CAGE

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

CAGE working paper no. 600

December 2021

Georgios Efthyvoulou
Vincenzo Bove
Harry Pickard

WARWICK
THE UNIVERSITY OF WARWICK
UKRI
Economic and Social Research Council

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

Georgios Efthyvoulou† Vincenzo Bove‡ Harry Pickard§

December 8, 2021

Abstract

When people migrate internally, do they tend to move to locations that reflect their political preferences? To address this question, we first compile a unique panel dataset on the universe of population movements in England and Wales across 346 local authority districts over the period 2002-2015, and estimate a gravity model of internal migration. We show that proximity in partisan composition exerts an important positive effect on migration flows, which is of a similar order of magnitude as wage differentials or ethnic proximity. We then use individual survey-based data over the same time period to investigate some of the micro-foundations underlying the "macromoves". We find that political alignment to the district of residence contributes to individuals' sense of belonging and 'fitting in' – consistent with the existence of a political homophily mechanism – and that a migrant's political ideology can predict the partisanship of the destination district.

Keywords: Internal migration; Residential mobility; Neighbourhood preference; Polarization; Political sorting; Gravity models

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

†Corresponding Author. Address: Department of Economics, University of Sheffield, 9 Mappin Street, Sheffield, S1 4DT, United Kingdom; Email: g.efthyvoulou@sheffield.ac.uk

‡Address: Department of Politics and International Studies and CAGE (Competitive Advantage in the Global Economy), University of Warwick, Coventry CV4 7AL, United Kingdom; Email: v.bove@warwick.ac.uk

§Address: Newcastle University Business School, Newcastle University, 5 Barrack Road, Newcastle upon Tyne, NE1 4SE, United Kingdom; Email: harry.pickard@newcastle.ac.uk

1 Introduction

The United Kingdom (UK) is one of the most highly mobile societies in Europe, with over 1 million people moving across regions within England and Wales every year (Swinney and Williams, 2016). The UK is also a politically polarized society. Since the Brexit referendum was announced, scholars and political commentators have often warned about the increasing "tribalization" of British politics (Duffy et al., 2019). Although the 2016 EU referendum vote cut across party and ideological lines, partisan identities have never disappeared (Schumacher, 2019). In fact, policymakers and commentators have often noted that a "divided" Britain is not a new phenomenon.[1] 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. In a recent work, Boxell et al. (2020) construct a measure of polarization that permits comparison across countries; they show that, since 1980, "affective polarization" – the extent to which citizens feel more negatively towards other political parties than towards their own – has been consistently higher in Britain than in the United States (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.[2]

When people migrate internally, do they tend to move to locations that reflect their political preferences? In other words, do internal migrants in the UK consider the pre-existing distributions of political opinion across destination communities? This paper contributes to the extant literature on internal migration and on the consequences of political polarization by undertaking a comprehensive analysis of the effect of political preferences on migration patterns. 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 detailed information on yearly bilateral migration flows across 346 local authority districts (LADs) – and combine evidence from this district-level dataset with evidence stemming from individual survey-based data over the same time period. The latter allows us to investigate how individuals' political preferences affect their destination choices, and to delve into the mechanism underpinning this relation.

To analyse the determinants of bilateral migration flows, we employ a gravity model of internal migration augmented with a measure of political similarity between districts. Following the latest developments in the gravity literature, we use Poisson pseudo-maximum likelihood (PPML) estimation to address issues related to heteroscedasticity and zeros (Silva and Tenreyro, 2006) and time-varying destination and origin fixed effects to account for changes in the 'multilateral resistance' constraints implied by the relevant theory (Anderson and van Wincoop, 2003; Feenstra,

[1] Available here: https://www.theguardian.com/commentisfree/2019/jan/13/divided-britain-not-new-why-do-todays-schisms-seem-intractable

[2] Interestingly, they also show that, in the UK, polarization actually slightly declined in recent decades.

2004). These fixed effects also control for all district-specific time-varying factors affecting both emigration and immigration decisions, and thus, under this setting, only the role of bilateral factors can be identified. To capture political similarity, we exploit information on election outcomes at the local level. Compared to the parliamentary elections, the existence of a rotation schedule for the election of councillors means that these elections can take place in any given year (see, e.g., Fetzer, 2019). Hence, by using outcomes of local elections – in lieu of national elections – we can leverage bilateral annual variations in political similarity between origins and destinations,[3] and combine this information with annual dyadic data on migration flows.

We consider two alternative measures of political similarity. Following studies on partisanship and geographic polarization in the US, our first measure is a binary indicator capturing whether the local council in the origin and the destination district is controlled by the same party (either the Labour or the Conservative party). This allows us to investigate whether (and to what extent) districts with the same political preferences have higher bilateral migration flows. The second measure is a continuous variable capturing pair-specific ideological spread (political distance) based on the two parties' seat shares in the local council. Although this continuous variable is highly correlated with the dichotomous classification of district pairs, it allows us to flexibly account for the role of political preferences in shaping destination choices even when people decide to move across politically mismatched districts.[4]

Our district-level analysis reveals that shared political ideologies have a strong positive impact on migration flows between two districts. 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%. Put differently, dyads/years with the highest value of political distance have, all else equal, about 22% lower migration flows than dyads/years with the lowest value of political distance. Reverse causality is not a major problem in our analysis since migration flows at the bilateral level are just too modest to have a sizeable effect on local election outcomes. A more serious concern, though, is the possibility of omitted variable bias arising from unobserved bilateral heterogeneity. To lend further credibility to our results, we employ three different approaches. First, we examine the sensitivity of our estimates to augmenting the gravity model with a wide set of controls capturing pair-specific differences in socio-economic and demographic characteristics. Second, we include origin-destination pair fixed effects in addition to the theoretically-motivated origin-year and destination-year fixed effects. This absorbs most of the linkages between the political similarity measure and the remainder error term in order to control

[3]The number of votes cast for each party across local council elections can be used as a "massive opinion poll". In addition to their scale, the advantage over conventional polling is the detailed information on actual voting behaviour rather than reported intentions. See `https://www.britishelectionstudy.com/bes-impact/what-do-the-2016-local-elections-tell-us-about-what-might-happen-in-2020/#.YAvi-S1Q1pQ`

[4]To provide further evidence, we also exploit information on the "political direction" of migration flows and investigate whether, for example, Conservative-district residents select the Labour-district destination with the highest relative support for the Conservative party.

for potential endogeneity of the former (Yotov et al., 2016), and identification in this case comes only from changes in political similarity within a specific migration corridor. Third, we adopt an instrumental variable strategy, where political distance is instrumented using a 'shift-share' instrument *a la* Altonji and Card (1991). 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. We believe that, 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 flows, in particular its political dimension.

Our district-level analysis is based on two premises. The first is that the main channel underpinning our result is the existence of a political homophily mechanism; i.e., the tendency to favour the company and presence of others who share similar political values (Bishop, 2009; Tam Cho et al., 2013). This is the foundation of Schelling's (1971, 1978) original model of racially segregated neighbourhoods, in which members of two groups relocate to achieve some degree of proximity to other residents of similar type.[5] To corroborate this mechanism and investigate some of the micro-foundations underlying the "macromoves", we employ a large individual-level panel dataset, obtained by combining the British Household Panel Survey (BHPS) with Understanding Society (UKHLS). Our analysis shows that a desire for political 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. For example, politically aligned individuals are 2 percentage points less likely to exhibit preference to move and 2-4 percentage points more likely to express positive perceptions and attitudes towards their neighbourhood. If anything, this suggests that individuals are attracted to "politically compatible" areas.

A second premise is that this desire for political homophily affects migration flows only once a decision to migrate (e.g., for economic reasons) has been taken. In other words, political alignment *per se* is not a reason to leave. This is consistent with both the literature on geographic sorting and the extant economic literature on internal migration, which points towards income prospects and other economic considerations as the main drivers (e.g., Greenwood, 1997; Kennan and Walker, 2011). Using our individual-level dataset, we show that this is indeed the case. Specifically, we find that, 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.

[5]One important implication of this model is that even when a relatively small fraction of people sort, they could cause the neighbourhood to "tip" from completely white to completely non-white over time. In our context, this implies that once a cycle of "homophily movements" has started, migration could lead to completely politically segregated communities. Yet, although theoretically fascinating, there is mixed evidence of the existence of a "tipping point" in racial segregation in the US (Card et al., 2008; Easterly, 2009). A more plausible implication for our study is that, once people choose destinations on a political basis, the cumulative effect in the long run can significantly increase population differences across space.

Our research contributes to extant studies on the factors shaping the destination choices of internal migrants. A wealth of research has demonstrated that economic considerations play an important role in the decision to relocate and that movers select destinations on the basis of better employment opportunities and higher wages (see, e.g., Jackman and Savouri, 1992; Greenwood, 1997; Kennan and Walker, 2011; Langella and Manning, 2019b).[6] At the same time, relocation patterns exhibit geographic sorting by a number of neighbourhood and municipality characteristics that affect overall satisfaction (see, e.g., Bracco et al., 2018; Langella and Manning, 2019a). We also contribute to recent studies on whether internal migrants sort geographically based on their desire to live with neighbours with similar status and values (Bishop, 2009; Florida and Mellander, 2009; Tam Cho et al., 2013; Carlson and Gimpel, 2019). In fact, the increasing presence of homogeneous pockets of political support in the US has stimulated a wealth of research in its own right 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; Rohla et al., 2018; Carlson and Gimpel, 2019). People care about the characteristics of the local community where their social interactions take place, and partisans differ starkly in their preferences for community type. Accordingly, this line of research shows that the geographic clusters of like-minded individuals are also shaped by political preferences (Sussell, 2013; Tam Cho et al., 2013). Extant research disproportionally focuses on the US, the archetypal case of a highly polarized society where the ideological divide is at a historic high and has been widening since the late 1970s (White and Lindstrom, 2005; Autor et al., 2020). We contend that the very high rate of within-country migration, coupled with a two-party strong predominance of the political process and the historical high levels of 'affective' polarization (Boxell et al., 2020), make the UK a suitable test-bed to examine whether partisanship affects internal migration outside the exemplary US case. Moreover, to the best of our knowledge, there are no studies that investigate partisan sorting across the entire population of a country and over such an extended period of time.

En route, we contribute to the literature on geographic mobility in the UK and the processes that cause people to move across regional boundaries (Jackman and Savouri, 1992; Andrews et al., 2011; Thomas et al., 2015; Langella and Manning, 2019b). In estimating the role of political proximity in affecting internal migration flows, we use more granular data at the district level, rather than at the government office region level (Jackman and Savouri, 1992), and exploit information on the vast majority of households rather than a representative sample (Andrews et al., 2011; Thomas et al., 2015). While not as comprehensive as the decennial population census (see Langella and Manning, 2019b), this data offers an uninterrupted series of yearly observations for district movers which is more suitable for the research question at hand. We ask to what extent each of the local characteristics compare to political similarity in determining and predicting migration flows. Consistent with past migration research, factors such as income, physical distance, and migrant

[6] Destination choices are also shaped by life-course events and housing and family structure transitions (White and Lindstrom, 2005; Molloy et al., 2011; Bernard et al., 2014).

networks all display a consistent relationship with destination choices. Yet, to reiterate our previous point, whereas the political similarity variable exerts an important effect, it is also of a similar order of magnitude as the effect of the wage differentials variable.

We proceed as follows. Section 2 describes the data and empirical strategy used for the district-level analysis, and reports the effects of political proximity on "macromoves"; i.e., migration between districts. Section 3 discusses the data and methods used for the individual-level analysis, and presents evidence supporting the political homophily mechanism and the positive relationship between a migrant's self-reported ideology and the destination's partisanship. Section 4 concludes.

2 District-Level Analysis

2.1 Data and variables

We obtain data on annual bilateral migration flows at the local authority district (LAD) level from the ONS's People, Population and Community theme.[7] Our sample covers all possible origin and destination districts in England and Wales (346×345) and spans a period of 14 years, 2002-2015.[8] 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, imply 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. In Figure 1, we present 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.[9]

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

[7] Migration flows are primarily based on data that flag up when people change their address with their doctor. The flows do not include 'special populations'; for example, prisoners and members of the armed forces. For reasons of disclosiveness, the data are reported in multiples of 10. As noted by the ONS, since most people change their address with their doctor soon after moving, these data provide a good proxy indicator of internal migration. This is broadly confirmed when we compare the ONS data with the decennial census data (when available). For instance, the mean of bilateral migration flows for the year 2011 as recorded by the ONS (vs the 2011 population census) is 21.37 (vs 20.99), with a standard deviation of 97.36 (vs 103.35), a minimum value of 0 (vs 0) and a maximum value of 4,530 (vs 4,752).

[8] The choice of the time period is determined by the availability of data for both the outcome variable (internal migration flows) and the main explanatory variable (districts' political preferences).

[9] Table B.2 in the Appendix provides a list of all districts with the corresponding government office region (GOR) to which the belong.

alternative measures of political similarity. The first one is a binary indicator taking value 1 if the local council in the two districts at time t is controlled by the same party (either the Labour or the Conservative party);[10] and 0 otherwise; namely, *Same party control*. The second one is a continuous measure of ideological 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 ideologies. Figure 2 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 immediate and 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 in our analysis is that it can account for the role of political preferences in shaping destination choices even when people decide to move across politically mismatched districts; i.e., Labour-district residents selecting the Conservative-district destination with the highest possible support for the Labour party (see Section 2.4.3 for further evidence on this). On the other hand, the binary measure comes with the advantage that it changes very slowly over time and thus it is less subject to potential endogeneity arising from changing migration flows.

To construct our political similarity measures, we consider local council elections rather than the parliamentary elections for two main reasons. First, data on local election outcomes can be easily matched to the internal migration data which are only available at the district level;[11] and second, local elections have an appealing feature in that, rather than happening uniformly across the UK every four years, they may take place in any given year across the country due to the rotating fashion by which councilors are elected (Fetzer, 2019). Exploiting information about the

[10] The UK political landscape is characterised by the presence of a two-party system. Since 1945, the combined Conservative and Labour share of the vote at the general elections has been around 70%, and after a small decline in 2007, it has increased to one of its highest levels in decades (Duffy et al., 2019). The dominance of the two parties is also apparent in local governments, with the two leading parties having, on average, more than 70% of local council seats. We follow recent studies on affective polarization in the UK which focus on the two largest parties given the large number of survey respondents identifying with them (Boxell et al., 2020). We expect partisan sorting to be more likely in a political system dominated by two parties, like in the US or the UK (Tam Cho et al., 2013). Note that including additional parties would be particularly challenging in the context of local elections given the presence of numerous successful local parties, with the additional difficulty of neatly classifying them along the classic ideological spectrum. We return to this issue in Section 2.4.3.

[11] Aggregating parliamentary election outcomes to the district-level is not possible due to overlapping boundaries.

share of seats is useful as it reflects the first-past-the-post electoral system used in England and Wales to elect the councilor in each council electoral division (electoral ward), and thus accounts for differences in political preferences across small geographic units within the same district. For more details on local government services, elections and reforms, see Appendix A.

[Figures 1 and 2 about here]

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 (Anderson, 2011; Beine et al., 2016, 2019). 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. In particular, we consider migration flows to be a function of relative wages, the "mass" of the two economies, and the physical distance between them, and add time-varying directional (origin and destination) fixed effects to account for all factors affecting emigration decisions and the choice of a particular destination over other alternatives. The main difference in our approach is the focus on within-country movements and the expectation that (in addition to the above factors) the political similarity between the two regions will also play a significant 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 the 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). Furthermore, when the gravity equation is estimated with PPML, the directional fixed effects estimates have been shown to be completely consistent with the outward and inward multilateral resistance terms (Fally, 2015).

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

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

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, $v_{ij,t}$ is an error term clustered at the dyad level.

As noted above, 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).[12] Specifically, origin-year fixed effects capture all the 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 the 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.[13] Specifically, to capture the argument that immigrant workers respond to differences in labour incomes between regions – as implied by the labour market model of migration (see, e.g., Friedberg and Hunt, 1995; Card, 2001) – we control for the ratio of destination-to-origin district average wages ($Wage_j/Wage_i$). To reflect differential economic opportunities, 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 ($Population_i \times Population_j$). As argued by Lewer and Van den Berg (2008), the more people there are in a source region, the more people are likely to migrate, and the larger the population in the destination region, the larger is the labour market for immigrants. 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.*),[14] as a measure of cultural differences between the two districts.[15] 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 depen-

[12] In many studies, the multilateral resistance terms are approximated by the co-called "remoteness indices" constructed as functions of bilateral distance, and Gross Domestic Products (GDPs). Head and Mayer (2014) criticize such approaches as they bear little resemblance to the theoretical counterpart of the multilateral resistance terms.

[13] Note that, in the presence of multilateral resistance terms, the right-hand-side of Eq. (1) can only include corridor-specific variables, and non-linear combinations of monadic (district-specific) variables at origin and destination, such as ratios, products and distances (Head and Mayer, 2014).

[14] As in Langella and Manning (2019a), 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. As ethnic diversity is a slow-moving variable, we do not expect interpolation to be an issue.

[15] The ethnic fractionalisation index is defined as $1 - \sum_g s_{gn}^2$, where s_{gn}^2 is the share of ethnic group g living in district n, computed for non-white groups (Langella and Manning, 2019a). The fractionalisation index is one of many possible ways to measure ethnic diversity. Using alternative measures of ethnic mix to proxy for cultural differences, such as the share of the white population, does not change our results.

dent variable (LDV). The inclusion of lagged migration flows as a regressor 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 destination region characteristics (Lewer and Van den Berg, 2008; Beine et al., 2019). In addition, estimating the gravity equation using a dynamic panel data setting allows for a flexible and comprehensive treatment of the multilateral resistance terms. As illustrated by Olivero and Yotov (2012), the dynamic theory-founded econometric specification (with a LDV and time-varying directional fixed effects) is superior to alternative fixed effects specifications.

Extant research in electoral geography shows how socio-economic and demographic backgrounds in the UK help explain local political preferences (Johnston et al., 2006). Whereas we control for a number of these local-level demographic covariates, a long tradition of research in social science also demonstrates that political identities are shaped by individual, historical, social and cultural factors, such as the level of faith at different points in the life of an individual – as well as by complex interactions between individuals and their environment (see, e.g., Druckman and Lupia, 2000; Green, 2010).[16] As such, to the extent that demographic patterns do correlate with political preferences, political similarity between districts would only be partially accounted for by our control variables.

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 determined 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 Eq. (1) 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.

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 (observed and unobserved) 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

[16]For example, social scientists have examined the psychological foundations of partisan loyalties in the general public. Accordingly, deep-seated personality traits – i.e., the stable tendencies to think, feel, and behave in particular ways – shape political preferences and ideological identities (see, e.g., Jost et al., 2003; Johnston et al., 2017).

the remainder error term $v_{ij,t}$ (Yotov et al., 2016). As a result, within this setting, identification comes from changes in political similarity (or the magnitude of political distance) 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 enormously (leading to more conservative estimates), and absorbs all time-invariant determinants of migration that are used standardly in gravity regressions, such as geographic distance and contiguity.[17] Furthermore, using PPML reduces the sample size, as it drops all corridors with zero migration flows in all sampled years (dyads with no variation in the dependent variable are treated as non-informative).

To further investigate the importance of omitted factors, we follow the methods developed by Altonji et al. (2005) and look at the stability of the political similarity estimates as follow-on information is added.[18] In particular, we compare different combinations of 'uncontrolled' and 'controlled' regressions and calculate the corresponding selection ratios, which allow us to assess how much larger the selection bias based on unobserved factors would have to be compared to observed factors to fully explain our results.

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 (even if we assume that all immigrants from a specific origin vote for the same party). Indeed, as shown in Figure B.1, 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%), and remains very small even when we exclude observations that correspond to zero flows (see Panels (a) and (b), respectively).

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,[19] where *Distance in party shares* is instrumented using a 'shift-share' instrument (Altonji and Card, 1991).[20] The

[17] It has also been argued that, even though PPML models with a single fixed effect and a two-way setting are asymptotically unbiased, a three-way fixed effect PPML model does not necessary inherit the same asymptotic properties and may suffer from an incidental parameter problem (Weidner and Zylkin, 2020).

[18] Oster (2019) has recently extended the Altonji et al. (2005) method to enable the estimation of an unbiased treatment effect in the presence of unobserved confounders. However, the assumptions necessary to apply the Oster (2019)'s approach are not satisfied in the context of a PPML model.

[19] 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.

[20] As noted in Section 2.1, the binary measure 'Same party control' changes slowly over time and thus it is less sensitive to marginal changes in the electorate's composition and political preferences.

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 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.[21] As such, identification in this setting is motivated by exogenous national 'shocks' (changes in national ideological spread over time), even when exposure shares are assumed to be endogenous (Borusyak et al., 2020).[22]

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.[23] 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)),

[21] Excluding the dyads that involve either i or j when calculating the yearly (national) average for each observational dyad ij has negligible effect on the value of the corresponding growth rates. This is not surprising given the large number of origin-to-destination corridors in our sample (119,370); i.e., only 1% of the dyads are dropped each time.

[22] There is an ongoing debate about the identification assumptions behind the shift-share instruments, which largely depend on the particular application and context (see Jaeger et al., 2018; Goldsmith-Pinkham et al., 2020; Borusyak et al., 2020). Shares and shifts may simultaneously provide valid identifying variation, but in practice it is unlikely for both sources of variation to be a priori plausible in the same setting (Borusyak et al., 2020). As noted above, identification in our setting is motivated by exogenous shifts, but we also add pair fixed effects to control for the potential endogeneity of shares. The inclusion of pair fixed effects means that we do not require initial political distances to be exogenous to the level of bilateral migration flows, only to changes in bilateral migration flows.

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

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. Specifically, in line with Lewer and Van den Berg (2008), we can see that the number of migrants moving from the origin to the destination 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. As emphasized in several migration studies (see, e.g., Beine and Parsons, 2015; Beine et al., 2016, 2019), 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 (even if the actual distance travelled is the same). 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 (positive and negative, respectively) 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%. Put differently, dyads/year with the highest value of political distance have, all else equal, about 22% lower migration flows than dyads/years with the lowest value of political distance. 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).[24]

[24]RF is a supervised machine learning algorithm which uses decision tree-based classification to evaluate a massive number of decision trees (known as the forest) generated using optimal splits in the data. It takes the predictions from the forest and then selects the best by means of a voting mechanism. We begin by splitting our data into train and test samples, we then iterate this process in order to optimise the algorithm by obtaining hyper-parameters for the number of trees to grow and the number of variables to be considered at each node, and we finally force our training data through the forest and obtain a prediction on the size of each migration flow. To avoid having too many categories to predict, we bin the flow data into multiples of 50. The data are stratified by dyad and then randomly split into test and training samples, 90% and 10%, respectively. The algorithm is optimised when we grow 500 trees and consider two variables at each split in the tree.

Figure 3 presents the RF variable importance measure for the specifications in columns (3) and (5) of Table 1; Panels (a) and (b), respectively. 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*. Specifically, the migrant network effect is three to four times as important as physical distance in predicting migration flows. 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.

[Table 1 and Figure 3 about here]

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. In the following section, we present the findings of these tests.

To alleviate concerns of omitted variable bias, we control for a wide set of explanatory variables that could distort our results. We start by considering 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*),[25] share the same genetic roots (*Same genetic group*),[26] and exhibit very similar socio-demographic characteristics (*Same similarity group*).[27] Table 2 presents the results when these variables are introduced (individually and jointly) into Eq. (1). The estimates of *Same party control* (columns (1)-(4)) and *Distance in party shares* (columns (5)-(8)) are remarkably similar to those reported in Table 1, pointing to the same conclusions.

[Table 2 about here]

We next consider corridor-specific characteristics that vary over time, and thus can be correlated with changes in our variables of interest. As before, these are first introduced separately and then jointly. In particular, to further account for relative economic conditions affecting migration, we add the ratio of destination-to-origin district nighttime light intensities ($Night\ lights_j/Night\ lights_i$).[28]

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

[26] 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).

[27] Specifically, 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.

[28] Nighttime light intensity is commonly used by social scientists as a proxy for economic activity or economic development in subnational regions. The measure is based on georeferenced images by the DMSP-OLS Nighttime Lights Time Series Dataset (version 4) of the National Oceanic and Atmospheric Administration, and is available for each district/year in our sample up until 2013. The values for the years 2014 and 2015 are imputed using linear interpolation.

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*). Columns (1)-(9) display the corresponding estimates on two different panels. Panel (a) features estimates for *Same party control* and Panel (b) for *Distance in party shares.* Finally, the last two columns of each panel (columns (10) and (11)) show the results when 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; before and after adding the extra controls. It should be stressed that, most of these added controls are highly correlated with one another, and their joint inclusion into the gravity model can introduce serious multicollinearity problems.[29] 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.

[Table 3 about here]

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). This allows us to eliminate corridor-specific factors that are time-invariant and inadequately controlled for by the aforementioned variables, and also to account for the possibility that district pairs select into voting for the same party for reasons related to internal migration. Table 4 presents the results when we add pair fixed effects to the regression set-up of Table 1.[30] Overall, we can see that employing this intensive set of fixed effects (origin-year, destination-year and origin-destination) 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 4 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.

[29]We also experimented with adding distances in the share of students and the share of home owners and, once again, our results do not change. Note that these variables are very highly correlated with other controls in Table 3, such as distances in the share of aged 18-64 or over 64 and the share of married/couples.

[30]It must be stressed that, when we focus on within-pair variation, the effect of *Distance in ethnic frac.* cannot be correctly identified since the (missing) values of this variable for the inter-censual and post-censual years are imputed using linear interpolation.

[Table 4 about here]

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). The goal of this exercise is to use selection on observable characteristics to provide information on selection along unobservable factors. We compare different combinations of 'uncontrolled' and 'controlled' regressions, assuming that the observable characteristics are captured by the key determinants of migration flows (included in vector $\mathbf{X}_{ij,t}$) and the LDV. 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 4 (see Table B.3 in the Appendix). Such a strong role of unobserved heterogeneity seems very unlikely.

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. This mitigates the impact of reverse causality, especially when we employ the binary measure that changes only when there is a change in the party that controls the local council. However, to further alleviate these concerns, 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 – even when we exploit within-pair variation only – suggesting that our results cannot be attributed to a contemporaneous reverse effect from outcome to treatment (see Table B.4 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 5 show the results of a 2SLS-IV estimation, 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).[31] In all regressions, we restrict the sample to exclude the first two years, 2002 and 2003. The instrument performs very well – as captured by high KP test statistic values – and, in all cases, the effect of *Distance in party shares* turns out to be negative and statistically significant at conventional levels, which provides further support for the arguments put forward in this paper.[32] 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 4; even though the standard errors are larger as well. It should be noted that, in the pair fixed effects specifications,

[31] Since the PPML model uses an estimate of the error term from the first stage, as opposed to the true error term, the asymptotic sampling variance of the second-stage estimates needs to take this extra source of variation into account. To do that we undertake 200 replications of the procedure to bootstrap the estimated standard errors.

[32] The first stage estimations are provided in Table B.5 of the Appendix. Note that our results in columns (5)-(8) of Table 5 persist when we add the quadratic estimated residual from the first stage and/or the residual interacted with the political distance measure.

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).

[Table 5 about here]

2.4.3 Robustness tests and further insights

The key finding that emerges from our analysis is that shared political ideologies have a positive impact on migration flows between two districts. To ensure robustness and gain further insights into this finding, we perform a number of tests, which are reported in the Appendix. These are based on our most preferred specification that includes the full set of fixed effects (which also produces the most conservative estimates); even though the inferences do not change if we omit the pair fixed effects.

Sensitivity to sampled regions and error clustering. In Table B.6, we check the sensitivity of our results to excluding intra-region migration flows; that is, dropping the set of district pairs that belong to the same GOR. Regardless of which GOR is excluded each time, the political distance estimates remain negative and statistically significant at the 1% level. However, the corresponding effect appears to be stronger when we drop London, suggesting that political similarity matters less when people move across London districts. In Table B.7, we assess how the correction of standard errors affects our results. Specifically, for each estimated coefficient in Table 1, 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 distance 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 political 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)

– making the choice of policies at the district level less subject to partisan influence. Furthermore, as also discussed below, 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 Deprivation (IMD) among the regressors.[33] 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, 2019a). As shown in Table B.8, 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 (the responsibilities are split between county and district councils in both the origin and the destination district) 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.9), suggesting that our results hold even when there is a weak relationship between amenity provision and local council partisanship.

Distance in Labour vs Conservative party shares. In Table B.10, 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 absolute difference (between the two districts) in the share of Conservative or Labour party seats in the local council, respectively. 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,[34] 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 political mismatched districts. 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_iLabj (capturing pairs of Conservative-origin and Labour-destination districts) and $1 - Con_iLab_j$ (capturing all the other possible district pairs). In

[33] 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, 2019a), the results are shown for districts in England only.

[34] 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.

this way, we can estimate the impact of the relative Conservative ratio on migration flows conditional on the partisan composition of the two districts. The results, displayed in Table B.11, 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 *Conservative ratio* $\times$ $(1-Con_i Lab_j)$ 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.11).

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 political 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 as in the district-level analysis, 2002–2015, from the British Household Panel Study (BHPS) and its successor Understanding Society (UKHLS). BHPS-UKHLS follow a representative sample of households over time, interviewing all individuals aged 16 or above (once per wave-year), and include a wide range of questions on political and social attitudes. Interviews are carried out face-to-face in respondents' homes by trained interviewers or through a self-completed online survey, and respondents are coded based on residence at the district level. The wave-annual observations can be disaggregated into wave-quarterly observations by exploiting information about the quarter of the year that the data is collected.

3.1 The desire for political homophily

3.1.1 Methods and results

To infer individuals' desire for political homophily, we investigate whether individuals' perceptions and attitudes towards the location where they live are systematically 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 in total); 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, 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 (two-way clustering).

The inclusion of district $\times$ wave $\times$ time fixed effects implies that we only exploit between individual variation within a district. This effectively accounts for any district-specific time-varying shocks affecting outcomes of respondents living in the same district in a common fashion, including economic and political shocks affecting the wider local economy and migration behaviour. Adding these fixed effects corresponds to estimating about 20,000 coefficients, and allows us to compare politically aligned 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 same party (Conservatives or Labour) across all survey waves.[35] In

[35]To ensure that this classification is pre-determined relative to the other variables used in our analysis, we also account for individuals' political preferences during the five years preceding our sample period. In other words, a respondent is coded as being a 'core supporter' if they express preference for the same party (Conservative or Labour) every time they were interviewed during a 19-year period (1997-2015).

this way, individual n's political alignment at a given point in time is only determined by changes in their district's political preferences (the variable $P_{n,d,w,s}$ in Eq. (2) is time-invariant), and thus it is less prone to endogeneity arising from unobserved time-varying individual characteristics or individual-specific time-shocks.

Table 6 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.[36] In columns (5)-(8), we replicate the regressions of columns (1)-(4), but we now restrict the sample of respondents to those defined as 'core supporters'. As noted above, to the extent that this sub-sample includes the loyal base of supporters for the two leading parties (who do not change their political preferences over time), the political alignment variable at a given point in time can be assumed to be less responsive to (unobserved) changes in individual characteristics. Focusing on core supporters 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 6 about here]

Table 7 shows the results for the three outcome variables on neighbourhood satisfaction based on the same regression set-up as in Table 6. 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 6: politically aligned individuals are 2-4 percentage points more likely to provide positive responses to the above statements, and this effect

[36] Table C.2 in the Appendix presents the full regression results of Table 6.

holds when we focus on the subsample of 'core supporters'. 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.

[Table 7 about here]

3.1.2 Robustness tests

In the Appendix, we present additional robustness and sensitivity checks. 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 drop respondents who live in the same GOR (one GOR at a time), 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.[37] The rationale here is that individuals who will become politically aligned in the future, or used to be politically aligned in the past, exhibit the same underlying traits in these pre- and post-treatment years as in the years in which they are politically aligned.[38] 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.[39]

[37] 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).

[38] 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).

[39] 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

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.[40] 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 (2019a), 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 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 effect of alignment is statistically different between the two groups, suggesting that the desire for political homophily is not a unique phenomenon of individuals with specific characteristics.

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.[41] Indeed, while political alignment can satisfy your need to belonging and 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, since the latter is mostly motivated by employment and income opportunities (Thomas et al., 2015). To explore this issue, we follow Langella and Manning (2019a) and test whether the variables considered in Section 3.1 can serve as

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.

[40] 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.

[41] 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.

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 $w-1$), and regress this indicator on the lagged value of the four outcome variables (*Preference to move*, *Plan to stay in neighbourhood*, *Belong to neighbourhood*, and *Similar to others in neighbourhood*), as well as the lagged value of the treatment variable *Alignment*. The estimates, reported in Table 8, 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.

[Table 8 about here]

The findings in Table 8, together with the strong evidence of partisan sorting at the district-level (based on actual movers), suggest that the desire for political homophily affects 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 run a final round of analysis and 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,[42] 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 likelihood of moving to a Conservative or a Labour district) includes political ideology, age, age squared, distance of the move, and partisanship of the origin district[43] – with the latter controlling for the fact that each kind of migrant (Conservative or Labour) is also more likely to originate in these kinds of districts.

Columns (1)-(4) of Table 9 report the corresponding second-stage estimates, both for the full sample of respondents and the subsample of 'core supporters';[44] whereas columns (5)-(8) check the robustness of these results to adding GOR $\times$ wave $\times$ time fixed effects.[45] 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

[42] Movers are generally not selected randomly from the population, as they tend to be younger, wealthier and better educated than non-movers (McDonald, 2011).

[43] 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.

[44] The first-stage estimates are reported in Table C.9 of the Appendix. Note that our results persist when we replace the alignment variable in the first stage with the political ideology of the respondent (Conservative or Labour supporter).

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

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 highly correlated with political preferences, we also experiment with an alternative specification that includes additional variables in the second stage; namely, income decile and educational background indicators.[46] As shown in Table C.10 of the Appendix, 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.

[Table 9 about here]

4 Conclusions

Internal migration reconfigures a country's economic, demographic and social landscape, plays a key role in national well-being and crucially affects the functioning of the labour and housing markets (e.g., UNDP, 2009; Boustan et al., 2010; Bartram et al., 2014; Bell et al., 2015; Kleemans and Magruder, 2018). As such, understanding the key drivers of internal migration can shed new light on its consequences. Destination choices are not random but, rather, driven by specific preferences, particularly once economic constraints, such as employment, are taken into account. In this paper, we focus on the political dimension of internal migration and explore the effects of partisanship on where people choose to live. To do so, we combine district-level with individual-level analyses, leveraging a nearly exhaustive dataset on the universe of internal migration in England and Wales across 346 local authority districts between 2002 and 2015, and a rich survey-based dataset over the same period.

The district-level analysis shows that political proximity between origins and destinations exerts a positive effect on bilateral migration flows. Although physical distance, wage differentials and migrant networks are the most important factors in the choice of the destination, as one would expect, partisan geographic sorting is strongly present. In fact, the estimated effects are not only statistically significant but also economically meaningful; for instance, a one-standard-deviation increase in political distance will lead to a decrease in migration flows by about 4%. The individual-level analysis allows us to gain further important insights into the underlying mechanism: the desire for political homophily. We demonstrate that political compatibility matters and individuals are more likely to report positive sentiments towards their neighbourhood, such as a more pronounced

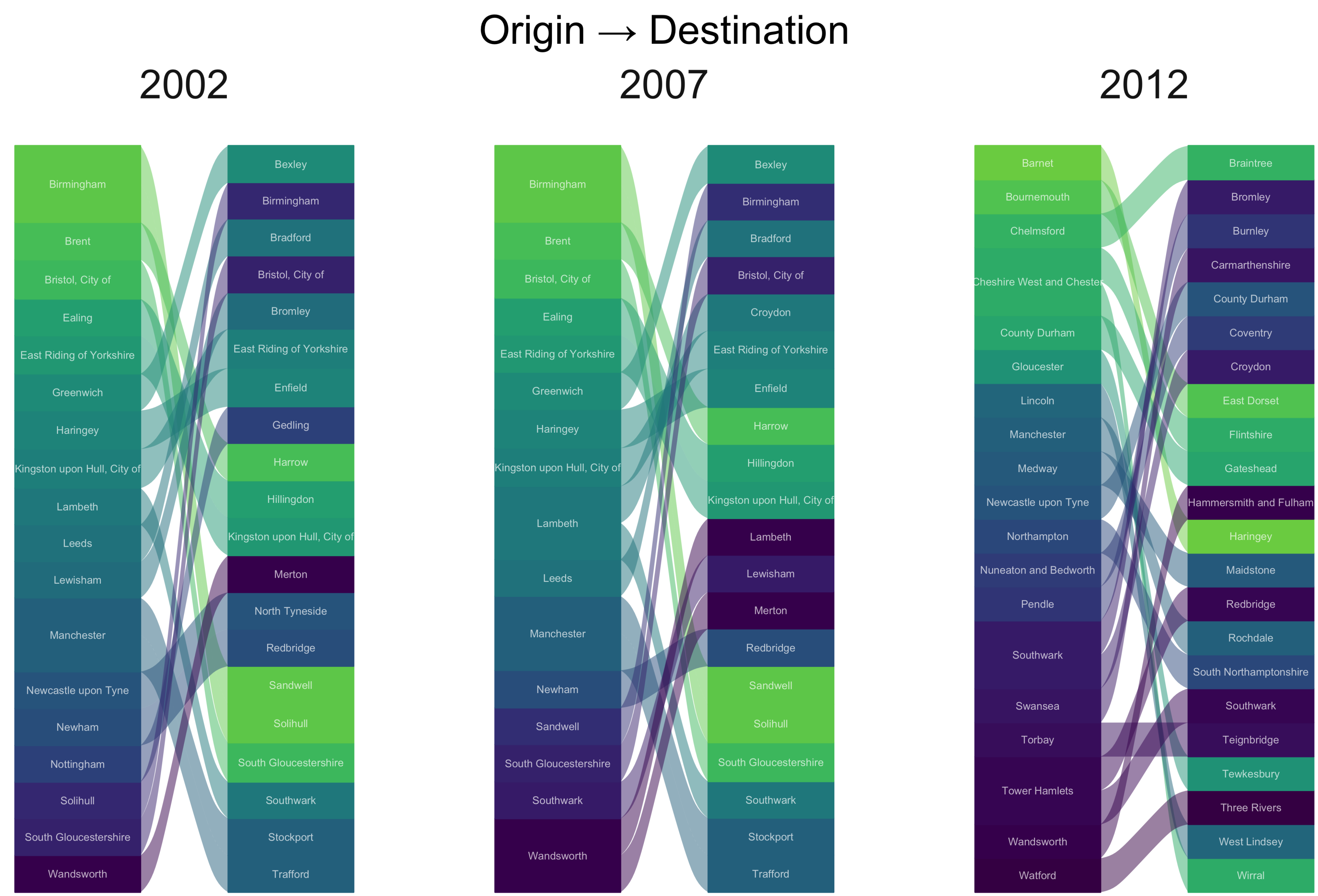
[46] Based on this specification, gender, employment status, and family-related variables (such as marital status, having children, and household size) are only included in the first stage. It should be noted, however, that the political ideology variables remain economically and statistically significant when we don't account for sample selection and employ the full set of controls in a probit model predicting the likelihood of moving to a Conservative or Labour district among movers.

sense of belonging and 'fitting in', when they are politically aligned to their district of residence. We also demonstrate that political ideology does help predict migrants' destination choices.

Voting patterns in US presidential elections suggest that the American electorate is geographically polarized and that this polarization has grown over recent decades. US regions are increasingly populated by people who think and vote alike, and recent research has shown that this polarization has partially resulted from selective migration patterns. While the US, as the main focus of research, is a useful reference point, there is much to learn about how political preferences matter for internal migration outside this emblematic case. We show that destination choices are strongly affected by partisanship also in the UK, a country where marked levels of political polarization and animosity have contributed to sharpening divisions within society.

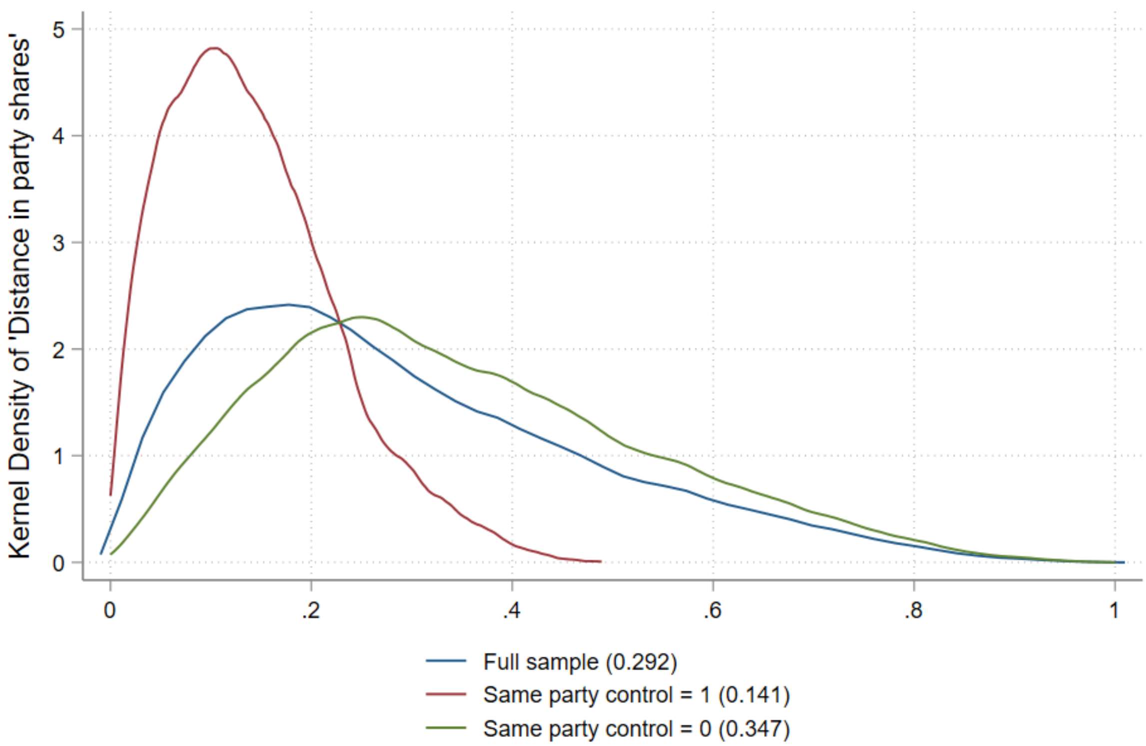
Our study illustrates that the migration patterns of a significant subset of the British population exhibit geographic sorting by political characteristics. This sorting of politically like-minded individuals can have a number of unfortunate consequences. For one, it is detrimental to the development of a diversity of opinions and can discourage political discourse. In turn, this could increase tensions between population parcels that are distinctive from each other in terms of core values and beliefs and can result into heightened intolerance in the long-run. Finally, the residential separation of Conservatives and Labour supporters can contribute to the decline in the number of voters living in politically competitive settings, which has practical consequences by imposing costs on non-competitive homogeneous communities, as politicians are less likely to respond to their needs.

Figure 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.

Figure 2: Distribution of ‘Distance in party shares’



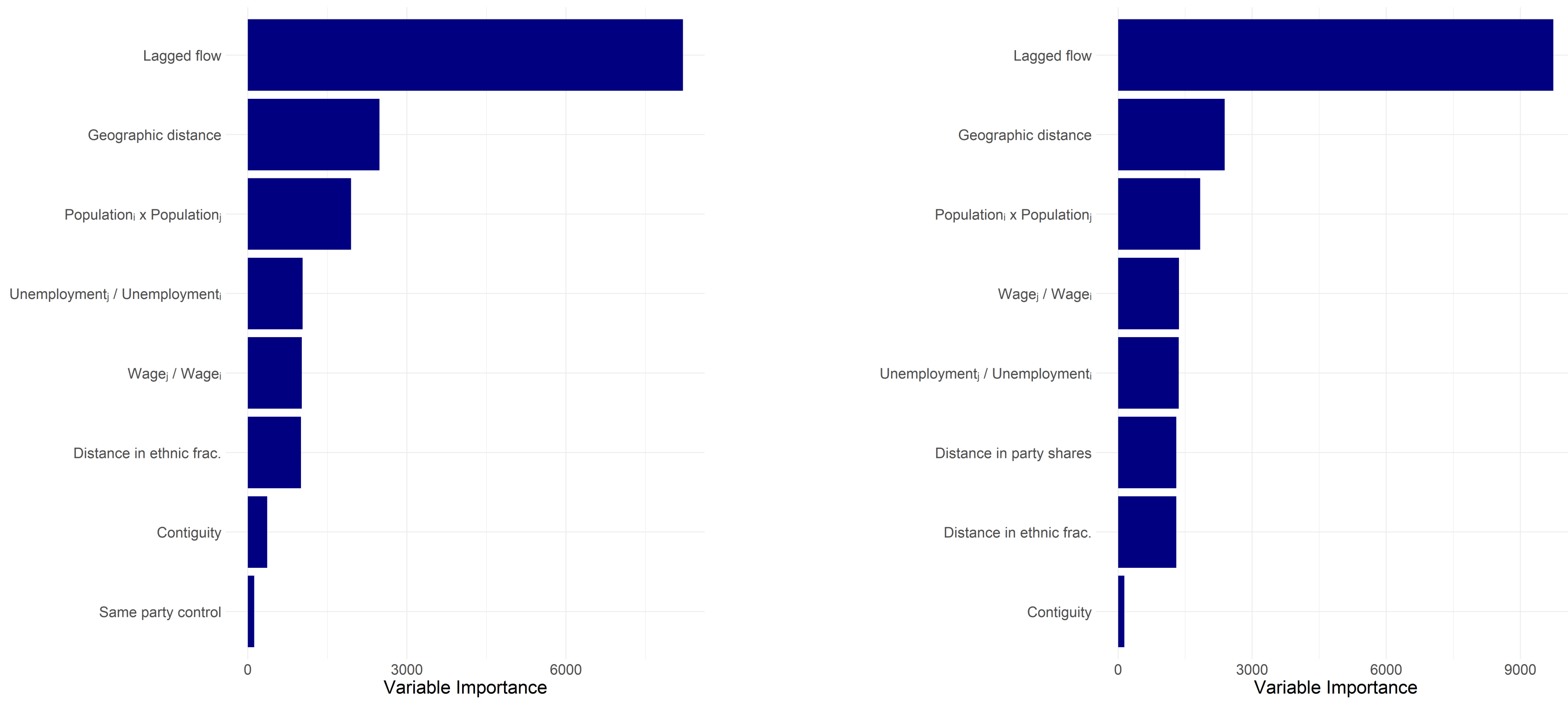
Notes: This figure shows the kernel density of the variable *Distance in party shares* for: (i) the full sample of district pairs; (ii) the pairs that share the same political preferences; (iii) the pairs that do not share the same political preferences. The corresponding mean values are reported in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

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: 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.

Figure 3: 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.

Table 2: 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. × Year	✓	✓	✓	✓	✓	✓	✓	✓
Orig. × 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: 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 3: 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. × Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Orig. × 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. × Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Orig. × 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: Standard errors clustered at the dyad (district-pair) level in parentheses. LDV is the lagged dependent variable. The estimate and standard error of *Lagged 5-year moving average* are multiplied by 1,000. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table 4: 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: 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.

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

Table 6: 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.

Table 7: 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: 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 8: 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: Standard errors clustered at the individual and district levels in parentheses (two-way clustering). 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, as shown in each column. All right-hand-side variables (x-var and vector $\mathbf{Z}_{n,d,w,s}$) are in lagged terms (as observed in survey wave $w-1$). ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table 9: 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 × Wave × 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. Columns (2), (4), (6) and (8) restrict the sample to include the 'core supporters' for the two parties. 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 References

Altonji, J. G. and Card, D. (1991). *The effects of immigration on the labor market outcomes of less-skilled natives, in Abowd, J.M. and Freeman, R.B. (eds).* Cambridge, MA: National Bureau of Economic Research.

Altonji, J. G., Elder, T. E., and Taber, C. R. (2005). Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools. *Journal of Political Economy*, 113(1):151–184.

Anaxagorou, C., Efthyvoulou, G., and Sarantides, V. (2020). Electoral motives and the subnational allocation of foreign aid in sub-Saharan Africa. *European Economic Review*, 127(C):103430.

Anderson, J. E. (2011). The gravity model. *Annual Review of Economics*, 3:133–160.

Anderson, J. E. and van Wincoop, E. (2003). Gravity with gravitas: A solution to the border puzzle. *The American Economic Review*, 93(1):170–192.

Andrews, M., Clark, K., and Whittaker, W. (2011). The determinants of regional migration in Great Britain: A duration approach. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 174(1):127–153.

Autor, D., Dorn, D., Hanson, G., and Majlesi, K. (2020). Importing political polarization? The electoral consequences of rising trade exposure. *American Economic Review*, 110(10):3139–3183.

Bartram, D., Poros, M., and Monforte, P. (2014). *Key concepts in migration*. Sage.

Beine, M., Bertoli, S., and Fernández-Huertas Moraga, J. (2016). A practitioners' guide to gravity models of international migration. *The World Economy*, 39(4):496–512.

Beine, M., Bourgeon, P., and Bricongne, J.-C. (2019). Aggregate fluctuations and international migration. *The Scandinavian Journal of Economics*, 121(1):117–152.

Beine, M. and Parsons, C. (2015). Climatic factors as determinants of international migration. *The Scandinavian Journal of Economics*, 117(2):723–767.

Bell, M., Charles-Edwards, E., Ueffing, P., Stillwell, J., Kupiszewski, M., and Kupiszewska, D. (2015). Internal migration and development: Comparing migration intensities around the world. *Population and Development Review*, 41(1):33–58.

Bernard, A., Bell, M., and Charles-Edwards, E. (2014). Life-course transitions and the age profile of internal migration. *Population and Development Review*, 40(2):213–239.

Bishop, B. (2009). *The big sort: why the clustering of like-minded America is tearing us apart*. Houghton Mifflin Harcourt.

Borusyak, K., Hull, P., and Jaravel, X. (2020). Quasi-experimental shift-share research designs. *The Review of Economic Studies*, DOI:10.1093/restud/rdab030.

Boustan, L. P., Fishback, P. V., and Kantor, S. (2010). The effect of internal migration on local labor markets: American cities during the Great Depression. *Journal of Labor Economics*, 28(4):719–746.

Boxell, L., Gentzkow, M., and Shapiro, J. M. (2020). Cross-country trends in affective polarization. *National Bureau of Economic Research*, (Working Paper, No. 26669).

Bracco, E., De Paola, M., Green, C. P., and Scoppa, V. (2018). The effect of far right parties on the location choice of immigrants: Evidence from Lega Nord mayors. *Journal of Public Economics*, 166:12–26.

Card, D. (2001). Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. *Journal of Labor Economics*, 19(1):22–64.

Card, D., Mas, A., and Rothstein, J. (2008). Tipping and the Dynamics of Segregation. *The Quarterly Journal of Economics*, 123(1):177–218.

Carlson, C. and Gimpel, J. G. (2019). Political implications of residential mobility and stasis on the partisan balance of locales. *Political Geography*, 71:103–114.

Crawford, R., Stoye, G., and Zaranko, B. (2021). Long-term care spending and hospital use among the older population in England. *Journal of Health Economics*, 78:102477.

Dreher, A., Fuchs, A., Hodler, R., Parks, B. C., Raschky, P. A., and Tierney, M. J. (2019). African leaders and the geography of China's foreign assistance. *Journal of Development Economics*, 140:44–71.

Druckman, J. N. and Lupia, A. (2000). Preference formation. *Annual Review of Political Science*, 3(1):1–24.

Duffy, B., Hewlett, K., McCrae, J., and Hall, J. (2019). Divided Britain? Polarisation and fragmentation trends in the UK. *The Policy Institute at King's College London.*

Easterly, W. (2009). Empirics of strategic interdependence: The case of the racial tipping point. *The BE Journal of Macroeconomics*, 9(1).

Fally, T. (2015). Structural gravity and fixed effects. *Journal of International Economics*, 97(1):76–85.

Feenstra, R. C. (2002). Border effects and the gravity equation: consistent methods for estimation. *Scottish Journal of Political Economy*, 49(5):491–506.

Feenstra, R. C. (2004). *Advanced international trade: Theory and evidence.* Princeton University Press: Princeton, NJ.

Fetzer, T. (2019). Did austerity cause Brexit? *American Economic Review*, 109(11):3849–86.

Florida, R. and Mellander, C. (2009). There goes the metro: How and why bohemians, artists and gays affect regional housing values. *Journal of Economic Geography*, 10(2):167–188.

Friedberg, R. M. and Hunt, J. (1995). The impact of immigrants on host country wages, employment and growth. *Journal of Economic Perspectives*, 9(2):23–44.

Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, 110:2586–2624.

Green, J. C. (2010). *The faith factor: How religion influences American elections.* Greenwood Publishing Group.

Greenwood, M. J. (1997). Internal migration in developed countries. *Handbook of Population and Family Economics*, 1:647–720.

Head, K. and Mayer, T. (2014). *Gravity equations: Workhorse, toolkit, and cookbook, in Gopinath, G., Helpman, E., and Rogoff, K. (eds).* Handbook of International Economics, Vol. 4, Oxford: Elsevier B. V.

Jackman, R. and Savouri, S. (1992). Regional migration in Britain: An analysis of gross flows using NHS central register data. *The Economic Journal*, 102(415):1433–1450.

Jaeger, D. A., Ruist, J., and Stuhler, J. (2018). Shift-share instruments and the impact of immigration. *National Bureau of Economic Research*, (Working Paper, No. 24285).

James, G., Witten, D., Hastie, T., and Tibshirani, R. (2013). *An introduction to statistical learning with applications in R*, volume 112. Springer.

Johnston, C. D., Lavine, H. G., and Federico, C. M. (2017). *Open versus closed: Personality, identity, and the politics of redistribution*. Cambridge University Press.

Johnston, R., Manley, D., and Jones, K. (2016). Spatial polarization of presidential voting in the United States, 1992–2012: "The big sort" revisited. *Annals of the American Association of Geographers*, 106(5):1047–1062.

Johnston, R., Pattie, C., et al. (2006). *Putting voters in their place: Geography and elections in Great Britain*. Oxford University Press.

Jost, J. T., Glaser, J., Kruglanski, A. W., and Sulloway, F. J. (2003). Political conservatism as motivated social cognition. *Psychological Bulletin*, 129(3):339.

Kennan, J. and Walker, J. R. (2011). The effect of expected income on individual migration decisions. *Econometrica*, 79(1):211–251.

Kleemans, M. and Magruder, J. (2018). Labour market responses to immigration: Evidence from internal migration driven by weather shocks. *The Economic Journal*, 128(613):2032–2065.

Langella, M. and Manning, A. (2019a). Diversity and neighbourhood satisfaction. *The Economic Journal*, 129(624):3219–3255.

Langella, M. and Manning, A. (2019b). Residential mobility and unemployment in the UK. *Centre for Economic Performance, LSE*.

Larch, M., Wanner, J., Yotov, Y. V., and Zylkin, T. (2019). Currency Unions and trade: A PPML re-assessment with high-dimensional fixed effects. *Oxford Bulletin of Economics and Statistics*, 81(3):487–510.

Leslie, S., Winney, B., Hellenthal, G., Davison, D., Boumertit, A., Day, T., Hutnik, K., Royrvik, E. C., Cunliffe, B., Lawson, D. J., Falush, D., Freeman, C., Pirinen, M., Myers, S., Robinson, M., Donnelly, P., and Bodmer, W. (2015). The fine-scale genetic structure of the British population. *Nature*, 519:309–314.

Lewer, J. J. and Van den Berg, H. (2008). A gravity model of immigration. *Economics Letters*, 99:164–167.

McDonald, I. (2011). Migration and sorting in the American electorate: Evidence from the 2006 Cooperative Congressional Election Study. *American Politics Research*, 39(3):512–533.

Molloy, R., Smith, C. L., and Wozniak, A. (2011). Internal migration in the United States. *Journal of Economic Perspectives*, 25(3):173–96.

Olivero, M. P. and Yotov, Y. V. (2012). Dynamic gravity: endogenous country size and asset accumulation. *Canadian Journal of Economics*, 45(1):64–92.

Oster, E. (2019). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics*, 37(2):187–204.

Rohla, R., Johnston, R., Jones, K., and Manley, D. (2018). Spatial scale and the geographical polarization of the American electorate. *Political Geography*, 65:117–122.

Schelling, T. C. (1971). Dynamic models of segregation. *Journal of Mathematical Sociology*, 1(2):143–186.

Schelling, T. C. (1978). *Micromotives and macrobehavior*. WW Norton & Company.

Schumacher, S. (2019). Brexit divides the UK, but partisanship and ideology are still key factors. *Pew Research Center, October*, 28.

Silva, J. S. and Tenreyro, S. (2006). The log of gravity. *The Review of Economics and Statistics*, 88(4):641–658.

Sussell, J. (2013). New support for the big sort hypothesis: An assessment of partisan geographic sorting in California, 1992–2010. *PS: Political Science & Politics*, 46(4):768–773.

Swinney, P. and Williams, M. (2016). The Great British brain drain. *London: Centre for Cities*.

Tam Cho, W. K., Gimpel, J. G., and Hui, I. S. (2013). Voter migration and the geographic sorting of the American electorate. *Annals of the Association of American Geographers*, 103(4):856–870.

Thomas, M., Stillwell, J., and Gould, M. (2015). Modelling multilevel variations in distance moved between origins and destinations in England and Wales. *Environment and Planning A: Economy and Space*, 47(4):996–1014.

UNDP (2009). Overcoming barriers: Human mobility and development. *Human Development Report*.

Weidner, M. and Zylkin, T. (2020). Bias and consistency in three-way gravity models. Technical report, The Institute for Fiscal Studies, Department of Economics, UCL, Cemmap Working Paper CWP1/20.

White, M. J. and Lindstrom, D. P. (2005). Internal migration. In *Handbook of Population*, pages 311–346. Springer.

Wooldridge, M. J. (2010). *Econometric analysis of cross section and panel data*. Cambridge, MA: MIT Press.

Yotov, Y. V., Piermantini, R., Monteiro, J.-A., and Larch, M. (2016). *An advanced guide to trade policy analysis: The structural gravity model*. Geneva, Switzerland: World Trade Organization.

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

APPENDIX

For Online Publication

A. Local Government Services, 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 organized 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 councilors are elected, local authority elections can, in practice, take place in any given year. To construct our political distance 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.

B. District-Level Analysis: Additional Tables & Figures

- 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 corresponding government office region (GOR) to which they belong.
- Figure B.1 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 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 4.
- Table B.4 shows robustness of the results reported in Tables 1 and 4 (before and after adding pair FEs) to using the 1-year and 2-year lagged values of the political similarity measures.
- Table B.5 presents the first-stage results of the 2SLS-IV and control function estimations reported in Table 5.
- Table B.6 shows robustness of the results reported in Table 4 to excluding intra-region migration flows; i.e., the set of district pairs that belong to the same GOR.
- Table B.7 shows robustness of the results reported in Table 4 to using three alternative types of standard errors: (i) heteroscedasticity-robust; (ii) clustered at the dyad (district-pair) level; and (iii) clustered at the origin, destination and year levels (three-way clustering).
- Table B.8 shows robustness of the results reported in Table 4 to including the ratio of destination-to-origin district Index of Multiple Deprivation (IMD) among the regressors.
- Table B.9 shows robustness of the results reported in Table 4 to running separate regressions for district pairs with two-tier authorities and those with at least one single-tier authority.

- Table B.10 shows robustness of the results reported in Table 4 to replacing the baseline 'composite' measure *Distance in party shares* with either *Distance in Con. party share* or *Distance in Lab. party share*, calculated by the absolute difference (between the two districts) in the share of Conservative or Labour party seats in the local council, respectively.
- Table B.11 examines 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 partisan composition of the two districts. According to the results, the value of these ratios matters the most when people move across political mismatched districts.

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

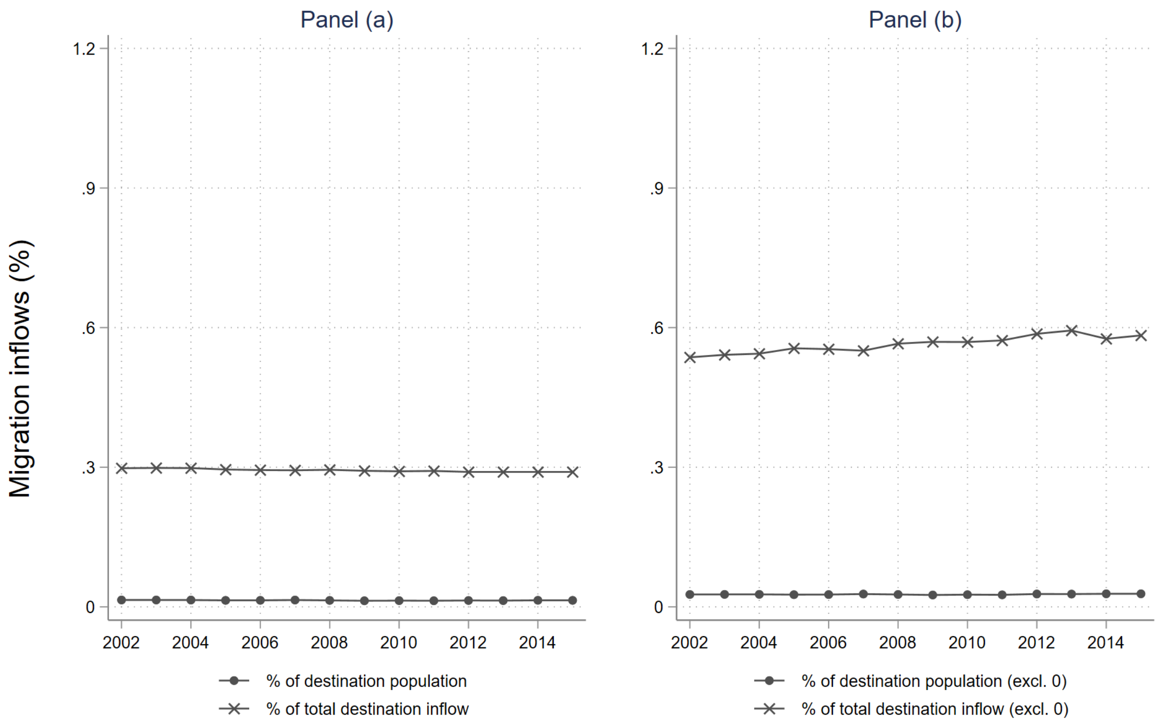
	Mean	Std. Dev.	Min.	Max.	Observations	Description
Migration flows	21.882	101.220	0.000	5,850	1,645,412	The number of migrants flowing from the origin district to the destination district in each year. ONS
Same party control	0.258	0.437	0.000	1.000	1,645,412	=1 if either the Conservative party or the 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.1: 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: Selection-On-Unobservables

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

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.4: 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.5: 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$_j$ $\times$ 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. $\times$ Orig. FE			✓	✓			✓	✓
Dest. $\times$ Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Orig. $\times$ 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 5 (second-stage estimation). LDV is the lagged value of *Migration flows*. ***,**,* Statistically significant at the 1%, 5% and 10% level respectively.

Table B.6: 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. × Orig. FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Dest. × Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Orig. × 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. × Orig. FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Dest. × Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Orig. × 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.7: 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. × Orig. FE	✓	✓	✓	✓
Dest. × Year FE	✓	✓	✓	✓
Orig. × 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.8: 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. × Orig. FE	✓	✓	✓	✓
Dest. × Year FE	✓	✓	✓	✓
Orig. × 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.9: Migration Flows and Political Similarity: Accounting for the Level of Local Government

	Migration flows							
	Intra-Two-Tier		All Else		Intra-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. × Orig. FE	✓	✓	✓	✓	✓	✓	✓	✓
Dest. × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Orig. × 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.10: 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.11: Migration Flows and Political Similarity:
Moving Across Politically Mismatched Districts

	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 × Con_iLab_j	0.040***	0.029**		
	(0.015)	(0.013)		
Conservative ratio × $(1-\text{Con}_i\text{Lab}_j)$	-0.000	-0.000		
	(0.000)	(0.000)		
Labour ratio × Lab_iCon_j			0.016	0.015
			(0.012)	(0.011)
Labour ratio × $(1-\text{Lab}_i\text{Con}_j)$			-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. × 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. 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 × Con_iLab_j and Conservative ratio × $(1-\text{Con}_i\text{Lab}_j)$ 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 × Lab_iCon_j and Labour ratio × $(1-\text{Lab}_i\text{Con}_j)$ 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: 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 6.
- Table C.3 shows robustness of the results reported in Table 6 to dropping respondents who live in the same GOR (one GOR at a time).
- Table C.4 shows robustness of the results reported in Table 6 to using alternative clustering of standard errors: at the district and survey wave levels, or at the district level alone.
- Table C.5 shows robustness of the results reported in Table 6 to replacing the alignment variable with its lagged value.
- Table C.6 shows robustness of the results reported in Table 6 to augmenting the regression model with a placebo variable capturing non-treatment years: a binary indicator taking value 1 either in the year before or in the year after an individual takes an alignment status.
- Table C.7 shows robustness of the results reported in Table 6 to augmenting the regression model with the spatially lagged alignment: 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.
- Table C.8 investigates the heterogeneity of the effects reported in Table 6 by splitting respondents into two groups based on one of the following characteristics: political ideology, age, income and education. In all cases, we fail to reject the null hypothesis that the effect of alignment is statistically different between the two sub-groups.
- Table C.9 presents the first-stage results of the Heckman probit selection model estimations reported in Table 9.
- Table C.10 shows robustness of the results reported in Table 9 to including additional controls in the second stage; namely, income decile and educational background indicators.

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 × 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). 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 × Wave × Time FE	✓	✓			✓	✓		
District × Wave × 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 × 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	0.071	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 × 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	0.071	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 × Wave × 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 × Wave × 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 9 (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 × Wave × 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. Columns (2), (4), (6) and (8) restrict the sample to include the 'core supporters' for the two parties. 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.

1 References

Altonji, J. G., Elder, T. E., and Taber, C. R. (2005). Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools. *Journal of Political Economy*, 113(1):151–184.

Fetzer, T. (2019). Did austerity cause Brexit? *American Economic Review*, 109(11):3849–86.

Leslie, S., Winney, B., Hellenthal, G., Davison, D., Boumertit, A., Day, T., Hutnik, K., Royrvik, E. C., Cunliffe, B., Lawson, D. J., Falush, D., Freeman, C., Pirinen, M., Myers, S., Robinson, M., Donnelly, P., and Bodmer, W. (2015). The fine-scale genetic structure of the British population. *Nature*, 519:309–314.