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London School of Economics and Political Science

Department of Psychological and Behavioural Science

PB 4D2: Master Dissertation

Supervisor: Dr. Georgios Melios

Summer Term 2023

Master Dissertation

Does My Neighbour Make Me Hate Labour?

Examining the Effects of Residential Context on Political Polarisation in the UK

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Abstract

Studies on political polarisation looking at individual factors using analyses like multivariate regressions have long ignored the effects of residential context on people's polarisation level. However, the influence of the proximal neighbourhood might explain parts of the geographic variation in local polarisation irrespective of demographic differences. Deploying an event-study specification to the British Election Survey Internet Panel (BESIP), I explore whether evidence for context driving polarisation exists for people moving from one UK political constituency (pcon) to another. The data is sampled in 19 survey waves and 632 pcons between February 2014 and May 2021 and totals to n = 89,834 nonmovers and n = 8,274 one-time movers for a cross-sectionally representative sample of the UK electorate. I use the answers on a left-right (ideological) and like-dislike scale (affective dimension) for the Labour and Conservative party to compute the local polarisation index (LPI) weighted by their relative vote share. A fixed-effect regression looking at the polarisation change at the wave of move finds no significant impact neither for moving in general nor for moving to a high or low polarised context. Further, results are also non-significant for young-old, high-low education, and male-female demographic subgroups, except partially for partisans. These findings suggest that residential context has no significant influence on geographic variation in polarisation leaving changes mostly attributable to fixed characteristics of people that they carry with them when they move. Future research should thus focus on testing the LPI for different datasets and countries and on better understanding the mechanisms behind individual and place effects.

Keywords: Political polarisation, ideological polarisation, affective polarisation, UK, movers, event-study, fixed-effect regression, BESIP

I. Introduction

In the United Kingdom (UK), research suggests that political polarisation causes growing social division between voters of different parties and is linked to recent political events like the 2016 Brexit (Grechyna 2023). Research outside the UK reveals a broad range of consequences associated with rising polarisation[1] including administrative dysfunction, such as legislative gridlock and diminished government effectiveness (Hetherington 2009); social ramifications, such as increased incivility among political elites (Iyengar, Sood, and Lelkes 2012), enhanced social group homophily and declining citizen engagement (Lupu 2015) as well as economic repercussions causing economic fluctuations and low growth rates (Azzimonti and Talbert 2014). Moreover, the intensification of polarisation poses democratic threats, as ruling parties may resort to undemocratic measures to maintain power or even exacerbate conflicts up to civil war (McCoy, Rahman, and Somer 2018). Hence, scholars, political leaders, and citizens in the UK and beyond are urging for an exploration into the underlying roots of polarisation.

But is the UK as politically polarized as it appears? As prevalent the term polarisation has become in the public discourse, researchers disagree to which extent countries are polarised or not and what causes polarisation for the individual. Research on political polarisation today is mostly focused on the United States (US) (e.g., Abramowitz and Webster 2016) or on comparative analyses investigating several countries at the same time (e.g., Westwood et al. 2018). Firstly, this is in part due the difficulty of constructing harmonized data series on partisan affect outside the US where evidence on long-term trends is limited (Boxell et al. 2020). Secondly, a part of the confusion about the extent and origin of polarisation originates from the lack of agreement about its conceptualisation and subdimensions. When measuring political polarisation, the traditional strand of research relies on measuring the left-right ideological polarisation, yet recent research primarily looks at the affective polarisation of partisans (Reiljan 2020). Empirical studies focusing on the UK are scarce and draw an undecisive conclusion over the trend and trajectory of political polarisation on a national level but suggest a surge in polarisation in the Thatcher years of the 1980s (wave 1), a depolarisation following her reign from 1990 to around 2010 (wave 2) and a repolarisation after 2010 (wave 3).

While evidence for recent increases in polarisation on a national level is established from the handful of studies that include the UK (see Table 1 & 2 in the literature review section II), research on the effects of a polarised local context on the individual is quasi non-existent. Nonetheless, the effects of one's residential context have tangible consequences for citizens,

[1] I use the terms political polarisation and polarisation interchangeably in this context.

for example, regarding mate selection, job search or housing decisions (Iyengar et al. 2012; Martin and Webster 2020). In fact, mate selection based on partisanship exceeds selection based on physical attributes like body shape or one's personality (Alford et al. 2011). Regarding partisanship, Martin and Webster (2020) show that people tend to residentially sort in into politically similar neighbourhoods in the US, but that the physical and social environment of one's residential location influences one's political beliefs more than small partisan bias in moving decisions. The researchers argue that voters who move to "less politically congruent locations are more likely to subsequently change their party affiliation to match that of the new location" (p. 217). The social influence of the local context seems to drive the partisan divide for the individual and, in consequence, the country.

In this paper, I present evidence on subsequent trends in political polarisation on a local level in the UK. In a first step, I create a novel polarisation measure – the *local polarisation index (LPI)* – that incorporates both ideological and affective polarisation using the British Election Study Internet Panel (BESIP). The BESIP is an online survey with a balanced sample of around 30,000 participants run three times a year from 2014 to 2021 by the polling company YouGov and supervised via a research team from the University of Manchester and Oxford (Fieldhouse et al. 2018). The BESIP incorporates most political constituencies (pcons) of the UK (632 of 650), and the question catalogue allows for the measurement of both forms of political polarisation for the composite LPI. I analyse the sensitivity of my findings to the top two parties in the UK, Labour (Lab) and Conservatives (Con), because independent of the number of parties in a party system, polarisation remains ultimately a bipolar phenomenon. In my baseline analysis, I find that the UK became fragmentedly more polarised from 2014–2021 in both affective (+14.96%) and ideological terms (+29.77%) with highly polarised pcons mostly found on the English countryside (South-West England, East of England), but less in Scotland and urban areas like London, Liverpool, or Manchester. The LPI thus offers the first comprehensive look at the timely and spatially development of local polarisation in the UK.

In a second step, the effects of different levels of local polarisation on individuals are analysed. For this, I deploy a new statistical design to this field: the *event-study mover specification* by Cantoni and Pons (2022). The researchers follow voters in the US moving across states and counties from 2008–2018 to analyse the destination's influence on the likelihood to register, vote, or affiliate with the Republican or Democratic party using a panel dataset with 250 million observations per election across 30 states. The event-study specification regresses individual participation of the movers on voter, state, and election fixed effects, uncovering the size of the post-move adjustment which reveals the contribution of the new context compared to the old[2]. They find that context is able to explain the movers' turnout jump of 0.4 or 40 percent of the difference in average participation between the origin and destination state.

Applying the mover's design, I examine whether moving changes the individual level of political polarisation. To see the intuition for my approach, imagine a person who moves from a high-polarisation pcon in South-England to a low-polarisation pcon in London. If all of the polarisation level difference between these pcons arises from pcon-side (i.e., context) differences like cultural offerings, the migrant's polarisation level is expected to drop right after the move, to a level similar to others in London. If all of the polarisation difference reflects the individual-side reality that residents of South-England are more polarisable, I would expect the migrant's polarisation level to stay constant to his or her pre-move level in South-England. Where the observed polarisation change falls between these two extremes identifies the relative importance of individual and context factors.

I make two distinct contributions to the current research gaps. Firstly, while many feel the political climate in the UK has become fierce, actual research on political polarisation is still scarce. This research contributes to the growing literature by offering the most detailed review and analysis on polarisation for the UK. Secondly, to the best of my knowledge, looking at movers and pcons is a novel approach to identify the place effects of polarisation on people that are exposed to it. Thus, my results – although lacking overall significance – present new research alleys and suggest that residential location exerts an influence on individuals' political preferences as they converge to the local average and in- or decrease their level of polarisation accordingly over time. Hence, this approach allows for a more nuanced discussion on UK's political status quo and has important implications for policy makers in the UK and beyond. In contrast to Martin and Webster (2020), however, I find changes in movers' level of political polarisation before a move, possibly due to anticipation to changes in polarisation levels.

The remainder of the paper is organized as follows: Section II offers a brief definition of the ideological and affective polarisation, followed by an extant literature review of existing research for the UK and my research questions. Section III outlines the BESIP data set and all sample restrictions. Section IV explains the methodology – the LPI and the event-study – in detail and checks for robustness. Section V presents the results of the regressions and Section VI discusses the results, limitations, and implications of the findings. Section VII concludes.

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[2] The mover methodology has also been used to investigate the sources of spatial variation in health care utilization (Finkelstein, Gentzkow, and Williams 2016), intergenerational mobility (Chetty and Hendren 2018), or brands' market shares (Bronnenberg, Dubé, and Gentzkow 2012).

II. Literature Review

A. Ideological Polarisation

Ideological polarisation (henceforth IP), or party polarisation, centres around the issue positions of parties (elite-level) or individuals (mass-level) and the distribution of these positions. The origins of IP date back to seminal works by Downs (1957) and Sartori (1976) who defines political polarisation as the ideological distance between the party poles, because "the distance between them covers a maximum spread of opinion" (p. 120). In short, IP reflects the degree of ideological differentiation among political parties in a system, meaning how ideologically apart parties are from each other and how coherent they are within, which usually grows with the number of parties and ideological fractionalisation (Dalton 2008). Researchers argue that this party system polarisation is somewhat desirable as it provides voting heuristics for candidates, strengthens party programmes (McCoy et al. 2018), stimulates participation (Dalton 2008) and ensures electoral stability in developing democracies (Lupu 2015). The most salient dimension to capture IP for citizens is the left-right dimension. If one imagines political viewpoints as moving from left to right, a non-polarised society would have a normal distribution – with most citizens and parties sitting around the centre – whereas a polarised society would approach a bimodal distribution with most citizens and parties sitting at one end of the left-right scale (Downs 1957, p. 903). Nonetheless, Lauka, McCoy, and Firat (2018) argue that "ideological polarisation of the political parties is neither necessary nor sufficient for political polarisation of the masses" (p. 109) and instead posit that "in contexts of deepening political polarisation, party identity increasingly acts as a social identity" (p. 110). In support of this thesis, the British public has recently been divided over issues like immigration or Europe, which do not fall on the traditional left–right spectrum (Lauka et al. 2018).

B. Affective Polarisation

Affective polarisation (henceforth AP) or partisan polarisation, has become the predominant measure of political polarisation, countering the policy-based division approach of IP. Early work by Lane (1959) and Converse (1964) found that public perceptions of parties are primarily affective rather than ideological, driven by a lifelong partisan identity acquired in early life (Jennings, Stoker, and Bowers 2009). Thus, AP naturally emerges as an extension of a salient partisan group identity, and requires not only emotional attachment towards one's in-group partisans, but also negative sentiment towards out-group partisans (see Tajfel et al. 1979 for research on social identity theory). Thus, Iyengar et al. (2019) state that a society gets more affectively polarised when people "increasingly dislike and distrust those from [another] party"

(p. 130). In this, AP reflects the degree to which individuals hold stronger negative sentiments towards political parties other than their own. In de-facto two-party systems such as the US or the UK, this antipathy is primarily directed towards members of the opposing party. Con (Lab) party leaners in the UK should not only differ ideologically from each other but should also indicate dislike for Lab (Con). Hence, AP is widely acknowledged as a negative phenomenon, eroding the political trust among supporters of the losing party, questioning the democratic legitimacy of elected leaders, impeding cooperation among party elites, and fostering discriminatory behaviour towards individuals beyond politics (e.g., Hetherington 2009; Iyengar and Westwood 2015). AP also exacerbates 'filter bubbles' and 'echo chambers,' as individuals become less inclined to interact with opposing partisans (Druckman and Levendusky 2019). Thus, scholars argue that affect and not ideology is a more appropriate construct measure of political polarisation as it captures the perceived social differences (e.g., Iyengar et al. 2012).

C. British Political Depolarisation until 2010 (Wave 1 and 2)

Aside from the US – which has seen a rise in IP over the past 50 years and a rise in AP more recently (e.g., Abramowitz and Webster 2016; Iyengar et al. 2019) – the UK stands out among the few contemporary Western democracies with significant political polarisation changes over the last six decades while also having two dominant parties (Lab, Con) and adequate national election survey data. The first "Thatcher wave" (~1975-1990) saw Britain re-polarise after the post-war social democratic consensus fuelled by ideological cleavages based on the new economic and political neoliberalism in response to the economic crises of the 1970s. Thatcher's political and economic reforms[3] shifted the Con party to the right while Lab tried to re-organise around traditional socialist ideas, leaving the electorate (ideologically) polarised behind. Following Thatcher's departure from office in 1990, the UK experienced a policy re-convergence between both parties when "New Labour" leader Tony Blair moved the Lab party more to the right, e.g. by pledging that Lab would not increase government spending (Crines 2017). This second wave (~1990-2010) led both parties going after similar votes in the 1990s and 2000s. In fact, researchers like Westwood et al. (2018) argue that class-based politics disappeared due to the strategic movement towards the centre by both parties and the growing importance of crosscutting valence factors (Adams, Green, and Milazzo 2012b; Green 2007).

The research on political polarisation in the UK reflects the political developments during this period. While research for the first wave of political polarisation under Thatcher is scarce

[3] The reforms under Thatcher (1979-1990) coined "Thatcherism" included cuts in the welfare programs, economic policies emphasizing privatization and deregulation, and the curbing of trade unions ending the post-war Keynesian economic and social policies of both parties (Adams et al. 2012a; Harvey 2007).

but supportive – results from the BES show high levels of IP between 1964 and 1983 (Iyengar et al. 2012) – there is research-wide consensus for a strong (ideological) depolarisation of the British public and party elites during the 1990s and 2000s, as displayed in Table 1. First studies from Laver (1998), who replicates the expert survey from Laver and Hunt (1992) by asking 117 political scientists from British universities to evaluate the change in political polarisation on eight policy issues, or Bara (2006), who looks for typical left-right policy statements in the 2001 and 2005 Lab and Con party manifestos, find a decrease in IP in the UK party system for the investigated time periods. Further, Dalton (2008) examines the development of IP for 22 countries and finds a moderate decrease in polarisation and a low overall level of polarisation for the UK. This study is among the first to use a large election survey dataset to measure political polarisation through the relative position of each party along the left–right scale compared to the party system average, and the party's prominence weighted by its vote share. Similarly, Green (2007) also records a drop from 2.7 to 0.9 between in the mean difference between Lab and Con supporters on the 0-10 left-right index using the British Election Study (BES). Further, Adams et al. (2012a) find that the British public moderately depolarised across three policy dimensions (social services, nationalisation, redistribution) and sharply concerning one policy dimension (inflation/unemployment) across the time period from 1987 to 2001. For measuring this depolarisation, the scholars look at the self-placements of respondents in the British General Election Study (BGES) and analyse the policy extremity share, i.e., the proportion of respondents who self-placed as a 1/2 (i.e., extreme left) or a 10/11 (i.e., extreme right). They also look at the change in standard deviations of respondents' self- placements and attitude constraint[4]. These studies on IP suggest that the British depolarisation is the mirror image of the growing elite and mass polarisation in the US during the 1990s and early 2000s.

As Table 1 shows, research on AP is scarce for this time period, but suggests a decrease in the 2000s and first evidence for an slight increase from 2010 onwards. Adams et al. (2012a) policy compute the Pearson correlations between the BES respondents' self-placements on the focal scale and the 'Net Conservative–Labour thermometer rating', being the difference between judging a party as hot (100) or cold (0). These correlations diminish sharply over time for all dimensions which suggests that the connection between respondents' policy beliefs and their party evaluations weakens, indicating depolarisation. In a second study, Adams et al. (2012b) show that the ideological and affective mass depolarisation extends across subgroups in the electorate – they speak of a "electorate-wide polarisation" (p. 644) – while being more

[4] Converse (2006) introduced the concept, which examines how citizens align their positions across multiple policy dimensions, potentially resulting in a polarized public, despite not holding extreme views on any single issue.

Table 1. Overview of Relevant Studies on Political Polarisation in the UK Before 2010

Author(s)	Year(s)	Data Source(s)	Definition of Polarisation	Measure(s) of Polarisation	Change in Polarisation
Laver (1998)	1989 – 1997	British Expert Survey	Ideological	Left-Right score based on four topics (expert judgements)	–
Bara (2006)	2001 – 2005	Party Manifestos	Ideological	Left-Right summary score indicator (text analysis)	–
Green (2007)	1987 – 2005	BES	Ideological	Left-Right score based on four topics (self-placement)	–
Dalton (2008)*	1996 – 2006	CSES	Ideological	Left-Right scale (party-placement)	–
Adams et al. (2012a)*	1987 – 2001	BGES	Ideological	Left-Right score based on four topics (self-placement)	–
			Affective	Like-Dislike scale 'Net Lab-Con thermometer rating' (self-placement)	–
Adams et al. (2012b)	1987 – 2001	BES	Ideological	Left-Right score based on four topics (self-placement)	–
			Affective	Like-Dislike scale 'Summed Lab-Con Feeling Differential' (self-placement)	–
Iyengar et al. (2012)*	1960 – 2010	Five-nation study (1960); YouGov polls (2008, 2010)	Affective	(1) Dissatisfaction scale for inter-party marriage (self-placement) (2) Trait ratings of Lab/Cons (self-placement)	+
Draca and Schwarz (2021)	1989 – 2010	WVS	Ideological	Left-Right score based on 29 issue questions (self-placement)	+

Notes: Own table based on papers found in my literature review. Most relevant papers are marked with an *. Data sets abbreviations as following: BES = British Election Survey; BGES = British General Election Study's (subset of the BES); CSES = Comparative Study of Electoral Systems; WVS = World Values Survey.

pronounced for highly educated, affluent, and informed citizens. Thus, during a period of dramatic elite depolarisation on economic and social welfare policies (elite-level IP), the British public did not depolarize dramatically in terms of its policy preferences on these issues (mass-level IP) but did depolarize sharply in terms of its partisan loyalties (mass-level AP).

Looking at political polarisation in the late 2000s, Iyengar et al. (2012) find an increase in AP using three studies from 1960, 2008 and 2010. The researchers look at the dissatisfaction with inter-party marriage and the differences in trait ratings. If partisanship is an important social identity in its own right, partisans should be averse to entering into close interpersonal relations with their opponents (Iyengar et al. 2019). They find a steep increase in opposition to inter-party marriage from 12% for Con (3% of Lab members) to 22% (24%). Similar developments are found for trait ratings in which party members rate other similar party members as more intelligent and less selfish over time. Draca and Schwarz (2021) support these findings and find a small increase in IP between Wave 2 (1989-1993) and Wave 5 (2005-2009).

D. British Political Repolarisation since 2010 (Wave 3)

The re-polarisation of British politics from around 2010 to today (wave 3) correlates with five major electoral shocks that fall in this time window: (1) The growth in immigration after 2004, (2) the Great Recession following the 2008 financial crisis, (3) the Con and Liberal Democrat coalition between 2010 and 2015, and the (4) referenda on Scottish independence in 2014 and (5) on European Union membership in 2016 (Fieldhouse et al. 2018). The Con party moved back to the right to counter the threat of UKIP, a backlash against the austerity of the coalition government, and Lab under Jeremy Corbyn tried to reinvigorate British social democracy by steering to the left. Thus, researchers argue that the process of elite depolarisation changed direction in the 2010s (e.g., Grechyna 2023; Perrett 2021).

Findings for a strong increase in AP (and a moderate one in IP) in the last decade are still limited; Table 2 provides an overview. It is apparent that the research paradigm changed from an ideological focus dominating the first two waves until 2010 (see Table 1) to an affective one (see Table 2). In this, few researchers have looked at the levels of polarisation and found high levels for the UK (e.g., Gidron, Adams, and Horne 2018; Hobolt, Leeper, and Tilley 2020; Reiljan 2020; Westwood et al. 2018). Westwood et al. (2018) find strong in-group favouritism and out-group animus for both Lab and Con leaners in a trust game (even exceeding mistrust based on other social divides like religious beliefs); Boxell et al. (2020) report an (insignificant) decrease in AP for the UK from 1987 to 2015 assessing AP using the Con-Lab thermometer 1-10 Likert scale; Gidron, Adams, and Horne (2018) findings show a comparably high level of AP in the UK for the aggregated mean scores of 1997, 2005 and 2015; Reiljan (2020) finds similar evidence for the CSES dataset in 2015 where Con and Lab affiliates alike rate their in-group significantly higher than the outgroups. In fact, he finds higher levels of AP (4.48) in the UK than for the US (4.38), a modest IP level (2.86) and a significant relationship between the two, suggesting higher levels of IP lead to higher levels of AP. Lastly, Hobolt, Leeper, and Tilley (2020) report that opinion-based groups like Brexit identifiers (i.e., Leavers, Remainers) generate AP as intense as partisanship in post-Brexit surveys from 2017 to 2019.

Nonetheless, longitudinal studies in the 2010s comparing levels of polarisation over time are scarcer. The few published quality papers with time trends including Perrett (2021) and Grechyna (2023) support the claims made and find increases in IP, while Patkós (2023) reports increases in AP. Perrett (2021) defines polarisation through the shares of extremist opinions in

Table 2. Overview of Relevant Studies on Political Polarisation in the UK After 2010

Author(s)	Year(s)	Data Source(s)	Definition of Polarisation	Measure(s) of Polarisation	Change in Polarisation
Westwood et al. (2018)	2013	SSI	Affective	(1) Like-Dislike scale 'feeling thermometer' (self-placement) (2) Trust game allocations w. 10£	n/a
Gidron et al. (2018)	1997 – 2015	CSES	Affective	Like-Dislike scale (party-placement)	n/a
Boxell et al. (2020)	1980 – 2015	BES	Affective	(1) Like-Dislike scale 'Net Lab-Con thermometer rating' (self-placement) in 1979, 1997-2015 (2) Like-Dislike scale 'Summed Lab-Con Feeling Differential' (self-placement) in 1987, 1992	–
Reiljan (2020)	2015	CSES	Ideological	Left-right combined index (self- and party-placement)	n/a
			Affective	Like-Dislike scale (self-placement)	n/a
Hobolt et al. (2020)	2017 – 2019	BES (2016-19; Tracker (2017-19); YouGov; Lodger; Sky; BBC (2017)	Affective	(1) Trait ratings of Lab/Cons (self-placement) (2) Dissatisfaction scale for inter-party marriage (self-placement)	n/a
Perrett (2021)*	1986 – 2018	BSA	Ideological	Left-Right score based on 5 questions	Until 2012 – After 2012 +
Grechyna (2023)*	1991 – 2018	BHPS (2007); ESS (2018)	Ideological	(1) Left-right score based on 3 public sector questions (self-placement) (2) Left-right score based on left-right scale and 1 public sector question (ESS, self-placement)	Until 2010 – After 2010 +
Patkós (2023)	2002 – 2018	ESS	Affective	Government-Satisfaction scale (self-placement)	+

Notes: Own table based on papers found in my literature review. Most relevant papers are marked with an *. Data sets abbreviations as following: BES = British Election Survey; BHPS = British Household Panel Survey; CSES = Comparative Study of Electoral Systems; ESS = European Social Survey; SSI = Survey Sampling International (Online Panel).

the variance of five items on the left-right scale from the British Social Attitudes (BSA) survey from 1986 to 2018. He finds an uptick in the variance of left-right opinions since 2012, signalling a recent increase in polarisation. Both trends, the decrease in polarisation up to 2005 and the increase since 2012 are explained by the Lab identifiers first moving to the right post-Thatcher and, amid the electoral shocks, back to the left while Con levels remained stable. In the study by Grechyna (2023), she first finds a decline in political polarisation across different polarisation measures from 1991 to 2007 using three statements from the British Household Panel Survey (BHPS) on the role of public sector in the economy, but a sharp increase when using data to related statements from the European Social Survey (ESS) from 2010 to 2018.

The data from the ESS shows a non-linear trend, also decreasing until approximately 2010, but sharply increasing until 2018. Further, Patkós (2023) creates a cross-national partisan polarisation index based on respondents' satisfaction with their national government, comparing the average satisfaction of cabinet and opposition supporters in the ESS dataset (i.e., framing government as the out-group), and finds partisan polarisation to be increased for 2018 (+10.45% compared to 2002, +5.6% to 2016). Hence, political developments and studies preceding the 2010s suggest a recent intensification of ideological and affective divisions.

E. Residential Context and Political Polarisation

While the levels of political polarisation on a national and regional level are closely linked, differences between regions with lower and higher polarisation levels are likely to occur due to differences in political representation or demographic composition of residents (Boxell et al. 2020). Thus, the findings on political polarisation in the UK on a national level are relevant to show that polarisation is prevalent but must be further differentiated when investigating the effect on people who move across pcons. Do urban or suburban environments inherently promote a shift towards liberal or conservative ideologies, as Walks (2006) proposes? Or do movers alternatively remain unaffected by changes in polarisation between their original and destination pcons, resulting in a region's polarisation level being merely an average of independent individual polarisation scores?

To date, there is no empirical research analysing whether mass-level polarisation extends across different geographic subgroups in the British electorate. For the causes of polarisation, recent studies have provided causal evidence on structural factors such as fiscal austerity (Hübscher, Sattler, and Wagner 2023), economic globalisation and digitalization (Baccini and Weymouth 2021), class politics (Halikiopoulou and Vlandas 2016) or the growing salience of cultural identities (Norris and Inlgehart 2018) as well as individual factors from social media use (Tucker et al. 2018) to partisan news consumption (Iyengar et al. 2019) or empathy (Simas, Clifford, and Kirkland 2020) by exploiting naturally occurring or experimental variation in these factors. Nonetheless, this approach is not well-suited for assessing the importance of both the individual and the context. Indeed, individual factors influencing polarisation change may reinforce or weaken each other, and it is impossible to pinpoint all of them; the same goes for contextual factors (Chyn and Katz 2021). The difficulty on detangling individual and contextual factors comes from the strong correlation between them: due to geographic segregation by ethnicity, age, and income, regions vary both in their institutions and their demography, such as racial mix, average age, or affluence (Martin and Webster 2020).

Current research on how residential context influences polarisation levels is scarce to non-existent. One related strand of research theorises that moving into neighbourhoods that are close to one's own preferences leads to a harmonisation of regions over time, a process called *residential sorting*: Partisans choose to move to neighbourhoods with like-minded neighbours due to differences in lifestyle tastes driving the emergence of the observed geographic pattern of partisanship or – based sociological concept of homophily – the desire to live among politically like-minded neighbours which drives the geographic sorting (Bishop and Cushing 2008; Lang and Pearson-Merkowitz 2015). In this perspective, individuals are intentionally "seeking politically compatible neighbours" when deciding on their residential locations, as opposed to coincidentally residing alongside co-partisans who share similar preferences for non-political housing attributes (Gimpel and Hui 2015).

However, if residential sorting alone would quickly generate a geographically homogeneous distribution of political preferences, then the fact that non-homogeneous and polarised patterns persist suggests that something else must be going on, namely that preferences of in-migrants adapt to match the modal preferences of their new neighbourhoods (Martin and Webster 2020). The researchers show that voters who move to neighbourhoods that are different from their previous residence on politically salient dimensions are much more likely to change their party affiliation to match that of their new neighbours (Martin and Webster 2020), countering the argument that people move to certain areas because those match their political views. Evidence for the influence of contextual factors is established from research fields outside political polarisation: Finkelstein, Gentzkow, and Williams (2016) suggest that 50 to 60 percent of variation in the spatial variation in health care utilization in the US is due to place-specific factors like doctor practices (using an event-study analysis similar to Cantoni and Pons (2022)); Chetty and Hendren (2018) find evidence that children moving into richer neighbourhoods converge to this higher income on average by 4% per year implying that much of the variation in intergenerational mobility is driven by causal effects of place rather than differences in the type of people living there and Bronnenberg, Dubé, and Gentzkow (2012) find that variation in people's past location where they acquired brand preferences subsequently explains 40 percent of geographic variation in market shares if people move to different places.

In line with both strands of research, the influence of pcons on individual polarisation levels is investigated. The theoretic explanation of the researchers favouring individual's geographic sorting would argue that individuals change their levels of polarisation before the move and then sort into corresponding regions. Given the event-study specification, this should be observable in pre-trends that indicate an anticipation of the post-move level. In turn, the strand of researchers supporting the influence of contextual factors would argue in favour of a convergence to the mean, meaning a highly polarised pcon increases the polarisation level for the individual and a low polarised pcon decreases it. This should be observable in flat pre-trends and a positive or negative estimated adjustment at the move (while further trends post-move could be due to peer-effects which are likely to manifest over longer time). Thus, for my main research question I hypothesise the following:

Hypothesis 1a: Moving in general does neither significantly increase nor decrease the political polarisation score compared to the pre-move level.

Hypothesis 1b: Moving into a highly polarised pcon (>90% of all pcons) leads to a significant increase in the political polarisation score compared to the pre-move level.

Hypothesis 1c: Moving into a less polarised pcon (<10% of all pcons) leads to a significant decrease in the political polarisation score compared to the pre-move level.

Further, my second research question looks into partisanship. The LPI allows me to look at Lab- and Con-dominated pcons by comparing the relative vote share for each pcon. Therefore, I investigate how the respondent's partisanship and the prevailing party in the destination pcon (i.e., >50% relative vote share) influence the levels of polarisation for the mover, suggesting that convergence of the two leads to higher levels while divergence leads to lower levels:

Hypothesis 2a (b): Lab (Con) leaners moving into a Lab-dominated (Con-dominated) pcon significantly increase their political polarisation score compared to the pre-move level.

Hypothesis 3 a (b): Lab (Con) leaners moving into a Con-dominated (Lab-dominated) pcon significantly decrease their political polarisation score compared to the pre-move level.

For my third research question block, I analyse the context effects for different subgroups of the UK electorate. I hypothesise that young individuals are more susceptible to external influences, as suggested by the impressionable years theory (e.g., Reiljan 2020). Additionally, I posit that socio-economically privileged citizens (e.g., university-educated) may differ from other citizens in their openness to elite policy persuasion – specifically, their readiness to alter their policy stances in response to policy shifts by their political party as suggested by Adams et al. (2012b). Lastly, I check whether general differences across gender exist.

Hypotheses 4a-c: Same as Hypothesis 1a-c but for young people (i.e., <30).

Hypotheses 5a-c: Same as Hypothesis 1a-c but for highly educated people.

Hypotheses 6a-c: Same as Hypothesis 1a-c but for women.

III. Data

A. The British Election Study Internet Panel (BESIP)

To test the influence of contextual factors of different pcons, I require both individual party evaluations on left-right and like-dislike issues and residential information for a representative sample of the UK population at multiple time points to track movers' behaviour as they cross pcon borders. The BESIP panel data meets these criteria and is publicly available (https://www.britishelectionstudy.com/data-objects/panel-study-data/).

Like the British Election Study (BES), the 2014-2023 BESIP is managed by a research team from the University of Oxford and Manchester under the current leadership of Prof. Ed Fieldhouse. Both surveys explore why people choose to vote (or not) and why they support one party rather than another, as well as wider questions about political preferences, attitudes, and behaviours to a probability sample representative of England, Wales, and Scotland (Fieldhouse et al. 2018). While the BES has been administered at every general election since 1964 via face-to-face interviews, the BESIP is an online survey and covers 21 waves in the period from February 2014 to May 2021, including the 2014 European Elections, the 2015, 2017 and 2019 General Elections, or the 2016 EU referendum.

The data collection is conducted by the private polling company YouGov and includes approximately 30,000 respondents at each wave, with regular top-ups to maintain a cross-sectionally representative sample of the UK electorate (see Table A1 in the Appendix A for details). YouGov samples from a pool of about one million British opt-in respondents creating a sample with equivalent characteristics as the initial target sample on the matched characteristics, meaning replacements resemble the kind of people who had dropped out. For this, YouGov collects longitudinal demographic information like age, gender, education, ethnicity, income, or residence which are updated every six months. According to the BESIP data, a total of 8,274 people moved across pcon borders exactly once between 2014 and 2021.

While the BESIP offers a representative UK data base for political analyses of all sorts, four data limitations have to be noted. Firstly, only 2% of the respondents in the original sample (Feb 2014) answer all waves until wave 21 (May 2021). The dropouts are disproportionately younger and less politically engaged and without top ups, this would result in a small sample of aging and politically very engaged people threatening external validity. As this analysis relies on longitudinal information, the drop out-top up process still results in less panel information for younger cohorts. Secondly, certain pcons are overrepresented in the data (e.g., Scottish pcons) or underrepresented, requiring weighting or exclusion. Thirdly, the left-right and like-dislike questions needed for computing the polarisation score are not part of the BESIP's mandatory catalogue, resulting in missing values and a smaller subgroup of usable responses. And fourthly, research shows that some countries appear to exhibit cyclicality in AP for election years (Boxell et al. 2020). Although the BESIP coincides with elections, suggesting that election years themselves are not the source of the apparent cyclicality, I find a strong AP cyclicality for the UK. As wave levels of political polarisation are averaged to an overall score for each pcon, this should, however, not threaten the validity of my results.

B. Sample Restrictions and Summary Statistics

In a first step, I remove all people with missing weights or missing values in the region variable. I further exclude wave 1 and 21, because of doubling values in both waves. I exclude values for people who moved to or from what was not a 2010 pcon. I further exclude twelve pcons with less than five unique respondents in each pcon[5]. This leaves me with data for 632 of 650 or 97.23% of all pcons ranging from 55 respondents (Na h-Eileanan an Iar) to 421 (Edinburgh North and Leith). The mean number of respondents per pcon is 175.1, the median is 168. Moreover, 459 or 72.6% of pcons fall within one standard deviation (*SD* = 44.9) of the mean, suggesting a balanced sample (see Figure A2, Appendix A). These findings support the principle of equal representation, known as "one person, one vote," which aims at ensuring a roughly equal number of voters in each pcon. In total, these exclusion criteria leave me with 606,058 answers for 99,445 unique ids, i.e., a respondent typically participates 6.09 times.

In a second step, I analyse movers and nonmovers. To simplify, movers changing pcons multiple times are excluded. Table 3 presents summary statistics for one-time movers and nonmovers. On average, movers are almost equally likely to be white and female compared to nonmovers, but movers are on average almost ten years younger and better educated which is plausible, given younger, well-educated people are more inclined to relocate for career reasons. Both groups have comparable numbers of Lab and Con party affiliation and residency in England, Wales, and Scotland. Further, liking of Lab or Con in-group partisans is high for both movers and nonmovers and low for out-group partisans while Cons give slightly higher like scores to Lab. Lab leaners also identify their party as left-leaning and Cons their party as right-leaning while each party judges the opposing as even more left- (Lab) or right-leaning (Con).

In a third step, for a single respondent to be included in IP (AP) computation for the LPI, he or she must evidently have answered the left-right (like-dislike) question for both Lab and Con.

[5] I excluded the following pcons: West Tyrone, Lagan Valley, East Londonderry, Fermanagh & South Tyrone, Upper Bann Belfast South, East Antrim, Mid Ulster, Newry & Armagh, North Antrim, North Down, South Antrim.

Table 3. Summary Statistics on Movers and Nonmovers

	Nonmovers (1)	Movers (2)
Female	0.540	0.526
Age	53.479	43.623
Race		
White	0.937	0.924
Asian	0.021	0.026
Black	0.007	0.011
Other	0.035	0.039
Education		
Postgraduate level	0.085	0.133
Undergraduate level	0.298	0.355
A-level	0.202	0.245
GCSE	0.215	0.153
Below GCSE	0.048	0.027
No qualifications	0.078	0.044
Geographic region		
England (London)	0.797 (0.101)	0.817 (0.152)
Scotland	0.127	0.121
Wales	0.076	0.062
Party affiliation[1]		
Lab	0.328	0.319
Con	0.343	0.299
Like-Dislike score (0 = Strongly dislike; 10 = Strongly like)		
Lab-Lab	7.156	7.232
Con-Lab	1.792	2.018
Con-Con	7.494	7.372
Lab-Con	1.704	1.606
Left-Right score (0 = Left; 10 = Right)		
Lab-Lab	2.918	2.997
Con-Lab	1.613	1.861
Con-Con	7.682	7.465
Lab-Con	8.283	8.168
Number of people	89,834	8,274
Average n waves participated	5.819	8.430
Number of total waves	522,782	69,749

Notes: Own table based on Cantoni and Pons (2022). Columns 1 and 2 report summary statistics, respectively, in the samples of nonmovers (i.e., never changed pcons) and movers (i.e., changed pcons exactly once).
[1] Followed by the Liberal Democrats (nonmovers: 0.083; movers: 0.095), UKIP (0.054; 0.046), SNP (0.046 or 0.339 in Scotland; 0.040 or 0.310), Green Party (0.020; 0.022), Plaid Cymru (0.007 or 0.084 in Wales; 0.06 or 0.096) and None/Don't know (0.105; 0.132).

I further require a question on party affiliation for AP computation, so all non-Lab or non-Con party leaners are excluded here. Excluding people with missing values leaves me with 80,483 unique ids (both movers and nonmovers) for the computation of an IP score and 65,716 for the computation of an AP score (see Table A3, Appendix A for an overview of all variables used).

IV. Methods

A. The Local Polarisation Index

For the computation of the LPI, I first operationalise the two dimensions given the methodologies from Dalton (2008) for IP and Reiljan (2020) for AP and then aggregate both measures to the weighted LPI. The construction of the new polarisation index is motivated by both theoretical and methodological reasons. While recent researchers on polarisation argue that the ideological differences are neither necessary nor sufficient elements of severe AP (e.g., Iyengar et al. 2019; Patkós 2023), others find a statistically significant positive relationship between a heightened level of IP and AP (e.g., Abramowitz and Webster 2016; Iyengar et al. 2012). Given the two-part conceptualisation of political polarisation from section II, political polarisation to me is best described as an umbrella term of multiple types of perceived cleavages that can exist as separate but distinct components of the larger concept (Lelkes 2016). Further, my hypotheses testing requires a local comparison of political polarisation levels in different pcons. I proxy the relative local vote share for Lab and Cons via election intent in the BESIP to compute the polarisation score for each pcon and survey wave separately.

For IP, researchers have in practice estimated it through indirect indicators, such as the number of parties, the size of extremist parties, the vote share for governing parties, expert judgements, or party manifestos (e.g., Adams, Green, and Milazzo 2012a). Starting about 15 years ago, IP in large election surveys is most often measured by evaluating the distribution of views on the left-right scale for each party and how far each party's average is positioned from the average party position (e.g., Lelkes 2016; Lupu 2015). In systems that are more polarized, parties should be further away from this mean position, the system's ideological centre of gravity (see Downs 1957). The variance-based approach in (1) reflects the formula from Dalton (2008) who approximates variance on the one-dimensional left-right scale but modifying the formula so it aggregates individual-level data instead of party-level data:

$$IP = \sqrt{\sum_{i=1}^{n} p_n \times 100 \times \frac{(\frac{I_i - \bar{I}_i}{5})^2}{n}} \tag{1}$$

Each respondent evaluates the Lab and Con party on the 0-10 left-right scale resulting in a value I_i of a party's ideological position for each respondent i. These single values are averaged across all parties to create a weighted overall average of all parties' positions ($\bar{I}_i$). I normalise the average distance between the parties' ideological position and the mean ideological position, with the division by 5 ensuring a value that ranges from 0 to 10. A value of 0 happens when all parties occupy the same position on the left–right scale, 10 when all parties are split between the two extremes of the scale. Each party's local prominence in the system is accounted by weighting its contribution to the system's polarisation through its share of the popular vote in the pcon (p_n)[6]. Vote intent instead of actual vote shares may not fully reflect the prominence of each party but serve as a reasonable proxy. An unweighted measure of polarisation risks generating high values as an artifact of small, fringe parties, because a large party at the extreme would signify greater polarisation than a small party in the same position (Dalton 2006).

Measuring AP is possible through experimental settings, such as assessing implicit bias or measuring in-group favouritism and discriminatory out-group behaviour (e.g., Iyengar and Westwood 2015). In recent research using US election studies, AP is measured through a 101-point 'feeling thermometer' scale rating different political groups from 0 (cold) to 100 (hot) (e.g., Iyengar et al. 2012; Lelkes 2016). Similarly, the BESIP asks respondents to rate their affect towards different political parties on a 0-10 like-dislike scale. I use the AP Index created by Reiljan (2020) who also uses the partisans' average divergence of affective evaluations between in-party and out-parties, again weighted by the relative local vote share. AP is present when the attitudes towards the in-and out-parties are on different sides of the neutral centre point, and the closer the evaluations are to the extremes of the affective spectrum. This requires a party affiliation of the respondent. To minimize the amount of people excluded from index calculations, I also include the *leaners* as partisans, i.e., people who do not identify as party members, but feel close to Lab or Con (see Table A3, Appendix A). Therefore, in a party system with *N* relevant parties, the relative AP of every party is:

$$AP = \sum_{n=1}^{N} [\sum_{\substack{m=1, \\ m \neq n}}^{n} ((\bar{A}_n - \bar{A}_m) \times (\frac{p_m}{1 - p_n}) \times p_n] \tag{2}$$

For the AP score of each partisan group the average in-party evaluation ($\bar{A}_n$) is subtracted from the average out-parties' evaluations ($\bar{A}_m$). The in-party/out-party subtractions will be weighted with the vote shares (p_n) of the out-parties and then summed up (2). Here, *n* denotes the in-party and *m* the out-party, p_n is the vote share of the party and both scores are summed up to get the weighted average.[7] Analogous to IP, the values range from 0-10 with a score of 0

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[6] Like Reiljan (2020) I normalise party vote shares for both AP and IP calculations meaning if a Labour got 40% of the votes and the aggregate vote share of both parties is 80%, then the relative vote share is 40/80 * 100= 50%.

[7] The "1 – vote share" excludes the in-party vote share from this part of the calculation in multiparty systems.

indicating equal liking for both the in-party/out-party, while a score of 10 represents maximum liking for the in-party (10) and maximum disliking for the out-party (0) among all individuals.

To create the LPI, the following assumptions are made: Firstly, only the vote shares of Lab, and Cons are compared (N = 2 for AP). Both parties unite between 61% and 70% of the voters in the estimated national equivalent in local elections from 2014-2021 (Cracknell, Uberoi, and Burton 2023). Focusing on only these two major parties is best practice in literature and is feasible for the UK where Lab and Cons established a quasi-dual hegemony. Secondly, non-partisans (i.e., people who do not lean to any political party) are not used for calculating AP. This is unavoidable, as affective attitudes can only be measured in relation to specific groups (Reiljan 2020). Thirdly, I aggerate both dimensions through weighted averages to a single 0-10 score according to the *Bollen approach* by Wuttke, Schimpf, and Schoen (2020). As such, once each type is calculated for a particular pcon year, both types will simply be averaged to create a single polarisation score as seen in (3) and (4) below:

$$LPI = 0.5 \times (IP + AP) \tag{3}$$

$$LPI = 0.5 \times (\sqrt{\sum_{i=1}^{n} p_n \times 100 \times \frac{\left(\frac{I_i - \bar{I}_i}{5}\right)^2}{n}}) + \sum_{n=1}^{2} [\sum_{\substack{m=1, \\ m \neq n}}^{n} ((\bar{A}_n - \bar{A}_m) \times p_n]) \tag{4}$$

I run several robustness checks given alternative questions from the dataset, namely a redistribution question proxying for IP and a trust in the members of parliament question dependent on government membership for AP (see Table A3, Appendix A). As Table 4 shows, LPI has high Pearson correlations of 0.679 to 0.804 with all measures except for the government trust measure, suggesting that they can almost be used interchangeably. While all other indexes increase over time, the trust measure remains almost constant suggesting a question about the trust level of all members of parliament (MP) does not serve as good proxy for affect and might be compromised for several reasons, e.g., by having a local in-party MP while having a out-party government or the other way around. Also, IP and AP show a lower positive correlation of .111 due to high cyclicality of the AP measure. I further run a robustness check by looking at a different dataset from the Chapel Hill Expert Survey (Jolly et al. 2022) and compare the level of IP to my results (CHES data is publicly available under https://www.chesdata.eu/ches-europe). This checks whether the electorate is able to correctly estimate the level of IP as some researchers state they rather estimate perceived IP more than actual IP because the average

Table 4. Pearson Correlations Between Indexes for Measuring Political Polarisation

	IP	AP	LPI	IP_redis	AP_govtrust
IP	1.000	0.111	0.804	0.858	-0.004
AP	0.111	1.000	0.679	0.088	0.026
LPI	0.804	0.679	1.000	0.686	0.012
IP_redis	0.858	0.088	0.686	1.000	0.025
AP_govtrust	-0.004	0.026	0.012	0.025	1.000

Notes: Own table based on the Pearson correlations for the different indexes (computed in R).

citizen likely struggles to accurately place political parties on many issues (e.g, Schmitt 2016). The evaluations of IP from the experts – 421 political scientists specialising in political parties and European integration – and the UK electorate in the BESIP remain comparable with the experts judging Cons to be 7.118 in general and 7.059 on economic issues on the 0-10 left-right IP scale (compared to values from 7.465 to 8.283 on my scale, see Table 3). The results for Lab hold up as well with 1.941 on both scales (and 1.613 to 2.997 on my scale). Thus, the robustness checks suggest that the LPI is a reasonable and valid measurement for political polarisation.

B. Event-Study

To investigate changes in political polarisation levels around moves, I estimate an event-study specification based on the methodology by Cantoni and Pons (2022). The researchers estimate the share of differences in voter behaviour across states that results from differences in contextual factors instead of differences in the individual characteristics of the people living in each state. An event-study specification can be seen as a form of discontinuity analysis which looks at the pre-event level and compares it to the post-event level (Binder 1998), in this case the event being the one-time move across pcons. To trace out changes in political polarisation around moves, the event-study specification decomposes the individual and contextual fixed effects and looks at person i who moves from origin state o(i) to destination state d(i):

$$y_{ijt} = \alpha_i + \gamma_{o(i)} + I_{r(i,t)\geq 0} \times S^{pcon}(d(i), o(i)) \times \delta_i + \tau_t + \rho_{r(i,t)} + \varepsilon_{ijt} \tag{5}$$

The outcome variable y_{ijt} is the estimate of the change in political polarisation scores for an individual that is attributable to the difference in the levels of political polarisation in the new pcon (i.e., the moved to pcon) compared to the old pcon (i.e., the moved from pcon). The variable α_i denotes individual, $\gamma_{o(i)}$ old pcon and τ_t wave fixed effects respectively. Wave fixed effects are normalized to be equal to zero on average, $I_{r(i,t)\geq 0}$ is an indicator for post-move wave. For movers, $r_{(i,\,t)} = t - ti^*$ is the wave relative to the first post-move wave ti^* (so $r_{(i,\,t)} = 0$ if t is the first wave after the move, $r_{(i,t)} = -1$ if it is the last wave before the move). Thus, $\rho_{r(i,t)}$ indicates fixed effects for a wave relative to move and captures any specific effects related to the timing of the wave concerning the person's move[8]. Y is scaled so that the direction and magnitude of the jump on move are informative regardless of the origin and destination. For a mover i whose origin and destination areas are o(i) and d(i) respectively, δ_i denotes the difference in average polarisation outcome between the mover's destination and origin pcon: $\delta_i = \bar{y}_{d(i)} - \bar{y}_{o(i)}$. Further, the equation (5) assumes additive separability in i, j, and t for the individual (both α_i and $\rho_{r(i,t)}$) and pcon-specific components ($\gamma_{o(i)}$) and the expected value of the residuals to be zero, i.e., $E(\varepsilon_{ijt}|i, j, t) = 0$). Since relative wave effects $\rho_{r(i,t)}$ do not depend on the specific pcon, additive separability implies that the absolute change in polarisation change for people moving from the old to the new pcon (experiencing a change in pcon factors equal to $\gamma_{(d(i)} - \gamma_{(o(i)}$) should – net of the effects of the $\rho_{r(i,t)}$ – be the same as for people moving the other way.

Combining $\alpha_i + \gamma_{o(i)}$ from (5) into a single voter fixed effect $\tilde{\alpha}_i$, replacing $I_{r(i,t)\geq 0}$ with indicators $\theta_{r(i,t)}$ for wave relative to move, and replacing δi with its sample analogue $\hat{\delta}_I = \hat{y}_{d(i)} - \hat{y}_{o(i)}$ using both movers and nonmovers, the final event-study specification is obtained (Table 5 provides an overview on all used variables).:

$$y_{it} = \tilde{\alpha}_i + \theta_{r(i,t)}\hat{\delta}_i + \tau_t + \rho_{r(i,t)} + \varepsilon_{it} \tag{6}$$

The parameters of interest are the relative-year specific coefficients $\theta_{r(i,t)}$s. In relative wave r(i,t), $\theta_{r(i,t)}$ measures movers' response in y_{it} to differences in average outcomes between the new and the old pcon in years around the move scaled relative to $\hat{\delta}_i$. Assuming heterogeneity in S^{pcon} is orthogonal to the other terms in the model, $\theta_{r(i,t)}$ is a weighted average of $S^{pcon}(d(i), o(i))$, with weights given by the relative frequency of all pairs of origin and destination pcon (Finkelstein et al. 2016). For comparison, $\theta_{r(i,t)}$ has a similar interpretation to $y_{it}^{scaled} = \frac{y_{it} - \bar{y}o(i)}{\delta i}$ which subtracts the individual i's level of polarisation at time t from the average level in the old pcon before the move and divides it by the difference between old-versus-new pcon of $\delta_i = \bar{y}_{d(i)} - \bar{y}_{o(i)}$. Thus, y_{it}^{scaled} will be 0 if the polarisation level is equal to the average in his origin, 1 if it is equal to the average in his destination, and between 0 and 1 if the mover's polarisation level falls between the two. If the model is correct, the expectation of should be flat both before and after the move and the jump on move will be equal to the average value of S^{pcon} across movers.

[8] For example, if a person moves from pcon A to B in 2018, for his or her polarisation score in 2020 (i.e., post-move), ρr(i,t) captures any specific effects associated with political polarisation levels in the two years following a move. For 2016 (i.e., pre-move), ρr(i,t) would capture any polarisation effects in the two years before the move.

Table 5. Overview of the Variables in the Event-Study Specification

Variable	Explanation
y_{it}	The outcome for person i at wave t, representing the difference in polarisation score attributable to the pcon.
$\tilde{\alpha}_i$	The combined individual fixed effect capturing individual characteristics and pcon-specific effects ($\alpha_i + \gamma_{o(i)}$) into a single fixed effect, due to the issue of collinearity between both for non-movers (since they only have one pcon, $\gamma_{o(i)}$ would be perfectly collinear with α_i).
$\theta_{r(i,t)}$	The parameter of interest that measures the response of movers' polarisation score to differences in average polarisation levels between their new and old pcon: It captures how much pcon-level factors influence individual-level polarisation scores after the move.
$\hat{\delta}_i$	The sample analogue of the difference in average outcomes between destination and origin pcons, i.e., the change in average political polarisation associated with the move.
τ_t	Wave fixed effect capture common effects that apply to all voters during a specific wave.
$\rho_{r(i,t)}$	These wave-relative-to-move fixed effects capture specific effects considering the time interval between a person's move and each wave. The value of r(i,t) depends on the specific wave and the wave of the voter's move.
ε_{it}	The error term or residual, representing the unobservable factors and random variation.

Notes: Own table explaining the variables in (6) for the event-study methodology by Cantoni and Pons (2022).

If geographic heterogeneity in polarisation is entirely driven by individual characteristics, then post-move changes in polarisation will be uncorrelated with differences in average polarisation levels across pcons of origin and destination. Conversely, if this heterogeneity is attributable to contextual factors, then movers' polarisation will converge toward the average in the destination pcon. Similar to y_{it}^{scaled}, the pattern of estimated effects $\theta_{r(i,t)}$ offers indirect testing of this assumption: if move-induced changes in pcon characteristics cause changes in movers' behaviour, then $\theta_{r(i,t)}$ should be approximately flat in all pre-move waves $r(i, t) < 0$. For post-move waves $r(i, t) \geq 0$, $\theta_{r(i,t)}$s describe the extent to which polarisation scores adjust to the difference in average outcomes between pcons of destination and origin. A discontinuity in the level of $\theta_{r(i,t)}$ after the move at $r(i, t) = 0$ indicates how much pcon-level factors influence individual-level polarisation scores. The larger the jump on move, the greater the share of variation attributed to pcon, and the smaller the share attributed to individuals. Moreover, the pattern of post-move coefficients can illuminate the underlying mechanisms: effects that appear suddenly on move and then remain stable suggest that discrete factors that are easy to get accustomed to are important drivers of polarisation change while effects that increase over time underscore the importance of "slow-moving" factors like the influence of peer effects.

Despite the flexibility given by the individual and relative wave fixed effects, a few restrictive assumptions about the model have to be made. First, like in other studies using movers to estimate value-added models, the crucial identifying assumption required to uncover unbiased estimates from equation (6) is that changes in individual drivers of polarisation scores for movers do not correlate systematically with differences in average outcomes between their new and old pcon. Importantly, the influence of individual factors that do not change over time is captured by the individual fixed effects, so I do not need to assume that the level of individual factors is uncorrelated with pcon differences. For instance, the possibility that Lab leaners sort to Lab-dominated pcons does not threaten the identification. What does is if people whose preferences converge to Lab over time disproportionately follow this trajectory or if people who become more politically polarised respond by moving to highly polarised pcons (i.e., residential sorting). Gradual changes in individual drivers of movers' behaviour that correlate with the outcomes would appear as pre-trends in the event-study analysis. I find some evidence for pre-trends and heightened or lowered polarisation scores pre-move, which indicates that the event-study estimates might also capture underlying changes in movers' individual characteristics.

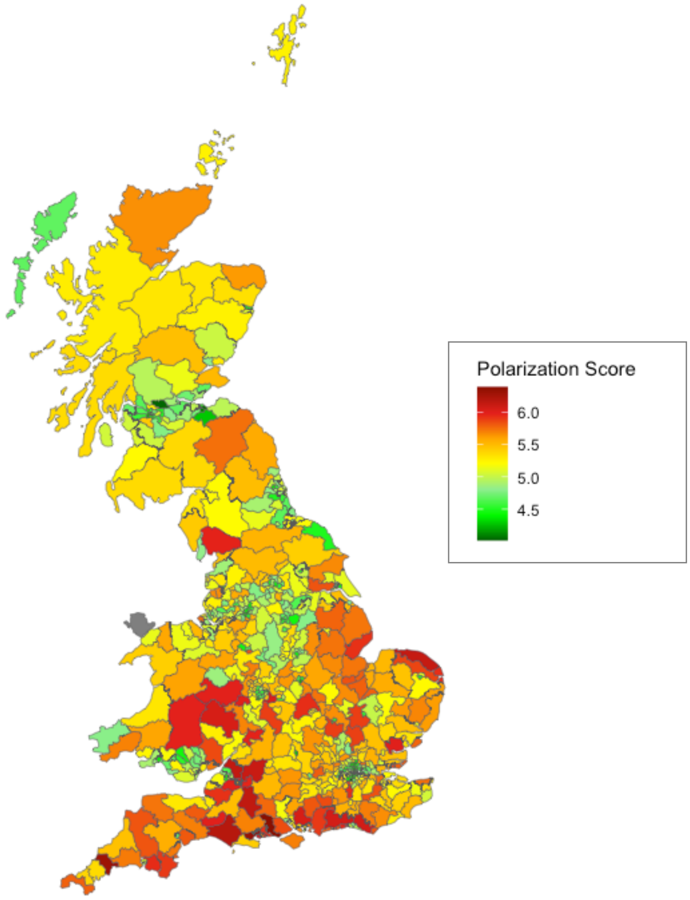
I check the robustness of our results by excluding voters below 30 or above 65, who may be affected by particularly impactful shocks such as entering or exiting the job market. I further check robustness for narrower observation periods, different time periods and a larger geographic entity. Reassuringly, the event study results remain similar to my results in V (see Table B1, Appendix B). I do not have any direct way to test for the presence of shocks to movers' polarisation uptake that coincide exactly with the year of the move or take place in the following years, and that also correlate with outcome differences between origin and destination. However, sudden shocks that are uncorrelated with old-minus-new pcon outcome differences are orthogonal to the state fixed effects γ. Thus, they simply enter the error term ε_{ijt} and do not threaten the validity of our estimates (Cantoni and Pons 2022). A second implication is that pcon fixed effects estimated based on movers of different race, gender, and age should be of similar magnitude. I test this implication by looking at the different demographic subgroups of young-old, male-female and educated-uneducated. Further, I must assume that movers and nonmovers face identical pcon effects γ. If movers differ from nonmovers in ways that alter the relevant pcon effects or if pcon effects also capture pcon-specific deviations from the average fixed effects for wave relative to move $\rho_{r(i,t)}$ (e.g., due to cross-pcon variations in regional identity), then the decomposition between pcon- and individual-level determinants of polarisation change only applies to movers, and not to the rest of the population.

V. Results

A. Local Polarisation: Descriptive Analysis

Figure 1 shows the average political polarisation levels for each of the 632 pcons based on the average wave score for the 19 waves between 2014 and 2021. In addition, Figure C1 in the

Figure 1. Local Political Polarisation in the UK from 2014 to 2021



Notes: Based on the individual LPI scores for waves 2 to 20 which are averaged for each wave across all movers/nonmovers. For the map, a simple average of all wave averages is used (each wave's weight = 1/19).

Appendix C shows the maps for wave 2 in 2014 and wave 20 in 2021 which illustrates the stark increase in polarisation levels across the UK during this observation period. As can be seen, highly polarized pcons are predominantly found in the English countryside of South-West England and East England, however, they are less prevalent in Scotland and urban areas like London and the former "Red Belt," which used to be the stronghold of traditional, working-class Lab voters around the cities of Liverpool and Manchester. Thus, the map reveals a light North-versus-South and a stark City-versus-Countryside divide. Overall, the average pcon polarisation level increased by 21.72% from 4.81 to 5.86 between 2014 and 2021, due to an increase in AP from 5.21 to 5.99 (+14.96%) and more so in IP from 4.41 to 5.73 (+29.77%). The increase in IP shows the public recognition of the aforementioned movement of both parties away from the political centre to their traditional positions. Over the 2014-2021 period, mean overall political polarisation is 5.17 (AP = 5.52; IP = 4.83). The top 10% most polarised pcons all exceed values of 5.92 with the highest polarised pcon being New Forest West in South England with 6.39. The bottom 10% are all below 4.53 with Mitcham and Morden in Greater

London being the least polarised pcon with 4.02. Scottish pcons score on average 4.97 (AP = 5.48; IP = 4.65), Welsh 5.17 (AP = 5.66; IP = 4.90), English 5.24 (AP = 5.66; IP = 4.92) and London pcons 5.09 (AP = 5.54; IP = 4.79).

B. Event Study: Overall Trends (H1)

My main findings from the event-study results are displayed in Table 6 reporting the regression results for differences between higher and lower polarised pcons of different magnitude, and Figure 2 showing the plots for the estimated $\theta_{r(i,t)}$ coefficients from equation (6) for all movers, for movers to the top 10% and for movers to the bottom 10% of polarised pcons. The 95 percent confidence intervals are constructed from robust standard errors. The plot (Panel A) reveals no correlation between pre-move polarisation change and old-minus-new-pcon differences in average polarisation levels: Estimates of $\theta-11$ to $\theta-1$ are mostly close to zero and statistically insignificant[9]. This indicates that movers are not systematically preceded by gradual changes in individual determinants of polarisation change (e.g., increases in political activism before moving to a highly polarised pcon) which would complicate the causal interpretation of post-move estimates. As aforementioned, looking at waves at and beyond the wave of move is important for two reasons: An immediate jump or drop in polarisation indicates that the adjustment of movers' polarisation change is complete by the first post-move wave due to institutional and macro factors (place effects); a change later on would suggest the influence of factors that take more time to materialise (peer effects) (Finkelstein et al. 2016).

The results in Table 6 do not report consistent findings (Table D2, Appendix D provides all regression results in detail). Estimates when comparing the top 5%-bottom 5% of pcons and the values for θ_5 report high standard errors and inconsistent estimates, potentially due to smaller sample sizes for these regressions. However, results for the fixed-effect regressions for θ_0 from top 50% to 10% of most polarised pcons (and from bottom 50% to 10% of lowest polarised pcons) suggest results between 0.073 and 0.283 (-0.092 and -0.249 respectively), meaning 7.3% to 28.3% (or 9.2% to 24.9%) of the post-move polarisation changes would be explained by the difference in polarisation levels between the new and the old pcon (if the results were significant). For my main analysis, the pattern of $\theta_{r(i,t)}$ does not jump discretely at the first post-move wave and remains insignificant afterwards. The insignificance of a move on individual polarisation scores immediately (θ_0=-0.042; p=0.646) and long-term (θ_5=0.064; p=0.645) confirms my first hypothesis (H1a) that moving alone does not change individual polarisation.

[9] I focus my analysis on the range from $\theta-5$ to $\theta+5$ as the number of respondents decreases sharply the further away from of $\theta = 0$ due to the average number of waves for a mover being only 8.43.

Table 6. Regression Results of $\theta_{r(i,t)}$ for Movers

	Top 50% / Bottom 50%	Top 25% / Bottom 25%	Top 10% / Bottom 10%	Top 5% / Low 5%
Estimate θ_0 (SD)	0.073 (0.144)	0.226 (0.188)	0.283 (0.304)	0.147 (0.428)
	-0.225 (0.153)	-0.092 (0.217)	-0.249 (0.346)	-0.963 (0.526)’
Estimate θ_5 (SD)	0.081 (0.201)	0.335 (0.273)	0.721 (0.540)	-0.684 (0.813)
	0.320 (0.240)	0.234 (0.384)	-1.107 (0.616)’	-0.994 (0.980)*
Overall difference	0.743	1.184	1.583	1.800

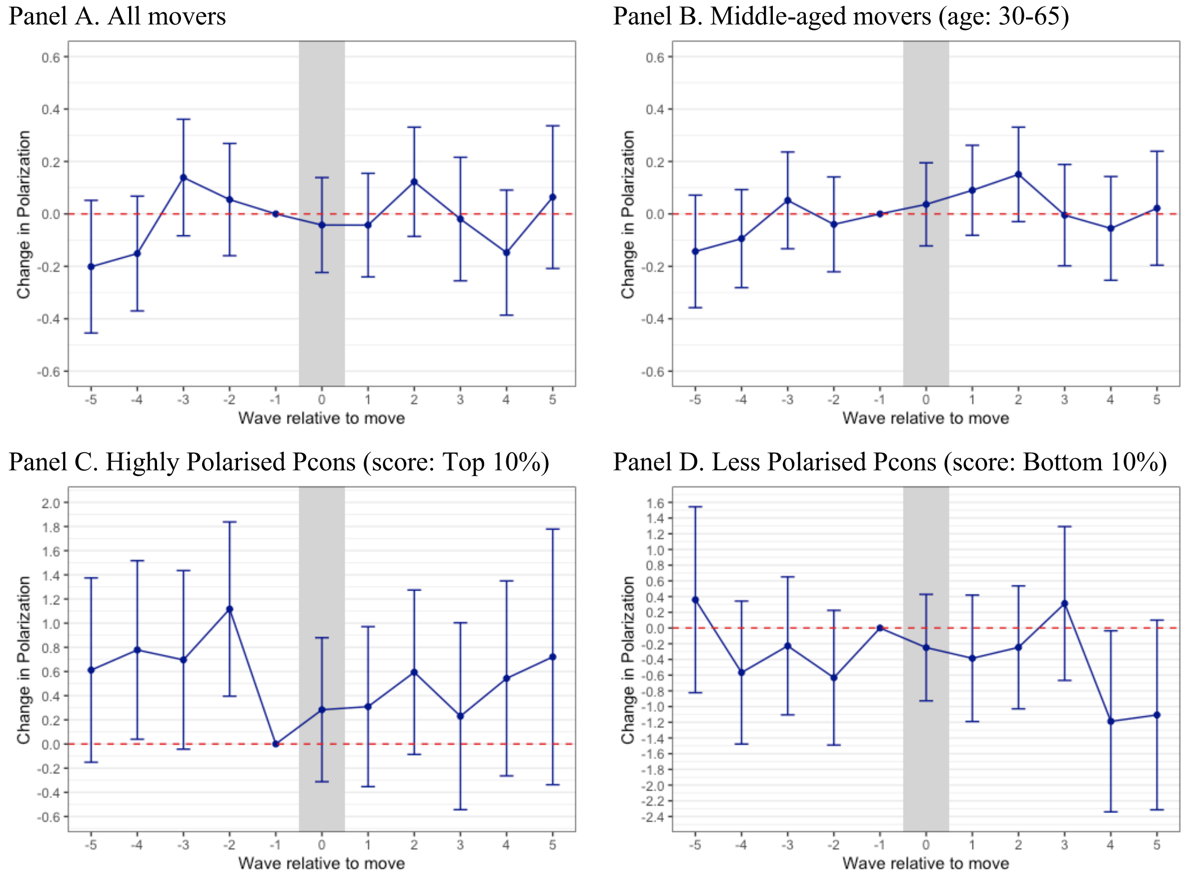
Notes: Each panel in this table replicates the event-study regressions from (6) for different subgroup, being 312 pcons for each group (N_{top50} = 972/N_{low50}= 856 movers) in column 1; 156 pcons ($N_{top/low25}$ = 538/455) in 2; 63 pcons ($N_{top/low10}$ = 228/219) in 3, and 36 pcons ($N_{top/low5}$ = 115/108) in 4. Overall difference is computed via the difference in old-versus-new pcon averages, $\hat{\delta}_i = \bar{y}_{top} - \bar{y}_{bottom}$. Significance levels: ‘p=0.1; *p=0.05.

Nonetheless, my hypotheses H1b and H2b both have to be rejected at the p = 5%-level. The plots show a small positive jump for θ_0 of 0.284 when moving into highly polarised regions (H1b) as well as a small negative drop of -0.249 when moving to less polarised regions (H1c), but the results are not significant (p=0.351 for H1b; p=0.471 for H1c). An overview of all hypotheses and the testing results are found in Table D1 in Appendix D. All findings are robust when excluding younger and older people (see Figure 1, Panel B). I further find no significant results when looking at AP and IP separately. The fact that coefficients do also not increase over time after moving in the new pcon (e.g., θ_5) suggests that peer effects or other factors involving slow changes are not driving post-move adjustments of polarisation for the average mover. Moreover, the pcons in Figure 2 show a positive (top 10%) and negative (bottom 10%) polarisation change trend pre-move which would suggest higher and lower polarisation scores respectively while still being in the old pcon, implying that the post-move levels may reflect the continuation of pre-existing trajectories in polarisation. Put differently, movers display changes in polarisation in anticipation of the move which could be evidence for residential sorting, i.e., an increased (decreased) individual polarisation level is followed by a move to a high (low) polarisation region.

C. Event Study: Partisan Trends (H2-H3)

While moving in general does not seem to have a significant effect, the effect for partisan mover might be different. After all, having a salient party identity and moving to a pcon dominated by the opposing party might lead to stronger animosity (or its dismantling) in the feelings towards opposing partisans. Figure 3 shows the event-study plots for each possible combination of Lab and Con partisans moving. When moving into a pcon that is dominated by

Figure 2. Event-Study Plots for Polarisation Change: Main Analysis



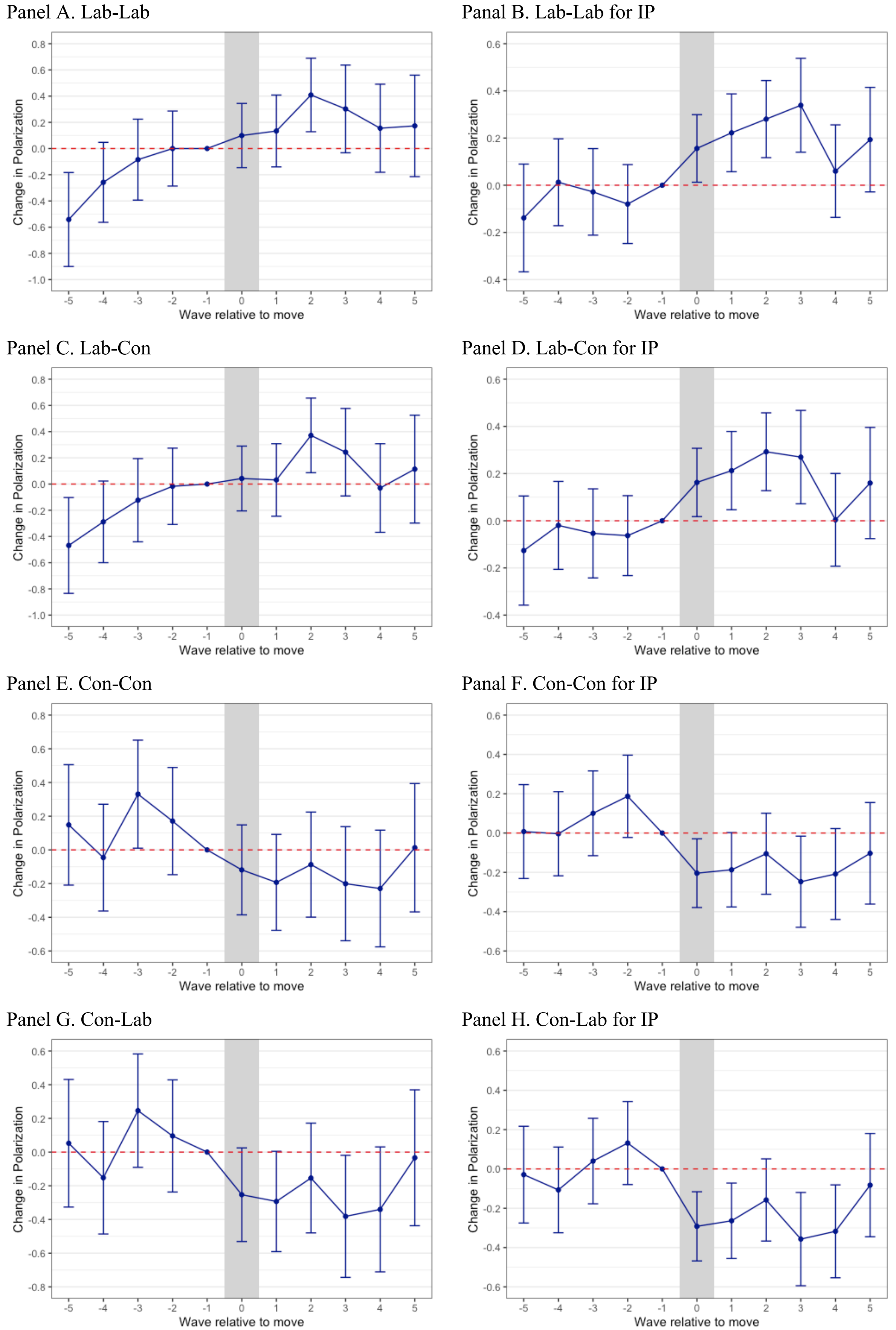
Notes: The figures plot estimates of $\theta_{r(i,t)}$ and 95 percent confidence intervals from event-study specification (6). The dependent variable y_{it} is the change in polarisation to one respondent i for survey wave t. For each mover, $\hat{\delta}_i$ is constructed using the difference in average polarisation level in the new minus old pcon across all waves.

the own party, Lab report slightly higher polarisation scores and Con slightly reduced polarisation scores (H2a + b). These results are insignificant overall (see Table D3, Appendix D), but significant when looking at IP (see Figure 3). The same trends are found when looking at party leaners moving to pcons dominated by the opposing party (H3a + b). Moving to a Con-dominated pcon, Lab leaners seem to significantly increase their IP level due to the move (Lab-Lab: 0.161; Lab-Con: 0.166) while Con leaners moving to Lab-dominated pcons seem to significantly decrease it (Con-Con: -0.213; Con-Lab: -0.300). Thus, H2a stating Lab leaners increase their polarisation in the presence of other Lab leaners and H3b that Con leaners decrease their polarisation in the presence of Lab leaners are partially accepted, but H2b (i.e., Con leaners moving to Con pcons leads to a polarisation score increase) and H3a (i.e., Lab leaners moving to Con pcons leads to a polarisation score decrease) are rejected at the 5%-level.

D. Event Study: Demographic Subgroups Trends (H4-6)

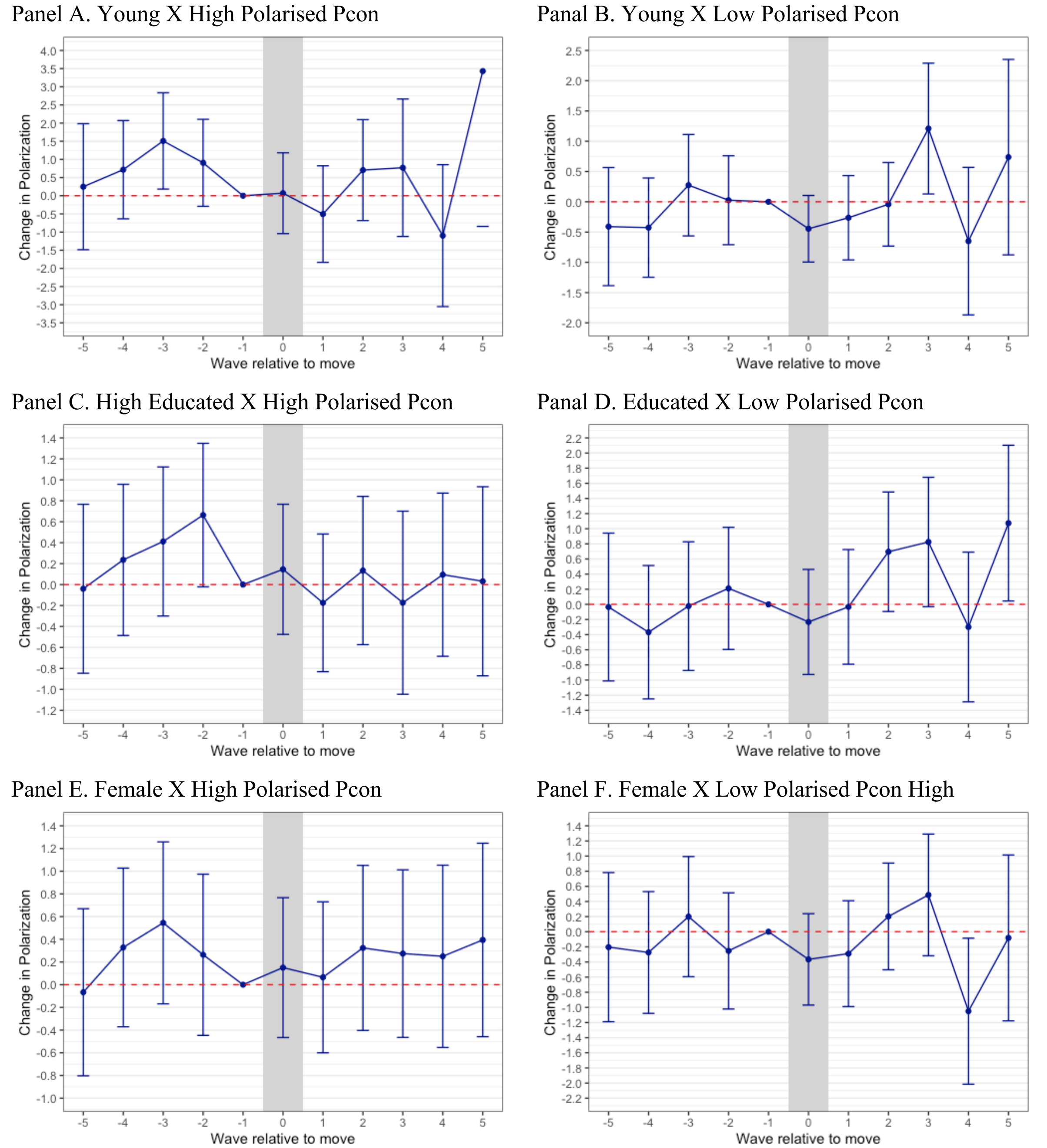
Lastly, the results in Figure 3 plots the results when examining the differences for younger (H4), university educated (H5) and female movers (H6) but also reports no significance when

Figure 3. Event-Study Plots for Polarisation Change: Partisans



Notes: Same computation procedure for Figure 2; Lab and Con pcons when the relevant vote share is >50%.

Figure 4. Event-Study Plots for Polarisation Change: Young, Educated, Female Movers



Notes: Same computation procedure for Figure 2. Young movers are movers under 30 ($N_{top/low25}$ = 67/218), female movers are all women ($N_{top/low25}$ = 272/231) and high educated are all people with an undergraduate or postgraduate degree ($N_{top/low25}$ = 251/302).

moving into either higher polarised (top 25%) or lower polarised (low 25%) pcons (see Table D3 and D4 for regression results and Figure D4 for the plots for older, lower educated and male subgroups, Appendix D). All three subgroups show an increasing pre-move trend that is not matched by the levels post-move when moving to a high polarised pcon, suggesting almost the reverse effect that moving halts the gradual, individual polarisation increase. For moving to a lower polarised pcon, the effects and trends remain pretty consistent around 0, showing no significant change in polarisation due to individual or contextual factors.

VI. Discussion

I have assessed the extent and manner in which British citizens moving to a different pcon within the UK between 2014 and 2021 alter their evaluations of the policy positions of the opposing political party (ideological dimension) and their sentiments toward individuals associated with that party (affective dimension) among supporters of the Labour and Conservative parties. Conceptualising both dimensions into a novel local polarisation measure (LPI), I find no significant evidence that geographic variation in the change of political polarisation is due to pcon-specific like the communal behaviour towards party leaners within the pcon and unobservable attributes (which might also cancel each other out). The event-study specification – a modified approach based on Finkelstein et al. (2016) – hints that around 20 percent of the change in polarisation is due to move-induced context effects, however, the results lack overall significance.

In general, moving to high polarised pcons (top 50 to 10 percent of the 632 pcons) is linked to an increase in overall average polarisation in the LPI of 0.743 to 1.583 compared to the bottom 50 to 10 percent of least polarised pcons. These changes are thus mainly attributable to fixed characteristics of people that they carry with them when they move. Thus, personal determinants of polarisation outcome will continue to hold greater significance. This is supported by some evidence for residential sorting based on significant pre-trends for different subgroups of movers (younger, older, less educated, male, high polarisation movers). Among these specific subgroups, individuals who relocate appear to anticipate shifts in polarization to some extent. This implies that relocations to constituencies with high (low) levels of polarization are preceded by increased (decreased) changes in individual polarization levels prior to the move.

Further, when looking at only the ideological component in the LPI which constitutes 50 percent of the individual polarisation attribution, I find significant results for party leaners (i.e., partisans and people leaning Labour or Conservative) when moving into pcons dominated by the same or the opposing party: For Labour leaners pcon context seems to explain a share in the increase (around 16 percent), for Conservative leaners a share in the decrease (around 20 to 30 percent). All these results are not replicated when singularly looking at the affective component and are stable across a number of robustness checks excluding certain waves, years, or age groups of movers (see Table B1, Appendix B). Overall, my findings do not indicate that pcon-side factors exert a more significant influence on geographic variation than what conventional wisdom may propose, however, they do exert an influence when looking at selected subgroups, in particular for movers with a salient partisan identity.

Furthermore, as stated in the introduction, my analysis of local political polarisation over time and space in the observation period from 2014 to 2021 – falling in a period I categorise as the third wave in post-war political polarisation – provides the most comprehensive survey-based comparison on (local) polarisation in the UK to date. The results show that the UK experienced a stark increase in average political polarisation levels based on the LPI measure of 21.72% from 4.81 to 5.86 for both AP from 5.21 to 5.99 (+14.96%) and IP from 4.41 to 5.73 (+29.77%) across all subgroups and most pcons in the electorate. While for the event-study specification, the polarization scores are averaged across all waves to construct a local polarization map of the UK for individuals who relocated (see Figure 1), the computation of the LPI can further provide a nuanced overview on the development for the UK (see Appendix C) which is of research interest in its own right.

The conclusions drawn from this study are subject to certain limitations arising from data constraints and the analytical framework employed resulting in avenues for future research. Firstly, it's important to note that the BESIP dataset has its own limitations, particularly related to the availability of usable participants due to incomplete responses. For instance, out of the total 8,274 movers, the primary analysis includes only around 22.09% of these individuals, specifically 1,828 participants. On average, these included participants have responded across 8.43 waves of data. With three waves per year, each individual is observed on average for less than three years, which may not be sufficient to detect the emergence of long-term contextual effects. The sample of movers is also younger and more educated, and these subgroups exhibit significant pre-trends. Further, for some years, waves of move coincide with years of election or other electoral shocks like the Brexit referendum (wave 6, 13, 20) that might correlate with outcome differences between origin and destination and do not enter the error term ε_{ijt}. Future research should analyse the effects of move dependent on distance or the influence of general elections years on polarisation change.

Secondly, while reducing the British party landscape to the two major parties (i.e., Lab and Con) is best-practice, other research suggests that most European countries including the UK should be seen as multiparty system and LPI therefore assess polarisation for all pairs of parties (Gidron, Adams, and Horne 2023). In fact, about 30% of respondents in the BESIP do not vote for either Lab or Cons across waves as, for example, the SNP wins most pcons in Scotland. Thus, pcons coined as Lab- or Con-dominated may actually be ruled by a third-party MP or being cast as such when the relative vote share is close to 50% for both and the differences thus marginal. I account for this in parts by computing AP based on government membership as a robustness check which includes Lab evaluations of Liberal Democrats for the waves of coalition. Future research should further investigate the role of smaller parties like UKIP or the Brexit party which have likely influenced the political sentiments in the UK.

Thirdly, the operationalization of the LPI measure may not fully capture the underlying latent IP and AP. Recent studies debate extensions of the one-dimensional left-right scale to a measure that incorporates more detailed evaluations on globalist-nativist dynamics, moral foundations or cultural issues (Gidron et al. 2023). Unfortunately, the BESIP data set is limited and does not offer comprehensive questioning for topics outside the left-right scale and a redistribution item like the party evaluations on inflation/unemployment, social services, or nationalisation of the BES. Furthermore, although AP is gauged by evaluating respondents' attitudes toward political parties, the scope is somewhat limited when contrasted with an analysis of affect toward individual party members. Also, the exact linkage between AP and IP is not fully established (Bougher 2017). For instance, European politics are structured by deep underlying cleavages, while the US partisanship has been characterised by less ideological constraint (Hetherington 2009; Reiljan 2020). Investigating and refining the LPI for different datasets like the BES or BSA and countries should thus be the subject of future research.

And lastly, while the event study offers a analysis on the combined influence of all variation in pcon and individual factors away from the isolated analysis of single factors in in distinction from correlated variables in multivariate regressions (Cantoni and Pons 2022), the causes for the underlying changes in pcons cannot be investigated with this empirical specification. While this paper takes a first step towards understanding the origin of local effects on individual's polarisation, future research could broaden the scope of my study by examining the main covariates of average individual and place-based effects to pinpoint the specific factors that contribute to the observed outcome.

Despite these inherent limitations, the current study offers valuable and innovative insights into our understanding of the interplay between contextual and individual-level factors influencing political polarisation at the pcon level within the UK. In the end, my findings suggest that your neighbours and the place you live in cannot be conveniently used as an excuse for the way opposing partisans are perceived. Reflecting on the thesis title, it is not your neighbour who makes you hate Labour (or like Labour, or hate Conservatives, or like Conservatives), so why not give them a chance after all.

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APPENDIX A

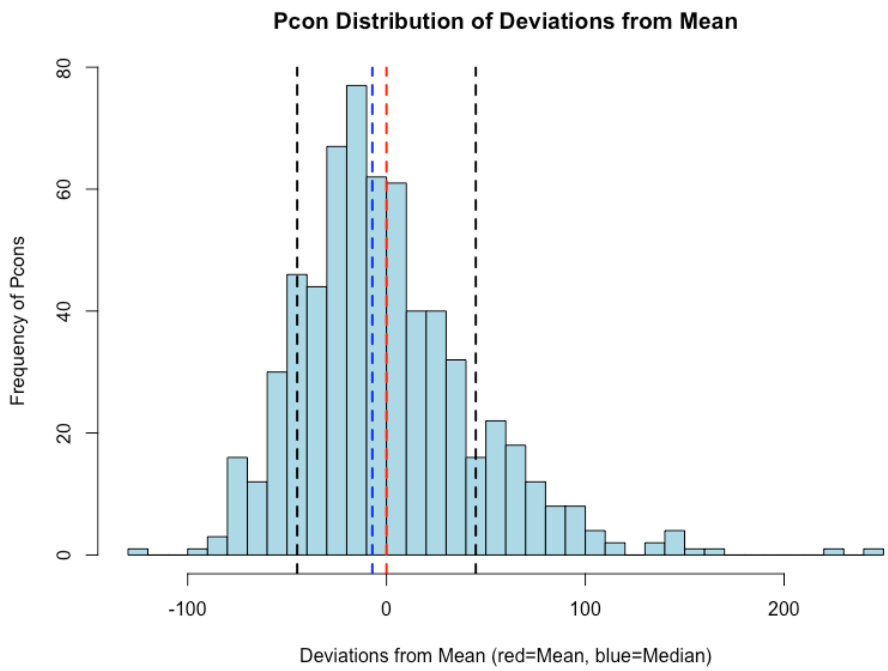
Appendix A includes supporting tables and graphs for the summary statistics in Section III. It includes Table A1 for an overview of top ups and number of people per wave; Figure A2 for the distribution of people over all pcons in reference to the mean, and Table A3 which shows all the questions from the BESIP data set which are used to operationalise the latent concepts.

Table A1. Overview of people and top-ups across the relevant waves

	Wave 2	Wave 3	Wave 4	Wave 5	Wave 6	Wave 7	Wave 8	Wave 9	Wave 10	Wave 11
Total people	30203	27822	31318	31318	30070	30862	33477	30015	30229	30949
Top-Ups	30203	3841	5664	0	318	8326	6467	0	7146	2888
	Wave 12	Wave 13	Wave 14	Wave 15	Wave 16	Wave 17	Wave 18	Wave 19	Wave 20	All waves
Total people	34387	31134	31056	30839	37895	34359	30136	37818	32171	606,058
Top-Ups	1942	8	5205	5132	13757	3575	4947	21	5	99,445

Notes: Waves 1 and 21 are excluded from the sample for safety reasons due to doubling values.

Figure A2. Histogram of the Distribution of Pcons from the Mean



Notes: Own figure computed in R. The dotted red line represents the normalised mean, the dotted blue line the median. The two dotted black lines show the borders of one standard deviation above and below the mean.

Table A3. Overview on the Questions used for the Data Analysis from the BESIP

Measure	Variable	Wording	Scale
Left-right	lr	"In politics people sometimes talk of left and right. Where would you place the following parties on this scale?"	0 = Left, 10 = Right
Like-dislike	partyLikeGrid1	And how much do you like or dislike each of the following parties?	0 = Strongly dislike, 10 = Strongly like
Vote share	generalElection Vote	"And if there were a UK General Election tomorrow, which party would you vote for?"	[1] Conservative [2] Labour ...
Party sentiment	partyId	"Generally speaking, do you think of yourself as Labour, Conservative, Liberal Democrat or what?"	[1] Conservative [2] Labour ...
	partyIdSqueeze[1]	"Do you generally think of yourself as a little closer to one of the parties than to the others? If yes, which party?"	[1] Conservative [2] Labour ...
Trust	trustMPs	How much trust do you have in Members of Parliament in general?	1 = No trust, 7 = A great deal of trust
Redistribution	redist	"Some people feel that government should make much greater efforts to make people's incomes more equal. Other people feel that government should be much less concerned about how equal people's incomes are. Where would you place yourself and the political parties on this scale?"	0 = Government should try to make incomes equal 10 = Government should be less concerned about equal incomes

Notes: Own table based on the relevant variables from the BESIP dataset (the variable column states the variable names in the BESIP). [1]Gets used if partyId = "Don't Know" to add the party leaners to the partisan group in AP computation.

APPENDIX B

Appendix B includes table B1 stating all robustness checks run for the event study specification based on Finkelstein et al. (2016) from section IV.

Table B1. Robustness Checks for the Event Study Model

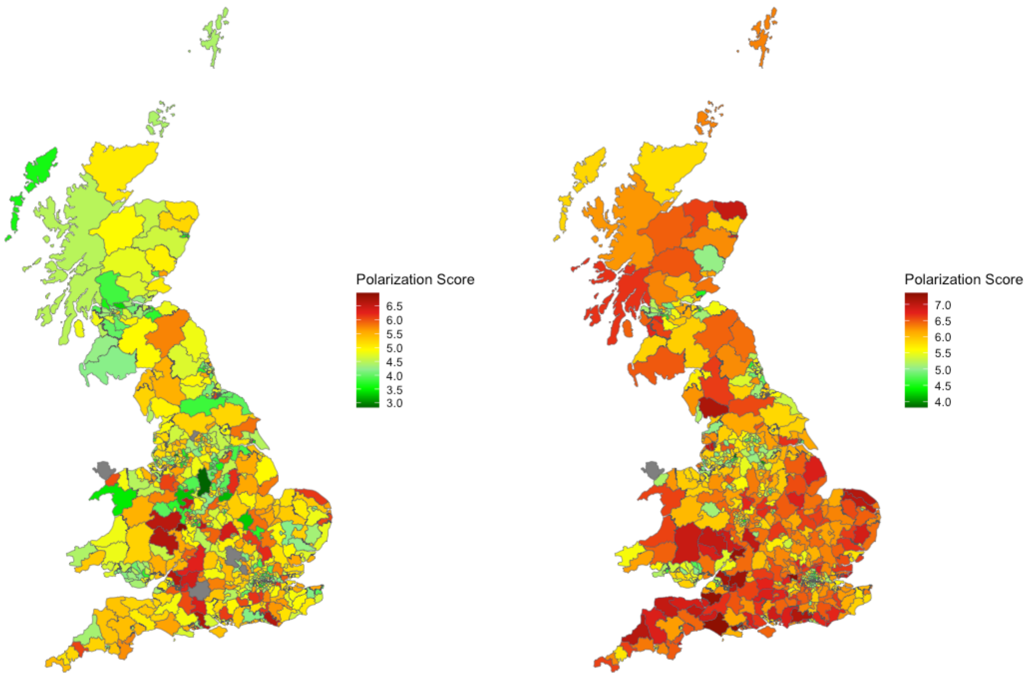
Specification	N at wave of move	Estimate at wave of move: θ_0
(1) Baseline	1307	-0.042 (0.092)
(2) Age 30-65	745	0.076 (0.137)
(3) Without years of General Elections	1086	-0.124 (0.152)
(4) Without years of General Elections or Brexit	956	-0.082 (0.167)
(5) Relative waves -5 to 5	1307	-0.031 (0.009)
(6) Relative waves -3 to 3	1307	-0.033 (0.009)
(7) Relative waves -1 to 1	1307	-0.075 (0.091)
(8) First third of sample only (wave 2-8: 2014 to 2016)	412	-0.056 (0.133)
(9) Second third of sample only (wave 2-8: 2014 to 2016)	508	-0.028 (0.064)
(10) Second third of sample only (wave 2-8: 2014 to 2016)	387	-0.404 (0.097)
(11) Cross GOR movers only	525	-0.345 (0.128)*

Notes: Table reports the share of the difference in polarisation between above and below median pcons for alternative samples and specifications. Columns report the sample size, overall absolute difference in polarisation at wave zero and the jump or drop at the wave which is explained via the place effects ($\theta_{0)}$). Row (2) shows the subsample excluding younger and older people prone to shocks; Rows (3) and (4) exclude years with potential external shocks; Rows (5) to (7) narrow the sample of years for movers to relative years -5 to 5, relative years -3 to 3, and relative years -1 to 1, respectively. Rows (8)-(10) limit the sample to people for different thirds of the observation period respectively, excluding movers whose move year falls outside the time window in question. Lastly, row (11) looks at movers who move not only to a different pcon, but to one of nine Government Office Regions (GORs) being North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East of England, London, South East, South West.

APPENDIX C

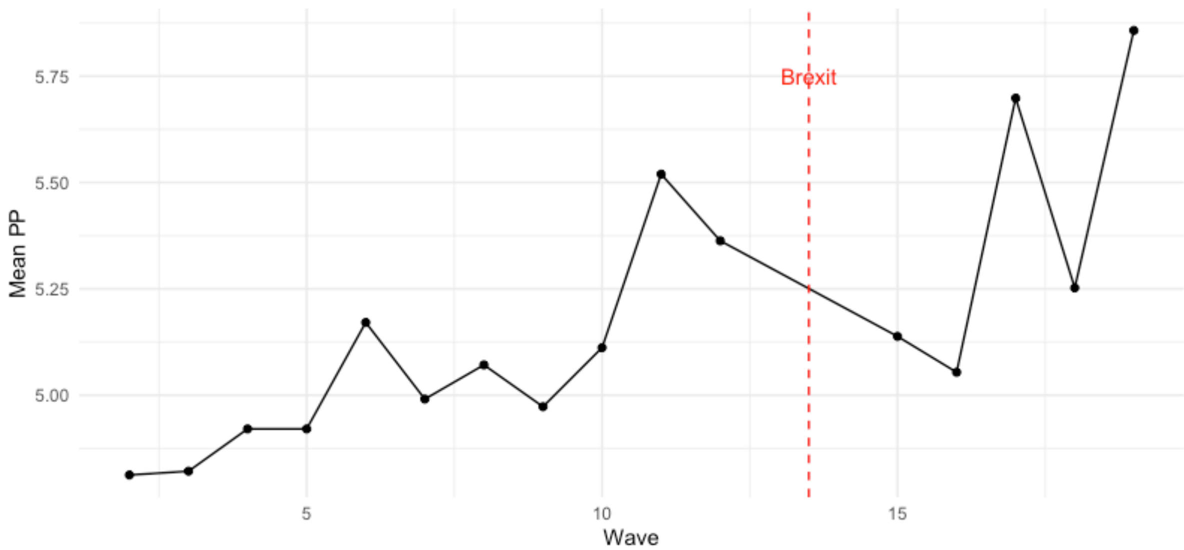
Appendix C includes supporting tables for the results on the LPI in section V. It includes Figure C1 mapping the development of political polarisation for 2014 and 2021; Figure C2 showing the increase of the LPI across time and Figures C3 and C4 plotting the graphs for AP and LP over this time period.

Figure C1. Political Polarisation Levels in the UK for 2014 (left) and 2021(right)



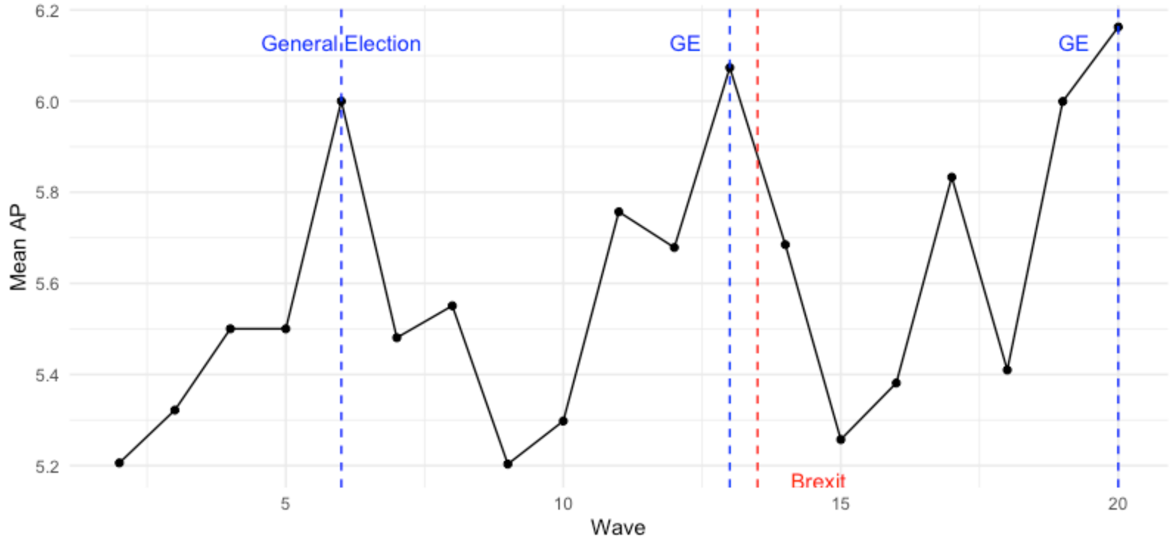
Notes: Own figure computed in R. Based on the LPI scores per pcon for wave 2 and wave 19.

Figure C2. Development of the LPI scores from 2014 to 2021



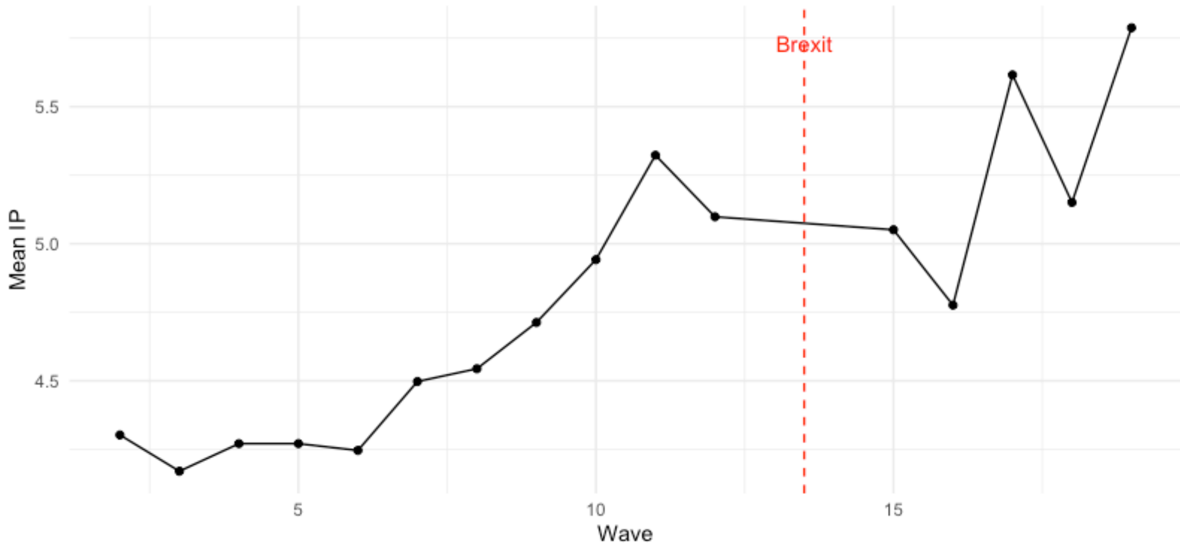
Notes: Own figure computed in R. Based on the LPI scores per wave from wave 2 to 19. The red dotted line presents the 2016 Brexit.

Figure C3. Development of the AP scores from 2014 to 2021



***Notes**:* Own figure computed in R. Based on the AP scores per wave from wave 2 to 19. The blue dotted lines indicate general elections, the red dotted line the 2016 Brexit.

Figure C4. Development of the IP scores from 2014 to 2021



***Notes**:* Own figure computed in R. Based on the IP scores per wave from wave 2 to 19. The blue dotted lines indicate general elections, the red dotted line the 2016 Brexit.

APPENDIX D

Appendix D includes supporting tables and graphs for the result section V. It includes Table D1 showing all tested hypotheses and their testing outcome (accepted, rejected or partially accepted); Table D2 presents the full regression results for the main analysis; Tables D3 to D5 which report all regression results for the analyses, and Figure D6 which presents the event-study plots for older, less educated and male movers (in contrast to younger, high educated and female movers reported in section V).

Table D1. Overview of the Results of the Hypotheses

Hypothesis	Outcome
H1a: Moving in general does not in- or decrease one's polarisation compared to pre-move.	A
H1b: Moving into a highly polarised pcon increases one's polarisation compared to pre-move.	R
H1c: Moving into a less polarised pcon increases one's polarisation compared to pre-move.	R
H2a: Lab leaners moving into a Lab pcon increases their polarisation compared to pre-move.	PA
H2b: Con leaners moving into a Con pcon decreases their polarisation compared to pre-move.	R
H3a: Lab leaners moving into a Con pcon decreases their polarisation compared to pre-move.	R
H3b: Con leaners moving into a Lab pcon decreases their polarisation compared to pre-move.	PA
H4a: Young moving in general does not in- or decrease one's polarisation compared to pre-move.	A
H4b: Young moving into a highly polarised pcon increases one's polarisation compared to pre-move.	R
H4c: Young moving into a less polarised pcon increases one's polarisation compared to pre-move.	R
H5a: Females moving in general does not in- or decrease one's polarisation compared. to pre-move.	A
H5b: Females moving into a highly polarised pcon increases one's polarisation compared to pre-move.	R
H5c: Females moving into a less polarised pcon increases one's polarisation compared. to pre-move.	R
H6a: High educated moving in general does not in- or decrease one's polarisation compared to pre-move.	A
H6b: High educated moving into a highly polarised pcon increases one's polarisation compared. to pre-move.	R
H6c: High educated moving into a less polarised pcon increases one's polarisation compared. to pre-move.	R

Notes: Overview of all the hypotheses tested – acronyms as follows: A – Accepted; PA – Partially Accepted (rejected for Political Polarisation but accepted for either AP or IP); R – Rejected. All tested at $p = 0.05$.

Table D2. Full Regression Results of $\theta_{r(i,t)}$ for Movers: Main Analysis

Wave Relative to Move	Moving in general	N	Moving: Top 10%	N	Moving: Low 10%	N
11 waves pre-move: Estimate θ_{-11}	0.514 (0.194)*	176	1.082 (0.584)'	19	-0.609 (0.861)	17
10 waves pre-move: Estimate θ_{-10}	0.300 (0.181)	197	1.287* (0.567)	25	1.293 (0.912)	17
9 waves pre-move: Estimate θ_{-9}	0.025 (0.157)'	231	0.575 (0.441)	29	0.359 (0.719)	21
8 waves pre-move: Estimate θ_{-8}	-0.027 (0.145)	346	0.453 (0.509)	48	-0.771 (0.719)	29
7 waves pre-move: Estimate θ_{-7}	0.204 (0.135)	405	0.273 (0.440)	61	-0.620 (0.545)	41
6 waves pre-move: Estimate θ_{-6}	-0.370 (0.140)*	322	0.083 (0.421)	51	-1.476 (0.603)*	29
5 waves pre-move: Estimate θ_{-5}	-0.201 (0.129)	500	0.612 (0389)	82	0.360 (0.604)	45
4 waves pre-move: Estimate θ_{-4}	-0.151 (0.112)	684	-0.778 (0.377)*	96	-0.567 (0.464)	64
3 waves pre-move: Estimate θ_{-3}	0.139 (0.113)	672	0.700 (0.368)'	90	-0.228 (0.612)	74
2 waves pre-move: Estimate θ_{-2}	0.055 (0.109)	639	1.112 (0.368)*	74	-0.632 (0.437)	72
1 wave pre-move: Estimate θ_{-1}	0	619	0	72	0	71
Wave of move: Estimate θ_{0}	-0.042 (0.092)	1307	0.284 (0.304)	172	-0.249 (0.399)	152
1 wave post-move: Estimate θ_{1}	-0.043 (0.101)	939	0.309 (0.338)	116	-0.386 (0.411)	105
2 waves post-move: Estimate θ_{2}	0.123 (0.106)	734	0.594 (0.347)'	89	-0.246 (0.399)	94
3 waves post-move: Estimate θ_{3}	-0.020 (0.120)	485	0.230 (0.394)	63	0.312 (0.500)	52
4 waves post-move: Estimate θ_{4}	-0.148 (0.122)	496	0.543 (0.411)	70	-1.188 (0.588)	45
5 waves post-move: Estimate θ_{5}	0.064 (0.139)	392	0.721 (0.540)	48	-1.107 (0.616)*	38
6 waves post-move: Estimate θ_{6}	0.296 (0.183)	188	1.041 (0.629)'	24	-0.660 (0.823)	14
7 waves post-move: Estimate θ_{7}	-0.024 (0.193)	167	0.137 (0.586)	28	0.6622 (0.908)	17
8 waves post-move: Estimate θ_{8}	0.081 (0.164)	229	0.508 (0.573)	29	-.318 (0.684)	20
9 waves post-move: Estimate θ_{9}	-0.502 (0.224)*	105	-0.345 (1.007)	12	-1.635 (0.664)*	15
10 waves post-move: Estimate θ_{10}	-0.065 (0.281)	78	-1.214 (1.363)	6	-0.582 (1.083)	9

Notes: The table reports the event-study estimates for the main analysis in detail. Standard errors are in parenthesis. Significance levels: ‘p=0.1; *p=0.05.

Table D3. Regression Results of $\theta_{r(i,t)}$ for Movers: Partisans

	Lab-Lab:	Lab-Con	Con-Con	Con-Lab
Estimate θ_0 (SD)	0.099	0.042	-0.119	-0.253
Estimate θ_5 (SD)	0.173	0.114	0.013	-0.034
Overall difference	0.268	0.214	0.226	0.250

Notes: Each panel in this table replicates the event-study regressions from (6) for all old-versus-new partisan permutations. The number of people is N_{LabLab} = 863 in column 1; N_{LabCon} = 822 in 2; N_{ConCon} = 897 in 3, and N_{ConLab} = 739 in 4. Overall difference is computed via the difference in new pcon where Lab leaners live in Lab pcons versus old pcon where these Lab leaners lived in Lab- or Con-dominated pcons versus -new pcon averages in column 1 and vice versa for the other columns. Significance levels: ‘p=0.1; *p=0.05.

Table D4. Regression Results of $\theta_{r(i,t)}$ for Movers: Young, Educated, Female Subgroups

	Young: Low Polarised/ High Polarised	Educated: Low Polarised/ High Polarised	Female: Low Polarised/ High Polarised
Estimate θ_0 (SD)	-0.446 (0.281)	-0.232 (0.354)	-0.366 (0.308)
	0.070 (0.568)	0.146 (0.317)’	0.151 (0.314)
Estimate θ_5 (SD)	0.738 (0.824)	1.074 (0.525)*	-0.081 (0.559)
	3.432 (2.182)	0.032 (0.461)’	0.394 (0.435)
Overall difference	0.815	0.560	0.884

Notes: Each panel in this table replicates the event-study regressions from (6) for different demographic subgroups. The number of people is $N_{YoungLow}$ = 218/$N_{YoungTop}$ = 67 in column 1; $N_{HighEducatedLow}$ = 302/$N_{HighEducatedTop}$ = 251 in 2; $N_{MaleLow}$ = 231/$N_{MaleTop}$ = 272 in 3in 3. Overall difference is computed via the difference in old-versus-new pcon averages, $\hat{\delta}_i = \bar{y}_{top} - \bar{y}_{low}$, for each subgroup respectively. Low and high polarised pcons are the top 25% and bottom 25% of polarised pcons. Significance levels: ‘p=0.1; *p=0.05.

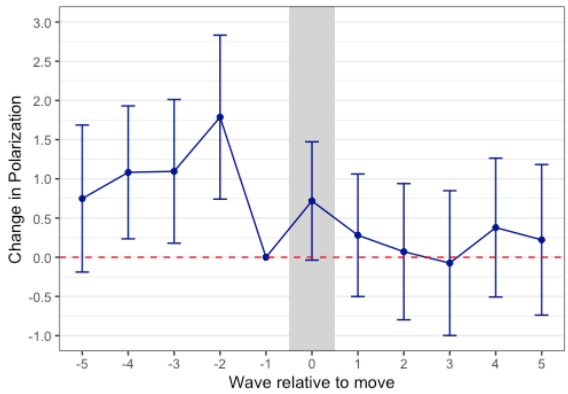
Table D5. Regression Results of $\theta_{r(i,t)}$ for Movers: Old, Uneducated, Male Subgroups

	Old: Low Polarised/ High Polarised	Low Educated: Low Polarised/ High Polarised	Male: Low Polarised/ High Polarised
Estimate θ_0 (SD)	0.125 (0.824)	-0.098 (0.353)	0.258 (0.311)
	0.718 (0.385)’	0.596 (0.318)’	0.182 (0.234)*
Estimate θ_5 (SD)	-0.575 (1.278)	-0.932 (0.890)	0.618 (0.551)
	0.222 (0.490)	0.810 (0.459)’	0.260 (0.347)*
Overall difference	0.248	0.975	0.678

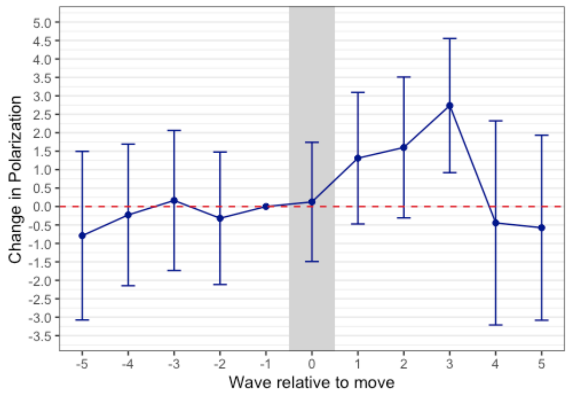
Notes: Each panel in this table replicates the event-study regressions from (6) for different demographic subgroups. The number of people is N_{OldLow} = 59/N_{OldTop} = 209 in column 1; $N_{LowEducatedLow}$ = 179/$N_{LowEducatedTop}$ = 266 in 2; $N_{MaleLow}$ = 224/$N_{MaleTop}$ = 266 in 3. Overall difference is computed via the difference in old-versus-new pcon averages, $\hat{\delta}_i = \bar{y}_{top} - \bar{y}_{low}$, for each subgroup respectively. Low and high polarised pcons are the top 25% and bottom 25% of polarised pcons. Significance levels: ‘p=0.1; *p=0.05.

Figure D6. Event-Study Plots for Polarisation Change: Old, Male, & Uneducated Movers

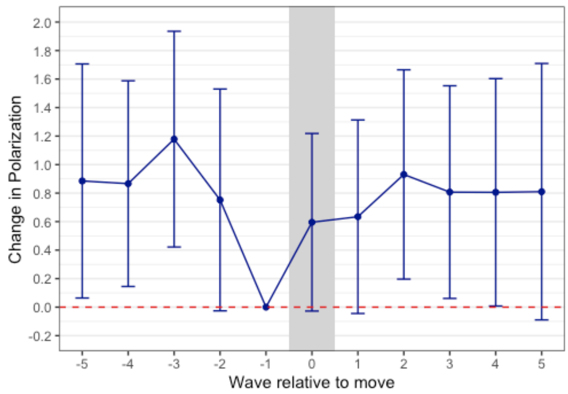
Panel A. Old Movers X High Polarised Pcon



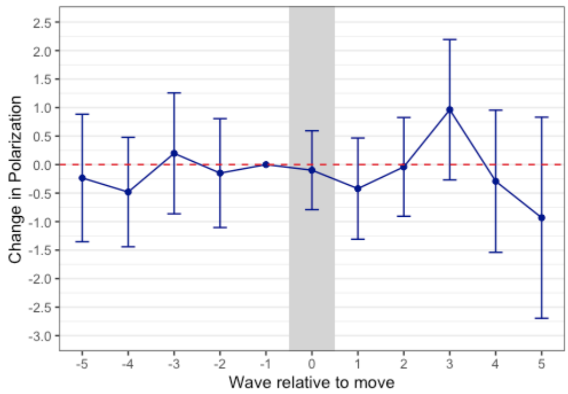
Panal B. Old Movers X Low Polarised Pcon



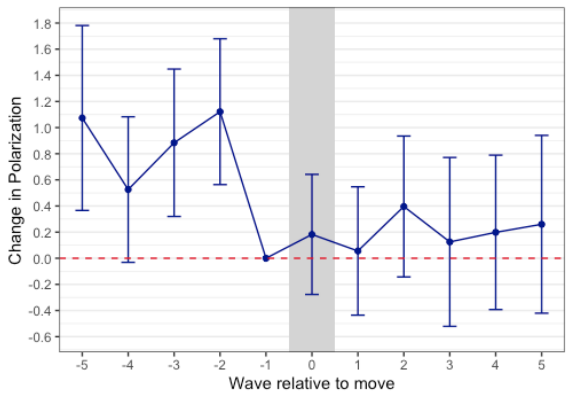
Panel C. Uneducated Movers X High Polarised Pcon



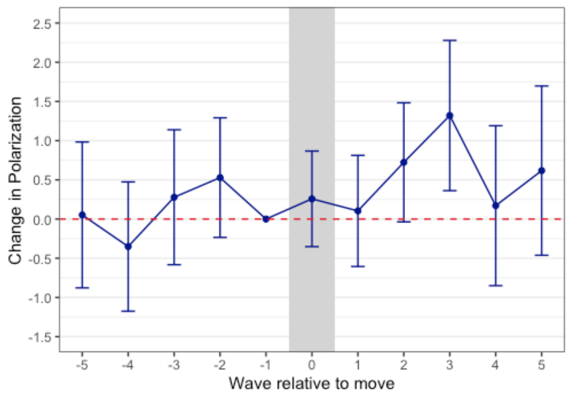
Panel D. Uneducated Movers X Low Polarised Pcon



Panel E. Male Movers X High Polarised Pcon



Panal F. Male Movers X Low Polarised Pcon



Notes: Same computation procedure for Figure 2. Old movers are movers over 65 ($N_{top/low25}$ = 209/59), male movers are all men ($N_{top/low25}$ = 224/266) and high educated are all people with GCSE education or below ($N_{top/low25}$ = 179/302).