Article:

Efthyvoulou, G. orcid.org/0000-0002-4473-0350, Bove, V. and Pickard, H. (2023) Micromotives and macromoves: political preferences and internal migration in England and Wales. Journal of Economic Geography, 23 (5). pp. 1145-1167. ISSN 1468-2702

https://doi.org/10.1093/jeg/lbad014

Micromotives and macromoves: Political preferences and internal migration in England and Wales*

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Abstract

When people migrate internally, do they tend to move to locations that reflect their political preferences? To address this question, we combine evidence from a unique panel dataset on population movements across local authority districts in England and Wales (2002-2015) with evidence stemming from individual survey-based data. Our results suggest that political similarity between two districts exerts an important positive effect on their bilateral migration flows. Our results also suggest that political alignment to the district of residence contributes to individuals' sense of belonging and 'fitting in', consistent with the existence of a homophily mechanism.

Keywords: Internal migration; Political sorting; Homophily; Gravity models

*We gratefully acknowledge financial support from the Competitive Advantage in the Global Economy. We would like to thank Apurav Yash Bhatiya, Ioanna Goutna, Andreas Kanaris-Miyashiro and Maria Padilla Montoya for excellent research assistance. We have benefited from comments and suggestions by Riccardo Di Leo, Michele Di Maio, Gunes Gokmen, Helios Herrera, Carlo Hofer, Arne Risa Hole, Jesse Matheson, Andrea Ruggeri, Cristina Tealdi, Mathias Thoenig, Farid Toubal, Orestis Troumpounis, Enrico Vanino, and two anonymous referees. We are indebted to the participants of research seminars at Birkbeck University of London, Royal Holloway University of London, Padova University, Sapienza University of Rome, University of Sheffield and Newcastle University. The usual disclaimer applies.

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1 Introduction

When people migrate internally, do they tend to move to locations that reflect their political preferences? Partisan geographic sorting has important implications for the the type of information that individuals receive, the attitudes they form, and the social interactions they experience (McPherson et al., 2001). Despite a considerable amount of research on the economic factors that influence migration decisions, we still lack a comprehensive understanding of the role that community ties, information, beliefs and values play in shaping internal migration patterns (Jia et al., 2023).

In this article, we undertake a systematic analysis of the effect of political preferences on within-country migration. To do so, we compile a unique panel dataset on the universe of internal migration in England and Wales over the period 2002-2015 – consisting of yearly bilateral migration flows across 346 local authority districts (LADs) – and employ a gravity model of migration augmented with a measure of political similarity between districts. We use Poisson pseudo-maximum likelihood (PPML) estimation to address issues related to heteroscedasticity and zeros (Silva and Tenreyro, 2006), and include time-varying destination and origin fixed effects to account for changes in the 'multilateral resistance' constraints (see, e.g., Beine et al., 2016). We complement this analysis with evidence stemming from individual survey-based data over the same time period, which allows us to delve into the micro-foundations underlying the "macromoves".

To capture political similarity, we exploit information on election outcomes at the local level. UK local elections are often used as barometers of public support for political parties between general elections (Prosser, 2016). Moreover, compared to parliamentary elections, the existence of a rotation schedule for the election of councillors means that these elections can take place in any given year (Fetzer, 2019), enabling us to leverage bilateral annual variations in political preferences. We consider two alternative measures of political similarity. The first is a binary indicator capturing whether the local councils in origin and destination districts are controlled by the same party (either the Labour or the Conservative party). The second is a continuous variable capturing the pair-specific distance in party shares for the two dominant parties. The latter flexibly accounts for the role of political preferences even when people decide to move across districts with a different political colour in a given year.

Our district-level analysis reveals that political similarity between two districts has a strong positive impact on their bilateral migration flows. For instance, according to the estimate of our continuous measure, a one-standard-deviation increase in political distance between the two districts will lead to a decrease in migration flows by about 4%. To address concerns about unobserved bilateral heterogeneity, we augment the gravity model with origin-destination pair fixed effects and instrument political distance using a 'shift-share' instrument. By paying greater attention to causality, and by reporting an array of different specifications and robustness tests, our paper makes a step forward in understanding the determinants of internal migration, in particular its political dimension.

The district-level analysis is based on two premises. The first is that the main channel underpinning our results is the desire for homophily; i.e., the tendency to favour the company and presence of others who share similar beliefs, interests, and values (Bishop, 2009; Tam Cho et al., 2013).[1] Political ideology is intimately connected to a broader range of preferences, attitudes, and cognitions (Jost et al., 2009), encompassing and amplifying differences in cultural affinities and social attitudes. Our measures of political similarity capture not only the basis of political homophily, but also a wider constellation of preferences and attitudes that constitute homophily more broadly.[2] In this way, the voting

[1] This is the foundation of Schelling's (1971, 1978) original model of racially segregated neighbourhoods, wherein members of two groups relocate to achieve some degree of proximity to other residents of similar type.

[2] We return to this point in Appendix A.1, where we discuss the relationship between political homophily

behaviour of a prospective destination area can provide a valuable cue about its cultural and social characteristics when first-hand experience is not available. To corroborate this mechanism, we employ a large individual-level panel dataset, obtained by combining the British Household Panel Survey with Understanding Society. Our analysis shows that a desire for homophily is indeed at play and living in areas with similar ideological views contributes to individuals' sense of 'fitting in' and 'feeling at home' and increases the overall satisfaction they have with the location where they live.

The second premise is that political preferences affect migration flows only once a decision to migrate has been taken. In other words, political alignment with the district of residence is not a reason to leave. Using our individual-level dataset, we show that this is indeed the case. Specifically, while political alignment does not have a direct and immediate impact on the decision to change district of residence, a migrant's political ideology can predict the partisanship of the destination district. This also implies that, at the aggregate level, out-migrants from a given origin district will broadly represent the political preferences of that district, and – driven by a sense of belonging and 'fitting in' – they will choose to move to a district that matches these political preferences (or to the closest one among the possible destination choices).[3]

Our research contributes to extant studies on the determinants of within-country migration. Economic considerations play an important role in the decision to relocate and movers tend to select destinations on the basis of better employment opportunities and higher wages (see, e.g., Langella and Manning, 2022; Jia et al., 2023). Relocation patterns are also influenced by neighbourhood and regional characteristics that enhance people's overall life satisfaction (see, e.g., Bracco et al., 2018; Langella and Manning, 2019). We

and other forms of homophily and the consequences of geographic sorting.

[3]To provide further support to this premise, we show that there is a strong positive correlation between the aggregate political preferences of a district and those of its out-migrants.

also contribute to recent studies on geographic sorting and political segregation (Bishop, 2009; Florida and Mellander, 2009; Tam Cho et al., 2013; Gimpel and Hui, 2015; Carlson and Gimpel, 2019). The increasing presence of homogeneous pockets of political support in the US has stimulated extensive research on whether liberal and conservative Americans have become spatially isolated from one another, the so-called "Big Sort hypothesis" (Sussell, 2013; Tam Cho et al., 2013; Johnston et al., 2016; Mummolo and Nall, 2017; Rohla et al., 2018; Carlson and Gimpel, 2019). This research disproportionally focuses on the US, the archetypal case of a highly polarised society. The UK provides an ideal setting for studying the impact of political preferences on internal migration (outside the exemplary US case), given the country's high rate of within-country migration, combined with a significant ideological divide and 'affective polarisation' (Boxell et al., 2022). As of yet, no studies have examined partisan geographic sorting across the entire population of a country and over an extended period of time.

2 District-Level Analysis

2.1 Data and variables

We obtain data on annual bilateral migration flows at the district level from the ONS's People, Population and Community theme. Our sample covers all possible origin and destination districts in England and Wales (346 $\times$ 345) and spans a period of 14 years, 2002-2015. By construction, this results in a dataset consisting of 119,370 origin-to-destination corridors and over 1.6 million corridor-year observations. The bilateral nature of the data, together with the large number of possible corridors, implies that migration flows in a given year are quite low relative to the population size of the two districts. In fact, about 48% of our observations correspond to zero flows. These zeros may arise for reasons that are related to factors explored in our analysis, and thus including them in our estimation can provide additional information on migration patterns.[4]

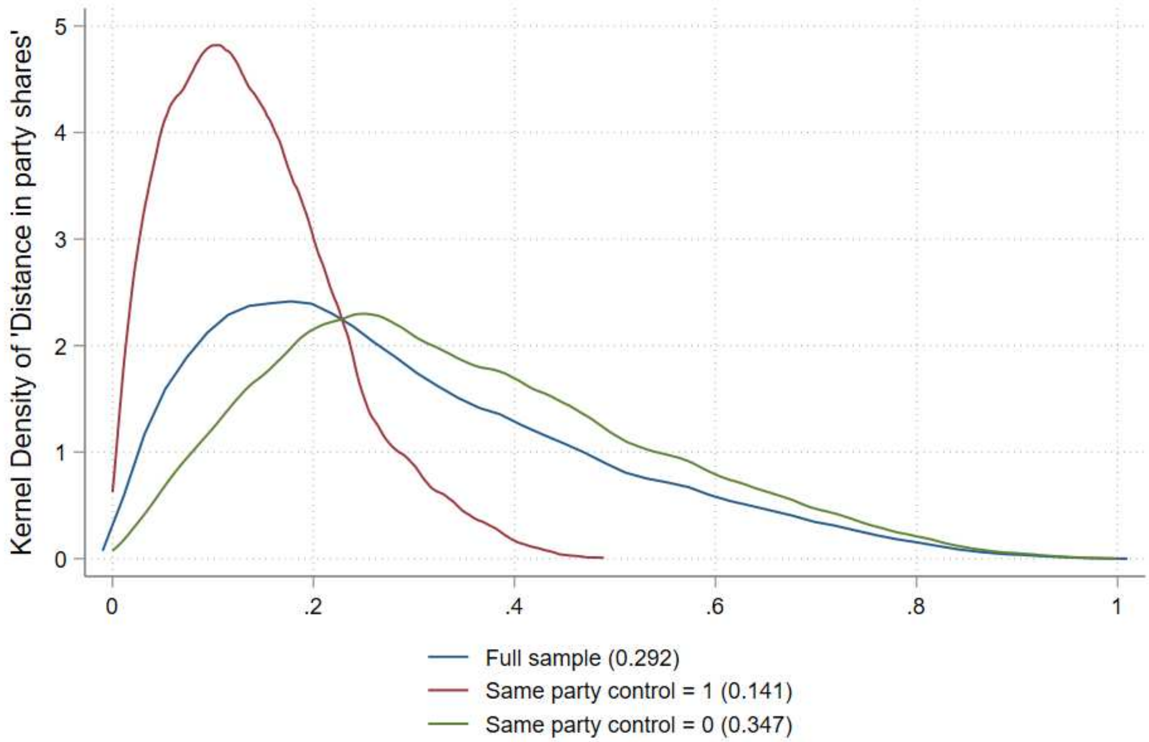
The key explanatory variable in our analysis is the political similarity between migrants' origin district i and destination district j (to be referred to as district pairs or dyads). We employ two alternative measures of political similarity. The first one is a binary indicator taking value 1 if the local councils in the two districts at time t are controlled by the same party (either the Labour or the Conservative party); and 0 otherwise; namely, *Same party control*. The second one is a continuous measure of partisan spread between the two districts, which is calculated by the average distance (absolute difference) in party shares for the two dominant parties, and formally defined as:

$$\textit{Distance in party shares}_{ij,t} = \frac{1}{2}\left(\left| S^L_{i,t} - S^L_{j,t} \right| + \left| S^C_{i,t} - S^C_{j,t} \right| \right)$$

where S^L and S^C represent the share of seats held by the Labour party and the Conservative party, respectively, in the local council. The continuous measure varies in the interval $[0, 1]$, with values close to 0 indicating that the two districts are homogeneous with respect to their political preferences. Figure 1 shows the distribution of this variable for the universe of district pairs, but also for pairs that share the same political preferences (*Same party control* $= 1$) and those that do not share the same political preferences (*Same party control* $= 0$). An important observation is that the continuous variable is highly correlated with the dichotomous classification of district pairs: low values of *Distance in party shares* reflect copartisan districts (two Conservative or two Labour districts), whereas high values of this variable mostly capture opposing-party districts. However, the advantage of using the continuous measure is that it can account for the role of political preferences even when people decide to move to districts with a different political colour; e.g., Labour-

[4]Figure B.1 in the Appendix presents Sankey diagrams for the top 20 migration corridors in years 2002, 2007 and 2012, and Table B.2 in the Appendix provides a list of all districts with the government office region (GOR) to which the belong.

Figure 1: Distribution of 'Distance in party shares'



Notes: This figure shows the kernel density of the variable *Distance in party shares* for: (i) the full sample of district pairs; (ii) the pairs that share the same political preferences; (iii) the pairs that do not share the same political preferences. The corresponding mean values are reported in parentheses.

district residents selecting the Conservative-district destination with the highest possible support for the Labour party (see Section B.2 in the Appendix for further evidence on this).

To construct our political similarity measures, we choose to use local council elections rather than parliamentary elections for two main reasons. First, local elections in the UK are often seen as a reflection of national politics, with voters using them as an opportunity to express satisfaction or dissatisfaction with the incumbent government. They can be treated as "large-scale opinion polls" that track political preferences over time, with more accuracy than traditional opinion polls. In fact, local election and by-election results have been successfully used to forecast general election outcomes in the UK (see, e.g., Rallings et al., 2011; Prosser, 2016). Second, local elections can take place in any given year across the country due to the rotating fashion by which councillors are elected (Fetzer, 2019), and their outcomes can be easily matched to the internal migration data which are only available at the district level. Exploiting information about the share of seats is useful as it reflects the first-past-the-post electoral system used in England and Wales to elect the councillor in each council electoral division, and thus accounts for differences in political preferences across small geographic units within the same district. Appendix A.1 provides a more detailed explanation of the advantages of utilising local election results to capture aggregate political preferences, whereas Appendix A.2 provides background material on local governments, elections and reforms in the UK.

2.2 Methodology

To examine the impact of political similarity on internal migration flows, we consider an augmented gravity model of migration with multilateral resistance (Beine et al., 2016). According to this model, migration is driven by the attractive force between source and destination locations and the impeded costs of moving from one region to another, as well as multilateral factors determining the overall inward and outward migration rates. The main difference in our approach is the focus on within-country movements and the expectation that the political similarity between the two districts will also play an important role for migration decisions.

Following the norm in the recent literature, we employ the PPML estimator, proposed by Silva and Tenreyro (2006), and estimate the gravity model in levels rather than logs. The use of PPML controls for heteroscedasticity which often plagues migration data, and takes into account the information contained in zero migration flows (Yotov et al., 2016). The latter allows us to rule out potential selection bias arising from district pairs with zero flows having a different population distribution compared to those with positive flows

(Beine and Parsons, 2015).

More formally, our PPML model specification takes the following form:

$$\textit{Migration flows}_{ij,t} = \exp\left(\alpha \mathbf{PS}_{ij,t} + \beta \mathbf{X}_{ij,t} + \gamma_{it} + \gamma_{jt}\right) + \upsilon_{ij,t} \tag{1}$$

where *Migration flows*$_{ij,t}$ represents the directional flows of migrants between two districts, measured by the number of migrants flowing from a district of origin i to a destination district j at time t; $\mathbf{PS}_{ij,t}$ is one of the two political similarly measures (*Same party control* or *Distance in party shares*), as defined in Section 2.1; $\mathbf{X}_{ij,t}$ is a vector containing time-varying and non-time-varying bilateral variables, specific to a migration corridor; γ_{it} and γ_{jt} represent origin-year and destination-year fixed effects, respectively; and, $\upsilon_{ij,t}$ is an error term clustered at the dyad level.

The inclusion of origin-year and destination-year fixed effects in our specification fully accounts for the multilateral resistance terms (Anderson and van Wincoop, 2003; Feenstra, 2002; Olivero and Yotov, 2012). Specifically, origin-year fixed effects capture all factors that determine the overall emigration rate from a district i, and the identification comes from the differential emigration rates to specific destination districts; whereas destination-year fixed effects capture all factors that determine the overall immigration rate for a district j and the identification comes from the differential immigration rates from all possible source districts. At the same time, these fixed effects control for all district-specific time-varying sources of omitted variable bias affecting both emigration and immigration decisions. As such, our model specification implies that only the role of bilateral factors, specific to a migration corridor, can be identified.

The variables included in vector $\mathbf{X}_{ij,t}$ are commonly used in the literature to reflect the economic, demographic, geographic and ethno-linguistic factors influencing migration flows between two districts. Specifically, to capture the argument that immigrant workers respond to differences in labour incomes between regions, we control for the ratio of destination-to-origin district average wages ($Wage_j/Wage_i$). To reflect differential business cycles, we control for the ratio of destination-to-origin district unemployment rates ($Unemployment_j/Unemployment_i$). To account for the role that gravitational "mass" plays for migration flows, we control for the product of the log of the populations of the two districts ($Population_i \times Population_j$). We also add to the specification the log of the physical distance between two districts (*Geographic distance*) and a dummy variable for pairs of districts that share a contiguous border (*Contiguity*) to proxy for geographical impediments to migration. Finally, vector $\mathbf{X}_{ij,t}$ includes the absolute difference in the ethnic fractionalisation index between origin and destination (*Distance in ethnic frac.*),[5] as a measure of cultural differences between the two districts. Table B.1 in the Appendix provides summary statistics and a full description of all variables used in the analysis.

Not accounting for migration persistence may potentially affect the estimates of the time-varying gravity estimates. To address this issue, we augment Eq. (1) with the lagged value of the dependent variable (LDV). The inclusion of lagged migration flows in the gravity model also controls for the impact of migrant networks; i.e., current migration flows being correlated with earlier flows because the cost of adapting to a new society is mitigated by the presence of family members and friends who are familiar with both the source and the destination areas (Lewer and Van den Berg, 2008; Beine et al., 2019). In addition, the dynamic theory-founded econometric specification – with a LDV and time-varying directional fixed effects – has been shown to be superior to alternative fixed effects specifications (Olivero and Yotov, 2012).

[5]As in Langella and Manning (2019), we rely on data from the 2001 and 2011 censuses, and impute values for the inter-censual and post-censual years using linear interpolation for each district.

2.3 Endogeneity issues

Endogeneity concerns may arise with the estimation of Eq.(1). If political similarity between two districts is influenced by unobserved bilateral factors that are also relevant for migration flows, omitted variable bias would prevent the identification of a plausibly causal effect. Similarly, if local election outcomes are partly affected by internal migration flows, reverse causality may confound the relationship between the two variables.

Omitted variable bias. To assess the possibility of omitted variable bias, we test the sensitivity of the political similarity effects to augmenting the gravity model with a large array of socio-economic and demographic controls, including pair-specific differences in age structure, education levels, industrial composition, religious composition, and genetic background (in addition to the variables in vector $\mathbf{X}_{ij,t}$ which capture, among others, pair-specific differences in labour incomes and business cycles).

As recommended in the gravity model literature, a more flexible and comprehensive way to control for such bias is to include pair fixed effects, in addition to the theoretically-motivated origin-year and destination-year fixed effects. First, the pair fixed effects capture all pull and push factors, as well as and the part of migration costs, that are pair-specific and time-invariant. Second, the inclusion of pair fixed effects can control for potential endogeneity of the political similarity variable by absorbing most of the linkages between this variable and the remainder error term $v_{ij,t}$ (Yotov et al., 2016). As a result, within this setting, identification comes from changes in political similarity within a specific migration corridor, as captured by changes in the local election outcomes of the two districts. The downside of this approach is that it reduces the variation used for identification, and absorbs all time-invariant determinants of migration that are customarily used in gravity regressions, such as geographic distance and contiguity.

Reverse causality. An important reason why reverse causality is less acute in our context is that we rely on bilateral migration flows. As stressed by Beine et al. (2019), the bilateral nature of this type of analysis makes concerns about reverse causality much less serious than in a unilateral analysis, since migration flows at the bilateral level are too modest to influence the outcome of local elections. Indeed, as shown in Figure B.2 of the Appendix, the average value of migration flows from district i to district j is very small relative to the population size of district j (about 0.02%) or the total size of migration flows to district j (about 0.30%).

Nevertheless, to tackle the issue of reverse causality – and also to ensure that omitted variable bias in not a major problem in our analysis – we take two complementary approaches. First, we replace our political similarity variables with their one-year and two-year lags. This allows us to mitigate the possibility that our results are driven by a contemporaneous effect of migration flows on election outcomes. Second, we adopt an instrumental variable (IV) strategy,[6] where *Distance in party shares* is instrumented using a 'shift-share' instrument (Altonji and Card, 1991). The intuition behind this approach is that, for historical reasons, two areas differ in terms of their political support for the two leading parties, and these historical differences can determine the degree to which a district pair is influenced by 'national' changes in ideological spread. More precisely, our instrument is constructed as follows:

$$\textit{Shift-share instrument}_{ij,t} = \begin{cases} \textit{Distance in party shares}_{ij,2002} \times (1 + g_t^{ij}) & \text{if year} = 2003 \\ \textit{Shift-share instrument}_{ij,t-1} \times (1 + g_t^{ij}) & \text{if year} > 2003 \end{cases}$$

where *Distance in party shares*$_{ij,2002}$ is the 2002 value of political distance between two districts, and g_t^{ij} is the growth rate of yearly average values of political distance across all

[6]As stressed by Beine et al. (2016), in the framework of a gravity model that controls for multilateral resistance, instrumentation is not necessary as long as the endogeneity problem is not due to reverse causality or as long as the multilateral resistance terms (and pair fixed effects) capture a big part of the omitted factors. Both conditions are largely satisfied in our context.

pairs of districts. In other words, variation in the instrument comes from the interaction between initial pair-specific political distance (the 'share' term) and the changing patterns of political distance in England and Wales as a whole (the 'shift' term). Since the national level of ideological spread reflects the combined political preferences of all district pairs in the two countries, no pair alone is large enough to have a sizeable impact on the national trend. As such, identification in this setting is motivated by exogenous national 'shocks', even when exposure shares are assumed to be endogenous (Borusyak et al., 2020).

The fixed-effect PPML gravity model may lead to inconsistent estimates when estimated with IV techniques (Weidner and Zylkin, 2020), and thus we apply our instrument in the original OLS specification, where the dependent variable is the log of bilateral migration flows.[7] However, to account for the non-linear nature of our modeling procedure, we also employ a control function correction approach (Wooldridge, 2010), whereby the estimated OLS residuals from the first stage are introduced as an additional control variable in the PPML specification of Eq. (1).

2.4 Empirical findings

2.4.1 Main results

Table 1 shows the results obtained from estimating Eq. (1). We start from a specification that includes the standard determinants of migration flows and multilateral resistance terms (column (1)), and we then add the two alternative political similarity measures (columns (2) and (4)). Overall, our results are consistent with the existing analyses in the gravity model literature (see, e.g., Lewer and Van den Berg, 2008; Beine et al., 2016, 2019). Specifically, we can see that the number of migrants moving from the origin to the desti-

[7] Following the norm in the literature, we add a value of one before taking the logarithm to avoid taking the logarithm of zero.

Table 1: Migration Flows and Political Similarity: Main Results

	Migration flows				
	(1)	(2)	(3)	(4)	(5)
Geographic distance	-1.268***	-1.268***	-1.252***	-1.267***	-1.250***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Contiguity	1.124***	1.123***	1.057***	1.122***	1.053***
	(0.022)	(0.022)	(0.026)	(0.022)	(0.026)
$\text{Population}_j \times \text{Population}_i$	0.091***	0.091***	0.072***	0.089***	0.070***
	(0.016)	(0.016)	(0.017)	(0.016)	(0.017)
Wage_j / Wage_i	1.168***	1.178***	1.150***	1.192***	1.163***
	(0.108)	(0.107)	(0.100)	(0.105)	(0.098)
Unemployment_j / Unemployment_i	-0.286***	-0.248***	-0.282***	-0.178***	-0.201***
	(0.034)	(0.033)	(0.034)	(0.034)	(0.036)
Distance in ethnic frac.	-0.485***	-0.479***	-0.547***	-0.460***	-0.529***
	(0.129)	(0.129)	(0.134)	(0.129)	(0.134)
Same party control		0.052***	0.055***		
		(0.012)	(0.012)		
Distance in party shares				-0.202***	-0.215***
				(0.037)	(0.037)
LDV			0.094***		0.097***
			(0.023)		(0.023)
Dest. × Year FE	✓	✓	✓	✓	✓
Orig. × Year FE	✓	✓	✓	✓	✓
Pseudo-R^2	0.828	0.829	0.830	0.829	0.830
Observations	1,645,412	1,645,412	1,514,238	1,645,412	1,514,238

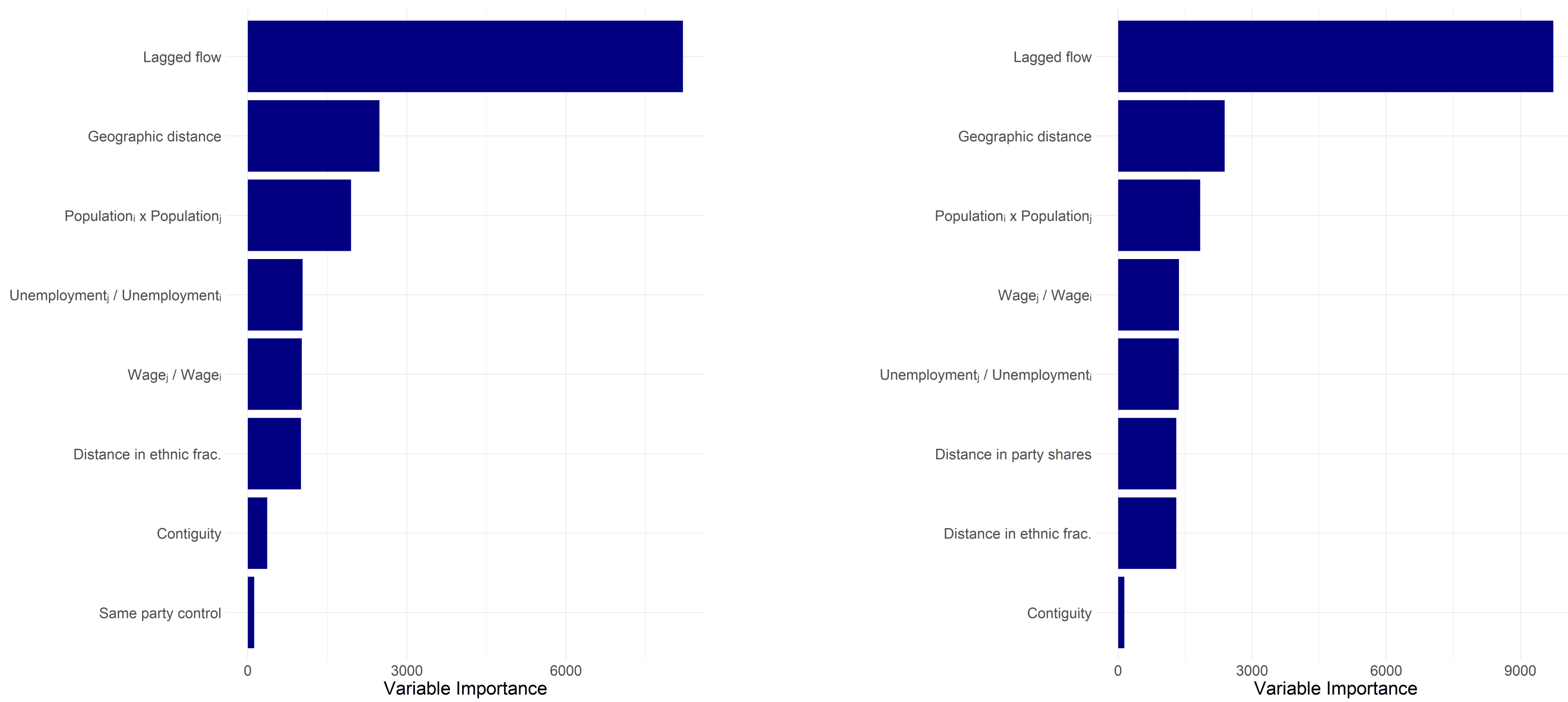
Notes: The dependent variable, *Migration flows*, captures the number of migrants flowing from a district of origin i to a destination district j at time t. Standard errors clustered at the dyad (district-pair) level in parentheses. LDV is the lagged dependent variable. The estimate and standard error of LDV are multiplied by 1,000. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

nation district is a positive function of the attractive "mass" of the two economies and the ratio of destination-to-origin district wages, and a negative function of the destination-to-origin unemployment rates. We can also see that geographic distance – used as a proxy for migration costs – is a major deterrent to internal migration, and that migrating to a neighbouring district is fundamentally different than to a non-neighbouring district. Finally, the results confirm that cultural norms play an important role in determining migration choices: people are more likely to migrate to districts whose ethnic mix is close to that of the origin district.

Turning now to the main variables of interest, we find strong evidence that bilateral migration flows increase when the destination and origin districts share the same political preferences: the variables *Same party control* (column (2)) and *Distance in party shares* (column (4)) enter the gravity equation with the appropriate sign and are statistically significant at the 1% level. Substantively, the estimate of *Same party control* suggests that migration flows between two Labour or two Conservative districts are 5% higher than those between other pairs of districts. On the other hand, the estimate of *Distance in party shares* suggests that a one-standard-deviation increase in political distance (around 19 percentage points) will lead to a decrease in migration flows by about 4%. Columns (3) and (5) of Table 1 investigate the robustness of these (baseline) results to augmenting Eq. (1) with lagged migration flows. As expected, the estimate of the LDV is positive and highly statistically significant, suggesting that popular migrant destinations for the citizens of a specific source district continue to attract a lot of emigrants. However, accounting for such network effects appears to have little effect on the estimates of the other regressors, including those of the political similarity measures.

To explore more thoroughly the relative importance of bilateral factors in predicting migration flows, we employ a Random Forest (RF) approach which allows us to calculate the mean decrease in prediction accuracy when a given variable is excluded from the model (James et al., 2013). Figure 2 presents the RF variable importance measure for the specifications in columns (3) and (5) of Table 1. According to the figure, the most important variable in predicting migration flows between two districts at time t is lagged migration flows, and this outstrips significantly the second ranked variable *Geographic distance*. The continuous measure of political similarity, *Distance in party shares*, ranks sixth overall (panel (b)), and exerts about the same influence as relative wages and distance in ethnic mix, suggesting that failure to account for this variable can lead to misspecification of the gravity equation.

Figure 2: Key Determinants of Migration Flows: Relative Importance



(a) Same party control

(b) Distance in party shares

Notes: The Random Forest (RF) variable importance measure is calculated based on the specifications in columns (3) and (5) of Table 1.

2.4.2 Endogeneity tests

As noted in Section 2.3, we take several approaches to get as close as possible to a causal interpretation of our political similarity effects.

To alleviate concerns of omitted variable bias, we control for a wide set of explanatory variables. We start by considering time-invariant indicators capturing geographic, historic and socio-demographic ties between destination and origin districts. We next consider corridor-specific characteristics that vary over time. Most of these added controls are highly correlated with one another, and their joint inclusion into the gravity model can introduce multicollinearity problems. However, throughout these specifications, the effect of the political similarity measures is highly statistically significant and stable in size, which is quite reassuring as regards to biases arising from the potential omission of unobserved bilateral characteristics (see Tables B.3 and B.4 in the Appendix).

A more comprehensive way to address the issue of omitted variable bias is to augment the model specification with pair fixed effects (Yotov et al., 2016). Table 2 presents the results when we add pair fixed effects to the regression set-up of Table 1. Overall, we can see that employing this intensive set of fixed effects does not change the inferences drawn from earlier findings: the estimates of the political similarity measures retain their sign and statistical significance across all columns, even though they are smaller in magnitude. This is not surprising since Table 2 exploits only within-pair variation and thus does not capture between-pair political similarity effects; for instance, two Labour party strongholds with no (or very slow) changes in their local council seat shares over the sampled period having higher migration flows.[8]

[8] As an additional step to evaluate the impact of omitted factors, we calculate selection ratios based on the method proposed by Altonji et al. (2005). We find that unobservable factors would have to be 4-53 times stronger than observables to explain away the full relationship between political similarity and migration flows, as reported in Table 2 (see Table B.5 in the Appendix). Such a strong role of unobserved heterogeneity seems very unlikely.

Table 2: Migration Flows and Political Similarity: Adding District Pair FEs

	Migration flows				
	(1)	(2)	(3)	(4)	(5)
Population$_j$ × Population$_i$	0.374***	0.367***	0.318***	0.353***	0.306***
	(0.037)	(0.037)	(0.035)	(0.037)	(0.035)
Wage$_j$ / Wage$_i$	0.126***	0.127***	0.097***	0.128***	0.098***
	(0.025)	(0.024)	(0.021)	(0.025)	(0.021)
Unemployment$_j$ / Unemployment$_i$	-0.051***	-0.053***	-0.062***	-0.055***	-0.064***
	(0.008)	(0.008)	(0.007)	(0.008)	(0.007)
Distance in ethnic frac.	0.135***	0.134***	0.141***	0.133***	0.139***
	(0.044)	(0.044)	(0.043)	(0.044)	(0.043)
Same party control		0.011***	0.010***		
		(0.002)	(0.002)		
Distance in party shares				-0.061***	-0.054***
				(0.008)	(0.008)
LDV			0.264***		0.264***
			(0.013)		(0.013)
Dest. × Orig. FE	✓	✓	✓	✓	✓
Dest. × Year FE	✓	✓	✓	✓	✓
Orig. × Year FE	✓	✓	✓	✓	✓
Pseudo-R^2	0.915	0.915	0.917	0.915	0.917
Observations	1,454,611	1,454,611	1,324,392	1,454,611	1,324,392

Notes: See notes for Table 1.

As pointed out in Section 2.3, migration flows at the bilateral level are extremely small to influence the outcome of local elections, at least in the short term. However, to further alleviate concerns of reverse causality, we replace our political similarity measures with their one-year and two-year lags and re-estimate the gravity model of Eq. (1) both with and without pair fixed effects. The lagged variables return estimates in line with the previous findings, suggesting that our results cannot be attributed to a contemporaneous reverse effect from outcome to treatment (see Table B.6 in the Appendix).

Finally, we address the possibility of reverse causality and remaining omitted variable bias by reporting IV estimates, where the continuous political distance measure is instrumented using a 'shift-share' instrument. In this way, we rely on variation stemming from the interaction of time-varying 'national' political distance and cross-dyad differences in initial political distance. Columns (1)-(4) of Table 3 show the results of a 2SLS-IV es-

Table 3: Migration Flows and Political Similarity: 2SLS-IV and Control Function Estimates

	2SLS-IV				Control Function			
	Ln(Migration flows + 1)				Migration flows			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance in party shares	-0.073***	-0.042***	-0.066**	-0.097***	-0.228***	-0.243***	-0.343***	-0.287***
	(0.015)	(0.011)	(0.033)	(0.035)	(0.018)	(0.019)	(0.021)	(0.020)
First-stage residuals					0.093***	0.106***	0.314***	0.259***
					(0.029)	(0.025)	(0.022)	(0.021)
Vector $\mathbf{X}_{ij,t}$	✓	✓	✓	✓	✓	✓	✓	✓
LDV		✓		✓		✓		✓
Dest. × Orig. FE			✓	✓			✓	✓
Dest. × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Orig. × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
KP stat	225,810	203,057	31,834	34,459				
Pseudo-R^2					0.830	0.832	0.917	0.918
Observations	1,414,024	1,288,126	1,414,024	1,288,126	1,414,024	1,288,126	1,218,323	1,094,549

Notes: All specifications exclude the initial years 2002 and 2003. 'KP stat' is the Kleibergen–Paap weak instrument statistic. In the Control Function estimation, the estimated OLS residuals from the first stage are introduced as an additional control variable in the PPML specification. Columns (5) to (8) report bootstrapped standard errors over 200 replications. See also notes for Table 1.

timation, where the dependent variable is the log of bilateral migration flows; whereas columns (5)-(8) show the results of a control function estimation, where the first-stage estimated residuals are added to the PPML model of Eq. (1).

The instrument performs very well – as captured by high KP values – and, in all cases, the effect of *Distance in party shares* turns out to be negative and statistically significant at conventional levels.[9] In terms of magnitude, the estimates in columns (5)-(6) are relatively close to those reported in Table 1, while the estimates in columns (7)-(8) are larger than those reported in Table 2 (even though the standard errors are larger as well). It should be noted that, in the pair fixed effects specifications, the first stage takes the form of a difference-in-differences estimator with continuous treatment: we compare political distance across district pairs with high or low initial values of political distance, in years where national political distance is higher or lower. The resulting estimates are local average treatment effects for the set of district pairs that increase their bilateral political distance in years when national political distance rises (see Crawford et al., 2021).

[9]The first stage estimations are provided in Table B.7 of the Appendix.

2.4.3 Robustness tests and further insights

The key finding that emerges from our analysis is that political similarity between two districts exerts a positive effect on their bilateral migration flows. In Section B.2 of the Appendix, we perform various tests to assess the robustness of this finding. Specifically, we examine the sensitivity of our estimates to: running the same regressions for ten different sub-samples, each time dropping the set of district pairs that belong to the same GOR (Table B.8); using three alternative types of standard errors (Table B.9); including the ratio of destination-to-origin district Index of Multiple Deprivations among the regressors (Table B.10); running separate regressions for district pairs with two-tier authorities and those with at least one single-tier authority (Table B.11); and running separate regressions for district pairs with the same urban-rural status and those with a different urban-rural status (Table B.12). Taken together, the results of these tests do not change our inferences.

In Table B.13, we replace our 'composite' political distance measure with either *Distance in Con. party share* or *Distance in Lab. party share*, calculated by the pair-specific distance in the local council seat share for each of the two parties. Both variables exhibit a significant effect on migration flows, even though the estimates of the latter appear to have a relatively larger magnitude. This is in line with recent survey-based evidence from the UK suggesting that more liberal and left-leaning people are more likely to say that they struggle to be friends with those who take the opposing point of view.[10] Finally, in Table B.14, we examine the impact of the relative Conservative or Labour ratio (the ratio of destination-to-origin district Conservative or Labour seat shares) on migration flows conditional on the political control of the two districts. According to the results, the value of these ratios matters the most when people move across districts with a different political colour. This validates the use of the continuous political similarity measure as a way to

[10]See, for example, the survey conducted by King's College London and Ipsos MORI (`https://www.kcl.ac.uk/policy-institute/assets/fault-lines-in-the-uks-culture-wars.pdf`).

flexibly account for the role of political preferences in choosing the destination district.

3 Individual-Level Analysis

In this section, we shed light into the micro-foundations underlying the politically-induced migration effects at the district-level. In particular, we investigate the main mechanism behind the political similarity-migration nexus (the desire for homophily), and examine the effect of individual political preferences on the choice of the destination district. To do so, we use individual-level data for the same time period (2002–2015) from the British Household Panel Study and its successor Understanding Society. Even though this survey is not specifically designed to capture the behaviour of internal migrants, it includes a wide range of questions on political and social attitudes and allows to identify district-to-district movers. Hence, by utilising this information, we can provide some evidence to support the premises underpinning our district-level analysis.

3.1 The desire for homophily

To infer a politically-induced desire for homophily, we investigate whether individuals' perceptions and attitudes towards the location where they live are affected by the extent of political alignment with their own district. We start by exploring individuals' answer to the question: *"If you could choose, would you stay here in your present home or would you prefer to move somewhere else?"*. This question appears in all waves, and thus it allows us to construct a large individual-level unbalanced panel with about 215K observations (4.8 observations, on average, per individual). We then consider three questions on neighbourhood satisfaction, which are asked less frequently (in 5 waves); namely, whether one agrees with the statements: *"I plan to remain a resident of this neighbourhood for a number of years."*, *"I feel like I belong to this neighbourhood."*, and *"I think of myself as similar to the people* *who live in this neighbourhood."* – all resulting in a sample of about 78K observations.

We define a subset of treated individuals as those who are 'politically aligned'; that is, those whose political preferences are aligned with the political preferences of their district. More formally, we define *Alignment* as:

$$Alignment_{n,d,w,s} = \begin{cases} 1 & \text{if } P_{n,d,w,s} = P_{d,w,s} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where $P_{n,d,w,s}$ captures the political preferences of individual n, living in district d, and interviewed in survey wave w and quarter s,[11] as proxied by the response to the question *"Which party do you feel closest to?"*, and $P_{d,w,s}$ captures the political preferences of district d, as proxied by the party that controls the local council at the same point in time.

We employ alternative specifications that include different combinations of fixed effects and individual-level controls, with the most demanding one taking the following form:

$$Y_{n,d,w,s} = \vartheta Alignment_{n,d,w,s} + \delta \mathbf{Z}_{n,d,w,s} + \lambda_{d,w,s} + u_{n,d,w,s} \tag{3}$$

where $Y_{n,d,w,s}$ is one of the four binary outcome variables; $\mathbf{Z}_{n,d,w,s}$ is a vector of individual-level control variables that includes (among others) age, age squared, gender, income decile, educational background, employment status, marital status, having children, and household size (see Table C.1 in the Appendix for the full list); $\lambda_{d,w,s}$ represents district $\times$ wave $\times$ time fixed effects; and $u_{n,d,w,s}$ is an error term, clustered at the individual and district levels.

The inclusion of district $\times$ wave $\times$ time fixed effects implies that we only exploit between individual variation within a district. This allows us to compare politically aligned

[11] The wave-annual observations are disaggregated into wave-quarterly observations by exploiting information about the quarter of the year that the data is collected.

individuals with a very small number of individuals who are not politically aligned but live in the same district and are interviewed in the same survey wave and quarter. Furthermore, the inclusion of vector $\mathbf{Z}_{n,d,w,s}$ in Eq. (3) controls for all important individual characteristics that may potentially affect the attitudes towards one's current location. However, to further mitigate concerns of omitted variable bias, we check the robustness of our results when we focus on the subsample of 'core supporters' for the Conservative or the Labour party; that is, the set of respondents who report being closest to the same party (Conservative or Labour) across all survey waves. In this way, individual n's political alignment at a given point in time is only determined by changes in their district's political preferences, and thus it is less prone to endogeneity arising from unobserved time-varying individual characteristics or individual-specific time-shocks.

Table 4 shows the linear probability model (LPM) estimation results for the outcome variable *Preference to move*, which takes value 1 if people report that they prefer to move (32% of observations), and 0 otherwise. Columns (1)-(2) present the estimates of *Alignment* when we employ district fixed effects and GOR $\times$ wave $\times$ time fixed effects, before and after the inclusion of vector $\mathbf{Z}_{n,d,w,s}$. This set of fixed effects absorbs any time invariant difference in migration attitudes across districts, and controls for non-linear time trends specific to each of the 10 GORs in England and Wales, thereby allowing us to exploit between-district and between-individual variation. On the other hand, columns (3)-(4) present the estimates of *Alignment* when we employ instead district $\times$ wave $\times$ time fixed effects (as in Eq. (3)), and thus only exploit between individual variation within a district. Throughout these specifications, there is a negative and highly statistically significant effect of alignment on the outcome variable, with the estimates suggesting that politically aligned individuals are about 2.5 percentage points less likely to report preference to move.[12] In columns (5)-(8), we replicate the regressions of columns (1)-(4), but we now

[12]Table C.2 in the Appendix presents the full regression results of Table 4.

Table 4: Political Alignment and Preference to Move

	Preference to move							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Alignment	-0.026***	-0.022***	-0.030***	-0.025***				
	(0.004)	(0.004)	(0.005)	(0.005)				
Alignment [core supporters]					-0.014***	-0.015***	-0.015**	-0.018***
					(0.005)	(0.005)	(0.007)	(0.007)
District FE	✓	✓			✓	✓		
Region × Wave × Time FE	✓	✓			✓	✓		
District × Wave × Time FE			✓	✓			✓	✓
Vector $\mathbf{Z}_{n,d,w,s}$		✓		✓		✓		✓
Mean of DV	0.315	0.315	0.315	0.315	0.314	0.314	0.314	0.314
Mean of Alignment	0.357	0.357	0.357	0.357	0.471	0.471	0.471	0.471
R^2	0.031	0.071	0.141	0.175	0.035	0.074	0.174	0.207
Observations	214,502	214,502	214,502	214,502	143,116	143,116	143,116	143,116

Notes: Standard errors clustered at the individual and district levels in parentheses (two-way clustering). DV is the dependent variable. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

restrict the sample of respondents to those defined as 'core supporters'. This has little effect on the results: the estimates of *Alignment* are once again negative and highly statistically significant, although slightly smaller in magnitude. Substantively, the estimate in column (8) implies that a Labour (Conservative) supporter who lives in a Labour (Conservative) district is about 2 percentage points less likely to exhibit preference to move than a Conservative (Labour) supporter who lives in the same district and is interviewed at the same time.

Table 5 shows the results for the three outcome variables on neighbourhood satisfaction based on the same regression set-up as in Table 4. We assign value 1 to the responses "Agree" and "Strongly agree" (and 0 to all the other responses) on whether people plan to stay in their current neighbourhood (71% of observations), think of themselves as similar to others in this neighbourhood (63% of observations), and feel that they belong to this neighbourhood (70% of observations), and estimate LPMs like before. Despite the fact that the sample size is now three times smaller, the evidence obtained is in line with the findings of Table 4. We consider this as evidence that a desire for homophily is indeed at play; i.e., living in areas with ideological views similar to your own can contribute to a sense of 'fitting in' and 'feeling at home' and increase the overall satisfaction you have with your neighbourhood.

In Section C.2 of the Appendix, we present additional robustness and sensitivity checks. Specifically, we demonstrate that our results are robust to: running the same regressions for ten different sub-samples, each time removing all respondents who live in a specific GOR (Table C.3); using alternative clustering of standard errors (Table C.4); replacing the alignment variable with its lagged value (Table C.5); augmenting the regression model with a placebo variable capturing non-treatment years (Table C.6); and augmenting the regression model with a variable capturing 'spatially lagged' alignment (Table C.7). Finally, in Table C.8, we show that the results persist when we split respondents into groups based on their political ideology, age, income and education.

3.2 The effect of political preferences on the destination choice

The results above demonstrate that people are attracted to "politically compatible" areas. This, however, does not mean that political preferences are the reason, or one of the main reasons, for a subsequent relocation.[13] Indeed, while political alignment can increase the satisfaction you have with your area, it is rather unlikely to have a large and immediate impact on your decision to change district of residence.[14] To explore this issue, we follow Langella and Manning (2019) and test whether the variables considered in Section 3.1 can serve as predictors of the decision to migrate in the immediate future. To this end, we construct an indicator for actual moving (taking value 1 if the respondent is observed in a different district in the year of survey wave w than in the year of survey wave $w-1$),

[13]Note that, while 32% of the total number of observations indicate preference to move, only 2.5% of them indicate a change in the district of residence.

[14]In Appendix A.3, we provide some evidence about the reasons for moving in the context of our study, based on data from the English Housing Survey. The top 3 reasons are related to housing, area quality, and employment.

Table 5: Political Alignment and Neighbourhood Satisfaction

Panel (a)	Plan to stay in neighbourhood							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Alignment	0.031***	0.020***	0.035***	0.023***				
	(0.005)	(0.005)	(0.006)	(0.005)				
Alignment [core supporters]					0.019***	0.017***	0.018**	0.017**
					(0.006)	(0.006)	(0.008)	(0.007)
District FE	✓	✓			✓	✓		
Region × Wave × Time FE	✓	✓			✓	✓		
District × Wave × Time FE			✓	✓			✓	✓
Vector $\mathbf{Z}_{n,d,w,s}$		✓		✓		✓		✓
Mean of DV	0.707	0.707	0.707	0.707	0.708	0.708	0.708	0.708
Mean of Alignment	0.354	0.354	0.354	0.354	0.464	0.464	0.464	0.464
R^2	0.031	0.125	0.146	0.228	0.037	0.124	0.182	0.255
Observations	77,520	77,520	77,520	77,520	53,943	53,943	53,943	53,943

Panel (b)	Belong to neighbourhood							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Alignment	0.033***	0.024***	0.035***	0.025***				
	(0.005)	(0.005)	(0.006)	(0.005)				
Alignment [core supporters]					0.025***	0.023***	0.025***	0.023***
					(0.006)	(0.006)	(0.008)	(0.007)
District FE	✓	✓			✓	✓		
Region × Wave × Time FE	✓	✓			✓	✓		
District × Wave × Time FE			✓	✓			✓	✓
Vector $\mathbf{Z}_{n,d,w,s}$		✓		✓		✓		✓
Mean of DV	0.695	0.695	0.695	0.695	0.694	0.694	0.694	0.694
Mean of Alignment	0.354	0.354	0.354	0.354	0.464	0.464	0.464	0.464
R^2	0.030	0.079	0.139	0.180	0.033	0.080	0.172	0.209
Observations	77,653	77,653	77,653	77,653	54,088	54,088	54,088	54,088

Panel (c)	Similar to others in neighbourhood							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Alignment	0.049***	0.034***	0.054***	0.039***				
	(0.006)	(0.005)	(0.006)	(0.006)				
Alignment [core supporters]					0.033***	0.029***	0.039***	0.035***
					(0.007)	(0.006)	(0.009)	(0.008)
District FE	✓	✓			✓	✓		
Region × Wave × Time FE	✓	✓			✓	✓		
District × Wave × Time FE			✓	✓			✓	✓
Vector $\mathbf{Z}_{n,d,w,s}$		✓		✓		✓		✓
Mean of DV	0.626	0.626	0.626	0.626	0.634	0.634	0.634	0.634
Mean of Alignment	0.354	0.354	0.354	0.354	0.464	0.464	0.464	0.464
R^2	0.030	0.104	0.136	0.201	0.033	0.109	0.169	0.231
Observations	77,515	77,515	77,515	77,515	53,939	53,939	53,939	53,939

Notes: See notes for Table 4.

Table 6: The Effects on Actual Moving

	Move district									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Preference to move	0.038***	0.030***								
	(0.002)	(0.002)								
Plan to stay in neighbourhood			-0.056***	-0.048***						
			(0.003)	(0.003)						
Belong to neighbourhood					-0.020***	-0.016***				
					(0.002)	(0.002)				
Similar to others in neighbourhood							-0.014***	-0.011***		
							(0.002)	(0.002)		
Alignment									-0.002	-0.003
									(0.002)	(0.002)
District FE	✓		✓		✓		✓		✓	
Region × Wave × Time FE	✓		✓		✓		✓		✓	
District × Wave × Time FE		✓		✓		✓		✓		✓
Vector $\mathbf{Z}_{n,d,w,s}$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean of Move district	0.025	0.025	0.026	0.026	0.026	0.026	0.026	0.026	0.025	0.025
Mean of x-var	0.305	0.305	0.725	0.725	0.698	0.698	0.642	0.642	0.357	0.357
R^2	0.068	0.322	0.083	0.314	0.064	0.301	0.063	0.301	0.056	0.316
Observations	125,156	125,156	36,885	36,885	36,886	36,886	36,880	36,880	125,156	125,156

Notes: The dependent variable, *Move district*, is a binary indicator taking value 1 if the respondent is observed in a different district in the year of survey wave w than in the year of survey wave $w-1$. x-var is the main independent variable. All right-hand-side variables (x-var and vector $\mathbf{Z}_{n,d,w,s}$) are in lagged terms (as observed in survey wave $w-1$). See also notes for Table 4.

and regress this indicator on the lagged value of the four outcome variables, as well as the lagged value of the treatment variable *Alignment*. The estimates, reported in Table 6, indicate that, while people's satisfaction with their current location influences their real-life migration decisions, political alignment does not have a direct and immediate impact on the probability of moving to another district.

The findings in Table 6, together with the strong evidence of partisan sorting at the district-level (based on actual movers), suggest that political preferences affect migration patterns only through the choice of the destination among migrants; that is, people who decide to migrate are more likely to move into a district that matches their ideological preferences. To further corroborate this argument, we examine whether an individual migrant's political ideology can predict the partisanship of the destination district. To ensure that the results are not subject to selection bias, we employ a Heckman probit selection model which allows us to estimate the likelihood of moving to a Conservative or a Labour district while accounting for the initial likelihood of actually moving. Following the work of McDonald (2011), the first-stage model (predicting the likelihood of moving to a new district) includes the full set of controls in $\mathbf{Z}_{n,d,w,s}$ together with the alignment variable; whereas the second-stage model (predicting the probability of moving to either a Conservative or a Labour district) includes political ideology, age, age squared, distance of the move, and partisanship of the origin district.[15] Adding the latter variable is important because it accounts for the fact that individuals with a particular political leaning are more likely to originate from a district that reflects this political leaning (McDonald, 2011).

Columns (1)-(4) of Table 7 report the corresponding second-stage estimates, both for the full sample of respondents and the subsample of 'core supporters';[16] whereas columns

[15]The right-hand-side individual-level variables in both stage equations are in lagged terms; i.e., as observed in the survey wave before the move.

[16]The first-stage estimates are reported in Table C.9 of the Appendix.

Table 7: Political Preferences and the Destination Choice

	Move to Con.		Move to Lab.		Move to Con.		Move to Lab.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Con. supporter	0.120***				0.088***			
	(0.016)				(0.018)			
Con. supporter [core supporters]		0.159***				0.128***		
		(0.020)				(0.023)		
Lab. supporter			0.086***				0.063***	
			(0.014)				(0.016)	
Lab. supporter [core supporters]				0.135***				0.110***
				(0.019)				(0.021)
Age	0.012***	0.015***	-0.010***	-0.010***	0.012***	0.022***	-0.012***	-0.018***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
Age sq.	-0.000***	-0.000***	0.000***	0.000***	-0.000***	-0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Con. origin	0.080***	0.086***	0.010	0.014	-0.011	-0.012	0.038*	0.075***
	(0.018)	(0.025)	(0.017)	(0.023)	(0.022)	(0.030)	(0.020)	(0.028)
Lab. origin	-0.095***	-0.062**	0.175***	0.163***	-0.026	0.028	0.052**	0.060**
	(0.019)	(0.026)	(0.018)	(0.024)	(0.024)	(0.032)	(0.022)	(0.031)
Ln(Distance of move)	-0.006	0.002	-0.028***	-0.027***	-0.008	0.013	-0.025***	-0.029***
	(0.007)	(0.009)	(0.006)	(0.008)	(0.008)	(0.010)	(0.007)	(0.010)
GOR $\times$ Wave $\times$ Time FE					✓	✓	✓	✓
Inverse Mill's ratio (Mill's λ)	0.019	-0.011	-0.069**	-0.025	0.071*	-0.039	-0.016	0.076
	(0.038)	(0.048)	(0.035)	(0.044)	(0.041)	(0.050)	(0.037)	(0.047)
Selected observations	4,084	2,358	4,084	2,358	3,146	1,731	3,146	1,731
Non-selected observations	155,300	104,588	155,300	104,588	122,185	77,544	122,185	77,544

Notes: This table shows the second-stage estimates of a Heckman probit selection model, predicting the likelihood of moving to a Conservative district (*Move to Con.*) or a Labour district (*Move to Lab.*). Standard errors are in parentheses. *Con. supporter* and *Lab. supporter* are binary indicators capturing supporters for the Conservative party and the Labour party respectively. All right-hand-side individual-level variables are in lagged terms (as observed in survey wave $w-1$). ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

(5)-(8) check the robustness of these results to adding GOR $\times$ wave $\times$ time fixed effects.[17] In all specifications, the estimate of the ideology variable is statistically significant at the 1% level and signed in the expected direction: being a Conservative or a Labour supporter increases the likelihood of moving into a Conservative district or a Labour district, respectively. Furthermore, this effect appears to be far more pronounced when we compare the core supporters of the two parties, who are arguably more responsive to the political environment of the potential destination districts. To address the possibility that the observed effects are driven by other individual characteristics which are correlated with political preferences, we also consider an alternative specification that includes income and educational background in the second stage. As shown in Table C.10 of the Appendix, the results are not affected by the inclusion of these extra controls.

3.3 Selection of out-migrants along political lines

As mentioned above, the observed partisan sorting at the district level relies on the premise that the outflow of migrants from a given district is representative of the political preferences of that district. In Section C.4 of the Appendix, we run a final round of analysis and explore the relationship between the share of out-migrants supporting the Conservative or the Labour party and the mean share of seats held by the Conservative or the Labour party, respectively (in each origin district). We find that the two shares are strongly positively correlated, which corroborates the interpretation of our findings.

[17]Due to the small number of movers in our sample, it is not possible to include district $\times$ wave $\times$ time fixed effects in this setting.

4 Conclusions

In this article, we investigate whether people tend to relocate to areas that align with their political preferences. We use data on the universe of population movements across local authority districts in England and Wales (2002-2015) and show that political similarity between two districts exerts an important positive effect on their bilateral migration flows. Leveraging individual survey-based data, we also find that political alignment to the district of residence contributes to individuals' sense of belonging and 'fitting in' and that a migrant's political ideology can predict the partisanship of the destination district.

Within-country migration has garnered significant attention from both researchers and policymakers, given its impact on wages, employment, health, marriage, and intergenerational mobility. Our research contributes to the literature on what affects internal migration patterns. Despite the extensive research on economic factors that drive migration decisions, community ties – specifically the impact of shared beliefs and values – have not received adequate attention (Jia et al., 2023). Our study focuses on political homophily but we note that this cannot be viewed independently from other forms of homophily. As an individual's political identity encompasses a diverse range of preferences, attitudes, and worldviews, a measure of political similarity among citizens or regions can be used as a comprehensive and observable marker of wider affinities. Whereas we assume in our analysis that people decide freely where to move, it is possible that, on the demand side, employers may choose to hire individuals from areas that share their political preferences. This could be due to discrimination based on political beliefs. Although this mechanism is unlikely to be significant as most people report non-job-related reasons for moving (see Appendix A.3), investigating this aspect would be a fruitful avenue for future research on the role of political preferences in shaping economic decisions.

The phenomenon of geographic sorting, where politically like-minded individuals tend to cluster within the same communities, has important implications for democracy. For one, by limiting the development of and exposure to diverse viewpoints, it perpetuates a politically homogeneous environment that can foster a hostile political culture. This clustering can lead to a less politically educated electorate, and intensify political polarisation. The rise in levels of 'affective polarisation' in Western democracies, including the UK, is a cause for concern, especially in the wake of the Brexit referendum which has further exacerbated this trend. The concentration of partisanship can contribute to the creation of a hostile culture of "othering" political rivals which spills into social relations. Geographic sorting also damages democratic performance because it reduces the number of politically competitive settings. This poses a threat to a democratic government's accountability function, as competitive elections are the means by which citizens reward or punish the performance of their representatives. It also leads parties to embrace "minimalist" electoral coalition strategies where policy platforms are tailored towards the geographic areas where they have a realistic chance of winning.

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Micromotives and macromoves: Political preferences and internal migration in England and Wales

Supplementary Information Appendix

For Online Publication

Contents

A Further Insights and Information

A.1 Theoretical insights

Political homophily and other forms of homophily

Political homophily is co-constitutive of broader forms of homophily, rather than existing as a separable phenomenon that exerts an independent causal influence. This is a standard assumption across a growing body of research on geographic sorting in the US (Brown and Enos, 2021; Johnston et al., 2016; Lang and Pearson-Merkowitz, 2015; Mummolo and Nall, 2017; Sussell, 2013; Tam Cho et al., 2013), and is rooted in a long lineage of psychology and political psychology research that demonstrates how individuals' political ideology is intimately connected to a broader range of preferences, attitudes, and cognitions (Jost et al., 2009). Rather than being a set of discreet, separable beliefs or attitudes, political ideologies are 'broad postures that explain and justify different states of social and political affairs' (Jost et al., 2009, p.311; see also Feldman, 2003). Put differently, individuals from different ends of the political spectrum possess divergent 'worldviews'; that is, they use different 'instinctive frameworks to respond to and make sense of their surroundings' (Hetherington and Weiler, 2020, p.3).

From a psychological point of view, this has been explained as a consequence of two mechanisms. First, it is argued that left- and right-wing political ideologies are rooted in a 'set of interrelated epistemic, existential, and relational needs or motives' which stem from basic social psychological orientations concerning uncertainty and threat (Jost, 2006; Jost et al., 2007). In short, political ideologies are, at least in part, generated 'bottom-up' from broad, dispositional characteristics (Barker and Tinnick, 2006; Block and Block, 2006; Caprara, 2007; Carney et al., 2008; Jennings and Stoker, 2019; Kemmelmeier, 2007; Leone and Chirumbolo, 2008; Ozer and Benet-Martinez, 2006; Sidanius and Pratto, 2001). For instance, a number of findings demonstrate a link between epistemic motives to reduce uncertainty and political conservatism (Jost et al., 2007). On the other hand, those who score high on the 'need for cognition scale' – measuring individuals' subjective enjoyment of thinking or contemplating – are more likely to gravitate toward liberal ideology (Sargent, 2004).

Second, social identity theory (SIT) suggests that partisanship has the effect of enhancing cultural and attitudinal differences (Greene, 1999). Humans instinctively categorise the world into myriad dichotomous groupings consisting of 'us' and 'them', and use these divisions to define themselves (Greene, 1999, p.395; Tajfel, 1978). These mechanisms cause individuals to seek to maximise differences between in-groups and out-groups (Greene, 1999). Increasingly, the political psychology literature has pointed out that partisanship is less a set of preferences for a bundle of policy positions, but more a form of social identity, like religious affiliation (Ruckelshaus, 2022, p.1478).

Political ideology and partisanship, under this view, require a subjective sense of belonging to the types of people one associates with one's ideology or party (Green et al., 2004; Huddy and Bankert, 2017; Huddy et al., 2015). As a result, political ideology encompasses and amplifies a wide range of differences in cultural affinities and social attitudes. This conceptualisation of partisanship helps explain the growing trend of 'affective polarisation'; that is, the tendency for partisans to dislike and distrust those from the other party while favouring those of their own (Druckman et al., 2021, p.28) – which is particularly evident in the US (Iyengar et al., 2019) and the UK (Hobolt et al., 2021). Affective polarisation means that political divisions increasingly exacerbate social divisions. For example, partisans avoid friendships with opposing party members (Huber and Malhotra, 2012),[1] discourage their children from marrying them (Iyengar et al., 2012), and socialise with them for shorter periods of time (Chen and Rohla, 2018). These two strands of the literature explain why, empirically, political preferences tend to predict a broad range of non-political preferences (Jost et al., 2009, p.324).[2]

Similarly, in the UK, where we situate our study, Kelly (1988, 1989, 1990a,b) finds extensive experimental evidence that social identity is the basis of partisanship. More recently, Sobolewska and Ford (2020) identify a divide between 'identity liberals' and 'identity conservatives' in the UK, each characterised by a constellation of beliefs, preferences, and attitudes. Party competition reflects differences in culture and values, including beliefs about such issues as national identity, criminal justice and adherence to authority (De Vries and Hobolt, 2020; Wager et al., 2022). 'Identity liberals' embrace ethnic and racial diversity, believe in non-discrimination, think of immigration as positive and part of a forward look-

[1]See also `https://www.pewresearch.org/politics/2017/10/05/8-partisan-animosity-personal-politics-views-of-trump/`

[2]To illustrate, Jost et al. (2008) find that self-identified liberals in the US possess significantly more favourable attitudes concerning foreign films, big cities, poetry, tattoos, and foreign travel, whereas self-identified conservatives in the US are more favourable towards fraternities and sororities, sport utility vehicles, drinking alcohol, and watching television. Similarly, Hetherington and Weiler (2018) find that Democratic versus Republican partisanship in the US predicts attitudes related to politics such as stances on immigration, multiculturalism, and race, but also differences in cultural affinities such as where [individuals] prefer to live (more urban or more rural areas), what they prefer to eat (American food or ethnic cuisine), and what they prefer to wear (traditional or fashionable).

ing society, while 'identity conservatives' feel that diversity has gone too far in favouring minorities or equalising rights, and that immigration is bad for the economy, crime, and solidarity, and 'hollows out' national culture (Sobolewska and Ford, 2020). Political polarisation in the UK thus encompasses broader, cultural dimensions, drawing comparisons with the US (Sobolewska and Ford, 2019).[3]

In short, a large empirical and theoretical literature suggests that political preferences are co-constitutive of a broad constellation of preferences and attitudes. As the eminent article by Jost et al. (2009, p.324) concludes, 'heterogeneous research programs yield the common conclusion that ideological commitments are robust predictors of a wide range of attitudes, preferences, judgments, and behaviours'. This points to a conceptualisation of political ideology as a cohesive cluster or constellation of beliefs. This is also consistent with the political economy literature's success in framing electoral competition as existing along a left-right political spectrum which maps a range of interrelated policy positions (Downs, 1957; Alesina, 1988; Eguia, 2011; Riker and Ordeshook, 1968). In turn, this understanding of political ideology points to the conclusion that homophily as a consequence of political preferences is not a separable causal phenomenon from the broader tendency to homophily (McPherson et al., 2001). As such, we can assume in our analysis that measures of political similarity between districts capture the bases of both political homophily and homophily more broadly conceived.

It is also important to note that our study focuses on election results, rather than some other measures of political preferences or cultural characteristics. This is because the voting behaviour of a prospective destination area can provide a valuable cue about its cultural and social characteristics when first-hand experience is not available. A comparison might be drawn between the assessments individuals face when moving and the choices that voters face in distinguishing between political candidates with a range of policy platforms, competencies, and personal characteristics. In the face of 'difficult information environments' citizens tend to utilise easily accessible shortcuts (Fiske and Taylor, 1991) and 'low-information' rationality (Popkin, 1991). Among the myriad of heuristics used as a 'shortcut' in political decision-making, perhaps the most important one is political party identification (Lodge and Hamill, 1986; Rahn, 1993; Rugeley and Gerlach, 2012). As Schaffner and Streb (2002, p.560-561) note, 'virtually every voting model proposed by po-

[3] In a similar vein, Hobolt et al. (2021) argue that voters with opposing positions on the Brexit referendum bear the hallmarks of social identity dynamics and affective polarisation, including in-group identification, group differentiation (especially prejudice towards members of the out-group), and evaluative bias in both perceptions and decision-making.

litical scientists since Campbell et al. (1960) has included party identification as a-if not the-central influence on candidate preferences'. Parties reduce the informational costs of voting by providing voters with reliable cues (Schaffner and Streb, 2002, p.561). The same process can occur when individuals assess prospective areas to migrate to. Information about which party has won in a local electoral contest provides an important cue as to the political climate in that area.

The consequences of geographic sorting

Regardless of whether political homophily or a broader form of homophily is driving our results, the policy implications that follow are the same: geographic sorting is causing conservative and labour supporters to cluster within the same communities. As McPherson et al. (2001, p.23) puts it, this phenomenon "limits people's social worlds in a way that has powerful implications for the information they receive, the attitudes they form, and the interactions they experience".

While recent literature has tended to focus on homophily within online social networks and its consequences (Cinelli et al., 2021; Conover et al., 2011; Colleoni et al., 2014), geographic sorting is just as consequential. In a manner which parallels the creation of online 'echo chambers', geographic sorting limits the exposure of individuals to divergent opinions and worldviews (Colleoni et al., 2014). Wojcieszak and Mutz (2009) observe that exposure to heterogeneous networks and political views often happens accidentally, and occurs in spaces that are not exclusively devoted to political discussion. The geographic area where people live is therefore a critical determinant of the political views they are exposed to. A lack of exposure to opposing views leads to a less politically educated electorate: the greater the network heterogeneity in which individuals are embedded, the bigger their desire for information on different topics (Scheufele et al., 2006). Politically diverse social networks lead to more understanding and tolerance of opposing viewpoints, while less politically diverse networks and exposure to divergent opinions lead to the adoption of more extreme positions, thus deepening political polarisation (Mutz, 2001; Stroud, 2010).

These mechanisms are particularly consequential in light of recent concerns over affective polarisation in advanced Western democracies (Druckman and Levendusky, 2019; Druckman et al., 2021; Iyengar et al., 2019), and in the UK in particular (Duffy et al., 2019) where the Brexit referendum has heightened this dynamic (Curtice, 2018; Hobolt et al., 2021). In fact, since the Brexit referendum was announced, scholars and political commentators have often warned about the increasing "tribalisation" of British politics (Duffy et al., 2019). Although the referendum vote cut across party and ideological lines, partisan identities have never disappeared (Schumacher, 2019).[4] For one, a degree of partisan concentration has always existed across the UK national landscape (Johnston et al., 2006); and bitter political divisions and negative views of opponents have long been present, such as during the miners' strike of 1984-85, the poll tax riots in the 1990s, and the 2003 protest against the war in Iraq.[5] As Duffy et al. (2019, p.11) note, this has created 'a hostile culture of "othering" political rivals' which has '[spilled] into social relations'.[6]

In addition to the effects on citizens' political attitudes, geographic sorting damages democratic performance because of its effects on electoral mechanisms. More precisely, geographic sorting results in increasingly homogeneous legislative districts in which election outcomes are a foregone conclusion (Martin and Webster, 2020, p.4). This poses a serious threat to a democratic government's accountability function, because competitive elections are the means by which citizens reward or punish the performance of their representatives (Ferejohn, 1986; Gordon et al., 2007). In the context of a single-member district majoritarian system such as is present in the UK, geographic sorting can also lead to an unrepresentative legislature when, for example, a particular party's voters tend to cluster in densely populated urban areas (Chen et al., 2013; Martin and Webster, 2020). It also leads parties to embrace 'minimalist' electoral coalition strategies where policy platforms are tailored towards the geographic areas where they have a realistic chance of winning (Jennings and Stoker, 2019). All these aspects are a cause of concern in the UK, where historically, left-wing parties have consistently drawn the core of their support from large, cosmopolitan urban centres, while right-wing parties have thrived in rural areas (Butler, 1973; Cox, 1969; Crewe and Payne, 1976; Steed, 1986; Taylor and Johnston, 2014).

[4]In fact, policymakers and commentators have often noted that a "divided" Britain is not a new phenomenon. Available here: `https://www.theguardian.com/commentisfree/2019/jan/13/divided-britain-not-new-why-do-todays-schisms-seem-intractable`

[5]In a recent work, Boxell et al. (2022) show that, since 1980, affective polarisation has been consistently higher in Britain than in the US, particularly when restricting attention to the two largest parties. This phenomenon of animosity and the tendency to dislike and distrust those from the other party has thus endured in the last four decades.

[6]Hobolt et al. (2021), for instance, find that it is increasingly unlikely that people on the opposite sides of the political spectrum and the Brexit debate would be willing to talk to each other or be happy for their children to marry someone from the other side. Similarly, Murray et al. (2017) find that both Leave and Remain supporters exhibit clear discrimination in their treatment of in-groups and out-groups.

Using local election results to capture aggregate political preferences

Local elections in the UK have been frequently understood as 'second-order' arenas wherein voters are able to express their satisfaction or dissatisfaction about the national government (Butler, 1973; Reif and Schmitt, 1980). Thus, national politics exert a considerable influence on local election results (Rallings and Thrasher, 1997). Feigert and Norris (1990), building on the work of Mughan (1988), find that post-war local elections in Britain are driven by assessments of political parties at the national level and can be considered 'referenda' on the incumbent government. More recently, Rallings and Thrasher (2013) find that local council seats can be used as pointers for future parliamentary elections because they capture local attitudes towards national parties. For these reasons, local election results are "regularly used by politicians and political commentators as barometers of public support for governments and parties between general elections" (Prosser, 2016, p.274).

Because local council elections can occur in any given year due to the rotating manner in which councillors are elected, local election results track the evolution of political attitudes within legislative districts in more detail than general elections (Fetzer, 2019). As such, local elections in the UK are like 'large-scale opinion polls' which track political preferences over time (Prosser, 2016, p.275). In addition to capturing the views of a larger sample of the electorate than traditional opinion polls, they are more accurate in capturing political preferences due to the well-recognised gap between reported voting intentions and actual voting behaviour caused by such factors as social desirability and late-deciding voters (Kellner et al., 2011). On this basis, we consider that local elections are the most effective measure for capturing jurisdictional political preferences.

That said, one might argue that voter turnout is generally low in local elections in the UK (see, e.g., Rallings and Thrasher, 2007, p.334), fluctuating between 50% to 60% of the general election turnout (Uberoi, 2019). Yet, note that this only presents a problem in capturing aggregate political preferences if voters during local elections hold systematically different views than non-voters. On the one hand, non-ideological factors including the perceived costs of voting and the belief that voting is a civic duty are the most significant ones in determining local election participation in Britain (Rallings and Thrasher, 2007; Orford et al., 2009). On the other hand, local election and by-election results have been utilised with great success in forecasting general elections in the UK (Rallings and Thrasher, 1999; Rallings et al., 2011; Prosser, 2016), demonstrating their relevance in capturing political preferences. The evidence, in fact, suggests that UK local elections mirror national electoral outcomes, especially in the case of England and Wales (Prosser, 2016).

A.2 Information on local governments, elections and reforms

The local government structure in the UK has both two-tier and single-tier components. In England, there are 27 upper-tier county councils with 201 district councils. Additionally, there are 145 districts (123 in England and 22 in Wales) which operate on a single-tier basis. Most responsibilities are split between counties and districts in two-tier authorities, whereas single-tier authorities must provide all public services. In the case of two-tier authorities, the county councils provide around 80% of the services, including schools, social services, public transportation, highways, waste disposal and trading standards, whereas the district councils provide more local services, including council housing, local planning, recycling and refuse collection and leisure facilities.

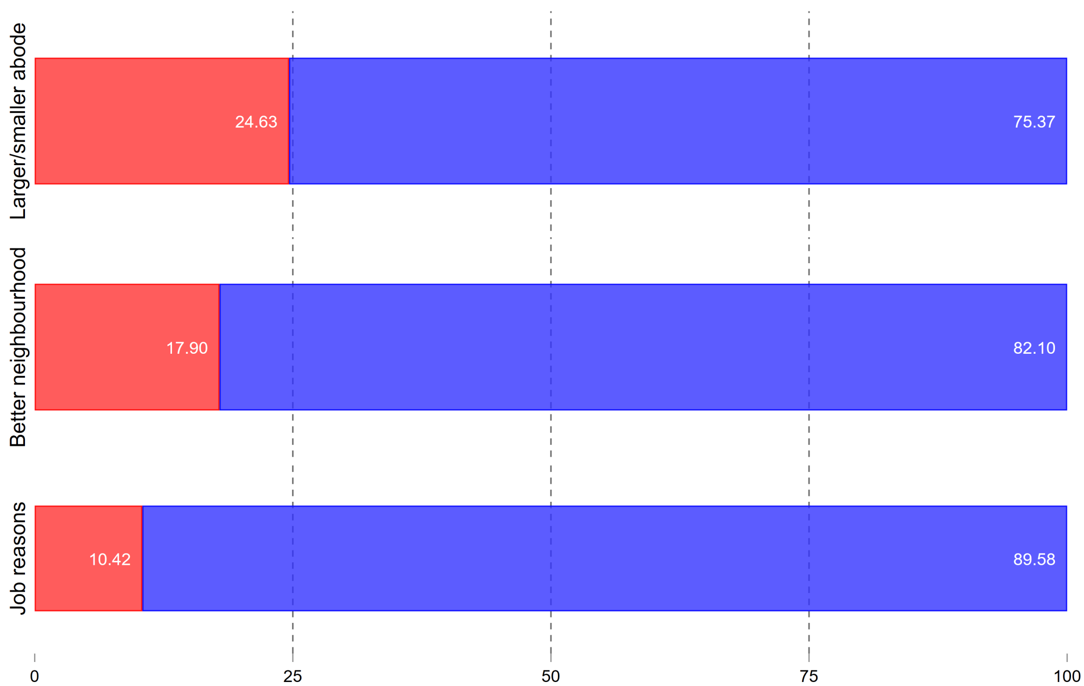
Elections are organised by subdivisions of local authorities, called electoral wards or electoral divisions. England and Wales use the first-past-the-post voting system to elect the councillor in each electoral ward. Terms last for four years, and most councils hold elections by "thirds", with one-third of the seats up for election each year, and with no election held one year. Due to this rotating fashion by which councillors are elected, local authority elections can, in practice, take place in any given year. To construct our political similarity measures, we follow Fetzer (2019) and use election results at the district council and single-tier authority level between 2002 and 2015.

The main change in the structure of local government since 2002 was the introduction of nine new unitary authorities (UAs) in England in 2009. In the first five county councils, the lower tier district councils were abolished, and all functions were undertaken by the new UA of the same name. In Bedfordshire, Mid- and South Bedfordshire merged to form the Central Bedfordshire UA. Bedford attained UA status, having previously been a district. In Cheshire, the UA of Cheshire West and Chester was formed from the districts of Ellesmere Port and Neston, Vale Royal, and Chester. The districts of Macclesfield, Congleton and Crewe and Nantwich merged to form Cheshire East. In order to compare the regions before and after this reform, we follow Fetzer (2019) and merge the district-level electoral results between 2002 and 2008 into the current UA boundaries. There is no concern of overlap, as no district council was split to form the new UAs.

A.3 Information on reasons for moving

In this section, we examine descriptively the reasons for moving in the context of our study. To do so, we use individual-level data over the period 2002-2013 from the English Housing Survey (previously known as the Survey of English Housing). The survey asks head-of-household respondents who have lived at their current address for less than three years to state the reason for their last move from a list of 17 possible reasons, including family circumstances, job-related reasons, and housing quality. We combine data from 12 waves into a repeated cross-section dataset and rank the reasons based on the percentage of individuals who cite them over the entire period. As can be seen in Figure A.1, the top 3 reasons are: "wanted a larger/small house/flat"; "to move to a better neighbourhood/more pleasant area"; and "job-related reasons".

Figure A.1: Top 3 Reasons for Moving (2002-2013)



Notes: The red bar shows the percentage of individuals who report that the reason for moving is the one stated on the y-axis. The blue bar shows the percentage of individuals who report other reasons than the one stated on the y-axis.

B District-Level Analysis

B.1 Additional tables and figures

- Figure B.1 presents Sankey diagrams for the top 20 migration corridors (in terms of size of flows) in years 2002, 2007 and 2012. A visual inspection of this figure highlights the importance of geography in determining internal migration: the origin and destination districts tend to be geographically close to one another, and very often, share contiguous borders. For example, we can observe a large number of people moving from Manchester to Trafford and Stockport in 2007 and 2012, and several cases of intra-London flows in all three years.
- Table B.1 presents summary statistics, detailed definitions and sources for each variable used in the district-level analysis.
- Table B.2 provides a list of all districts in England and Wales and the government office region (GOR) to which they belong.
- Figure B.2 presents the average value of bilateral migration flows relative to: (i) the population size of the destination district; (ii) the total size of migration flows to the destination district.
- Table B.3 shows that the results of Table 1 persist when we control for time-invariant indicators capturing geographic, historic and socio-demographic ties between the destination and origin districts. Specifically, we add to the baseline specification dummy variables for pairs of districts that belong to the same government office region (*Same GOR*),[7] share the same genetic roots (*Same genetic group*),[8] and exhibit very similar socio-demographic characteristics (*Same similarity group*).[9]
- Table B.4 shows that the results of Table 1 persist when we control for corridor-specific characteristics that vary over time. In particular, to further account for relative economic conditions affecting migration, we add the ratio of destination-to-

[7] England and Wales are divided in 10 GORs.

[8] This is based on a fine-scale genetic map of the UK created by analysing DNA samples from more than 2,000 people whose four grandparents were all born in the same area (Leslie et al., 2015).

[9] This dummy variable takes value one if the origin district is in the destination's top 5 most similar districts, as determined by similarity across 59 census statistics.

origin district nighttime light intensities (*Night lights*$_j$/*Night lights*$_i$).[10] To control for socio-economic and demographic factors that can potentially serve as predictors of political similarity, we include the absolute difference in: the share of the population with no formal qualifications (*Distance in share of no qual.*); the share of the population who are highly educated (*Distance in share of high qual.*); the share of the population who are aged 18 to 64 (*Distance in share of aged 18-64*); the share of the population who are aged over 64 (*Distance in share of aged over 64*); the share of the population who are married or in a relationship (*Distance in share of married/couples*); and, finally, the share of total gross value added generated by the manufacturing sector (*Distance in share of manuf. GVA*). To capture the role of religious diversity in determining migration choices, we also include the absolute difference in the share of the population who are Muslims (*Distance in share of Muslims*). Finally, we replace the LDV with the moving average of migration flows over the past 5 years (*Lagged 5-year moving average*) as an alternative proxy for pre-existing migrant networks.

- Table B.5 reports selection ratios based on the method proposed by Altonji et al. (2005). According to these ratios, unobservable factors would have to be 4-53 times stronger than observables to explain away the full relationship between political similarity and migration flows, as reported in Table 2.

- Table B.6 shows robustness of the results reported in Tables 1 and 2 (before and after adding pair FEs) to using the 1-year and 2-year lagged values of the political similarity measures.

- Table B.7 presents the first-stage results of the 2SLS-IV and control function estimations reported in Table 3.

[10]Nighttime light intensity is commonly used by social scientists as a proxy for economic activity or economic development in subnational regions.

B.2 Robustness tests

The key finding that emerges from our district-level analysis is that political similarity between two districts exerts a positive effect on their bilateral migration flows. To ensure robustness and gain further insights into this finding, we perform a number of tests. These are based on our most preferred specification that includes the full set of fixed effects; even though the inferences do not change if we omit the pair fixed effects.

Sensitivity to sampled regions and error clustering. In Table B.8, we check the sensitivity of our results to running the same regressions for ten different sub-samples, each time dropping the set of district pairs that belong to the same GOR. In all cases, the political similarity estimates remain negative and statistically significant at the 1% level. However, the corresponding effect appears to be relatively stronger when we drop London, suggesting that political similarity matters less when people move across London districts. In Table B.9, we assess how the correction of standard errors affects our results. Specifically, for each estimated coefficient in Table 2, we examine three different types of standard errors: (i) heteroscedasticity-robust; (ii) clustered at the dyad (district-pair) level, which is the method employed throughout our main analysis and commonly used in similar settings (see, e.g., Yotov et al., 2016); and (iii) clustered at the origin, destination and year levels (three-way clustering). The latter allows for correlation in the error term within all six possible cluster dimensions (i, j, t, it, jt, ij), and, as such, it generally leads to more conservative inferences of all estimated coefficients (Larch et al., 2019). Nevertheless, our results are little affected by the method used: even though the standard errors are relatively larger when a three-way clustering is used, the estimates of political similarity retain their statistical significance throughout (e.g., at the 1% level when the LDV is included).

Accounting for the role of local amenities. If one of the two leading parties tends to favour policies directed towards improving local amenities like schools and roads (and its supporters are more sensitive to this type of policies), one could potentially argue that a larger flow of internal migrants between two districts governed by this party is driven by amenity provision rather than the desire for homophily. However, this is unlikely to be the case in England and Wales due to the complex and heterogeneous local government system – with the majority of services being provided by county councils rather than district councils in two-tier authorities (see Appendix A.2) – making the choice of policies at the district level less subject to partisan influence.[11] Furthermore, as also discussed below,

[11] See also Lockwood et al. (2022) who show that political control of the council has no effect on local fiscal policy in England and Wales.

our results hold when we experiment with political similarity indices that distinguish between the two leading parties. To further address this concern, we perform two additional checks. First, we include the ratio of destination-to-origin district Index of Multiple Deprivations (IMD) among the regressors.[12] This index combines information on different domains including education, barriers to housing and services, and living environment, and thus can serve as a proxy for the quality of life at the district level (Langella and Manning, 2019). As shown in Table B.10, adding this variable has no effect on the estimates of political similarity. Second, we estimate our regressions separately for district pairs with two-tier authorities (where the responsibilities are split between county and district councils) and those with at least one single-tier authority. In both cases, the political similarity measures have the expected sign and are highly statistically significant (see Table B.11), suggesting that our results hold even when there is a weak relationship between amenity provision and local council partisanship.

Accounting for the urban-rural classification. Historically, in the UK, the Labour party has performed better in big cities and urban areas, while the Conservative party has performed better in rural areas. Thus, one may be concerned that our political similarity effects may be confounded, to some extent, by a rural-urban divide and unobserved factors associated with the population size of the origin and destination districts. Our analysis addresses this concern in two ways. First, the inclusion of the gravitational "mass" of the two economies – as captured by the product of the log of the populations of the two districts (Lewer and Van den Berg, 2008) – allows us to account for higher migration flows between two larger cities or two population-growing areas. Second, by augmenting the gravity model with pair fixed effects we can eliminate all corridor-specific factors that are time-invariant, including the urban-rural characteristics of the two districts. In this way, we rely on variation in political similarity within each pair for identification. As a further check, we run our regressions separately for district pairs with the same urban-rural status (when both districts are classified as urban or rural) and those with a different urban-rural status (when one district is classified as urban and the other one as rural).[13]

[12]The IMD is published at five-year intervals so it has to be interpolated for intervening years. Since England and Wales use different and non-comparable indices (Langella and Manning, 2019), the results are shown for districts in England only.

[13]We classify a district as urban or rural using their supergroup category, which the ONS derives from the 2011 census statistics. Urban districts are those that belong to the following supergroup categories: business, education and heritage centre; ethnically diverse metropolitan living; London cosmopolitan; and urban settlements. Rural districts are those that belong to the following supergroup categories: affluent England; countryside living; services and industrial legacy; and town and country living.

As can be seen in Table B.12, changes in political similarity within a migration corridor can affect its migration flows regardless of whether the two districts belong to the same urban-rural category or not.

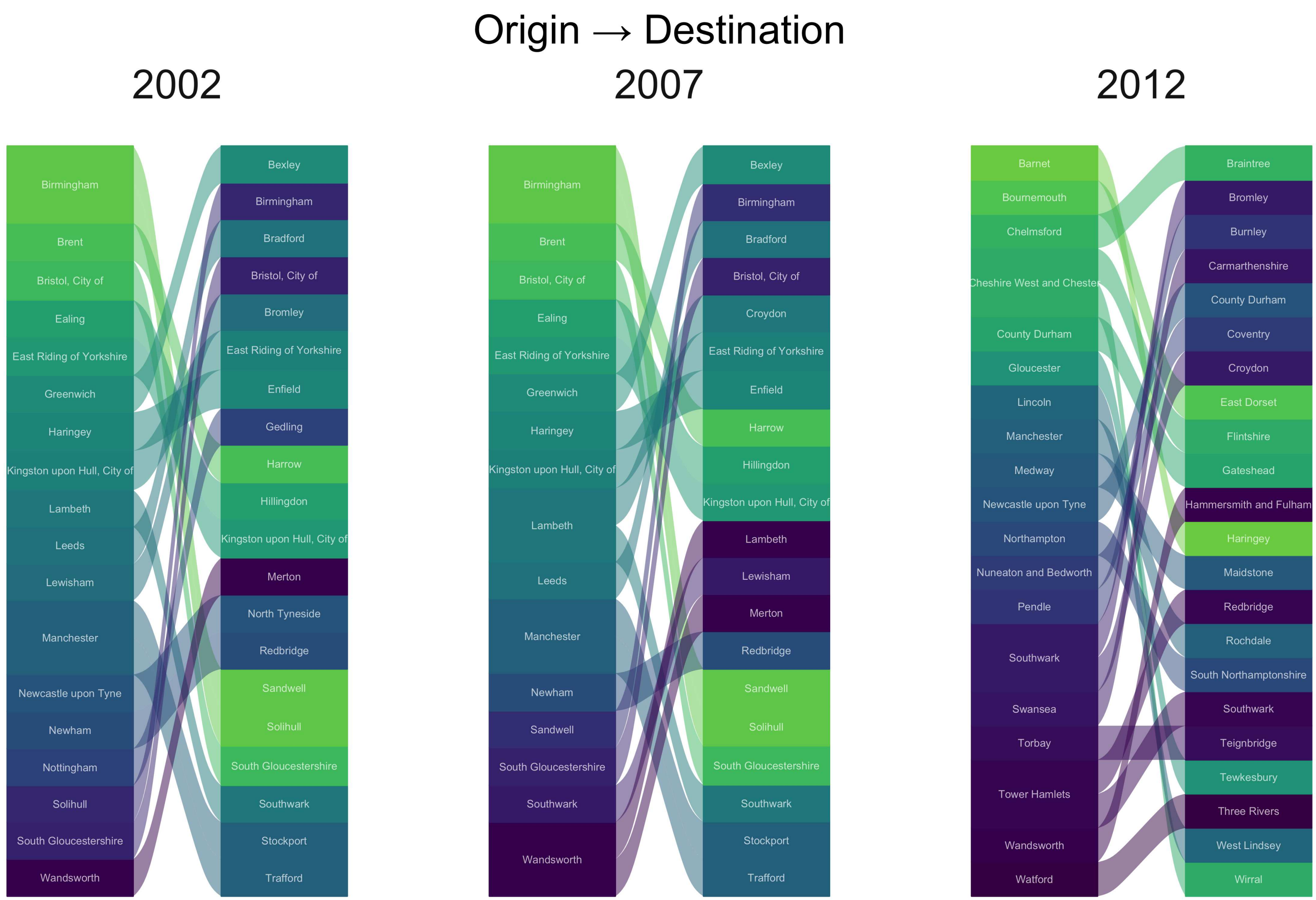
Distance in Labour vs Conservative party shares. In Table B.13, we check the robustness of our results to replacing our 'composite' political distance measure with either *Distance in Con. party share* or *Distance in Lab. party share*, calculated by the pair-specific distance in the share of local council party seats for each of the two parties. This allows us to test whether our results can be attributed to similarities with respect to the support for one of the two leading parties alone. Both variables exhibit a negative and highly statistically significant effect on migration flows and do not change the inferences from earlier findings; even though the estimates of the latter variable (*Distance in Lab. party share*) appear to have a relatively larger magnitude. This is in line with recent survey-based evidence from the UK suggesting that people who support more "liberal" or left-leaning sides of debates on party politics are more likely to say that they struggle to be friends with those who take the opposing point of view,[14] and, as a result, have a stronger desire for political homophily.

The additional information provided by the continuous measure. As stressed in Section 2.1, while the continuous political similarity measure largely reflects the dichotomous classification of district pairs into copartisan and opposing-party ones, it can also account for the role of political preferences when people move across districts with a different political colour. To illustrate this, we construct the ratio of destination-to-origin district Conservative seat shares (*Conservative ratio*), and interact this with the binary measures $Con_i Lab j$ (capturing pairs of Conservative-origin and Labour-destination districts) and $1 - Con_i Lab_j$ (capturing all the other possible district pairs). In this way, we can estimate the impact of the relative Conservative ratio on migration flows conditional on the political control of the two districts. The results, displayed in Table B.14, indicate that the value of this ratio matters mostly when people move to a district with a different political colour than the origin: the interaction term *Conservative ratio* $\times$ $Con_i Lab_j$ is positive and has a large magnitude – suggesting that Conservative-district residents select the Labour-district destination with the highest relative support for the Conservative party – whereas the interaction term

[14] According to the survey conducted by King's College London and Ipsos MORI (`https://www.kcl.ac.uk/policy-institute/assets/fault-lines-in-the-uks-culture-wars.pdf`), 35% of Labour supporters say it would be hard to be friends with people who vote Conservative – five times the proportion of Conservative supporters (7%) who say the same about those who vote Labour. Similarly, Labour supporters are more likely to describe Conservatives as selfish (74% vs 30%), closed-minded (75% vs 59%) and hypocritical (67% vs 52%) than the reverse.

Conservative ratio $\times$ $(1-Con_iLab_j)$ is close to zero and statistically smaller. Performing the same analysis using the *Labour ratio* and focusing on the Labour-district residents moving to a Conservative district leads to the same conclusions (see Table B.14).

Figure B.1: Bilateral Migration Flows



Notes: This graph shows the top dyads in our sample, in terms of size of migration flows, for the years 2002, 2007 and 2012.

Table B.1: Summary Statistics and Definitions of Model Variables

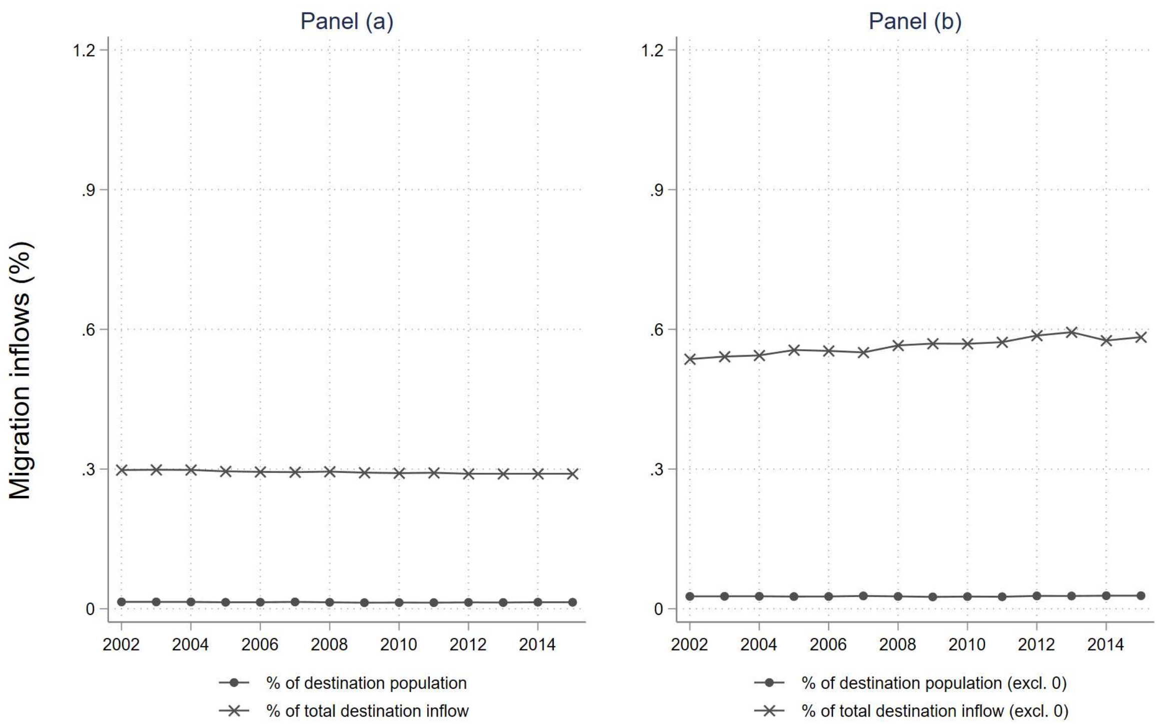
	Mean	Std. Dev.	Min.	Max.	Observations	Description
Migration flows	21.882	101.220	0.000	5,850	1,645,412	The number of migrants flowing from the origin district to the destination district in each year. ONS
Same party control	0.258	0.437	0.000	1.000	1,645,412	=1 if either the Conservative party or the Labour party holds the majority of local council seats at both the origin and destination; 0 otherwise. BLED
Distance in Con. share	0.297	0.215	0.000	1.000	1,645,412	Absolute difference (between the two districts) in the share of Conservative party seats in the local council. BLED
Distance in Lab. share	0.286	0.227	0.000	1.000	1,645,412	Absolute difference (between the two districts) in the share of Labour party seats in the local council. BLED
Distance in party shares	0.291	0.186	0.000	1.000	1,645,412	The average value of Distance in Con. share and Distance in Lab. share. BLED
Geographic distance	5.046	0.707	0.740	6.345	1,645,412	Distance (KMs) between the destination district and the origin district (in logs). Authors' calculation
Contiguity	0.015	0.122	0.000	1.000	1,645,412	=1 if the destination district and the origin district share a contiguous border; 0 otherwise. Authors' calculation
Population$_j$ $\times$ Population$_i$	6.825	1.972	1.597	20.487	1,645,412	Product of the natural log populations (divided by 10,000) of the two districts. ONS
Wage$_j$ / Wage$_i$	1.052	0.370	0.155	6.440	1,645,412	Destination average yearly wage divided by the origin average yearly wage. ONS
Unemployment$_j$ / Unemployment$_i$	1.122	0.564	0.090	11.167	1,645,412	Destination unemployment rate divided by the origin unemployment rate. ONS
Distance in ethnic frac.	0.068	0.066	0.000	0.656	1,645,412	Absolute difference (between the two districts) in the ethnic fractionalization index, measured for all non-white ethnic groups. The groups are: Indian; Pakistani; Bangladeshi; Chinese; Black Caribbean; Black African; other Asian; other Black; and a residual category grouping together all other non-white ethnicities. Linearly interpolated for non-census years. ONS via Nomis
Same region	0.117	0.321	0.000	1.000	1,645,412	=1 if the destination district and the origin district belong to the same government office region (GOR); 0 otherwise. Authors' calculation
Same genetic group	0.511	0.500	0.000	1.000	1,645,412	=1 if the destination and the origin district share the same genetic roots; 0 otherwise. Leslie et al. (2015)
Top 5 most similar origin	0.014	0.120	0.000	1.000	1,645,412	=1 if the origin district is in the destination's top 5 most similar districts, as determined by similarity across 59 census statistics; 0 otherwise. ONS
Night lights$_j$ / Night lights$_i$	1.717	2.536	0.013	77.865	1,645,412	Destination nighttime light intensity divided by the origin nighttime light intensity. DMSP-OLS
Distance in share of no qual.	0.058	0.043	0.000	0.290	1,645,412	Absolute difference (between the two districts) in the share of the population with no formal qualifications, linearly interpolated for non-census years. ONS via Nomis
Distance in share of high qual.	0.079	0.067	0.000	0.413	1,645,412	Absolute difference (between the two districts) in the share of the population who have level 4 or above qualifications, linearly interpolated for non-census years. ONS via Nomis
Distance in share of aged 18-64	0.033	0.031	0.000	0.232	1,645,412	Absolute difference (between the two districts) in the share of the population who are aged 18 to 64, linearly interpolated for non-census years. ONS via Nomis
Distance in share of over 64	0.042	0.034	0.000	0.256	1,645,412	Absolute difference (between the two districts) in the share of the population who are aged over 64, linearly interpolated for non-census years. ONS via Nomis
Distance in share of married/couples	0.066	0.059	0.000	0.358	1,645,412	Absolute difference (between the two districts) in the share of the population who are married or in a relationship, linearly interpolated for non-census years. ONS via Nomis
Distance in share of manuf. GVA	0.082	0.067	0.000	0.461	1,645,412	Absolute difference (between the two districts) in the share of total gross value added (GVA) generated by the manufacturing sector. ONS
Distance in share of Muslims	0.040	0.058	0.000	0.364	1,645,412	Absolute difference (between the two districts) in the share of the population who are Muslims, linearly interpolated for non-census years. ONS via Nomis
IMD$_j$ / IMD$_i$	0.033	0.158	0.000	9.830	1,435,339	The destination district's rank in the Index of Multiple Deprivations divided by the origin district's rank in the same index, linearly interpolated for non-recorded years. ONS.

Notes: **ONS** - Office for National Statistics; **BLED** - British Local Election Database; **DMSP-OLS** - DMSP-OLS Nighttime Lights Time Series Dataset (version 4).

Table B.2: GOR - LAD list

Government office region	Local authority district
East	Babergh; Basildon; Bedford; Braintree; Breckland; Brentwood; Broadland; Broxbourne; Cambridge; Castle Point; Central Bedfordshire; Chelmsford; Colchester; Dacorum; East Cambridgeshire; East Hertfordshire; Epping Forest; Fenland; Forest Heath; Great Yarmouth; Harlow; Hertsmere; Huntingdonshire; Ipswich; King's Lynn and West Norfolk; Luton; Maldon; Mid Suffolk; North Hertfordshire; North Norfolk; Norwich; Peterborough; Rochford; South Cambridgeshire; South Norfolk; Southend-on-Sea; St Albans; St Edmundsbury; Stevenage; Suffolk Coastal; Tendring; Three Rivers; Thurrock; Uttlesford; Watford; Waveney; Welwyn Hatfield
East Midlands	Amber Valley; Ashfield; Bassetlaw; Blaby; Bolsover; Boston; Broxtowe; Charnwood; Chesterfield; Corby; Daventry; Derby; Derbyshire Dales; East Lindsey; East Northamptonshire; Erewash; Gedling; Harborough; High Peak; Hinckley and Bosworth; Kettering; Leicester; Lincoln; Mansfield; Melton; Newark and Sherwood; North East Derbyshire; North Kesteven; North West Leicestershire; Northampton; Nottingham; Oadby and Wigston; Rushcliffe; Rutland; South Derbyshire; South Holland; South Kesteven; South Northamptonshire; Wellingborough; West Lindsey
London	Barking and Dagenham; Barnet; Bexley; Brent; Bromley; Camden; Croydon; Ealing; Enfield; Greenwich; Hackney; Hammersmith and Fulham; Haringey; Harrow; Havering; Hillingdon; Hounslow; Islington; Kensington and Chelsea; Kingston upon Thames; Lambeth; Lewisham; Merton; Newham; Redbridge; Richmond upon Thames; Southwark; Sutton; Tower Hamlets; Waltham Forest; Wandsworth; Westminster
North East	County Durham; Darlington; Gateshead; Hartlepool; Middlesbrough; Newcastle upon Tyne; North Tyneside; Northumberland; Redcar and Cleveland; South Tyneside; Stockton-on-Tees; Sunderland
North West	Allerdale; Barrow-in-Furness; Blackburn with Darwen; Blackpool; Bolton; Burnley; Bury; Carlisle; Cheshire East; Cheshire West and Chester; Chorley; Copeland; Eden; Fylde; Halton; Hyndburn; Knowsley; Lancaster; Liverpool; Manchester; Oldham; Pendle; Preston; Ribble Valley; Rochdale; Rossendale; Salford; Sefton; South Lakeland; South Ribble; St. Helens; Stockport; Tameside; Trafford; Warrington; West Lancashire; Wigan; Wirral; Wyre
South East	Adur; Arun; Ashford; Aylesbury Vale; Basingstoke and Deane; Bracknell Forest; Brighton and Hove; Canterbury; Cherwell; Chichester; Chiltern; Crawley; Dartford; Dover; East Hampshire; Eastbourne; Eastleigh; Elmbridge; Epsom and Ewell; Fareham; Gosport; Gravesham; Guildford; Hart; Hastings; Havant; Horsham; Isle of Wight; Lewes; Maidstone; Medway; Mid Sussex; Milton Keynes; Mole Valley; New Forest; Oxford; Portsmouth; Reading; Reigate and Banstead; Rother; Runnymede; Rushmoor; Sevenoaks; Shepway; Slough; South Bucks; South Oxfordshire; Southampton; Spelthorne; Surrey Heath; Swale; Tandridge; Test Valley; Thanet; Tonbridge and Malling; Tunbridge Wells; Vale of White Horse; Waverley; Wealden; West Berkshire; West Oxfordshire; Winchester; Windsor and Maidenhead; Woking; Wokingham; Worthing; Wycombe
South West	Bath and North East Somerset; Bournemouth; Bristol, City of; Cheltenham; Christchurch; Cornwall; Cotswold; East Devon; East Dorset; Exeter; Forest of Dean; Gloucester; Mendip; Mid Devon; North Devon; North Dorset; North Somerset; Plymouth; Poole; Purbeck; Sedgemoor; South Gloucestershire; South Hams; South Somerset; Stroud; Swindon; Taunton Deane; Teignbridge; Tewkesbury; Torbay; Torridge; West Devon; West Dorset; West Somerset; Weymouth and Portland; Wiltshire
Wales	Blaenau Gwent; Bridgend; Caerphilly; Cardiff; Carmarthenshire; Ceredigion; Conwy; Denbighshire; Flintshire; Gwynedd; Isle of Anglesey; Merthyr Tydfil; Monmouthshire; Neath Port Talbot; Newport; Pembrokeshire; Powys; Rhondda Cynon Taf; Swansea; Torfaen; Vale of Glamorgan; Wrexham
West Midlands	Birmingham; Bromsgrove; Cannock Chase; Coventry; Dudley; East Staffordshire; Herefordshire, County of; Lichfield; Malvern Hills; Newcastle-under-Lyme; North Warwickshire; Nuneaton and Bedworth; Redditch; Rugby; Sandwell; Shropshire; Solihull; South Staffordshire; Stafford; Staffordshire Moorlands; Stoke-on-Trent; Stratford-on-Avon; Tamworth; Telford and Wrekin; Walsall; Warwick; Wolverhampton; Worcester; Wychavon; Wyre Forest
Yorkshire and The Humber	Barnsley; Bradford; Calderdale; Craven; Doncaster; East Riding of Yorkshire; Hambleton; Harrogate; Kingston upon Hull, City of; Kirklees; Leeds; North East Lincolnshire; North Lincolnshire; Richmondshire; Rotherham; Ryedale; Scarborough; Selby; Sheffield; Wakefield; York

Figure B.2: Bilateral Migration Inflows Relative to Destination Population Size and Total Inflows



Notes: This figure shows the average value of migration flows from district i to district j relative to the population size of district j and the total size of migration flows to district j (before and after excluding observations that correspond to zero flows).

Table B.3: Migration Flows and Political Similarity: Additional Time-Invariant Similarity Indices

	Migration flows							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Same party control	0.055***	0.050***	0.052***	0.048***				
	(0.012)	(0.012)	(0.013)	(0.012)				
Distance in party shares					-0.212***	-0.200***	-0.207***	-0.189***
					(0.036)	(0.036)	(0.037)	(0.036)
Same GOR	0.242***			0.234***	0.242***			0.233***
	(0.015)			(0.015)	(0.015)			(0.015)
Same genetic group		0.120***		0.096***		0.116***		0.092***
		(0.019)		(0.018)		(0.019)		(0.018)
Same similarity group			0.053*	0.063**			0.046	0.056*
			(0.031)	(0.030)			(0.031)	(0.031)
Vector $\mathbf{X}_{ij,t}$	✓	✓	✓	✓	✓	✓	✓	✓
LDV	✓	✓	✓	✓	✓	✓	✓	✓
Dest. $\times$ Year	✓	✓	✓	✓	✓	✓	✓	✓
Orig. $\times$ Year	✓	✓	✓	✓	✓	✓	✓	✓
Pseudo-R^2	0.831	0.830	0.830	0.831	0.831	0.830	0.830	0.832
Observations	1,514,238	1,514,238	1,514,238	1,514,238	1,514,238	1,514,238	1,514,238	1,514,238

Notes: See notes for Table 1.

Table B.4: Migration Flows and Political Similarity: Additional Time-Varying Controls

Panel (a)	Migration flows										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Same party control	0.054***	0.054***	0.055***	0.054***	0.056***	0.053***	0.056***	0.050***	0.049***	0.059***	0.058***
	(0.012)	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)	(0.013)	(0.013)	(0.012)	(0.014)	(0.013)
Night lights$_j$ / Night lights$_i$	-0.002								-0.005		-0.006
	(0.005)								(0.005)		(0.005)
Distance in share of no qual.		-1.634***							-2.355***		-2.353***
		(0.190)							(0.244)		(0.279)
Distance in share of high qual.			-0.229						0.870***		0.835***
			(0.149)						(0.184)		(0.198)
Distance in share of aged 18-64				-0.002					-0.198		-0.168
				(0.282)					(0.437)		(0.455)
Distance in share of over 64					0.192				0.874**		0.869**
					(0.235)				(0.373)		(0.381)
Distance in share of married/couples						-0.068			-0.316*		-0.213
						(0.157)			(0.182)		(0.193)
Distance in share of manuf. GVA							-0.773***		-0.676***		-0.715***
							(0.116)		(0.117)		(0.120)
Distance in share of Muslims								-0.559**	-0.754***		-0.755***
								(0.248)	(0.285)		(0.277)
Lagged 5-year moving average										0.075***	0.076***
										(0.025)	(0.025)
Vector $\mathbf{X}_{ij,t}$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
LDV	✓	✓	✓	✓	✓	✓	✓	✓	✓		
Dest. $\times$ Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Orig. $\times$ Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Pseudo-R^2	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.831	0.833	0.834
Observations	1,514,238	1,514,238	1,514,238	1,514,238	1,514,238	1,514,238	1,514,238	1,514,238	1,514,238	1,065,640	1,065,640

Panel (b)	Migration flows										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Distance in party shares	-0.215***	-0.215***	-0.217***	-0.220***	-0.232***	-0.217***	-0.219***	-0.204***	-0.216***	-0.185***	-0.206***
	(0.037)	(0.037)	(0.037)	(0.037)	(0.036)	(0.036)	(0.037)	(0.037)	(0.036)	(0.037)	(0.036)
Night lights$_j$ / Night lights$_i$	-0.000								-0.004		-0.006
	(0.005)								(0.005)		(0.005)
Distance in share of no qual.		-1.635***							-2.264***		-2.317***
		(0.189)							(0.245)		(0.279)
Distance in share of high qual.			-0.244*						0.802***		0.794***
			(0.148)						(0.184)		(0.198)
Distance in share of aged 18-64				0.157					-0.296		-0.255
				(0.283)					(0.432)		(0.449)
Distance in share of over 64					0.432*				1.123***		1.093***
					(0.235)				(0.369)		(0.376)
Distance in share of married/couples						0.031			-0.203		-0.113
						(0.158)			(0.181)		(0.191)
Distance in share of manuf. GVA							-0.781***		-0.701***		-0.733***
							(0.116)		(0.117)		(0.119)
Distance in share of Muslims								-0.527**	-0.771***		-0.773***
								(0.249)	(0.284)		(0.276)
Lagged 5-year moving average										0.077***	0.078***
										(0.025)	(0.025)
Vector $\mathbf{X}_{ij,t}$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
LDV	✓	✓	✓	✓	✓	✓	✓	✓	✓		
Dest. $\times$ Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Orig. $\times$ Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Pseudo-R^2	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.830	0.831	0.833	0.834
Observations	1,514,238	1,514,238	1,514,238	1,514,238	1,514,238	1,514,238	1,514,238	1,514,238	1,514,238	1,065,640	1,065,640

Notes: The estimate and standard error of *Lagged 5-year moving average* are multiplied by 1,000. See also notes for Table 1.

Table B.5: Selection-On-Unobservables

Uncontrolled regression	Controlled regression	Selection ratio ($\mathcal{SR}$)
Dest. × Orig. FEs Dest. × Year FEs Orig. × Year FEs	Dest. × Orig. FEs Dest. × Year FEs Orig. × Year FEs Vector $\mathbf{X}_{ij,t}$	Same party control $\mathcal{SR}: 26.65$ Distance in party shares $\mathcal{SR}: 22.43$
Dest. × Orig. FEs Dest. × Year FEs Orig. × Year FEs	Dest. × Orig. FEs Dest. × Year FEs Orig. × Year FEs LDV Vector $\mathbf{X}_{ij,t}$	Same party control $\mathcal{SR}: 4.85$ Distance in party shares $\mathcal{SR}: 4.63$
Dest. × Orig. FEs Dest. × Year FEs Orig. × Year FEs LDV	Dest. × Orig. FEs Dest. × Year FEs Orig. × Year FEs LDV Vector $\mathbf{X}_{ij,t}$	Same party control $\mathcal{SR}: 53.30$ Distance in party shares $\mathcal{SR}: 23.02$

Notes: LDV is the lagged dependent variable. $\mathcal{SR}$ is the Altonji et al. (2005)'s selection ratio, which indicates the degree of selection on unobservables relative to observables (the additional controls in the 'controlled' regression) that would be needed to fully explain our results by omitted variable bias.

Table B.6: Migration Flows and Political Similarity: Lagged Effects

	Migration flows							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Same party control $_{t-1}$	0.047***				0.008***			
	(0.013)				(0.002)			
Same party control $_{t-2}$		0.038***				0.009***		
		(0.013)				(0.002)		
Distance in party shares $_{t-1}$			-0.208***				-0.052***	
			(0.038)				(0.008)	
Distance in party share $_{t-2}$				-0.191***				-0.048***
				(0.040)				(0.008)
Vector $\mathbf{X}_{ij,t}$	✓	✓	✓	✓	✓	✓	✓	✓
LDV	✓	✓	✓	✓	✓	✓	✓	✓
Dest. $\times$ Orig. FE					✓	✓	✓	✓
Dest. $\times$ Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Orig. $\times$ Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Pseudo-R^2	0.830	0.830	0.830	0.831	0.917	0.917	0.917	0.917
Observations	1,513,570	1,400,153	1,513,570	1,400,153	1,323,737	1,207,890	1,323,737	1,207,890

Notes: Standard errors clustered at the dyad (district-pair) level in parentheses. LDV is the lagged dependent variable. $t-1$ and $t-2$ indicate the first-year and second-year lagged values of the variables respectively. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table B.7: Migration Flows and Political Similarity: 2SLS-IV and Control Function First-Stage Estimates

	Distance in party shares							
	2SLS-IV				Control Function			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Shift-share instrument	0.822***	0.814***	1.424***	1.475***	0.822***	0.814***	1.418***	1.465***
	(0.002)	(0.002)	(0.008)	(0.008)	(0.002)	(0.002)	(0.009)	(0.009)
Geographic distance	0.009***	0.009***			0.009***	0.010***		
	(0.000)	(0.000)			(0.000)	(0.000)		
Contiguity	0.005***	0.006***			0.005***	0.003		
	(0.002)	(0.002)			(0.002)	(0.002)		
Population$_j$ × Population$_i$	-0.009***	-0.010***	0.035***	0.029***	-0.009***	-0.010***	0.004	-0.004
	(0.001)	(0.001)	(0.010)	(0.011)	(0.001)	(0.001)	(0.011)	(0.012)
Wage$_j$ / Wage$_i$	0.019***	0.019***	0.024***	0.033***	0.019***	0.019***	0.031***	0.040***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Unemployment$_j$ / Unemployment$_i$	0.173***	0.195***	0.002	0.015***	0.173***	0.195***	-0.001	0.013***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Distance in ethnic frac.	-0.016***	-0.014**	-0.037***	-0.039***	-0.016***	-0.014**	-0.045***	-0.047***
	(0.005)	(0.006)	(0.009)	(0.009)	(0.005)	(0.006)	(0.010)	(0.010)
LDV		✓		✓		✓		✓
Dest. × Orig. FE			✓	✓			✓	✓
Dest. × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Orig. × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1,414,024	1,288,126	1,414,024	1,288,126	1,414,024	1,288,126	1,218,323	1,094,549

Notes: See notes for Table 3 (second-stage estimation). LDV is the lagged value of *Migration flows*. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table B.8: Migration Flows and Political Similarity: Exclude Intra-GOR Flows

GOR excluded:	East Midlands	West Midlands	East of England	Wales	South West	South East	Yorkshire and The Humber	North West	North East	London
Panel (a)	Migration flows									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Same party control	0.010***	0.011***	0.009***	0.008***	0.009***	0.010***	0.010***	0.008***	0.010***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Vector $\mathbf{X}_{ij,t}$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
LDV	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Dest. $\times$ Orig. FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Dest. $\times$ Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Orig. $\times$ Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Pseudo-R^2	0.914	0.912	0.914	0.915	0.913	0.913	0.913	0.912	0.915	0.899
Observations	1,304,527	1,313,147	1,296,637	1,318,524	1,308,484	1,267,466	1,318,932	1,305,388	1,322,678	1,311,496
Panel (b)	Migration flows									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Distance in party shares	-0.057***	-0.061***	-0.046***	-0.045***	-0.047***	-0.047***	-0.051***	-0.050***	-0.050***	-0.078***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Vector $\mathbf{X}_{ij,t}$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
LDV	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Dest. $\times$ Orig. FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Dest. $\times$ Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Orig. $\times$ Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Pseudo-R^2	0.914	0.912	0.914	0.915	0.913	0.913	0.913	0.912	0.915	0.899
Observations	1,304,527	1,313,147	1,296,637	1,318,524	1,308,484	1,267,466	1,318,932	1,305,388	1,322,678	1,311,496

Notes: Standard errors clustered at the dyad (district-pair) level in parentheses. LDV is the lagged dependent variable. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table B.9: Migration Flows and Political Similarity:
Alternative Types of Standard Error

	Migration flows			
	(1)	(2)	(3)	(4)
Same party control	0.011		0.010	
	(0.002)***		(0.002)***	
	[0.002]***		[0.002]***	
	{0.004}***		{0.004}**	
Distance in party shares		-0.061		-0.054
		(0.005)***		(0.006)***
		[0.008]***		[0.008]***
		{0.018}***		{0.017}***
Vector $\mathbf{X}_{ij,t}$	✓	✓	✓	✓
LDV		✓		✓
Dest. $\times$ Orig. FE	✓	✓	✓	✓
Dest. $\times$ Year FE	✓	✓	✓	✓
Orig. $\times$ Year FE	✓	✓	✓	✓
Pseudo-R^2	0.915	0.915	0.917	0.917
Observations	1,454,611	1,454,611	1,324,392	1,324,392

Notes: Heteroscedasticity-robust standard errors in parentheses. Standard errors clustered at the dyad (district-pair) level in brackets. Standard errors clustered at the origin, destination and year levels (three-way clustering) in curly brackets. LDV is the lagged dependent variable. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table B.10: Migration Flows and Political Similarity:
Controlling for the Relative Index of Multiple Deprivations

	Migration flows			
	(1)	(2)	(3)	(4)
IMD_j / IMD_i	-0.009	0.025	-0.009	0.025
	(0.009)	(0.024)	(0.009)	(0.024)
Same party control	0.009***	0.008***		
	(0.002)	(0.002)		
Distance in party shares			-0.054***	-0.049***
			(0.008)	(0.008)
Vector $\mathbf{X}_{ij,t}$	✓	✓	✓	✓
LDV		✓		✓
Dest. $\times$ Orig. FE	✓	✓	✓	✓
Dest. $\times$ Year FE	✓	✓	✓	✓
Orig. $\times$ Year FE	✓	✓	✓	✓
Pseudo-R^2	0.919	0.920	0.919	0.920
Observations	1,280,908	1,168,077	1,280,908	1,168,077

Notes: Standard errors clustered at the dyad (district-pair) level in parentheses. LDV is the lagged dependent variable. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table B.11: Migration Flows and Political Similarity: Accounting for the Level of Local Government

	Migration flows							
Authorities:	Two-Tier		All Else		Two-Tier		All Else	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Same party control	0.014***	0.014***	0.011***	0.010***				
	(0.004)	(0.004)	(0.003)	(0.003)				
Distance in party shares					-0.103***	-0.100***	-0.042***	-0.038***
					(0.014)	(0.013)	(0.010)	(0.009)
Vector $\mathbf{X}_{ij,t}$	✓	✓	✓	✓	✓	✓	✓	✓
LDV		✓		✓		✓		✓
Dest. $\times$ Orig. FE	✓	✓	✓	✓	✓	✓	✓	✓
Dest. $\times$ Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Orig. $\times$ Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Pseudo-R^2	0.912	0.913	0.917	0.919	0.912	0.913	0.917	0.919
Observations	653,067	591,864	801,544	732,528	653,067	591,864	801,544	732,528

Notes: Standard errors clustered at the dyad (district-pair) level in parentheses. LDV is the lagged dependent variable. Columns (1)-(2) and (5)-(6) show the results for district pairs with two-tier authorities. Columns (3)-(4) and (7)-(8) show the results for district pairs with at least one single-tier authority. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table B.12: Migration Flows and Political Similarity: Accounting for the Urban-Rural Status

	Migration flows							
Urban-Rural Category:	Same		Different		Same		Different	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Same party control	0.013***	0.011***	0.016***	0.018***				
	(0.003)	(0.003)	(0.004)	(0.004)				
Distance in party shares					-0.067***	-0.062***	-0.096***	-0.104***
					(0.012)	(0.011)	(0.013)	(0.014)
Vector $\mathbf{X}_{ij,t}$	✓	✓	✓	✓	✓	✓	✓	✓
LDV		✓		✓		✓		✓
Dest. × Orig. FE	✓	✓	✓	✓	✓	✓	✓	✓
Dest. × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Orig. × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Pseudo-R^2	0.923	0.924	0.906	0.907	0.923	0.924	0.906	0.907
Observations	787,971	713,952	666,640	610,440	787,971	713,952	666,640	610,440

Notes: Standard errors clustered at the dyad (district-pair) level in parentheses. LDV is the lagged dependent variable. Columns (1)-(2) and (5)-(6) show the results for district pairs that belong to the same urban-rural category. Columns (3)-(4) and (7)-(8) show the results for district pairs that belong to a different urban-rural category. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table B.13: Migration Flows and Political Similarity:
Disaggregated Political Distance

	Migration flows			
	(1)	(2)	(3)	(4)
Distance in Con. party share	-0.030***	-0.029***		
	(0.006)	(0.006)		
Distance in Lab. party share			-0.049***	-0.041***
			(0.007)	(0.006)
Vector $\mathbf{X}_{ij,t}$	✓	✓	✓	✓
LDV		✓		✓
Dest. × Orig. FE	✓	✓	✓	✓
Dest. × Year FE	✓	✓	✓	✓
Orig. × Year FE	✓	✓	✓	✓
Pseudo-R^2	0.915	0.917	0.915	0.917
Observations	1,454,611	1,324,392	1,454,611	1,324,392

Notes: Standard errors clustered at the dyad (district-pair) level in parentheses. LDV is the lagged dependent variable. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table B.14: Migration Flows and Political Similarity:
Moving Across Districts with a Different Political Colour

	Migration flows			
	(1)	(2)	(3)	(4)
Con_iLab_j	-0.030***	-0.024***		
	(0.006)	(0.005)		
Lab_iCon_j			-0.010**	-0.008*
			(0.005)	(0.004)
Conservative ratio $\times$ Con_iLab_j	0.040***	0.029**		
	(0.015)	(0.013)		
Conservative ratio $\times$ $(1-\text{Con}_i\text{Lab}_j)$	-0.000	-0.000		
	(0.000)	(0.000)		
Labour ratio $\times$ Lab_iCon_j			0.016	0.015
			(0.012)	(0.011)
Labour ratio $\times$ $(1-\text{Lab}_i\text{Con}_j)$			-0.000***	-0.000***
			(0.000)	(0.000)
Diff-test	0.003	0.011	0.081	0.087
Vector $\mathbf{X}_{ij,t}$	✓	✓	✓	✓
LDV		✓		✓
Dest. $\times$ Orig. FE	✓	✓	✓	✓
Dest. $\times$ Year FE	✓	✓	✓	✓
Orig. $\times$ Year FE	✓	✓	✓	✓
Pseudo-R^2	0.915	0.917	0.915	0.917
Observations	1,454,611	1,324,392	1,454,611	1,324,392

Notes: Standard errors clustered at the dyad (district-pair) level in parentheses. LDV is the lagged dependent variable. Conservative (Labour) ratio is the ratio of destination-to-origin district Conservative (Labour) seat shares. Con_iLab_j indicates pairs of Conservative-origin and Labour-destination districts. Lab_iCon_j indicates pairs of Labour-origin and Conservative-destination districts. Diff-test in columns (1)-(2) reports the p-value of a one-sided test, where H0: the difference between the estimates of Conservative ratio $\times$ Con_iLab_j and Conservative ratio $\times$ $(1-\text{Con}_i\text{Lab}_j)$ is equal to zero, and H1: the difference between the two estimates is positive. Diff-test in columns (3)-(4) reports the p-value of a one-sided test, where H0: the difference between the estimates of Labour ratio $\times$ Lab_iCon_j and Labour ratio $\times$ $(1-\text{Lab}_i\text{Con}_j)$ is equal to zero, and H1: the difference between the two estimates is positive. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

C Individual-Level Analysis

C.1 Additional tables

- Table C.1 presents summary statistics and detailed definitions for each variable used in the individual-level analysis.
- Table C.2 reports the full regression results of Table 4.
- Table C.9 presents the first-stage results of the Heckman probit selection model estimations reported in Table 7.

C.2 The desire for homophily: robustness tests

In this section, we discuss additional robustness and sensitivity checks for the key results presented in Section 3.1. For brevity and comparability, we report these checks for the variable *Preference to move*. However, performing the same tests using the other three outcome variables leads to the same conclusions.

In Table C.3, we run the same regressions for ten different sub-samples, each time removing all respondents who live in a specific GOR, whereas in Table C.4, we experiment with alternative clustering of standard errors (at the district and survey wave levels, or at the district level alone). In all cases, we can observe a statistically robust effect of political alignment on the outcome variable. In Table C.5, we replace the alignment variable with its lagged value. The estimates of the lagged measure have the same sign as those on the contemporaneous one, but appear to be economically and statistically less significant (as expected), since they account for individuals who were not politically aligned in the previous wave.

In Table C.6, we explore the dynamics of the alignment effects around the period of treatment. To do so, we augment the regression model with a placebo indicator that takes value 1 either in the year before or in the year after an individual takes an alignment status. This exercise allows us to evaluate the presence of omitted variable bias due to unobserved individual-specific, time-invariant factors.[15] The rationale here is that individuals who will become politically aligned in the future, or used to be politically aligned in the

[15] An alternative approach to completely eliminate such unobserved factors is to exploit within-individual variation. However, controlling for individual fixed effects is not appropriate in our case, as we only have a small number of observations per individual and the political alignment measure exhibits little within-individual variation (it changes over time for about 22% of individuals in our sample).

past, exhibit the same underlying traits in these pre- and post-treatment years as in the years in which they are politically aligned.[16] Hence, statistically significant estimates of these placebo years would indicate the presence of omitted variable bias and would cast doubt on a causal interpretation of the reported effects. The placebo variable produces estimates which fail to reach statistical significance and are statistically smaller than those on *Alignment* (during the treatment period). Moreover, the alignment estimate is not affected by the inclusion of the placebo dummy and remains statistically significant in all regressions, suggesting that our key finding cannot be explained by similar patterns in non-treatment years.[17]

In Table C.7, we augment Eq. (3) with the spatially lagged alignment, reflecting respondents' alignment with respect to the political preferences of the neighbouring (contiguous) districts.[18] This allows us to account for differences in the outcome variable caused by variation in the political preferences of the surrounding area. At the same time, this controls for the possible sample selection of individuals into districts. As pointed out by Langella and Manning (2019), the fact that people have to live somewhere means that the choice of district in each year can potentially be influenced by the characteristics of this district – its political preferences in our case – relative to those of other possible choices, and thus individuals are more likely to be found (in a given year) in districts that offer them higher utility. Including the spatial lagged term into our model makes no difference to the estimates of *Alignment*, and leaves our conclusions unchanged.

Finally, in Table C.8, we consider the heterogeneity of the observed effects with respect to four individual characteristics: political ideology, age, income and education. To do so, we split the sample of 'core supporters' into Conservative and Labour supporters, and re-estimate Eq. (3) with *Alignment* replaced by its interaction terms with binary variables

[16]This test is motivated by recent studies on the impact of political alignment on foreign aid allocation (see, e.g., Dreher et al., 2019; Anaxagorou et al., 2020).

[17]The *Placebo* and *Placebo* [*core supporters*] years correspond to 7% and 6.5% of the total number of observations, respectively. It must be noted that we pool together the pre- and the post-treatment years to increase the number of available placebo events. However, running the same regression set-up using separate indicators for pre- and post-treatment years does not change our results: the estimates of both placebo dummies fail to reach statistical significance and the estimate of alignment remains the same.

[18]Specifically, the variable *Spatially Lagged Alignment* is a binary indicator taking value 1 if individual n's political preferences are aligned with the political preferences of the majority of the contiguous districts. For example, if 70% of the contiguous districts are classified as 'Labour' (based on the party that holds the majority in the local council), the variable *Spatially Lagged Alignment* will take value 1 for a Labour supporter and 0 for the supporters of other parties. Using a continuous measure (rather than a binary one), reflecting the percentage of contiguous districts whose political preferences are the same as those of individual n, does not change our results.

capturing the two sub-samples. In the same way, we construct models that allow us to compare the alignment effects between low-income and high-income people (as defined by the median value of the income variable), between young-age and old-age people (as defined by the median value of the age variable), and between people with a degree (or higher qualification) and those without a degree. In all four cases, we fail to reject the null hypothesis that the difference between the two estimates is equal to zero, suggesting that the desire for homophily is not a unique phenomenon of individuals with specific characteristics.

C.3 Political preferences and the destination choice: robustness tests

In this section, we address the possibility that the effects reported in Table 7 (Section 3.2) are driven by other individual characteristics which are correlated with political preferences. To do so, we consider an alternative specification that includes additional variables in the second stage; namely, income deciles and educational background indicators. Based on this specification, gender, employment status, and family-related variables (such as marital status, having children, and household size) are only included in the first stage. As shown in Table C.10, the results are not affected by the inclusion of these extra controls: once again, we find strong evidence that an individual migrant's ideology helps predict the migrant's destination.

C.4 Selection of out-migrants along political lines

The observed partisan sorting at the district level relies on the premise that the outflow of migrants from a given district is representative of the political preferences of that district. To strengthen our confidence in the validity of this premise, we utilise again the individual-level dataset and examine the relationship between the political preferences of people leaving district d (the share of out-migrants supporting the Conservative or the Labour party) and the aggregate political preferences of district d (the mean share of local council seats held by the Conservative or the Labour party, respectively). The scatterplots in Figure C.1 show that the two shares are strongly positively correlated, which corroborates the interpretation of our findings: in districts with stronger support for the Conservative (Labour) party, there are more Conservative (Labour) out-migrants.[19]

[19] In our analysis, we exclude districts with less than 10 out-migrants. However, including these districts produces very similar correlation coefficients.

Table C.1: Summary Statistics and Definitions of Model Variables

	Mean	Std. Dev.	Min.	Max.	Observations	Description
Preference to move	0.315	0.465	0	1	214,502	=1 if respondent answers "Prefer to move" to the following: "If you could choose, would you stay here in your present home or would you prefer to move somewhere else?"; 0 otherwise.
Plan to stay in neighbourhood	0.707	0.455	0	1	77,516	=1 if respondent answers "Strongly agree" or "Agree" to the following:"I plan to remain a resident of this neighbourhood for a number of years"; 0 otherwise.
Belong to neighbourhood	0.695	0.460	0	1	77,649	=1 if respondent answers "Strongly agree" or "Agree" to the following: "I feel like I belong to this neighbourhood"; 0 otherwise.
Similar to others in neighbourhood	0.626	0.484	0	1	77,511	=1 if respondent answers "Strongly agree" or "Agree" to the following: "I think of myself as similar to the people who live in this neighbourhood"; 0 otherwise.
Alignment	0.357	0.479	0	1	214,502	=1 if individual prefers a particular party and that party holds the majority of seats in the local district council; 0 otherwise.
Alignment [core supporters]	0.275	0.447	0	1	214,502	=1 if individual prefers a particular party (Conservatives or Labour), has not changed their preference over time and that party holds the majority of seats in the local district council; 0 otherwise.
Move to Con.	0.430	0.495	0	1	4,084	=1 if respondent has moved to a Conservative majority district; 0 otherwise
Move to Lab.	0.295	0.456	0	1	4,084	=1 if respondent has moved to a Labour majority district; 0 otherwise
Con. supporter	0.333	0.471	0	1	4,084	=1 if the respondent supports the Conservative party; 0 otherwise
Lab. supporter	0.399	0.490	0	1	4,084	=1 if the respondent supports the Labour party; 0 otherwise
Con. origin	0.382	0.486	0	1	4,084	=1 if respondent has moved from a Conservative majority district; 0 otherwise
Lab. origin	0.316	0.465	0	1	4,084	=1 if respondent has moved from a Labour majority district; 0 otherwise
Ln(Distance of move)	3.666	1.160	1	6	4,084	Distance (KMs) between the destination district and the origin district (in logs)
Vector $\mathbf{Z}_{n,d,w,s}$						
Female	0.536	0.499	0	1	214,502	=1 if respondent is female; 0 if male.
Age	50.603	17.995	16	104	214,502	Age of the respondent.
Age squared	2,884.479	1,879.997	256	10,816	214,502	Age of the respondent squared.
Income decile	5.741	2.854	1	10	214,502	Monthly income decile, where 10 represents individuals with the highest monthly income in the month prior to their interview and 1 the lowest.
Self employed	0.079	0.270	0	1	214,502	=1 if respondent is self-employed; 0 otherwise.
Employed	0.470	0.499	0	1	214,502	=1 if respondent is employed; 0 otherwise.
Unemployed	0.036	0.186	0	1	214,502	=1 if respondent is unemployed; 0 otherwise.
Retired	0.277	0.448	0	1	214,502	=1 if respondent is retired; 0 otherwise.
Maternity leave	0.005	0.071	0	1	214,502	=1 if respondent is on maternity leave; 0 otherwise.
Family care	0.052	0.222	0	1	214,502	=1 if respondent is a family carer; 0 otherwise.
Student	0.042	0.200	0	1	214,502	=1 if respondent is a student; 0 otherwise.
Sick/Disabled	0.032	0.177	0	1	214,502	=1 if respondent is sick/disabled; 0 otherwise.
Govt. training scheme	0.001	0.024	0	1	214,502	=1 if respondent is on a government training scheme; 0 otherwise.
Other job status	0.005	0.074	0	1	214,502	=1 if job status is not described above; 0 otherwise.
Degree	0.238	0.426	0	1	214,502	=1 if the respondent's highest level of education is a first degree; 0 otherwise.
Other degree	0.112	0.315	0	1	214,502	=1 if the respondent's highest level of education is above a first degree; 0 otherwise.
A-level	0.201	0.400	0	1	214,502	=1 if the respondent's highest level of education is A-levels; 0 otherwise.
GCSE	0.199	0.399	0	1	214,502	=1 if the respondent's highest level of education is GCSE's; 0 otherwise.
Other qualification	0.101	0.302	0	1	214,502	=1 if the respondent's highest level of education is not listed above; 0 otherwise.
No qualifications	0.150	0.357	0	1	214,502	=1 if the respondent has no formal education; 0 otherwise.
Married	0.676	0.468	0	1	214,502	=1 if the respondent is married or living together; 0 otherwise.
Never married	0.168	0.374	0	1	214,502	=1 if the respondent is single or never married; 0 otherwise.
Divorced, widowed or separated	0.156	0.363	0	1	214,502	=1 if the respondent is divorced, widowed or separated; 0 otherwise
Household size	2.760	1.426	1	16	214,502	The number of individuals living in the respondent's household.
Has children	0.263	0.440	0	1	214,502	=1 if the respondent has children living at home; 0 otherwise.

Table C.2: Political Alignment and Preference to Move:
Full Regression Results

	Preference to move							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female		-0.003		-0.002		-0.003		-0.002
		(0.003)		(0.003)		(0.004)		(0.004)
Age		-0.002***		-0.002***		-0.001		-0.001
		(0.001)		(0.001)		(0.001)		(0.001)
Age squared		-0.000***		-0.000***		-0.000***		-0.000***
		(0.000)		(0.000)		(0.000)		(0.000)
Second income decile		0.003		0.002		-0.006		-0.010
		(0.006)		(0.006)		(0.007)		(0.008)
Third income decile		0.002		0.001		-0.003		-0.002
		(0.006)		(0.006)		(0.008)		(0.008)
Fourth income decile		-0.007		-0.005		-0.007		-0.004
		(0.007)		(0.007)		(0.008)		(0.009)
Fifth income decile		-0.016**		-0.014*		-0.021**		-0.017*
		(0.007)		(0.008)		(0.009)		(0.009)
Sixth income decile		-0.017**		-0.016**		-0.022***		-0.022***
		(0.007)		(0.008)		(0.008)		(0.009)
Seventh income decile		-0.034***		-0.035***		-0.037***		-0.035***
		(0.008)		(0.008)		(0.009)		(0.010)
Eighth income decile		-0.052***		-0.052***		-0.046***		-0.045***
		(0.008)		(0.008)		(0.009)		(0.010)
Ninth income decile		-0.057***		-0.057***		-0.053***		-0.048***
		(0.008)		(0.009)		(0.010)		(0.011)
Tenth (top) income decile		-0.092***		-0.088***		-0.096***		-0.090***
		(0.010)		(0.010)		(0.011)		(0.012)
Self employed		0.006		0.002		0.030		0.023
		(0.017)		(0.017)		(0.019)		(0.020)
Employed		0.021		0.016		0.038**		0.030
		(0.015)		(0.016)		(0.018)		(0.019)
Unemployed		0.048***		0.041**		0.060***		0.053**
		(0.017)		(0.018)		(0.020)		(0.021)
Retired		-0.014		-0.018		-0.004		-0.011
		(0.016)		(0.017)		(0.019)		(0.020)
Maternity leave		0.043*		0.039*		0.063**		0.048*
		(0.022)		(0.023)		(0.025)		(0.027)
Family care		-0.011		-0.013		0.003		-0.004
		(0.017)		(0.018)		(0.020)		(0.021)
Student		-0.088***		-0.092***		-0.075***		-0.077***
		(0.017)		(0.018)		(0.020)		(0.021)
Sick/Disabled		0.024		0.013		0.041*		0.027
		(0.017)		(0.018)		(0.021)		(0.022)
Govt. training scheme		0.048		0.036		0.045		0.032
		(0.048)		(0.052)		(0.047)		(0.052)
Other job status		0.000		0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Degree		0.008		0.011		0.014*		0.016*
		(0.007)		(0.007)		(0.008)		(0.008)
Other degree		0.021***		0.023***		0.024***		0.023***
		(0.007)		(0.007)		(0.008)		(0.009)
A-level		0.017***		0.021***		0.026***		0.026***
		(0.007)		(0.007)		(0.008)		(0.008)
GCSE		0.012*		0.014**		0.019**		0.018**
		(0.007)		(0.007)		(0.007)		(0.007)
Other qualification		0.017**		0.016**		0.020**		0.016*
		(0.007)		(0.008)		(0.009)		(0.009)
No qualifications		0.000		0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Married		-0.008		-0.005		-0.008		-0.001
		(0.006)		(0.007)		(0.008)		(0.009)
Divorced, widowed or separated		0.005		0.005		0.005		0.007
		(0.007)		(0.007)		(0.009)		(0.009)
Household size		-0.002		-0.004		-0.007**		-0.009***
		(0.003)		(0.003)		(0.003)		(0.003)
Has children		0.003		0.004		0.023***		0.027***
		(0.006)		(0.007)		(0.008)		(0.008)
Alignment	-0.026***	-0.022***	-0.030***	-0.025***				
	(0.004)	(0.004)	(0.005)	(0.005)				
Alignment [core supporters]					-0.014***	-0.015***	-0.015**	-0.018***
					(0.005)	(0.005)	(0.007)	(0.007)
					(0.005)	(0.005)	(0.007)	(0.006)
District FE	✓	✓			✓	✓		
GOR × Wave × Time FE	✓	✓			✓	✓		
District × Wave × Time FE			✓	✓			✓	✓
Mean of DV	0.315	0.315	0.315	0.315	0.314	0.314	0.314	0.314
Mean of Alignment	0.357	0.357	0.357	0.357	0.471	0.471	0.471	0.471
R^2	0.031	0.071	0.141	0.175	0.035	0.074	0.174	0.207
Observations	214,502	214,502	214,502	214,502	143,116	143,116	143,116	143,116

Notes: Standard errors clustered at the individual and district levels in parentheses (two-way clustering). DV is the dependent variable. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table C.3: Political Alignment and Preference to Move: Exclude GORs

GOR excluded:	North East	North West	Yorkshire & Humber	East Midlands	West Midlands	East of England	London	South East	South West	Wales
Panel (a)	Preference to move									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Alignment	-0.023***	-0.023***	-0.026***	-0.027***	-0.025***	-0.026***	-0.027***	-0.024***	-0.026***	-0.027***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
District × Wave × Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Vector $\mathbf{Z}_{n,d,w,s}$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean of DV	0.316	0.316	0.314	0.316	0.313	0.317	0.306	0.314	0.318	0.323
Mean of Alignment	0.352	0.351	0.359	0.353	0.356	0.360	0.339	0.355	0.367	0.377
R^2	0.175	0.176	0.180	0.173	0.176	0.171	0.175	0.170	0.175	0.180
Observations	206,506	189,130	194,860	197,117	195,935	194,017	188,224	184,329	194,660	185,740
Panel (b)	Preference to move									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Alignment [core supporters]	-0.015**	-0.018**	-0.017**	-0.020***	-0.020***	-0.018***	-0.021***	-0.016**	-0.017**	-0.019***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
District × Wave × Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Vector $\mathbf{Z}_{n,d,w,s}$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean of DV	0.314	0.315	0.312	0.315	0.311	0.315	0.303	0.313	0.316	0.321
Mean of Alignment	0.471	0.473	0.481	0.473	0.478	0.478	0.457	0.470	0.485	0.497
R^2	0.207	0.209	0.213	0.204	0.208	0.201	0.208	0.200	0.205	0.211
Observations	136,939	124,909	129,678	131,035	129,538	130,324	122,877	124,662	131,411	126,671

Notes: Standard errors clustered at the individual and district levels in parentheses (two-way clustering). DV is the dependent variable. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table C.4: Political Alignment and Preference to Move: Alternative Error Clustering

	Preference to move							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Alignment	-0.026	-0.022	-0.030	-0.025				
	(0.004)***	(0.004)***	(0.005)***	(0.005)***				
	[0.004]***	[0.004]***	[0.005]***	[0.004]***				
	{0.004}***	{0.004}***	{0.005}***	{0.004}***				
Alignment [core supporters]					-0.014	-0.015	-0.015	-0.018
					(0.005)***	(0.005)***	(0.007)**	(0.007)***
					[0.006]**	[0.005]***	[0.008]*	[0.007]**
					{0.005}***	{0.005}***	{0.007}**	{0.007}***
District FE	✓	✓			✓	✓		
GOR $\times$ Wave $\times$ Time FE	✓	✓			✓	✓		
District $\times$ Wave $\times$ Time FE			✓	✓			✓	✓
Vector $\mathbf{Z}_{n,d,w,s}$		✓		✓		✓		✓
Mean of DV	0.315	0.315	0.315	0.315	0.314	0.314	0.314	0.314
Mean of Alignment	0.357	0.357	0.357	0.357	0.471	0.471	0.471	0.471
R^2	0.031	0.071	0.141	0.175	0.035	0.074	0.174	0.207
Observations	214,502	214,502	214,502	214,502	143,116	143,116	143,116	143,116

Notes: Standard errors clustered at the individual and district levels in parentheses (two-way clustering). Standard errors clustered at the district and survey wave levels in brackets (two-way clustering). Standard errors clustered at the district level alone in curly brackets (one-way clustering). DV is the dependent variable. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table C.5: Political Alignment and Preference to Move: Lagged Effects

	Preference to move							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged alignment	-0.021***	-0.017***	-0.025***	-0.020***				
	(0.005)	(0.005)	(0.005)	(0.005)				
Lagged alignment [core supporters]					-0.011*	-0.012**	-0.013*	-0.016**
					(0.006)	(0.005)	(0.008)	(0.007)
District FE	✓	✓			✓	✓		
GOR $\times$ Wave $\times$ Time FE	✓	✓			✓	✓		
District $\times$ Wave $\times$ Time FE			✓	✓			✓	✓
Vector $\mathbf{Z}_{n,d,w,s}$		✓		✓		✓		✓
Mean of DV	0.302	0.302	0.302	0.302	0.302	0.302	0.302	0.302
Mean of Lagged Alignment	0.350	0.350	0.350	0.350	0.463	0.463	0.463	0.463
R^2	0.032	0.071	0.152	0.186	0.036	0.075	0.187	0.219
Observations	160,058	160,058	160,058	160,058	107,419	107,419	107,419	107,419

Notes: Standard errors clustered at the individual and district levels in parentheses (two-way clustering). DV is the dependent variable. *Lagged alignment* is the lagged value of *Alignment* (as observed in survey wave $w-1$). ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table C.6: Political Alignment and Preference to Move: Placebo Tests

	Preference to move							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Alignment	-0.022***	-0.022***	-0.025***	-0.025***				
	(0.004)	(0.004)	(0.005)	(0.005)				
Placebo		-0.001		0.002				
		(0.005)		(0.005)				
Alignment [core supporters]					-0.015***	-0.016***	-0.018***	-0.018***
					(0.005)	(0.005)	(0.007)	(0.007)
Placebo [core supporters]						-0.001		0.003
						(0.006)		(0.009)
District FE	✓	✓			✓	✓		
GOR $\times$ Wave $\times$ Time FE	✓	✓			✓	✓		
District $\times$ Wave $\times$ Time FE			✓	✓			✓	✓
Vector $\mathbf{Z}_{n,d,w,s}$	✓	✓	✓	✓	✓	✓	✓	✓
Mean of DV	0.315	0.315	0.315	0.315	0.314	0.314	0.314	0.314
Mean of Alignment	0.357	0.357	0.357	0.357	0.471	0.471	0.471	0.471
R^2	0.071	0.071	0.175	0.175	0.074	0.074	0.207	0.207
Observations	214,502	214,502	214,502	214,502	143,116	143,116	143,116	143,116

Notes: Standard errors clustered at the individual and district levels in parentheses (two-way clustering). DV is the dependent variable. *Placebo* is a binary variable, taking value 1 either in the year before or in the year after an individual takes an alignment status. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table C.7: Political Alignment and Preference to Move: Adding a Spatially Lagged Term

	Preference to move							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Alignment	-0.022***	-0.020***	-0.025***	-0.023***				
	(0.004)	(0.004)	(0.005)	(0.005)				
Alignment [core supporters]					-0.015***	-0.016***	-0.018***	-0.018***
					(0.005)	(0.005)	(0.007)	(0.007)
Spatially lagged alignment		-0.013***		-0.012**		0.001		0.003
		(0.005)		(0.006)		(0.005)		(0.007)
District FE	✓	✓			✓	✓		
GOR $\times$ Wave $\times$ Time FE	✓	✓			✓	✓		
District $\times$ Wave $\times$ Time FE			✓	✓			✓	✓
Vector $\mathbf{Z}_{n,d,w,s}$	✓	✓	✓	✓	✓	✓	✓	✓
Mean of DV	0.315	0.315	0.315	0.315	0.314	0.314	0.314	0.314
Mean of Alignment	0.357	0.357	0.357	0.357	0.471	0.471	0.471	0.471
R^2	0.071	0.071	0.175	0.175	0.074	0.074	0.207	0.207
Observations	214,502	214,502	214,502	214,502	143,116	143,116	143,116	143,116

Notes: Standard errors clustered at the individual and district levels in parentheses (two-way clustering). DV is the dependent variable. *Spatially lagged alignment* is a binary indicator taking value 1 if an individual's political preferences are aligned with the political preferences of the majority of the contiguous districts. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table C.8: Political Alignment and Preference to Move: Heterogeneity Across Individuals with Different Characteristics

	Preference to move			
	(1)	(2)	(3)	(4)
Con. Alignment	-0.014			
	(0.012)			
Lab. Alignment	-0.022*			
	(0.012)			
Young Alignment		-0.015*		
		(0.008)		
Old Alignment		-0.020***		
		(0.007)		
Poor Alignment			-0.023***	
			(0.008)	
Rich Alignment			-0.014*	
			(0.007)	
No degree Alignment				-0.020***
				(0.007)
Degree Alignment				-0.015
				(0.009)
Diff-test	0.688	0.572	0.160	0.603
District $\times$ Wave $\times$ Time FE	✓	✓	✓	✓
Vector $\mathbf{Z}_{n,d,w,s}$	✓	✓	✓	✓
Mean of DV	0.314	0.314	0.314	0.314
R^2	0.207	0.203	0.206	0.206
Observations	143,116	143,116	143,116	143,116

Notes: Standard errors clustered at the individual and district levels in parentheses (two-way clustering). All columns show the results for the subsample of 'core supporters'. DV is the dependent variable. *Con. Alignment* and *Lab. Alignment* are the interaction terms of *Alignment* with binary variables capturing Conservative and Labour supporters. *Young Alignment* and *Old Alignment* are the interaction terms of *Alignment* with binary variables capturing young-age and old-age people (as defined by the median value of the age variable). *Poor Alignment* and *Rich Alignment* are the interaction terms of *Alignment* with binary variables capturing low-income and high-income people (as defined by the median value of the income variable). *No degree Alignment* and *Degree Alignment* are the interaction terms of *Alignment* with binary variables capturing people with a degree (or higher qualification) and those without a degree. The non-interacted variables for Conservative supporters, young people, low-income people, and people without a degree, are included in the corresponding specifications. Diff-test reports the p-value of a two-sided test, where H0: the difference between the two estimates (shown in each column) is equal to zero. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table C.9: Political Preferences and the Destination Choice:
First-Stage Estimates

	Move district							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age	-0.045***	-0.037***	-0.045***	-0.037***	-0.048***	-0.045***	-0.048***	-0.045***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
Age sq.	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.018	-0.016	-0.018	-0.016	-0.029*	-0.014	-0.029*	-0.014
	(0.015)	(0.019)	(0.015)	(0.019)	(0.017)	(0.023)	(0.017)	(0.023)
Second income decile	-0.084**	-0.122***	-0.084**	-0.122***	-0.064	-0.116**	-0.064	-0.116**
	(0.035)	(0.047)	(0.035)	(0.047)	(0.043)	(0.059)	(0.043)	(0.059)
Third income decile	-0.088**	-0.048	-0.088**	-0.048	-0.041	-0.039	-0.041	-0.039
	(0.036)	(0.046)	(0.036)	(0.046)	(0.043)	(0.058)	(0.043)	(0.058)
Fourth income decile	-0.114***	-0.127***	-0.114***	-0.127***	-0.057	-0.097	-0.057	-0.097
	(0.037)	(0.048)	(0.037)	(0.048)	(0.044)	(0.060)	(0.044)	(0.060)
Fifth income decile	-0.189***	-0.157***	-0.189***	-0.157***	-0.126***	-0.100*	-0.126***	-0.100*
	(0.038)	(0.049)	(0.038)	(0.049)	(0.045)	(0.061)	(0.045)	(0.061)
Sixth income decile	-0.087**	-0.103**	-0.087**	-0.103**	-0.045	-0.080	-0.045	-0.080
	(0.037)	(0.048)	(0.037)	(0.048)	(0.044)	(0.060)	(0.044)	(0.060)
Seventh income decile	-0.087**	-0.050	-0.087**	-0.050	-0.054	-0.043	-0.054	-0.043
	(0.037)	(0.047)	(0.037)	(0.047)	(0.044)	(0.060)	(0.044)	(0.060)
Eighth income decile	-0.099***	-0.061	-0.099***	-0.061	-0.084*	-0.043	-0.084*	-0.043
	(0.037)	(0.048)	(0.037)	(0.048)	(0.045)	(0.060)	(0.045)	(0.060)
Ninth income decile	-0.074**	-0.009	-0.074**	-0.009	-0.039	-0.004	-0.039	-0.004
	(0.037)	(0.048)	(0.037)	(0.048)	(0.045)	(0.060)	(0.045)	(0.060)
Tenth income decile	-0.004	0.123***	-0.004	0.123***	0.010	0.113*	0.010	0.113*
	(0.037)	(0.047)	(0.037)	(0.047)	(0.046)	(0.060)	(0.046)	(0.060)
Self-employed	-0.158*	-0.099	-0.158*	-0.099	-0.180*	-0.211	-0.180*	-0.211
	(0.082)	(0.114)	(0.082)	(0.114)	(0.100)	(0.141)	(0.100)	(0.141)
Employed	-0.217***	-0.155	-0.217***	-0.155	-0.226**	-0.199	-0.226**	-0.199
	(0.079)	(0.110)	(0.079)	(0.110)	(0.096)	(0.136)	(0.096)	(0.136)
Unemployed	-0.222***	-0.091	-0.222***	-0.091	-0.185*	-0.098	-0.185*	-0.098
	(0.085)	(0.116)	(0.085)	(0.116)	(0.103)	(0.144)	(0.103)	(0.144)
Retired	-0.168**	-0.025	-0.168**	-0.025	-0.160	-0.095	-0.160	-0.095
	(0.084)	(0.116)	(0.084)	(0.116)	(0.101)	(0.143)	(0.101)	(0.143)
Maternity leave	-0.138	-0.151	-0.138	-0.151	-0.187	-0.118	-0.187	-0.118
	(0.112)	(0.151)	(0.112)	(0.151)	(0.136)	(0.183)	(0.136)	(0.183)
Family care	-0.105	-0.031	-0.105	-0.031	-0.115	-0.076	-0.115	-0.076
	(0.085)	(0.116)	(0.085)	(0.116)	(0.103)	(0.144)	(0.103)	(0.144)
Student	-0.087	-0.059	-0.087	-0.059	-0.017	0.006	-0.017	0.006
	(0.082)	(0.113)	(0.082)	(0.113)	(0.101)	(0.141)	(0.101)	(0.141)
Sick/Disabled	-0.365***	-0.266**	-0.365***	-0.266**	-0.377***	-0.338**	-0.377***	-0.338**
	(0.093)	(0.128)	(0.093)	(0.128)	(0.113)	(0.159)	(0.113)	(0.159)
Govt. training scheme	-0.257	-0.354	-0.257	-0.354	-0.089	-0.532	-0.089	-0.532
	(0.258)	(0.341)	(0.258)	(0.341)	(0.308)	(0.482)	(0.308)	(0.482)
Degree	0.395***	0.433***	0.395***	0.433***	0.358***	0.402***	0.358***	0.402***
	(0.033)	(0.042)	(0.033)	(0.042)	(0.039)	(0.053)	(0.039)	(0.053)
Other degree	0.180***	0.249***	0.180***	0.249***	0.171***	0.217***	0.171***	0.217***
	(0.037)	(0.046)	(0.037)	(0.046)	(0.043)	(0.058)	(0.043)	(0.058)
A-level	0.195***	0.226***	0.195***	0.226***	0.150***	0.207***	0.150***	0.207***
	(0.033)	(0.042)	(0.033)	(0.042)	(0.040)	(0.053)	(0.040)	(0.053)
GCSE	0.079**	0.104**	0.079**	0.104**	0.063	0.095*	0.063	0.095*
	(0.034)	(0.042)	(0.034)	(0.042)	(0.040)	(0.053)	(0.040)	(0.053)
Other qualification	0.096**	0.141***	0.096**	0.141***	0.060	0.118*	0.060	0.118*
	(0.039)	(0.049)	(0.039)	(0.049)	(0.046)	(0.060)	(0.046)	(0.060)
Married	-0.004	-0.026	-0.004	-0.026	0.023	0.017	0.023	0.017
	(0.022)	(0.028)	(0.022)	(0.028)	(0.026)	(0.035)	(0.026)	(0.035)
Divorced, widowed or separated	0.066**	0.068*	0.066**	0.068*	0.111***	0.126***	0.111***	0.126***
	(0.030)	(0.039)	(0.030)	(0.039)	(0.035)	(0.047)	(0.035)	(0.047)
Household size	-0.107***	-0.114***	-0.107***	-0.114***	-0.123***	-0.145***	-0.123***	-0.145***
	(0.008)	(0.009)	(0.008)	(0.009)	(0.009)	(0.012)	(0.009)	(0.012)
Has children	-0.148***	-0.083***	-0.148***	-0.083***	-0.153***	-0.082**	-0.153***	-0.082**
	(0.022)	(0.027)	(0.022)	(0.027)	(0.026)	(0.034)	(0.026)	(0.034)
Alignment	-0.015		-0.015		-0.023		-0.023	
	(0.015)		(0.015)		(0.018)		(0.018)	
Alignment [core supporters]		-0.005		-0.005		-0.021		-0.021
		(0.018)		(0.018)		(0.023)		(0.023)
GOR $\times$ Wave $\times$ Time FE					✓	✓	✓	✓
Selected observations	4,084	2,358	4,084	2,358	3,146	1,731	3,146	1,731
Non-selected observations	155,300	104,588	155,300	104,588	122,185	77,544	122,185	77,544

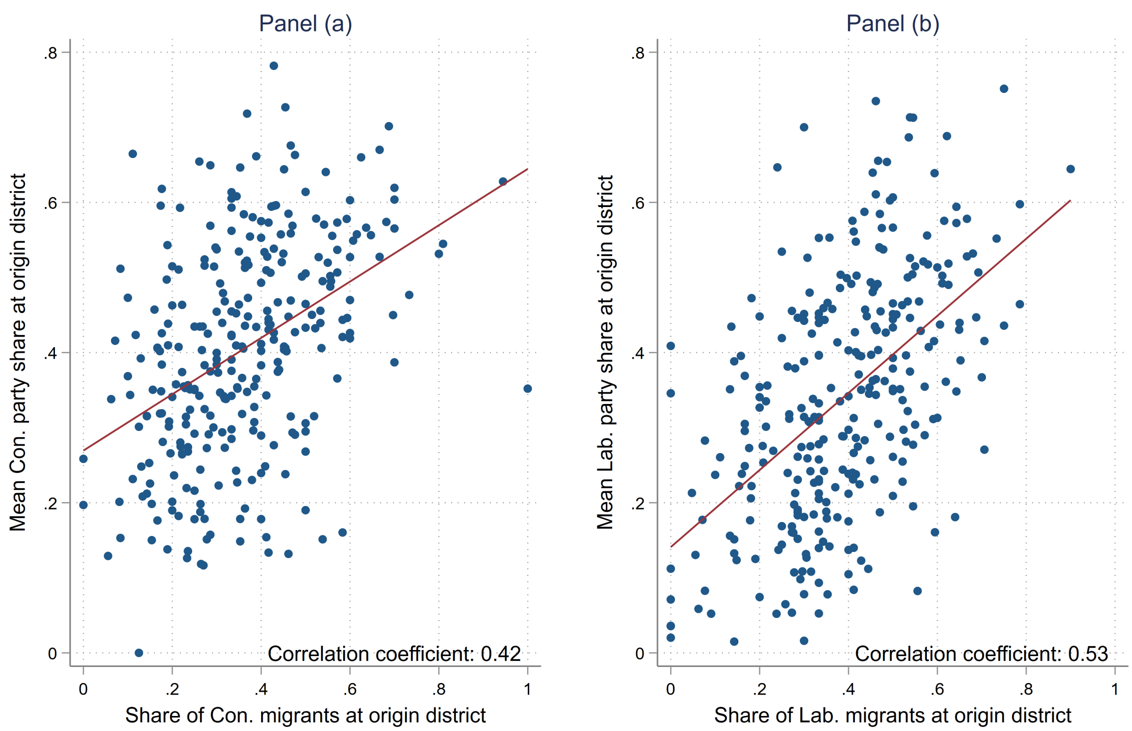
Notes: This table shows the first-stage estimates of a Heckman probit selection model, predicting the likelihood of moving to a new district. See also notes for Table 7 (second-stage estimates). Standard errors are in parentheses. All right-hand-side individual-level variables are in lagged terms (as observed in survey wave $w-1$). ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table C.10: Political Preferences and the Destination Choice:
Controlling for Income and Education

	Move to Con.		Move to Lab.		Move to Con.		Move to Lab.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Con. supporter	0.114***				0.084***			
	(0.016)				(0.018)			
Con. supporter [core]		0.155***				0.130***		
		(0.021)				(0.023)		
Lab. supporter			0.082***				0.058***	
			(0.014)				(0.016)	
Lab. supporter [core]				0.127***				0.102***
				(0.019)				(0.022)
Age	0.011***	0.014***	-0.011***	-0.010**	0.012***	0.025***	-0.012***	-0.018***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.005)	(0.003)	(0.004)
Age sq.	-0.000***	-0.000***	0.000***	0.000**	-0.000***	-0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Con. origin	0.079***	0.085***	0.010	0.017	-0.011	-0.011	0.039*	0.077***
	(0.018)	(0.025)	(0.017)	(0.023)	(0.022)	(0.030)	(0.020)	(0.028)
Lab. origin	-0.092***	-0.063**	0.172***	0.164***	-0.027	0.021	0.051**	0.069**
	(0.019)	(0.026)	(0.018)	(0.024)	(0.024)	(0.033)	(0.022)	(0.030)
Ln(Distance of move)	-0.005	0.002	-0.028***	-0.028***	-0.008	0.013	-0.026***	-0.030***
	(0.007)	(0.009)	(0.006)	(0.008)	(0.008)	(0.010)	(0.007)	(0.010)
Second income decile	-0.086**	-0.093*	0.081**	0.123**	-0.090**	-0.060	0.043	0.092
	(0.038)	(0.053)	(0.035)	(0.049)	(0.042)	(0.060)	(0.038)	(0.056)
Third income decile	-0.090**	-0.036	0.069*	0.020	-0.068	-0.005	0.008	-0.033
	(0.038)	(0.050)	(0.035)	(0.046)	(0.042)	(0.055)	(0.038)	(0.052)
Fourth income decile	-0.026	-0.087	0.073**	0.093*	-0.053	-0.086	-0.025	-0.025
	(0.039)	(0.053)	(0.036)	(0.049)	(0.042)	(0.059)	(0.038)	(0.055)
Fifth income decile	-0.033	-0.043	0.028	-0.038	-0.003	-0.044	-0.053	-0.105*
	(0.041)	(0.054)	(0.038)	(0.050)	(0.044)	(0.058)	(0.040)	(0.054)
Sixth income decile	-0.020	-0.024	0.016	0.024	-0.043	-0.057	-0.023	0.026
	(0.037)	(0.051)	(0.034)	(0.047)	(0.041)	(0.056)	(0.037)	(0.053)
Seventh income decile	0.040	-0.033	0.020	0.010	0.024	-0.042	-0.042	-0.020
	(0.037)	(0.048)	(0.034)	(0.045)	(0.041)	(0.054)	(0.037)	(0.051)
Eighth income decile	-0.056	-0.103**	0.062*	0.090**	-0.067	-0.119**	0.009	0.083
	(0.037)	(0.049)	(0.034)	(0.045)	(0.041)	(0.055)	(0.038)	(0.051)
Ninth income decile	0.032	-0.043	0.001	-0.007	0.011	-0.041	-0.074**	-0.054
	(0.036)	(0.047)	(0.033)	(0.043)	(0.040)	(0.053)	(0.037)	(0.050)
Tenth income decile	-0.003	-0.047	0.015	0.005	-0.038	-0.093*	-0.037	-0.015
	(0.035)	(0.044)	(0.032)	(0.040)	(0.039)	(0.050)	(0.035)	(0.047)
Degree	0.018	0.084	-0.002	-0.045	0.024	0.030	-0.015	-0.036
	(0.047)	(0.061)	(0.043)	(0.056)	(0.050)	(0.064)	(0.045)	(0.060)
Other degree	0.033	0.097	-0.023	-0.063	0.078	0.086	-0.052	-0.084
	(0.047)	(0.060)	(0.043)	(0.055)	(0.051)	(0.065)	(0.046)	(0.061)
A-level	0.041	0.108*	-0.027	-0.052	0.044	0.084	-0.020	-0.043
	(0.043)	(0.056)	(0.040)	(0.051)	(0.047)	(0.061)	(0.042)	(0.057)
GCSE	0.044	0.122**	-0.055	-0.099**	0.036	0.073	-0.072*	-0.081
	(0.043)	(0.054)	(0.039)	(0.050)	(0.046)	(0.059)	(0.042)	(0.055)
Other qualification	0.033	0.058	-0.023	-0.021	0.052	0.076	-0.012	0.026
	(0.049)	(0.062)	(0.045)	(0.058)	(0.052)	(0.066)	(0.047)	(0.062)
GOR $\times$ Wave $\times$ Time FE					✓	✓	✓	✓
Inverse Mill's ratio (Mill's λ)	0.012	0.007	-0.043	-0.022	0.062	-0.063	0.031	0.097
	(0.054)	(0.070)	(0.050)	(0.065)	(0.054)	(0.067)	(0.049)	(0.063)
Selected observations	4,084	2,358	4,084	2,358	3,146	1,731	3,146	1,731
Non-selected observations	155,300	104,588	155,300	104,588	122,185	77,544	122,185	77,544

Notes: This table shows the second-stage estimates of a Heckman probit selection model, predicting the likelihood of moving to a Conservative district (*Move to Con.*) or a Labour district (*Move to Lab.*). *Con. supporter* and *Lab. supporter* are binary indicators capturing supporters for the Conservative party and the Labour party respectively. All right-hand-side individual-level variables are in lagged terms (as observed in survey wave $w-1$). ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Figure C.1: Selection of Out-Migrants Along Political Lines



Notes: Scatterplots with linear fit (solid red line); correlation coefficient in lower right corner. Panel (a) plots the mean share of local council seats held by the Conservative party (in each district) on y-axis; and the share of out-migrants supporting the Conservative party (in each district) on x-axis. Panel (b) plots the corresponding shares for the Labour party.

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