‘Nationally Poor, Locally Rich’ in the British Context: An Investigation of the Income and Vote in the 2019 British General Election

Abstract

In this paper, I investigate the relationship between income and support for the Conservative party in the 2019 British general election. I consider both the effect of income and the effect of a voter’s position in their local income distribution. Using logistic regression, I find that higher incomes are negatively associated with supporting the Conservatives, but a higher position in the local income distribution is positively associated with voting Conservative. These relationships are reconciled by the Conservatives’ disproportionate support in poorer areas. Thus, 2019 Conservative voters are ‘nationally poor, locally rich’.

1 Introduction

On June 23rd 2016, the UK voted to exit the European Union, against popular and elite expectations. This result was described by many as a working-class revolt against the preferences of economic and cultural elites (Goodwin and Heath 2016; Hobolt 2016). Just over three years later, Boris Johnson, one of the Conservative politicians most associated with Brexit, won the Conservative party a majority in the 2019 election. Again, this victory was in part attributed to Johnson winning support from working-class voters who had supported Brexit (Cutts et al. 2020). For Britain, this represented an enormous shift in the relationship between class and vote. Historically, there was a strong association between the working-class and the Labour party (Evans and Tilley 2017).

The ostensible 'revolt' was not limited to Britain. Across Europe and North America, the right-wing populism's growth was attributed to economic insecurity among the working-class. However, more recent studies have questioned the link between economic precarity and support for the populist right. Liberini et al. (2019) find Brexit supporters *felt* more financially insecure than average but the effect of objective financial indicators was weak. Outside the UK, Green and McElwee (2019) find a weak relationship between income and support for Trump among white voters. Thus, the relationship between income and support for right-populists remains contested.

In this paper, I investigate the relationship between income and support for the Conservative Party in the 2019 UK general election. Following Ogorzalek, Piston, and Puig's (henceforth OPP) results in the US, I model vote as a function of income *and* position in the local income distribution using logistic regression. Combining data from the Office for National Statistics and the British Election Study, I find that while 2019 Conservative voters were relatively poor in the national context, they were wealthy for their local areas. This finding suggests the relationship between income and vote is more complex than prior work acknowledges and emphasizes the crucial mediating role of local economic circumstances.

1.1 Theoretical Connections Between Income and Vote

Political scientists have long theorized connections between an economic circumstances and ideology. The traditional argument connecting income and vote choice assumes people vote in their economic self-interest. In particular, poorer people will vote for high taxes on the wealthy to facilitate redistribution, while wealthier people will support low taxes to keep more of their earnings. Thus, voters identify their place in the income distribution, decide whether they are going to benefit from redistribution, and vote accordingly (Meltzer and Richards 1981).

In a novel contribution, OPP argue this process is mediated by local economic circumstances. First, the cost-of-living varies across areas. Making the median salary in a large urban area with high housing costs results in less disposable income than in a rural area where housing is cheaper. Thus, a given salary's meaning varies across place. Second, people use their local circumstances to estimate national economic variables. Xu and Garand (2010) find Americans perceptions of national inequality are associated with their state's inequality level, and Minkoff and Lyons (2019) replicate this at the neighbourhood level. Thus, people may estimate their place in the national income distribution by observing their local income position. Because of these two factors, someone's place in their local income distribution may affect their politics.

OPP apply this framework to the 2016 US presidential election. They regress whether someone voted for Trump on their total income *and* their income decile for their local area. The authors find higher income is negatively associated with supporting Trump but higher local income decile is positively associated with supporting Trump. This may seem paradoxical. However, because Trump received more support in poorer areas, these two effects are reconciled. OPP thus conclude Trump voters were 'nationally poor, locally rich'.

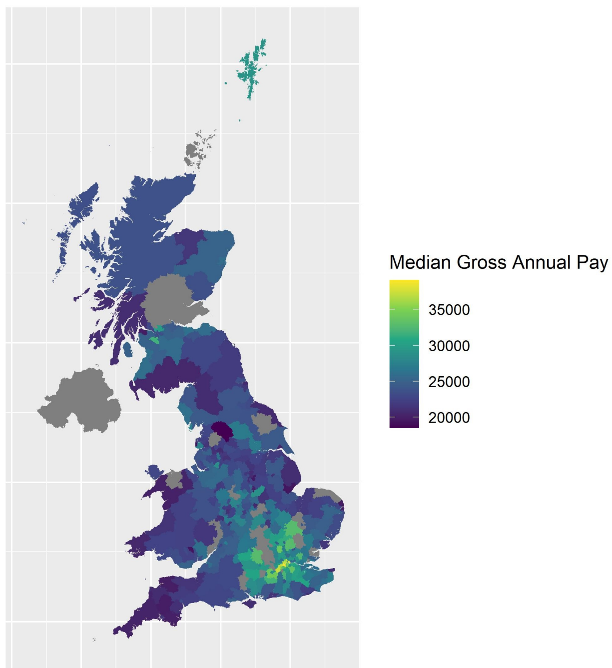
1.2 The British Case

I apply this framework to the 2019 British election. This provides a nice extension to OPP's work:

As with Trump, the Conservative Party in 2019 adopted a right-wing populist position (Evans, de Geus, and Green 2021). Thus, using the UK, we can test if OPP's findings apply cross-nationally.

Additionally, the UK has large geographic variation in income. Figure 1 shows median gross annual pay by UK local authority. Pay is highest in London and the Southeast and lower elsewhere. Median pay in the best paid local authority was more than £15,000 greater than median pay in the worst paid local authority. Thus, a voter's place in the national income distribution might differ significantly from their place in their local income distribution.

Figure 1: Median 2019 Gross Annual Pay by UK Local Authority



Data source: Office for National Statistics
Grey indicates that insufficient data was availible to estimate median annual pay.
No data was availible for Northern Ireland.

Finally, cost-of-living varies across the country; consider rents as a proxy for living costs. Figure 2 shows the median monthly rent for one bedroom apartments across English local authorities. This varies widely, from over £2,000 in inner London to less than £500 in parts of the North; this means the same salary gives different disposable incomes in different areas. Moreover, because of differences in living costs, income thresholds for some government programs vary by area. Therefore, the economic meaning of a given salary varies by place.

As OPP's work indicates, these conditions mean local income position may influence voting. I investigate how voters' positions in their local and the national income distributions affected vote choice in the 2019 UK general election. Given OPP's findings in the US, I test the following two hypotheses:

Hypothesis 1: Holding someone's position in their local income distribution constant, higher income is associated with a lower probability of supporting the Conservative Party.

Hypothesis 2: Holding income constant, being higher in the local income distribution is associated with a higher probability of supporting the Conservative Party.

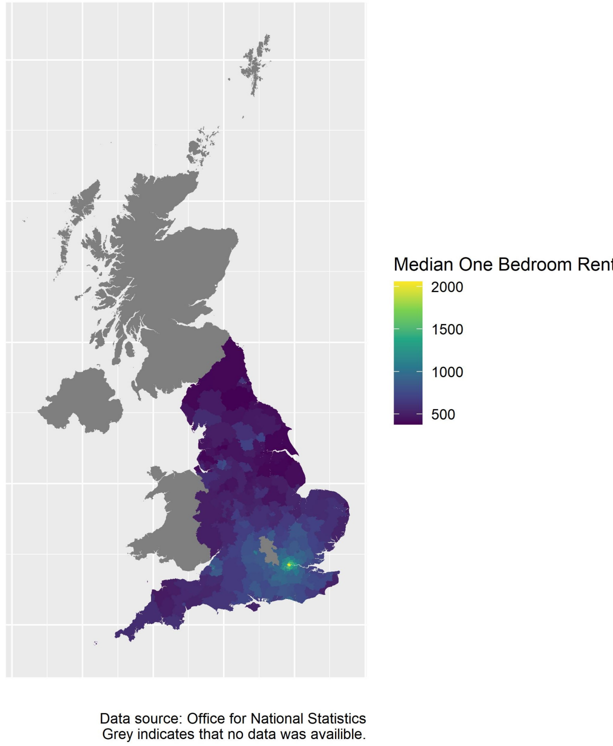
2 Methods

2.1 Data

I combine two datasets:

First, I use data from Wave 19 of the British Election Study's Internet Panel (2019). This data was collected via an internet survey following the 2019 election and contains data on 32,177 British adults. This is a non-representative sample, but the data includes weights which I use to correct for non-representativeness.

Figure 2: Median 2021 Monthly Rent for a One Bedroom Flat by Local Authority in England



The dataset contains each respondent's reported electoral behaviour, demographic information, policy preferences/ideology, and place of residence.

Second, I have data about local authorities from the Office for National Statistics. Local authorities are administrative units for local government in the UK. On average, they contain around 150,000 people. The dataset I use is from the 2019 Annual Survey for Hours and Earnings and gives 2019 annual earnings deciles for all local authorities in England, Scotland, and Wales (Office for National Statistics 2020). For example, the first decile (10^{th} percentile) in Darlington is £8,426; this means approximately 10% of workers in Darlington earned less than £8,426 in 2019. This data comes with several caveats. First, it lacks estimates for some deciles in some areas because of small sample sizes. Second, it only includes labour market earnings, so does not include investment or pension income. Third, these are estimates calculated from a representative sample, so each estimate is somewhat uncertain. Nonetheless, over the entire sample, these uncertainties should average out without affecting results.

I merge these datasets by local authority. My final dataset has each individual's survey responses and their local authority's income deciles.

2.2 Variables

My dependent variable is whether the respondent voted for the Conservative party in 2019. All respondents who reported voting for the Conservatives were coded as 1; everyone who voted for a different party was coded as 0. Like OPP and others in the field (Grynberg, Walter, and Wasserfallen 2020; Cutts, Goodwin, and Milazzo 2017), I drop non-voters.

I have two independent variables of interest. First, to measure personal income, I use the question 'Gross PERSONAL income is an individual's total income received from all sources, including wages, salaries, or rents and before tax deductions. What is your gross personal income?'. Respondents have 14 response options: under £5,000; £5,000 to £9,999; £10,000 to £14,999; £15,000 to £19,999; £20,000 to £24,999; £25,000 to £29,999; £30,000 to £34,999; £35,000 to £39,999; £40,000 to £44,999; £45,000 to £49,999; £50,000 to £59,999; £60,000 to £69,999; £70,000 to £99,999; and £100000 and over. Following OPP, I

Table 1: Descriptive Statistics for Independent and Dependent Variables

Variable	N	Wt. Mean	Wt. SD	Min	Pctl. 25	Median	Pctl. 75	Max
conservative	7073	0.361	0.48	0	0	0	1	1
income (£1000)	7073	23.02	10.83	2.5	1.75	22.50	32.50	100
local_decile	7073	0.482	0.221	0.1	0.3	0.5	0.7	1
gender	7073	0.514	0.5	0	0	1	1	1
attended_university	7073	0.441	0.497	0	0	0	1	1
religion	7073	0.393	0.488	0	0	0	1	1
age	7073	43.753	12.875	18	37	48	58	84
owns_home	7073	0.611	0.488	0	0	1	1	1

estimate income as the *midpoint* of their income category. So, if an individual reports their personal income as £15,000 to £19,999, their income is estimated as £17,500; I rescale income to be measured in £1000s for coefficient interpretability. Because I am interested in labour income, I filter out non-employed people, excluding students, pensioners, and the unemployed.

My second independent variable of interest is someone's place in their local income distribution. Following OPP, I estimate this by comparing each respondent's estimated income to the earnings deciles for their local authority. So, respondents are placed in the first decile if their income is lower than the 10$^{\text{th}}$ percentile in their local authority; if their income is greater than the 10$^{\text{th}}$ percentile but lower than the 20$^{\text{th}}$ percentile, they are placed in the second decile, and so on. Because some deciles are missing for some areas, I cannot estimate a decile for certain respondents. This is particularly problematic for high income individuals: About 80% of respondents making less than £35,000 per year can be matched to a decile, but only 5% of those making more £60,000 per year can be matched. However, high earners comprise a small portion of the total data (only 5% of all respondents report an income greater than £60,000).

Following OPP and the broader literature, I control for demographic variables known to affect vote choice. OPP include: gender (female = 1, male = 0, no other options listed), education (university = 1, no university = 0), religion (1 = belongs to religion, 0 = no religion). Following prior studies of British electoral behaviour (Campbell and Shorrocks 2021), I also control for age and home ownership (1 = owns home). Unlike England, Scotland and Wales have nationalist parties, so I also include nation dummies (reference category = England).

Finally, I use the analysis weights provided by the survey. These weights correct for the deliberate oversampling of small population groups as well as correcting for non-response bias (the unweighted sample over-represents young, wealthy, and educated people).

Table 1. shows descriptive statistics for these variables, weighted by survey weights. For these statistics, I dropped missing observations listwise. The sample size (N = 7073) is substantially smaller than the original sample. Most lost observations were lost because the respondent was not employed or could not be matched to a decile. I check the descriptive statistics against population averages to check to representativeness of this sample. 36% of this sample voted for the Conservatives, less than their actual vote share of 43%. The sample's median personal income was approximately £23,000, about the same as median earnings in Great Britain (Office for National Statistics 2020). The local_decile variable has a 25$^{\text{th}}$ percentile of 0.3, a median of 0.5, and a 75$^{\text{th}}$ percentile of 0.7. If we had perfect data, we would expect equal numbers in each decile, giving a 25$^{\text{th}}$ percentile of 0.25, a median of 0.5, and a 75$^{\text{th}}$ percentile of 0.75. The distribution is close to this, suggesting the inability to match high-income individuals to deciles has not seriously biased the sample. 51.4% of the sample was female, which is close to the population proportion. 44% of the sample attended university, higher than in the population but roughly matching the proportion of degree-holders in the labour force (Office for National Statistics 2017). The sample is younger than the voting-aged population since retirees were dropped. The sample's proportion of home-owners is about the same as in the population as a whole (English Housing Survey 2020). Thus, overall this sample is younger, more educated, and less Conservative than the population at large. The sample better reflects the British *labour force*, which is younger and more educated than the population.

2.3 Modelling Strategy

Given the binary dependent variable, I use multivariate logistic regression to model the probability of voting Conservative as a function of the specified independent variables. I specify the following model:

$$\mathrm{P}(\text{conservative} = 1|\text{income}, \text{local\_decile}, x) = F(\beta_0 + \beta_1 * \text{income} + \beta_2 * \text{local\_decile} + \Gamma x'),$$

where F is the logistic function $F(x) = \frac{1}{1+e^{-x}}$, x is a vector of the controls, and Γ is a vector of coefficients for the controls. Using this model, we can restate the hypotheses mathematically:

$$\mathrm{H1} : \beta_1 < 0$$
$$\mathrm{H2} : \beta_2 > 0$$

This modelling strategy differs from OPP, who use probit regression. I use logistic regression instead because its coefficients are more interpretable. The choice of model rarely affects substantive conclusions (Gill 2001), so comparison to OPP should not be affected.

3 Results

3.1 Main Results

Table 2. shows the main results. Model 1 regresses Conservative vote only on personal income. Model 2 adds local income decile, and Model 3 adds the control variables. I estimated all models on the reduced dataset of 7,703 observations. Log-odds coefficient estimates are shown with standard errors in parentheses; significance is indicated by stars.

Table 2: Relationship between Voting Conservative and Income in 2019 General Election

	Dependent variable: Voted Conservative		
	(1)	(2)	(3)
Personal Income	−0.001 (0.002)	−0.030*** (0.006)	−0.016* (0.006)
Local Income Decile		1.517*** (0.289)	1.048*** (0.305)
Gender			−0.041 (0.054)
Attended University			−0.912*** (0.056)
Religious Observance			0.452*** (0.053)
Age			0.025*** (0.002)
Home Ownership			0.290*** (0.059)
Scotland			−1.171*** (0.109)
Wales			−0.476*** (0.131)
Constant	−0.543*** (0.058)	−0.615*** (0.060)	−1.664*** (0.151)
McFadden Pseudo R^2	0	0.003	0.094
Observations	7,073	7,073	7,073
Log Likelihood	−4,827.341	−4,812.132	−4,365.205
Akaike Inf. Crit.	9,658.682	9,630.264	8,750.411

Note: *p<0.05; **p<0.01; ***p<0.001
Entries are log-odds coefficients. Standard errors are shown in parentheses

In model 1, there is no significant relationship between income and vote choice. When I add local income decile in model 2, personal income is negatively associated with voting Conservative ($p < 0.001$). Local income decile is significantly and positively associated with Conservative support ($p < 0.001$). In model 3, I add the specified demographic controls. The coefficient on personal income remains negative and significant

($\hat{\beta}_1 < 0$, $p < 0.05$), and the coefficient on local income decile remains positive and significant ($\hat{\beta}_2 > 0$, $p < 0.001$),though coefficient magnitudes are slightly reduced.

Logistic coefficients give the relationship between independent variables and the log-odds of the dependent variable, making it difficult to interpret the substantive meaning of the coefficient magnitudes. Thus, I plot the predicted probability of voting Conservative against personal income and local income decile using model 3 (my preferred model specification).

Figure 3 shows the predicted probability of voting Conservative against personal income, holding all other variables at their means. Increasing income from £17,500 to £35,000 is associated with a 7 percentage-point decline in the predicted probability of Conservative vote.

Figure 3: Negative Association Between Personal Income and Probability of Voting Conservative Controlling for Local Income Decile, Gender, Education, Religion, Age, Home Ownership, and Nation

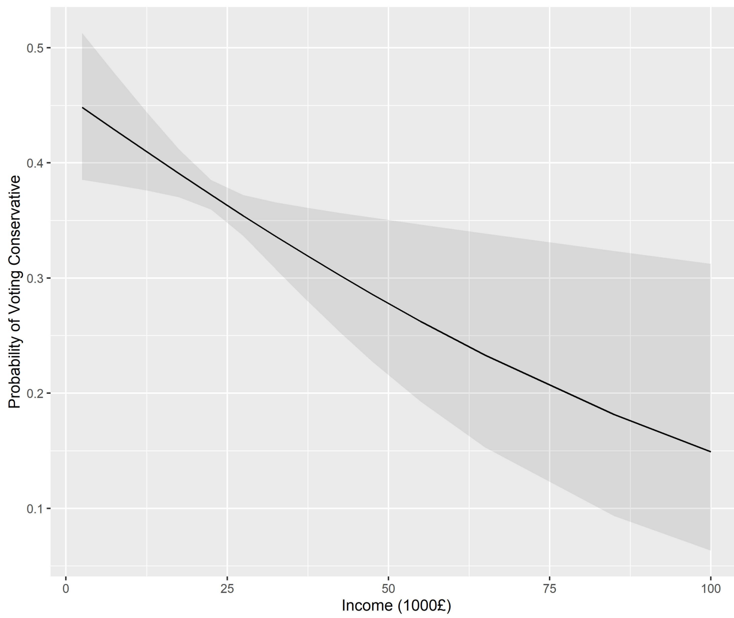


Figure 4 plots the predicted probability of supporting the Conservatives against local income decile, holding all other variables at their means. Moving from the 3^{rd} to 7^{th} local decile is associated with a 10 percentage-point increase in the predicted probability of voting Conservative.

3.2 Model Diagnostics

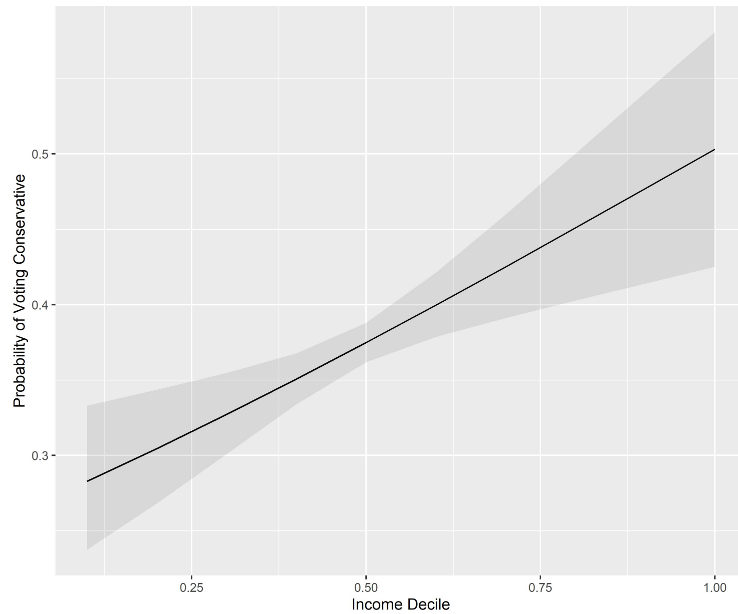
Logistic regression's validity depends on several assumptions. In this section, I test whether my model violates these assumptions.

3.2.1 Specification

Logistic regression assumes linearity between the independent variables and log-odds on the dependent variable. This condition is always met for categorical variables, but we need to test it for continuous variables. In model 3, there are three continuous variables: personal income, local income decile, and age. I plot the Pearson residuals against each of these, as suggested by Zhang (2016). These plots are show in appendix figure A1. There are no systematic relationships between the predictors and the residuals, supporting the linearity assumption. Appendix table A1 shows the results of a specification test suggested by Fox and Weisberg (2019). For each continuous variable X, a new model is estimated adding an X^2 term; the table shows t-tests for whether the coefficients are significant. Here, none are significant, providing further evidence for linearity.

Omitting important determinants of the dependent variable can also bias coefficient estimates. There is no simple test for omitted variables, but R^2 provides an indicator of whether we have included the major

Figure 4: Positive Association Between Local Income Decile and Probability of Voting Conservative Controlling for Personal Income, Gender, Education, Religion, Age, Home Ownership, and Nation



determinants of the dependent variable. Model 3's McFadden adjusted R^2 is 0.09. This is quite low, indicating important predictors of vote have been omitted. Thus, in the robustness section, I re-estimate the model including further controls.

3.2.2 Multicollinearity

Standard inference also requires we do not have strong multicollinearity between predictors. Multicollinearity inflates standard errors, reducing statistical power (Allen 1997). A standard test metric is the variance inflation factor (VIF), which gives how much the variance of each coefficient increases when the other predictors are included. A large VIF on coefficient β_k indicates high collinearity between variable k and the other variables. VIFs greater than 5 indicate the presence of multicollinearity, though 10 is sometimes used as a more liberal cutoff. Table A2 shows the VIF for each coefficient in model 3. The VIFs for personal income and local income decile are 6.63, indicating moderate collinearity between these variables. Thus, the standard errors on personal income and local income decile may be inflated. Since both coefficients are significant, this is unlikely to substantively affect inference.

3.2.3 Outliers, Leverage Points, and Influential Points

Menard (2002) suggests identifying logistic regression outliers by plotting standardized residuals. Residual magnitude greater than 2.5 indicates an outlier. Figure A2 shows the standardized Pearson residuals from model 3 with horizontal lines +2.5 and -2.5. The has multiple outlying observations.

However, observations with high discrepancy only bias coefficients if they have high leverage (Fox 1991). Leverage is measured using hat-values; a typical threshold for high leverage is two times the average value. Figure A3 shows the hat-values for model 3 with the red line showing $2 * \overline{hat - value}$. A substantial number of observations have high leverage.

Thus, there are possibly influential values biasing results. In my robustness checks section I check if this influences results.

3.2.4 Error Distribution

Unlike linear regression, logistic regression assumes a binomial error distribution, which is approximately normal in large samples (Menard 2002). Menard suggests checking for a normal error distribution but states non-normality does not substantially affect inference. To check normality, I plot a Q–Q plot of the Pearson residuals, shown in figure A4. If the residuals were normal, they would approximately follow the red line in the plot. The residuals appear to not follow a normal distribution, but as Menard argues this should not affect inference.

3.3 Robustness Checks

In this section, I test my results' fragility:

First, given the low R^2, I estimate a model with additional controls to check for omited variable bias. I add controls for self-identification with the Conservative party, whether the respondent voted Conservative in 2015, left-right ideological placement, support for redistribution, attention to politics, and trust in MPs. These variables are all plausible determinants of vote choice. However, I did not include them in my preferred specification because they are plausibly *caused* by income. For instance, I argued income may affect vote choice by altering redistribution preferences. Thus, including redistribution in the model may be inappropriate. Table A3 shows the results when these variables are included. Personal income and local income decile retain their prior signs and significance; both have *increased* coefficient magnitudes. The R^2 has also substantially improved to 0.47.

Second, I re-estimate the model, removing the possibly influential points identified in the previous section. Observations were considered influential if they had a standardized residual magnitude greater than 2.5 and a hat-value greater than 2 times the mean, in accordance with Fox's rule that influence = discrepancy$\times$leverage. 627 observations were removed. Table A4 shows the results. Personal income's sign is the same but it is no longer significant ($p = 0.13$). Local income decile remains significant and in the same direction.

Third, I consider whether the dependent variable is misspecified. OPP suggest their results apply to *populist* right parties. Perhaps instead the results apply to right-wing parties generally. To check this, I re-estimate my model with two different dependent variables. First, I use voting Conservative in 2015 as the dependent variable; at this point the Conservative Party did not support Brexit and the populist faction was less powerful. Second, I use voting for Brexit as the dependent variable. If the *populist* right thesis is correct, the results should hold for the Brexit vote but not the 2015 election. Table A5 shows the results. When Brexit vote is used as the dependent variable, both variables retain their signs and significance. When Conservative vote in 2015 is used as the dependent variable, neither is significant.

Fourth, I consider whether the inability to match many high-income respondents to a decile is driving results. I filter to only respondents who earned less than £40,0000 per year. This limits the population we can extrapolate to but mitigates the risk data quality issues are driving results. The results are shown in Table A6. The coefficients remain significant and retain their signs and approximate magnitudes.

Fifth, I consider whether it is appropriate to specify personal income and local income decile as continuous variables since they are collected as binned responses. Since my diagnostics did not detect non-linearities, this is unlikely to bias results but should still be considered. I instead treat each variable as categorical. The lowest income/decile is treated as the reference category. Table A7 shows the results. In the first model, only personal income is treated as categorical and local income decile remains continuous. In the second, only local income decile is treated as categorical as personal income remains continuous. In the third model, both are treated as categorical. In the first model, the signs on the categorical income variables are all negative, but rarely significant. In the second model, the coefficients on the categorical decile variables are almost all positive and significant. In the third model, the signs mostly remain the same, but the coefficients are rarely significant. These models' coefficients have high VIFs (VIF > 20), suggesting standard errors may be inflated. Thus, the signs remaining the same is perhaps a better indicator of robustness than significance.

Sixth, I consider whether I misspecified the model's functional form. I reestimate using a probit model. The results are shown in Table A8. The coefficients on personal income and local income decile remain significant and in the same direction.

Finally, I examine whether my observations are not independent due to clustering at the local authority level. Dependence between observations would compress standard errors, leading to erroneous rejection of the null. To correct, we would need to recalculate standard errors clusered at the local authority level.

Abadie et al. (2022) argue the mere presence of hierarchical data does not necessitate clustering standard errors. Instead, they argue clustering should be applied if observations are sampled from clusters or if the 'treatment' was assigned at the cluster level. Neither is the case here, but I nonetheless consider whether standard errors are compressed because of dependence. I correct for this possibility in two ways. First, I re-estimate model 3 with standard errors clustered at the local authority level. Second, I estimate a random intercept model, where the intercept is allowed to vary by local authority; in this model I remove the nation-level fixed effects since all local authorities are wholly in one nation. This method accounts for variance within the clusters, removing the need to cluster errors (Primo, Jacobsmeier, and Milyo 2007). Multilevel modelling is not entirely appropriate for this setting because local income decile is perfectly predicted by personal income and local authority. Thus, 'controlling' for variation between local authorities will reduce the variation explainable for local income decile, biasing the coefficient downwards. The results from these models are shown in table A9. When the clustered standard errors are used, personal income is no longer significant, but local decile retains its sign and significance. In the multi-level model, neither coefficient is significant, though local income decile is negative and significant at the 10% level.

Overall, the results are mostly robust to alternative specifications. Personal income is sometimes rendered insignificant, but the results for local income decile are relatively robust.

4 Discussion

My results support H1 and H2. In line with H1, the estimated coefficient on personal income was negative ($\hat{\beta}_1 < 0$) and significant; at $\alpha = 0.05$, we can reject the null hypothesis $\beta_1 = 0$. While this result was not robust to all alternative specifications, it survived most robustness checks. The results for H2 are stronger. The estimated coefficient on local income decile was positive ($\hat{\beta}_2 > 0$) and significant; we can reject the null hypothesis $\beta_2 = 0$ at $\alpha = 0.001$. This is also a substantively important effect: moving from the third to seventh decile is associated with a 10 percentage-point increase in the probability of voting Conservative in the 2019 election, the same change associated with increasing age by 20 years. Furthermore, this result was robust to most alternative specifications.

As with OPP, my findings are reconciled by the Conservatives attracting disproportionate support from poorer areas. However, it is the wealthier residents of these areas who are most likely to support the Conservatives. This yields the overall null relationship between income and support for the Conservatives observed in model 1. Thus, like OPP I conclude that 2019 Conservative voters are 'nationally poor, locally rich'.

My findings contribute to literature on class voting and the populist right:

First, my results provide further support of OPP's conclusions. Their finding that Trump voters were 'nationally poor, locally rich' is not limited to the United States. It also applies to 2019 Conservative voters, showing this is a cross-national phenomenon. In my robustness checks, I show these relationships did not exist at 2015 general election, only appearing for the 2019 election and Brexit vote. These are both distinguished by being *populist* right causes rather than merely right-wing. Thus, my results suggest the wealthier occupants of poorer areas provide a receptive constituency for the populist right. This complicates the 'left-behind' narrative which characterizes popular discussion of populist voters. The voters I identify live in left-behind areas, but they are not especially deprived themselves.

My results also suggest the literature on the relationship between income and electoral behaviour is too general. They cast doubt on the empirical literature which simply regresses vote choice on income or class without considering local variation. In my results, there is no relationship between personal income on its own and Conservative vote. But when I add local income decile, personal income is significant and negatively associated with voting Conservative; without considering local income position, we may derive spurious results. Moreover, my results complicate the theoretical literature on income-based voting. The precise mechanisms connecting income/class and vote are highly contested (Weakliem and Heath 1994; Evans and De Graaf 2013; Heath 2015), but almost all assume individuals identify themselves with a national class or income group. My results suggest this is not the case; local variation matters. While local income distribution does not affect the objective impacts of taxation/redistribution, it does affect how individuals *experience* their income. Thus, my results suggest we need to consider the subjective experience of income alongside objective economic effects. Other authors' findings suggest the same (see Liberini et al. 2019) but this has not been incorporated into the broader literature.

My findings also carry certain limitations. First, I cannot conclude the relationships I observe are causal. While the results are robust to including further controls, but there may always be some unmeasured variable confounding results. Thus, my main conclusion is descriptive (2019 Conservative voters were the wealthier residents of poorer areas) rather than causal. Second, because my local authority level data is limited to labour earnings, my findings are limited to workers. This excludes a large portion of voters, including influential constituencies like pensioners. Third, my local authority level income data has missing observations. This led to sparse coverage of high earners. Thus, effects may differ for the highest earners. Fourth, local authorities vary in their area and population. Some are quite large, so an individual's income position in their local authority may not be indicative of their income position in their local area.

My results also suggest several areas for further research:

First, the findings could be further replicated with new data. I showed OPP's findings also apply to the UK, but they may also apply in other countries with populist right movements. Within the UK, better data could bolster conclusions. The 2021 Census will contain data on income for smaller geographies; re-estimating the relationship between local income and vote choice using this finer-grained data could bolster my conclusions.

Second, more research is needed to determine the mechanisms driving this relationship. The current literature does not have an explanation for why local and national income would have divergent effects, or why this particularly affects the populist right. More theoretical and empirical work is needed to determine why these variables matter. I suggested in the introduction two reasons local position might matter are cost-of-living differences across areas and that individuals proxy for the national position by observing their local position. The relative weight of these and other factors is an important area for future research.

5 Conclusion

In this paper, I investigate the relationship between income and voting Conservative in the 2019 British election. I replicate OPP's results from the US, finding that income was negatively associated with voting Conservative, while local income decile was positively associated with Conservative support. Thus, 2019 Conservative voters were 'nationally poor, locally rich'. Furthermore, I find the same relationship exists for Brexit support but does not exist for the 2015 election. This suggests the relationship is limited to the *populist* right rather than the general right-wing. Combined with OPP's prior work, these results suggest the 'nationally poor, locally rich' provide a cross-national constituency for the populist right. They also suggest the current literature on the relationship between class and electoral behaviour fails to adequately consider the role of local circumstances. Overall, my results suggest the local income distribution profoundly affect the relationship between income and vote. Political scientists need to take these effects seriously in order to understand to income's political effects.

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A Appendix

A.1 Model Diagnostics

Figure A.1: Pearson Residuals Plotted Against Personal Income, Local Income Decile, and Age Demonstrating Approximate Linearity Between Continuous Predictors and Log-Odds

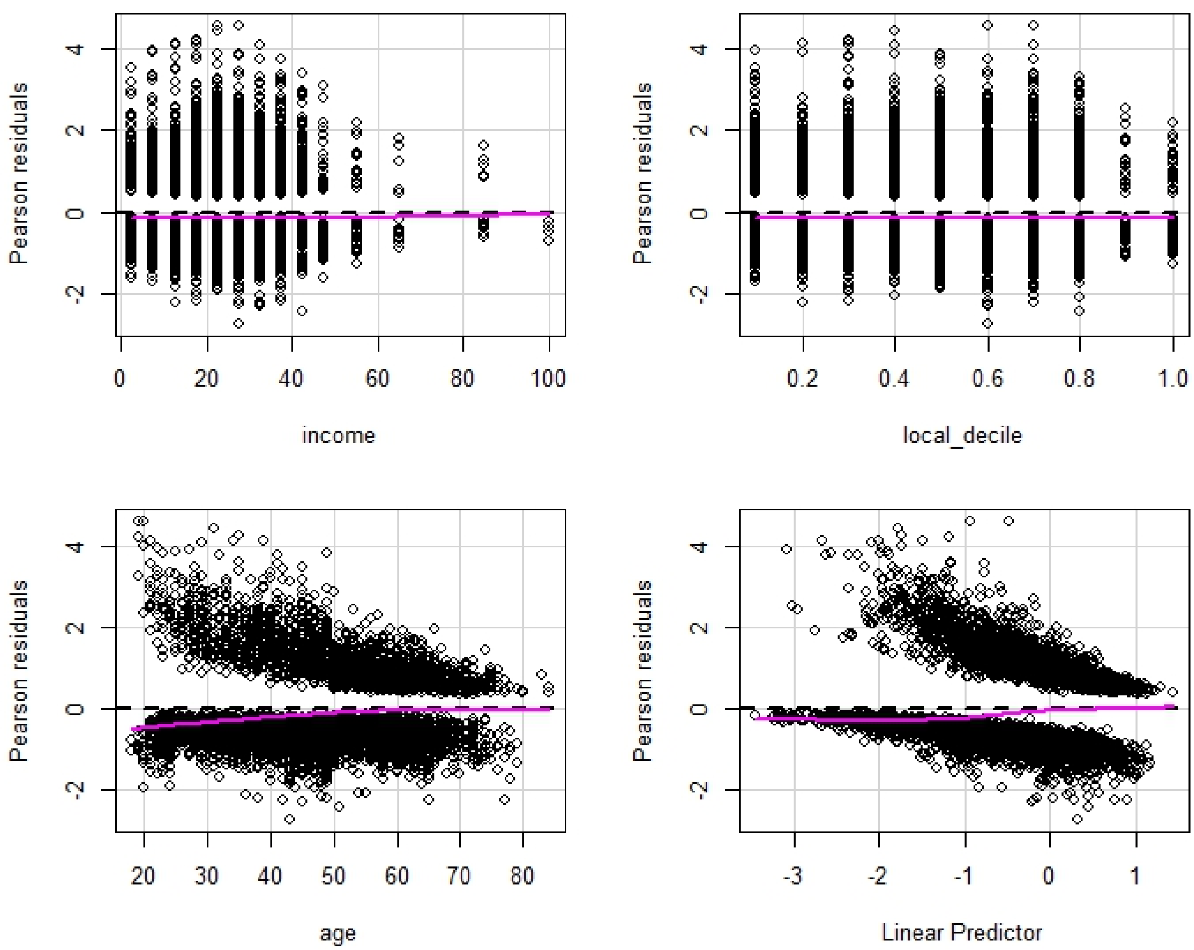


Table A.1: Specification Tests for Continuous Variables in Model 3

Variable	Test stat	Pr(>)
income	0.037	0.847
local_decile	0.063	0.802
age	1.603	0.205

Table A.2: Variance Inflation Factor for Coefficients in Model 3

Variable	VIF
income	6.63
local_decile	6.63
gender	1.084
attended_university	1.07
religion	1.02
age	1.17
owns_home	1.17
scotland	1.01
wales	1.02

Figure A.2: Standardized Pearson Residuals for Model 3 with Lines at ±2.5 to Detect Outliers

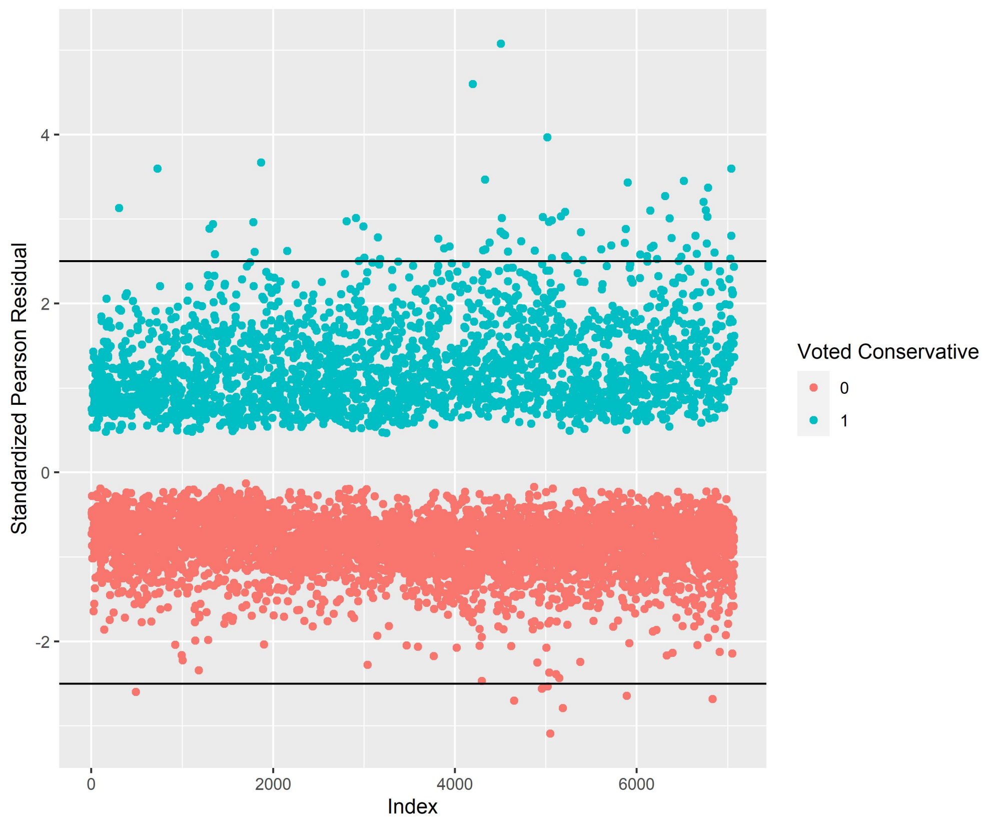


Figure A.3: Hat-Values from Model 3 with Line at Two Times Average Hat-Value to Detect Points with Leverage

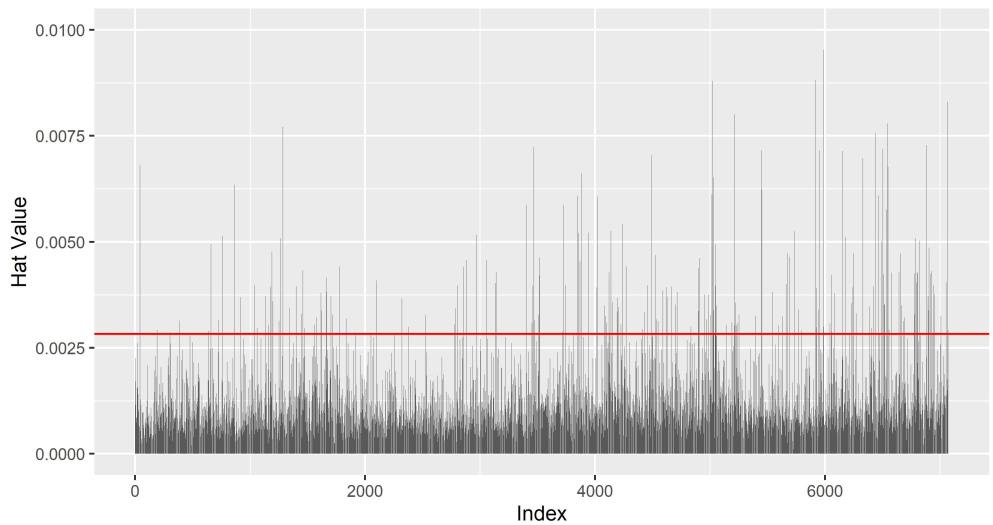
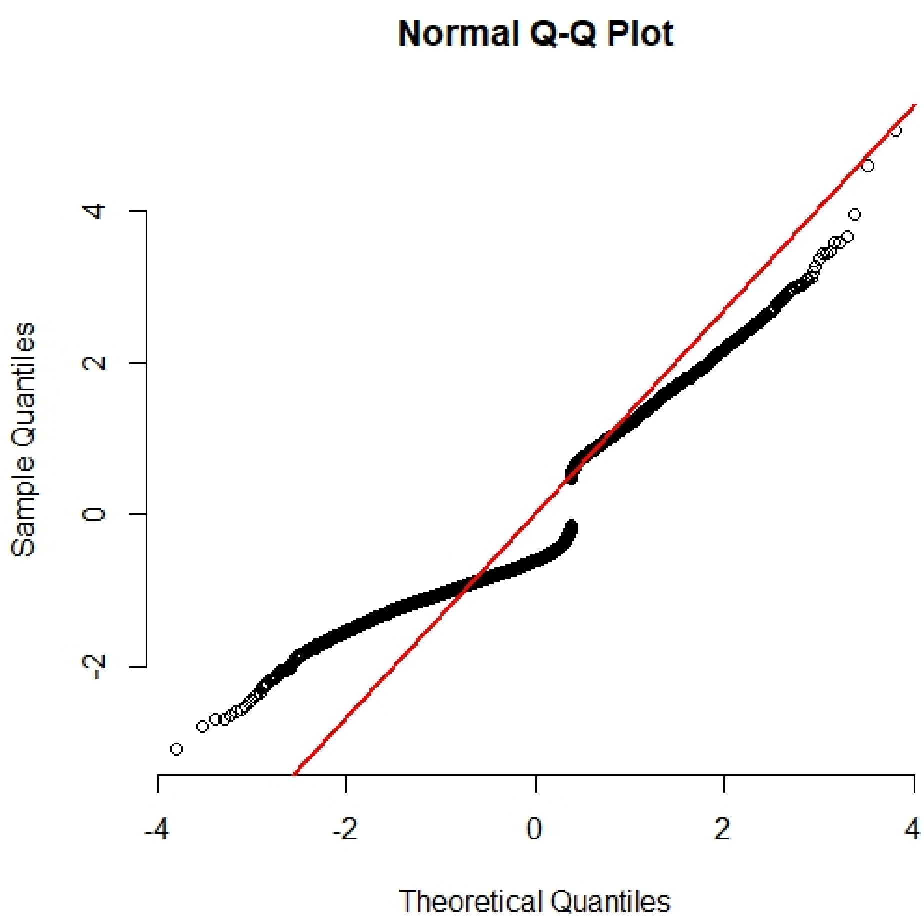


Figure A.4: Q-Q Plot of Standardized Residuals Against Theoretical Normal Distribution



A.2 Robustness Checks

Table A.3: Robustness Check 1: Adding Additional Controls

	Dependent variable: Conservative Vote
Personal Income	-0.028^{*} (0.00001)
Local Income Decile	1.366^{**} (0.523)
Gender	0.066 (0.095)
Attended University	-0.723^{***} (0.096)
Religious Observance	0.023 (0.092)
Age	0.019^{***} (0.004)
Home Ownership	-0.011 (0.101)
Scotland	-0.739^{***} (0.175)
Wales	-0.250 (0.214)
Left-Right Placement	0.572^{***} (0.029)
Redistribution Attitudes	0.00003 (0.00002)
Conservative Self-ID	1.608^{***} (0.115)
Conservative 2015 Vote	0.914^{***} (0.100)
Political Attention	-0.013 (0.022)
Trust in MPs	0.100^{**} (0.032)
Constant	-5.157^{***} (0.348)
McFadden Pseudo R^2	0.471853827432219
Observations	5,305
Log Likelihood	$-1{,}709.829$
Akaike Inf. Crit.	3,451.659
Note:	$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table A.4: Robustness Check 2: Removing Influential Observations

	Dependent variable: Conservative Vote
Personal Income	-0.012 (0.008)
Local Income Decile	0.791^{*} (0.377)
Gender	0.042 (0.061)
Attended University	-0.941^{***} (0.061)
Religious Observance	0.550^{***} (0.060)
Age	0.027^{***} (0.003)
Home Ownership	0.260^{***} (0.066)
Scotland	-0.939^{***} (0.132)
Wales	-0.528^{*} (0.225)
Constant	-1.846^{***} (0.186)
McFadden Pseudo R^2	0.103720653112772
Observations	6,446
Log Likelihood	$-3{,}580.849$
Akaike Inf. Crit.	7,181.698
Note:	$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

A.3 Code

Table A.5: Robusntess Check 3: Changing Dependent Variable

	Dependent variable:	
	Conservative Vote 2015	Brexit Vote
	(1)	(2)
Personal income	0.010 (0.006)	-0.035^{***} (0.006)
Local Income Decile	0.020 (0.308)	1.132^{***} (0.303)
Gender	0.055 (0.056)	-0.172^{***} (0.052)
University	-0.461^{***} (0.058)	-1.032^{***} (0.052)
Religious Observance	0.337^{***} (0.055)	0.239^{***} (0.052)
Age	0.003 (0.002)	0.025^{***} (0.002)
Home Ownership	0.394^{***} (0.061)	-0.086 (0.055)
Scotland	-1.341^{***} (0.126)	-0.647^{***} (0.093)
Wales	-0.358^{**} (0.131)	-0.291^{*} (0.116)
Constant	-1.285^{***} (0.164)	-0.331^{*} (0.147)
McFadden Pseudo R^2	0.038	0.085
Observations	6,644	7,151
Log Likelihood	$-4{,}096.178$	$-4{,}733.508$
Akaike Inf. Crit.	8,212.356	9,487.015
Note:		*p<0.05; **p<0.01; ***p<0.001

Table A.6: Robustness Check 4: Dropping High Income Respondents

	Dependent variable: Conservative Vote
Personal Income	-0.018^{*} (0.008)
Local Income Decile	1.118^{**} (0.356)
Gender	-0.019 (0.056)
Attended University	-0.917^{***} (0.058)
Religious Observance	0.453^{***} (0.055)
Age	0.025^{***} (0.002)
Home Ownership	0.309^{***} (0.060)
Scotland	-1.184^{***} (0.112)
Wales	-0.480^{***} (0.131)
Constant	-1.711^{***} (0.157)
McFadden Pseudo R^2	0.096
Observations	6,695
Log Likelihood	$-4{,}143.877$
Akaike Inf. Crit.	8,307.754
Note:	*p<0.05; **p<0.01; ***p<0.001

Table A.7: Robustness Check 5: Categorical Independent Variables

	Dependent variable: Conservative Vote		
	(1)	(2)	(3)
Personal Income—7.5	−0.043 (0.162)		0.031 (0.170)
Personal Income—12.5	−0.135 (0.159)		0.050 (0.272)
Personal Income—17.5	−0.198 (0.175)		−0.061 (0.309)
Personal Income—22.5	−0.293 (0.205)		−0.140 (0.330)
Personal Income—27.5	−0.491* (0.236)		−0.379 (0.340)
Personal Income—32.5	−0.641* (0.265)		−0.515 (0.349)
Personal Income—37.5	−0.523 (0.290)		−0.372 (0.362)
Personal Income —42.5	−0.576 (0.324)		−0.429 (0.388)
Personal Income—47.5	−0.897* (0.397)		−0.653 (0.450)
Personal Income—55	−0.909 (0.490)		−0.097 (0.725)
Personal Income—65	−1.230 (0.752)		−0.290 (0.994)
Personal Income—85	−0.694 (0.764)		0.245 (1.003)
Personal Income—100	−13.082 (186.538)		−12.144 (186.525)
Personal Income (Continuous)		−0.014* (0.007)	
Local Income Decile—2		−0.061 (0.134)	−0.173 (0.220)
Local Income Decile—3		0.281* (0.132)	0.169 (0.262)
Local Income Decile—4		0.276 (0.147)	0.201 (0.291)
Local Income Decile—5		0.366* (0.166)	0.324 (0.308)
Local Income Decile—6		0.460* (0.184)	0.490 (0.314)
Local Income Decile—7		0.589** (0.209)	0.669* (0.323)
Local Income Decile—8		0.632* (0.249)	0.646 (0.337)
Local Income Decile—9		1.064** (0.392)	1.008* (0.451)
Local income Decile—10		0.738 (0.483)	0.163 (0.729)
Local Income Decile (Continuous)	1.222*** (0.369)		
Gender	−0.043 (0.054)	−0.040 (0.054)	−0.043 (0.055)
Attended University	−0.908*** (0.056)	−0.914*** (0.056)	−0.911*** (0.056)
Religious Observance	0.454*** (0.054)	0.452*** (0.053)	0.456*** (0.054)
Age	0.025*** (0.002)	0.025*** (0.002)	0.025*** (0.002)
Home Ownership	0.294*** (0.059)	0.292*** (0.059)	0.291*** (0.059)
Scotland	−1.175*** (0.109)	−1.169*** (0.109)	−1.171*** (0.109)
Wales	−0.479*** (0.131)	−0.460*** (0.131)	−0.464*** (0.132)
Constant	−1.766*** (0.185)	−1.557*** (0.161)	−1.645*** (0.181)
McFadden Pseudo R^2	0.092	0.093	0.091
Observations	7,073	7,073	7,073
Log Likelihood	−4,360.326	−4,362.972	−4,356.782
Akaike Inf. Crit.	8,764.651	8,761.944	8,773.563
Note:			*p<0.05; **p<0.01; ***p<0.001

Table A.8: Robustness Check 6: Probit Model

	Dependent variable: Conservative Vote
Personal Income	−0.010** (0.004)
Local Income Decile	0.654*** (0.183)
Gender	−0.026 (0.033)
Attended University	−0.550*** (0.033)
Religious Observance	0.277*** (0.032)
Age	0.015*** (0.001)
Home Ownership	0.176*** (0.036)
Scotland	−0.690*** (0.062)
Wales	−0.283*** (0.078)
Constant	−1.014*** (0.091)
McFadden Pseudo R2	0.094
Observations	7,073
Log Likelihood	−4,364.327
Akaike Inf. Crit.	8,748.654
Note:	*p<0.05; **p<0.01; ***p<0.001

Table A.9: Robusntess Check 7: Accounting for Clustering at the Local Authority Level

	Dependent variable:	
	Clustered SEs	*Multilevel*
	(1)	(2)
Personal income	-0.016 (0.009)	−.008 (0.009)
Local Income Decile	1.048 (0.458)*	0.772 (0.453)
Gender	−0.041 (0.061)	−0.047 (0.060)
University	−0.912*** (0.069)	−0.878*** (0.061)
Religious Observance	0.452*** (0.069)	0.498*** (0.059)
Age	0.025 (0.003)***	0.029*** (0.003)
Home Ownership	0.290*** (0.070)	0.262*** (0.064)
Scotland	−1.171*** (0.159)	
Wales	−0.476** (0.152)	
Constant	−1.664*** (0.164)	−1.96*** (0.064)
McFadden Pseudo R^2	0.094	NA
Marginal R^2	NA	0.137
Observations	7,073	7,073
Log Likelihood	−4,365.205	−3940.681
Akaike Inf. Crit.	8,750.411	7899.362
Note:		*p<0.05; **p<0.01; ***p<0.001