, and highlight the correlation between average number of rooms with percentage of owner occupiers (r=0.740), percentage of detached houses (r=0.755) and percentage of flats (r=-0.716). Average number of rooms was included in the regression analysis as it has the strongest relationship with both fuel types. These other variables were not included in the study.

Table. 3 Correlation Matrix of Studied Variables

3.3 Building Models, Benchmarks and Consumption Indices

The three input variables to the gas model – average number of rooms, median household income, heating degree days – account for 65.3% of the variation in square root per meter domestic gas consumption (R^2=0.653, Table 4). This result is statistically significant at the 0.05 level ($F_{3,31956}$=19844, p<0.001). The model's residual plot against the predicted values was checked for evidence of heteroscedasticity. This plot showed a random scatter of residuals around the y=0 line. The model's form is shown in equation 2:

(Equation 2. Per Meter Gas Consumption Model)

$$\mathbf{BMG = (-25.53 + 9.88ANR + 0.63MHI + 16.36HDD)^2}$$

Where BMG=Benchmark Gas Consumption, ANR=average number of rooms, MHI=median annual household income (£ 000), HDD=Heating Degree Days (1000's of °C days)

The electricity consumption model included three variables to account for 73.1% of the variation in per meter electricity consumption (R^2=0.731, Table 5). This result is statistically significant at the 0.05 level ($F_{3,32466}$=26724, p<0.001). The model's residual plot against the predicted values was checked for evidence of heteroscedasticity. This plot showed a random scatter of residuals around the y=0 line. The model for electricity consumption is given in equation 3.

(Equation 3. Per Meter Electricity Consumption Model)

$$\mathbf{BME = (51.47 + 3.86ANR - 15.34RGE + 0.22MHI)^2}$$

Where BME=Benchmark Electricity Consumption, ANR=average number of rooms, RGE = Ratio of Gas to Electricity Meters, MHI=median household income (£ 000)

Table. 4 Multiple Regression Model for Square Root Per Meter Gas Consumption

Table. 5 Multiple Regression Model for Square Root Per Meter Electricity Consumption

Graphical displays of predicted gas against actual gas consumption are shown in Figure 4, and the corresponding graph for electricity consumption is given in Figure 5. In both cases the line indicates where actual consumption is equal to the benchmark. LSOAs above the line are consuming more than the benchmark, and those below less.

Fig.4 Plot of Predicted Values against Recorded Square Root Per Meter Gas Consumption

Fig.5 Plot of Predicted Values against Recorded Square Root Per Meter Electricity Consumption

ECIs for each LSOA were calculated from the ratio of actual consumption to the calculated benchmarks. As an example, the geographical and spatial variation in gas ECIs for the Leicester and Milton Keynes Local Authorities are shown in Figure 6. The darker areas are the LSOAs with the most potential to benefit from energy efficiency improvements, as these areas are those with recorded consumption levels in excess of the benchmarked level. In Leicester there is a concentration of LSOAs with high ECIs around the City Centre. These areas contain some of the oldest properties in the city. Clustering of dwellings of high energy consumption is hypothesised by Tian et al. (2014) and there is some evidence of this occurring here. Within this group are ‘green’ LSOAs, given by lighter shading, which may indicate a greater number of energy efficient properties as their consumption levels are lower than the national average predicted by the benchmark, indicated in Figures 4 and 5 by lighter shading. For Milton Keynes, a far higher proportion of LSOAs have ECIs below 100, though with notable exceptions of areas of the original settlements that existed prior to the development of the planned settlement. What these results highlight are the differences between Local Authorities: Leicester is primarily an (ex-) industrial city; Milton Keynes a largely post-1960 planned urban area and therefore expected to have housing stock that is more thermally efficient.

Fig.6 Gas Consumption Indices for Leicester and Milton Keynes Local Authorities

3.4 Plausibility Studies

It was not possible to validate the model comprehensively. However a number of checks were carried out. The first plausibility test involves comparing Local Authorities with New or Expanded Towns (termed ‘New Towns’) against Local Authorities without these developments (termed ‘Pre-Existing’). Local Authorities were classified as being ‘New Town’ if they contained planned settlements listed in DCLGs (2006) ‘Lessons Learned from New Towns’. There are 51 Local Authorities with New Town developments, and 302 ’pre-existing’. New Town Local Authorities had an average of 36% of LSOAs with a gas ECI >

100, while pre-existing Local Authorities had an average of 47%. Running a t-test at 0.05 level (t_{352}=4.74, p<0.001, Table 6) shows that there is a statistically significant difference in the proportion of ECIs above 100 between New Towns and Pre-Existing Authorities This strongly indicates that new towns have more efficient housing stocks and gives confidence in the results of the model.

Table. 6 Comparing the proportion of LSOAs with higher than expected gas consumption in new/expanded towns and pre-existing settlements

Repeating this analysis for electricity consumption shows that the average proportion of LSOAs with higher than expected consumption is 47% for New Town Local Authorities, and the corresponding figure is 48% for the Pre-Existing Local Authorities. This difference is not statistically significant at the 0.05 level (t_{352}=0.349, p=0.73, Table 7). This is an expected finding as the thermal efficiency of the housing stock is not likely to impact on average electricity consumption. Policy options will clearly be different when reducing electricity consumption and verification of this model is problematic.

Table. 7 Comparing the proportion of LSOAs with higher than expected electricity consumption in new/expanded towns and pre-existing settlements

3.5 Exploring the Changes in the ECIs Temporally

The over-time analysis showed that ECIs for both gas and electricity consumption between 2008 and 2010 were relatively stable. Table 8 shows that the mean change is approximately zero and over 99% of LSOAs change by less than 20 points between years for both gas and electricity consumption. There are a small number of LSOAs for which ECIs change dramatically. Examination of the results for these LSOAs highlight that these fluctuations were due to changes in the underlying data. For example, the gas ECI changes by over 40 points in 2009 for 13 LSOAs because the number of gas meters recorded in the 2009 dataset is significantly different to those recorded for 2008 and 2010. Other reasons for large changes in the energy consumption index included changes in the number of gas and electricity meters, which may be due to housing developments, and significant increases in income (particularly in four London LSOAs between 2009 and 2010). Whilst the number of LSOAs experiencing large swings in ECIs is small, it is important for users of these data to be aware of why any large changes arise. This could be realised by supplying the underlying data alongside the ECIs.

Table. 8 Number and Percentage of LSOAs by Change in Absolute Values of Consumption Indices

3.6 Ranking of Local Authorities

Local Authorities in the Leicestershire/Derbyshire/Nottinghamshire areas of the East Midlands region of England were ranked as shown in Figure 7. The best performing local authority had only 30% of LSOAs with ECIs above 100, whilst the worst performing had over 80%. From the map of the performance of Local Authorities in England it can be seen that there is a pattern towards urban areas having higher proportions of Local Authorities with gas consumption indices above 100 (Figure 8). This fits with the analysis comparing Leicester and Milton Keynes, and the trend of former industrial cities having a higher percentage of inefficient housing stock than the rest of England.

Fig.7 Ranking Local Authorities in Leicestershire/Derbyshire/Nottinghamshire

Fig.8 Percentage of LSOAs within English Local Authorities with Consumption Indices >100

4. Discussion

The UK Government recognises the potential for domestic energy demand to play an important role in reducing CO_2 emissions. The publication of domestic gas and electricity demand statistics at LSOA level are intended to provide an evidence base for targeting areas of housing that offer the biggest opportunity for demand reduction. But high energy demand does not necessarily mean that there is high potential for energy demand reduction.

The aim of this paper was to demonstrate a new method for benchmarking domestic energy demand that accounted for factors outside of the control of domestic energy policy tools, such as the Green Deal. This was achieved using a simple and easy to understand statistical model with readily available and regularly updated data. The relative performance of an area, compared with its benchmark, offers a method to assess the housing stock and to target areas for intervention. It also enables the relative performance of the stock to be monitored and the effectiveness of policy interventions to be assessed, by comparing annual results.

4.1 The Method

The approach used here to rating the LSOAs is not without precedent. In fact, it is similar in principle to the methods used in the UK, and elsewhere in Europe, to produce the operational rating (OR) of large public buildings. In both systems: the benchmark is based on actual measured energy use with fossil fuels and electricity considered separately; the benchmark is the average consumption for all buildings of the same type; the effects on energy demand of 'external factors' such as the local weather (expressed as heating degree-days), size of building and occupancy are accounted for; and the performance of the actual building is compared to the benchmark and represented on a scale from 0 (excellent performance) upwards, with 100 being the benchmark value. Nonetheless, there are some differences: in the present method there is just one building type, a home, whereas non-domestic buildings are divided into 29 types (schools, offices, small retail etc); here the average number of rooms is a proxy for size, ORs are based on energy demand normalised by floor area (kWh/m^2); and here the occupancy factors is encapsulated as median annual household income, ORs account for the daily duration of building use.

A further difference is that in the present method ECIs are produced separately for gas and electricity. This makes sense for UK homes because gas is used primarily for space and hot water heating, whereas electricity is used for lighting, appliances etc. Energy efficiency measures that target gas use are quite different from those that target electricity use. The former being primarily, insulation, draft proofing, more efficient heating equipment and better heating controls, whereas the latter might entail the purchase of more efficient white goods or behaviour changes (turning off lights, using a cooler wash) encouraged by information campaigns. In non-domestic buildings, the heating and cooling systems often use both fossil fuel (for heating) and electricity (for fans, pumps, and chillers).

Finally, it is worth noting that the OR is based on the carbon dioxide released through the use of the fossil fuel and electricity (standard carbon intensity ($kgCO_2/kWh$) values are used). It would be quite straight forward to combine the ECIs for gas and electricity, using standard carbon intensity values, to derive a single measure (although, as just noted, this would lose valuable energy efficiency targeting information). Using a CO_2 measure would though be valuable if LSOAs (or Local Authorities) had extensive deployment of house-integrated or community renewable energy schemes that resulted in locally lower carbon intensity figures. But there would still be merit in separately reporting the CO_2 originating from fossil fuels and electricity use. It is important to note that these models are designed to be easy to understand and interpret. The aim of the study is not to model the predicted energy consumption for specific households, but to provide metrics that identify areas with potential for undergoing energy efficiency interventions. This method would more reliably identify and define opportunities for intervention, but also to learn from their own actions and the actions of other Local Authorities (Bale et al. 2013; Keirstead 2013).

4.2 Gas Consumption

The modelled benchmark for gas consumption accounted for 65% of the variation in gas demand across English LSOAs by considering the average number of rooms (2001 Census), the median household income (Experian Mosaic), and the average annual heating degree days (MET Office). The influence of house size, income, and the ambient temperature is supported by studies in the literature. It is assumed that the remaining variation is due to the thermal performance of the houses, the efficiency of their heating systems, and the behaviour of the occupants. In this way, LSOAs with recorded gas consumption that is higher than the benchmark calculated by the model are assumed to have a significant number of households that would benefit from refurbishment. This could also be applied to behavioural strategies such as turning down the thermostat by 1°C depending on the nature of the housing stock in these LSOAs. The calculation of heating degree days for each LSOA was the most complicated part of the modelling process and required a competent GIS user. However, this derived degree day data can be used for subsequent years' analysis as the gas consumption data are always corrected to the same 1998-2004 average base year.

ECIs were calculated from the ratio of actual consumption to the benchmark figure, with a result of 100 indicating they were equal. The results of the model showed that Local Authorities that contain post-1950 new town developments have statistically significant lower proportion of LSOAs with ECIs above 100. This finding is logical as, at present, there is a strong link between the age of houses and their thermal performances (see for example, Boardman 2007, Dowson et al. 2012, DECC 2012, 2013b). It is expected that this link would weaken as areas of older housing are refurbished, and their thermal performance is improved. In this way the method presented here is better for identifying inefficient houses than relying on the age of the housing stock. The ECIs are derived using an approach analogous to that used to produce the operational rating of non-domestic buildings, which is represented on a scale from 0 (energy efficient) through 100 (expected consumption for the building type) and upwards for less efficient buildings. The method has the potential to enable Local Authorities to isolate the inherent energy efficiency of housing stocks as influenced, for example, by the extent of wall, roof and floor insulation or the heating system efficiency. It could also identify those households with higher than anticipated energy demands due to behavioural factors, for example higher internal temperatures (MacKay 2009; Leaman et al. 2010). The additional provisions of data at a smaller spatial scale would aid in developing both a detailed area-based assessment of potential energy efficiency in LSOAs and identifying individual properties within these areas.

The highest calculated ECIs might result from a combination of houses with poor thermal performance and occupants with high energy using behaviours. These are houses that have most to gain from refurbishment as their higher than average energy use will result in higher than average savings. The EPC data does not contain this combination of household energy use with house potential. The method presented here would also be less expensive to deliver than EPC data, especially if the benchmarks are generated centrally and published alongside the sub-national fuel consumption figures.

The method presented here will not be suitable for dealing with areas of housing that fall within the definition of fuel poverty. This is because the energy demand in these houses may be low, even though the housing is inefficient. Other methods exist for identifying fuel poverty (see Fahmy and Gordon 2007 for example). Also, households in fuel poverty are less suitable for refurbishment schemes like the Green Deal as the lower use of heating results in longer payback times, which was acknowledged from the ECO consultation. Another limitation of the method presented here is that areas of housing heated by fuels other than gas and electricity may not be well represented. The model presented here used 2001 Census data on the average number of rooms in each LSOA to help predict gas consumption for 2010. This could be problematic in areas with new housing developments, and it is recommended that 2011 Census data are used as they become available.

The use of these benchmarks is proposed as an improvement on using the raw domestic energy consumption data to monitor the performance of Local Authorities based on the energy demand in their area. This is because it removes the advantages of Local Authorities that benefit from what Keirstead and Schulz (2010 p4876) termed as 'a benign climate, unique economic structure or other fortuitous circumstances'. Constructing the ECIs at the

LSOA level ensures that the results have practical applications for Local Authorities and their commercial partners in large scale refurbishment schemes. This was highlighted as desirable in the Green Deal policy literature (DECC 2011b).

4.3 Electricity Consumption

Considering the average number of rooms (2001 Census), the median household income (Experian Mosaic), and the ratio of gas to electricity meters (DECC), the modelled benchmark for electricity consumption accounted for 73.1% of domestic electricity consumption across English LSOAs. The influence of house size, income, and proportion of electric heating supports previous findings in the academic literature. However, unlike gas consumption, the factors accounting for the remaining variation are not as well understood. Despite the fact that the three variables included in the model were able to account for a greater proportion of the variation in consumption, the dependent variable was more heavily skewed and it was not possible to verify results in the same way as domestic gas consumption. The current Green Deal and ECO policies are unlikely to achieve large-scale reductions in electricity consumption (Dowson et al. 2012). This is because they focus on the condition of the housing stock and the thermal efficiency of the dwelling, whereas our model demonstrates the need to develop alternative approaches to reducing electricity consumption – something which is likely to be driven by household behaviour and the use of electricity generating technologies, such as photovoltaic (PV) panels.

The results from this method could be used to monitor the impacts of localised policy trials such as energy efficiency educational campaigns, community-based action, or the rollout of smart metering technologies that provide households with feedback on electricity demand – with more work clearly needed to explore the characteristics of households in areas with high electricity ECIs.

4.4 Ranking

The method presented in this paper, provides a way to rank local authorities, based on the proportion of their LSOAs that have ECIs above a chosen ECI threshold; illustrations are given herein for a threshold of 100. For Central Government, this ranking offers a means to identify the Local Authorities that can make the most energy savings. This can also indicate to commercial companies, such as Green Deal providers, which Local Authorities offer the greatest opportunities from collaboration. It will also enable Local Authorities to compare their performance with neighbouring areas and can be used by Councils to justify their focus on domestic energy consumption to their communities.

5. Conclusions

This paper offers a method to benchmark domestic gas and electricity consumption for small areas of housing (approximately 500-700 homes). Multiple linear regression models to generate benchmark domestic energy consumption show that three variables account for approximately 65% of the variation in per meter gas consumption, and 73% of per meter electricity consumption. These three variables are drawn from the use of secondary data that described the variation in the size of housing, median household income, external air temperature, and proportion of gas heating. This benchmarking process removes the effects of climate, infrastructure, and wealth, enabling the energy efficiency of the housing stock in one area to be fairly compared with the stock in a different area. Comparing the actual gas and electricity demand of the houses in each LSOA with the modelled benchmark yields an ECI which clearly identifies those areas with the greatest potential for demand reduction. The model could be run centrally every year, new benchmarks published, progress monitored, and the priority areas re-assessed. With this method there will always be 50% of all the LSOAs with 'below average' ECI values and this ensures that Local Authorities which take no action will see their LSOAs energy performance decline temporally in relative terms.

The proposed gas ECIs offer advantages over energy demand, age of the housing, or EPC data: areas of housing with high energy demand will not necessarily have a high potential for demand reduction; areas with older housing may already be refurbished and so offer no further potential; EPC data is incomplete and ignores the actual consumption of the households, although it should be noted that a supplementary Green Deal Occupancy Assessment does take the actual consumption into account if that information is available. Areas of housing with the highest gas ECIs represent relatively high energy consuming households living in houses with relatively poor thermal performance. These are precisely the households that have most to gain from refurbishment and the Green Deal policy tool. Electricity ECIs offer an intriguing opportunity for furthering our understanding of electricity demand, but much more work is needed in this area. The authors argue that the current data provision is inadequate to assess the progress and success of area-based energy reduction strategies can be measured. The method presented in this paper provides improved data and a model to enable this in a way that does not mandate 'one size fits all' targets to all Local Authorities in the UK. The recommendation is that these benchmark and ECI data be published by DECC, as part of their ongoing commitment to providing data resources to

Local Authorities, as well as being of interest to private Green Deal providers and energy efficiency companies, aiding the targeting of their marketing activities.

The main limitations of this model concerns the applicability towards identifying areas for fuel poverty interventions, particularly where households are consuming less than expected. While policies to reduce heating energy consumption in the UK are relatively well advanced further work is needed to develop policy to reduce electricity consumption. The electricity benchmarking method described in this paper could provide new insights into the consumption behaviours of households and offers a means of monitoring the impact of reduction schemes. Ultimately it is hoped that this will help the UK Government to achieve its emissions reductions targets, and there is no reason that the method could not, in principle, be applied in other countries.

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List Figures

Figure1

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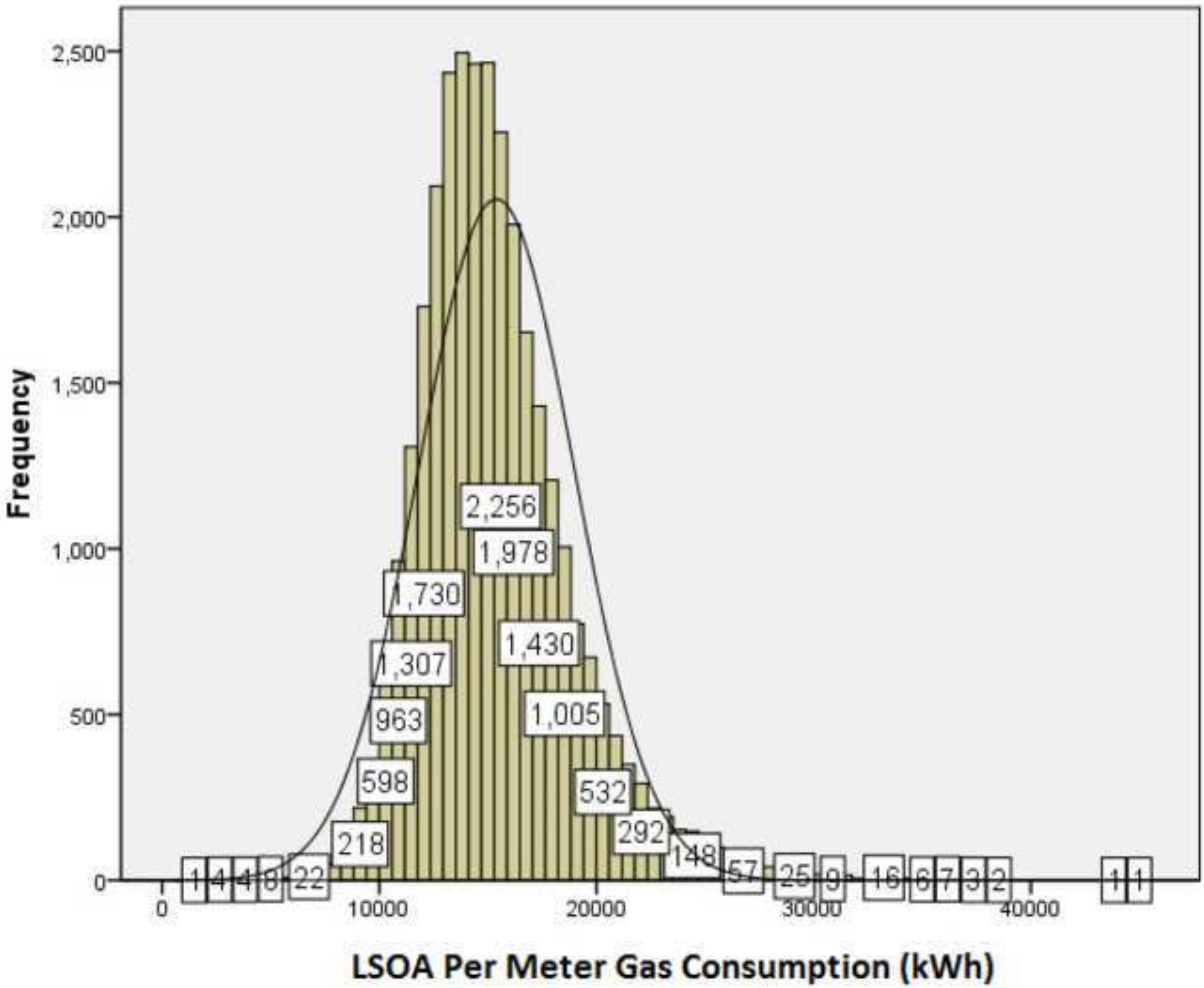

Figure2

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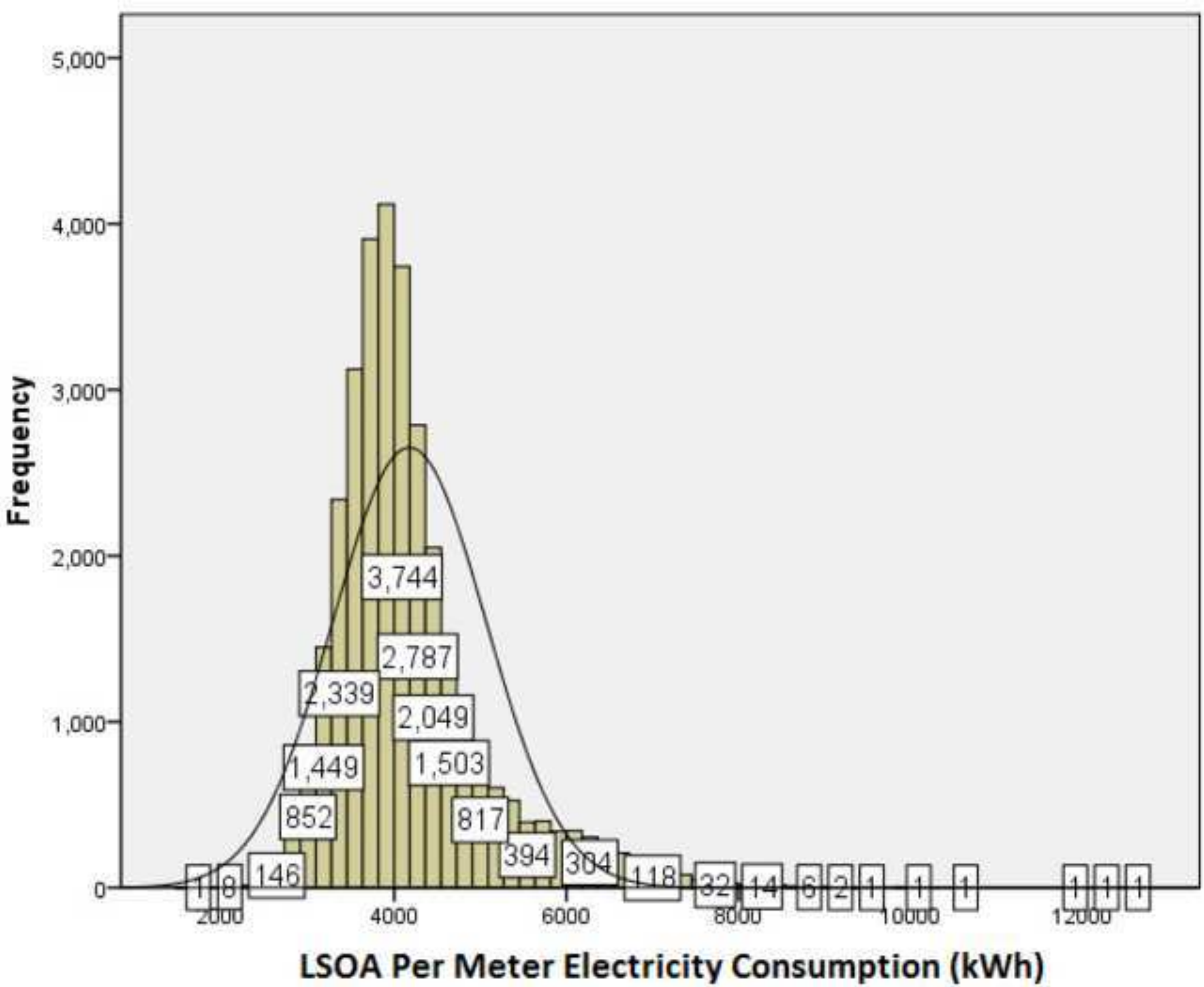

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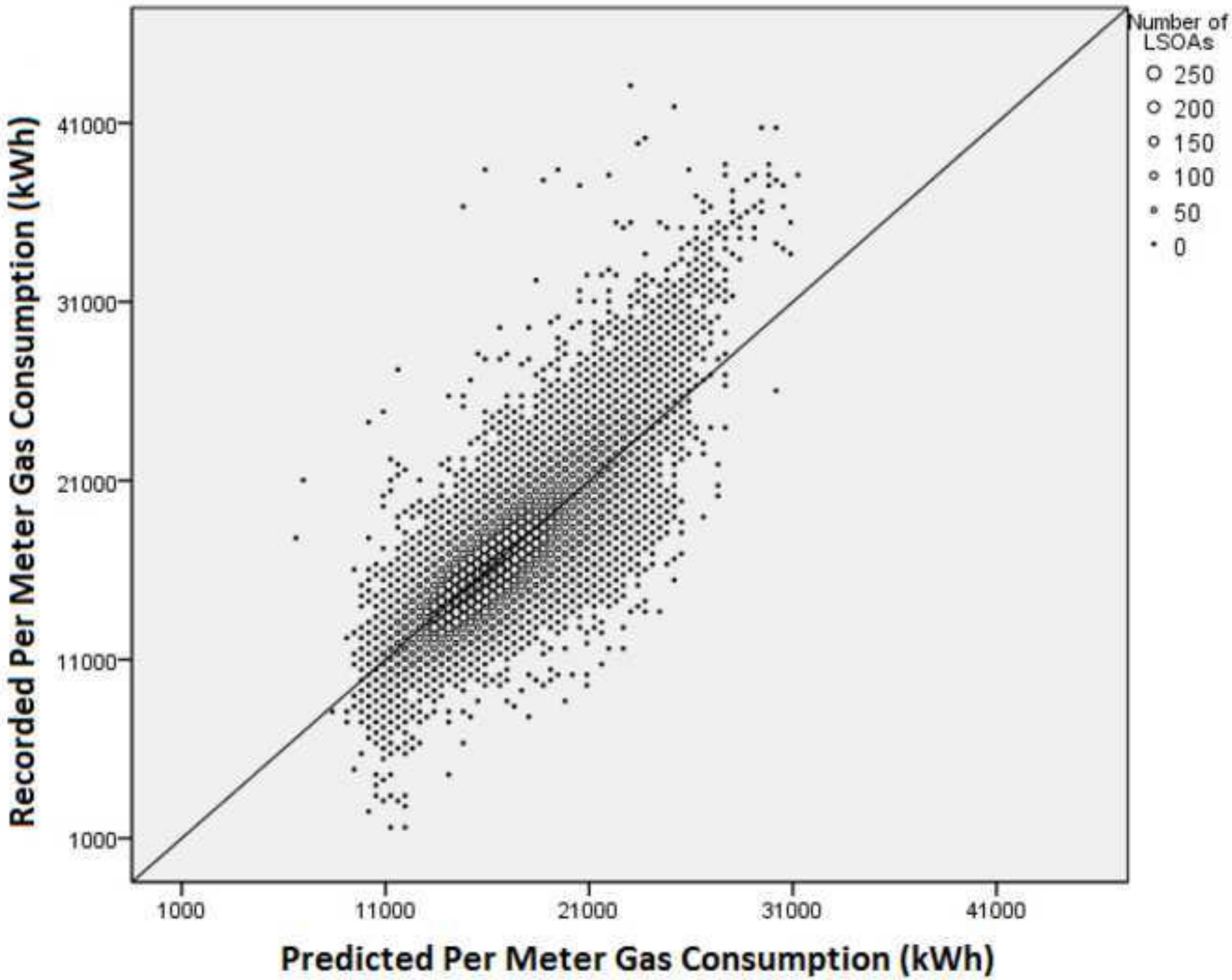

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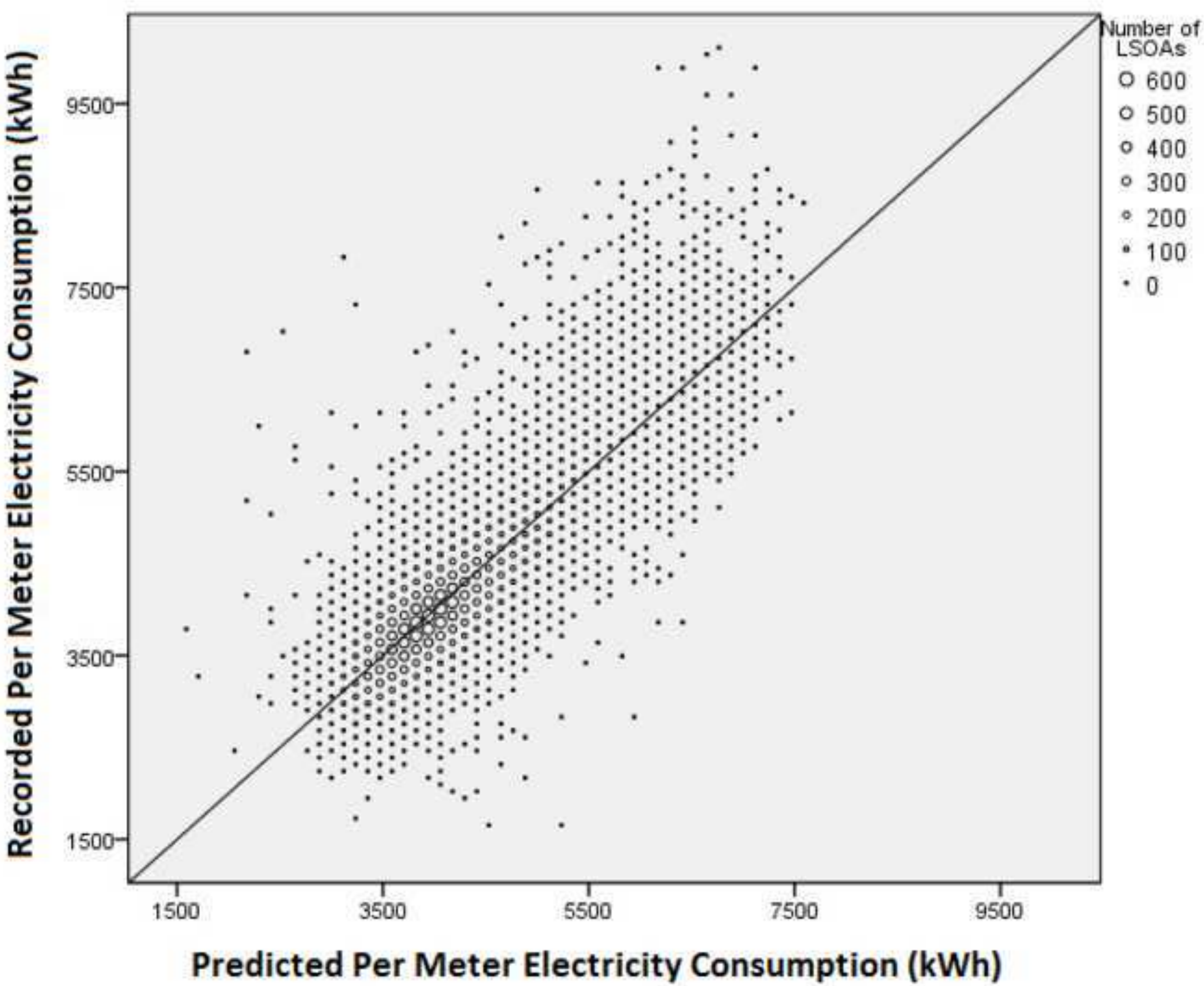

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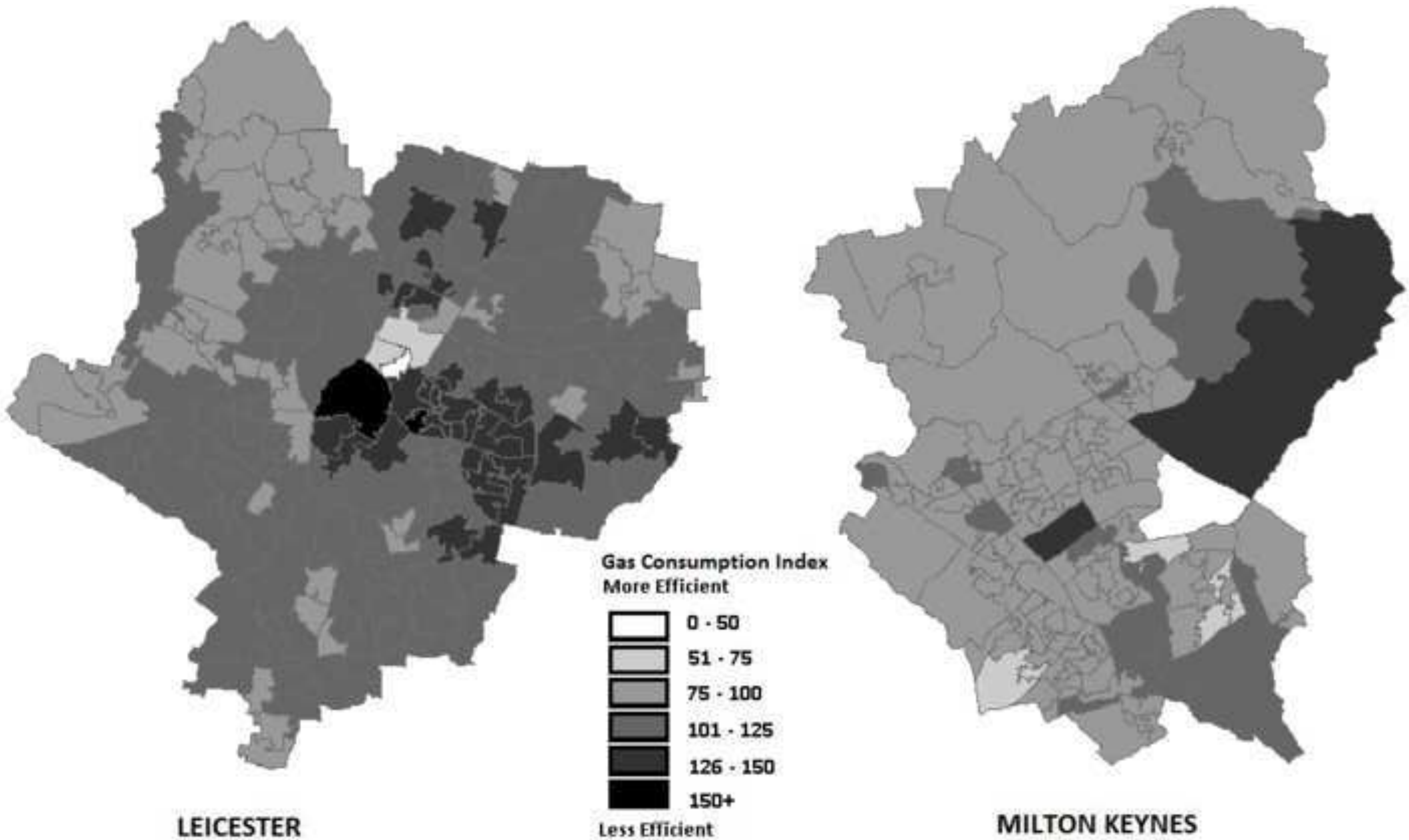

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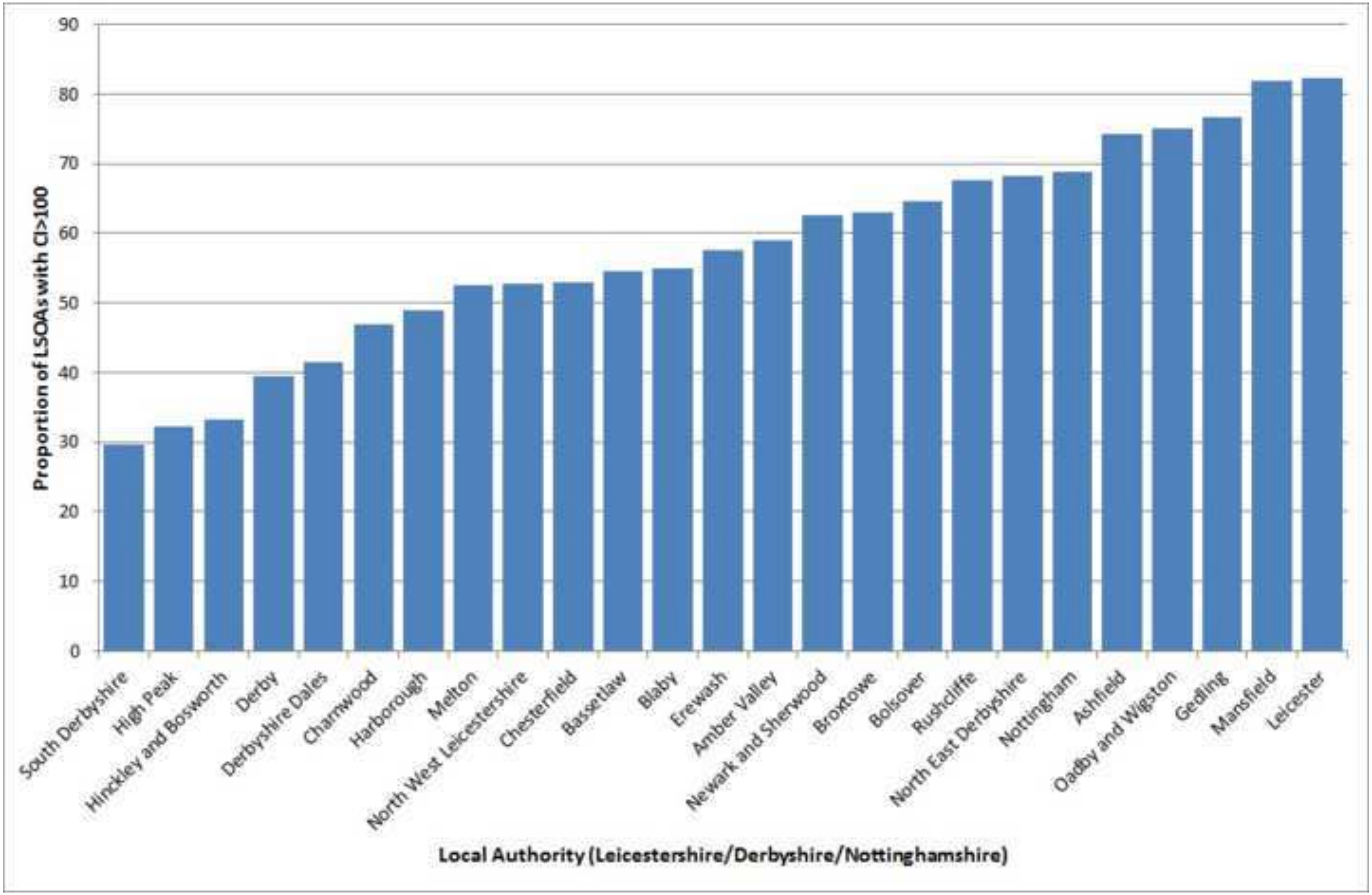

Tables

Table 1: Data sources used in study

Data Source	Organisation	Published Variables (Year Described)	Year	Published at LSOA	Official Statistics	Frequency of Update	Measured or Modelled
DECC (2013c)	DECC	Total Electricity Consumption	2010	✓	×	Annual	Measured
		Total Gas Consumption		✓	×	Annual	Measured
		Per Meter Electricity Consumption		✓	×	Annual	Measured
		Per Meter Gas Consumption		✓	×	Annual	Measured
		Number of Gas Meters		✓	×	Annual	Measured
		Number of Electricity Meters		✓	×	Annual	Measured
Census Dissemination Unit (2013a)	Experian Mosaic	Median Household Income	2010	✓	×	Annual	Modelled
Census Dissemination Unit (2013b)	2001 Census	Average Number of Rooms Per House	2001	✓	✓	10 Years	Measured
		Percentage of Owner Occupiers		✓	✓	10 Years	Measured
		Percentage of Social Renting Households		✓	✓	10 Years	Measured
		Percentage of Private Renting Households		✓	✓	10 Years	Measured
		Percentage of Detached Houses		✓	✓	10 Years	Measured
		Percentage of Semi Detached Houses		✓	✓	10 Years	Measured
		Percentage of Terraced Houses		✓	✓	10 Years	Measured
		Percentage of Flats		✓	✓	10 Years	Measured
MET Office (2013)	MET Office	Heating Degree Days 1988-2006	2006	×	×	Constant	Modelled

Table 2: Descriptive statistics of gas and electricity consumption statistics

		Mean	Median	Standard Deviation	Skew	Kurtosis
Gas	Untransformed (kWh)	15732	14875	3581	1.168	3.196
	Transformed (√kWh)	123	122	13.9	0.60	1.80
Electricity	Untransformed	4140	3969	851	1.71	5.13
	Transformed (√kWh)	64	63	6.2	1.23	2.77

Table 3: Correlation Matrix of Studied Variables

	Per Meter Electricity Consumption	Per Meter Gas Consumption	Ratio of Gas to Electricity Meters	Average Number of Rooms Per House	% Owner Occupiers	% of Social Renting	% of Private Renting	Median Income	% of Detached Houses	% of Semi Detached Houses	% of Terraced Houses	% of Flats	Heating Degree Day
Per Meter Electricity Consumption	1	.341**	-.628**	.596**	.360**	-.402**	-.014**	.638**	.588**	-.040**	-.356**	-.257**	.013*
Per Meter Gas Consumption	.341**	1	.165**	**.727****	.470**	-.450**	-.108**	.667**	.386**	.130**	-.264**	-.278**	.220**
Ratio of Gas to Electricity Meters	-.628**	.165**	1	-.108**	.037**	.042**	-.125**	-.129**	-.263**	.169**	.188**	-.051**	-.015**
Average Number of Rooms Per House	.596**	**.727****	-.108**	1	**.740****	-.637**	-.342**	.531**	**.755****	.244**	-.321**	**-.716****	.252**
% Owner Occupiers	.360**	.470**	.037**	**.740****	1	**-.898****	-.345**	.495**	.587**	.302**	-.278**	-.637**	.146**
% of Social Renting Households	-.402**	-.450**	.042**	-.637**	**-.898****	1	-.097**	-.559**	-.506**	-.117**	.209**	.452**	-.056**
% of Private Renting Households	-.014**	-.108**	-.125**	-.342**	-.345**	-.097**	1	.067**	-.277**	-.442**	.196**	.505**	-.239**
Median Income	.638**	.667**	-.129**	.531**	.495**	-.559**	.067**	1	.514**	-.130**	-.397**	-.044**	-.173**
% of Detached Houses	.588**	.386**	-.263**	**.755****	.587**	-.506**	-.277**	.514**	1	-.085**	-.540**	-.465**	.164**
% of Semi Detached Houses	-.040**	.130**	.169**	.244**	.302**	-.117**	-.442**	-.130**	-.085**	1	-.355**	-.499**	.252**
% of Terraced Houses	-.356**	-.264**	.188**	-.321**	-.278**	.209**	.196**	-.397**	-.540**	-.355**	1	-.043**	.031**
% of Flats	-.257**	-.278**	-.051**	**-.716****	-.637**	.452**	.505**	-.044**	-.465**	-.499**	-.043**	1	-.434**
Heating Degree Day	.013*	.220**	-.015**	.252**	.146**	-.056**	-.239**	-.173**	.164**	.252**	.031**	-.434**	1

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 4: Multiple regression model for square root per meter gas consumption

				Coefficients			Variable Significance Test		Model Statistics		
Independent Variable	**Change in R^2**	**Adjusted R^2**	**p**	**Unstandardised**	**Standard Error**	**Standardised**	**t-value**	**P**	**Model R^2**	**F-Statistic**	**P**
Constant	-	-	-	-25.53	0.59	-	44	<0.001	0.653	19844	<0.001
Average Number of Rooms	0.534	0.534	<0.000	9.88	0.09	0.45	106	<0.001			
Median Household Income (£ 000)	0.079	0.613	<0.000	0.63	0.01	0.43	102	<0.001			
Heating Degree Day (1000 K-days)	0.040	0.653	<0.000	16.36	0.27	0.22	60	<0.001			

Table 5: Multiple regression model for square root per meter electricity consumption

				Coefficients			Variable Significance Test		Model Statistics		
Independent Variable	Change in R^2	Adjusted R^2	p	Unstandardised	Standard Error	Standardised	t-value	P	Model R^2	F-Statistic	P
Constant	-	-	-	51.47	0.18	-	285	<0.001	0.731	26724	<0.001
Average Number of Rooms	0.382	0.382	<0.000	3.86	0.03	0.39	113	<0.001			
Ratio of Gas to Electricity Meters	0.276	0.658	<0.000	-15.34	0.09	-0.50	-172	<0.001			
Median Household Income (£ 000)	0.073	0.731	<0.000	0.22	0.00	0.32	94	<0.001			

Table 6: Comparing proportion of LSOAs with higher than expected gas consumption in new/expanded towns and pre-existing settlements

	Number of Local Authorities	Mean Proportion of LSOAs where CI>100	Standard Deviation	Interquartile Range
Pre-Existing	302	46.81%	22.63%	39% (26.5-65.5)
New/Expanded	51	32.61%	19.26%	29% (14.6-43.6)

Table 7: Comparing proportion of LSOAS with higher than expected electricity consumption in new/expanded towns and pre-existing settlements

	Number of Local Authorities	Mean Proportion of LSOAs where CI>100	Standard Deviation	Interquartile Range
Pre-Existing	302	48.13%	20.37%	29% (35.5-64.5)
New/Expanded	51	47.17%	17.77%	20% (39-59)

Table 8: Number and Percentage of LSOAs by Change in Absolute Values of Consumption Indices

Change in Consumption Index	Gas Consumption		Electricity Consumption	
	2008-09	**2009-10**	**2008-09**	**2009-10**
>|1|	24640 (83%)	25198 (79%)	26168 (80%)	25742 (79%)
>|5|	5443 (17%)	6229 (19%)	8284 (26%)	2950 (9%)
>|10|	755 (2%)	849 (3%)	1715 (5%)	1021 (3%)
>|20|	115 (0.3%)	85 (0.3%)	179 (0.6%)	92 (0.3%)
>|25|	72 (0.22%)	60 (0.19%)	95 (0.29%)	43 (0.13%)
>|50|	20 (0.06%)	20 (0.06%)	4 (0.01%)	2 (0.02%)
>|75|	11 (0.03%)	10 (0.03%)	1 (0.003%)	1 (0.003%)
>|100|	2 (0.006%)	3 (0.06)	1 (0.003%)	1(0.003%)