Migrant Population Effect on UKIP Support in 2015 UK General Elections

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1 Introduction and Literature Review

The increasing support for right-wing populist parties/ candidates in Western societies in the past decade has elicited substantial academic interest. The rise of the United Kingdom Independence Party (UKIP) in the United Kingdom, for one, has been the catalysing force behind UK's exit from the United Kingdom. Anti-immigration has been the forefront of UKIP's agenda, as is shown in promotional materials in Fig.1 and Fig.2. Goodwin (2015) argues that the focus of UKIP's message has shift from one exclusively about the EU to one with immigration and anti-establishment at its heart.

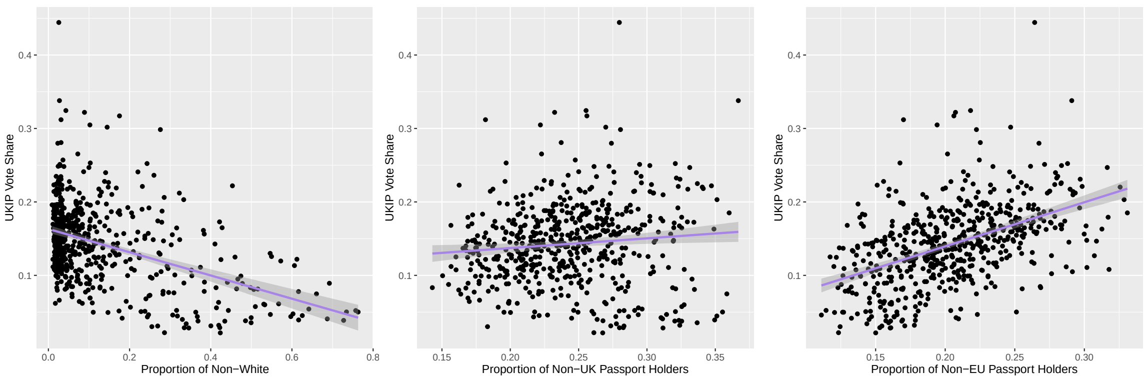
There are two dominant hypotheses which explain how immigrant presence in the neighbourhood can affect support for anti-immigration policies. The threat hypothesis (Putnam 2007) suggests that immigrants are perceived to threaten the economic resources of natives (Quillian 1995). Immigrants such as Muslims who may be perceived as holding vastly different values from those of natives, for example, may also be perceived as threatening national identities (Anderson 2006). When such threats are perceived, the institutions that govern members of the national community are likely to be called into question (McLaren 2012). The contact hypothesis, on the other hand, suggests that natives become more comfortable with immigrants through interactions in the neighbourhood (Allport, Clark, and T. Pettigrew 1954; T. F. Pettigrew and Tropp 2006)

Level of minority presence, measured as proportion of non-native population, has been a common measure to test the contact and threat hypotheses in the literature. Most of these studies rely on survey data (Billiet, Meuleman, and De Witte 2014; Strabac and Listhaug 2008; Neumann and Moy 2018) instead of elections outcome, which is less prone to the response biases. They also ignore the fact that a large share of non-White population could reflect a large share of eligible non-White voters (as first generation immigrants obtain citizenships), and are thus unable to distinguish the effect between interaction with non-Whites vis-a-vis non-Whites voting for liberal parties. As the bivariate regressions in Fig. 3 shows, the correlation changes sign as one changes measure from non-white population to non-EU-passport holder.

Although recent studies have advocated using ethnic change (measured as the increase of local non-native population) in addition to ethnic level to test the hypotheses (Kaufmann and Goodwin 2018), it is hard to measure ethnic change without longitudinal data. This problem is relevant for migrant attitude studies using election results as anti-immigration has only become a prominent platform in the late 2000s and general elections in the UK are only held every 5 years. General elections reduce self-selection biases as they have higher turnouts (60-70%) than other elections such as the European Parliament Elections (25-40%). Balancing between the strengths and weaknesses of different approaches, I choose to study the cross-sectional data on 2015 General Elections.

Figure 1: A UKIP billboard ahead of the 2014 European Parliament elections (Source: Channel 4 News)

Figure 2: UKIP's campaign poster for the 2015 General Elections (Source:politicaladvertising.co.uk)



(a) Correlation between non-White ethnic presence and UKIP vote share: -0.152; p-value: $< 2e-16; R^2$: 0.19

(b) Correlation between non-UK passport holder presence and UKIP vote share: 0.132; p-value: 0.0128; R^2: 0.11

(c) Correlation between non-EU passport holder presence and UKIP vote share: 0.599; p-value: $< 2e-16; R^2$: 0.233

Figure 3: Three graphs showing correlation when different measures are used

The aim of this paper is to test whether a higher proportion of migrant population in a constituency might explain more support for UKIP using 2015 UK General Elections data, and whether neighbouring constituencies' outcome and characteristics also matter.

2 Data

A cross-sectional dataset is used for this analysis. The dataset only includes 573 out of 650 Westminster parliamentary constituencies in the 2015 UK General Elections. This is because the 2011 census data which provided most of the constituency controls, is only available for England and Wales. This means the 53 constituencies in Scotland and 18 constituencies in Northern Ireland are removed from the voting result dataset.

Description of all variables can be found in the appendix. The dependent variable UKIP Vote share measures the share of vote UKIP obtains in each constituency and is directly computed by the UK Parliament. The key indepenedent variable $MigrantProportion$ measures the number of non-EU passport holders as a proportion of constituency population. I choose non-EU instead of non-UK passport holders to define migrants because of the more noticeable traits of former as ”outsiders”. The scatter plots in Fig. 3 also provide reasons to believe that non-EU passport holders prompt more response from the constituency. The data for this variable is obtained from the 2011 census data measured at constituency level. Five variables, namely Income multiple, Proportion of 0-18, Proportion of 65 and above, Male and Population density multiple are computed from 2015 annual population survey data. All other variables, namely Proportion of high school and above, Unemployment rate and Rurality are computed from 2011 census data. Rurality is a calculated using data reassigned from local authority/ county level (usually regions larger than constituency), which contains 174 observations. To keep the range of variables compact, most variables are expressed in percentages or as a multiple of constituency sample average.

Although voter-level microdata will be ideal to understand the possible effects of interaction with migrant neighbours, UKIP vote data is only available at constituency level. The data aggregation at a constituency level moves ”points on a map to units in a box” (Duranton and Overman 2005) and is prone to information loss which makes it harder to test for departures from randomness. Such aggregation is prone to the ”scale problem” (Openshow 1979) as the correlation between the dependent and independent variables can vary widely at different areal scale. This is one type of modifiable areal unit problem (MAUP) (Gehlke and Biehl 1934) where patterns at ward level might be lost through aggregation (Flowerdew 2011). Past empirical evidence shows that ethnic minority presence and support for right-wing parties are especially prone to the MAUP. Kaufmann and Goodwin’s (2018) meta-analysis find a nonlinear relationship between diversity levels and anti-immigration sentiments. Their review reports that in smallest (under 1,000 population) and largest (national) geographies, micro- and macro-threats are significant. In units of 5,000 - 10,000 people, however, greater diversity is associated with reduced threat as contact theory dominates. The estimated average constituency population in mid-2015 is 101,022 (ONS 2019), which is when anti-immigration sentiments start to rise in response to increased diversity in Kaufmann and Goodwin’s review. I therefore expect to see a positive relationship between non-EU-passport holders and vote support for UKIP.

The descriptive statistics are reported in Table 1.

Table 1: Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	2%5	75%	Max
Migrant Proportion	573	0.205	0.045	0.111	0.171	0.235	0.331
Unemployment	573	0.043	0.014	0.018	0.032	0.052	0.095
Proportion of 0-18	573	0.223	0.026	0.150	0.210	0.240	0.350
Proportion of 65 or above	573	0.183	0.050	0.050	0.150	0.220	0.340
Male	573	0.493	0.009	0.471	0.488	0.496	0.541
Population Density Multiple	573	1.000	1.267	0.010	0.137	1.496	7.411
Proportion of High School or Above	573	0.268	0.084	0.121	0.206	0.310	0.574
Income Multiple	573	1.000	0.356	0.672	0.819	1.056	4.736
Rurality	573	0.164	0.199	0.000	0.002	0.263	0.852

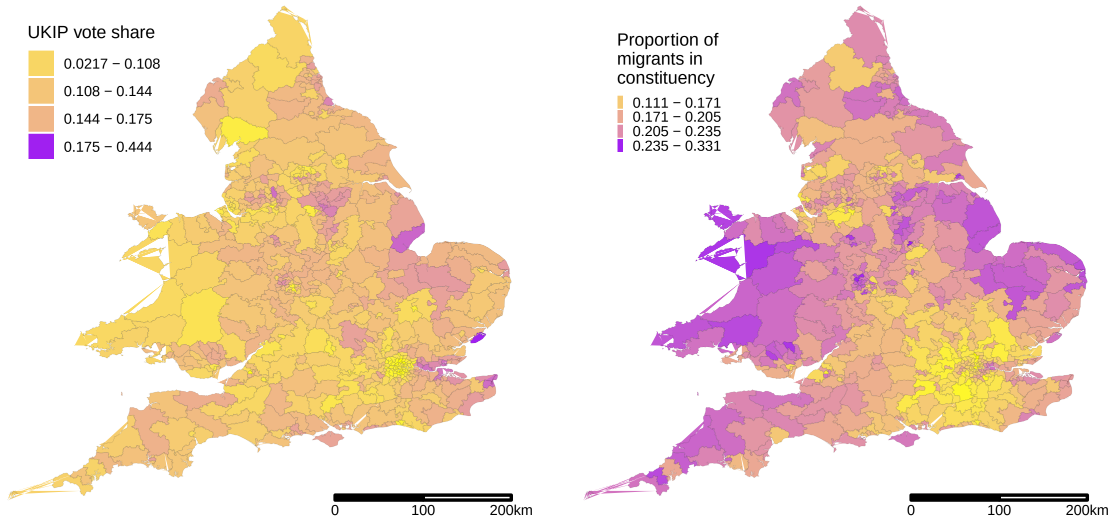
3 Data Exploration

Exploratory analyses in this section help to inform model decisions. Global Moran’s I is used to test for global trends of spatial association, while local Moran’s I, a local indicator of spatial association (LISA), is used to check local clusters.

3.1 Raw Data

The two maps in Fig. 4 visualise the distribution of the two key variables for this analysis at constituency level: UKIP vote share and migrant proportion. Fig. 4a shows the proportion of votes UKIP won at each constituency in the 2015 General Elections. Fig. 4b shows migrant population as a proportion of total constituency population. Since UKIP did not win more than 40% of vote at any constituency, the range in Fig. 4a is between 0-40%. The range in Fig. 4b, on the other hand, is between 0-100%. High values are reflected in purple while low values are reflected in yellow. The four colour labels state the quartile values of the data. In general, constituencies in the east seem more likely to vote for UKIP than those in the west, as is reflected by slightly more purple areas.

However, the clustering pattern is not clear. The clustering pattern of migrants in Fig. 4b is clearer than that of vote share, with more migrants living in coastal areas.



(a) UK Vote Share

(b) Proportion of Migrants at Constituency Level

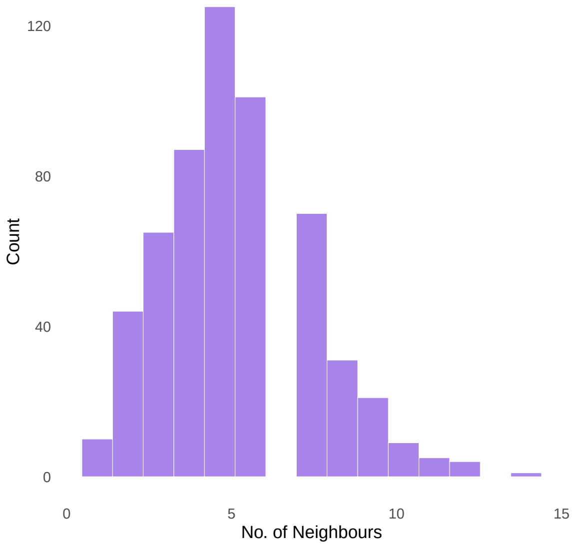
Figure 4: Two maps visualising raw data

3.2 Tests of Autocorrelation

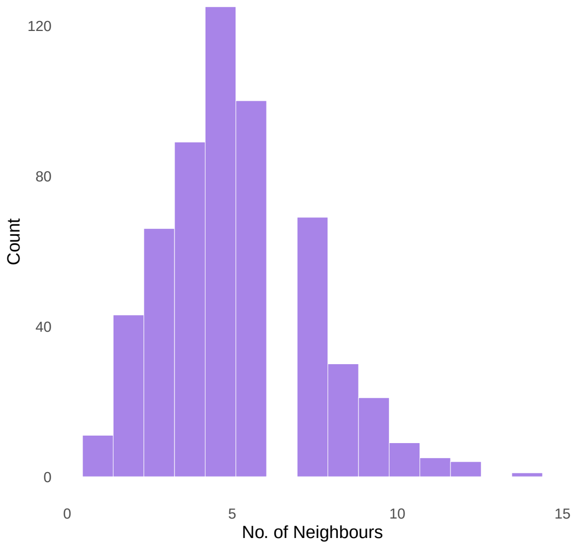
To test the spatial dependence empirically, I conduct a global Moran's I test. The spatial relationships in the data are summarised by a weight matrix which can then be used to test for the presence of auto-correlation. Since the true spatial structure is usually unknown, the choice of spatial weights is often based on the researcher's (potentially strong) assumptions (Dubin 2009). As estimates are sensitive to weights choice, this is an identification problem that plagues many spatial econometric analyses. (Anselin 2002; Stephen Gibbons and Overman 2012).

To ameliorate the problem introduced by the arbitrary choice of weighting scheme, I use two weighting schemes-queen and rook contiguity-to test if the number of neighbours vary. In queen contiguity, neighbours are those that share boundaries together. On the other hand, only those that of due north, south, east and west of a region are assigned as neighbours in rook contiguity (Dubin 2009). Both contiguity weighting schemes used are row-normalised and discrete. I use contiguity instead of distance-based schemes such as inverse distance because the large variation in constituency sizes will result in great variation in the number of neighbours for each constituency. For instance, large constituencies will have no neighbours if the distance threshold is set too low. In results not reported in this analysis, I used fixed distance measure to find the number of neighbours with inverse distance weighting and a threshold of 100km. The threshold is deliberately set high to make sure that large constituencies will still have neighbours. The mean number of neighbours is 124 and ranges from 7 to 195.

In contrast, the frequency distribution of constituency neighbours (Fig. 5) in discrete contiguity-based schemes is narrower. In addition, it can be seen that the distribution is almost identical in queen and rook contiguities, implying that a different weighting scheme should still give fairly similar results.



(a) Queen contiguity



(b) Rook contiguity

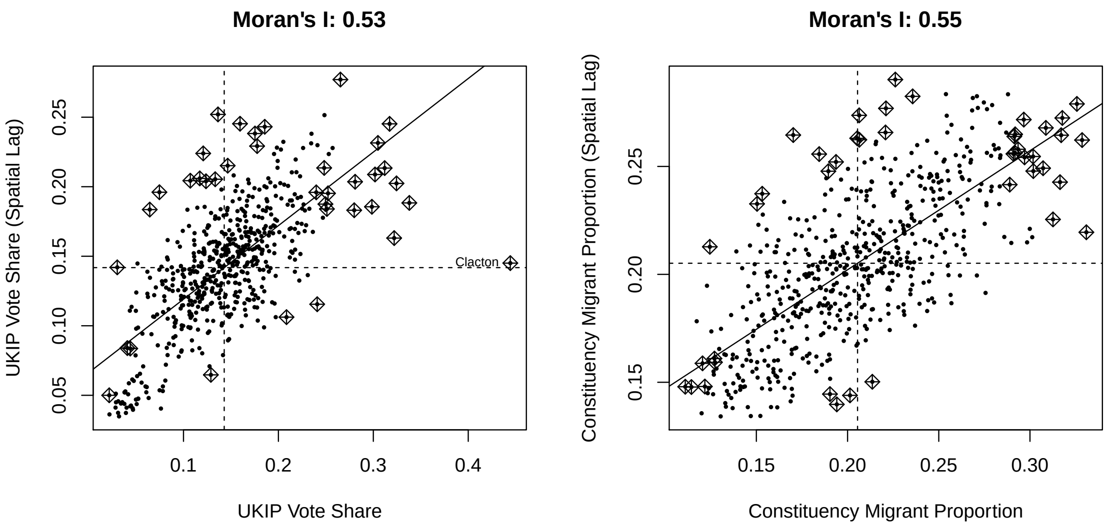
Figure 5: Frequency distribution of neighbours in contiguity weighting schemes

As the United Kingdom is an island country, many coastal constituencies have few neighbours. Nearly 10% of constituencies (54) have only 1 or 2 neighbours. To remedy this potential source of bias, I use a k-nearest neighbours scheme with k = 5, the median value in both queen and rook contiguities. The results estimated with queen and rook contiguity schemes are reported in the appendix with minimal differences.

Fig. 6 show the Global Moran's I statistics for UKIP vote and migrant population using the knn (k=5) weighting scheme. The Global Moran's I measures the overall spatial distribution of a variable (Moran 1948). A Global Moran's I of 0.53 shows that there is a clear, arguably strong spatial autocorrelation in UKIP vote share. For constituency migrant proportion, the Moran's I value is slightly higher at 0.55, indicating clear correlation.

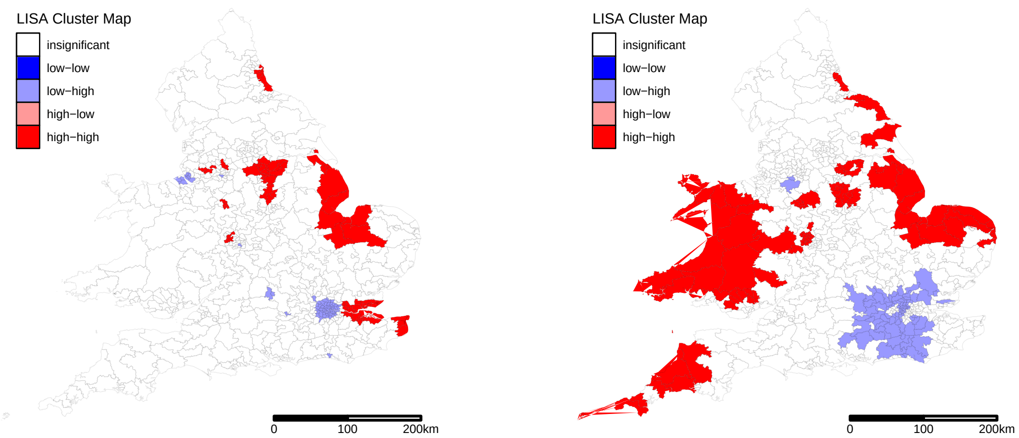
Fig. 7 show the LISA maps for UKIP vote share and migrant proportion at 5% significance level. In the UKIP map, the high-high clusters are mainly found in northeast England. Constituencies around London are in a low-high cluster. The colours of clusters are similar in the LISA cluster map of migrant proportion in Fig. 7b but much bigger. Wales itself is a high-high cluster, with another high-high cluster in southwestern England. Constituencies near London remains a low-high cluster in the migrant proportion LISA map.

Based on the global Moran's I and LISA results, I believe there is spatial dependence in the data. The similar location of high-high clusters in both UKIP vote and migrant proportions provide more reasons to believe that the presence of non-EU passport holders at constituency can affect support for anti-immigration political parties.



(a) UKIP Vote Share (b) Migrant Population

Figure 6: Global Moran's I Results



(a) LISA results on UKIP vote share (b) LISA results on migrant proportion

Figure 7: LISA Results

4 Model Specification

The base model for this analysis is a linear Spatial Durbin (SD) model. Since it is a mix of spatial autoregressive (SAR) model and the spatial lag of X (SLX) model, I will also use these two models as a robustness check. The reduced form model is:

$$UKIPVoteShare_i = \beta_0 + \beta_1 MigrantProportion_i + \beta_2 X_i + \rho WUKIPVoteShare_i + \beta_3 WMigrantProportion_i + \beta_4 WX_i + \varepsilon_i \tag{1}$$

where $UKIPVoteShare_i$ represents the share of votes UKIP wins at constituency i, $MigrantProportion_i$ is the proportion of non-EU passport holders in constituency i, X is a column vector of constituency characteristics that are used as controls. W is the weight matrix used to assign weights to i's neighbours. As discussed in Section 3, I use a k-nearest neighbours scheme with k = 5, the median number of neighbours when queen or rook contiguity is used to define neighbours. To show that the results are not sensitive to weighting schemes, I also report the results using queen contiguity. ε_i is an idiosyncratic error term whose expected value is 0.

I use a spatial Durbin model as spatial dependence is likely to arise in census data where boundaries rarely reflect neighbourhoods. It is very likely that vote decisions are influenced by interactions with voters and migrant proportions in other constituencies. British residents often commute to other constituencies to work, as is reflected in the often larger sizes of travel-to-work areas (areas where population generally commute to work) compared to constituency areas (see Fig. 8). The view that voters' decisions are likely to be influenced by voters in neighbouring constituencies has some empirical evidence in the high value of Global Moran's I at 0.53 with a p-value below 0.01. In addition, the simultaneity in voting behaviour provides strong justification for the inclusion of $WUKIPVoteShare_i$ (Steve Gibbons, Overman, and Patacchini 2015).

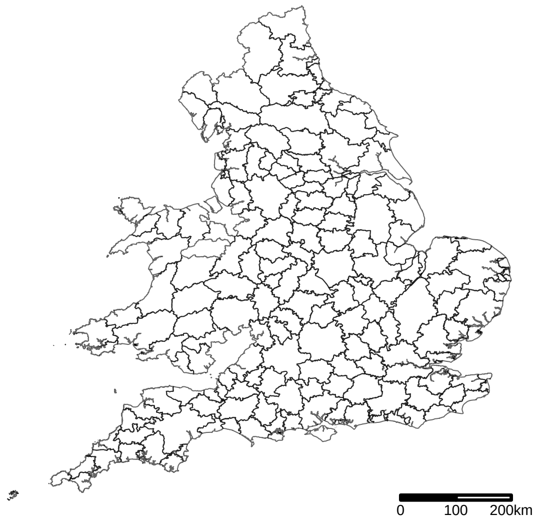
Furthermore, as supply and demand of the labour market often operates on a regional and national level (Gordon and Turok 2005), migrants might commute to other constituencies. Whether it is competition in the labour market or interaction at the workplace, migrants who commute are likely to interact with voters at the destination constituency and influence their stance on anti-immigration parties. Because of these two sources of spatially correlated variables, SAR or SLX models which ignore the spatial lags of either dependent or independent variables are prone to omitted variable bias.

4.1 Empirical Challenges

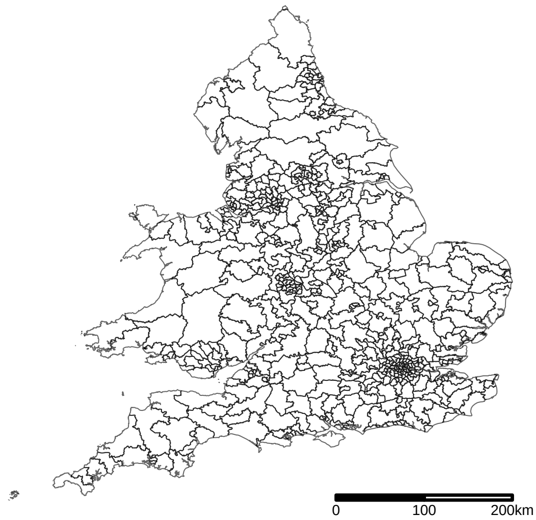
However, this model is challenged with multiple issues. Two main empirical challenges are elaborated below:

4.1.1 Reflection Problem

The SD model is prone to the reflection problem (Manski 1993) as the aim is to separately estimate ρ (effect of neighbour's outcome), β_3 and β_4 (effects of neighbour's characteristics) in situations where there are unobservable factors that also vary at the group level (Steve Gibbons, Overman, and Patacchini 2015). A group in this analysis is a set of constituencies which are defined as i's neighbours by the weighting scheme (k's nearest neighbour). To estimate Equation 1, there must be differences between the spatial means defined by $WUKIPVoteShare$, $WMigrantProportion$ and WX. But if group-specific differences lead to variation in $WUKIPVoteShare$, $WMigrantProportion$ and WX, they almost certainly lead to differences between groups in terms of unobservables. As the group outcomes for constituency i, $WUKIPVoteShare_i$, are explicitly correlated with constituency i's own unobservables, the OLS estimate of ρ is biased and inconsistent. Instead of recovering ρ and β_4 from parameters on the exogenous variable X in the reduced form (Steve Gibbons, Overman, and Patacchini 2015), this analysis uses the maximum likelihood method.



(a) Travel to Work Area boundaries in 2011, England and Wales only



(b) Westminster parliamentary constituency boundaries in 2015, England and Wales only

Figure 8: The generally larger size of TTW areas show that voters and migrants in constituencies are likely to interact beyond their own neighbourhoods

4.1.2 Autocorrelated unobservables

There are two types of spatially autocorrelated unobservables (ε): (A) uncorrelated with observables (B) correlated with observables.

Unobservables which are uncorrelated with observables, also known as "common shocks" (Steve Gibbons, Overman, and Patacchini 2015), can occur in two ways: (1) individuals might interact across constituencies in an unobserved fashion that leads to spatial correlation. (2) individuals in neighbouring constituencies can be exposed to similar unobservables that lead to correlation. These two channels might not necessarily affect the UKIP vote share in the constituency but lead to the model capturing noise that biase the estimation of ρ (reflection problem), as $WUkip$ is correlated with the unobservables of constituency i. Autocorrelated unobservables are almost inevitable when estimation is based on census data (Steve Gibbons, Overman, and Patacchini 2015). By using maximum likelihood estimation, this problem can be eliminated.

Unobservables which are correlated with observables can occur in two ways in this study: (1) Sorting of right-wing/ left-wing voters into constituencies with different ε, which leads to correlation between ε_i and X_i. For instance, young people might be attracted more to big cities which give them more exposure to ethnic diversity and adopt a more liberal attitude. Elderly, on the contrary, are more likely to be left behind in rural areas with homogeneous communities. (2) There is no sorting, yet constituencies might be similar in unobserved ways. For example, constituencies with large migrant proportions might have more migrant rights group that led to lower availability of public services (unobservable in this study). This violates the basic assumption that the independent variables are exogenous and again biases the coefficient estimates. If panel data is used, this bias can be reduced with a fixed effect term. Yet since fixed effect models cannot be used in this instance, spatially autocorrelated unobservables remains a concern when interpreting the estimate of ρ.

4.1.3 Maximum Likelihood Method

ρ can be recovered by the maximum likelihood estimation as the general form of the SD model

$$y = \beta_0 + \rho W y + X\beta_1 + W X \beta_2 + \varepsilon \tag{2}$$

can be written as

$$y = (I - \rho W)^{-1} Z\beta + \varepsilon \tag{3}$$

where $y \sim N((I - \rho W)^{-1} Z\beta, \sigma^2 I)$, $Z = [IXWX]$ and $\beta = [\beta_0\beta_1\beta_2]^T$

The matrix Z can then replace the matrix X in the SAR maximum likelihood estimation to yield the probability (likelihood) of observing data y, given a value of ρ, σ, β, the other characteristics X and the weights matrix W (Bekti 2013).

The ML estimation requires the assumption that ε is normally distributed with no heteroscedasticity or serial correlation. Since it is not possible to add fixed effects which can eliminate the effect of spatially correlated unobservables which correlate with the observables, the validity of this assumption remains to be seen when the spatial residuals are plotted after the regression.

5 Results

Table 3 shows the various models using the knn weighting scheme. Regression (1) and (2) are ordinary least squares models without any spatial variables. (3) - (6) are spatial models with spatial lags added. The main independent variable is migrant proportion in (1)- (5). All coefficient estimates for migrant proportion is positive. The coefficient estimate on migrant proportion in the SD model is 0.137, significant at 5% level. Neighbouring constituencies' migrant proportion do not show significant results in the SLX and SD specifications. In contrast, the coefficient on of neighbours' vote outcome (ρ) is significant at below 1% level in all the maximum-likelihood estimated models. Its value of 0.500 in the SD model shows a strong spatial autocorrelation in voting outcome.

For comparison, (6) shows the coefficient estimate when share of non-White instead of passport holders is used. As expected, the sign of the coefficient turns negative (-0.172) as more non-White population could also represent more non-White UK citizens. This justifies of model's definition of migrant proportion based on passport nationality instead of ethnic status.

Several variables remain highly significant with the same sign in all specifications. Proportion of high school and above has a value of -0.507 in the SD model and a p-value below 0.01 in all specifications. It concur with the expectation that individuals with more education are less likely to support xenophobic movements. The signs of income multiple and rurality are not what I have expected - higher constituency income is associated with more support for UKIP. Rurality, which I expect to associate with immobility (Lee, Morris, and Kemeny 2018) and less exposure to multiculturalism, has a negative sign. A spatially lagged control to be noted is unemployment rate: the more unemployed neighbours a constituency have, the less likely the constituency is to vote for UKIP. Similarly, the wealthier the neighbours, the more likely the constituency is to vote for UKIP.

To see if errors are normally distributed to justify the use of maximum likelihood estimation, I plot the residuals of the SD model using knn weighting in Fig. 9.

Most of the residuals are less than +/- 1.42% from the actual value. Clustering seems likely in Wales and the midland areas of England. The confounding issue of autocorrelated unobservables remains.

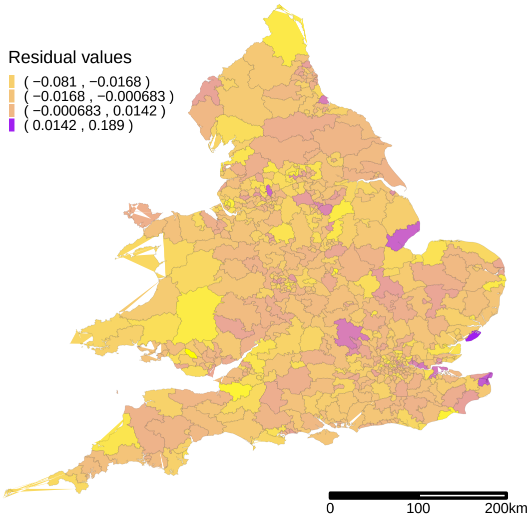


Figure 9: Map of residuals on the SD

5.1 Robustness Checks

Table 4 shows the regression results when the queen contiguity weighting scheme is used. The signs of coefficient estimates are generally similar, except that the value has been magnified.

I construct two dummy variables, migrant education and migrant children, to see if interaction with a migrant population that is relatively more educated/ with more children will lead to different voting behaviour. To construct migrant education, I calculate the ratio of migrants with level 4 or above qualifications relative to natives. For migrant children, I calculate the ratio of 0-16 migrant relative to native children population. Both variables take on a value of 1 if they are in the fourth quartile.

Table 5 reports 5 interaction models using the knn weighting scheme. The sign of migrant proportion remains positive, although it loses its significance in a few specifications. The interaction between migrant education and migrant proportion is positive and significant at 5% level in two specifications. This provides some support for the view that more skilled migrants are perceived as threats in the local job market. The coefficient estimates on migrant children, on the other hand, are not significant. Table 6 reports the same models using queen contiguity weighting scheme. The results are similar.

6 Limitations and Conclusion

Although model results are largely in line with current literature, there are limitations to this study and much to improve.

The use of knn as the main weighting scheme does not seem to affect coefficient estimates as the regression results remain similar despite using other weighting schemes in Section 5.

However, the assumption that the spatial unobservables are uncorrelated with the individual characteristics is at best weak. It is likely that there is some degree of sorting of voters into constituencies with certain characteristics that are unobservable and spatially autocorrelated. For example, more educated professionals might be attracted to constituencies in big cities which are perceived to have more economic opportunities (unobserved to the researcher) and more globalised. Education is thus correlated with the perceived economic opportunities, which are unobserved in this study. Restrained by the inability to use fixed effect due to the cross-sectional nature of the data, this study is unable to eliminate the possibility of voting behaviour being a result of constituency's idiosyncratic traits (e.g. culture, industry composition) rather than the proportion of migrants. Lastly, the normality assumptions in the maximum likelihood method can be violated as a certain degree of autocorrelation can be seen in the residual map (Fig. 9). Although the coefficient levels reported stand to be challenged, the robustness checks provide some confidence that the direction of coefficient estimate on migrant proportion is accurate.

The analysis is prone to the MAUP, as Kaufmann and Goodwin 2018 point out. Contact effects are more likely in small geographies than larger units. Individual in small locales are able to meet immigrants in person, challenging fears or misperceptions, whereas one experiences only limited inter-ethnic contact at city or county level especially when segregation is high (Kaufmann and Harris 2015; Schlueter and Scheepers 2010). This macro-threat view suggests that as the size of unit increases, more ethnic diversity can shift from reducing to enhancing perceptions of ethnic threat. On the other hand, the micro-threat view argues that at close quarters, diversity may cause more perceived threat perceived (Biggs and Knauss 2012) as co-ethnics tend to trust each other more than members of out-groups (Dinesen and Sønderskov 2015). The fact that the coefficient is positive could be due to the fact that a large area (Westminster constituencies have an average population of 100,000 people in 2015) is chosen.

There are at least three ways to improve this study in response to the issues stated above. First, panel data can be used to exploit fixed effect models. Second, an instrument variable can be used to eliminate the effect of possible sorting of voters/ migrants. Third, more areal units can be tested to see if the coefficient estimates remain robust.

In conclusion, this study finds a positive relationship between migrant proportion and support for right-wing party using the case of 2015 General Elections in the United Kingdom. It makes the contribution of using passport nationality instead of ethnic background to measure migrant and finds that high migrant proportion in a constituency where migrants are highly educated can incite more anti-immigration sentiments. The significance of spatial lagged dependent variable and controls justify the use of a spatial model specification. While results are robust to different weighting schemes and interaction of dummy variables, the issues of spatially autocorrelated unobservables and modifiable areal unit problem confound the interpretation of a causal relationship between high migrant proportion and high vote support for right-wing parties.

References

Gehlke, C. E. and Katherine Biehl (Mar. 1934). "Certain Effects of Grouping Upon the Size of the Correlation Coefficient in Census Tract Material". In: *Journal of the American Statistical Association* 29.185, p. 169. ISSN: 01621459. DOI: 10.2307/2277827. URL: https://www.jstor.org/stable/2277827?origin=crossref (visited on 06/21/2020).

Moran, Patrick AP (1948). "The interpretation of statistical maps". In: *Journal of the Royal Statistical Society. Series B (Methodological)* 10.2, pp. 243–251.

Allport, Gordon Willard, Kenneth Clark, and Thomas Pettigrew (1954). "The nature of prejudice". In:

Openshow, S (1979). “A million or so correlation coefficients, three experiments on the modifiable areal unit problem”. In: *Statistical applications in the spatial science*, pp. 127–144.

Manski, Charles F. (July 1993). “Identification of Endogenous Social Effects: The Reflection Problem”. In: *The Review of Economic Studies* 60.3, p. 531. ISSN: 00346527. DOI: 10.2307/2298123. URL: https://academic.oup.com/restud/article-lookup/doi/10.2307/2298123 (visited on 06/23/2020).

Quillian, Lincoln (Aug. 1995). “Prejudice as a Response to Perceived Group Threat: Population Composition and Anti-Immigrant and Racial Prejudice in Europe”. In: *American Sociological Review* 60.4, p. 586. ISSN: 00031224. DOI: 10.2307/2096296. URL: http://www.jstor.org/stable/2096296?origin=crossref (visited on 06/24/2020).

Anselin, Luc (Nov. 2002). “Under the hood Issues in the specification and interpretation of spatial regression models”. In: *Agricultural Economics* 27.3, pp. 247–267. ISSN: 0169-5150, 1574-0862. DOI: 10.1111/j.1574-0862.2002.tb00120.x. URL: http://doi.wiley.com/10.1111/j.1574-0862.2002.tb00120.x (visited on 06/20/2020).

Duranton, Gilles and Henry G. Overman (Oct. 2005). “Testing for Localization Using Micro-Geographic Data”. In: *The Review of Economic Studies* 72.4, pp. 1077–1106. ISSN: 1467-937X, 0034-6527. DOI: 10.1111/0034-6527.00362. URL: https://academic.oup.com/restud/article-lookup/doi/10.1111/0034-6527.00362 (visited on 06/22/2020).

Gordon, Ian and Ivan Turok (2005). “How urban labour markets matter”. In: *Buck, N. et al, Changing Cities: Rethinking Urban Competitiveness, Cohesion and Governance, London: Palgrave.*

Anderson, Benedict (2006). *Imagined communities: Reflections on the origin and spread of nationalism.* Verso books.

Pettigrew, Thomas F. and Linda R. Tropp (2006). “A meta-analytic test of intergroup contact theory.” In: *Journal of Personality and Social Psychology* 90.5, pp. 751–783. ISSN: 1939-1315, 0022-3514. DOI: 10.1037/0022-3514.90.5.751. URL: http://doi.apa.org/getdoi.cfm?doi=10.1037/0022-3514.90.5.751 (visited on 06/24/2020).

Putnam, Robert D (2007). “E pluribus unum: Diversity and community in the twenty-first century the 2006 Johan Skytte Prize Lecture”. In: *Scandinavian political studies* 30.2, pp. 137–174.

Strabac, Zan and Ola Listhaug (Mar. 2008). “Anti-Muslim prejudice in Europe: A multilevel analysis of survey data from 30 countries”. In: *Social Science Research* 37.1, pp. 268–286. ISSN: 0049089X. DOI: 10.1016/j.ssresearch.2007.02.004. URL: https://linkinghub.elsevier.com/retrieve/pii/S0049089X07000142 (visited on 06/24/2020).

Dubin, Robin (2009). “Spatial weights”. In: *The Sage handbook of spatial analysis*, pp. 125–158.

Schlueter, Elmar and Peer Scheepers (Mar. 2010). “The relationship between outgroup size and anti-outgroup attitudes: A theoretical synthesis and empirical test of group threat- and intergroup contact theory”. In: *Social Science Research* 39.2, pp. 285–295. ISSN: 0049089X. DOI: 10.1016/j.ssresearch.2009.07.006. URL: https://linkinghub.elsevier.com/retrieve/pii/S0049089X09000829 (visited on 06/24/2020).

Flowerdew, Robin (2011). “How serious is the modifiable areal unit problem for analysis of English census data?” In: *Population trends* 145.1, pp. 106–118.

Biggs, Michael and Steven Knauss (2012). “Explaining membership in the British National Party: A multilevel analysis of contact and threat”. In: *European Sociological Review* 28.5, pp. 633–646.

Gibbons, Stephen and Henry G. Overman (May 2012). “Mostly Pointless Econometrics?” In: *Journal of Regional Science* 52.2, pp. 172–191. ISSN: 00224146. DOI: 10.1111/j.1467-9787.2012.00760.x. URL: http://doi.wiley.com/10.1111/j.1467-9787.2012.00760.x (visited on 06/20/2020).

McLaren, Lauren (Jan. 2012). “Immigration and Trust in Politics in Britain”. In: *British Journal of Political Science* 42.1, pp. 163–185. ISSN: 0007-1234, 1469-2112. DOI: 10.1017/S0007123411000251.

URL: https://www.cambridge.org/core/product/identifier/S0007123411000251/type/journal_article (visited on 06/24/2020).

Bekti (Mar. 1, 2013). "MAXIMUM LIKELIHOOD ESTIMATION FOR SPATIAL DURBIN MODEL". In: *Journal of Mathematics and Statistics* 9.3, pp. 169–174. ISSN: 1549-3644. DOI: 10.3844/jmssp.2013.169.174. URL: http://thescipub.com/abstract/10.3844/jmssp.2013.169.174 (visited on 06/27/2020).

Billiet, Jaak, Bart Meuleman, and Hans De Witte (2014). "The relationship between ethnic threat and economic insecurity in times of economic crisis: Analysis of European Social Survey data". In: *Migration Studies* 2.2, pp. 135–161.

Dinesen, Peter Thisted and Kim Mannemar Sønderskov (2015). "Ethnic diversity and social trust: Evidence from the micro-context". In: *American Sociological Review* 80.3, pp. 550–573.

Gibbons, Steve, Henry G. Overman, and Eleonora Patacchini (2015). "Spatial Methods". In: *Handbook of Regional and Urban Economics*. Vol. 5. Elsevier, pp. 115–168. ISBN: 978-0-444-59533-1. DOI: 10.1016/B978-0-444-59517-1.00003-9. URL: https://linkinghub.elsevier.com/retrieve/pii/B9780444595171000039 (visited on 06/22/2020).

Goodwin, Matthew J. and Caitlin Milazzo (2015). *UKIP: inside the campaign to redraw the map of British politics*. First Edition. Oxford, United Kingdom ; New York: Oxford University Press. 445 pp. ISBN: 978-0-19-873611-0.

Kaufmann, Eric and Gareth Harris (Oct. 2015). ""White Flight" or Positive Contact? Local Diversity and Attitudes to Immigration in Britain". In: *Comparative Political Studies* 48.12, pp. 1563–1590. ISSN: 0010-4140, 1552-3829. DOI: 10.1177/0010414015581684. URL: http://journals.sagepub.com/doi/10.1177/0010414015581684 (visited on 06/24/2020).

Kaufmann, Eric and Matthew J. Goodwin (Nov. 2018). "The diversity Wave:A meta-analysis of the native-born white response to ethnic diversity". In: *Social Science Research* 76, pp. 120–131. ISSN: 0049089X. DOI: 10.1016/j.ssresearch.2018.07.008. URL: https://linkinghub.elsevier.com/retrieve/pii/S0049089X17305902 (visited on 06/24/2020).

Lee, Neil, Katy Morris, and Thomas Kemeny (Mar. 10, 2018). "Immobility and the Brexit vote". In: *Cambridge Journal of Regions, Economy and Society* 11.1, pp. 143–163. ISSN: 1752-1378, 1752-1386. DOI: 10.1093/cjres/rsx027. URL: https://academic.oup.com/cjres/article/11/1/143/4788094 (visited on 06/27/2020).

Neumann, Rico and Patricia Moy (Apr. 2018). "You're (Not) Welcome: The Impact of Symbolic Boundaries, Intergroup Contact, and Experiences With Discrimination on Immigration Attitudes". In: *American Behavioral Scientist* 62.4, pp. 458–477. ISSN: 0002-7642, 1552-3381. DOI: 10.1177/0002764218760370. URL: http://journals.sagepub.com/doi/10.1177/0002764218760370 (visited on 06/25/2020).

A Appendix

A.1 Variable descriptions

A.2 Table results

A.3 Spatial autocorrelation tests using different weighting schemes

Table 2: Descriptive Statistics

Variable Name	Definition	Year	Source
UKIP vote share	Proportion of votes won by UKIP in 2015 general elections	2015	UK Parliament
Migrant Proportion	Proportion of non-EU passport holder	2011	2011 Census
Share of non-White	Proprotion of non-White ethnic groups	2011	2011 Census
Unemployment rate	Those who were not in employment the week before the Census, were seeking work, and were available to start work in 2 weeks, or those waiting to start a job already obtained	2011	2011 Census
Proportion of 0-18	Proportion of population aged 0-18	2015	2015 Annual Population Survey
Proportion of 65 and above	Proportion of population aged 65 or above	2015	2015 Annual Population Survey
Proportion of male	Proportion of male population	2015	2015 Annual Population Survey
Population density multiple	Constituency population divided by mˆ2, divided by average across constituencies	2015	2015 Annual Population Survey
Proportion of high school and above	Proportion of population with highest qualification being level 4 or above	2011	2011 Census
Income multiple	Sum of self-employment, employment and pension income, averaged in constituency and divided by average across constituencies	2015	2015 Annual Population Survey
Rurality	Share of residents living in rural areas, reassigned from local authority/ county level	2011	2011 Census
Migrant education	Number of non-EU passport holders with level 4 qualifications or above, divided by number of UK passport holders with level 4 qualifications or above	2011	2011 Census
Migrant children	Number of 0-16 non-EU passport holders divided by UK passport holders	2011	2011 Census

Table 3: Regression results using knn (k=5) weighting scheme

	Dependent variable: UKIP Vote Share					
	OLS		*SAR*	*SLX*	*SD*	
	(1)	(2)	(3)	(4)	(5)	(6)
Migrant proportion	0.599***	0.074	0.073	0.129*	0.137**	
	(0.046)	(0.054)	(0.049)	(0.070)	(0.061)	
Share of non-White						−0.172***
						(0.020)
Unemployment rate		−0.627***	−0.597***	0.196	0.250	0.863***
		(0.222)	(0.205)	(0.272)	(0.241)	(0.220)
Proportion of 0-18		−0.084	0.011	−0.307***	−0.303***	0.022
		(0.081)	(0.076)	(0.095)	(0.084)	(0.090)
Proportion of 65 and above		0.051	0.062	0.157**	0.188***	0.281***
		(0.067)	(0.061)	(0.072)	(0.063)	(0.060)
Proportion of male		−0.338	−0.493**	−0.448*	−0.383*	0.405*
		(0.220)	(0.202)	(0.240)	(0.212)	(0.218)
Population density multiple		−0.003	0.001	−0.006*	−0.006**	−0.0002
		(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Proportion of high school and above		−0.637***	−0.525***	−0.532***	−0.507***	−0.438***
		(0.037)	(0.036)	(0.043)	(0.038)	(0.035)
Income multiple		0.045***	0.041***	0.025***	0.025***	0.008
		(0.006)	(0.006)	(0.009)	(0.008)	(0.008)
Rurality		−0.034***	−0.027***	−0.028**	−0.031***	−0.026***
		(0.009)	(0.008)	(0.012)	(0.010)	(0.010)
Lag of UKIP Vote share (ρ)			0.363***		0.500***	0.529***
Lag of migrant proportion				0.055	−0.045	
				(0.097)	(0.086)	
Lag of share of non-White						0.143***
						(0.031)
Lag of unemployment rate				−2.352***	−1.439***	−1.715***
				(0.379)	(0.342)	(0.305)
Lag of proportion of 0-18				0.521***	0.456***	0.201
				(0.138)	(0.122)	(0.161)
Lag of proportion of 65 and above				−0.308**	−0.275**	−0.292***
				(0.123)	(0.108)	(0.104)
Lag of proportion of male				−0.267	−0.209	−0.506
				(0.424)	(0.375)	(0.359)
Lag of population density multiple				0.012***	0.011***	0.006*
				(0.004)	(0.004)	(0.004)
Lag of proportion of high school and above				−0.366***	0.040	0.013
				(0.073)	(0.074)	(0.069)
Lag of income multiple				0.045***	0.012	0.023*
				(0.014)	(0.012)	(0.012)
Lag of rurality				−0.002	0.014	0.023
				(0.017)	(0.015)	(0.014)
Constant	0.020**	0.465***	0.434***	0.700***	0.465**	0.188
	(0.010)	(0.126)	(0.116)	(0.216)	(0.193)	(0.196)
Observations	573	573	573	573	573	573
R^2	0.233	0.639		0.676		
Adjusted R^2	0.231	0.633		0.666		
Log Likelihood			1,172.992		1,213.334	1,245.370
σ^2			0.001		0.001	0.001
Residual Std. Error	0.049 (df = 571)	0.034 (df = 563)		0.032 (df = 554)		
F Statistic	173.214*** (df = 1; 571)	110.602*** (df = 9; 563)		64.257*** (df = 18; 554)		

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4: Table showing regression results using queen contiguity weighting scheme

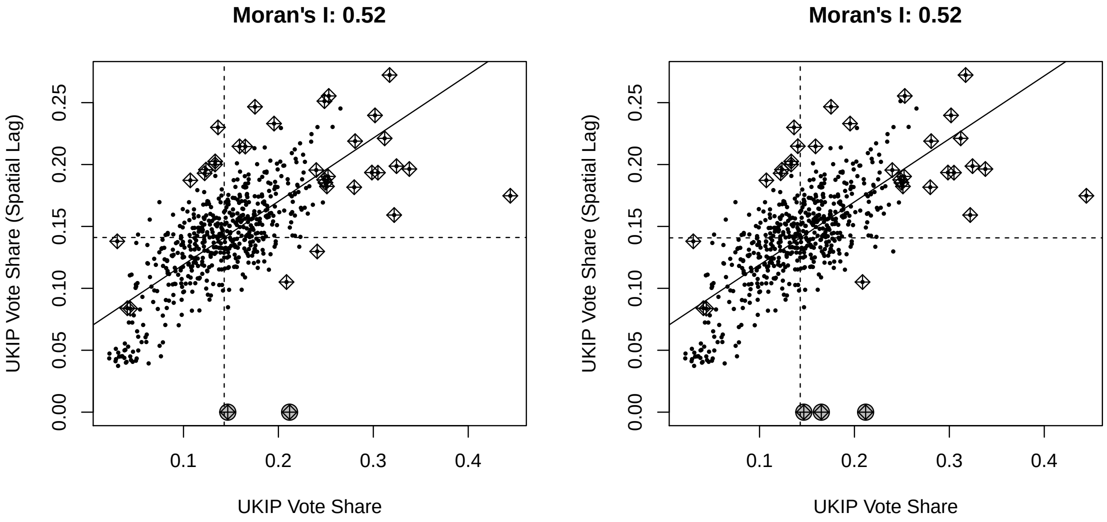
	Dependent variable: UKIP Vote Share					
	OLS		*SAR*	*SLX*	*SD*	
	(1)	(2)	(3)	(4)	(5)	(6)
Migrant proportion	0.599***	0.074	0.093*	0.170**	0.171***	
	(0.046)	(0.054)	(0.049)	(0.069)	(0.060)	
Share of non-White						−0.181***
						(0.020)
Unemployment rate		−0.627***	−0.484**	0.201	0.372	0.880***
		(0.222)	(0.203)	(0.288)	(0.250)	(0.227)
Proportion of 0-18		−0.084	−0.037	−0.317***	−0.318***	−0.020
		(0.081)	(0.075)	(0.093)	(0.081)	(0.086)
Proportion of 65 and above		0.051	0.058	0.120*	0.172***	0.219***
		(0.067)	(0.061)	(0.069)	(0.060)	(0.058)
Proportion of male		−0.338	−0.416**	−0.491**	−0.360*	0.303
		(0.220)	(0.201)	(0.216)	(0.188)	(0.192)
Population density multiple		−0.003	0.0001	−0.010***	−0.010***	−0.003
		(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Proportion of high school or above		−0.637***	−0.511***	−0.492***	−0.461***	−0.423***
		(0.037)	(0.036)	(0.045)	(0.039)	(0.035)
Income multiple		0.045***	0.042***	0.020**	0.019**	0.005
		(0.006)	(0.006)	(0.009)	(0.007)	(0.007)
Rurality		−0.034***	−0.025***	−0.028**	−0.027**	−0.022**
		(0.009)	(0.008)	(0.013)	(0.011)	(0.010)
Lag of UKIP Vote share (ρ)			0.370***		0.530***	0.558***
Lag of Migrant proportion				−0.080	−0.121	
				(0.095)	(0.082)	
Lag of Share of non-White						0.158***
						(0.031)
Lag of Unemployment rate				−2.154***	−1.587***	−1.795***
				(0.413)	(0.362)	(0.326)
Lag of Proportion of 0-18				0.451***	0.347***	0.260*
				(0.145)	(0.126)	(0.138)
Lag of Proportion of 65 and above				−0.225**	−0.281***	−0.221***
				(0.092)	(0.080)	(0.075)
Lag of Proportion of male				0.198*	−0.055	−0.144
				(0.117)	(0.104)	(0.093)
Lag of Population density multiple				0.016***	0.016***	0.010**
				(0.005)	(0.004)	(0.004)
Lag of Proportion of high school or above				−0.444***	−0.061	−0.028
				(0.072)	(0.071)	(0.064)
Lag of Income multiple				0.054***	0.024**	0.029***
				(0.013)	(0.012)	(0.011)
Lag of Rurality				0.006	0.017	0.019
				(0.017)	(0.015)	(0.013)
Constant	0.020**	0.465***	0.394***	0.518***	0.422***	0.056
	(0.010)	(0.126)	(0.116)	(0.127)	(0.110)	(0.114)
Observations	573	573	573	573	573	573
R^2	0.233	0.639		0.676		
Adjusted R^2	0.231	0.633		0.665		
Log Likelihood			1,172.406		1,217.372	1,250.952
σ^2			0.001		0.001	0.001
F Statistic	173.214*** (df = 1; 571)	110.602*** (df = 9; 563)		64.184*** (df = 18; 554)		
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 5: SD interaction models using knn (k=5) weighting scheme

	Dependent variable: UKIP Vote share				
			share		
	(1)	(2)	(3)	(4)	(5)
Migrant education	-0.040^{**}	-0.035^{**}			-0.037^{**}
	(0.017)	(0.015)			(0.016)
Migrant children			-0.031	-0.007	0.010
			(0.029)	(0.024)	(0.025)
Migrant proportion	0.614^{***}	0.099	0.516^{***}	0.111	0.097
	(0.056)	(0.066)	(0.066)	(0.072)	(0.072)
Migrant education x migrant proportion	0.082	0.130^{**}			0.139^{**}
	(0.076)	(0.064)			(0.069)
Migrant children x migrant proportion			0.135	0.041	-0.033
			(0.118)	(0.097)	(0.104)
Lag of UKIP Vote share (ρ)	0.660^{***}	0.494^{***}	0.693^{***}		0.500^{***}
0.490^{***}					
Lag of Migrant education	-0.059^{*}	-0.005			-0.015
	(0.030)	(0.029)			(0.030)
Lag of Migrant children			0.094^{*}	0.028	0.052
			(0.053)	(0.046)	(0.048)
Lag of Migrant proportion	-0.586^{***}	-0.094	-0.264^{***}	-0.005	-0.041
	(0.082)	(0.098)	(0.102)	(0.118)	(0.120)
Lag of Migrant education x migrant proportion	0.333^{**}	0.086			0.138
	(0.140)	(0.127)			(0.134)
Lag of Migrant children x migrant proportion			-0.423^{**}	-0.120	-0.219
			(0.215)	(0.186)	(0.196)
Controls		✓		✓	✓
Spatial lags of controls		✓		✓	✓
Constant	0.045^{***}	0.526^{**}	-0.005	0.453^{**}	0.521^{**}
	(0.014)	(0.214)	(0.016)	(0.193)	(0.215)
Observations	573	573	573	573	573
Log Likelihood	1,064.581	1,218.445	1,047.201	1,213.756	1,219.273
σ^2	0.001	0.001	0.001	0.001	0.001
Note:					*p<0.1; **p<0.05; ***p<0.01

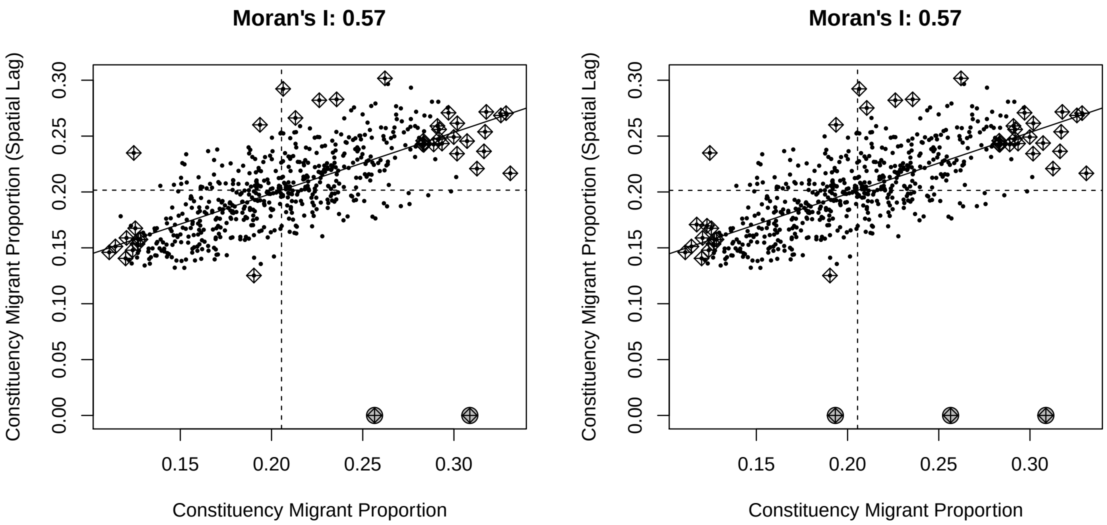
Table 6: SD interaction models using queen contiguity weighting scheme

	Dependent variable: UKIP vote share				
			share		
	(1)	(2)	(3)	(4)	(5)
Migrant education	-0.034^{**}	-0.037^{**}			-0.039^{**}
	(0.016)	(0.015)			(0.016)
Migrant children			-0.011	-0.004	0.011
			(0.027)	(0.024)	(0.025)
Migrant proportion	0.602^{***}	0.135^{**}	0.554^{***}	0.143^{**}	0.125^{*}
	(0.050)	(0.065)	(0.059)	(0.070)	(0.072)
Migrant education x migrant proportion	0.078	0.143^{**}			0.150^{**}
	(0.074)	(0.064)			(0.068)
Migrant children x migrant proportion			0.055	0.031	-0.032
			(0.112)	(0.096)	(0.102)
Lag of UKIP Vote share (ρ)	0.695^{***}	0.523^{***}	0.738^{***}		0.529^{***}
0.522^{***}					
Lag of Migrant education	-0.027	-0.014			-0.018
	(0.026)	(0.029)			(0.031)
Lag of Migrant children			0.059	0.004	0.014
			(0.053)	(0.047)	(0.053)
Lag of Migrant proportion	-0.439^{***}	-0.113	-0.376^{***}	-0.094	-0.091
	(0.064)	(0.090)	(0.077)	(0.109)	(0.109)
Lag of Migrant education x migrant proportion	0.106	0.046			0.066
	(0.121)	(0.121)			(0.136)
Lag of Migrant children x migrant proportion			-0.227	-0.031	-0.065
			(0.205)	(0.185)	(0.214)
Controls		✓		✓	✓
Lag of Controls		✓		✓	✓
Constant	0.015	0.337^{***}	-0.0003	0.414^{***}	0.329^{***}
	(0.011)	(0.117)	(0.013)	(0.111)	(0.118)
Observations	573	573	573	573	573
Log Likelihood	1,077.454	1,221.347	1,061.743	1,217.829	1,221.835
σ^2	0.001	0.001	0.001	0.001	0.001
Note:					*p<0.1; **p<0.05; ***p<0.01



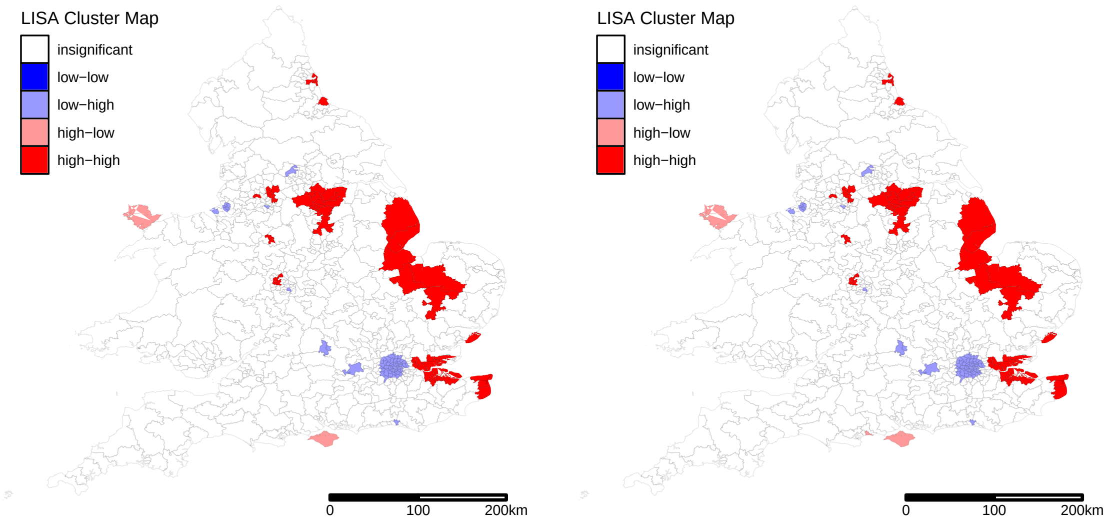
(a) Queen contiguity (b) Rook contiguity

Figure 10: Global Moran's I results for UKIP vote share



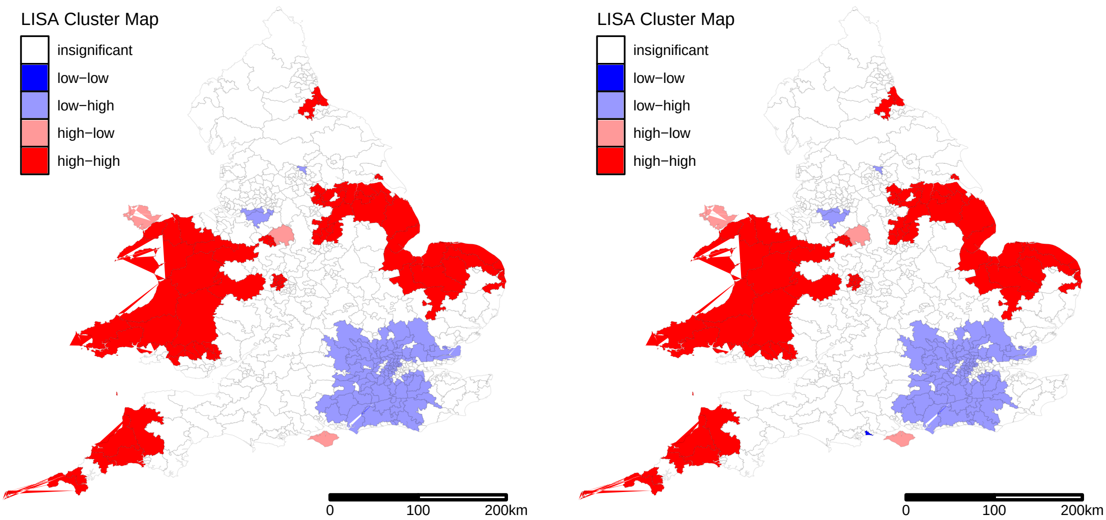
(a) Queen contiguity (b) Rook contiguity

Figure 11: Global Moran's I results for migrant proportion



(a) Queen contiguity (b) Rook contiguity

Figure 12: LISA results for UKIP



(a) Queen contiguity (b) Rook contiguity

Figure 13: LISA results for migrant proportion