The 'Left Behind'?: reconciling individual and aggregate UK Independence Party voting*

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Abstract

This article makes the case that social forces are more important for predicting voting behaviour between districts than between individuals. The UK Independence Party (UKIP) came first in the 2014 European elections and its vote held up well in the 2015 UK general election. UKIP voters have been characterized as 'left behind' by modernity, but revisionist work claims they elude social profiling. This research finds that UKIP districts are, but UKIP voters are not, 'left behind'. This raises wider questions about when aggregate data and social theories of voting are appropriate. Using aggregated individual data, I argue that an older tradition of aggregate social analysis represented in works such as Key's Southern Politics is required in order to understand the 'where', as opposed to 'why', of voting. This carries important implications for ecological inference in the social sciences.

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The UK Independence Party (UKIP), a populist right party, came first in the 2014 European elections with 27.9 percent of the vote and went on to win a respectable 12.6 percent in the 2015 General election. This in sharp contrast to 2009-10, when its vote collapsed from 16 to 3 percent. Why UKIP's newfound success? According to a high-profile narrative based on the work of Ford and Goodwin (2014), UKIP's vote taps into the grievances of a 'left behind' demographic: older unskilled white men who have experienced downward mobility with modernization and globalization.

Yet this claim has been contested, most forcefully by Evans and Mellon (2015). While aggregate electoral patterns seem to support the 'left behind' thesis, these authors find that demographics predict only a modest share of the variation in individuals' propensity to vote UKIP. This paper concurs with Evans and Mellon that Ford and Goodwin's popular explanation tells us little about why *individuals* opt for the party, yet defends the utility of the 'left behind' account for explaining why certain *places* are more UKIP-friendly. Both are important questions, and one is not reducible to the other.

Beyond its substantive interest for scholars of the rising phenomenon of populist right parties, the UKIP case helps answer a longstanding puzzle in the social sciences: why individual-level models generate substantially lower model fits than similarly specified aggregate ones. Political scientists often focus on effect sizes and sometimes do not even report model fit. Aggregate-level models are rare: due to the risk of ecological fallacy, few use them when individual-level data are available. Even when the two are discussed alongside each other, as is true of work on Extreme Right Parties (ERPs), individual and aggregate models are treated as non-overlapping magisteria. The discrepancy in model fit between the two levels often passes without comment.

Political methodologists (i.e. Achen and Shively 1995; King 1997; Cho 2002) show that, though counterintuitive, similarly-specified individual and aggregate models, in which individual responses are converted to district means, should display similar model fit. Why don't they in practice? Robinson (1950) wrote the seminal article comparing individual and aggregate level specifications and explained that inflation of model fit occurs as one moves from individual to aggregate models because variables cluster geographically. Robinson and others ended their discussion there, but this paper goes further to ask why certain variables cluster while others do not, and what this means for political science.

Here the paper makes a new claim which is relevant for political science theory and methodology: that social and economic traits vary more over space than psychological attitudes and are therefore more important when it comes to explaining inter-district variation in the vote. Granted, if we wish to account for why individuals vote as they do, aggregate models exaggerate the role of socioeconomic background compared to attitudes and issue positions. Scholars are therefore correct to be sceptical of aggregate work and to cite the ecological fallacy. But many are intrinsically interested not only in why people differ politically, but why places do. In addition, as the 2015 British general election starkly revealed, electoral geography exerts an independent effect on election results in majoritarian systems. If the unit of comparison moves up a level from individuals to districts, socioeconomic characteristics become almost as predictive of the vote as attitudes. This is not fallacious but arises because socioeconomic variables vary more over space than psychological ones. While attitudes enhance predictive power even at the aggregate level, their advantage over social models is greatly reduced compared to survey models. Since psychological variables are generally impossible to measure over space, this points to a new role for aggregate social analysis, reviving an approach which fell out of favour following the publication of Robinson's article in 1950.

People and Place in Electoral Studies

Psephologists' interest in why people vote as they do is both intrinsic and instrumental. Scholars are substantively interested in why individuals differ in their appraisal of parties, but – along with politicians - are pragmatically concerned about identifying the forces which predict parties' share of the vote. Likewise for place: the fact different parts of the country vote differently is an intrinsically intriguing phenomenon, viz. the popular interest in generalizations such as 'red' and 'blue' states and counties in America. But political scientists and practitioners also pragmatically wish to know how the vote is dispersed across electoral districts as this can radically affect the number of seats a party wins in a majoritarian system. In the 2015 British general election, for instance, UKIP's dispersed 12.6 percent vote gave it just one seat while the Scottish Nationalist Party (SNP) won 56 seats with their concentrated 4.7 percent. Likewise, in the 1994 elections for the House of Representatives in Iowa, the Democrats' dispersed 42 percent of the vote failed to earn it a single one of the state's five House seats.

Why do different parts of a country vote differently? Do the theories and data used to analyse individuals serve equally well in explaining why places vote as they do? Not necessarily. It is not only contextual and supply-side effects such as incumbency that render the 'where' question distinct from the 'why' of voting, but, more importantly, differences in the extent to which variables vary over space. The individual and aggregate levels of analysis are not identical because the forces which affect the vote pass through a filter of aggregation when we move from votes to seats. As King remarks, 'individual-level variability is obliterated in the aggregation process' (King 1997: 120). This paper claims that socio-demographic differences such as region or ethnicity survive aggregation better since these vary more between places than psychology and less within them. This elevates the importance of socioeconomic characteristics in explaining the 'where' of voting. Over space, social theories of voting close the distance with psychological theories and the 'funnel of causality' (Lewis-Beck 2008: 10, 22-23) compresses.

Psychological theories (Knoke 1974) best explain differences in individual voting behaviour - the 'why' of voting. However, this work will show that aggregate social analysis using census and election data performs almost as well as psychological explanations in accounting for cross-district variation in UKIP voting. This is critical because when it comes to the 'where' of voting, survey data at district level is usually unavailable. Moreover, psychological explanations consist of proximate variables such as issue positions and leader images which are at greater risk of being contaminated by endogeneity or discriminant invalidity. That is, those who are convinced by a party may simultaneously or subsequently like its leader and issue positions (Evans and Andersen 2006). All of which weighs in favour of revisiting the tradition of aggregate social analysis embodied in classic works such as V.O. Key's *Southern Politics* (1949).[1]

[1] In Key's work, maps of counties were used to illustrate the correlation between, for example, local black percentage and the intensity of segregationist voting (Key 1949: 234, 237, 343).

The Ecological Fallacy Redux

(Robinson, 1950: 353-4) explained that differences between aggregate and individual-level versions of the same model are of two kinds. In one set of cases, the sign of the relationship at aggregate level differs from that at individual level. A popular example is the relationship between voting and income, with wealthy northern coastal states tending to support the Democrats even though within states, wealthier voters back the Republicans (Gelman 2008: ch. 1). This part of Robinson's oeuvre, in combination with his injunction to avoid the 'meaningless correlations' that aggregate analysis produces, has shaped the attitudes of many social scientists to ecological regression notwithstanding advances in ecological inference techniques. In many instances, however, the sign of coefficients is the same across levels. In one of Robinson's examples, states with a higher percentage of African-Americans had lower literacy rates, a relationship which also held at the individual level. Robinson showed that the correlation between proportions African-American and illiterate among individuals was .203, but inflated to .773 when comparing illiteracy rates and racial composition across counties. Geographic clustering drives inflation in model fit between the two levels. Subsequent authors generally accepted this 'fit inflation' hypothesis (i.e. Firebaugh 1978).

Since Robinson, the use of aggregate data in political science has fallen into abeyance, superseded by survey methodology (King 1997: 5). Meanwhile, socio-demographic approaches to voting behaviour, important in Key's work and that of the Columbia School, have retreated to the back of the causal line. Thus while political scientists admire older political science such as *Southern Politics* for its style and insights, it is perceived to be methodologically unsophisticated and overly social in outlook. At best, socio-demographics such as age, ethnicity or class are viewed as occupying the mouth of the 'funnel of causality' – factors whose power successively ebbs away as we approach the dependent variable of party vote.

Compared to proximate models, socioeconomic specifications predict little of the variation in individual voting. Yet there is a quandary. At the aggregate level, socioeconomic models account for much of the variation in seat-level outcomes. While scholars of voting downplay socio-demographics, these are enjoying a renaissance among election forecasters, who have augmented polls with census data to refine seat-level predictions (Romano 2008). These outperform blanket vote-to-seat conversion rules such as the Cube Law (Kendall and Stuart 1950). Panel studies deploying aggregate data which consider the effects of variables such as economic change, 'homegrown' candidacy and incumbency on election results perform extremely well in predicting seat-level changes over time (Kahane 2009; Fair 2009). The paradox, I argue, has little to do with spurious aggregate models or selection bias, and is only partly attributable to contextual effects. It exists because socio-demographics are more strongly associated with the spatial distribution of votes than the psychological quirks – more rooted in biography and biology - which shape individuals' attitudes and leader images.

Ecological Inference

Despite the victory of survey methodology, some criticized the neglect of aggregate data. For Achen and Shively (1995: 7), surveys' 'victory was too complete…[this] magnified the already pronounced American emphasis on individuals and on individualistic explanations of behaviour.' Subsequent authors thus clarified Robinson's propositions, arguing that correlations needn't always rise with aggregation but are just as likely to fall, hence the so-called modifiable area unit problem (Piantadosi 1988: 899). Hanushek et. al (1974) add that many of the objections raised by Robinson were only present in bivariate specifications, and could have been adequately addressed through multivariate models, i.e. adding a term for access to education.

Work combining aggregate and individual-level analyses was rare in the period after Robinson (King 1997 : 17-19). Since then, more studies have been conducted, but the aim has been more practical than theoretical: to use individual-level data to hone methods of ecological inference (Achen and Shively 1995; King 1997; Cho 2002). Nevertheless, whether criticizing or defending aggregate models, those who examine cross-level differences in model fit share the view that the quantity of interest lies at the individual level. Since individual-level models are the gold standard, inflation or deflation in model fit with aggregation represents statistical noise to be eliminated. My work departs from previous research in uncovering useful information in the noise: regularities in cross-level differences in model fit which are theoretically important.

Electoral Geography

Robinson noted that the ecological fallacy is caused by the spatial clustering of independent and dependent variables, but did not ask *why* some variables are more clustered than others, and how this might be theoretically important. Achen and Shively (1995:224-25) partly address this by discussing the self-selection of partisans with particular social characteristics into like-minded, socially and politically similar areas. Yet even in the absence of selection bias, clustering can occur due to historic settlement patterns which initially had nothing to do with partisanship but whose social morphology subsequently become germane to it.

The spatial aspect of voting behaviour is a subset of the wider question of explaining voting. Yet the field of electoral geography, the study of the spatially uneven causes and effects of political behaviour, concentrates more on the effects than the causes of geography. The stress on the irreducible distinctiveness of place, how it channels interests, identities and institutions in unique ways (Agnew 1996; Johnston 2005) is important, but geography also plays an indirect role as the medium through which socioeconomic forces influence voting. The possibility that socioeconomic characteristics vary more over space than psychological variables, and therefore exert a disproportionate influence on the 'where' of voting, i.e. voting differences between places, has attracted little comment.

In political science, there is an important body research on contextual effects (Key 1949; Blalock 1967; Johnston 2006; Huckfeldt 1995: 103). While this is pertinent to what follows, I concentrate mainly on compositional effects. The social composition of a geographic unit does not undermine the place of electoral geography but reinforces it: social characteristics such as ethnicity and income shape the residential choices which affect both a given social geography and the electoral outcomes associated with it. Space is an intervening variable which magnifies the connection between social characteristics and the vote.

Regularities in the Spatial Clustering of Variables

A clue to regularities in the spatial patterning of variables is hinted at by Tranmer and Steele (1998) who found that age, ethnicity and housing cluster more than gender. Piantadosi et. al. (1988) also remarked that model fit for the relationships between diet, calories, height, weight and fat levels were fairly consistent between individual and higher levels of aggregation whereas those linking race, age, income and education were not. Though unmentioned by the authors, it seems biological variables behave differently from those tied to culture or economics. While they did not remark upon substantive differences between classes of variable in how they relate to the dependent variable at individual and aggregate levels, their data suggests that where variables are socioeconomic (age, education, income) and signed in the same direction at both levels, there is a greater change in model fit as one moves from individual to aggregate level than is true for biological parameters (Pianatdosi et. al. 1988: 900).

This is evident in the UK census data in figure 1. This shows the distribution of means for four 2011 UK census variables and the vote for both UKIP and the Conservatives in the 2015 General Election for the UK's 650 parliamentary constituencies. Note the striking difference in geographic dispersion between ethnicity and gender, the first two variables. Moreover, variation in ethnic composition endures even as one amalgamates constituencies into regions, revealing spatial autocorrelation (Clark 1976). Ethnically distinctive constituencies tend to aggregate into similarly skewed regions, with London far more diverse than elsewhere. We would thereby expect an inflation of vote model fit as the unit of analysis increases in size. The contrast with gender, a largely biological variable, which varies very little over space, is stark. Gender, as with height or weight, tends not to be salient for communal identity or the ability to realize residential desires, hence doesn't cluster people the way ethnicity, age or income does. We would therefore expect little change in fit in gender models of voting between individual and aggregate levels.

[Figure 1 here]

Consider that the variance of independent variable x^1 may be partitioned into two components, x_b^1 and x_w^1, where x_b^1 is the between-unit share of the variation and x_w^1 the within-unit component. If a second independent variable, x^2, shows a higher proportion of between-unit than within-unit variation compared to the first, then $x_b^2 > x_b^1$ and $x_w^2 < x_w^1$. In the extreme case of a model of Scottish National Party (SNP) support, the dependent variable consists of a between-region component, y_b, and a within-region component, y_w. Scotland is one region, thus in an inter-regional aggregate model when the dependent variable is SNP vote share, $y=y_b$. For the independent variable, Scotland, $x^1=x_b^1$ and $x_w^1=0$. Assuming a consistent universal relationship between x^1 and y at all levels, we would expect R-squared to be 1 in a cross-regional model. The Scotland dummy variable perfectly predicts SNP vote across *regions*. When we move to examine variation in SNP vote across *individuals*, the correlation weakens. This is because only a portion of y is accounted for by y_b, but all of x^1 consists of x_b^1: Scotland is an entirely spatial variable. SNP vote, y, contains more variation when we include its intra-Scotland aspects, y_w, but x^1 still equals x_b^1. R-squared measures the portion of the variation in y accounted for by x, and this is necessarily smaller when we also consider intra-Scotland variation, i.e. when $y=y_b + y_w$ than when $y=y_b$. This means social variables such as region survive aggregation to carry outsized weight in ecological analyses such as an inter-regional model of SNP voting. The corollary is that attempts to infer individual-level SNP voting from aggregate SNP vote share across regions risks overstating social drivers of voting, i.e. region, compared to psychological ones.

Relationship to Voting Theory

Social variables such as age, ethnicity, education, income and marital status strongly shape residential choice (Massey et. al 2009) and thus vary more over space than psychological characteristics. Consider extroversion, one of the so-called 'big 5' personality traits. In the UK's Understanding Society survey (UKHLS 2014), the mean extroversion score in a Local Authority accounted for just .005 of the variation in extroversion scores between individuals. Though weakly linked to age, class, ethnicity and other spatially-clustered social patterns, most of the variation in extroversion stems from genetics, birth order and biographical influences which bear only lightly on residential choice.[2]

Figure 2 illustrates the relationship between aggregates and socio-demographics graphically. Consider a world in which socioeconomic variation was entirely spatial and psychological variation entirely non-spatial. The between-district variation in voting, y_b, is associated with socioeconomic predictors x_s. Psychological explanatory variables x_p explain the variation within districts (y_w), but none of the inter-district variation. In figure 1, x_p is identical across districts and fails to 'break the surface' to affect y_b. The only 'topography' from which inferences can be drawn at the aggregate level are socioeconomic variables. The

[2] See appendix 6 for details.

socioeconomic model has a high inter-district model fit despite its low fit at individual level. All of the covariation of x_s and y is cross-district but none of the covariation between x_p and y is. If y_w greatly exceeds y_b, as is almost always true for a party's vote, then y varies less over space than within a given space. This means x_s – socioeconomic variables - account for an elevated share of the variation in inter-district vote (y_b).

[Figure 2 here]

Theories of Voting

Ever since the Michigan Model eclipsed the sociological Columbia Model, political scientists have tended to bypass social factors in favour of psychological attitudes. As Campbell wrote, 'attitudes toward the objects of politics, varying through time, can explain short-term fluctuations in partisan division of the vote, whereas party loyalties and social characteristics, which are relatively inert through time, account but poorly for these shifts' (Campbell et al. 1960: 65). While a residual social focus survives more among those who focus on the durability of party identity (Green 2002) than among scholars who adopt a positional (Fiorina, 1981) or valence (Clarke et. al. 2009: 44-52) approach, even the former ground their claims in proximate psychological drivers. Party identity is the explanatory variable rather than the ultimate socioeconomic forces further up the causal chain.

The fact social models – despite respectable effect sizes - poorly fit survey data is one of the most important reasons for their reduced standing. Even if all African-Americans voted Democratic, much of the variation in voting would be left unexplained because a sizeable majority of American voters are not black. The mainstream view of socioeconomic models is aptly summarized by Clarke et. al in the UK context: 'Although statistically significant, these [socio-demographic] relationships do not impress… The estimated R^2 is only .09…Socio-demographic characteristics cannot explain voting behaviour in 2001' (Clarke et.al. 2004: 98). The argument from model fit is about providing a complete explanation and an accurate prediction of the vote. On this measure, social models do not perform as well as psychological ones: they rarely exceed a pseudo r-squared of .10 while leading psychological models often reach over .65 or even .80 (Green et. al. 2002: 212; Clarke et. al. 2009: 165).

Poor model fit is key because in other respects socioeconomic models have advantages. For instance they provide what Lewis-Beck et. al (2008: 25-6) term a 'broader' understanding of voting, pointing to ultimate rather than proximate causes. Not many are satisfied with the truism that those who voted Tory in 2015 tended to like David Cameron. By contrast, when presented with a class-based explanation of voting, few would insist on moving up the causal chain to explain the origins of stratification.

Somewhat related to the above, endogeneity presents a challenge to models based on proximate psychological predictors. Issue positions, party identities and candidate evaluations involve psychological states that lie close to reported vote choice in conceptual and causal space. Voters who cast a ballot for a party may be inclined to adopt its issue positions, identify with it and endorse its candidates (Lewis-Beck et. al 2008: 25). Those who support an incumbent party are more likely to render a positive verdict on its performance on valence issues such as retrospective handling of the economy (Evans 2006; Anderson 2004). Socioeconomic variables such as ethnicity are less contaminated than proximate psychological ones like party identification. Discriminant validity is also a concern since candidate evaluations, party identity and voting intention may tap an underlying latent variable. Finally the availability of data is an important barrier to psychological theories: surveys and polls cannot address voting prior to the 1930s, when surveys began, or for geographical units below the national level, especially in the absence of constituency polling (King 1997: 9).

Psychological models are strong on effect size and model fit while socioeconomic theories score well on depth, exogeneity and data availability. This paper suggests the optimal model depends on level of analysis. At the individual level (the ‘why’ of voting), psychological models are superior. At the aggregate level (the ‘where’), however, social models narrow the distance on model fit while psychological theories encounter data constraints. Thus the drawbacks of the latter (depth, data quality, endogeneity, discriminant validity) arguably tip the scales in favour of socioeconomic approaches.

The UK Independence Party

UKIP came first in the May 2014 European elections with 27.9 per cent of the vote, two and a half points ahead of Labour, four more than the currently governing Conservatives. This was an unprecedented achievement for a third party in British politics. Ford and Goodwin’s influential work (2014) helped shift the image of the median UKIP supporter from that of rural, middle-class Conservative to what the authors term the ‘left behind’: older unskilled workers bypassed by modern Britain. Ford and Goodwin anchor their work in the literature on extreme right parties (ERPs) (i.e. Sniderman 2004; Mudde

2007). Tests of competing arguments in the ERP literature have utilized either aggregate or individual-level data, but not both. In some cases model fit is not even reported. Table 1 presents model fits across a sample, by no means exhaustive, of the ERP voting literature. Note the marked disparity in fit between socioeconomic analyses at the two levels, as indicated by the difference between columns 3 and 4. The pattern conforms to what Robinson might expect, namely that aggregate models fit the data better than individual-level ones. Our analysis would aver that the numbers in column 3 reflect the social determinants of the 'where' of ERP support, which tend to lose power in the 'why' models in column 4.

[Table 1 here]

This analysis postulates the following:

H_1 More of the variance in social variables is spatial than is true for psychological variables, therefore:

H_2 Social models of UKIP voting experience more inflation in model fit than psychological models when data are aggregated from individual to Local Authority level, thus:

H_3 Social parameters perform better in explaining variation in UKIP support across Local Authorities than within them

H_4 In aggregate analyses of UKIP vote share, the predictive advantage of psychological over social specifications is greatly reduced

H_5 The ‘old, white, underqualified’ UKIP social profile has difficulty predicting which individuals will vote UKIP but is useful for identifying UKIP-friendly seats. The median ‘left behind’ individual is not a UKIP voter but the median ‘left behind’ Local Authority is UKIP-friendly, with above-average levels of UKIP support

Data and Methods

Data is drawn from waves 1 and 2 of the British Election Study (BES) Combined 2015 Internet Panel survey (Fieldhouse et. al. 2015), a sample of over 24,000 individuals across the UK. Wave 1 was collected during February-March 2014 and wave 2 during May-June 2014. The dependent variable is a dummy for reported UKIP vote in the May 2014 European elections (1=UKIP vote, 0=No UKIP vote, including non-voters) based on responses in wave 2. Independent variables are, with the exception of the Farage leader evaluation scale, drawn from wave 1 to limit endogeneity. The wording for independent variables, and summary statistics, are provided in appendix 2 in the supplemental files.[3] The analysis proceeds as follows. First I use a binomial logit model in Stata 13.0 to analyze survey data. In the second stage I use an OLS regression model based on the same data albeit aggregated into 335 Local Authorities (LAs) in England and Wales.[4] The dependent variable for this stage

[3] See www[url tbc]

[4] Using ‘egen’ command in Stata. Scotland and Northern Ireland are excluded. There is little difference in result if OLS is used in place of logistic regression on individual level data.

is UKIP vote share in an LA. This specification is then replicated using actual election results and 2011 census data (ONS 2013), also denominated in percentages.

Results

There is support in the BES for Ford and Goodwin's 'male, pale, stale' image of the typical UKIP voter. As table 2 reveals, 24.7% of White British respondents but just 5.3% of ethnic minorities in the sample said they voted UKIP in 2014.[5] Nearly 30 percent of White British men but less than 20 percent of White British women did. Within the White British population, there is support for the 'left behind' thesis: nearly 4 in 10 of those who left school before age sixteen voted UKIP compared to just 15 percent among those leaving at age twenty or above; 21 percent of self-identified middle-class whites voted UKIP, rising to 29 percent among the working-class; 19.5 percent of the wealthiest income band backed UKIP against over 25 percent of the poorest.

Psychological variables – issues and leader images – appear towards the bottom of table 2. Their extreme values are associated with a wider span of UKIP support than is true for socio-demographic variables.

[Table 2 here]

[5] Ethnic minorities excludes 'any other white background' (Irish, European), 17 percent of whom claim to have voted UKIP in 2014.

A logistic regression on reported UKIP vote, with standard errors clustered on Local Authorities (LAs), is provided in table 3. The model reflects many of the tabulations in table 2, with especially strong effects recorded for education, age and gender. Note that we use independent variables from wave 1 (conducted in early 2014) with the dependent variable from wave 2, in the field in mid-2014. The exception is the question on feelings toward Nigel Farage, which are drawn from wave 2 to maximize proximity to the dependent variable.[6] The 'male, pale, stale' characterization appears to be borne out in this analysis, though the interaction between these variables (not shown) runs in the wrong direction.

White British are significantly more likely to have voted UKIP than other ethnic groups. Rerunning the model with non-White British respondents excluded (not shown) reveals that, holding other variables at their means, 85-year old White British respondents have a predicted probability of having voted UKIP of .36, compared to just .14 for 15 year-olds of the same ethnic background. White British men have a predicted probability of voting UKIP ten points greater than that for White British women. Evidence for the 'left behind' thesis mirrors the pattern in tabular data. The poor and low educated were more likely to back UKIP. Education level is the stronger predictor of the two: an increase in the age at which a White British respondent left formal education - from under 16 to 20-plus - is associated with a decrease from .35 to .18 in the probability of having voted UKIP. Multicollinearity arises when running class, income and education together, so class, which has a weaker effect than education, has been dropped from the model. Model 1 in table 3

[6] Though ordinarily wave 1 data would be used to minimize endogeneity, the aim here is to illustrate the effect of a maximally proximate variable, hence the use of wave 2 leader evaluations.

shows that the baseline socioeconomic model has a pseudo R-squared of .072, in line with the ERP literature as presented in column 4 of table 1.

Contextual effects are present too. Holding other variables at their means, a move from the least (5%) to most (52%) UKIP-voting LA is associated with a 20-point increase in the predicted probability of an individual voting UKIP. Drawing on 2011 census data (ONS 2013) at Local Authority (LA) level to construct level-2 variables reveals that there are significant positive contextual effects for white average age and negative contextual effects for white average qualifications (not shown due to collinearity with UKIP vote share). These are signed in the same direction as these variables' individual-level coefficients. Shifting from the youngest to oldest LA corresponds to an increase from 21 to 29 percent in the predicted probability of voting UKIP with other variables held constant. Individuals residing in districts with the lowest white education level are ten points more likely to have voted UKIP than those in LAs with the highest white education level.[7] There are no contextual effects for proportion White British, which may reflect cross-pressures on whites between the contact and threat effects of minority presence (Putnam 2007; Pettigrew and Tropp 2006; Kaufmann and Harris 2015). Despite often impressive effects, the social and contextual model provided in column 2 has a pseudo R-squared of just .078. Only when issues are added does fit rise substantially.

[7] Major cross-level interactions (white x White British %, age x LA age profile, education x LA education profile), not shown, were all signed in a negative direction, suggesting that contextual effects do not reinforce compositional effects.

Valence issues, notably dissatisfaction with the government's handling of the National Health Service (NHS) and economy, are either signed in the wrong direction, as with the NHS, or not significant. Populist political issues, specifically trust in politicians and satisfaction with British democracy, are significant in different specifications, but do not increase model fit as much as a supply-side variable for being contacted by UKIP. Together, these political items reach a pseudo R-squared of .067 in the model in column 3, though the party contact variable more than halves sample size as this question was asked of less than half of respondents.

Immigration and membership of the EU are, as Ford and Goodwin note, defining UKIP issues. The BES probes respondents' views about the effect of immigration on Britain's culture, economy and welfare state. These three questions are strongly correlated and load onto one factor, accounting for 84 percent of the variation, with parameter loadings of between .89 and .93. Furthermore, there is an item on whether a respondent would vote for Britain to leave the EU, transformed into a dummy variable taking the value of 1 for voting to leave, 0 to stay. Together, the latent immigration variable and EU questions generate a model fit of .278. A variable measuring feelings toward UKIP leader Nigel Farage in wave 2 is even more proximate to the dependent variable, hence a model fit of .382 in column 5. The final composite model shows an increase in fit to .535. Socioeconomic variables, with the exception of age and, to a limited degree, gender, wash out in the final specification.

[table 3 here]

Table 4 seeks to compare the variables along three performance dimensions: effect size, z-score (combining effect size and standard error) and model fit. Effect size and z-score for each variable are extracted from the separate sociological, political issues, cultural issues and leadership evaluation multivariate models. Fit is measured using a bivariate specification consisting only of the independent variable and data weights. Comparing the results of these individual-level models shows that psychological variables outperform sociological ones across all dimensions. The performance is not even across metrics, however. Social predictors are relatively competitive with psychological variables on effect size. The range of predicted probabilities of having voted UKIP between the oldest and youngest respondents in the dataset, holding other variables at their means, is .226, 78 percent as wide a range as for extremes of immigration attitudes (.289). Education has a range of .176, which is over 60 percent as broad as the immigration attitude span. Gender has 30 percent as wide a range as immigration attitudes. Also note the size of the UKIP contextual effect (.198), at nearly 70 percent of the spread of immigration attitudes.

Performance differences between leading sociological and psychological variables widen, however, when considering z-score. Now age (12.99) and education (-18.34) have less than half the absolute value of immigration attitudes (41.5). This reflects the larger standard error of age and education as compared to immigration attitudes, though this is not true for gender, which looks better on z-score (-14.22) than effect size. A further erosion of the social model occurs with model fit in column three of table 4. Immigration attitudes (.169) account for three to four times as much of the variance in UKIP vote as age and education, and 7-8 times more than gender, income and ethnicity. This is because, in addition to their higher standard errors as reflected in z-scores, social variables are less evenly distributed than key psychological variables, which further lowers model fit. The EU 'in/out' variable, for example, is almost evenly split across its two categories and there are many respondents at the extremes of the immigration attitudes scale. By contrast, the oldest and youngest respondents, with their extreme UKIP support, comprise a small fraction of the age distribution. In addition, the education variable contains considerable unevenness in sample size across response categories. The point to take away from table 4 is that differences between socioeconomic and psychological models are modest for effect size, but increase due to the noisiness and uneven distribution of these variables. Individuals are complex, varying more within than between social groups. Psychological variables like immigration attitudes therefore have markedly tighter relationships with UKIP voting than social predictors.

[Table 4 here]

The model suggests that those who strongly oppose immigration, or desire to leave Europe, whatever their social origins, are significantly more likely to vote UKIP. This pushes Ford and Goodwin's social profile into the background. For data on UKIP voting at the individual level, the Michigan Model and its descendants arguably outperform socioeconomic models enough to override concerns about endogeneity and theoretical depth. Conversely, the 'left behind' predictors, while displaying strong effects, contain considerable statistical noise. Individuals' psychological idiosyncrasies attract them to UKIP from outside the profile while failing to direct many who fit the profile to vote UKIP.

Comparing Individual and Aggregate-level Models

Earlier I suggested that socioeconomic models are better suited to explaining differences in the vote across places rather than individuals. Before downgrading the UKIP profile developed by Ford and Goodwin, we therefore need to ask how the 'left behind' template fares at predicting where UKIP is strong. One reason research which triangulates individual and aggregate voting is rarely attempted is because data have not been unavailable. Crewe and Payne (1976), for instance, aggregated an election survey of just 1200 individuals into four sampling units to compare its class composition with similarly classified aggregate data from the census and election results. Sample size restricted the analysis to summary statistics. The BES, by contrast, contains over 24,000 individuals. Across 335 LAs in Britain covered by the BES, the mean number of respondents per LA is 117.7, with a standard deviation of 90.9 and a minimum count of 11. Though imperfect, this enables a meaningful ecological regression using aggregated individual-level data, which may be directly compared to individual-level results, a similar methodology to that used by Piantadosi et. al. Though counterintuitive, a logistic regression on the probability of an individual voting UKIP and an ecological OLS regression of mean UKIP share across LAs should generate similar model fit - at least if variables are randomly distributed over space and there are no contextual or selection effects. The dataset, after all, is identical.

The focus of interest in figure 3 is the ratio in fit between individual and aggregate-level models of UKIP vote. The dependent variable, as noted previously, is a dummy for UKIP vote at individual level, and UKIP vote share at aggregate level. Independent variables are likewise transformed into percentages for the aggregate analysis. Identical data guards against sampling error. The thick line shows the model fit ratio between the two levels, which is largest for White British ethnicity. We see this at the leftmost part of the chart in figure 3 where the thick line compares the R-squared for proportion White British in a bivariate OLS regression of UKIP vote share with the pseudo R-squared in a bivariate logistic regression of UKIP vote on White British ethnicity.[8] Note that comparing the aggregate OLS with an individual OLS of UKIP vote (or with a related individual-level continuous variable such as the Farage like scale) yields a similar multiple. The figure shows that, with the White British variable as predictor, model fit is over ten times greater in aggregate than individual specifications. Inflation due to aggregation is large for other social variables - with the notable exception of gender - followed by issues, and then gender. This broadly conforms to H_2. Recall that ethnicity, unlike gender, structures residence and is thus highly clustered over space.

Issues generally display less magnification across levels than social variables, in line with H_2. Care is needed because the model fit ratio encompasses both compositional and contextual effects. Since UKIP vote share in an LA is correlated with mean immigration and Euroskeptic attitudes in an LA, we might assume that contextual effects inflate model fit ratios for the immigration attitude and EU variables somewhat. The same is not true for trust or satisfaction with British democracy, whose aggregates do not exhibit contextual

[8] Aside from survey weights using the 'wt_full_W1W2' variable in the BES.

effects. On the other hand, the contextual effect of the UKIP variable in table 3, which is more substantial than the contextual effects of age, ethnicity or education, is not large enough to greatly affect the differential in model fit between levels.

Figure 3 shows the connection between model fit inflation and the ratio of spatial to non-spatial variation (x_b/x_w) in a given variable. Dotted and dashed lines provide alternative measures of spatial bias (x_b/x_w) in a variable. Notice how the three lines are related. The dotted line reflects the share of the variation in the individual-level variable predicted by its mean value at aggregate level, a measure of how much individual variation is driven by aggregate variation. Thus over 10 percent of the variation in White British ethnicity at individual level is predicted by the share of White British people in the respondent's district. By contrast, for gender, local sex ratios matter little: the equivalent figure is just 1 percent. Most attitudinal variables lie between 1 and 2 percent, with sociological predictors in the 2 to 8 percent range, as one would expect from H_1. Supply-side variables such as local campaigning and incumbency tend to vary geographically, as indicated by the spatial nature of the 'contacted by UKIP' variable.

A third, dashed line compares the Coefficient of Variation (standard deviation of a variable divided by its mean) for aggregate and individual-level variables. This provides another measure of how much of the variance in a variable is between-unit as opposed to within-unit. Once again, the familiar pattern asserts itself: socioeconomic and supply-side variables exhibit the most geographic clustering, followed by attitudes and gender. The dependent variable lies between social and psychological variables as one would expect because both play a part in voting behaviour. The three series in the figure load onto one factor, which explains 85 percent of the variation, with each loading at between .89 and .98.

Overall, these results confirm H_1 - that more of the variation in social predictors is spatial than is true for psychological variables or the dependent variable (UKIP voting).

[Figure 3 here]

Coefficients are significant and signed the same way in models across levels. Certainly contextual effects for local age, education and EU attitude composition partly explain the patterns in figure 3, but their effect on model fit in table 3 is small, thus they contribute minimally to the cross-level inflation pattern shown by the thick line in figure 3. For instance, the proportion White British in an LA has no significant contextual effect on the probability that an individual will vote UKIP, yet predicts 18.6 percent of the variation in UKIP voting across LAs. Its model fit inflation ratio is above 10 and reaches a staggering 33 when actual LA census data is substituted for aggregated individual-level data (not shown). Compositional, not contextual, effects drive this relationship.

Ethnic composition usefully illustrates why model fit varies between levels. It has a significant effect on UKIP voting, but around 9 in 10 respondents are White British so this variable doesn't explain much of the overall variation in UKIP voting. With aggregate data, however, there is a wide distribution of units by ethnic composition such that proportion White British explains more of the variation in the UKIP vote: 11.6 percent using the aggregated BES sample, and, as we shall see, fully 47 percent using census data and official election results.[9] By contrast with ethnicity, sex ratios vary only slightly across districts (LAs), thus the cross-level model fit ratio for the gender term is nearly even, at 1.06. On the other hand, a supply-side variable, contact by UKIP, shows greatly increased model fit at aggregate level and a strong spatial bias in its distribution. This reflects the fact that the degree of UKIP contact is related to the party's local organizational capacity, which varies markedly across districts.

Only a fraction of the variation in UKIP voting in the 2014 European elections is cross-district in nature. The standard deviation of UKIP vote at individual-level is .42, but for variation across LAs in the aggregated BES data, this drops to .08, both around a mean of .235 (23.5 percent) of the vote. A bivariate logit model of individual UKIP voting with aggregated UKIP vote share as the sole parameter explains just 4.8 percent of the variation, compared – obviously - to 100 percent when the dependent variable is aggregate UKIP vote. This alerts us to a key point: only a small share of variation in vote choice is cross-district. Even for exceptions such as the geographically-concentrated Welsh nationalist Plaid Cymru, region (i.e. Wales) explains less than half the variation in its vote among individuals in the BES. Inter-unit variation has special properties, chief of which is that the 'noise' of individual idiosyncrasy is vastly reduced, raising the predictive power of many socioeconomic variables in relation to psychological ones. Gender, largely a biological variable, shows the opposite pattern due to its limited geographic variability.

The BES aggregates suffer from sampling bias and contain more deviation from their means than census data, but aggregated BES data, using the same technique as Piantadosi

[9] The discrepancy is partly due to BES sample skew: for example, the proportion of minorities in the BES is little more than a quarter of that recorded in the census.

et. al., is useful as it offers a direct comparison with the individual-level model in table 3. The aggregate BES specification is presented in table 5. In column 1 we see that the proportion female in a district, though signed in the right direction and significant, is a weak predictor of UKIP vote. The gender model in column 1 predicts barely 1 percent of the variation, little more than the .089 recorded at individual level in table 3. The model based on White British ethnicity in column 2, by contrast, accounts for 11.9 percent of the variation in LA-level UKIP vote. At individual-level, gender outperforms ethnicity on both effect size and model fit. At the aggregate level, fit for the gender model barely improves while it inflates more than ten times for the ethnicity model. Again, this reflects the relative spatial skew (x_b/x_w) in the ethnicity variable compared to gender.

In addition to sampling error, questions on ethnicity and education are not precisely identical between the census and BES, and the undersample of ethnic minorities in the BES may be affecting the performance of the White British variable in terms of model fit.[10] Nonetheless, column 3 shows that the signs of all socioeconomic variables are the same between models, with age and education significant in both. This questions the Robinsonian charge of spuriousness. More importantly, table 5 exhibits the pattern in model fit inflation identified in figure 3. For example, the social model explains 30.5 percent of the variation in UKIP voting – rising to 33.6 if region is included. The political model in column 4, whose fit was roughly similar to the social model in the individual data in table 5, now explains just half as much of the variation in UKIP vote. This is due to the non-spatial skew of the satisfaction with democracy and trust items. Only UKIP contact has a high x_b/x_w ratio.

[10] See appendix 2 in supplemental files for question wording.

Without it, the political model's fit would decline to .08, similar to its individual-level equivalent.

Cultural attitudes in column 5 show a marked increase in model fit to .464. Leader evaluations increase this to .583 in column 6. While impressive, this is a much smaller increment than was the case in the individual-level data where the top psychological models explained 4 to 8 times as much of the variation as socioeconomic ones. The funnel of causality operates at both levels but is compressed in the aggregate data: psychological variables add comparatively less to model performance, confirming H_4. The same models, run with regrouped data from wave 4 (March 2015), the most recent BES survey, on vote intention in the May 2015 general election for 523 parliamentary constituencies rather than the 335 LAs, are shown in appendix 4. This modification of the areal unit produces broadly similar results, with psychological models accounting for 2-3 times the variation compared to social ones.

[Table 5]

Table 6 offers a robustness check of the aggregated BES data against census data. It presents an LA-level model of 2014 UKIP European vote based on complete census and electoral data. Just one variable, proportion White British, explains 47 percent of the variation in UKIP vote share. A rise of 1 percent in ethnic majority share predicts a third of a point rise in UKIP vote share. Adding a variable for the education level of the White British population raises R-squared to 62 percent; including a further parameter for the share of

White British who identify as English rather than British or Celtic increases fit to 69 percent.[11] Allowing for the inclusion of region as a fixed effect boosts model fit to 79 percent, a powerful confirmation of H_5.

The BES sample contains far fewer ethnic minorities (3.4 percent) than England and Wales as a whole (14 percent) and suffers, as an internet panel, from sampling bias. Component units have far fewer observations than the census, all of which contributes to lower accuracy than with actual census and electoral data. Nevertheless, aggregated individual responses on the anti-European and anti-immigration variables increase census model fit from .690 to .740, reducing some of the explanatory power of socioeconomic variables. Including a leader evaluation term for Nigel Farage raises R-squared from .690 to .730. As in the aggregated-individual model, the gain from including these predictors is far smaller than in the individual-level model in table 5, reinforcing H_4. Psychological variables are still superior predictors, but the lead over social parameters is much narrower.

Rerunning the model using May 2015 general election vote (see appendix 5) yields similar results, except for the disappearance of age from the model, capturing a shift of older white voters from UKIP to the Conservatives between 2014 and 2015 which caught observers by surprise. In the general election model, psychological variables from the BES do not improve model fit, in contrast to the European model in table 6. If there were census questions on party identification or issue positions, these would likely improve fit. However,

[11] The larger minority population in the census necessitates the use of crosstabulated White British age and education variables. Substituting parameters for White British age and education in table 5 only affects the coefficients for age and education on the fourth decimal place, so comparability is not in question.

the leading socio-demographic specifications in table 6 reach an R-squared of between .690 and .789 (.681 in appendix 6). Even if accurate attitudinal data were available for aggregates, their potential for improving goodness-of-fit is limited. The path analysis in figure 4 shows that social variables gain far more predictive power than attitudes when moving up levels, resulting in a compressed funnel of causality in aggregate specifications. The inflation pattern is similar with major parties: identical models of Conservative party vote show inflation from an R-squared of .03 in individual to .184 for aggregated individual and .657 for census-electoral data.

Socioeconomic variables also improve on predictive models. 2009 UKIP, British National Party and Conservative vote share accounts for 80.6 percent of the variation in 2014 UKIP vote, but this rises to 92.5 percent when ethnicity, education and region are included, again reinforcing H_5. For 2015 UKIP share, the rise is considerably greater, from .317 with 2010 UKIP vote only to .736 with the addition of census data.[12]

[Table 6 here]

The median UKIP supporter is older, less educated and whiter than average, but the median older, less educated white man is not a UKIP supporter: 59.4 percent of this demographic did not vote UKIP in 2014 in the BES.[13] Now consider UKIP-friendly districts. Like UKIP-voting individuals, LAs with an above-average UKIP vote are older, whiter and less

[12] Results available upon request.
[13] Based on White British men aged over 51 with below-average education level.

educated than average. But unlike individuals, most older, whiter, less educated LAs are *also* distinctly UKIP-friendly: 69 of 350 Local Authorities are above-average for White British and white age and below average for white education in the 2011 census. 59 of these voted for UKIP at above-average rates in 2014, confirming H^5. Individual and aggregate level 'left behind' profiles should, in the absence of compositional and contextual effects, carry the same predictive power. Yet this is clearly not the case.

Creating an index from the product of percent White British, mean White British qualifications and age yields the map at left in figure 4. It is coded into five standard deviations, from green, the lowest score, to red, highest. Comparing this with a map of 2014 UKIP vote share reveals a resemblance akin to that in V.O. Key's side-by-side maps of racial composition and the segregationist vote in the South.

[Figure 4 here]

Could UKIP voters be selecting into White British areas, thus generating the spatial relationship observed on the maps, along the lines mooted by Achen and Shively (1995: 224-5)? While intuitively plausible, empirical work using the longitudinal UKHLS with appended census data shows that while White British people tend to move to whiter wards than minorities, white UKIP voters *do not* move to whiter wards than whites who vote for other parties (Kaufmann and Harris 2015). Longitudinal analysis using the same data finds that Conservative voters do not move to more Conservative constituencies than other voters (Gallego et. al. 2014). A similar modelling strategy with the same dataset, albeit attached to LA-level data, shows that white UKIP supporters at time t_{-1} do not move to whiter or more UKIP-voting LAs than other white voters at time t.[14] Similar results have been found using US registration data (Cho et. al. 2013), casting doubt on the 'big sort' hypothesis (Bishop and Cushing 2008). Historic and socioeconomic factors, not partisan preferences, seem to explain residential clustering, thus endogeneity is unlikely to be driving the results in tables 3-6.

Given the power of socioeconomic models to predict outcomes across political and administrative units, it is little wonder that Key and his predecessors drew useful inferences from it. It is also the case that his work fascinated readers not so much because it offered an insight into voter psychology as due to its ability to explain why certain places - in all their richness – tended to vote a certain way. In using aggregate patterns to infer individual behaviour, ecological analyses assume x_b=x and y_b=y, which, as we have shown, is not the case. Yet for the aim of explaining the 'where' (spatial aspect) of voting, i.e. y_b, the models, provided they are adequately specified, are accurate. Moreover, y_b and x_b are components of the variation of y on x, thus in a well-specified model, the coefficients typically point in the same direction across levels. When the outcome of interest is a property of a spatial unit, as is true for the share of votes in a constituency, aggregate analysis reduces the noisiness of individual variation to enhance predictive accuracy.

These findings are also important for cross-level inference in the social sciences in general. Results suggest that ecological regression will tend to overstate the role of social and structural forces on individual voting while underplaying proximate psychological factors. Econometric analyses which posit individual-level mechanisms such as expected

[14] See appendix 7 in supplemental data.

utility maximization as the source of observed macroeconomic relationships may likewise be guilty of occluding the role of mediating perceptual and attitudinal variables. While political science is insufficiently social, mainstream economics may – as behavioural economists such as Akerlof and Shiller (2009) suggest – need to pay closer attention to psychological factors. Economists and others who focus on aggregate panel data could routinely be overstating the power of socioeconomic forces on individuals while neglecting the psychological perceptions that mediate individual decisions.

Discussion

The UK Independence Party (UKIP) shocked many observers by coming first in the 2014 European elections. Do UKIP voters consist of the 'left behind', as Ford and Goodwin (2014) surmise? Yes and no. The median underqualified older White British man is not a UKIP voter, but the median underqualified, whiter and older Local Authority voted for UKIP at above-average rates in 2014. Researchers are intrinsically interested *both* in why individuals vote UKIP and why UKIP support is stronger in some places than in others. So are politicians and forecasters. Yet the two questions are not one because geographic variation in the vote is more associated with spatially-variant characteristics. Socioeconomic predictors of voting, such as ethnicity, vary widely from place to place while psychological or biological traits, such as sex, do not. Minor influences in models of individual voting, such as ethnicity, can therefore explain a great deal of the difference in vote share between districts. Ford and Goodwin's individual 'left behind' social profile is noisy, but when applied to voting districts it solidifies into a tighter generalization. The social predicts 'where UKIP?' much better than 'why UKIP?' Both are interesting, and substantively independent, questions.

This study contains important lessons for the study of voting behaviour, and for the social sciences more broadly. Since the publication of Robinson's (1950) article on the ecological fallacy, political scientists have worked almost exclusively with survey rather than aggregate data. Around the same time, the Michigan School, associated with the first national election studies, placed the accent on proximate psychological causes, eclipsing social explanations such as those of the Columbia School. The method and argument of V.O. Key's *Southern Politics*, which combines socio-demographic approaches with aggregate analysis, came to epitomise an outdated tradition.

While ecological regression has fallen out of favour among political scientists, it has experienced a resurgence among election forecasters seeking to improve seat-level accuracy. The case against socioeconomic explanations rests on poor model fit; that against aggregate analysis on the ecological fallacy. Yet on the first point, socio-demographic census-based models predict much of the variation in UKIP voting across districts. On the second, individual and aggregate models of UKIP voting look similar: the same coefficients are generally significant and signed the same way across levels. In individual data, socioeconomic predictors perform well on effect size but slip in terms of model fit against issues, leader evaluations and other psychological explanations. At the aggregate level, by contrast, socioeconomic models close the distance on model fit considerably while data difficulties constrain psychological specifications.

Many have followed Robinson in treating the difference between aggregate and individual models as spurious noise. Ecological inference seeks to approximate to the 'true' individual-level relationship. The approach here differs by finding patterns in the noise. Namely, that social characteristics such as ethnicity and education, which drive residential choice, vary more over space than psychological traits. Therefore social and economic variables are better predictors of voting differences between constituencies than within them. The gap between individual and aggregate model fit is related to whether variables vary spatially or not. Ethnicity is a paradigm case: a tenth of the variation in White British ethnicity in the British Election Study arises from the district in which a person resides. This is much less true for attitudes. As a result, while ethnicity explains little of the variation in individual UKIP voting it accounts for nearly half the variation in inter-district UKIP support.

Aggregate social analysis should not be viewed as the last resort of the data-poor analyst, but as a distinctive tool for explaining *where* votes cluster that complements the 'why' of survey-based approaches. When examining clustering, the predictive distance between socioeconomic and psychological approaches shrinks while psychological models run into data constraints. Bartels (2010) writes that contemporary political scientists could do worse than to learn from the depth and breadth of V.O. Key's *Southern Politics*, which concentrated on voting differences between places such as Piedmont and Coastal South Carolina. Accordingly, this work points to a mixed economy, in which Michigan-style models are deployed to interpret individual voting while earlier aggregate approaches are revived to explain why districts vote the way they do. Finally, better forecasting of seat-level performance among parties in majoritarian systems, especially minor ones such as UKIP, calls for this integrated strategy.

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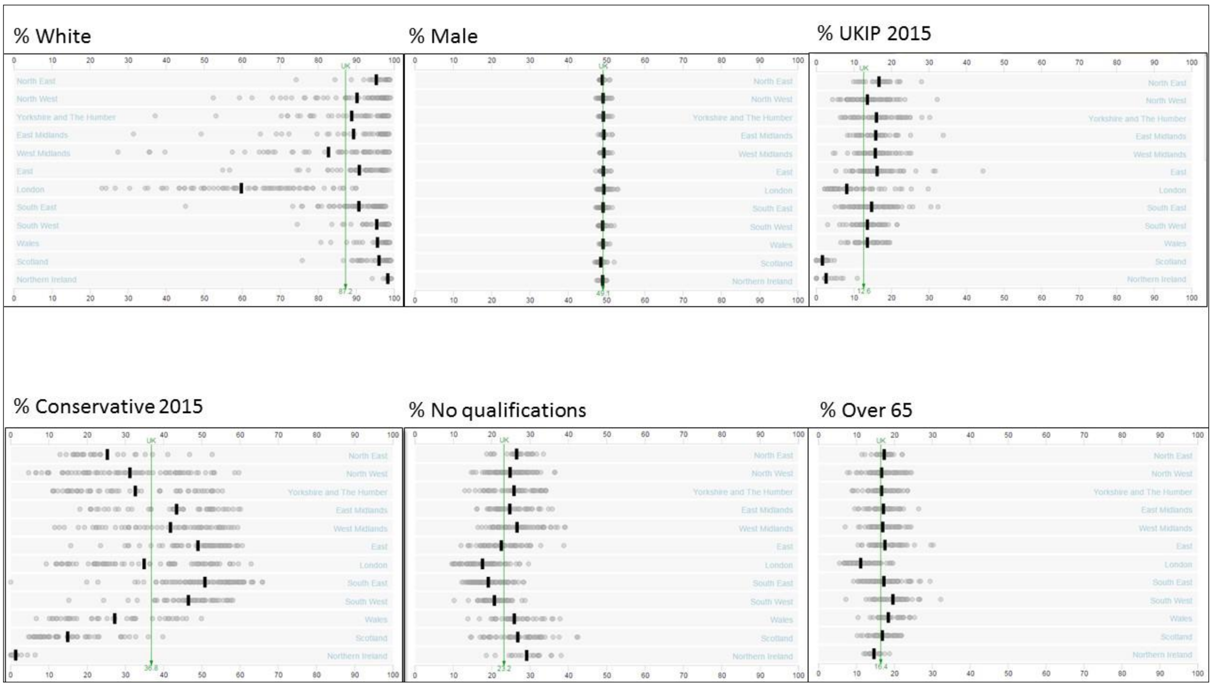
Figure 1. Variation of Selected 2011 Census Variables and 2015 Election Results



Source: http://www.constituencyexplorer.org.uk. Includes Scotland and Northern Ireland. Circles represent LA means, dark lines means for regions, green line the mean for the UK.

Figure 2. Representation of Social Inter- and Psychological Intra- Unit Variation

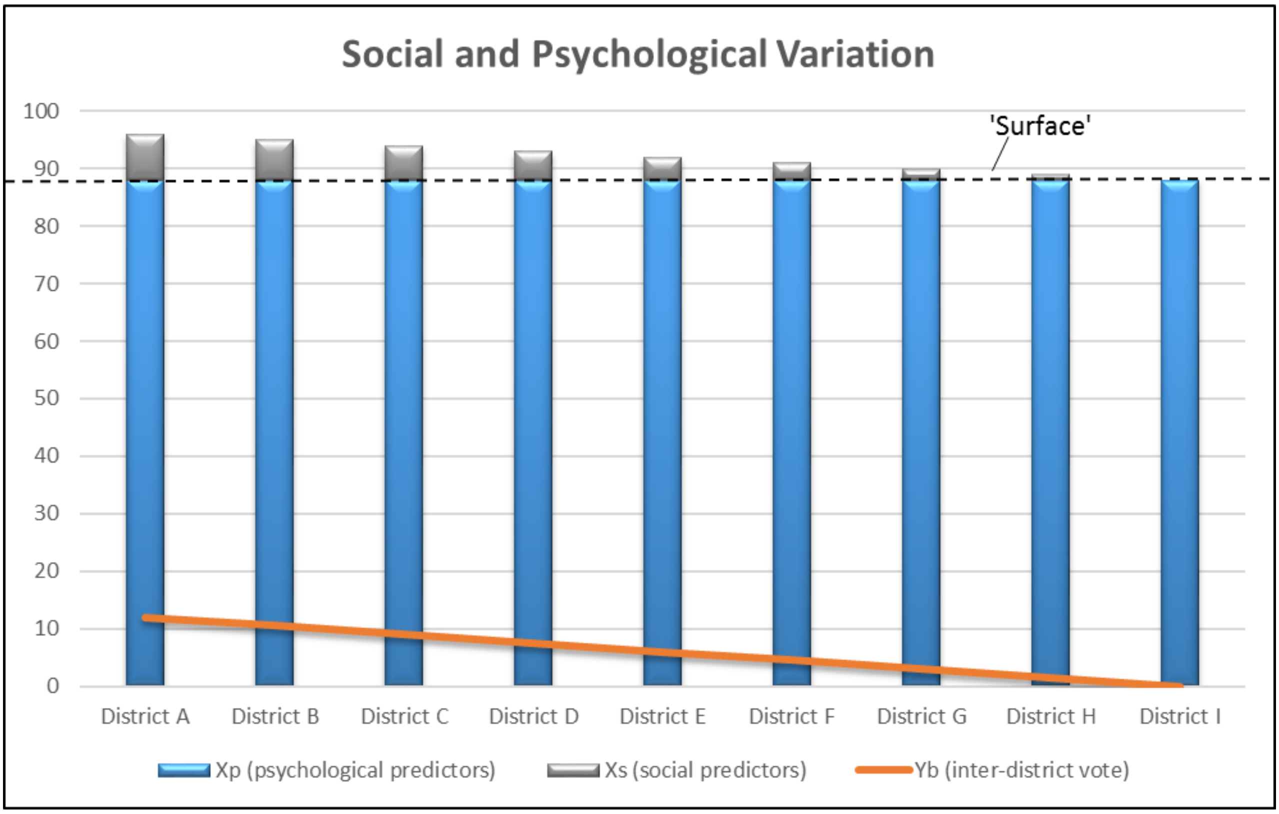


Table 1. Comparative Model Fit Table for work on Populist and Extreme Right Parties

AUTHORS	OUTCOME VOTE	AGGREGATE MODEL FIT	INDIVIDUAL SOCIAL CHARACTERISTICS MODEL FIT	INDIVIDUAL CHARACTERISTICS + ISSUES MODEL FIT
HARRIS 2012	BNP	.917		
JACKMAN AND VOLPERT 1996	European ERPs	.896		
STEINER 2014	UKIP	.873		
MEGUID 2005	European ERPs	.865		
KNIGGE 1998	European ERPs	.821		
FITZGERALD AND LAWRENCE 2011	Switzerland	.750		
JESUIT ET. AL 2009	European ERPs	.746		
POZNYAK ET. AL 2011	European ERPs	.643		
RYDGREN AND RUTH 2013	Sweden Democrats	.275		
CUTTS ET. AL 2012	UKIP		unreported	unreported
LUBBERS ET. AL 2002	European ERPs		unreported	unreported
CUTTS, FORD AND GOODWIN 2011	BNP		.100	.550
BIGGS AND KNAUSS 2012	BNP members		.080	
WEBB AND BALE 2014	UKIP		.079	.301
FORD AND GOODWIN 2014	UKIP		.073	.255
RYDGREN 2008	European ERPs		.070	.190
FORD AND GOODWIN 2010	BNP		.065	
LUCASSEN AND LUBBERS 2012	European ERPs		.046	.177
VAN DER BRUG ET AL 2000	European ERPs			.370

For bibliographic details, see appendix 1 in supplemental notes.[1]

[1] See www[url removed for anonymity]

Table 2. Descriptive Statistics for Selected BES 2015 Variables (for White British respondents only except ethnic variables)

	Share reporting having voted UKIP in 2014	N	Share of Sample
White British	24.7%	21660	88.7%
***Minority**	5.3%	830	3.4%
Left school before age 16	39.7%	2805	13.7%
Left education aged 20 or older	15.4%	7006	34.3%
Male	29.9%	10855	50.1%
Female	19.5%	10805	49.9%
Middle Class	21.8%	7524	34.7%
Working Class	29.4%	8882	41.0%
Lowest income band	25.3%	6213	28.7%
Highest income band	19.5%	4636	19.0%
Immigration Undermines Cultural Life (Strongly Agree)	49.5%	5604	25.9%
Immigration Undermines Cultural Life (Strongly disagree)	2.4%	1625	7.5%
Would Vote to leave the European Union	46.8%	10140	46.8%
Would Vote to remain in the European Union	5.2%	11520	53.2%
Strongly like Nigel Farage	83%	1245	5.8%
Strongly dislike Nigel Farage	1.4%	6332	29.3%
Entire dataset	23.5%	24430	

Unweighted sample, 2015 British Election Internet Panel Survey (BES), wave 2. * Excludes Other White, unspecified and mixed-race respondents.

Table 3. Individual-Level Models of UKIP Voting

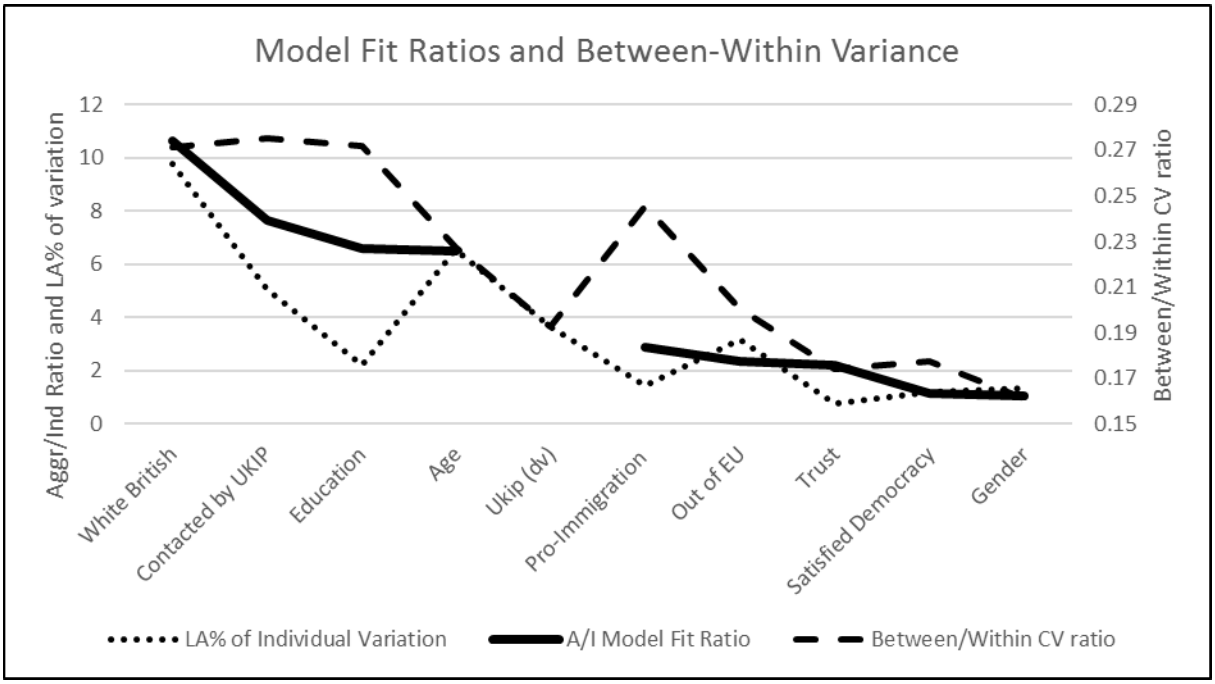
	Socio-economic	Social + Context	Political Issues	Cultural Issues	Leader Evaluation	Composite
Age	.020*** (.001)	.019*** (.001)				.015*** (.003)
Female	-.513*** (.036)	-.512*** (.036)				-.177* (.087)
White British	.271** (.079)	.106 (.070)				.222 (.172)
Education	-.254*** (.013)	-.237*** (.013)				-.028 (.032)
Income (ref: highest band)						
Lowest income band	.156** (.055)	.139* (.054)				.037 (.115)
Middle income band	.042 (.053)	.039 (.052)				-.033 (.114)
Refused to give income	.194** (.060)	.172** (.060)				-.038 (.131)
UKIP Share of vote (LA level)		.025*** (.003)				.003 (.005)
Trust MPs			-.348*** (.109)			-.280*** (.031)
Contacted by UKIP			.658*** (.051)			.578*** (.078)
Satisfied UK Democracy			-.027 (.034)			-.142** (.052)
Pro-immigration				-.680*** (.027)		-.351*** (.052)
Vote to leave EU				2.297*** (.055)		1.524*** (.097)
Like Farage (wave 2)					.581*** (.009)	.527*** (.015)
Data weights	-.179*** (.030)	-.210*** (.030)	-.186*** (.035)	-.386*** (.033)	-.306*** (.027)	-.115* (.049)
Constant	-.863*** (.162)	-1.400*** (.165)	-.114 (.095)	-2.384*** (.063)	-3.541*** (.064)	-4.379*** (.410)
N	20345	20560	8738	19800	20543	8176
Pseudo R^2	.072	.078	.067	.278	.382	.535

*p<.05; **p<.01;***p<.001

Table 4. Summary of Results for Bivariate and Limited Multivariate Models for Variables

	Effect size (multivariate max - min)	z-score (multivariate)	Model Fit (bivariate pseudo R^2)
Like Nigel Farage	.800	50.89	.284
Would vote to leave EU	.339	43.97	.242
Trust MPs	.329	-18.55	.038
Pro-Immigration latent variable	.289	-41.50	.169
Age	.226	12.99	.046
UKIP Vote Share (LA)	.196	8.49	.029
Age left full-time education	.170	-18.34	.050
UKIP contact	.115	12.95	.026
Gender	.089	-14.22	.025
Income	.031	3.00	.016
White British	.028	2.08	.017
Satisfied UK Democracy	.014	-.81	.021

Figure 3.



Note: ‘A/I’ refers to Aggregate/Individual level, CV to coefficient of variation.

Table 5. Models of UKIP Vote Share by LA for Aggregated Individual BES Data

	Gender	Ethnicity	Social	Political	Cultural	Leader	Composite
% Female	-.184* (.062)		-.049 (.056)				-.037 (.041)
% White British		.352*** (.051)	.053 (.065)				-.030 (.051)
Age (mean)			.006*** (.001)				.002 (.001)
Education (mean)			-.078*** (.012)				.002 (.013)
Trust MPs (mean)				-.092*** (.019)			-.044** (.015)
Satisfied Democracy (mean)				.071* (.032)			.002 (.023)
Contacted by UKIP (mean)				.167*** (.030)			.035 (.023)
Pro-immigration (mean)					-061** (.021)		.024 (.022)
Leave Europe (mean)					.452*** (.051)		.197*** (.052)
Like Farage (mean)						.096*** (.004)	.070*** (.007)
Weight (mean)	.007 (.017)	-.002 (.016)	.027 (.017)	.001 (.015)	-.021 (.012)	.002 (.011)	.011 (.013)
constant	.479*** (.092)	-.068 (.050)	.088 (.154)	.271** (.079)	.059 (.028)	-.098*** (.021)	-.045 (.122)
N	308	338	308	338	338	338	308
R^2	.012	.116	.305	.145	.460	.581	.605

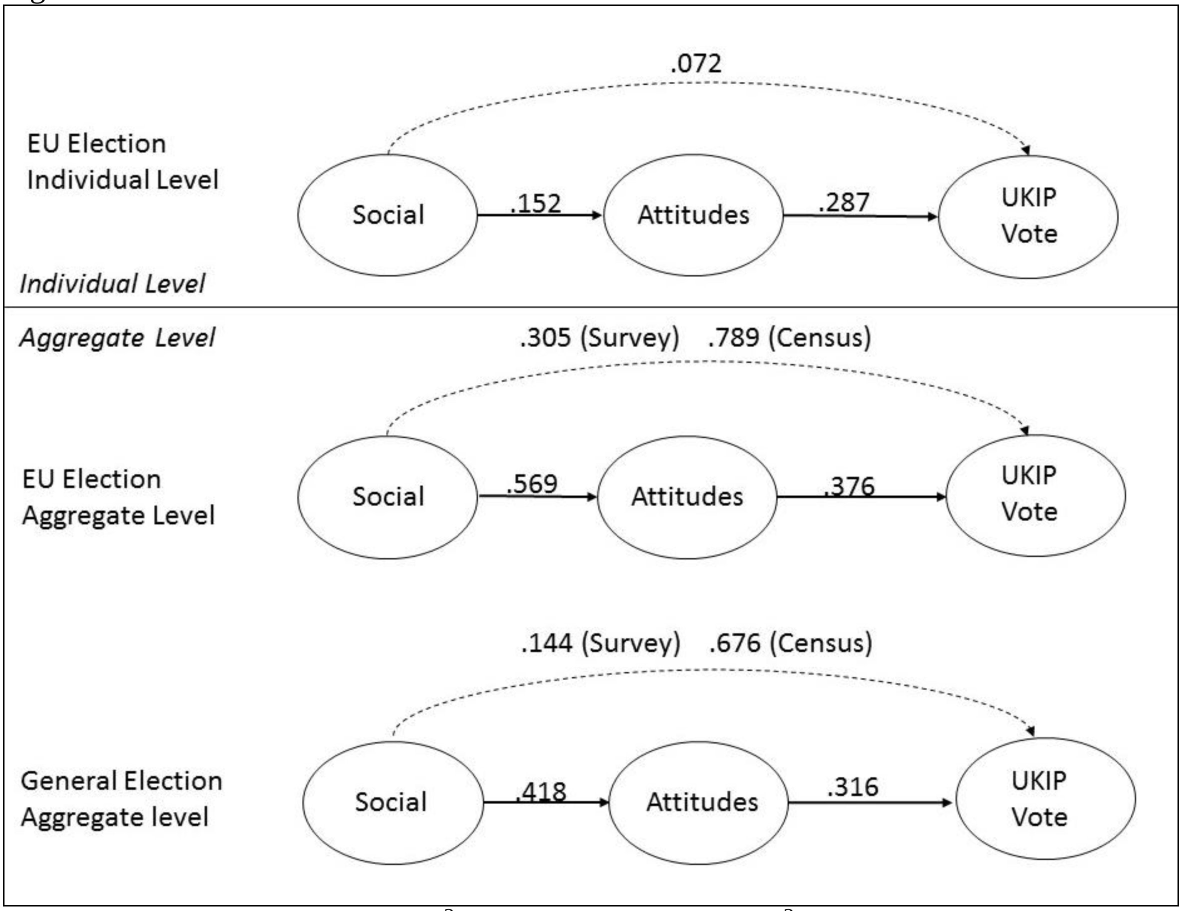
*p<.05; **p<.01;***p<.001. Note: lower N occurs in some specifications because data on age, gender and education are not found in all LAs in the BES survey data.

Table 6 Models of UKIP Vote Share by LA for Aggregate Census and Electoral Data

	Ethnicity	Social	Social with English	Social and Region	Social and Attitudes	Social and Leader	Composite
% White British	.334*** (.019)	.261*** (.018)	.271*** (.017)	.311*** (.021)	.224*** (.017)	.248*** (.016)	.227*** (.017)
Age (mean White British)		.272* (.134)	.256* (.123)	.132 (.105)	.087 (.114)	-.016 (.120)	-.005 (.117)
Education (mean White British)		-15.870*** (1.362)	-14.467*** (1.255)	-15.474*** (1.503)	-9.135*** (1.358)	-12.399*** (1.197)	-9.756*** (1.358)
% English (mean White British)			13.178*** (1.610)	26.282*** (6.190)	9.138*** (1.544)	11.118*** (1.519)	9.227*** (1.527)
Pro-immigration (mean)					-3.037* (1.487)		-1.607 (1.547)
Leave Europe (mean)					18.528*** (3.399)		14.246*** (3.657)
Like Farage (mean)						2.830*** (.383)	1.428** (.482)
Region FE				Yes			
Constant	2.621 (1.684)	36.882*** (6.610)	24.224*** (6.231)	13.984 (8.381)	15.878** (5.761)	23.499*** (5.780)	17.831** (5.732)
N	335	335	335	335	335	335	335
R^2	.467	.624	.690	.789	.740	.730	.746

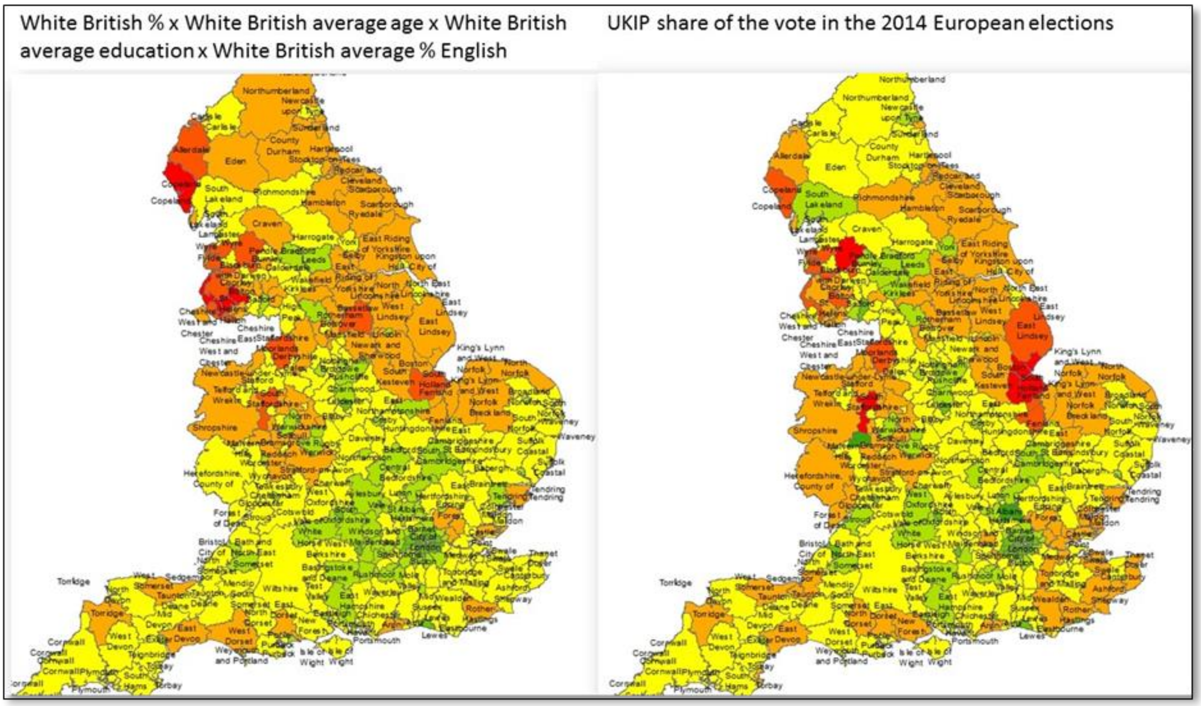
*p<.05; **p<.01;***p<.001. Note: Immigration, Europe and Farage variables drawn from aggregated BES sample. Education variable based on average qualifications.

Figure 4. Path Chart of Model Fit Statistics



Top path corresponds to pseudo-R^2 from table 3, second to R^2 from tables 5 and 6, third to R^2 in appendices 4 and 5. Indirect paths all from survey data.

Figure 5. Census Variable Index and UKIP 2014 Vote by Local Authority, England Only



Note: 5 Standard deviations, from highest in red to lowest in green.