Geographically varying explanations behind the UK's vote to leave the EU: an aggregate-level analysis

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1 Motivation, data and research questions

On 23rd June 2016 the United Kingdom held its second referendum on its political association with Europe. The outcome of the first – held on 5th June 1975 – was emphatic, with 67% of voters expressing a preference for continued membership of the then European Community (EC). The result of the most recent vote – this time on the European Union (EU) – was more fractured. Whilst the overall outcome was a slight preference for leaving the EU (51.9%), this result varied greatly across the country. Of the 11 regions of Great Britain (GB, which excludes Northern Ireland), only Scotland and London voted in favour of Remain (62% and 60% respectively). At a Local Authority (LA) level, this was the case for just 30% of the 378 LAs in GB.

Political Scientists have argued that the spatially-fragmented vote is symptomatic of widening social divisions in the UK linked to structural change [12]. Since the 1970s, opportunities have increasingly concentrated in the South East of England and particularly London, whilst more provincial locations, particularly those cities and regions with economies once monopolised by single-industries, saw limited growth and depopulation [4]. The social-geography of the UK is, then, today more socially distinct than it was in 1975. Thus, spatial differences in the 2016 referendum vote might be linked to *place-based* factors: LAs recording the strongest preference for Leave have been described as 'left-behind' places, characterised by chronic low skills, socially conservative and often nativist values, whilst those associated strongly with Remain with more affluent, highly-educated and diverse populations [11].

Our analysis uses area-based data by Local Authority, thus our findings will relate to aggregate behaviour within LAs, rather than individuals. For each LA, we have the number of votes for Leave, the number of votes for Remain and the number of people who voted. We combined this with demographic and socio-economic data as measured by the 2011 Census, aggregating these data to LAs. We decided to exclude Northern Ireland from our analysis because some of the data we required were not available. Some normalisation was needed. We calculated vote proportions for each Local Authority to normalise by population. In some of our analysis, we used z-scores to standardise the values by their range. This is indicated in the relevant section.

Our aim is to identify the most discriminating and generalisable socio-economic variables that appear to drive spatial differences in voting preference, and then to interpret these in the context of existing theories on the social and economic reasons by people voted in the way they did. We are particularly interested in whether these theories hold equally well across the whole country. Analysis is structured around the following research questions:

- What factors best explain geographic differences in voting behaviour in the 2016 referendum?
- Do these factors explain geographic differences in voting behaviour equally well across Great Britain?

2 Tasks and approach

2.1 Visually characterise spatial variation using cartographic techniques

Spatial variation in voting preference (by LA) is the main effect that we wish to explain. To investigate how voting preference varies at this level of geography we used a choropleth map (Fig. 1, left) with a diverging colour scheme that distinguishes LAs with majority Leave votes (green) from those with majority Remain (brown) (Fig. 1).

LAs vary in size according to population, with urban LAs that have high population density being small and rural LAs that have low population density being large. A problem with depicting social phenomena in such spatial units on a conventional map is that rural areas are given greater visual saliency. One way of overcoming this problem is to plot the data for different regions separately (Fig. 1, middle). Another is to use population-weighted cartograms (Fig. 1, right) [9], where spatial units are sized by the number of people voting.

2.2 Identify spatial patterns in relevant population characteristics using geovisualization and local statistics

We need to select population characteristics that may explain LA-level differences in voting behaviour. Themes discussed widely in the media around the Leave vote being a symptom of 'blue-collar disaffection' and the Remain vote of affluent, liberal values (e.g. [6, 3]), helped inform this decision-making. Spatial variations in selected population attributes were explored in choropleth maps. Geographically-weighted means and standard deviations were calculated using the GWmodel package [10]. The local smoothing helped identify trends over space and local contexts. Studying these maps alongside the result map (Figs. 1 and 2) enabled associations between variables to be suggested.

2.3 Identify associations between populations characteristics and referendum results using scatter plots

We used the Pearson's correlation coefficient to assess correlation between LA population characteristics and voting preference. This allowed us to rank Census 2011 variables according to their association with voting preference. Pearson's correlation coefficient is not robust to outliers and scatterplots with accompanying regression lines were also used to assess linearity of associations, as well as supporting judgements around normality of variables. Points in the scatterplot were coloured by region, enabling assessment of whether certain regions are more predisposed to outliers or substantial departures from the regression line.

2.4 Explore geographic variation in relationships using visualization and local statistics

The scatterplots suggested that outliers were indeed concentrated within certain regions. Geographically-weighted correlation coefficients, again calculated using the GWmodel package [10], helped identify the extent to which associations were geographically variable. We characterised this geographic variation by displaying local statistics in choropleth maps.

2.5 Build explanatory models that control for population characteristics using regression

Since our research question is concerned with the factors driving geographic differences in voting behaviour, we built multivariate regression models to investigate possible explanatory variables more formally. Regression modelling is widely used for explanatory model building in the social sciences [1] and has been variously applied in Political Science to study voting preference, often as we do in this study using aggregate-level data (e.g. [13]).

As a parametric technique, regression requires a set of assumptions about explanatory variables. Visual analysis helped with evaluating these assumptions. Scatterplots enabled assessment around the degree to which relationships between explanatory variables and the outcome (share of Leave vote) were linear. Most important for this study is the assumption of limited collinearity of explanatory variables; place-based social-demographics tend to be collinear.

Collinearity was assessed visually using correlation coefficient matrices and algorithmically using Variance Inflation Factors (VIF). VIF measures how much the variance of regression coefficients are inflated as compared to when explanatory variables are not linearly related. There are published heuristics around the level of collinearity that can be tolerated for each variable as measured by VIF (e.g. [14]). Our procedure for variable selection and model development is summarised below:

- Identify variables that appear to be discriminating (based on strength of correlation against the outcome).
- Identify variables that appear to co-vary and that are conceptually similar.
- Explore the effect of removing explanatory variables on VIF scores and model fit, as measured by R^2.
- Identify geographic variations in model fit by plotting model residuals as choropleth maps, again using a diverging scheme.

One means of automatic variable selection is least absolute shrinkage and selection operation (LASSO) [18]. LASSO minimises the sum of squared differences between the observed outcome and the model (e.g. OLS) whilst also penalising against the absolute sum of regression coefficients. This latter constraint – penalising the sum of regression coefficients – enables variable selection as regression coefficients are shrunk to 0 and therefore less important variables are excluded from the model.

2.6 Evaluate generalisability of explanatory models using local regression models

Since our research questions suggest a concern for how factors driving voting preference vary spatially, we investigate how well the models hold for different regions of the country. We do this by analysing model residuals spatially, again using choropleth maps and geographically-weighted summary statistics [2]. Specifically, we cluster LAs by their geographically-weighted correlation coefficients and identify groups of LAs exhibiting distinct associations with Leave voting.

3 Analytical steps

3.1 Spatial variations voting preference

Fig. 1 displays voting preference by LA: intensity of green represents strength of vote in favour of Leave; intensity of brown, strength of vote in favour of Remain. The maps expose a very obvious contrast between most of England and Wales (in favour of Leave) and Scotland and London (in favour of Remain). As we already knew, London and Scotland are clearly distinct in their preference for Remain. This also appears to be true for certain university cities and towns (e.g. Cambridge in the East region). The faceted view also reveals variation within London: more peripheral LAs such as Barking & Dagenham that express a strong preference in favour of Leave.

3.2 Spatial patterns in population characteristics

Population characteristics, as measured in 2011 Census, were selected based on the media discourse around *place-based* histories: the varying responses to, and experiences of, de-industrialisation [3]. We selected variables that might be used as proxies for the 'post-industrial successfulness' of a LA, or rather its residents. These variables are listed in Table 1.

Table 1: *Proposed 2011 Census variables for explaining Local Authority share of Leave vote.*

variable	justification/theory
degree-educated *professional occupations* *younger adults*	post-industrialisation / knowledge-economy
English speaking *single-ethnicity* *not good health* *white British/Irish* *Christian*	diversity / values
own home *don't own car* *private transport to work*	metropolitan / urban-rural / outcomes

The proportion of *degree-educated* residents and residents working in *professional* occupations appear particularly prescient given the media discourse around the Leave:Remain vote and post-industrialisation: highly-educated, professionalised workers epitomise the so-called *knowledge-economy* [5]. The proportion of younger adults, a generally more upwardly mobile group, also provides some indication of a LA's success. So too might variables associated with ethnic and cultural diversity. The *no car household* and *mode of travel to work* variables might initially appear to be a strange choice. Car ownership has traditionally been used in market research as *the* proxy for household income. We hypothesise that this is changing and the relationship with EU voting preference may well be fluid, especially so when analysed spatially.

The maps in Fig. 2 display geographically-weighted means and standard deviations (variation) of these population characteristics. They reveal the unique context of London and the South East. Other parts of the country show variation in the diversity measures: the North West contains high proportions of residents identifying as *Christian*; Scotland appears comparatively diverse; South West Wales, parts of the Midlands and North East contain the highest levels of *not good health*.

3.3 Associations between population characteristics and referendum results

Crucial to this study is establishing how these population variables relate to our outcome – LA-level voting preference. In Fig. 3 scatterplots displaying each population variable at the LA-level against share of Leave vote are presented with regression lines and Pearson's correlation coefficients. Points representing LAs are sized by electorate and coloured by Region.

3.4 Geographic variation in relationships

Fig. 4 displays geographically-weighted correlation coefficients for each population variable against share of Leave vote. The maps confirm that *degree-educated* and *professionals* appear to be strongly negatively correlated with the Leave vote. Although the strength of relationship varies – e.g. Scotland for *degree-educated* and to a lesser extent *professionals* and London, Leicester and parts of the North West for *professionals* – the direction of the relationship (the sign of the coefficients) remains the same. *Private transport to work* and *not good health* are both associated positively with Leave. This appears to be particularly so for the East and North of England (*not good health*) and London and and LAs surrounding Oxford, Cambridge, Bristol and Leeds. From a cursory glance at Fig. 4, there is a sense of London's unique context. The *no car* variable is very strongly negatively associated with Leave around London; elsewhere this variable is less discriminating and in fact is positively associated with Leave in the North

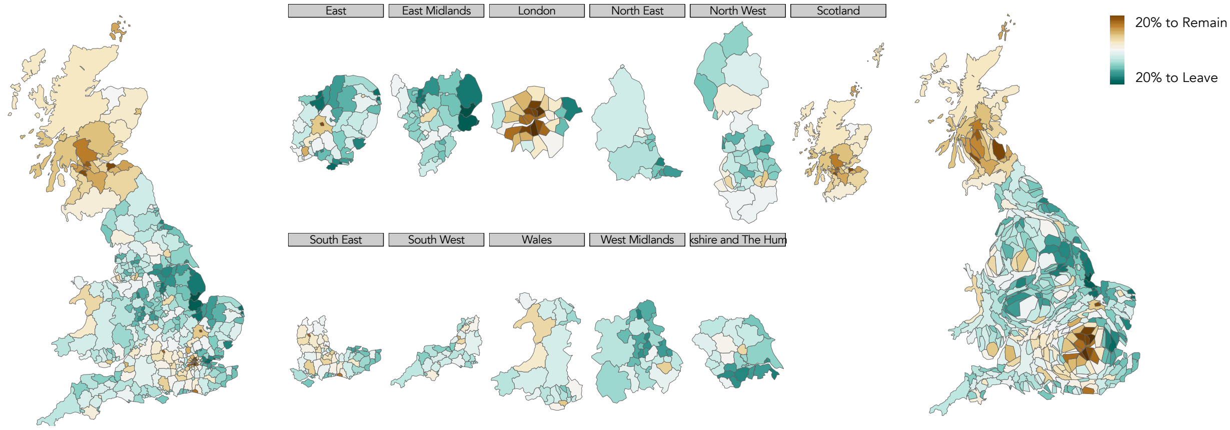

Fig. 1: Maps displaying share of vote in favour of Leave (green) and remain (brown). Left-to-right respectively, results data are displayed using a conventional choropleth map, a choropleth faceted on region and as a cartogram.

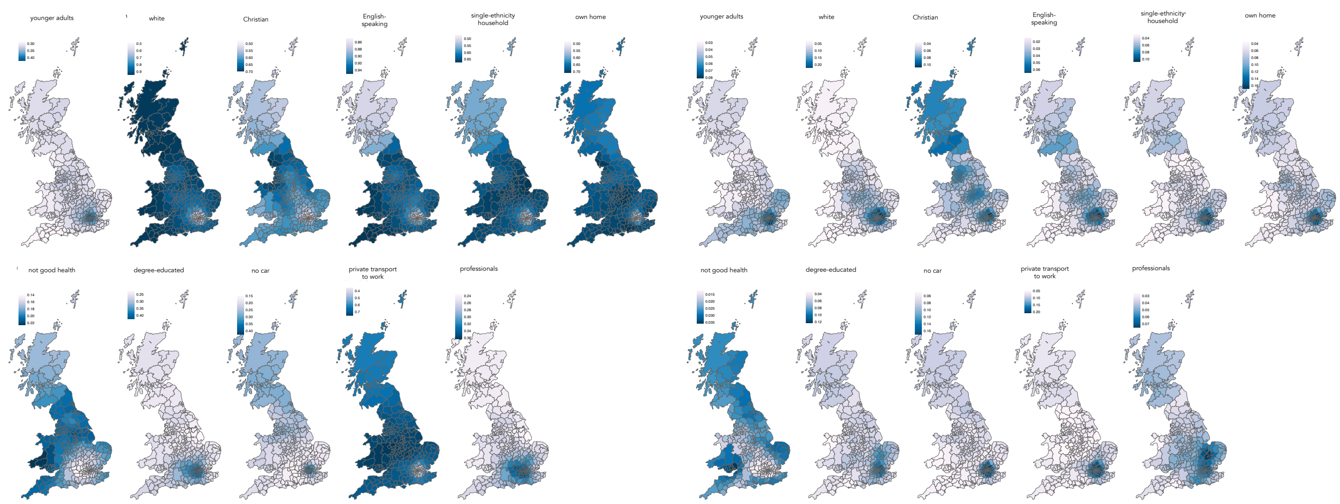

Fig. 2: Left: geographically-weighted mean values for 2011 Census variables (bw=50). Right: geographically-weighted standard deviation values for 2011 Census variables.

East. A similar pattern, though in the opposite direction, is present in the *own home* variable. The association with variables related to diversity is interesting. *Christians* has a strong and positive relationship with the Leave vote in the East, LAs towards the East of London and the Scottish borders and to a lesser extent the South West. This spatial pattern is also true of the *English speaking* and *white* variables.

3.5 Build explanatory models that control for population characteristics

We wished to fit a multivariate model that draws on the separate concepts described in Table 1. The scatterplots in Fig. 3 suggest a very obvious explanatory variable: *degree-educated*. We therefore first fit a simple regression model where the assume that the Leave vote is a linear function of the *degree-educated* variable. Model residuals are presented in Fig. 5. The very strong negative residuals for Scotland can also be observed from the scatterplots in Fig. 3: the model overestimates the Leave vote in Scotland. This obvious spatial autocorrelation in residuals suggests that a separate model may be required for Scotland. Reinspecting the scatterplots (Fig. 3) there is also an argument for fitting a model for England & Wales that excludes London. When we do this, model fit substantially improves (Table 2). We then fit a multivariate model, using the LASSO method for variable selection. The four variables that are given non-zero coefficients, and therefore included in the model, are summarised in Table 2. In multivariate regression, these coefficients can be understood as the change in outcome (share of Leave vote) due to a variable if all other variables are held constant. Thus, if the proportion of *degree-educated*, *no car* and *white* does not change, a 1% point increase in the proportion of of residents identifying as *Christian* will result in a 0.13% increase in the Leave vote.

Table 2: *Linear regression coefficients. Multivariate model is fit using lasso variable regularisation and selection.*

variable	b coefficient	p-value	r^2	geography
degree-educated	-0.96	<0.001	0.57	GB
degree-educated	-1.02	<0.001	0.73	EW not Ldn
degree-educated	-1.11	lasso		
no car	-0.26	lasso	0.84	EW not Ldn
christian	0.13	lasso		
white	-0.03	lasso		

3.6 Evaluate generalisability of explanatory models

Our aim is to develop a model that efficiently and coherently explains place-based variation in voting preference. Ideally these explanations would generalise: that is, our model could be used to predict reasonably well the share of Leave vote given the population structure of a LA. In Fig. 5 we show that the residuals for the model including the whole of GB do indeed vary, with Scotland in particular containing large negative residuals. Smaller residuals appear in the models that exclude data from London and Scotland. However, the distribution of residuals remains non-random (Moran's I [15] 0.57): areas of blue and red generally concentrate together. This, and the fact that relationships between certain explanatory variables change over space (e.g. Fig. 4),

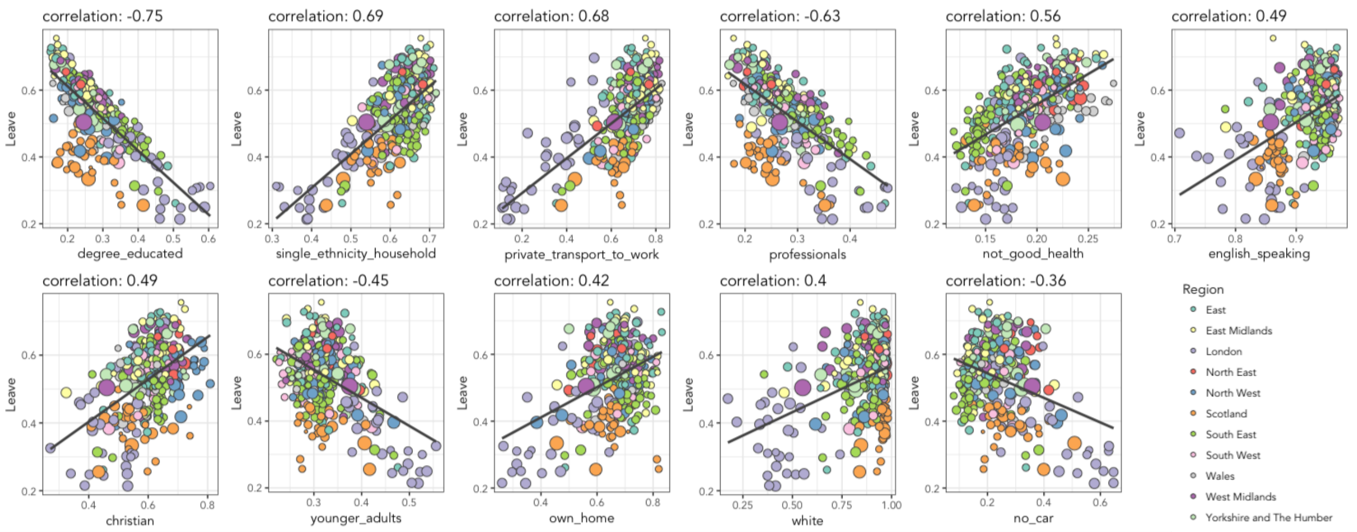

Fig. 3: Scatterplots of 2011 Census variables against the outcome variable – % of LA vote in favour of Leave. Points are sized according to the size of electorate and coloured by region.

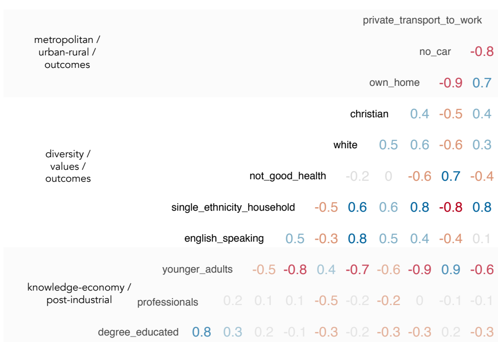

Fig. 6: Correlation matrix of geographically-weighted correlation coefficients.

is justification for developing a geographically-weighted model.

Such model development is beyond the scope of this analysis. We instead begin to explore spatial variation in relationships between explanatory variables by clustering LAs on their geographically-weighted correlation coefficients. Each LA is summarised according to its geographically-weighted correlation coefficient (2011 Census variables with share of Leave vote) and agglomerative hierarchical cluster analysis (HCA) is used to identify groups of LAs that share similar combinations of relationship. A distance matrix describing pairwise differences between each LA is constructed; LAs are then 'agglomerated' into groups iteratively by merging the most similar LAs. This continues until all LAs are merged into a single group. Visually inspecting the output dendrogram of this process as well as Average Silhouette Width (ASW) values [17], calculated at different cuts of the dendrogram, we find that a 4-cluster solution results in the most stable and coherent clustering. Collinearity of input variables is a concern in cluster analysis: if two variables are included that represent the same concept, then that concept is given undue weight. Variables were carefully selected by visually inspecting correlation matrices of the geographically-weighted correlation coefficients (in a similar way as described in section 2.5). This correlation matrix of geographically-weighted correlation coefficients can be seen in Fig. 6. Notice that variables are arranged according to the concepts they represent; as with variable selection in regression, it is important to select variables that are intuitively *and* numerically different.

Fig. 7 displays cluster memberships spatially and for the variables on which groups are defined. Density plots are used to summarise the distribution of values (geographically-weighted correlation coefficients) for each LA. The cluster labels are an attempt to characterise these distributions.

4 Findings

This study is concerned with factors that explain geographic differences in voting preference and whether and how those factors vary across Great Britain. The scatterplots in Fig. 3 show that variables associated with post-industrialisation and the knowledge-economy – *degree-educated* and *professionals* – most obviously discriminate differences in voting preference. To a lesser extent variables concerned with *diversity*, *values* and *outcomes* are also discriminating. The scatterplots also suggest some regional variation in these effects. Across all variables, LAs in London (purple) and Scotland (orange) are distinct.

In section 3.5, a linear model is presented that explains more formally geographic differences in voting preference. The spatial autocorrelation in residuals from this model (Fig 5) is important to our research questions: it suggests that explanations are indeed spatially specific. Excluding LAs in London and Scotland substantially improves model fit and using the *degree-educated* variable only we can explain 73% of the variation in votes between LAs in the rest of England and Wales. Including *no car*, *Christian* and *white* further improves model fit (R^2 : 0.84). However, the regression coefficients for these variables are weak and may be locally-specific. For example, after controlling for *degree-educated*, *Christian* and *white*, the *no car* variable, representing the concept metropolitan living, has a negative effect on the Leave vote. This makes intuitive sense. However, the meaning of the *no car* variable may change with context: in rural locations it might be related to lack of material outcome. This, and the fact that the residuals for the multivariate model still exhibit spatial autocorrelation (e.g. Fig. 5), is justification for investigating locally-varying relationships further (section 3.6).

The most coherent cluster grouping (ASW: 0.6) identified in this section is *group 4*. Here the association between each 2011 Census variable and Leave is consistent – none of the density plots cross the 0 line on the $x-axis$. For *degree-educated* and *no car*, the distributions are extremely peaky. Variables relating to values and diversity are reasonably consistent: *Christian* and *white* are positively associated with Leave. We suggest this group most closely resembles the media caricature: it contains LAs in central London associated with high skills, metropolitan values and a strong Remain vote and those towards the East (Thurrock, Rochford and Southend-on-Sea) associated with far less diverse and educated demographics and a strong Leave vote. *Group 3* is less well-defined (ASW: 0.45) and whilst the relationship with *degree-educated* holds, the relationship is not as strong

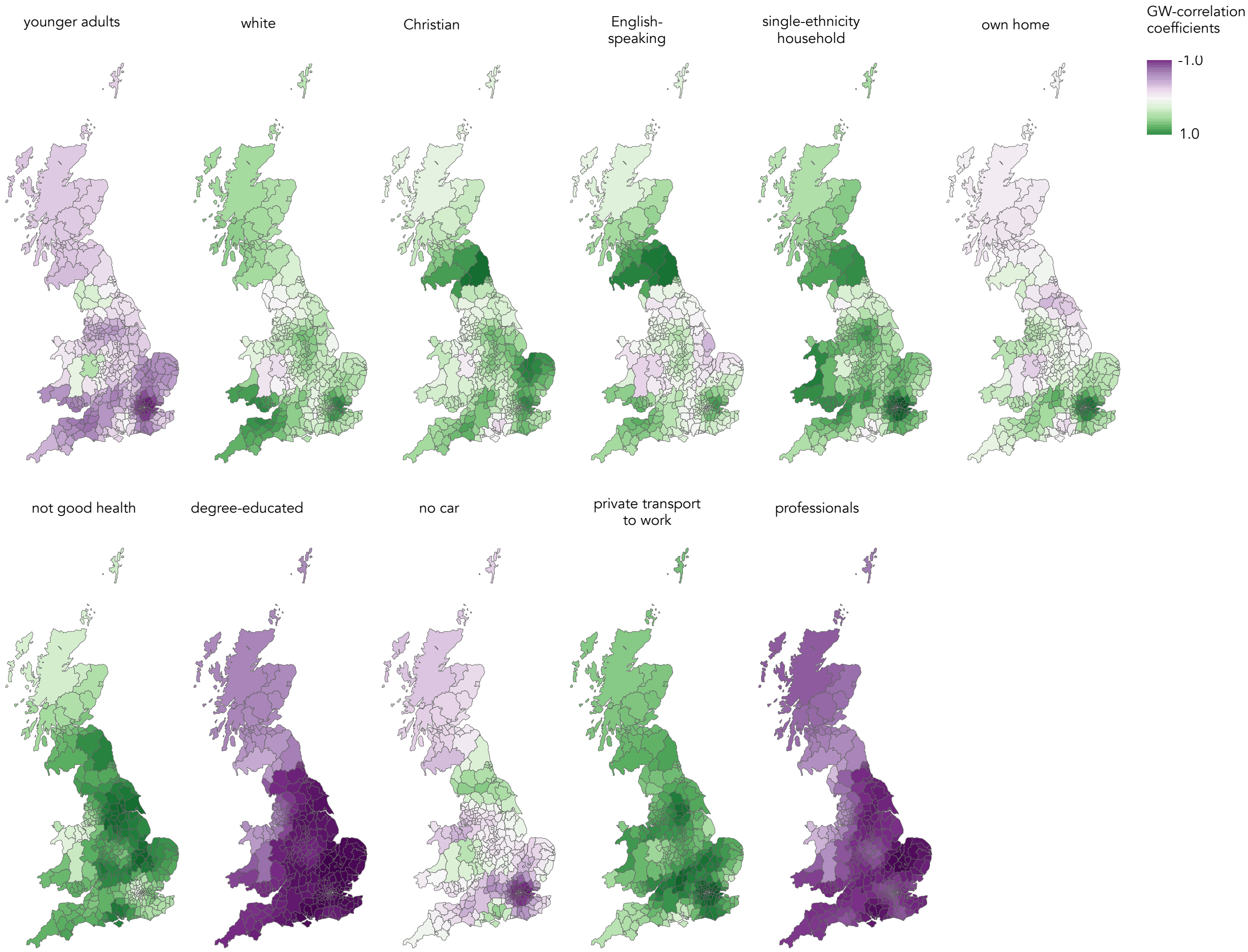

Fig. 4: Choropleths displaying gw-correlation coefficient for selected population variables against LA share of Leave vote. Data are mapped to a diverging colour scheme.

as for *group 4*. The motivation behind the cluster label (*material outcomes*) is that *not good health* appears discriminating for this group. Additionally, although less obvious, the *no car* variable is *positively* associated with Leave. This can be understood by the LAs included in *group 3*: a mix of rural locations, some of which affluent (Harrogate, South Lakeland and Winchester) and others less so (Stockton-on-Tees, Isle of Wight and Telford and Wrekin), where lack of *car ownership* is associated more with material disadvantage than metropolitan values. *Group 2* is poorly-defined and includes many parts of England and South Wales. It is most similar to *group 3*; however, *white* and *Christian* are correlated reasonably well with Leave. Finally, for *group 1*, none of the correlation coefficients very large. Despite the fact that this cluster group covers LAs in rural and urban locations there is a slight negative association with the *no car* variable. The extent to which material outcomes and experiences inform attitudes towards EU membership is less clear for these LAs.

5 Critical reflection

5.1 Implications of findings for domain

Our aim was to provide empirical support for the arguments made widely within the UK media around Leave – that it represented a vote of those left behind by globalisation [6, 3]. We used area-based statistics as proxies to the reasons suggested in the media. Although we did not validate whether these were good proxies, we used reasoned arguments supported by the literature.

Assuming these were good proxies, our results seem to support many of the reasons presented in the literature. The most convincing variables are those relating to *post-industrialisation* and the *knowledge-economy* – the *degree-educated* and *professionals* variables. Variables linked to traditional values (e.g. *Christian*), metropolitan living and material outcomes are also discriminating and help to further explain variations in voting preference. When these more minor variables are considered, relationships appear to be more spatially-specific. For example, whilst at the global level the *no car* variable seems to represent metropolitan experiences and is negatively associated with Leave, for provincial rural areas of the country this variable seems to reflect a lack of material outcome and, along with variables such as *not good health*, is positively associated with Leave. In parts of the country towards the East of England, where population change due to migration has been more keenly felt [**?**], variables relating to traditional values, as well as levels of education, may be important: it is perhaps here where the narrative of being adversely effected by globalisation through labour market deregulation and increased competition, is most heavily focussed. That voting preference can be explained less well in Scotland is an important observation. There may be some unique context that informs attitudes towards membership of the EU here: the extent to which material outcomes and experiences inform attitudes towards membership of the EU is far less clear for Scottish LAs than it is for those in England and Wales. In addition to developing a full geographically-weighted regression model, an immediate future research therefore might be to collect a wider set of variables for explaining voting preference in Scotland. Additionally, variables freely available at the LA level, such as levels of EU migration and past support for UKIP (a measure of historical Euroscepticism), may be revealing.

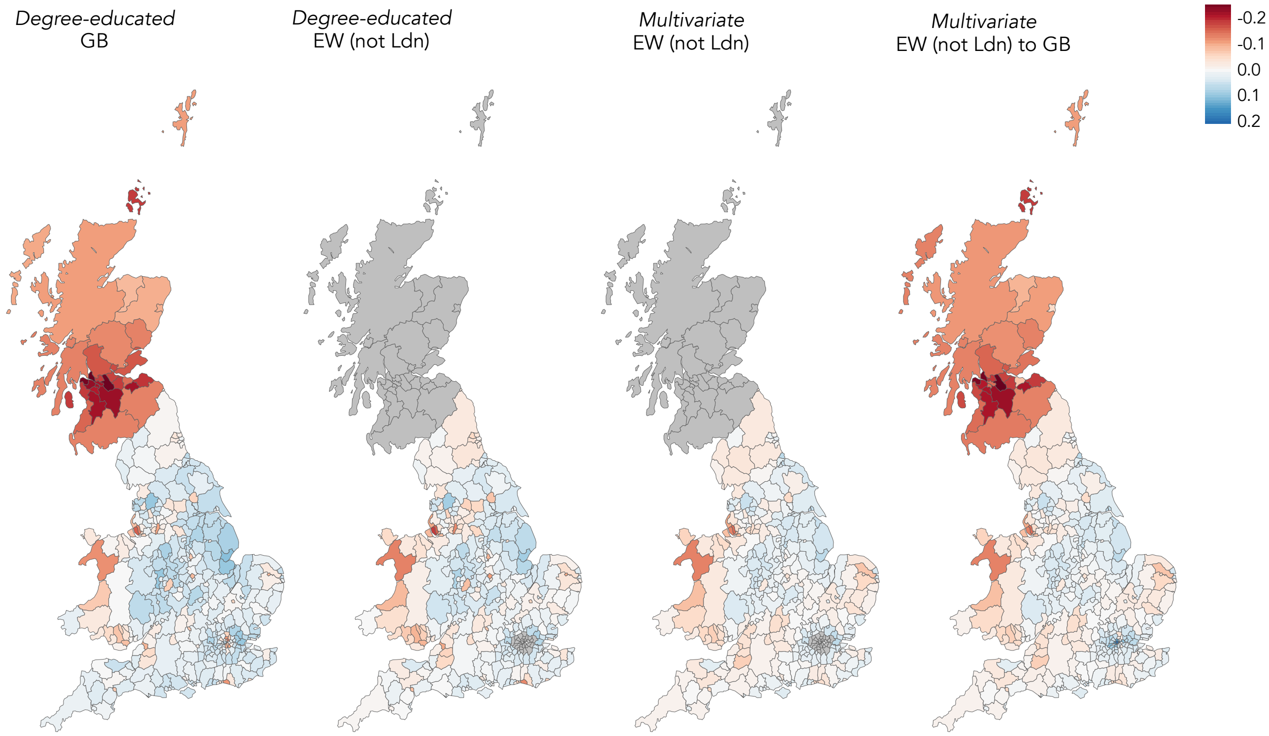

Fig. 5: Maps of model residuals. Left-to-right, linear regressions explaining share of Leave vote from *degree-educated* for Great Britain, for England & Wales excluding London using a refined set of outcome variables (*degree-educated* , *not good health*, *christian*, *younger adults*).

If research claims are to be made from this analysis, the limitations need to be made explicit. Firstly, our analysis attempts to explain why certain *places* vote for Leave:Remain using information on the local demographics of those areas. Our findings do not necessarily hold for individuals. This concern around making conclusions around individuals based on analysis of groups has been termed the *ecological fallacy* [16]. Arguments around the ecological fallacy are well-rehearsed in Political Science and have been used to question area-based analyses of political preferences; they likely overstate the importance of social demographics (measured at the area-level) at the expense of more inter-subjective, attitudinal explanations [13]. Given the given the democratic *milieu* of the UK, however, the political identities of*places* clearly matters. That the UK continues to experience widening geographic inequalities in outcome [4], and that links have been made with this and EU voting preference, is further justification for the area-based focus.

A second concern is that *a priori* reasoning, specifically the media discourse around 'Brexit', heavily informed the research design. Thus, there is a danger that we simply read-off this narrative onto our analysis. We accept this, but would argue that no data analysis is value-free and that the focus on spatially-varying relationships in these suggested explanations was an attempt to expose departures from, or at least question, the dominant media discourse.

5.2 How well the data and visual analytics approaches enabled answers to research questions

Using area-measures was suitable for our research questions as the reasons we were investigating about broad societal issue that relate to groups of people rather than individuals. We ensured that the variables we used and conclusions were not individual-based. Other decisions and analysis techniques were justified in sections 2 and 3 of this report. Since this study was concerned area-based differences in voting preference, choropleth maps were variously used: to analyse spatial patterns of voting preference, of material outcome, of relationships between outcomes and voting preference, and for analysing model residuals. Visually scanning across these maps, especially where they were juxtaposed for comparison as small multiples (e.g. Fig. 4), allowed local contexts to be identified.

In terms of statistical and computation methods, regression is a very widely used technique in social science research [1]. It has been used extensively in Political Science to analyse voting preference [13, 12]. We employed accepted techniques for evaluating our data given the assumptions of linear regression. Scatterplot matrices are an effective technique for visually diagnosing collinearity and Variance Inflation Factors allowed us to explore the effect of collinearity on regression coefficients [14]. LASSO is a conceptually simple technique for automatic variable selection [18] and was validated by comparing against the variables suggested via our manual process of variable selection (using VIFs and correlation matrices).

We again use standard procedures to develop and evaluate cluster solutions – a hierarchical cluster analysis, using ASW [17] to validate cluster membership and correlation matrices to check for collinearity of input variables. Whilst numeric validation is important, a cluster solution must be conceptually meaningful. By characterising groups according to the variables on which they were clustered (e.g. the density plots in Fig. 7) we were able to ascribe names to cluster groups that made sense within the study context.

Finally, the motivation behind using geographically-weighted statistics is clear. Our concern was not only with explaining spatial differences in voting preference, but in exploring whether and how these explanations vary in different spatial contexts. Computing local, geographically-weighted correlation coefficient values using the GWmodel package, enabled us to explore this local context.

5.3 Applications of approach to other domains

This work has identified factors that may explain an outcome. As this is a common analytical task, our approach may be valid in many of these cases. However, there are a number of factors that make this study distinctive and may affect applicability to other domains.

Firstly, we were studying a phenomenon of which much had been

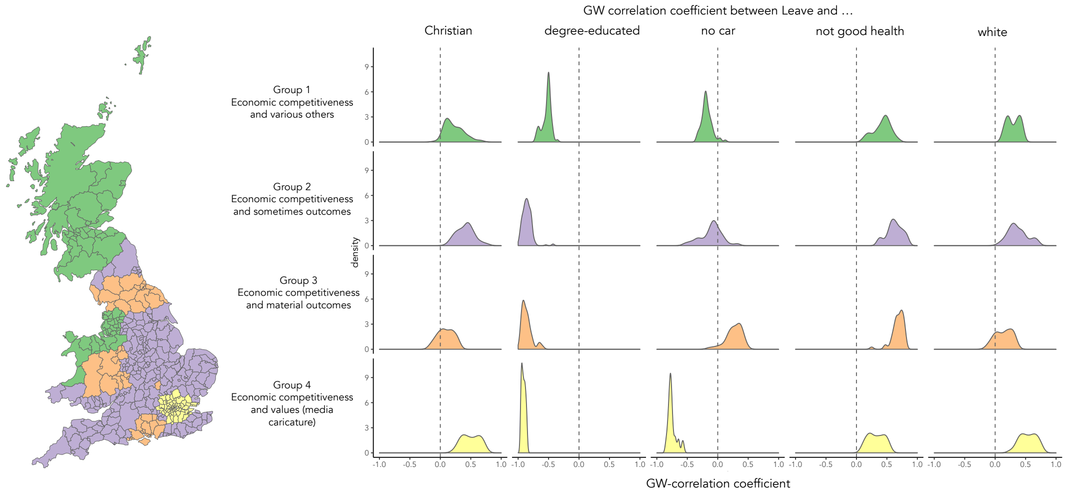

Fig. 7: LAs are clustered according to local (geographically-weighted) associations between voting preference and selected Census 2011 variables.

written about in the popular press and the reasons of which regularly studied in political science using census variables as proxies. This allowed us to the approach that we did and it considerably reduced the pool of variables we had to consider. In other domains, there may not be other reasons offered and how variables related to this may not be so clear. For example, the ways variables that relate to molecular structure in biology relate to function may not be well-understood.

Secondly, we were doing area-based analysis and this influenced the methods that we used; e.g. use of choropleth maps and the faceting of scatter plots by region. Since parts of the country have dense population, we employed cartograms to help reveal these patterns. LAs are regularly used in this context and were appropriate to our research question. In some other domains, individual data may be more important or there may be no meaningful units of analysis.

Finally, perhaps more importantly, not only are our data inherently spatial, but the identification and quantification spatial difference in the relationships of the variables were part of the research question. Geographically-weighted statistics [2] are not often used outside the spatial sciences and may enhance area-based analyses in Political Science. This argument seems prescient at a time when geographic differences in political preference are widening: for example, a similar set of explanations and patterns are being suggested around the recent US presidential election [8]. If this fact precipitates a renewed interest in area-based analyses (e.g. [12]), it is important that researchers pay attention to concepts such as spatial non-stationarity, especially given the very obvious spatial autocorrelation in residuals observed in our global models (Fig. 5).

Acknowledgments

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