Fuel Poverty and Income Deprivation in Bristol, UK

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Summary

Fuel poverty is an important question to balance social equity in the UK. Traditional methods mostly use interviews to understand fuel poverty. In this paper, we incorporate the individual household level Energy Performance Certificates (EPCs) with the Indices of Multiple Deprivation (IMD) and England Census datasets to explore the relationship between fuel poverty and various neighbourhood characteristics using multi-scale geographically weighted regression (MGWR). The initial findings show that fuel poverty as a phenomenon is influenced by multiple factors and cannot be understood solely as an architectural or sociological question.

KEYWORDS: Fuel poverty, income deprivation, energy efficiency, MGWR

1. Introduction

Fuel poverty – the inability to afford adequate warmth in a household – is an important policy question affecting a large part of the population in both developed and developing countries (Bosch et al., 2019; Zhao et al., 2020). Existing research show that fuel poverty affects between 50 and 125 million Europeans with varying degrees in different regions (Bouzarovski & Petrova, 2015). The UK occupies an intermediate position within the EU with 'moderate' number of fuel poor households. In England, 11.1% of them – or 2,5 million people – is estimated to experience fuel poverty, while the same is true for 650,000 households in Scotland (Baker et al., 2018).

Fuel poverty is an important policy question for various reasons. It is a key determinant of health, especially among low-income households. Adequate warmth is a public health question as the lack of heating can result in excess winter morbidity and mortality via circulatory and respiratory diseases, which increases the number of deaths and illnesses occurring during colder months (Teller-Elsberg et al., 2016). However, inadequate temperatures can have multiple detrimental outcomes for individuals beyond health and well-being. For example, children in energy poor households are found to miss school more often than their peers (Teller-Elsberg et al., 2016).

The definition of 'fuel poverty' – or the often interchangeably used 'energy poverty' – varies in the literature. The UK government classifies households as fuel poor if 'they have required fuel costs that are above the average (the national median) or, were they to spend that amount, they would be left with a residual income below the official poverty line' (Department for Business, Energy & Industrial Strategy, 2019). The literature often uses the '10% measure' – those who spend more than 10% of their income on energy related costs (Price et al., 2012). However, fuel poverty is caused by different interrelated phenomena, such as income, climate conditions, energy efficiency, energy costs, or the housing quality. Therefore, there are various measures that can be used to understand this question.

Most of the existing research have used interviews or official census to understand fuel poverty. In this paper, we use a new form of urban big data, the openly available Energy Performance Certificates (EPCs) in the individual household level to further explore this question in Bristol. Energy efficiency

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rating is chosen as the key indicator of fuel poverty from the EPC dataset. In order to understand how households in different neighbourhood are affected by fuel poverty, this paper analyses its spatial distribution and driving factors. The city chosen for the analysis is Bristol, the UK's seventh biggest city, which lends itself well to the analysis given its size, social history, and physical fabric of the city.

2. Data

Several different data sources were selected for the analysis. The Ministry of Housing, Communities and Local Government (MHCLG) provides a comprehensive and open access dataset on EPCs for England and Wales (Ministry of Housing, Communities & Local Government, 2019a). The variables in the dataset includes energy consumption, costs, energy efficiency ratings, insulation (wall, roof, window), the quality of the heating systems, and total yearly emissions. The total energy consumption is broken down by heating, hot water, and lighting to provide detailed information of each household's consumption pattern. The information is registered on the individual household level.

The English Indices of Multiple Deprivation (IMD) dataset was used as a poverty measure to understand the socioeconomic characteristics of each neighbourhood (Ministry of Housing, Communities & Local Government, 2019b). The primary variable used for the analysis is Income Deprivation, which provides a score based on the proportion of the population experiencing income deprivation in the area. The area units are all lower super output areas (LSOAs), which allow to capture a small-scale neighbourhood trend.

The 2011 Census data was used to extract demographic information on the areas under study. The variables selected for the analysis include – among others – tenure (social rented, private rented, owner occupied), age, country of birth, economic activity, household composition, qualification, and social grade on the LSOA geographical scale.

As mentioned, fuel poverty is usually defined as the expenditure on energy as a percentage of income. Since there is no available information on households' income, the IMD income score was used to calculate the fuel poverty measure used in this paper. The direction of the original income score was reversed so the larger the value the wealthier the area is. The equation is as follows (1):

$$\alpha_i = \frac{e_i}{s_i} \tag{1}$$

where s_i is the income score and e_i is all household energy costs – such as lighting and heating – for each observation *i*. A small value of α_i indicates that the area is less likely to experience fuel poverty than those LSOAs where the metric is larger.

3. Multiscale Geographically Weighted Regression (MGWR)

The newly designed MGWR method allows the conditional relationships between the dependent variable and independent variables to vary at different spatial scales (Fotheringham et al., 2017).

The MGWR model can be presented as an equation (2):

$$y_i = \sum_{j=0}^{m} \beta_{bwj}(u_i, v_i)x_{ij} + \epsilon_i \tag{2}$$

where (u_i, v_i) are coordinate locations for each location i, x_{ij} is the *j*th predictor variable, *bwj* in β_{bwj} indicates the bandwidth used for estimation of the *j*th conditional relationship (Fotheringham et al., 2017).

4. Analysis

The UK government is committed to improve the energy efficiency of the country's housing stock, especially regarding private rented properties. The government set a target 'to improve the home of fuel poor households (…) to EPC band C by 2030' (House of Commons, 2019). The two interims 'milestones' are a minimum EPC rating of E by 2020 and EPC band D by 2025 for all households.

Table 1 Current Energy Efficiency Ratings

A	B	C	D	E	F	G
171	9087	31531	51404	23835	5132	1213

However, according to the dataset (Table 1), 5% of households still fall into a band of G and F in Bristol. This represents around 6300 households. Figure 1 shows the mean energy efficiency at the LSOA level in Bristol. The darker colour represents higher EPC rating. Darker spots appear to be scattered over the city, with some concentration in the inner city. The poor EPC areas are mostly in the inner city and old town of Bristol.

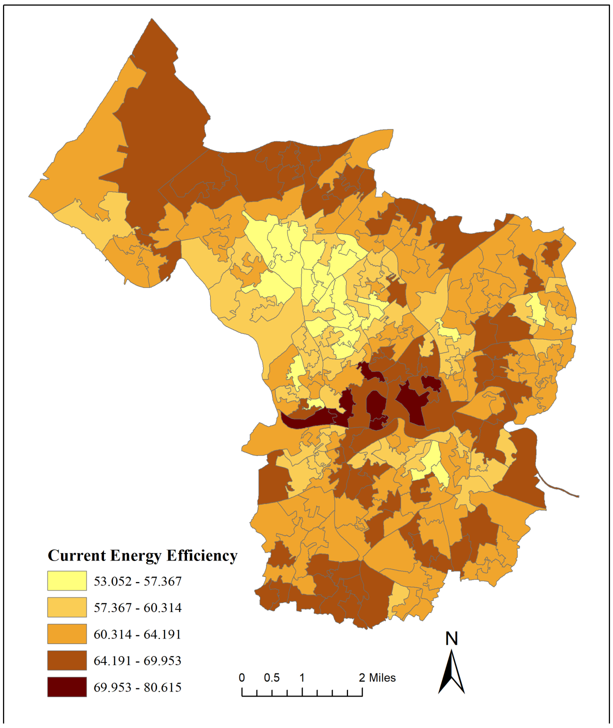

Figure 1 Current Mean Energy Efficiency of Bristol

MGWR 2.2.1 software was used for the MGWR analysis (Oshan et al., 2019). The model used a weighted adaptive bi-square kernel with AICc as optimization criterion. The final OLS and MGWR results are shown in Table 2. Three variables in the model has a negative relationship with the fuel poverty measure including mean EPC, percentage of employment, and percentage of UK origin. Areas with higher employment percentage, higher EPC, and more UK born residents are less likely to experience fuel poverty. Both ownership and social rented tenure have a positive association with fuel poverty. These finding indicates that fuel poverty is evident across different tenure types and is indeed intertwined with the built fabric of the housing unit. From MGWR results, most of the variables have a local pattern except the percentage of UK origin. Percentage of employment needs to be further explored since it has both positive and negative parameter coefficients in the MGWR results.

Table 2 OLS and MGWR Model Results

Variables	OLS est.	p-value	Mean	Min	Median	Max	Bandwidth
Intercept	0.000	1.000	-0.036	-0.318	-0.069	0.320	49.000
Mean EPC	-0.932	0.000	-0.800	-0.946	-0.764	-0.710	120.000
Employed %	-0.216	0.000	-0.092	-0.252	-0.078	0.023	103.000
UK origin %	-0.127	0.002	-0.329	-0.333	-0.321	-0.315	262.000
Owner occupied tenure	0.515	0.000	0.701	0.517	0.705	0.830	92.000
Social rented tenure	0.660	0.000	0.730	0.325	0.696	1.199	53.000
OLS Adj R^2=0.768; MGWR Adj R^2=0.888; Global AICc=371.921; MGWR AICc= 217.048.							

5. Discussion and Future work

The results of the preliminary show that fuel poverty is indeed linked to various social factors and housing conditions. While the findings show some interesting patterns, there are some limitations to the research. The datasets are registered on different geographic scales, which means that their units are different. The EPC dataset is registered on the household level, while IMD and the Census datasets are only available for LSOAs. Further analysis can be performed to better understand the relationship between multiple deprivation measures and fuel poverty.

The future research aims to expand upon the current analysis by using Zoopla housing price and private rental price dataset. Linking the dataset to information about ownership and house prices could reveal whether dwellings with poor energy efficiency ratings are private rented or owned and if house prices in an area are affected by the ratings. The current aggregated analysis sets the basis of a more comprehensive, individual level analysis in this field.

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7. Biography

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