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Ron Johnston, Kelvyn Jones, David Manley

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ABSTRACT

There has been a substantial switch in approaches to the study of British voting behaviour in recent decades, with much less attention being paid to individual voters' social positions. This paper argues that such approaches can mis-represent the contexts within which voters are socialised and mobilised and are also technically problematic because social positions and attitudes may well be collinear – in which case 'true' relationships are difficult to uncover. Further, regression models that include variables representing social positions almost invariably look at the main effects only and pay no attention to the interactions among those variables. Using a newly-developed multilevel modelling approach to the analysis of multi-way contingency tables, this paper explores the relationships between respondents' age, sex and qualifications and their voting at the last three general elections in England, using a large data set. It indicates that, contrary to recent work, respondents' social positions are linked – through their attitudes – to their partisan choices, and that exploration of the interactions among those variables identifies important differences in how they voted.

KEY WORDS: voting; England; class; exploratory analysis; large contingency tables

1. Introduction

There has been a substantial switch in approaches to the study of British voting behaviour over recent decades. The stress in early work was on social class, hence Pulzer's (1967) statement that 'Class is the basis of British politics: all else is embellishment and detail'. Butler and Stokes' (1969, 1974) classic work was firmly set in that mould, while paying considerable attention to aspects of the 'embellishment and detail'. By the 1980s, however, the emphasis on class was challenged by work on dealignment, which observed increased variation in the degree to which a class's members remained committed to 'their' party (Sarlvik and Crewe, 1983; Evans and de Graaf, 2013). Nevertheless, the social class model (suitably modified to reflect changes in the country's class structure) continued to inform major studies of voting at British elections, notably the series of books produced by the team that conducted the British Election Studies between 1983 and 1992 (Heath et al., 1985; 2001: see also the critique in Crewe, 1986, and Heath et al.'s, 1987, response; and Franklin, 1985; Evans, 2000). Increasingly, however, the focus shifted away from an attention on class and towards behavioural models that focused on voters' attitudes.

One such approach, drawing its inspiration from Downs (1957; Grofman, 2004), looked to issues (such as the desirability of state involvement in the economy) on which voters and parties took distinctive ideological positions; voters support the party closest to them in ideological space. An alternative approach – advanced in Stokes's critique of Downsian models – became known as valence voting (Stokes, 1963: for their British application see Clarke et al, 2004, 2010; Whiteley et al., 2013); voters determine which party to support not on ideological grounds but rather on their perceptions of which party can best govern the country, based on both its record and its policy proposals. Thus, for example, all parties may have manifesto commitments to promote economic growth and keep unemployment, inflation and interest rates low; voters decide which is most likely to deliver on those promises – although in many cases using short-cut heuristics, such as the perceived quality of the party leaders, when making their decisions.

The valence model has not gone unchallenged, however. Evans and Chzhen (2016a), for example, focus on an endogeneity issue: those who think a government has performed well in office are more likely to be those who voted for it at the preceding election than those who did not. Whiteley et al. (2016, 236) responded that 'The variables in the valence politics model … do not explain everything about electoral choice, but they provide powerful theoretical and empirical insights into what is going on in the minds of the voters. Supplemented by selected variables from [Downsian] spatial theory, the result is a parsimonious composite model that goes a long way toward providing a satisfactory explanation of voting in Britain and elsewhere' – a conclusion with which Evans and Chzhen (2016b, 246) continued to disagree, claiming that '*party preference dictates party performance evaluation, not vice versa*' (their emphasis).

In response to Evans and Chzhen, Whiteley at al. (2016, 236) claimed there is 'no need to rummage around one more time in the dark recesses of the famed "funnel of causality"' model of voting behaviour to seek explanations of British voting behaviour'. That model, initially developed by the 'Michigan School' of voting behaviour (Campbell et al., 1960; Bartels, 2016, provides an overview), presents the influences on voters' decisions as located within a funnel.[1] At its exit point is the vote decision. Furthest from it – at the funnel's mouth – are relatively fixed variables, such as a voter's age, sex, and social status. Moving into the funnel, those characteristics are causally linked to slightly more transient variables – such as the groups with which the individuals identify and their value orientations. These in turn are linked to their attitudes to the political parties and whether individuals identify with them; and then – approaching the funnel's point – they are linked to their evaluations of candidates and parties and their policies, which are also influenced by perceptions of the external environment (economic conditions, for example).

An approach to uncovering those various stages in the funnel of causation model – in particular, the links between voting behaviour and socio-demographic characteristics at the funnel's mouth, which are the possible precursors of valence – is illustrated here with reference to recent British work, developing both substantive and technical arguments. Substantively, along with Evans and Tilley (2017), we claim that elements of the sociological model have been unnecessarily underplayed in recent analyses. Technically, we argue that most analyses insufficiently explore the relationships between sociological factors and voting behaviour – specifically the interactions among those factors – and use a recently-developed method for exploratory data analysis to identify them.

This paper develops three main arguments, therefore. First, it contends that socio-demographic variables remain important influences on British voting behaviour, so it is insufficient for analyses to focus at the end of the causal pathway to partisan choice; those variables located at the funnel's mouth continue to influence voter choices through their relationship to individuals' general political attitudes (even ideology: Scarbrough, 1984) and their positions on contemporary political issues. Secondly, it suggests that standard modelling approaches – such as binomial and multinomial logistic regressions – are limited in their capacity to uncover all of the relationships between the independent and dependent variables in voting studies, especially those involving interactions among the socio-demographic influences on voter choice. Finally, recognising these first two points, it deploys an exploratory modelling procedure whose outputs have a very natural interpretation: it enables a clear identification of those socio-demographic groups who have a propensity both to hold particular attitudes on contemporary political issues and to vote in a particular way.

Most studies of voting patterns – not only in the UK – are basically exploratory in their approach. They select a number of variables – respondent characteristics derived from survey instruments, for example – believed to be related to voter choices, and assess whether that is the

[1] See the large number of images of the funnel at https://www.google.co.uk/search?q=funnel+of+causality&biw=1333&bih=569&tbm=isch&tbo=u&source=univ&sa=X&sqi=2&ved=0ahUKEwj_x_yR7cnKAhWHXRoKHfkSBJoQsAQIHg – accessed 10 October 2017.

case using regression analyses. Although there are general expectations regarding the direction of the individual relationships, there are rarely specific hypotheses regarding their strength and intensity (both absolute and relative to other variables in the equation) – the theory on which the analyses are based does not specify the expected outcome in such detail. Hence the potential benefits of improved exploratory procedures, such as that advanced here.

2. Funnelling voting decisions: from age, sex and qualifications to party choice

Although the funnel of causation model implicitly underpins many discussions of British voting behaviour, it is rarely referred to explicitly and is often incorrectly implemented in analytical models and their empirical testing.

2.1 Fixtures at the mouth of the funnel

Three socio-demographic and -economic variables – or their equivalents – have been widely used in most studies of British voting: class, age, and sex. Traditionally, individuals' class status was identified according to their occupation (in the simplest formulation between those in white-collar and blue-collar jobs) although as that distinction became increasingly blurred and the balance between the public and private employment sectors changed alternative formulations were sought (Dunleavy, 1979). More recently, alongside – if not replacing – occupational status analysts have employed individuals' educational qualifications as an important indicator. In an economy increasingly dominated by the service sector, individuals' skills as reflected in their qualifications provide the entrée to the higher-paid, more prestigious jobs; lifestyle differences follow from these contrasts in income and status, and may be reflected in political attitudes and partisan preferences. (Empirically, since their qualifications can be directly obtained from most adult respondents to questionnaires, this is a preferred indicator of status to occupation – and also to incomes, given the British reluctance to provide information on them – as a large proportion of the adult population may not currently be in the workforce. Further, qualifications reflect a lifetime cumulative experience; with income and occupational status people may move either up or down the ladder at points in their careers. Finally, as the questions are relatively straightforward for respondents to answer and for researchers to code they are less likely to be affected by misclassification error and consequent attenuation of effects.)

Many empirical studies have identified variations in partisan preferences across different age groups (for example, Tilley, 2005; Tilley and Evans, 2014); in general, older people are more 'conservative' in their views than their younger counterparts, and this is reflected in the relative preferences for different political parties. The usual 'explanation' for such differences is that older people have a greater 'stake in society' through, for example, home-ownership and aspirations for their children, and are more likely to vote for a 'conservative' party that promotes those individual values – hence the British Conservative party's policies of promoting home ownership. Empirical studies have also identified differences between males and females in voting at British General Elections (Norris, 1996, 1999; Inglehart and Norris, 2000; Annesley and Gains, 2016).

There is considerable empirical evidence that different socio-demographic groups tend to favour one political party rather than others in the UK, therefore. The arguments regarding both class/partisan dealignment and the importance of valence issues have pushed these relationships into the background in many recent studies, however. In analyses of the 2010 British General Election, for example, Whiteley et al. (2013, 137) dismiss models of party choice using socio-demographic variables alone on the basis that they provide only a poor goodness-of-fit – although they successfully predicted 71.5 per cent of respondents' party choices in binomial logit models. Valence models, on the other hand, successfully predicted 87.7 per cent, and when the two models were combined (with others) that only increased to 88.8 per cent. They concluded that use of the socio-demographic variables (age, gender, ethnicity, social class) is 'obsolescent' – unnecessary to a parsimonious model that can successfully predict how most people vote, even though socio-demographic characteristics such as age, sex and qualifications may be important determinants of voters' attitudes. But without including such variables in choice models the understanding of who votes what, and why, is compromised. Exactly the same stance is taken in their comparable analyses of voting at the 2015 election: 'socio-demographics have the weakest explanatory power' (Clarke et al., 2015, 118). Nevertheless, those variables are included in the final models in both books – they are, according to the usual phrasing, held constant (Whiteley et al., 2013, 115). This is an odd decision, for two reasons.

The first reason is substantive. If the analyses were applying the funnel of causation model fully, they would be presenting the voting decision as – at least – a two-step process. People are socialised into adopting particular attitudes and partisan preferences, in which process their age, sex and social class/educational qualifications may be important. Those variables would then be related to their responses on the valence issues – as also would be their prior electoral decisions; in turn, their partisan choices might reflect their valence positions and, indirectly, their socio-demographic characteristics. This sequence can be recognised methodologically in a number of ways, as in path analysis models (which, however, are more readily fitted to data measured on interval and ratio scales than to those largely reliant on nominal categorisations, as in the example below).

Secondly, by not employing the funnel of causation in this or a similar way, the implicit assumption underlying the modelling is that attitudes develop and partisan positions are taken in what are, in effect, socio-political vacuums (as in Clarke et al., 2016), which is clearly not the case. Most people learn in context, interacting not only with the political environment in general (through media reports, for example) but also with other voters, both individually and in groups – both informal and formal; much research demonstrates the important role of discussions within social networks in the formulation of attitudes and behaviour patterns (Johnston and Pattie, 2017). Inclusion of such background variables allows analysts to discover not only what those who support a particular party think but also who they are – and where they live, which may be very important too. (Paradoxically, although claiming that socio-demographics are of little relevance in models predicting individual voting behaviour, Clarke et al. – 2015, 142 – report ecological analyses at the constituency scale which suggest that individual characteristics play a major role in predicting variations in attitudes in different places, and hence in party choice: you can predict how people in an area vote by knowing what type of people they are.) Political parties also know that they are most likely to win support from those who share their values and policy positions – but they need to know who those people are most likely to be, and where they live, if they are to develop and successfully target electoral campaigns.

Of course, as noted above, those promoting valence models nevertheless include socio-demographic variables in their analyses. This repeats an error common to much analytical work on British voting behaviour (Johnston et al., 2017). In a multiple regression including two independent variables, the regression coefficients do not show change in the value of the dependent variable with a unit change in the value of the relevant independent variable. If the independent variables are X_1 and X_2 and the dependent is Y, then the coefficient for X_1 shows the change in the value not of Y, but of the residuals of a regression of Y on X_2, relative to the change in the values of residuals from a regression of X_1 on X_2. If the relationship between X_1 and X_2 is relatively weak (i.e. there is only slight collinearity between the two) this is not very problematic. If they are closely related, however, the residual ('unexplained') variances of Y, X_1 and X_2 may be little more than random and the multiple regression coefficients uninformative. (In a paper presented as 'improving empirical analysis', Bramber et al. – 2006 – note that some may respond that their points 'are so obvious that surely everyone already knows' this. That was not borne out by their literature survey. The same appears to be the case regarding collinearity and its potential confounding impact on regression coefficients.)

If valence attitudes are strongly related to socio-demographic variables, therefore, the relative importance of one set, and perhaps both, in accounting for voting patterns may be mis-represented, and one's influence under-stated relative to the other: Clarke et al.'s analyses of the 2010 and 2015 elections may understate the importance of the socio-demographic variables.

2.2 Exploring interactions

Very few analyses of British voting behaviour, especially of categorical data derived from surveys, explore the full richness of the available data. For example, they may include variables for educational qualifications and sex, and fit regression models predicting whether respondents abstained at an election. Such models compare the marginal differences in the relevant contingency table (two sexes, by four qualification levels, by whether voted or not, perhaps) and may establish that women were more likely to turnout to vote than men and that those with degrees were less likely to abstain than those with no qualifications. But they do not indicate whether, for example, women with degrees were more or less likely than men with degrees to turn out. The interactions – differences across the internal cells of the contingency table rather than just between the row and column totals – are usually ignored, thus assuming that each of the variables under consideration is homogeneous across the other (that men and women do not differ depending on their qualifications; and/or that people with a particular qualification do not differ depending on whether they are male or female). The two groups may indeed be homogeneous and there are no (substantial and/or statistically significant) intra-group variations – but we do not know because the question isn't asked (though see Russell, 1997).

Despite pressure from a number of authors regarding the issue more generally (see, for example, Gelman, 2008; Elwert and Winship, 2010; Hainemuller et al., 2016), such oversight of interaction effects is a very common feature of studies of British voting behaviour. This is unfortunate because many of those studies are, in effect, exploratory analyses addressing the main effects only without investigating multiplicative effects through interaction terms. In addition, few test specific hypotheses; independent variables are included in the expectation that they may be related to the dependent variables, perhaps just because previous studies have found them to be. The potential full richness of the data is thus not realised; clear and strong relationships may lay undiscovered and full understanding of voting behaviour retarded as a consequence.

2.3 A way forward?

Two conclusions have been drawn from the above discussion as the basis for further work to be reported here:

- That analyses of British voting behaviour should not downgrade the relative importance of socio-demographic variables in seeking to appreciate patterns of party choice. Different social groups may, for a variety of reasons, develop different attitudes on the important issues being addressed at an election, and by exploring those attitudes alone without any appreciation of how they vary across the population only an incomplete understanding of who votes for what, and why, is obtained.
- That those analyses should investigate the interactions among a model's independent variables so as to explore more fully how groups differ not only between each other but also internally in their attitudes and behaviour.

The remainder of this paper uses a recently-developed approach to the study of large contingency tables – characteristic of British voting studies deploying survey data – to explore the sorts of variations that the preceding discussion has suggested lie very largely unaddressed. It does not deploy, as is commonly the case, multiple regression-like models – especially in their binomial and multinomial forms using categorical data. Most analyses use relatively small samples and yet divide their respondents into a substantial number of different, many of them multiple, categories. With these, extracting robust – and interpretable – estimates of interaction coefficients is difficult, indeed sometimes technically infeasible. The approach developed here – set out in full methodological detail elsewhere (Jones et al., 2015, 2016; Johnston et al., 2015, 2016) – avoids those problems while providing clear indications of the patterns within a relatively large data set – although even with over 20,000 observations and a contingency table comprising only three independent and one dependent variable the problems of robustness remain.

3. Modelling large contingency tables

Many social science data sets that involve the calculation of ratio values face the problem that some of those calculations involve small numbers – either as the numerator or the denominator, or both (Jones and Kirby, 1980; Clayton and Kaldor, 1987). A small change in either can result in a substantial change in the derived ratio – one that may reflect little more than the chance variation associated with a stochastic generating process. It is therefore difficult to determine whether there are significant differences in the derived ratios between contingency table cells when many are derived from small numbers of observations. Even what appear, on the surface, to be large sample sizes can become problematic when relatively large contingency tables are analysed as such cells with small numbers could be relatively frequent. A 2 x 6 x 4 x 6 table (such as the one analysed later in this paper) has 288 cells, for example, so that for an average of 20 per cell the dataset would need to comprise 5,760 respondents – much larger than many voter surveys. With anticipated variation around that average there would be cells with few observations. In addition, many data sets have non-uniform distributions; those that are positively-skewed would have a large number of fairly empty cells. Moreover, collinearity between predictor variables will lead to bunching of respondents in certain cells of the table and a dearth of observations elsewhere. Relatively few voter surveys are very large, and many of their analyses involve more than four multi-member nominal classifications. In such cases, full exploration of the interactions between variables are difficult to conduct without, in effect, stabilising the incidence rates to take cell sizes into account (Manda and Leyland, 2006).

A way forward for addressing this problem has recently been proposed, using multilevel, random-effects modelling in a Bayesian statistical framework (Jones et al., 2015, 2016). For each multi-way contingency table cell it derives an expected value, by assuming that the proportion of individuals with that characteristic is the same as for all age and qualification groups, across both sexes. If 15 per cent of the total sample voted UKIP, for example, the model expects that figure to apply to every age by sex by qualifications cell of the contingency table as the null model of no effect. It then takes the ratio of the observed (O) – the number that did vote UKIP – to expected (E) value for each cell (O/E) and log transforms it. Those logged ratios could be modelled in a saturated Poisson regression model, with a separate parameter for each cell to derive an estimated ratio along with its credible intervals (CIs; these are interpreted in the same way as confidence intervals in standard regression models, although because they are Bayesian estimates they need not be symmetric around the estimated ratio value). These estimates from the saturated model may be unstable if based on small observed and/or expected values, so in the multilevel modelling the estimated logged O/E ratios are down-weighted towards no effect of the observed being equal to the expected when they are based on small absolute numbers. In this way the analysis is protected from any over-interpretation of unreliable effects (i.e. substantial differences between the observed and expected values) in cells where either O or E, or both, is small, whereas distinctively high or low ratios based on reliable evidence (i.e. large numbers of observations) are not down-weighted. As the equivalent of fully-saturated models are fitted, all of the interactions among the 'independent' variables (in the example here, age, sex, and qualifications) are taken into account.

Little is gained by simple modelling of the O/E ratios with a separate parameter for each cell, as in, for example, multinomial logistic regression models. The main advantage of deploying a multilevel, random effects model is that it involves the pooling of information across all cells (Gelman and Hill, 2006). The estimated ratios are precision-weighted so that where they are based on small numbers they are shrunk back towards a value (when exponentiated) of 1.0 (i.e. the null hypothesis of no difference between the observed and expected values) This procedure involves Bayesian pooling of information – a data-driven adaptive procedure for handling the uncertainty associated with sparse data within the contingency table (Beck and Katz, 2007; Jones and Spiegelhalter, 2011; Gelman, 2014).

For each contingency table cell, therefore, the model produces a logged (O/E) precision-weighted rate, where an exponentiated value of 1.0 indicates that the observed value is equal to the expected. These exponentiated estimated rates have a natural interpretation: an estimate of 2.0 for a particular group indicates that they voted at twice the rate for UKIP across all types of respondents; while a value of 0.5 indicates that support is only half the overall rate for the entire sample. Moreover, the associated credible intervals indicate the degree of support for that estimate; we have used 95% credible intervals to distinguish types of people who are more or less typical in support for a party. Frequentist confidence intervals apply to the data and allow an inference about what would happen in repeated samples; thus you would expect 95 per cent of the intervals of repeated samples to include the population parameter. Bayesian credible intervals are more natural and apply to the parameter and not the data, giving a 95 per cent probability that the parameter falls between the lower and upper values given the span of the uncertainty. Bayesian credible intervals can thus be interpreted in a similar way to frequentist confidence intervals (although formally they should not be), which is why we have appropriated the term 'significant' for cells which have good empirical support that they are distinctively high or low.

This explicitly exploratory procedure seeks patterns in a contingency table but by anchoring the results to the null hypothesis of no effect we gain greater confidence in all of the estimated values than would be the case from other modelling strategies based on a saturated model. Shrinkage automatically makes for more appropriately conservative comparisons while at the same time not reducing the power to detect true differences. Appendix 1 give the specification of the model version applied here and more technical details about estimation.

4. Age, sex, qualifications and voting in England, 2005-2015

To illustrate the approach, we used the 2015 British Election Study (BES) Wave 6 data; respondents were asked immediately after the election if they had voted then and, if so, for which party; they were also asked how they had voted at the previous two elections (in 2010 and 2015). To reduce the size of the contingency table and to focus on a situation in which all respondents faced the same set of party choices, we excluded respondents from both Scotland and Wales (Northern Ireland is not included in the BES), along with the very small number who reported voting for other than the parties that contested virtually all of the 532 English constituencies – Conservative, Labour, Liberal Democrat, UKIP and Green; we also omitted respondents in the constituency where the Speaker was a candidate as, by custom, this is not contested by the major parties. This gave a sample of 20,966 respondents (unweighted); the reported voting behaviour substantially under-estimated the number of abstentions – as is common in such studies – but as our main interest is to demonstrate relative differences between and within groups, this is not important to our findings. We also analysed the respondents' recalled votes at each of the two preceding general elections – in 2005 and 2010 – to explore whether there was continuity or change in partisan preferences by the different groups across the three elections.

The models were fitted using MCMC estimation within the standard MLwiN software with default priors imposing as little prior information as possible on the estimates, so that the results are data-driven, a highly desirable situation in an exploratory data analysis (Jones and Subramanian, 2014). Three 'independent' variables are deployed: sex is the usual binary division; age is divided into six groups (18-25; 26-35; 36-45; 46-55; 56-65; and 66 and over); and educational qualifications is in four groups (1 – none; 2 – up to and including those obtained at the normal school leaving age; 3 – those obtained after age 16, except for degrees and diplomas; and 4 – degrees and diplomas; for shorthand in the tables these are referred to as four classes). The 'dependent' variable has six categories – voted Conservative, Labour, Liberal Democrat, Green, and UKIP, plus Did Not Vote. This gives a 2 x 6 x 4 x 6 contingency table comprising 288 cells, giving a mean of 73 respondents per cell but a median of 44 indicates a positively skewed distribution.

For each of the dependent variable's six categories, the modelling procedure provides an estimate of the ratio of the observed number of respondents to the expected number in each of the 48 cells of the sex-by-age-by-qualifications cross-classification, with the latter derived from the underlying assumption that the proportion voting for each party – or abstaining – is invariant across all 48 cells. A ratio of 1.0 indicates that the observed and expected numbers are the same; a ratio greater than 1.0 that the observed number is greater than expected; and a ratio less than 1.0 that there are fewer there than expected. Because those ratios have associated credible intervals, whether any ratio is 'significantly' less or greater than 1.0 can also be assessed.

The resulting estimated rates are shown in Figures 1-6; those significantly larger than 1.0 are shown in bold and underlined, and those significantly smaller than 1.0 are underlined and italicised. Each figure relates to one of the six voting options. Horizontally, each is divided into two blocks, one each for males and females, and each of those is divided into six rows for the age groups. Vertically, the tables are divided into three blocks for the three elections, with each block divided into four columns for the educational qualifications – those with no qualifications are in the left-hand column, those with degrees/diplomas in the right. Because age is held constant (i.e. the respondent's age in 2015), there are no estimated rates for those aged 18-25 in 2015 for the 2005 and 2010 elections.

For voting *Conservative* (Figure 1) the dominant pattern – for both males and females – is significantly greater than expected support from those aged over 65 in 2015, across all four qualification groups; in both 2005 and 2015 (but not 2010) the party also got significantly more support than expected – though not across all groups – from those aged 56-65. But there is also a substantial difference between males and females. Among females, younger voters – especially those in the higher two qualification groups – were significantly less likely than expected to vote Conservative (with rates as low as 0.46); this was not the case for males, however, for whom the rates were not only much larger (close to 1.0) but also statistically insignificantly different from 1.0.

Figure 2 also shows a major difference between males and females in their propensity to vote *Labour*. At the 2015 election, the party gained significantly more support than expected in each of the two most qualified groups across all age groups below 56, as well as from middle-aged females among those with lower or no qualifications. But there was no such strong support among males of the same age and with the same qualifications: most of the estimated rates there are larger than 1.0, but only two of them are significantly greater than 1.0. These differences are more muted at the previous two elections, when Labour got significantly above average support from older males with no qualifications and from middle-aged females across all qualification categories.

Figure 3 shows that the *Liberal Democrats* got significantly greater support than expected at both the 2015 and 2010 elections from those with the highest qualifications – degrees and diplomas – with little difference between males and females. Countering that, their support was significantly less than average among those with either no, or only up to school-leaving age, qualifications; in many of the cells, however, although the estimated rates were low (below 0.7 in several cases) they were not significantly smaller than 1.0, reflecting the small number of observations in many of those categories (e.g. young people with no qualifications). At the 2005 election, however, there were fewer significant differences than at the later contest, especially among males. Support for the Liberal Democrats was relatively widespread then; when their vote share collapsed by two-thirds between 2010 and 2015, their support base became socially more polarised between those with degrees and others (on which see Fieldhouse et al., 2006; Cutts et al., 2010; Cutts and Russell, 2015).

For the *Green* party (Figure 4), support was sufficient for estimates of variations across qualifications, sex and age groups to be calculated for the 2015 contest only. (The Greens got only 1 per cent of the votes in 2010, when they contested 335 seats; in 2015 they fielded 573 candidates and gained 3.8 per cent of the votes.) Not unsurprisingly, the pattern of their support is very clear: significantly higher than expected among the younger and better-qualified voters, especially females; significantly less than expected among those who were older and less-qualified.

UKIP's support – as much other analysis has indicated (e.g. Goodwin and Milazzo, 2015; Evans and Mellon, 2016; Ford and Goodwin, 2016; Mellon and Evans, 2016) – was concentrated among the old and those with no or only school-leaving age qualifications (Figure 5), with a substantial difference between males and females. At each election, the estimated rates were significantly greater than 1.0 for all males aged 56 and over in the lower two qualification categories; for females, there were many fewer significantly high rates – none in 2005 and only one in 2010, and at all three contests females with degrees/diplomas were significantly less likely to vote for UKIP than expected for all those aged under 65, whereas there was only one such low rate for males in 2010 and none in 2005. This exploration of interactions shows UKIP's support was clearly differentiated not only separately by age, sex and qualifications but also in combination. Well-qualified old males were significantly more likely than expected to vote UKIP in both 2010 and 2015; well-qualified females in the same age group were not.

Finally, Figure 6 shows the pattern for those who reported that they *Did Not Vote*. Here the differences are as expected – those with no or few qualifications were significantly more likely to abstain than the better-qualified, and the young were much less likely to turn out than their older peers; countering that, the estimated rates for older people and those with the highest qualifications were significantly smaller than 1.0. Those differences were largely common across both sexes, but the estimated rates were generally more pronounced (i.e. different from 1.0) among males than females. In 2015, for example, the estimated rates for females with no qualifications were higher in all but the oldest age group than those for males.

These analyses sustain the argument that exploration of the interactions among 'independent' variables may uncover important differences both between and within groups that 'traditional' analyses cannot. An example of such a 'traditional' analysis is given in Table 1, which reports a multinomial logistic regression analysis of the 2015 election outcome. The significant coefficients reported there in part replicate the general patterns shown in Figures 1-6 – females, young people and less-qualified individuals were more likely to vote Labour than Conservative than were males, old people and those with degrees, for example – but they do not highlight (as Figure 2 so clearly does) that the differences between males and females in their propensity to support Labour is significant among those with higher qualifications but not among those with none.

(Because in multinomial logistic regressions one of the categories of the dependent variable is set as the comparator, no direct information is given by the regression output of the pattern of voting for that component – in this case the Conservative party – and it has to be computed separately. The modelling approach employed here does not suffer from that disadvantage.) Similarly, the regression coefficients indicate very little difference across the four qualification groups, because (as Figure 4 shows) there are differences within each of those groups by age. Further the regression shows a significant difference between their propensities to vote Liberal Democrat rather than Conservative only between the oldest and youngest age groups – mainly, it would seem, because the differences between age groups in their support for the Liberal Democrats vary substantially by qualifications (Figure 3).

Overall, the main significant differences in Figures 1-6 show that in 2015:

- Older people – at all qualification levels – were more likely to vote Conservative than their younger counterparts among females, but among males whereas older people were also significantly more likely than expected to vote Conservative there was not a compensating significant likelihood that younger males did not vote Conservative.
- Females, especially those with either post-school or degree-level qualifications, were significantly more likely to vote Labour than expected, but a similar pattern was not apparent for males.
- There was significantly greater support for the Liberal Democrats among the well-qualified than expected, and less than expected among those with few or no qualifications – across both sexes.
- Young, well-qualified individuals of both sexes were more likely than expected to vote Green whereas older, less-qualified individuals were significantly less likely to.
- Older, less-qualified males – and, to a lesser extent, females too – were significantly more likely to vote UKIP whereas younger, more-qualified females – and, to a lesser extent, males too – were significantly less likely to.[2]
- Young females – to a greater extent than young males – were significantly more likely to abstain than expected, whereas older persons were less likely to.

While some of these differences – notably those for voting Liberal Democrat and Green – were clearly revealed by the multinomial logistic regression model, fitted without interactions, many of them were not.[3] Furthermore, several of the patterns exposed in Figures 1-6 show substantial and significant changes over the three most recent elections: the growing trend for well-qualified females, but not males, to vote Labour, for example; and the increase in the significant small numbers of well-qualified females, and to a lesser extent males, voting UKIP.

5. Did the patterns change?

Figures 1-6 contain a great deal of information. To summarise the general patterns– and in particular to confirm whether there were substantial differences in voting by age, sex and qualification across

[2] This undoubtedly reflects differences in respondents' attitudes towards the UKIP leader, Nigel Farage. The 2015 BES data show that at the time of the 2015 election (i.e. in wave 6) whereas on an 11-point scale, where 0 equals strongly dislike and 10 strongly like, 10.8% of males aged 18-25 gave Farage a rating of 8, 9 or 10, only 3.6% of females in that age group did so.

[3] We did fit further models including the interactions. If the three two-way interactions alone are entered, 11 of the 25 possible interactions between sex and age were significant, as were 7 of the 15 involving sex and qualifications and 24 of the 90 interacting age and qualifications (11 of those 24 were for those not voting). When the three-way interactions are also added, 7 of the 90 were significant, compared to just 3 of the 15 two-way sex and age interactions, 3 of the 15 sex and qualifications interactions, and 27 of the 90 for age and qualifications. When the three-way interactions are fitted, however, the SPSS© output indicates collinearity among the variables and that the validity of any estimated coefficients is uncertain.

the three elections – we have extended the analysis using a hybrid model with fixed effects (Jones et al., 2016). The models described above allow for maximum differences in the random part; the hybrid model additionally includes estimated fixed effects for Vote (i.e. the six categories deployed in Figures 1-6) when interacted with age, sex and qualifications to distinguish the main patterns. Table 2 gives the results.

The initial Model 1 in Block 1 consists of a single term in the fixed part which is simply an overall average, while the estimated variance and its credible intervals summarises the unexplained differences between cells around this average. The lower 2.5% credible intervals do not approach zero so that there are genuine differences between the cells. Models 2 and 3 include the main effect of Vote plus Vote by Year interactions so that there are now 6 and 18 terms in the model. The unexplained between cell-variance has clearly been reduced as we distinguish the underlying main patterns. To assist model selection we use the Deviance Information Criterion, which is a badness of fit measure penalized for estimated model complexity; this is a by-product of the Bayesian MCMC estimation (Spiegelhalter et al 2002). Better models have a smaller DIC and some commonly applied rules of thumb are that a difference of 4-7 from the best model has considerably less support, while a model with difference of 10 or more indicates that the worse model has virtually no support and can be omitted from further consideration (Jones and Subramanian, 2014). The introduction of the terms for Vote and Vote by Year have resulted in substantial improvement shown in the sizeable reduction in the DIC and this latter model is taken into successive blocks.

Subsequent modelling blocks add to the Vote by Year interaction by including an additional variable initially as an interaction between the new variable and the Vote, and then as a two-way interaction with Year and then as three-way interaction with Vote and Year. Block 2 thus introduces terms for Sex and the key improvement comes with the Vote by Sex interaction but the further interactions do not lead to further improvement. Block 3 introduces Qualifications and there is a very substantial lowering of the DIC when a Vote by Qualifications interaction is included but a worsening of fit when Qualifications by Year interactions are included. Block 4 gives the results when Age is included and this time the best model does involve an interaction between Age and Year – there is evidence that the age effects have changed over elections. The final block includes Age, Sex and Qualifications and the best model with the lowest DIC is Model 2 in which there is an Age by Year interaction and interactions between Vote and Sex and Vote and Qualifications. Further elaborations do not bring about improvements. It is also clear from examining the variance term that the residual unexplained differences between the cells have become negligible so that the main patterns have indeed been captured by the fixed effects.

The easiest way to appreciate the results of the preferred Model 5.2 (especially since it has 80 terms) is graphically in Figure 7, shown without credible intervals for clarity. The graphs show the modelled rate for each Vote outcome for different Age groups at the three elections when Qualifications and Sex are held constant at their average values.[4] For voting Conservative and Labour there is no change over the three elections; at each, voting Conservative increased by the same amount with age – holding year, sex and qualifications constant – whereas for Labour there was a slight downward trend with age at each contest. The pattern of voting Liberal Democrat was invariant with age – ceteris paribus – with the decline in its level of support apparent in 2015.

Voting for UKIP and for the Green party, and non-voting, differed much more by age across the three elections than was the case with voting Conservative, Labour and Liberal Democrat – with sex and qualifications held constant. For both voting Green and Not Voting there was a very substantial decline with age, with its intensity greater in 2015 than at the previous two contests;

[4] The marginal predictions are readily made by the customised predictions facility in MLwiN which has been designed for this specific purpose (Rasbash et al, 2012).

complementing that pattern, the intensity of the difference between age groups voting UKIP also increased across the three contests – with older people much more likely than their younger counterparts to vote for that party in 2015 than in 2005 and 2010. At the 'core' of British voting patterns, therefore, variations in support by age remained largely constant for the three parties that dominated British politics for some four decades, but the age divide widened very considerably on the 'periphery' – both in voting for the newer, growing parties and in abstentions.

6. Voting and attitudes

This paper has argued that 'holding constant' socio-demographic variables in regression models of voting behaviour means that analyses are unable fully to uncover the roots of party support; they cannot answer the question 'do members of specified social groups vary in their attitudes, and hence in their propensity to support one party rather than others?'. To address that question, this section takes the patterns identified in Figures 1-6 and, for selected examples, inquires whether there are attitudinal differences – as explored in the 2015 BES surveys – consistent with those differences in voting propensities.

For the first example, Table 3 shows the percentage of respondents in each sex, age and qualifications category who said in 2015 that measures to protect the environment have either not gone nearly far enough (NF) or have gone much too far (TF). Those who gave the former response should have been more likely to vote Green than those who gave the latter response, so the pattern of responses should match that of significant differences in Figure 4. With very few exceptions, that is the case: across each row increasing percentages saying NF and decreasing percentages saying TF indicate greater support for the Green party's position among the more qualified; whereas down each pair of columns the increasing percentages saying TF and the declining percentages saying NF indicate that older voters were less inclined towards the Green position than their younger counterparts.

To evaluate this conclusion further, we modelled the numbers giving each of the five responses to that attitude question (not gone nearly far enough; not gone far enough; about right; gone too far; and gone much too far) by age, sex and qualifications – as in the analyses of voting patterns. The left-hand block of four columns in Figure 8 identifies those groups significantly more or less likely to believe that environmental policy had not gone nearly far enough: those with degrees and diplomas were significantly more likely to say that this was the case than expected; older people in the lower classes were significantly less likely to. The central block similarly identifies the groups who thought that policy had gone much too far: most of the significant ratios were for the better-educated females, who were much less likely than expected to think policy had gone too far. The final block of columns shows voting Green in 2015 (repeating the relevant parts of Figure 4): comparison between it and the previous two blocks shows that voting Green was concentrated among those groups who wanted more environmental protection. This clearly sustains our argument that we get a fuller appreciation of who votes for which party, and why, by analytical strategies that incorporate both socio-demographic and attitudinal variables, since the latter are not independent of the former. This was formally confirmed by regressing the estimated ratios for those voting Green in 2015 against those for respondents saying that environmental policies had not gone nearly far enough (i.e. across the 48 sex by age by qualifications cells; the standard errors associated with the regression coefficients are in brackets):

$$\underset{}{VG} = \underset{(0.171)}{-0.181} + \underset{(0.154)}{1.169}NFE \qquad r^2 = 0.545$$

where VG is the modelled O/E ratio for voting Green and NFE is the modelled O/E ratio for environmental protection policies have not gone far enough.

The second example, in Table 4, looks at attitudes to immigration in 2015 – whether respondents thought it was bad or good for the economy, on a seven-point scale. Given that one of UKIP's main arguments at the election was that immigration should be restricted – claiming that it was depressing wages (especially for the lower-paid) and putting pressure on social services – the expectation was that anti-immigration attitudes should characterise the older and less-qualified respondents, especially males; Figure 5 shows they were more likely than expected to vote UKIP. These expectations are largely borne out. Among males, for example, the percentage saying that immigration was bad for the economy (i.e. a score of 1 on the 7-point scale) fell very substantially in all age groups across the four qualifications categories; one-quarter of those aged 18-25 with no qualifications said it was bad compared to just 7 per cent among those with the highest-level qualifications. Similarly, the percentage within each qualification category saying it was bad increased with age – more than tripling among those with degrees/diplomas. Very similar patterns emerged in responses to a question on whether immigration enriches or undermines cultural life.

These data were also modelled and the left-hand block of estimated ratios in Figure 9 shows that well-qualified respondents were significantly less likely to say immigration was bad for the economy than expected, whereas those with lower qualifications or none were significantly more likely to express the opposite opinion. The next block shows that the well-qualified were more likely than expected to believe that immigration is good for the economy whereas older people – especially females – were less likely. These patterns coincide markedly with the patterns of support for UKIP in 2015 shown in the right-hand block: well-qualified people, who were pro-immigration, were unlikely to vote UKIP; older, less-qualified individuals were very likely to. This is confirmed by the regression:

$$\underset{}{VUKIP} = \underset{(0.103)}{0.101} + \underset{(0.081)}{0.840}IBE \qquad r^2 = 0.695$$

where VUKIP is the modelled O/E ratio for voting UKIP and IBE is the modelled O/E ratio for immigration is bad for the economy.

A similar analysis was undertaken using a question asking individuals whether they thought immigration undermined or enriched British culture. The pattern of O/E ratios is shown in Figure 10, and the relevant regression:

$$VUKIP = \underset{(0.151)}{0.459} + \underset{(0.074)}{0.810}IUC \qquad r^2 = 0.742$$

where VUKIP is the modelled O/E ratio for voting UKIP and IUC is the modelled O/E ratio for immigration undermines British culture.

A core argument here is that voters' socio-economic and -demographic characteristics are very likely to be related to their political attitudes – and thence to their voting behaviour. Such inter-relationships are smothered in the analytical procedures deployed in most British voting studies based on survey data, however. Conventionally, in recent work they are 'held constant' by incorporating the socio-demographic variables in regression equations, which are then largely ignored. The two-stage procedure adopted here illustrates the relative poverty of that approach – which largely ignores what types of individual have what attitudes underpinning their electoral choices.

7. Discussion and conclusions

Two main arguments have been developed in this paper – both substantive and technical. First, many recent British voting studies have wrongly claimed that socio-economic and -demographic characteristics are no longer important influences on party choice and worthy of study in their own right (though see Evans and Tilley, 2017); instead, an over-emphasis is placed on the links between attitudes and behaviour without any detailed exploration of their socio-structural underpinnings. There is little doubt that the decline of partisan alignment means a greater fluidity in voter decision-making than in earlier decades (hence the need for more exploratory data analysis), but, as demonstrated here, age, sex and educational differences remain very clear influences on the pattern of attitudes and voting at recent elections in England.

Secondly, the favoured technical approaches to analysing voter survey data prevent their richness being fully explored. One clear example of that demonstrated here concerns the interactions among the variables – almost invariably ignored in regression analyses. It is wrong to assume intra-group homogeneity without inquiring whether, for example, older, well-qualified males vote in the same way as their female contemporaries. Greater attention to the interactions is needed – although this may often be difficult. The analyses reported here used a very large survey data set with an average of 78 observations per cell of the 288-cell matrix, and yet – as Figure 11 shows – many of those cells had few observations, making the computation of reliable rates difficult. Most voting studies include more than three 'independent' categorical variables – and in most of them, therefore, exploring the full richness of their relationships with the 'dependent' variable is restricted.

Most British – and other – voting studies using survey data are quasi-exploratory; few test specific hypotheses and instead seek expected relationships based on other empirical findings and general expectations rather than any 'strong theory'. As such, methods of exploratory data analysis should be more frequently deployed in teasing out the relationships within a data set. The method advanced here offers considerable potential to that end.

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Appendix. Specification and estimation of the model

Initially, we fit a two-level random-effects Poisson model separately for each election. We do this to impose as little as possible structuring on the results. (We also impose as little structure as possible in the model formulation so that the individual cell estimates are shrunk towards an overall average and not say the main effect for age – we are trying as much as possible to let the data speak for themselves.) The specification of each model is:

$$O_{ij} \sim Poisson(\pi_{ij})$$
$$\pi_{ij} = e^{(\beta_0 + u_j)}$$
$$Log_e(\pi_{ij}) = Log_e(E_{ij}) + \beta_0 + u_j$$
$$u_j \sim N(0, \sigma_u^2);\ Var(O_{ij}|\pi_{ij}) = \pi_{ij}$$

Where individuals, *i*, are placed in cells, *j*, the latter being defined by all combinations of the categorical variables so that *j* here is 2 sexes by 6 age groups by 4 educational categories by 6 parties, that is 6 outcomes for 48 types of people. The term O_{ij} is the observed count for, say, voted UKIP in 2015; while $E_{ij}$is the expected count of the number of people that voted UKIP if the overall rate of support for that party applies to each and every cell. So if overall 15% voted UKIP and there are 100 people in that cell; then the expected value will be 15. As is common with count data we assume that they come from an underlying Poisson distribution with a mean of π. This mean rate is non-linearly related to an overall average rate (β_0) plus a random departure – the random effect (u_j) for each cell. This exponential relationship is transformed to a linear model by taking the natural logarithm (the log link). The $Log_e(E_i)$ is known as the offset which has its parameter constrained to 1 (McCullagh and Nelder, 1989). The effect of this is that the model analyses differences not in the log of the counts but rather the log relative rate taking account of E_i, the expected values. Because the overall sums of the observed and expected values are the same, the overall average (β_0) can be anticipated to be zero, which becomes 1.0 when exponentiated. The random differentials (u_j) if positive indicate that the cell has a higher rate than expected; if negative, a lower rate. Exponentiating these values give the relative rate so that the value 2 represents a doubling of the rate. Assuming that these differentials come from a Normal distribution, they are summarized by the variance term, σ_u^2, which captures the differences between all cells (having taken account of Poisson variation) and is based on information for all the different subgroups.

The final line of the specification (as is the norm in Poisson models) states that the variance of the observed counts conditional on the underlying rate is equal to the underlying rate (the mean and variance of a Poisson distribution are always exactly the same). This allows the other estimates in this generalized linear model to take account of the Poisson stochastic nature of the underlying counts. In practice in this two-level model there is exactly the same set of units – the cells – at level 1 and level 2; that is, each level 2 unit has exactly one level 1 unit. This views the aggregated counts at level 2 as consisting of replicated responses for individuals at level 1. This use of a pseudo-level is explained in Browne et al. (2005) in relation to the binomial model and allows the separation of the variance into exact Poisson at level 1 and over-dispersion at level 2 so that the higher-level variance summarizes the 'true' differences between cells over and above those expected from a random variation due to the absolute size of the count. The estimated u_j are shrunken or precision-weighted estimates (Jones and Bullen, 1994) – on the log scale they will be shrunk back to zero when they are unreliable; equivalently when exponentiated they will be shrunk back to the value of 1 of no effect. Reliability will be at a maximum when there are 'true' sizeable differences between cells and when the count is large enough to give a precise estimate of the log rate in any particular cell.

The hybrid model used subsequently in the paper to analyse the changing vote has the same basic structure but there are many more cells (768) to reflect we have different types of people at three elections. The fixed part of the model is also extended to include m main effects and interactions (β_k) associated with a set of dummy variables (x_{ij}) indicating cell membership in terms of the observed variables of Vote, Year, Age, Qualifications and Sex.

$$Log_e(\pi_{ij}) = Log_e(E_{ij}) + \beta_0 + \sum_{k=1}^{m} \beta_k x_{ij} + u_j$$

The level 2 variance (σ_u^2) now summarises the between cell differences that remain after taking account of the underlying patterns that have been extracted through the fixed terms.

All the models were estimated in MLwiN software as Fully Bayesian models by using MCMC procedures, this allows the degree of support for the estimate, in the form of credible intervals to be obtained (Browne, 2012; Jones and Subramanian, 2014). As is common with Poisson models a long run of the MCMC simulation was used with 0.5 million monitoring runs after 5000 discarded burn-in iterations with default priors following an initial quasi-likelihood estimation. We checked that the burn-in was sufficient to achieve convergence to the equilibrium using a range of diagnostics and also examined via diagnostics the reasonableness of the between cell Normality assumption and this was met in all the analyses.

Table 1.
Multinomial logistic regression of party choice against sex, age and qualifications at the 2015 British General Election (regression coefficients, with those significant at the 0.05 level or better shown in bold)

	Labour	LibDem	Green	UKIP	DNV
Intercept	**-0.63**	**-1.16**	**-3.05**	**-1.90**	**-3.02**
Sex (comparator: Female)					
Male	**-0.10**	**0.10**	**-0.14**	**0.23**	**-0.20**
Age group (comparator: 65<)					
18-25	**0.76**	**0.22**	**2.15**	**-0.23**	**2.21**
26-35	**0.68**	0.10	**1.50**	-0.07	**1.98**
36-45	**0.70**	0.08	**1.33**	**0.22**	**1.46**
46-66	**0.62**	0.11	**0.98**	**0.45**	**1.13**
56-65	**0.34**	-0.02	**0.58**	**0.30**	**0.73**
Qualifications (comparator: None)					
School leaving-age	**0.65**	**-0.60**	-0.29	**0.99**	**1.43**
Post school leaving age	**0.19**	**-0.74**	**-0.56**	**0.68**	**0.83**
Degree/Diploma	**0.08**	**-0.20**	-0.14	**0.29**	**0.34**
-2 log-likelihood					
Intercept only	4052.5				
Full model	1844.3				

Table 2.

Model comparisons for examining changing vote preferences

Block	Model	Terms in the fixed part	No. of Terms	Between cell Variance	CIs 2.5	CIs 97.5	DIC
1	1	Constant	1	0.38	0.33	0.42	5535.7
1	2	Vote	6	0.37	0.32	0.41	5525.6
1	3	Vote by Year	18	0.18	0.16	0.20	5510.6
2	1	Vote by Year + Vote by Sex	24	0.17	0.15	0.19	5458.4
2	2	Vote by Year + Vote by Sex + Sex by Year	26	0.17	0.15	0.19	5459.3
2	3	Vote by Year + Vote by Sex + Sex by Year + Vote by Sex by Year	36	0.17	0.15	0.20	5461.2
3	1	Vote by Year + Vote by Qual	36	0.11	0.10	0.13	5421.7
3	2	Vote by Year + Vote by Qual + Qual by Year	42	0.11	0.10	0.13	5423.1
3	3	Vote by Year + Vote by Qual + Qual by Year + Vote by Qual by Year	72	0.12	0.10	0.14	5429.1
4	1	Vote by Year + Vote by Age	24	0.18	0.15	0.20	5466.5
4	2	Vote by Year + Vote by Age + Age by Year	56	0.08	0.07	0.09	5434.2
4	3	Vote by Year + Vote by Age + Age by Year + Vote by Age by Year	96	0.08	0.07	0.10	5445.2
5	0	Vote by Year + Vote by Age + Age by Year	56	0.08	0.07	0.09	5434.2
5	1	Vote by Year + Vote by Age + Age by Year + Vote by Gender	62	0.07	0.06	0.08	5416.1
5	**2**	**Vote by Year + Vote by Age + Age by Year + Vote by Sex + Vote by Qual**	**80**	**0.01**	**0.01**	**0.01**	**5190.2**
5	3	Vote by Year + Vote by Age + Age by Year + Vote by SEx + Vote by Qual + Sex by Year	82	0.01	0.01	0.01	5190.6
5	4	Vote by Year + Vote by Age + Age by Year + Vote by Sex + Vote by Qual + Sex by Year + Vote by Sex by Year	92	0.01	0.01	0.01	5195.1
5	5	Vote by Year + Vote by Age + Age by Year + Vote by Gender + Vote by Qual + Qual by Year	86	0.01	0.01	0.01	5193.5
5	6	Vote by Year + Vote by Age + Age by Year + Vote by Gender + Vote by Qual + Qual by Year + Vote by Qual by Year	116	0.01	0.01	0.01	5199.8

The most parsimonious model is given in **Bold**.

Table 3.
Percentage of respondents to the 2015 BES saying that measures to protect the environment have gone not far enough (NF) or too far (TF), by sex, class and age.

Qualifications	None		School		Post-School		Degree	
	NF	TF	NF	TF	NF	TF	NF	TF
Male								
Age group								
18-25	38	50	38	30	58	13	66	11
26-35	61	11	34	27	46	17	49	14
36-45	37	15	36	18	40	21	50	13
46-55	31	26	38	19	41	20	52	17
56-65	42	24	36	24	38	24	46	20
66<	35	23	35	24	34	27	39	25
Female								
Age group								
18-25	42	8	48	18	59	11	63	7
26-35	51	18	41	16	50	12	57	5
36-45	52	20	41	14	40	16	57	8
46-55	40	21	42	13	45	12	48	10
56-65	37	18	35	16	44	15	58	12
66<	37	17	37	13	41	17	57	14

Table 4.
Percentage of respondents to the 2015 BES saying that saying that immigration is good (G) or bad (B) for the economy

Qualifications	None		School		Post-School		Degree	
	B	G	B	G	B	G	B	G
Male								
Age group								
18-25	25	56	12	20	16	47	7	44
26-35	22	10	21	39	21	37	10	50
36-45	28	26	34	19	27	32	12	45
46-55	48	10	39	22	25	34	18	43
56-65	49	17	36	24	27	34	15	44
66<	45	20	34	31	26	32	23	42
Female								
Age group								
18-25	38	10	27	22	18	32	12	41
26-35	49	10	42	14	27	26	13	44
36-45	60	12	44	21	31	23	18	40
46-55	64	4	46	17	33	24	20	34
56-65	45	10	42	18	33	23	17	42
66<	53	19	39	21	31	30	17	43

Figure 1. Ratios of observed:expected numbers voting Conservative by Sex, Age and Qualifications in 2005, 2010 and 2015. Ratios significantly larger than 1.0 are shown in bold and underlined; ratios significantly smaller than 1.0 are shown in italics and underlined. (The four qualification levels are: 1. None; 2. No more than school-leaving age; 3. Post school-leaving age; 4. Degree.)

		2005				2010				2015			
M	Qual.	1	2	3	4	1	2	3	4	1	2	3	4
Age	18-25									0.89	0.63	0.90	0.88
	26-35	0.80	*0.66*	*0.67*	0.92	0.99	0.82	0.84	1.03	0.74	0.91	0.98	**1.19**
	36-45	0.70	0.93	1.04	0.96	0.86	1.06	1.00	1.00	0.63	1.04	1.07	1.07
	46-55	0.89	1.05	1.12	1.06	0.86	0.93	1.06	1.07	*0.61*	0.88	1.07	1.08
	56-65	0.96	**1.13**	**1.23**	1.09	0.95	1.02	1.05	1.09	0.82	1.02	**1.12**	**1.16**
	66<	1.19	**1.49**	**1.50**	**2.40**	**1.19**	**1.32**	**1.37**	**1.28**	1.08	**1.18**	**1.56**	**1.28**
		2005				2010				2015			
F	Qual.	1	2	3	4	1	2	3	4	1	2	3	4
Age	18-25									0.62	*0.46*	*0.70*	*0.80*
	26-35	0.73	0.68	*0.66*	*0.58*	0.85	0.85	*0.71*	*0.70*	*0.56*	0.79	*0.76*	0.87
	36-45	*0.60*	0.70	*0.73*	*0.74*	0.65	*0.83*	*0.78*	*0.75*	0.50	1.00	0.94	*0.85*
	46-55	1.00	0.92	0.91	0.89	0.88	0.96	0.91	0.90	0.85	1.04	1.03	1.05
	56-65	0.87	**1.32**	**1.22**	0.99	0.83	1.23	1.11	1.00	0.85	1.28	1.34	1.18
	66<	**1.28**	**1.61**	**1.54**	**1.23**	**1.32**	**1.18**	**1.43**	1.05	1.30	1.64	1.56	1.28

Figure 2. Ratios of observed:expected numbers voting Labour by Sex, Age and Qualifications in 2005, 2010 and 2015. Ratios significantly larger than 1.0 are shown in b old and underlined; ratios significantly smaller than 1.0 are shown in italics and underlined. (The four qualification levels are: 1. None; 2. No more than school-leaving age; 3. Post school-leaving age; 4. Degree.)

		2005				2010				2015			
M	Qual.	1	2	3	4	1	2	3	4	1	2	3	4
Age	18-25									1.18	0.99	1.03	1.09
	26-35	0.99	1.09	1.22	0.88	0.79	0.98	1.08	1.03	0.77	1.10	1.20	1.01
	36-45	1.13	**1.32**	1.02	1.05	1.19	1.07	0.91	1.09	1.48	1.01	1.10	1.06
	46-55	1.00	**1.22**	1.02	1.10	1.18	1.18	1.09	**1.20**	1.15	**1.15**	1.06	**1.14**
	56-65	**1.27**	1.11	0.94	1.03	**1.24**	1.05	0.95	1.14	1.07	0.99	1.00	1.02
	66<	**1.22**	0.98	0.81	*0.77*	**1.27**	1.18	0.76	0.94	0.98	0.89	*0.72*	*0.81*
		2005				2010				2015			
F	Qual.	1	2	3	4	1	2	3	4	1	2	3	4
Age	18-25									1.27	1.10	**1.34**	**1.31**
	26-35	0.71	0.80	0.93	0.89	1.06	1.05	1.06	1.03	1.27	1.10	**1.28**	**1.30**
	36-45	1.27	**1.31**	**1.26**	1.07	1.20	**1.20**	1.22	1.09	0.80	**1.21**	**1.25**	**1.40**
	46-55	1.05	**1.30**	**1.28**	**1.11**	1.29	**1.18**	**1.17**	**1.20**	**1.30**	**1.15**	**1.19**	**1.24**
	56-65	**1.31**	1.00	0.98	1.11	**1.28**	1.01	0.85	1.14	1.14	0.92	0.98	**1.15**
	66<	**1.32**	0.91	0.86	0.92	1.16	0.88	0.82	0.94	1.09	*0.72*	0.82	0.94

Figure 3. Ratios of observed:expected numbers voting Liberal Democrat by Sex, Age and Qualifications in 2005, 2010 and 2015. Ratios significantly larger than 1.0 are shown in b old and underlined; ratios significantly smaller than 1.0 are shown in italics and underlined. (The four qualification levels are: 1. None; 2. No more than school-leaving age; 3. Post school-leaving age; 4. Degree.)

		2005				2010				2015			
M	Qual.	1	2	3	4	1	2	3	4	1	2	3	4
Age	18-25									0.84	0.59	1.31	**1.66**
	26-35	0.75	0.74	0.89	1.20	0.95	0.93	0.93	**1.21**	0.96	*0.52*	1.08	**1.37**
	36-45	0.75	*0.48*	0.90	1.16	0.76	*0.71*	1.09	**1.27**	0.77	*0.44*	0.91	**1.80**
	46-55	0.69	*0.73*	**1.29**	**1.20**	*0.61*	*0.78*	1.07	**1.18**	*0.49*	*0.71*	1.27	**1.66**
	56-65	*0.68*	0.85	1.23	1.39	*0.75*	0.89	**1.22**	1.16	*0.56*	*0.70*	1.19	1.37
	66<	0.68	0.91	1.04	1.48	0.63	*0.82*	0.94	**1.18**	0.89	*0.71*	0.95	**1.63**
		2005				2010				2015			
F	Qual.	1	2	3	4	1	2	3	4	1	2	3	4
Age	18-25									1.04	*0.49*	0.77	1.14
	26-35	0.70	*0.57*	0.84	**1.57**	0.83	*0.59*	1.01	**1.50**	0.82	0.64	0.93	**1.47**
	36-45	0.66	*0.55*	0.87	**1.40**	0.66	*0.72*	1.08	**1.40**	0.95	*0.65*	0.67	**1.43**
	46-55	0.67	*0.71*	1.20	1.16	0.65	0.91	**1.22**	**1.26**	0.52	*0.63*	1.14	1.13
	56-65	0.73	0.92	1.15	1.47	0.77	*0.81*	1.15	1.29	0.67	0.82	1.21	1.37
	66<	*0.53*	0.81	1.09	**1.53**	*0.67*	*0.74*	1.02	1.24	*0.53*	1.01	1.31	**1.80**

Figure 4. Ratios of observed:expected numbers voting Green by Sex, Age and Qualifications in 2015. Ratios significantly larger than 1.0 are shown in b old and underlined; ratios significantly smaller than 1.0 are shown in italics and underlined. (The four qualification levels are: 1. None; 2. No more than school-leaving age; 3. Post school-leaving age; 4. Degree.)

		2005				2010				2015			
M	Qual.	1	2	3	4	1	2	3	4	1	2	3	4
Age	18-25									0.88	1.15	**2.55**	**2.11**
	26-35									0.92	0.94	0.76	**1.70**
	36-45									0.87	0.74	1.04	**1.61**
	46-55									0.65	*0.52*	0.84	1.09
	56-65									*0.51*	*0.49*	0.93	1.10
	66<									*0.53*	*0.36*	*0.54*	*0.51*
		2005				2010				2015			
F	Qual.	1	2	3	4	1	2	3	4	1	2	3	4
Age	18-25									0.97	1.35	**2.67**	**2.80**
	26-35									0.81	0.73	**1.46**	**1.88**
	36-45									0.88	*0.58*	**1.48**	**1.64**
	46-55									0.89	*0.58*	0.79	**1.38**
	56-65									0.68	*0.53*	0.69	1.26
	66<									*0.53*	*0.55*	*0.46*	0.99

Figure 5. Ratios of observed:expected numbers voting UKIP by Sex, Age and Qualifications in 2005, 2010 and 2015. Ratios significantly larger than 1.0 are shown in b old and underlined; ratios significantly smaller than 1.0 are shown in italics and underlined. (The four qualification levels are: 1. None; 2. No more than school-leaving age; 3. Post school-leaving age; 4. Degree.)

		2005				2010				2015			
M	Qual.	1	2	3	4	1	2	3	4	1	2	3	4
Age	18-25									0.91	1.10	<u>*0.63*</u>	<u>*0.58*</u>
	26-35	1.24	1.01	0.99	0.68	1.13	0.84	0.72	<u>*0.54*</u>	1.34	0.96	0.73	<u>*0.48*</u>
	36-45	0.89	0.83	0.71	0.65	0.96	1.31	1.00	0.78	0.95	<u>**1.63**</u>	1.03	<u>*0.68*</u>
	46-55	1.43	<u>**1.67**</u>	0.81	1.02	1.43	<u>**1.69**</u>	1.11	0.96	<u>**2.23**</u>	<u>**1.91**</u>	1.26	1.06
	56-65	<u>**1.87**</u>	<u>**2.05**</u>	0.72	1.15	<u>**1.58**</u>	<u>**1.81**</u>	1.08	1.06	<u>**2.14**</u>	<u>**2.05**</u>	1.24	1.14
	66<	<u>**1.78**</u>	<u>**2.08**</u>	1.62	1.26	<u>**1.59**</u>	<u>**1.55**</u>	<u>**1.56**</u>	<u>**1.55**</u>	<u>**1.89**</u>	<u>**1.60**</u>	<u>**1.40**</u>	<u>**1.22**</u>
		2005				2010				2015			
F	Qual.	1	2	3	4	1	2	3	4	1	2	3	4
Age	18-25									0.79	0.75	<u>*0.39*</u>	<u>*0.30*</u>
	26-35	0.89	0.90	0.69	<u>*0.54*</u>	0.90	0.98	0.85	<u>*0.57*</u>	1.16	0.80	<u>*0.69*</u>	<u>*0.35*</u>
	36-45	0.85	0.87	0.66	<u>*0.57*</u>	0.87	0.77	0.77	<u>*0.56*</u>	1.48	1.17	0.91	<u>*0.51*</u>
	46-55	0.88	1.04	0.64	0.79	1.04	0.86	0.62	<u>*0.59*</u>	0.77	<u>**1.46**</u>	1.03	<u>*0.69*</u>
	56-65	1.22	1.29	0.83	<u>*0.51*</u>	1.29	<u>**1.32**</u>	0.82	<u>*0.56*</u>	<u>**1.67**</u>	<u>**1.49**</u>	0.90	<u>*0.69*</u>
	66<	1.13	1.04	1.23	0.69	1.02	1.21	1.01	0.72	<u>**1.57**</u>	1.21	0.99	0.84

Figure 6. Ratios of observed:expected numbers Not Voting by Sex, Age and Qualifications in 2005, 2010 and 2015. Ratios significantly larger than 1.0 are shown in b old and underlined; ratios significantly smaller than 1.0 are shown in italics and underlined. (The four qualification levels are: 1. None; 2. No more than school-leaving age; 3. Post school-leaving age; 4. Degree.)

		2005				2010				2015			
M	Qual.	1	2	3	4	1	2	3	4	1	2	3	4
Age	18-25									1.39	**2.96**	1.31	1.18
	26-35	1.60	**2.24**	**1.72**	**1.67**	1.37	**2.20**	**1.97**	1.22	**2.04**	**2.30**	**1.61**	1.05
	36-45	1.65	**1.53**	**1.45**	**1.21**	1.43	**1.47**	1.31	0.86	**1.61**	**1.49**	1.2	0.90
	46-55	**1.60**	1.10	0.89	*0.78*	**1.74**	**1.35**	0.80	*0.60*	**1.67**	1.11	0.97	*0.55*
	56-65	1.10	0.87	0.84	*0.68*	1.22	1.09	0.85	*0.67*	**1.40**	0.96	*0.66*	*0.61*
	66<	0.75	*0.52*	0.59	*0.52*	0.70	*0.55*	*0.52*	*0.48*	0.78	*0.62*	0.62	*0.57*
		2005				2010				2015			
F	Qual.	1	2	3	4	1	2	3	4	1	2	3	4
Age	18-25									1.80	**4.13**	**1.91**	**1.34**
	26-35	2.73	3.10	2.48	**1.96**	**1.69**	**2.60**	**2.21**	**1.41**	**2.10**	**3.16**	**1.96**	**1.31**
	36-45	2.15	2.00	1.50	**1.30**	**2.57**	**2.28**	1.32	1.20	**2.40**	**1.56**	1.34	0.94
	46-55	1.53	1.25	0.84	*0.79*	**1.73**	**1.44**	0.90	077	**1.91**	1.19	1.03	0.93
	56-65	1.26	*0.81*	0.81	*0.71*	**1.47**	0.89	1.03	*0.53*	**1.46**	0.92	0.84	*0.65*
	66<	0.72	*0.56*	*0.39*	*0.57*	0.71	*0.59*	*0.48*	0.60	*0.52*	*0.49*	0.91	*0.52*

Figure 7. The relationship between Age and voting for each political party and abstaining, with Sex and Qualifications held constant at their average values, across the three elections 2005-2015

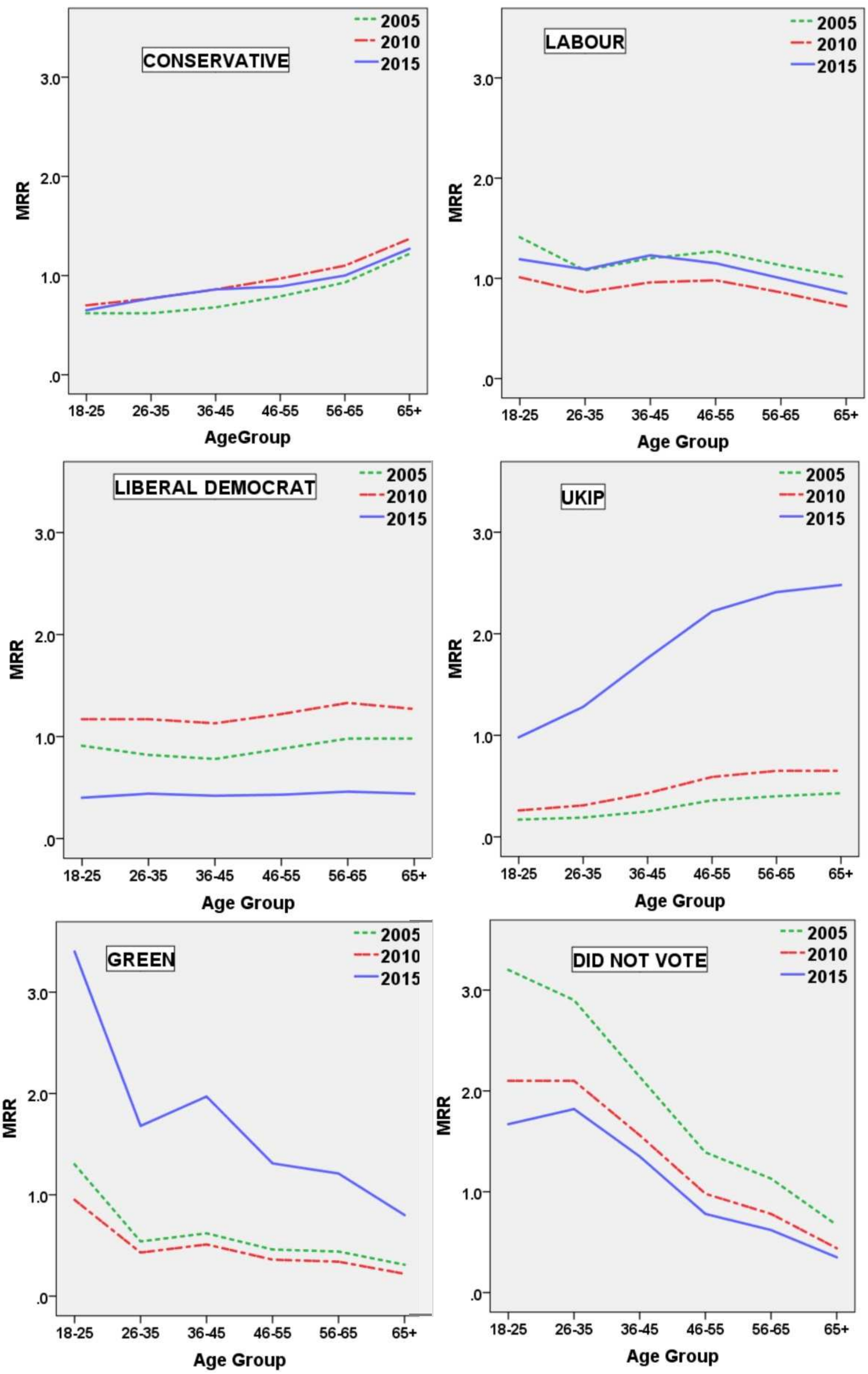

Figure 8. Ratios of observed:expected numbers saying that Policies to Protect the Environment Have Gone Not Far Enough and Have Gone Too Far, and Voting Green in 2015, by Age, Sex and Qualifications. Ratios significantly larger than 1.0 are shown in b old and underlined; ratios significantly smaller than 1.0 are shown in italics and underlined. (The four qualification levels are: 1. None; 2. No more than school-leaving age; 3. Post school-leaving age; 4. Degree.)

		Not Far				Too Far				Vote 2015			
M	Qual.	1	2	3	4	1	2	3	4	1	2	3	4
Age	18-25	0.97	1.00	**2.03**	**1.97**	1.14	1.10	0.95	0.77	0.88	1.15	**2.55**	**2.11**
	26-35	1.09	0.83	0.89	**1.54**	1.14	1.11	0.90	0.75	0.92	0.94	0.76	**1.70**
	36-45	0.81	0.84	1.23	**1.63**	1.10	1.39	1.02	1.15	0.87	0.74	1.04	**1.61**
	46-55	1.05	*0.76*	0.84	**1.23**	1.78	1.51	1.03	1.20	0.65	*0.52*	0.84	1.09
	56-65	0.83	*0.66*	0.97	**1.29**	1.93	1.76	1.53	1.44	*0.51*	*0.49*	0.93	1.10
	66<	*0.56*	*0.62*	*0.79*	**1.91**	1.74	1.44	1.73	1.70	*0.53*	*0.36*	*0.54*	*0.51*
		Not Far				Too Far				Vote 2015			
F	Qual.	1	2	3	4	1	2	3	4	1	2	3	4
Age	18-25	1.01	0.89	**1.39**	**1.61**	0.91	0.79	*0.42*	*0.46*	0.97	1.35	**2.67**	**2.80**
	26-35	0.97	*0.75*	0.89	**1.55**	1.05	0.87	0.66	*0.41*	0.81	0.73	**1.46**	**1.88**
	36-45	0.93	*0.53*	1.05	**1.38**	1.11	0.71	0.76	*0.51*	0.88	*0.58*	**1.48**	**1.64**
	46-55	0.64	*0.72*	0.81	**1.51**	1.35	0.85	0.73	*0.65*	0.89	*0.58*	0.79	**1.38**
	56-65	*0.92*	*0.67*	0.93	**1.22**	0.97	1.04	0.82	*0.67*	0.68	*0.53*	0.69	1.26
	66<	*0.68*	*0.66*	0.84	1.25	1.04	1.11	0.85	0.99	*0.53*	*0.55*	*0.46*	0.99

Figure 9. Ratios of observed:expected numbers saying that Immigration is Bad and is Good for the Economy, and Voting for UKIP in 2015, by Age, Sex and Qualifications. Ratios significantly larger than 1.0 are shown in b old and underlined; ratios significantly smaller than 1.0 are shown in italics and underlined. (The four qualification levels are: 1. None; 2. No more than school-leaving age; 3. Post school-leaving age; 4. Degree.)

		Bad				Good				Vote			
M	Qual.	1	2	3	4	1	2	3	4	1	2	3	4
Age	18-25	1.14	0.74	*0.43*	*0.35*	1.03	0.87	**2.45**	**2.73**	0.91	1.10	0.63	*0.58*
	26-35	1.19	1.19	*0.65*	*0.31*	1.54	0.85	**1.49**	**2.09**	1.34	0.96	0.73	*0.48*
	36-45	1.14	**2.34**	0.92	*0.55*	1.40	*0.70*	1.07	**1.61**	0.95	**1.63**	1.03	*0.68*
	46-55	**2.11**	**1.55**	0.82	*0.66*	1.05	*0.65*	0.69	**1.48**	**2.23**	**1.91**	1.26	1.06
	56-65	**2.31**	**1.62**	0.88	*0.73*	*0.73*	*0.60*	0.93	**1.33**	**2.14**	**2.05**	**1.24**	1.14
	66<	**1.98**	**1.43**	0.91	0.88	*0.75*	*0.57*	*0.61*	**1.13**	**1.89**	**1.60**	**1.40**	**1.22**
		Bad				Good				Vote			
F	Qual.	1	2	3	4	1	2	3	4	1	2	3	4
Age	18-25	1.16	1.02	*0.48*	*0.36*	0.84	1.11	**1.29**	**2.06**	0.79	0.75	*0.39*	*0.30*
	26-35	2.13	1.66	0.92	*0.50*	0.92	0.68	0.73	**1.79**	1.16	0.80	*0.69*	*0.35*
	36-45	**1.62**	**2.10**	**1.53**	*0.57*	0.77	0.54	1.03	**1.44**	1.48	1.17	0.91	*0.51*
	46-55	**2.06**	**1.34**	1.17	*0.70*	*0.76*	*0.31*	0.86	**1.22**	0.77	**1.46**	1.03	*0.69*
	56-65	**2.69**	**1.78**	0.99	*0.71*	*0.46*	*0.40*	*0.68*	**1.16**	**1.67**	**1.49**	0.90	*0.69*
	66<	**2.35**	**1.65**	0.97	*0.63*	*0.40*	*0.54*	*0.52*	**1.32**	**1.57**	1.21	0.99	0.84

Figure 10. Ratios of observed:expected numbers saying that Immigration Undermines (Bad) and Enriches (Good) Society, and Voting for UKIP in 2015, by Age, Sex and Qualifications. Ratios significantly larger than 1.0 are shown in b old and underlined; ratios significantly smaller than 1.0 are shown in italics and underlined. (The four qualification levels are: 1. None; 2. No more than school-leaving age; 3. Post school-leaving age; 4. Degree.)

		Bad				Good				Vote			
M	Qual.	1	2	3	4	1	2	3	4	1	2	3	4
Age	18-25	1.03	0.90	*0.46*	*0.49*	0.99	0.95	**1.74**	**2.01**	0.91	1.10	*0.63*	*0.58*
	26-35	1.35	1.17	*0.69*	*0.44*	1.31	0.78	1.21	**1.81**	1.34	0.96	0.73	*0.48*
	36-45	1.03	1.49	0.91	*0.58*	1.00	0.74	0.96	**1.63**	0.95	1.63	1.03	*0.68*
	46-55	**1.66**	**1.46**	0.95	0.85	0.91	*0.67*	0.80	1.14	**2.23**	**1.91**	1.26	1.06
	56-65	**1.92**	**1.71**	1.07	0.91	*0.59*	*0.56*	0.77	**1.22**	**2.14**	**2.05**	**1.24**	1.14
	66<	**1.89**	**1.63**	1.15	**1.15**	*0.57*	*0.57*	0.82	0.87	**1.89**	**1.60**	**1.40**	**1.22**
		Bad				Good				Vote			
F	Qual.	1	2	3	4	1	2	3	4	1	2	3	4
Age	18-25	1.11	0.78	*0.39*	*0.33*	0.94	1.36	**2.25**	**2.04**	0.79	0.75	*0.39*	*0.30*
	26-35	**1.61**	1.15	0.81	*0.48*	0.94	0.70	0.90	**1.80**	1.16	0.80	*0.69*	*0.35*
	36-45	1.32	**1.63**	1.00	*0.53*	0.90	*0.59*	0.99	**1.69**	1.48	1.17	0.91	*0.51*
	46-55	**1.59**	**1.58**	1.02	*0.67*	0.75	*0.48*	0.94	**1.54**	0.77	**1.46**	1.03	*0.69*
	56-65	**2.15**	**1.68**	1.02	*0.75*	0.52	0.44	0.87	1.18	**1.67**	**1.49**	0.90	*0.69*
	66<	**2.13**	**1.49**	1.16	*0.70*	0.43	0.58	0.65	**1.57**	**1.57**	1.21	0.99	0.84

Figure 11. Histogram showing the number of observations in each cell of the Age by Sex by Qualifications by Voting (6 x 2 x 4 x 6) matrix